Development of Emergency Response Systems by Intelligent and Integrated Approaches for Marine Oil Spill Accidents

by

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ABSTRACT

Oil products play a pervasive role in modern society as one of the dominant energy fuel sources. Marine activities related to oil extraction and transportation play a vital role in resource supply. However, marine oil spills occur due to such human activities or harsh environmental factors. The emergency accidents of spills cause negative impacts on the marine environment, human health, and economic loss. The responses to marine oil spills, especially large-scale spills, are relatively challenging and inefficient due to changing environmental conditions, limited response resources, various unknown or uncertain factors and complex resource allocation processes. The development of previous research mainly focused on single process simulation, prediction, or optimization (e.g., oil trajectory, weathering, or cleanup optimization). There is still a lack of research on comprehensive and integrated emergency responses considering multiple types of simulations, types of resource allocations, stages of accident occurrence to response, and criteria for system optimizations. Optimization algorithms are an important part of system optimization and decision-making. Their performance directly affacts the quality of emergency response systems and operations. Thus, how to improve efficiency of emergency response systems becomes urgent and essential for marine oil spill management. The power and potential of integrating intelligent-based modeling of dynamic processes and system optimization have

been recognized to better support oil spill responders with more efficient response decisions and planning tools. Meanwhile, response decision-making combined with human factor analysis can help quantitatively evaluate the impacts of multiple causal factors on the overall processes and operational performance after an accident.

To address the challenges and gaps, this dissertation research focused on the development and improvement of new emergency response systems and their applications for marine oil spill response in the following aspects: 1) ***Realization of coupling dynamic simulation and system optimization for marine oil spill responses* -** The developed Simulation-Based Multi-Agent Particle Swarm Optimization (SA-PSO) modeling investigated the capacity of agent-based modeling on dynamic simulation of spill fate and response, particle swarm optimization on response allocation with minimal time and multi-agent system on information sharing. 2) ***Investigation of multi-type resource allocation under a complex simulation condition and improvement of optimization performance*** - The improved emergency response system was achieved by dynamic resource transportation, oil weathering and response simulations and resource allocation optimization. The enhanced particle swarm optimization (ME-PSO) algorithm performed outstanding convergence performance and low computation cost characteristics integrating multi-agent theory (MA) and evolutionary population dynamics (EPD). 3) ***Analysis and evaluation of influencing factors of multiple stages of spill accidents based on human***

factors/errors and multi-criteria decision making - The developed human factors analysis and classification system for marine oil spill accidents (HFACS-OS) framework qualitatively evaluated the influence of various factors and errors associated with the multiple operational stages considered for oil spill preparedness and response (e.g., oil spill occurrence, spill monitoring, decision making/contingency planning, and spill response). The framework was further coupled with quantitative data analysis by Fuzzy-based Technique for Order Preference by Similarity to Idea Solution (Fuzzy-TOPSIS) to enhance decision-making during response operations under multiple criteria. 4) ***Development of a multi-criteria emergency response system with the enhanced optimization algorithm, multi-mode resource transportation and allocation and a more complex and realistic simulation modelling -*** The developed multi-criteria emergency response system (MC-ERS) system integrated dynamic process simulations and weighted multi-criteria system optimization. Total response time, response cost and environmental impacts were regarded as multiple optimization goals. An improved weighted sum optimization function was developed to unify the scaling and proportion of different goals. A comparative PSO was also developed with various algorithm-improving methods and the best-performing inertia weight function. The proposed emergency response approaches in studies were examined by oil spill case studies related to the North Atlantic Ocean and Canada circumstances to analyze the modelling performance and evaluate their practicality and applicability. The developed optimization algorithms were tested by benchmarked functions, other optimization algorithms, and an oil spill case.

The developed emergency response systems and the contained simulation and optimization algorithms showed the strong capability for decision-making and emergency responses by recommending optimal resource management or evaluations of essential factors. This research was expected to provide time-efficient, and cost-saving emergency response management approaches for handling and managing marine oil spills. The research also improved our knowledge of the significance of human factors/errors to oil spill accidents and response operations and provided improved support tools for decision making. The dissertation research helped fill some important gaps in emergency response research and management practice, especially in marine oil spill response, through an innovative integration of dynamic simulation, resource optimization, human factor analysis, and artificial intelligence methods. The research outcomes can also provide methodological support and valuable references for other fields that require timely and effective decisions, system optimizations, process controls, planning and designs under complicated conditions, uncertainties, and interactions.

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LIST OF ABBREVIATIONS

ABL	Agent behavior layer
ABM	Agent-based modeling
BAT	Best available technology
BB	Barebones theory
BPSO	Binary particle swarm optimization
BBPSO	Barebones PSO
CCG	Canadian Coast Guard
CERCs	Coastal emergency response centers
CFI	Canada Foundation for Innovation
C-PSO	Comparative particle swarm optimization
CPU	Central processing unit
CREATE	Collaborative research and training experience program
DSS	Decision support system
DFO	Fisheries and Oceans Canada
DWH	Deepwater Horizon oil spill
EA	Evolutionary algorithm
EPD	Evolutionary popular dynamics
ERS	Emergency response system
FTA	Fault tree analysis
FTL	Full-truckload truck

Fuzzy-TOPSIS	Fuzzy set theory-based technique for order preference by similarity to ideal solution
GA	Genetic algorithm
GIS	Geographic information system
HFACS	Human factors analysis and classification system
HFACS-OS	HFACS model for offshore oil spill accidents
ICS	Incident Command System
ISB	In-situ burning
ITOPF	International Tanker Owners Pollution Federation Limited
LTL	Less-than-truckload truck
MA	Multi-agent theory
MAPSO	Multi-agent particle swarm optimization
MAS	Multi-agent system
MCDM	Multi-criteria decision-making
MC-ERS	Multi-criteria emergency response system
ME-PSO	Enhanced particle swarm optimization based on multi-agent system and evolutionary population dynamics
MIS	Marine Information System
MOO	Multi-objective optimization
MPRI	Multi-partner research initiative
MUN	Memorial university of Newfoundland
NEBA	Net environmental benefit analysis
NIS	Negative ideal solution

NL	Newfoundland and Labrador
NOBE	Newfoundland offshore burn experiment
NRDA	Natural resource damage assessment
NRPOP	Northern region persistent organic pollution control laboratory
NSERC	Natural Sciences and Engineering Research Council of Canada
ORSs	Onshore resource storages
PAH_d	Concentration of dissolved PAH
PAHs	Polycyclic Aromatic Hydrocarbons
PAHs	Polycyclic aromatic hydrocarbons
PIS	Positive ideal solution
POL	PSO optimization layer
ppm	Parts per million
PSO	Particle swarm optimization
SA-PSO	Simulation-based multi-agent particle swarm optimization
SDS	Shortest distance selection approach
SIL	Social interaction layer
TFN	Triangular fuzzy numbers
TOPSIS	Technique for order preference by similarity to ideal solution
U.S.	United States
UAV	Unmanned aerial vehicle
VECs	Valued ecosystem components
WAD	Work-as done
WAI	Work-as imagined

WSM Weighted sum model

LIST OF SYMBOLS

$(\%)\mathrm{Ev}$	Percentage of evaporated oil
$\overrightarrow{\mathrm{V_0}}$	Turbulent fluctuation of the drift velocity
$\overrightarrow{\mathrm{V_c}}$	Depth-averaged current velocity
$\overrightarrow{\mathrm{V_w}}$	Wind velocity
$\vec{\mathrm{V}}$	Advection or drift velocity
$\widetilde{\mathrm{A}}$	Fuzzy set
$\mathrm{x}_{\widetilde{\mathrm{A}}}(\mathrm{t})$	Triangular membership function
$\mathrm{A_{k,t}}$	Area of spill *k* at time t
A	Spill area
A_t	Spill area at time t
AC	Administrative costs
AD	Additive dollar amount for impacted habitat
Asph	Percentages of asphaltenes content
B	Base rate
B_{volume}	Unit volume of booms
C	Cost
$C_{boom-setup}$	Operation cost of boom setup
$C_{highway}$	Cost of highway transportation
$C_{i,j}^m$	Unit cost of a type *m* truck from ORS *i* to CERC *j*
C_j^n	Unit cost of type n vessels from CERC j to the spill site

$C_{response}$	Operation cost of spill response by skimmers
C_{total}	Total response cost
$C_{waterway}$	Cost of waterway transportation
c, d	Empirical parameters for specific oil
c_1, c_2	Learning factors from the personal and global best particles
C_{0e}	Oil concentration after absorption balance
C_3	Final fraction water content
C_A, C_B	Non-dimensional constant
C_C	Constant for specific oil
$C_h(t)$	Amount of a hydrocarbon component at time t
d_0	Oil droplet diameter
d_s	Sediment particle diameter
D_s	Depth of sediments on the beach
DE	Dispersion rate
Df_t	Descending factor
DV	Dispersed oil
EL	Environmental loss
ETS	Endangered/threatened species
$f_{ORR_{sk,i,t}}$	Net oil recovery rate of skimmer *i* at time *t*
FD	Dispersion rate
F_{emul}	Fractional water content
F_{emul}^{final}	Maximum water volume that can be incorporated in the emulsion

$F_{score}^{Variant}$	The overall score of a PSO variant
$f_m(x)$	Objective function for a minimum value
$f_m^{lb}(x)$	Lower boundary of $f_m(x)$
$f_m^{ub}(x)$	Upper boundary of $f_m(x)$
FE	Evaporation rate
FV	Evaporated oil
F_{wc}	Fraction of the sea surface hit by breaking waves
G_{best} (p_{gd})	Best solution of all particles
H	Significant wave height
$iter_{max}$	Maximum iteration
$iter_t$	Current iteration
k	Mooney constant
K_1, K_2	Empirical dimensionless constants
K_A	Curve fitting constant relating to wind speed
k_a	Sum of the values for all wavelengths of sunlight absorbed by the PAH
K_d	Dissolution mass transfer coefficient
K_E	Mass transfer coefficient
K_e	Coefficient evaluated from experiments
k_{max}	Maximum fist-order hydrocarbon biodegradation rate
K_n	Half-saturation concentration for a specific nutrient
k_{obs}	Observed fist-order hydrocarbon biodegradation rate
K_p, K_{ab}	Absorption parameters

L	Local factor
L(t)	Ratio of the average residual nitrogen concentration to oil loading
L_{ow}	Vertical length-scale parameter
L_s	Length of sediments on the beach
lb	Lower bound of parameters
Ln()	Natural logarithm
M	Molecular weight
N	Interstitial pore water residual nutrient concentration
N_A	Number of optimization algorithms
Nb	Number of benchmarked functions
$N_{i,j}$	Neighbor agent of Agent_{ij}
N_{best}	Neighbor best solution
N_p	Number of test functions
$N()$	Gaussian distribution
NIS	Negative ideal solution
ORR_{sk}	Hourly amount of recovered oil of slick *sk*
$ORR_{k,t}$	Hourly amount of recovered oil at time *t*
$p^{l}_{spill,t}$	Quantity of type *l* pump at the spill site at time *t*
$P_{best,i}$ (p_{id})	Best solution of ith particle so far
P^{sat}	Vapor pressure
p(t)	Polar fraction of oil
P_0	Initial vapor pressure

P^{l}_{volume}	Unit volume of type l pump
PAH_d	Concentration of dissolved PAH
PAHs	Polycyclic aromatic hydrocarbons
PC	Type of pollutant
PIS	Positive ideal solution
$pump\ eff_l$	Pumping efficiency of a type *l* pump
Q	Entrainment rate of oil droplets
$Q^{m,o}_{i,j}$	Quantity of type *m* truck in round *o*
Q_{max}	Maximum capacity of a beach for oil
Q_s	Total absorption capacity by sediment
Q^{m}_{Space}	Unit carrying space of trucks
R	Gas constant
R_0	Rank value of the reference algorithm
R_j	Rank values of the rest of the algorithms
$R^{Vairant}_{i}$	Result of a PSO variant to ith benchmarked function
R^{PSO}_{i}	Result of the original PSO to ith benchmarked function
r_1, r_2	Random numbers
$R^{n,o}_{j}$	Quantity of type n vessels from CERC j to the spill site
R^{n}_{Space}	Unit carrying space of vessels
RE	Response efficiency
rand ()	A uniform random value between 0 and 1
S_0	Solubility for fresh oil

S_{cov}	Sea coverage factor of oil
S_d	Total dissolution rate of the oil slick
$\mathrm{Sigmoid}(v_{id})$	A sigmoid probability distribution transformation
$Sk^k_{spill,t}$	Quantity of type *k* skimmer at the spill site at time *t*
Sk^k_{volume}	Unit volume of type k skimmer
SMA	Factor of the special management area
SR_{truck}	Space restriction factors of trucks
SR_{vessel}	Space restriction factors of vessels
ST	Slick thickness
$ST_{k,t}$	Slick thickness of spill *k* at time *t*
S_t	Interface tension between oil and water
SV	Removed oil by skimmers
T	Temperature
TV_t	Total recovered oil in time t
t	Time
t_0	Response start time
t_{end}	Response end time
T_0	Initial boiling point
T_G	Gradient of the boiling point
U	Wind speed
ub	Upper bound of parameters
V_0	Initial spill volume

$V_{0,k}$	Initial volume of spill *k*
$V_{loss,k,t}$	Oil loss at time t through oil response and natural weathering processes
$V_{remained\ oil}(t)$	Volume of remained oil
V_{sk}	Total recovered oil amount by all skimmers during the response period
V_b	Volume of oil on the shoreline
w	Inert weight
w_{ini}	Initial weighting value
w_{end}	End weighting value
W_s	Width of sediments on the beach
Wax	Percentages of waxes content
Y	Fraction of water in oil
Y_w^F	Stable water content of the emulsion
Z	Amount of oil fraction
α_b, δ_b, γ_b, ω_b	Fitting parameters determined from the multiple regression analysis
α_c	Current drift factor
α_d	Decay constant
α_h	Coefficient for the mixing depth
α_w	Wind drift factor
α, β	Empirical coefficients
γ	Dimensionless damping coefficient
ΔV_b	Volume of beached oil reenter to the sea
ε	Assumed multiplicative error term

η_{eff}	Effective porosity of the sediments
θ	Evaporation open factor
λ_h	Half-life
μ	Oil viscosity
μ_0	Initial dynamic viscosity of the oil
ρ	Oil density
ρ_w	Density of water
ϕ	Molar yield coefficient
ω	Wave frequency

CHAPTER 1 INTRODUCTION

1.1 Background

The rapid and vigorous developments of the marine industry and transportation influenced and altered the marine environment (Vanem et al., 2008). The subsequent contamination from accidental or operational releases of oil is a growing concern. Spilled oil cause marine and coastal pollutions, thereby threatening human health and ecosystems (Li et al., 2016a). Approximately 1.25 million tons of oil entered the global marine environment annually due to marine activities (Betti et al., 2011). Nearly 35 years have passed after the Exxon Valdez spill. Significant efforts have been made to study oil spills. However, such knowledge has not kept pace with the growth in oil and gas development (Li et al., 2016a). National Research Council (2003) stated that the sources of oil into the marine environment included natural seepage from the seabed (46%), operational discharge from ships and offshore facilities (37%), accident spills (12%), and extraction of oil (3%). The amount of oil spilled in accidents ranged from a few hundred tons to several hundred thousand tons. For example, the Deepwater Horizon oil spill (DWH) in 2010 caused a release of over 4.9 million barrels of oil into the Gulf of Mexico with a negative impact of 180,000 km^2 of ocean pollution. Over 8,000 species were killed or affected and over 8.7 billion U.S. dollars were taken for recovery (Griggs, 2011; Sumaila et al., 2012). "Both the industry and government were woefully unprepared." according to the U.S. National Commission on the Deepwater Horizon Oil Spill and Offshore Drilling (Graham et al., 2011). With the improvements in technologies, experiments and supervision levels, the frequency of oil spills over 7 tons from tankers showed a marked downward trend. ITOPF (2021) reported the average number of spills per year has decreased by more than 90 percent from about 79 cases in the 1970s to 6 cases in the 2010s. The declining number is a great thing. However, once a large oil spill occurs, its impact is still massive. For example, the Sanchi oil spill, caused by the collision of oil tanker Sanchi with a cargo vessel, resulted in fire, explosions and sinking, killing all 32 crewmembers, spilling or burning more than 100,000 tons of petroleum products (Ye et al., 2021a). Proper decision-making and planning can provide reliable guidance for marine oil spill prevention and response.

Canada has the third largest proved crude oil reserves globally, with an estimated amount of 171 billion barrels (10.3% of the world total). About 166.3 billion barrels are extracted from Alberta’s oil sands, and an additional 4.7 billion barrels are from conventional, offshore, and tight oil formations (National Research Council, 2021) . Canadian oil and natural gas generated $ 105 billion to Canada’s gross domestic product in 2020 (CAPP, 2021). Marine oil activity in Newfoundland and Labrador (NL) provided over 4.3% of Canadian oil production, including 25% of Canada’s conventional light crude. From the beginning of exploration and production in 1997, Newfoundland and Labrador's offshore oil industries have produced 1.7 billion barrels of oil (Gov. NL, 2020). NL’s oil and gas and related service industries contributed \$6.7 billion to nominal GDP in 2019, which accounted for 20.6% of the provincial total nominal GDP (Gov. NL, 2021). Oil spilling incidents occurred in NL offshore more often than the frequency predicted by environmental assessments. Terry (2008) indicated that roughly 2,703 barrels of drilling fluids and other hydrocarbons were estimated to be spilled into the marine environment through about 340 spills reported from the offshore of NL region. Relatively low temperature, strong wind, high waves, and a large amount of floating ice make the ocean condition of the North Atlantic Ocean a harsh environment. Due to the difficulties in physical oil recovery and negative impacts on marine ecosystems and eventually human health, oil spills occurred in harsh marine environments are arising more concerns (Chen et al., 2012).

According to prompt coordination of actions concerning persons or property, emergency response or operation protects the health, safety, or welfare of people, or to limit damage to property or the environment (Public Safety Canada, 2011). The emergency plan demonstrates assigned responsibilities, actions, and procedures in an emergency response. How to organize response resources in a sound and optimized way is an important problem that needs to be solved. A timely and high-efficient response to a marine oil spill accident can have more promising consequences and cause less damage to the entire environment. Even though preventing oil spills is the best way, controlling and cleaning up oil spills needs to be taken seriously and implemented quickly and effectively (Lee et al., 2015). An integrated system, including comprehensive prevention and preparedness, efficient spill response and cleanup options, as well as an optimized response decision support, can improve oil spill countermeasure and significantly reduce the environmental impact and severity of spills (Chen et al., 2019a). The Canadian Coast Guard (CCG), a strategic operating agency under the Fisheries and Oceans Canada (DFO) portfolio, is the operational unit of the Canadian government taking the responsibility to ensure an appropriate response to ship-source and mystery-source pollution incidents in Canadian waters, which constitutes a major part of the overall marine pollution response capacity in Canada. The CCG announced that the Incident Command System (ICS) would be applied as the common and standard incident response methodology for all marine pollution accidents and as the Incident Commander for the federal government for incident responses. (Canadian Coast Guard, 2018). The ICS acts as a standard for on-site command and control of emergency incidents and planned events. ICS Canada provides the network of organizations to enhance incident management responses cooperatively through improved interoperability (ICS, 2021). According to the spilled volumes, oil spills can be categorized as small spills and large spills. The information is usually appropriate for dealing with small spills. By reporting small spills and establishing and maintaining good relationships with regulatory agents, companies are better likely not to be blamed for unreported spills that the companies are not responsible for. In the case of large spills, booms and skimmers are the typical options to be deployed. (PDAC, 2009).

There are numerous physical, chemical and biological methods to responding to marine oil spills (Fingas, 2016). Growing concerns, research and development efforts worldwide have recently been given to more challenging environmental conditions, such as in the Arctic and Northern Atlantic/Pacific oceans (Pavlov, 2020). Meanwhile, the effectiveness of oil spill response options much depends on a variety of factors, such as oil types and properties, oceanic and metrological conditions, environmental and ecological concerns, as well as many technical, logistical and financial strains (Sarhadi et al., 2020). Some of these factors are temporally dynamic and interactive, which should be comprehensively considered in oil spill contingency planning and in-situ oil spill response decision-making and implementation (Van Hung, 2020; Ye et al., 2019b). Once a spill occurs and response actions are triggered, making sound and timely decisions becomes critical and vital. Inadequate decision support has been clarified as one of the major challenges that shrink the efficiency of current response practices (García-Garrido et al., 2016). The development and operational acceptance of decision support systems for marine oil accident responses can dynamically and interactively integrate early warning, spill modeling, human factor/causal factor/risk analysis, response process simulation/control, system optimization, and efficiency evaluation.

1.2 Statement of Problems

The modeling of marine oil spill response is based on numerical models of the predictive changes of oil properties with the effects of weathering and trajectory processes (e.g., oceanic circulation, winds, waves, oil fate and transport, prevailing environmental conditions, and oil chemistry characteristics) and the simulated performances of response options (e.g., booms, skimmers, in-situ burning and dispersants). The time period of modeling could be short-term (e.g., hours to days) or long-term (e.g., months to years). Numerical models, with the aid of high-performance computer simulation and optimization, can assist researchers, stockholders, and decision-makers quickly understanding and controlling the accident circumstance, improve the probability of making the appropriate decisions and reduce the risk and uncertainty in the operation of spill responses. Oil spill models are developed and served in multiple means, including decision support systems for spill response, process planning for spill response, the environmental impact analysis of oil-related industry infrastructure and the assessment of risk or impacts of a post-accident situation (Barker et al., 2020). Well-prepared decision support modeling could reduce the negative impacts of spilled oil in the marine environment and make the finite resource (i.e., clean-up equipment, vehicles, and human resources) carried out with the utmost efficiency. These kinds of modeling require estimating the location and amount of spilled oil from hypothetical simulations and predictions. Thus, the models always need to integrate with multiple types of spill models for oil trajectory and weathering. The outcomes and responses of such modeling could contain the estimations of oil types, amount, and best practices of allocating response resources to mount an effective response. Based on different concerns, the modeling can be done with the coupling of optimization algorithms, statistical methods, and multiple-scenario simulations to evaluate the uncertainty and risk in the process. The objective is to generate response plans to best protect vulnerable environmental and socio-economic resources with the maximum removal of spilled oil from the oceans.

Human errors and mistakes, such as wrong actions made at an inappropriate time and in an unsafe place, are significant factors in the accidents and incidents within complex systems, such as marine oil exploration and spill response systems (Schorsch et al., 2017). As a necessary condition for the accident, human errors figure prominently in casualty situations in the marine system (Islam et al., 2018). Ishak et al. (2020) declared that human errors are the most significant factor in oil spills. They are common, important, and highly related but often neglected. Human factors are concerned with understanding interactions between people and other elements of complex systems. The human factor analysis provides systematic approaches to classify and evaluate the differences between work-as-imagined (WAI) by designers, managers, or regulatory authorities and work-as-done

(WAD) by the field operators or crew (Clay-Williams et al., 2015). However, the concepts and understandings of human factors are unclear, especially for marine oil spill responses. The considerations and requirements for incorporating human factors in offshore operations are inadequate. The lack of practical human factor training and management tools also leads to the deficiency of organizational learning and safety performance (esp., no clear distinction between personal safety and process safety). Besides, a cumulative/long-term benefits of an offshore oil response operation with a comprehensive human factor consideration is never analyzed.

Emergency response and decision support systems are vital to managing resources to reduce the harmful effects of all types of unpredicted events (Rustamov et al., 2020; Sohrabi et al., 2020). Emergency response systems (ERSs) are how emergency response teams locate and move resources to emergency sites for accident rescue and pollution treatments. The emergency response systems and decision support systems (DSSs) aim to help responders and decision-makers to deal with consequence management. The applications can effectively reduce the waste of resources, time, and effort. Analyzing human factors and errors has significant achievements for marine oil spill response management. According to current studies, how to avail of advanced modeling tools to improve the efficiency of response operation and decision making with consideration of dynamic changes of oil spills has been recognized as a vital and urgent task in the field

(Huang et al., 2020a; Shi et al., 2019). Furthermore, limited studies have attempted to establish efficient ERSs for marine oil spill response and realize dynamic spill simulation and response optimization in decision-making models. Harsh oceanic circumstances (e.g., rough seas, cold water, sea ice) tend to make an emergency response to oil spills even more challenging due to the dramatic changes of oil properties and operational conditions, which inevitably hinder and affect the efficiency of response actions (e.g., booming, skimming, dispersion, and in-situ burning) (Afenyo et al., 2016; Beegle-Krause et al., 2017). Additionally, to most information on offshore oil spills, human judgements or preferences are expressed by vague descriptive words (e.g., high, medium, low) (Madi et al., 2016). And few studies considered the efforts of human factor analysis to offshore oil spill accidents. Besides, few studies have utilized PSO in marine spill response management (Ye et al., 2019b), and PSO efficiency is limited by premature convergence with local minima, especially when encountering complex problems. Therefore, it is urgent and critical to develop novel or improved knowledge and technical efforts on more effective and optimized response with emerging approaches to accidental spills, especially in harsh environments.

1.3 Research Objectives and Tasks

To help address the above challenges, this research aimed to develop a sort of integrated emergency response decision supporting approaches for marine oil spill management. The developed system integrated artificial intelligence technologies (i.e., agent-based modeling and multi-agent system), marine oil spill simulation modules (i.e., oil weathering processes and resource dispatches and storages), human factor-based evaluations (i.e., improved human factor analysis and classification system and Fuzzy-Technique for Order Preference by Similarity to Ideal Solution (Fuzzy-TOPSIS)) and system optimization algorithm (i.e., developed particle swarm optimization algorithms). The developed methodologies were applied for four studies shown in Chapter 3 to 6. These four studies include:

1) A simulation-based multi-agent particle swarm optimization (SA-PSO) approach for supporting marine spill decision-making was developed through the integrated simulation and optimization of response device allocation and process control. As an emerging simulation method, agent-based modeling was first applied for simulating oil spill fate and response. The particle swarm optimization method was adopted to optimize response device/vessel allocation and performance with minimal cost and time. The multi-agent system finally controlled and transmitted the results from agent-based modeling and particle swarm optimization as a dynamic and interactive system.

2) An improved emergency response system was developed based on dynamic process simulation and resource allocation optimization techniques. The development of an enhanced particle swarm optimization algorithm (ME-PSO) achieved with outstanding convergence performance and low computation cost characteristics which integrated multi-agent theory (MA) and evolutionary population dynamics (EPD). The proposed optimization algorithm was further used to allocate and schedule response resources for a large-scale marine oil spill.

3) An integrated human factor analysis and decision support process was developed to investigate the influences of active operational failures and unsafe latent factors in offshore oil spill accidents. The system was comprised of a Human Factors Analysis and Classification System (HFACS) framework to qualitatively evaluate the influence of various factors and errors associated with the multiple operational stages considered for oil spill preparedness and response (e.g., oil spill occurrence, spill monitoring, decision making/contingency planning, and spill response) and coupled with quantitative data analysis by Fuzzy Set Theory and the Technique for Order Preference by Similarity to Ideal Solution (Fuzzy-TOPSIS) to enhance decision making during response operations.

4) A multi-criteria emergency response system (MC-ERS) was developed to improve the efforts of the simulation-optimization decision support system for marine oil spill accidents. A developed weighted sum model (WSM) to convert multi-objective problems

into single-objective ones to enhance optimization performance. The developed PSO algorithms were further mutated with different PSO improving tools and inertia weighting functions to generate a comparative PSO algorithm (C-PSO). The C-PSO was further applied for the developed multi-criteria emergency response system. The system considered the factors from response efficiency, response cost and environmental impacts.

1.4 Structure of This Thesis

This proposal consists of seven chapters. Chapter 1 outlines the general research, scopes, objectives, and proposal structure. Chapter 2 provides the literature reviews of the relevant topics, including 1) marine oil spill response and management, 2) emergency response system and decision support system, 3) Agent-based approach, 4) environmental optimization methods, and 5) human factor analysis. Chapter 3 presents a simulation-based multi-agent particle swarm optimization approach to support dynamic decision-making in marine oil spill responses. Chapter 4 describes an improved simulation-optimization emergency response system for marine oil spill dynamic response. Chapter 5 indicates an integrated decision-making approach for marine oil spill responses by human factor analysis and fuzzy preference evaluation. Chapter 6 proposed a multi-criteria response system for marine oil spill accidents by comparative particle swarm optimization. Finally, Chapter 7 concluded the thesis with summarized contributions and recommendations for future research.

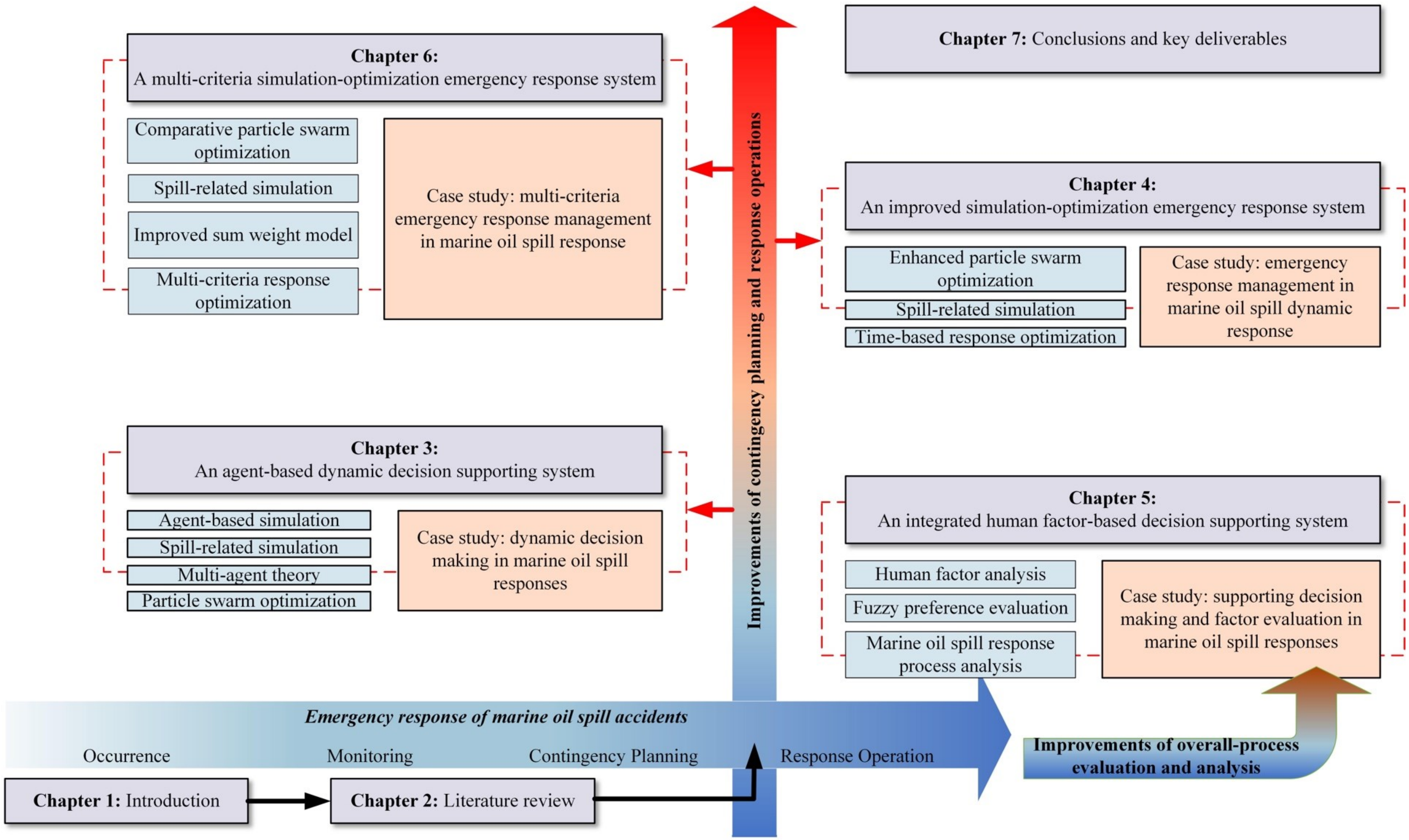

Figure 1.1 Roadmap of the thesis

CHAPTER 2 LITERATURE REVIEW*

* This chapter is mainly based on the following referred publications in three books and journals:

- Zhang BY, Matchinski EJ, Chen B, **Ye XD,** Jing L, Lee K (2019). Marine oil spills—oil pollution, sources and effects. In World Seas: An Environmental Evaluation (pp. 391-406). Academic Press. https://doi.org/10.1016/B978-0-12-805052-1.00024-3

  Contributions: Ye XD, writing - original draft and revision; Zhang BY, writing-original draft and revision, conceptualization; Matchinski EJ, writing-original draft, data collection; Chen B, writing-review and editing; Jing L, conceptualization and analysis; Lee K, writing-review and editing.

- Chen B, **Ye XD,** Zhang BY, Jing L, Lee K (2019). Marine Oil Spills—Preparedness and Countermeasures. In World Seas: An Environmental Evaluation (pp. 407-426). Academic Press. https://doi.org/10.1016/B978-0-12-805052-1.00025-5

  Contributions: Ye XD, conceptualization, data collection, writing - original draft and revision; Chen B, analysis, writing-original draft, revision and editing; Zhang BY, writing-review and editing; Jing L, data collection; Lee K, writing-revision and editing.

- **Ye XD,** Chen B, Storesund R, Zhang BY (2021). System control and optimization in wastewater treatment: a particle swarm optimization (PSO) approach. Soft Computing Techniques in Solid Waste and Waste Water Engineering. Elsevier. http://dx.doi.org/10.1016/B978-0-12-824463-0.00027-6

  Contributions: Ye XD, conceptualization, methodology, modeling, validation, formal analysis, writing - original draft and revision; Chen B, conceptualization and writing-revision; Storesund R, writing-revision and editing; Zhang B, writing-revision and editing.

- **Ye XD,** Zhu ZW, Merlin F, Yang M, Chen B, Lee, K, Zhang BY (2021). Ecological Impact of Dispersants and Decision Making. *Journal of Environmental Informatics Letters.* https://doi.org/10.3808/jeil.202100058.

2.1 Marine Oil Spill Cleanup and Response

Oil spilled into the marine environment undergoes a series of physical and chemical changes. Some changes are related to oil removal from the sea surface, while others cause it to persist (Li et al., 2016b). The fate of spilled oil in the ocean depends on several factors from the oil itself and the surrounding environment with interactive influences and complicated varieties, such as the quantities of spilled oil, the initial physical and chemical characteristics of oil phases, the prevailing chemical and oceanic conditions as well as motion status of remained oil and oily water (at sea or to shorelines) (Fingas, 2012). It is fundamental to all aspects of marine oil spill response to understand the involved processes and the interactions of multiple phases and roles (e.g., oil, water, weather, animal, and human) to alter the nature, composition and behavior of oil with time (ITOPF, 2014a). Determining oil types and possible behaviors in an active response is likely to make response options and process effectively. The weathering process is a comprehensive effect of various natural processes acting on spilled oil, including spreading, evaporation, dispersion, emulsification, dissolution, photo-oxidation, sedimentation and sinking, and biodegradation (Fingas, 2016). These factors affect oil fate immediately or chronically. Of

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Contributions: Ye XD, data collection, writing - original draft and revision; Zhu ZW, writing-original draft and revision; Merlin F, conceptualization, data collection, writing-original draft; Yang M, writing-revision; Chen B, writing-revision and editing; Lee K, writing-revision and editing; Zhang BY, writing-revision and editing.

them, spreading, evaporation, dispersion, emulsification, and dissolution are the significant processes as an active response in the days or months following an incident (Ye et al., 2019b). The fate of oil spilled in the marine environment has vital implications for all options of a response operation, and the changes in oil behaviors should also be considered in conjunction with response operations.

Marine oil spills attract the attention of both the public and the media, which often refer to the releases of liquid petroleum hydrocarbons into the ocean or coastal areas due to human activities (Li et al., 2016a). In the past decades, the attention generated a global awareness of the risks of oil spills and their damage to the environment. According to Figure 2.1, Oil spills may be due to releases of crude oil from tankers, offshore platforms, drilling rigs and wells, as well as spills of refined petroleum products (such as gasoline, diesel) and their by-products, heavier fuels used by large ships such as bunker fuel, the spill of any oily refuse or waste oil, subsea pipeline leaking or natural oil seeps (Ding and Yu, 2014). Oil spills can have disastrous consequences for society; economically, environmentally, and socially. For example, the Deepwater Horizon oil spill in 2010 was one of the most catastrophic environmental disasters in human history, releasing over 4.9 million barrels of crude oil, directly impacting 180,000 km^2 of the ocean (Griggs, 2011). As a result, marine oil spill cleanup response is the study and practice of reducing the number of oil or hazardous substances released into the environment and limiting the amount released during those incidents. There are a large group of physical, chemical, and biological methods to respond to marine oil spills. Growing concerns, research and development efforts worldwide have recently been given to more challenging environmental conditions such as in the Arctic and Northern Atlantic/Pacific oceans. Generally, the traditional and major offshore oil spill cleanup methods are shown in Figure 2.1, including manual recovery, booms, skimmers, sorbents, in-situ burning, dispersant and bioremediation. Different types of techniques would be used based on environmental conditions, available resources, and cost considerations. In particular scenarios, several methods may combine and work together to achieve the target. Meanwhile, the effectiveness of oil spill response options depends on a variety of factors, such as oil types and properties, oceanic and metrological conditions, environmental and ecological concerns, and many technical, logistical, and financial strains (Chen et al., 2019b). Weathering processes of oil in a marine environment largely depend on the type of material released and highly affect cleanup efficiency. The weathering processes occurred by different oil types, rates and durations vary the compositional and behavioral changes of spilled oil with progressive weathering and differentiation processes (Zhang et al., 2019a). Some of those factors are temporally dynamic and interactive, which should be comprehensively considered in oil spill contingency planning and on-site response decision making and implementation (Dave and Ghaly, 2011; Pezeshki et al., 2000; Venosa, 2004).

Considering the changes in oil characteristics, site condition, weather, and uncertainties will effectively make the planning and decisions for response processes and increase the difficulties.

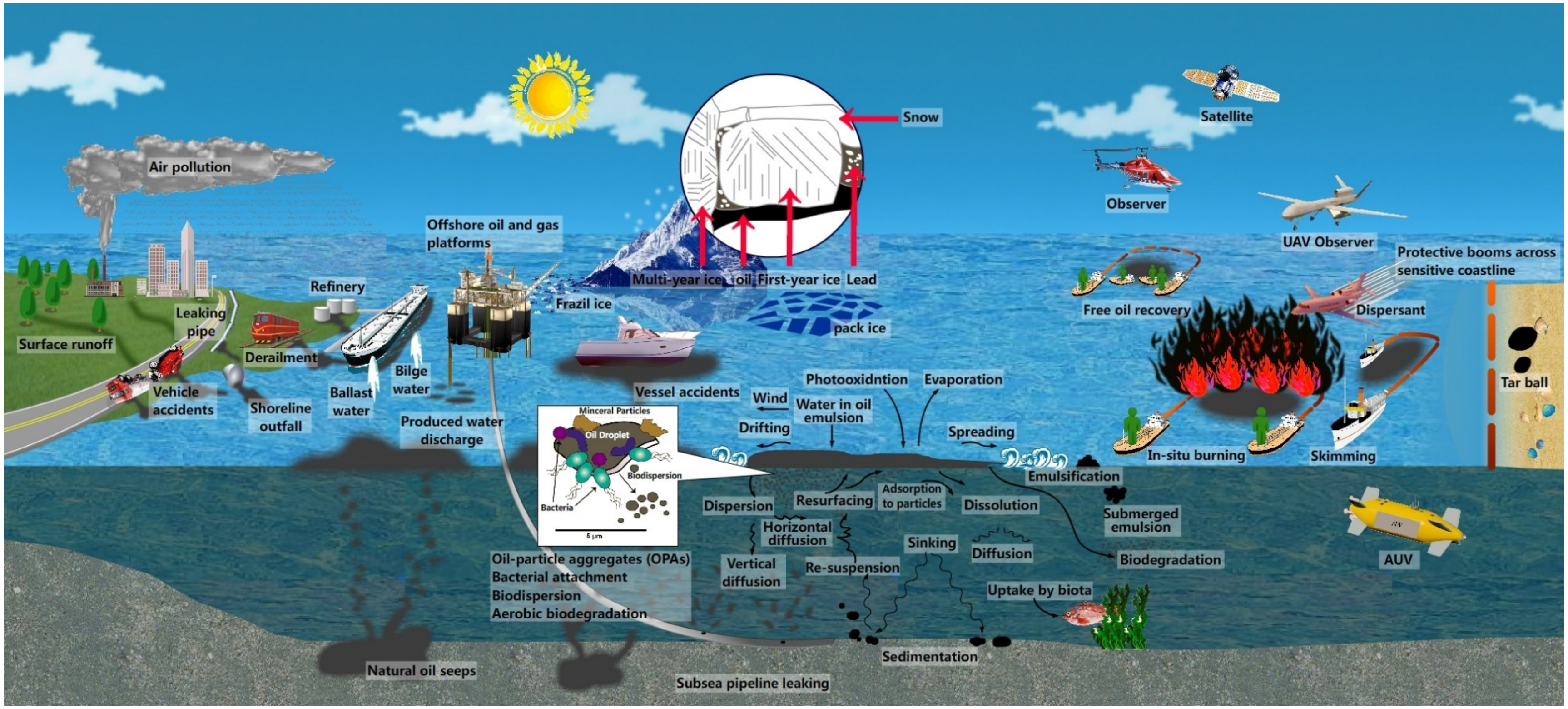


Figure 2.1 The schematic of offshore oil spill source and cleanup methods

2.1.1 Manual recovery

The manual recovery method, the primary way for coastal oil cleanup, mainly uses cleanup tools to physically remove oil on shorelines, including oil and debris removal and cleaning and scrubbing (Walther III, 2014). Sometimes, small oil spills or those in remote areas are recovered by hand. Heavier oils are more accessible to remove in this way than lighter oil. Cleaning up with shovels, rakes, or cutting the oiled vegetation is usually used in the spills on the water close to shorelines. Workers can use hand bailers, which resemble a small bucket on the end of a handle, to recover oil from the water surface. However, manual recovery is tedious and dangerous due to causes of physical injury from falls on the shore (Revie, 2015).

2.1.2 Booms

Booms are mechanical barriers that protect natural resources from the spreading of crude oil. They serve in water areas mainly as a technology to contain the oil spill to facilitate further cleaning steps (Walther III, 2014). Using booms can gather oil and prevent it from spreading to protect harbors, bays, and biologically sensitive areas. They can divert oil to areas where it can be recovered or disposed of. Booms concentrate oil and maintain an even thickness for skimmers cleanup or other cleanup techniques, such as in-situ burning.

Although booms can be used in calm water (e.g. for streams, canals, ponds, lakes), open water (for harbors and open ocean conditions) and some fast water environments (for rivers, streams, estuaries and moving water lakes), their effective operational range is limited by rough weather and winds that induce strong currents and breaking waves (Fang and Johnston, 2001; Sutherland and Melville, 2015).

2.1.3 Skimmers

Skimmers are mechanical devices designed to remove oil from the water surface without causing changes in its physical or chemical properties and transfer it to the storage tanks onboard the vessel. Skimmers are designed on boats and other devices (e.g. weirs) and are usually used together with the booms (Muizis, 2013). Typically, two boats will tow a collection boom to concentrate the oil to facilitate its recovery.

Skimmers work effectively in several forms, concerning independent units built into a vessel or containment devices and units that operate in either a stationary or mobile mode. Furthermore, skimmers can be classified based on their basic operating principles: oleophilic surface skimmers; weir skimmers; suction skimmers or vacuum devices; elevating skimmers; and submersion skimmers (Sivashanmugam, 2007).

The skimmer's efficiency is rated according to the amount of recovered oil and oily water. The performance of most skimmers operates best when the oil slick is relatively thick, and most perform not efficiently on thin slicks. High waves may compromise the ability of boom containment and skimmers to remain in contact with the oil. In addition, the performance of the skimmer is also affected by factors including viscosity, the presence of debris, and wind/current conditions at the time of recovery operations wind/current (Prendergast and Gschwend, 2014; Ventikos et al., 2004).

2.1.4 Sorbents

Sorbents are materials that soak up oil from the water through either absorption or adsorption. Sorbents play an essential role to clean up the final traces of oil spills on water or land, make a backup to other containment means, act as a primary recovery way for oil-contaminated shorelines, sensitive habitats such as wetlands and salt marshes, and small spills on water; and work as a passive technique of cleanup (Bayat et al., 2005; Teas et al., 2001).

The primary uses of sorbents include the following (adapted from Lee et al., 2015):

- Containment and recovery by rapid deployment in coastal areas, ports and harbors, estuaries, and rivers.
- Containment of slicks associated with a standard boom (to improve watertight seal).

- Protection of areas that are difficult to clean (e.g., riprap, reed beds, mangroves).
- Immobilization or recovery of floating pollutants on lakes or in stagnant waters.
- Rapid application on terrestrial spills or ground surfaces to prevent or at least reduce infiltration of the pollutant to the substrate.
- Sorption of leaks below a recovery worksite.
- Sorption of effluents from the cleanup of rocks, structures, and embankments.
- Sorption by filtration of pollutants suspended in the water column (water intakes, rivers).
- Cleanup or decontamination of personnel and equipment on cleanup sites. And
- Lining and protection of pathways.

Sorbents can be made of natural or synthetic materials. Natural sorbents include organic materials (i.e., peat moss or wood products) and inorganic materials (i.e., vermiculite or clay). Sorbents are available in a loose form, including granules, powder, chunks, and cubes, usually using bags, nets, or "socks" to hold. Moreover, sorbents could be made into pads, rolls, blankets, and pillows. Formed sorbents could also be formed into sorbent booms and sweeps. For example, one type of plastic sorbent is made into flat strips or "pom-poms," which efficiently recovers very heavy oils (Revie, 2015).

2.1.5 In-situ burning

In-situ burning, or ISB is a typical oil spill cleanup technique involving controlled oil burning at or near the spill site (Sahai et al., 2007). ISB is simple, quick, requires minimal but specialized equipment (i.e., fire-resistant boom, igniters), and can remove the mass of oil spilled at very high rates. Environment Canada successfully demonstrated ISB in a large-scale field experiment, the Newfoundland Offshore Burn Experiment (NOBE), on August 12, 1993, and conclusively validated it as an operational physical oil spill response countermeasure following controlled burns near a swamp and at sea during the DWH incident (Fritt-Rasmussen et al., 2013; Ramseur, 2010). ISB has been widely used to remove spilled oil and jet fuel in ice-covered waters and snow leaking from accidents of pipelines, storage tanks and ships in the U.S. and Canada and several European and Scandinavian countries (Mullin and Champ, 2003). The advantages of ISB are simple to implement, high elimination rates, high burn efficiencies, a small amount of burn residue and cost. It is a final solution to spilled oils. Burning can be used on fresh and saltwater, lakes, streams, oceans, onshore, or wetland/marshes with only a few centimeters of water. It can also be used under tropical and Arctic conditions (Mullin and Champ, 2003). The most significant disadvantage of burning oil is the large black smoke plume. The toxic emissions can cause potential air pollution and human health problems during burning. The second disadvantage is that the oil will not ignite and burn quantitatively uselessly if it is thick enough. Moreover, burning oil can sometimes be treated as an alternative for reuse. However, sometimes, recovered oil may contain too many contaminants for reuse. The third disadvantage is fear of flashbacks and secondary fires that could threaten human life, property and resources (Gregoli et al., 2000).

When properly utilized, it can provide a noticeable contribution to an overall response strategy. It has many advantages over other means of recovery, including the efficiency of elimination, low waste disposal and low cost. In the in-situ burning process, 5%–15% of the oil is converted to smoke particles migrating into the air. The smoke will be a temporary pollutant without taking any action. However, evaporating oil can also cause air quality concerns during other cleanup means. It may be the only alternative when spill locations are remote or have restricted access due to terrain, weather or other factors, and the oil should be considered to be removed quickly to prevent its spread or further environmental damage (Mullin and Champ, 2003). In situ burning is vital when other cleanup options work ineffectively or cause more harmful effects to the environment. In addition, it is potentially a valuable tool for mitigating the effects of a medium to a large oil spill.

2.1.6 Dispersant

Dispersants are chemical or biological spill treating agents that can accelerate the formation of small oil droplets and promote the oil disperse through the up layer of the water column (Chen et al., 2019b). The use of dispersants could reduce the impacts on the shoreline and biota on the water surface and promote the biodegradation of oil (Zhu et al., 2020). Chemical dispersants have been widely adopted as marine oil spill treating agents. Nearly 7 million liters of chemical dispersants, mainly Corexit® 9500A, were applied as a response to the Deepwater Horizon incident in 2010. It is an effective application of dispersants to treat marine oil spills (Wise and Wise, 2011).

Dispersants include surfactants, and chemicals like the components in soaps and detergents, with molecules with water-soluble (hydrophilic) and oil-soluble (lipophilic) components. Instead of directly decreasing the amount of spilled oil, dispersants help to reduce the interfacial tension between oil and water. Thus, the small-size droplets, broken up from oil slicks, can be dispersed into the water column. The immediate dissolution of oil droplets into the water column could substantially increase the oil concentration to 1000 ppm in the first minutes (Prince, 2015). There, they gather themselves so that the lipophilic end of the molecule is attached to the oil phase, and the hydrophilic end extends into the water phase. That reduces the interfacial surface tension between water and oil, allowing oil to mix into the top 5–10 m of the water column as tiny (1–70 μm) droplets (Lessard and DeMarco, 2000).

Based on the study from Lessard and DeMarco (2000), the advantages of dispersant use on a spill are broad application scope, low toxicity, and synergistic action with other treatments. Accordingly, adverse environmental impacts would be weakened due to the increased bioavailability of dispersed oil. Dispersants in the field are a trade-off between reducing the risk of coastal habitats and possibly increasing environmental losses in waters (Ye et al., 2021b). The effectiveness of a dispersant is determined by measuring the amount of oil that it disperses into the water and then comparing it to the amount of oil that remains on the water surface. Effectiveness is affected by many factors, which include the composition and degree of weathering of the oil, the amount and type of dispersant applied, sea energy, the salinity of the water, and water temperature, oil slick thickness, sea energy as well the composition of the target oil (Chandrasekar et al., 2006; Lindstrom and Braddock, 2002).

The application tool for dispersant is called a spray system. The most popular application method is aerial spraying, which is done from small and large fixed-wing aircraft and helicopters. Their capacity varies from about 250 ~1000L (small aircraft) to about 20,000L (large aircraft). When using helicopters, spray buckets are available in sizes from about 500 to 2000L. In addition, in some cases, spray systems are also available for boats varying in size from 10-to-30-m wide spray booms to tanks from 1000 to 10,000 L.

2.1.7 Bioremediation

Bioremediation is an oil spill treatment option enhancing the efficacy of the natural biodegradation process of the ocean. It is the process that uses decomposers and green plants, or their enzymes, to improve the condition of the contaminated environment due to hydrocarbons (Atlas and Hazen, 2011). Many hydrocarbons (including normal and cyclic alkanes, most monoaromatics and some PAHs) are biodegradable under aerobic conditions, even though several polar resins, most hopanes and asphaltenes are resistant to microbial actions. Bioremediation enhances the ability of microorganisms to transfer pollutants (i.e., petroleum hydrocarbons) into biomass, carbon dioxide, water, and innocuous oxygenated end products. The microbes treat oil as food and digest it to produce energy and carbon for reproduction and growth. Light crude oils are more biodegradable than diluted bitumen and heavy refined products, such as fuel oils (Wahab, 2015). Bioremediation is a promising option for remediation since it is effective and economical in removing oil with more minor undue environmental damages. It is human intervention, whereas biodegradation is a natural property of microorganisms. Thus, bioremediation is a viable response technique for cleaning up a shoreline contaminated by spills.

Bioaugmentation and biostimulation are two primary approaches used in bioremediation. Bioaugmentation adds an exogenous oil-degrading microorganic supply (grown offsite or in the laboratory) to the spills environment to augment microbial populations and accelerate biodegradation. Biostimulation is the process of adding nutrients or other growth-limiting chemicals, such as electron acceptors, to accelerate biodegradation by the existing indigenous microbial communities (Adams et al., 2015). Both these approaches have been extensively studied in the laboratory and the field. Current studies describe several cases that worked successfully in the polar region, particularly in the Arctic and sub-Arctic regions (Yang et al., 2009).

2.2. Emergency Response System and Decision Support System

An oil spill response is usually a series of dynamic, time-sensitive, multifaceted and complex processes with various constraints and challenges (Chen et al., 2012). It is essentially a specific setting of the broader field of environmental resources management because many environmental variables and competing stakeholder priorities should be considered and incorporated into the decision-making process. Consequently, response decision-making can become very complex (Davies and Hope, 2015). The success and effectiveness of a response must rely on the effectiveness and accuracy of the information (e.g., location, oil properties, weather, currents) and the availability of response resources (e.g., devices, human resources, and money) and how optimally the decisions and actions can be made from the committee. Even though the policy or regulations focusing on framework or infrastructure are relatively consummate, inadequate decision support may be one of the significant challenges to constraining the efficiency of spill response. In the past decades, many models have been developed mainly focusing on individual oil spill response activities, including early warning and detection, cost-benefit analysis, risk and impact assessment, cleanup process simulation and techniques selection control, as well as response operation optimization and decision making (Davies and Hope, 2015; Leschine et al., 2015; Passos et al., 2014). However, up to date, the integration of models in the mentioned aspects and the realization of multiple models' linkage for an integrated response decision support system is still insufficient. This section will review the current research and practice in oil spill response decision-making.

2.2.1 Early warning and monitoring

A reliable and integrated system for early warning and real-time monitoring can significantly improve effectiveness and efficiency and reduce the workload and pressure from spill cleanup or oil spill emergency response. Early warning and automated response capabilities can reduce the early containment of oil pollution by shrinking the oil volume spilled and minimizing damage to the environment, wildlife, public waterways, and commercial assets. The prevention and early warning of spills have benefits for: the public, stakeholder committees, business interests, the ecology of the natural habitats, and even the whole environment. Spill prevention and early warning reduction through remote early detection provide a "win-win" solution and, when implemented, dramatically reduces the risk of significant spills as well as cumulative harm to the environment (Mahr and Chase, 2009).

The integration of in-situ and remote monitoring hardware with pollution analysis software is of necessity and has been gaining attention. An automated monitoring system was developed for oil spills in water bodies by Barenboim et al. (2013). The system contains a remote sensing subsystem using fluorescent LIDAR, a network of automatic monitoring stations and an oil pollution identification subsystem based on hydrocarbon contents, alteration of radioactivity and water conductivity. The system provides an efficient tool for early warning and monitoring oil spills from oil and gas facilities (Barenboim et al., 2013). Moroni et al. (2016) proposed a novel oil spill early detection buoy system equipped with advanced sensors. The buoy is provided with various sensors for evaluating meteorological and marine parameters (e.g., waves, wind, temperature) and chemical/physical data acquired by an electronic nose system specifically designed to detect hydrocarbons. The electronic nose comprises a flow chamber, a chamber equipped with photoionization sensors, pumps and valves for air inlet and outlet, and a low-cost electronic board. The designed system samples the air above the water and produces data processed through two artificial neural networks allowing for the classification of detected hydrocarbons and overall pollution level. Suitable network interfaces and a connector toward a Marine Information System (MIS) allow real-time data visualization and long-term assessment of water quality.

One efficient way of improving the capacities to prevent and reduce the impacts of major oil spill events is to use early warning indicators. Table 2.1 summarizes the typical early warning indicators and compares their strengths and weaknesses (Lee et al., 2015a). The indicators can be used as a regulatory means to avoid unwanted events. Most current oil spill response systems are still absent or weak, with ineffective early warning capacity to identify, diagnose and react promptly to minimize the oil discharge into the environment at an early but critical stage of the emergency. Furthermore, it is challenging to incorporate the selected indicators into the early warning and real-time monitoring systems and the spill response decision-making processes. In future studies, an early warning should be taken seriously. Proverbially, "a good beginning is half done."

Table 2.1 Summary of early warning indicators and their strengths and weaknesses

(Source: Lee et al., 2015)

Early warning indicator	**Description of approach**	**Advantages**	**Disadvantages**
Safety performance-based indicator	• Describes the safety level within an organization, activity, or work unit • Starts with a set of factors that have potential effects on safety • Becomes not only useful for describing safety levels, but also applicable to early warning	• It is favorable when it comes to practicality, simplicity, and documentation • Is very relevant as an early warning	• The risk significance and the relative importance between the chosen influencing factors are unknown
Risk-based indicator	• Utilizes risk models as bases, and the development of risk models are part of the method	• Provides indicators for major accidents	• Rather resource intensive, especially for organizational risk indicators, which are

	• Regards risk control as the main function of the risk indicators • Becomes preferred with sufficient data • Particularly focuses on organizational risk indicators in the case of early warning	• Easily determines the risk significance • Depends on either accident investigation or events that occurred • Indicates potential scenarios without the occurrence of accidents	most relevant as early warnings
Incident based indicator	• Depends on detailed analysis of incidents or accidents • Assumes that if the contributing factors are efficient then the incident or accident has not been analyzed and similar ones have not occurred	• Closely related to major accidents • Easily communicates with stakeholders based on a factual incident or accident	• Requires very thorough review and documentation • The risk significance and relative importance of the underlying causes are unknown

	• Mainly focuses on identifying and measuring the factors that contribute to the incident or accident with the use of indicators		
Resilience based indicator	• Questions capability of recognizing, adapting to, and coping with unexpected events by providing specific approaches to manage risk in a proactive manner • Indicates the engineering resilience in organizations and safety management approach with methods, tools and management approaches under complexity	• Focuses on positive signals with failures that may be lack of data • Does not rely on information from occurred events and the indicators are relevant as early warnings	• The risk significance and relative importance of the influencing factors are unknown

2.2.2 Response technology screening and evaluation

A spill response strategy usually starts by identifying available and appropriate technologies to accommodate the site-specific environmental conditions and increase the probability of a favorable outcome. Contingency plans and emergency response operations must consider many factors for spill response selection and procedure choices. The factors involve the probability of an oil spill occurring; the spilled oil characteristics of the possible volume, type, and properties; the environmental-influence factors to the releasing fate and hydrocarbons behavior, the sensitivity of the most valued ecosystem components (VECs) to oil pollution, the potential impacts of oil spill countermeasures.

Insufficient knowledge could be one of the critical challenges in selecting and developing suitable response strategies and cleanup technologies. It includes the technical limitations, influencing factors and ecological impacts, especially related to critical emerging concerns, such as diluted bitumen, aging or subsea pipelines, spill impacts to freshwater ecosystems and Arctic conditions. According to the challenges, new or updated regulations needed to be announced to govern the application of response technologies by filling the gap in knowledge lacking.

To help address the traditional problem of regulatory failures, which usually happen in spill accidents. Best Available Technology (BAT) standards are promoted(Uth, 2014). Some agencies have adopted BAT standards since 1990, and Alaska is among the first (Salminen et al., 2017). In advocating a BAT regulatory standard, regulators must adequately identify the best available technology to respond to specific risks according to each industrial category. The identification should be proceeded based on the response effectiveness and technical/economic constraints, especially in cold and harsh environments. Consequently, regulators must proactively investigate the oil industries' safety records, the safety regulations and standards, and the industries interested in advancing cleanup technology.

Bayesian inference is an important and powerful statistical tool used for environmental decision-making systems. Bayesian inference is an alternative statistical inference method that is frequently used to evaluate ecological and environmental models and hypotheses. In a Bayesian analysis model, available information in a pre-spill condition is summarized in a quantitative model or hypothesis by the prior probability distribution. Bayes' Theorem utilizes the prior probability distribution and the likelihood of the data to generate a posterior probability distribution. Posterior probability distributions are an epistemological alternative to P-values and directly measure the degree of belief that can be placed on models, hypotheses, or parameter estimates. Moreover, Bayesian information-theoretic methods provide robust measures of the probability of alternative models, and multiple models can be averaged into a single model that reflects uncertainty in model construction and selection (Ellison, 2004). Bayesian networks have been demonstrated as an appropriate application for facilitating the re-assessment and re-validation of contingency plans following pollutant release, thus helping undertake the optimum response strategy. The method can minimize the possibility of suboptimal response strategies causing additional environmental and socioeconomic damage beyond the actual pollution event.

2.2.3 Net environmental benefit analysis (NEBA) and risk assessment

Oil spill responders try to optimize net environmental benefits when considering how to deal with a spill problem. The effects on the environment brought by applied cleanup techniques need to be weighed against their damage to the site. Net Environmental Benefit Analysis (NEBA) is used as the tool to deal with this dilemma by assessing oil spill countermeasures, including both active (e.g., in situ burning and mechanical recovery) and passive (e.g., monitoring of natural attenuation processes) (Efroymson, 2004). It is a structure-based system used to compare the environmental benefits of potential response tools and formulate response strategies and feasible and safe measures to minimize the impacts of spills on the environment (Whicker et al., 2004). Response communities and stakeholders in the oil industry and governments use it as an extensive step in pre-spill planning, response operation and post-accident restoration (DFO, 2014). NEBA determines if promising response actions will cause additional environmental damage. A reliable strategy of appropriate selections of response options to a specific spill can be provided by NEBA to decision-makers through analyzing the environmental trade-offs considering the use of the various responses (Coelho et al., 2013). In all cases, the purpose of NEBA is to serve as a decision support system to select acceptable and informed oil spill strategies (Koubrak, 2017). The development of NEBA involves the systematic assessment and evaluation of multiple factors and inputs from many stakeholders. All perspectives and viewports should be considered (ISCO, 2019). In addition, it is a key element for successful oil spill preparedness, response planning and execution by providing a mechanism for open communication, transparent decision making, clarifying policies and realistic response expectations (IPIECA-IOGP, 2015b). The NEBA process can be used to establish the most important resources at risk before or in an oil spill for environmental conservation, including protected species, ecosystem service or ecological relevance, economic value, or human use. NEBA serves as an integral tool for designing sensible response strategies for different planning scenarios in an emergency planning process. NEBA is used to help understand evolving conditions and adjust necessary response strategies to manage individual response actions and endpoints.

NEBA helps to select and optimize response options before and during a spill. No matter at what stage NEBA is employed, its process does not change. The NEBA process includes four main stages (IPIECA-IOGP, 2015a; National Academies of Sciences and Medicine, 2020):

- **Compile and evaluate data:** identify and prioritize social and environmental assets, exposure scenarios and potential response options and understand the potential relative impact of spill scenarios.
- **Predict the outcomes:** choose practical and feasible techniques for the given scenarios based on the review and comparisons from historical spill cases.
- **Balance trade-offs:** weigh and evaluate the feasible solutions through a series of environmental, social, and ecological pros and cons, as well as a balance tradeoff assessment of benefits and costs of response options.
- **Select the best response options:** select and combine tools and techniques for a given scenario to minimize spill impacts with an establishment of plans and decisions.

NEBA tends to be a vital part of contingency plans because post-spill decisions are usually relatively better and quicker made based on pre-spill analysis, consultations and agreements involving all of the appropriate organizations and parties (Daling et al., 2014).

The determination of priorities in NEBA depends on preparing a list of risky local environments, predictive oil weathering and trajectory models results, in situ or remote monitoring data. Identifying/quantifying cumulative impacts of response actions (e.g., application of dispersants), especially for long periods, could be complex when incorporating cumulative impact analysis to NEBA for oil spill response (Efroymson, 2004).

A NEBA process promotes identifying the relevant factors affecting options' effectiveness and selecting the best response strategy. However, human inference and judgement in making the trade-offs are usually involved in NEBA for prioritizing response options. Decision-making committees usually use qualitative evaluation approaches (including questionnaire surveys) and introduce unavoidably uncertainties into the results due to incomplete information and subjective judgement based on personal knowledge, experience and opinion (Reynolds, 2014).

Risk assessment undertakes all preparation and planning for oil spill response and contains the assessment of both the possibility of a spill occurring and the consequences or effects caused by a spill (Zealand, 2006). It is a formal, structured examination of an oiled environment to determine how many of each species was affected by the oil spill. The aim is to quantify the environmental risks as much as possible and assess the total effects of a specific spill. Data are used to develop long-term recovery or contingency plans to assess costs and provide a spill damage database.

A relative risk assessment of oil spills includes the following components (Lee et al., 2015a): a) Estimation of the probability of various sizes of spills based on past and projected future incident rates; b) Vulnerability of the environment to oil spill impacts; and

c) Selection of the oil spill scenario(s) to be assessed, for example, maximum most-probable discharge and/or worst-case discharge. The assessments should consider a regional and seasonal basis by oil type. The detailed levels of assessments are based on the spatial and temporal scope and the available data.

A general environmental/ecological risk response means the probability of spills occurring multiplied by the potential impacts on environmental or ecological systems. In general, the first step of risk assessment is hazard identification, which declares the qualitative scenario of the potentially harmful consequences caused by the response actions or contaminants. The second step is dose-response analysis, which indicates the relationship between dose/frequency of actions and the probability or the incidence of effect from dose-response assessment. The third step is exposure quantification, which illustrates the amount of contamination that individuals and populations will receive. And the last step is risk management, including the coordinated and economical application of resources to minimize, monitor and control the probability and/or impact of risks (Board, 2014). Health risk assessment supports individuals by evaluating their health risks and life quality. The main objectives involve assessing human health, estimating the health risk levels, and providing feedback to participants to motivate behavioral change to reduce risk. The results can reflect the impacts of oil spills and response activities on human health and assist in decision-making and confirming the responses degrees (Bostrom et al., 2015).

2.2.4 Oil trajectory and weathering

After an offshore oil spill, various transformation processes will occur, and many of these processes relate to oil's behavior. Spill response personnel need to know the direction in which an oil spill is moving to protect sensitive resources and coastline (Chen et al., 2019b). In order to help accomplish this target, computerized mathematical models have been developed to predict the trajectory or pathway, the fate of oil, and weathering processes associated with oil behaviors. Weathering is a series of changes of spilled oil in physical and chemical properties on the water. The weathering process contains evaporation, emulsification, natural dispersion, dissolution, photo-oxidation, sedimentation, adhesion to materials, interaction with mineral fines, biodegradation, and the formation of tarballs (Fingas, 2016).

Current sophisticated spill models combine the latest information on oil fate and behavior with computer technology to predict the real-time oil locations, current oil characteristics and predicted transportation statements with periods. Additionally, a series of processes variations regarding the physical and chemical properties of the oil occur right after the oil spill, which are the weathering processes with the essential processes of evaporation and emulsification. Moreover, weathering processes are closely related to oil movement in offshore situations. The major limitation of spill models to accurately predict an oil slick's movement is the lack of accurate estimates of water current and wind speeds along the predicted path (Fingas, 2012). The weathering and movement processes have strong interaction in offshore circumstances. When predicting the trajectory, spill models need to estimate the weathering conditions, including the amount of evaporation, the possibility of emulsification, the amount of dissolution and the trajectory of the dissolved component, the amount and trajectory of the portion that is naturally dispersed, and the amount of oil deposited and remaining on shorelines. It is undeniable that the oil properties, hydrodynamics, meteorological and environmental conditions play essential roles in the physical, chemical, and biological processes of the spilled oil transport and fate. Accurate spill modeling is currently a vital part of both contingency planning and actual spill response. Some frequently used models for the weathering and movement processes of offshore spilled oil are listed in Table 2.2.

Spill models work in a variety of approaches. The most typical is the trajectory model, which predicts the trajectory and weathering of the oil. The stochastic model predicts various scenarios for the oil spill in terms of available data, including the direction, fate, and property changes in the oil slick. Another one, called the receptor mode, is the model choosing a site on the shore or water and then calculating the trajectory from the oil spill source. In spill models, statistical methods usually generate estimated data to compensate for the primary data on winds and currents.

Integrated models have been recently developed for spilled oil transport and fate based on the trajectory method. A subset of them focuses on the surface movement of spilled oil. These systems have been applied in the river-lake and seas (Goeury et al., 2014; Goni et al., 2015). Some commercial oil spill models, such as COZOIL (Reed et al., 1989), OILMAP (Howlett et al., 1993), and WOSM (Korotenko et al., 2000), have been used to determine the oil movement and distribution in the ocean. However, only a few research focuses on the transport of spilled oil associated with the simultaneous tidal currents, and few study considered the situation between strong tide and tidal currents. Furthermore, there are limited studies on the vertical distribution of oil droplets and the advection forces (Wang et al., 2008).

Table 2.2 Weathering and movement processes of offshore spilled oil

(Source: Chen et al. (2019b))

Process	Description of process
Evaporation	• Volatile components escape from the spilled oil surface to the atmosphere. • The most important weathering process. • The primary reason of oil volume reduction in the initial stage of spill (about 20~50% of crude oil and over 75% of refined products). • Components with boiling points that are lower than 200 °C will evaporate within 24 hours after spill. • It relies on the physicochemical properties of oil, temperature, wind, and wave. • Can increase the viscosity and density of oil
	$\mathrm{FE} = \frac{c + d \times (T - 273.15) \times ln(t)}{100}$ $\mathrm{FE} = \frac{\ln P_0 + \ln\left(C_C K_E \mathrm{t} + \frac{1}{P_0}\right)}{C_C}$ $\mathrm{FE} = \frac{K_E AZP\ t}{RT}\frac{M}{\rho}$ $\mathrm{FE} = 1 - \exp\left(-\left(\frac{\left(\frac{1.5 \times 10^{-5} T U_w^{0.5}}{M^2}\right)\left(\frac{pM}{\rho RT}\right)}{h_s}\right)\mathrm{t}\right)$

	$$\mathrm{FE} = \frac{BT_G}{T}\ln\left(1 + C_B\frac{T_G}{T}\exp\left(C_A - C_B\frac{T_0}{T}\right)\right)$$
Dissolution	• Soluble components (light aromatic hydrocarbons compounds) dissolve into the water column. • Immediately after the oil spill. • Relies on the physicochemical properties of the spilled oil. • More less than the evaporative amount (about 1/100 to 1/10). • Dissolved components can be quickly diluted. • Environmental consequences are of significance due to toxic effect on marine organisms.
	$$S_d = K_d A S_0 exp(-\alpha_d t)$$ $$S_d = K_d AZS_0 t\frac{M}{\rho}$$
Emulsification	• Water droplets enter the oil slick. • Unstable (30–40% of water), semi-stable (40–60% of water), and stable (60–80% of water) forms in the oil slick. • Can lead to emulsion with up to 70% of water. • Significantly changes the physicochemical properties of oil (i.e., density and viscosity). • Light oil is usually not emulsified, while the crude oil is easily emulsified.
	$$\frac{dY}{dt} = 2 \times 10^{-6}(U_w + 1)^2\left(1 - \frac{Y}{C_3}\right)$$

	$Y = \left(1 - \exp\left(-\frac{K_{\alpha}}{Y_{w}^{F}}(1 + U_{w})^{2}t\right)\right)$
Dispersion	• Spilled oil is breaking into small droplets and enters the water column due to waves or turbulence. • Relies on the oil properties and the energy from the surrounding environment. • Reduces the volume of spilled oil on the sea surface. • Will not change the physicochemical properties of the spilled oil. • The droplets will not reenter the surface if their sizes are small. • Is a major part of oil removal from the sea surface in practice.
	$\frac{\partial Q}{\partial d}\rvert_{d_0} = C_0 D_{ba}^{0.57} S_{cov} F_{wc} d_0^{0.7}$ $DE = \frac{K_e \overline{\omega} \gamma H}{16 \alpha_h L_{ow}}$ $DE = (0.11(U + 1)^{2}) \times (1 + 50\mu^{0.5} s_t SOT)^{-1}$
Spreading	• Pour point should be lower than the sea surface temperature. • Occurs quickly after the oil spill until the slick thickness achieves 0.1 mm or less. • Relies on the interaction of gravity, wind, current, inertia, viscosity, and surface tension of oil. • Stops when the slick thickness of crude oil reaches 0.01 mm or the slick thickness of light oil (i.e., gasoline) reaches 0.001 mm.

	• Significantly affect the evaporation, dispersion, and emulsification.
	$$A = 10^5 V^{\frac{3}{4}}$$ $$\frac{dA}{dt} = K_1 A^{\frac{1}{3}} \left(\frac{V}{A}\right)^{\frac{4}{3}}$$
Biodegradation	• Some compounds can be digested by microorganisms or microbes. • Transforms the compounds into water soluble compounds and eventually carbon dioxide and water. • Highly depends on the level of nutrients, the temperature, and the oxygen. • Can only occur at the oil-water interface and can be strengthened by dispersion and spreading. • Degradation rate is very low and difficult to be described by any general mathematical model in the marine environment.
	$$k_{obs} = k_{max} \left(\frac{N}{K_n + N}\right)$$ $$C_h(t) = \alpha\big(1 - p(t)\big)^{\gamma_b} e^{\delta_b L(t)} + \bar{\omega}_b t_{\varepsilon b}$$
Photolysis	• Some compounds can react with oxygen by promoting sunlight. • Relies on the type of oil and the form in which it is exposed to sunlight. • Transforms the compounds into soluble products or persistent ones.

	• Occurs at a very low rate even with strong sunlight. • Affects less than 1% (or 0.1% per day) of spilled oil.
	$\frac{dPAH_d}{dt} = \phi k_a(PAH_d)$
Sedimentation	• Heavy compounds with densities greater than the density of sea water sink to the bottom of the sea. • Usually happens due to the adhesion of particles or organic matter from the sea water to the oil slick. • Insignificant in the initial stage because most of the oils have not enough density. • The percentage can be increased with emulsification and in-situ burning. • Oil washed off from the shoreline can also sink after reach back to the sea.
	$Q_s = \frac{bK_{ab}C_{0e}}{1 + K_{ab}C_{0e}} + K_p d_s^m$
Advection	• The movement of oil slick is due to the influence of overlying winds and/or underlying currents. • The advection velocity of the spilled oil on the sea surface is a vector sum of a wind-induced drift and a water-current drift.
	$\vec{V} = \vec{V_c} + +\vec{V'}$ $\vec{V} = \alpha_w \vec{V_w} + \alpha_c \vec{V_c}$

Oil–shoreline interactions	• The spilled oil can deposit or reenter to the sea after reaching the shoreline. • Mainly relies on the oil properties, types of shorelines, wind, and tidal. • Stranded oil often mixes with the sand. • Will sink if washed back into near-shore waters by tidal rise or precipitation. • Interaction with very small particles (b4 μm) can lead to the formation of oil–shoreline interactions.
	$\frac{\Delta V_b}{V_b} = 1 + 0.5^{\frac{\Delta t}{\lambda_h}}$ $Q_{max} = L_s W_s D_s \eta_{eff}$

Note: FE is the evaporation rate, $m^3/h/m^3$; T is the temperature, K; U is the wind speed, m/s; P_0 is the vapor pressure, Pa; M is the molecular weight, g/mol; ρ is the density of oil, kg/m^3; R is the gas constant, 8.314 $m^3Pa/mol/K$, SOT is the slick thickness, mm; t is time; c and d are equation parameters for specific oil; T_0 is the initial boiling point, K; T_G is the gradient of the boiling point, K; θ is evaporation open factor; C_A and C_B are non-dimensional constant; K_E is the mass transfer coefficient, m3/h; P_0 is the initial vapor pressure, Pa; C_C is the constant for specific oil; A is the area of the oil slick, m^2; Z is the amount of oil fraction; S_d is the total dissolution rate of the oil slick, g/hour; K_d is the dissolution mass transfer coefficient, m^3/hour; S_0 is the solubility for fresh oil, g/L; α_d is the decay constant; Y is the fraction of water in oil; C_3 is the final fraction water content; K_A is the curve fitting constant relating to wind speed; Y_w^F is the stable water content of the emulsion; DE is the dispersion rate, $m^3/s/m^3$ of oil; μ is the oil viscosity, cSt; s_t is the oil–water interfacial tension, dyne/m; Q is the entrainment rate of oil droplets, $kg/m^2/s$; S_{cov} is the sea coverage factor of oil; d_0 is the oil droplet diameter, mm; C_0 is the oil dispersion parameter related to oil viscosity; F_{wc} is the fraction of the sea surface hit by breaking waves; K_e is the coefficient evaluated from experiments; ω is the wave frequency, Hz; γ is the dimensionless damping coefficient; H is the significant wave height, m; α_h is the coefficient for the mixing depth; L_{ow} is the vertical length-scale parameter; K_1 is the constant with default value of 150 s^{-1}; ρ_w is the density of water, kg/m^3; $C_h(t)$ is the amount of a hydrocarbon component at time t; p(t) is the polar fraction of oil; L(t) is the ratio of the average residual nitrogen concentration to oil loading; α_b, δ_b, γ_b, and ω_b fitting parameters determined from the multiple regression analysis; ε is the assumed multiplicative error term;

k_{obs} and k_{max} are the observed and maximum fist-order hydrocarbon biodegradation rate, mg/kg/day; K_n is the half-saturation concentration for a specific nutrient, mg/L; N is the interstitial pore water residual nutrient concentration; ϕ is the molar yield coefficient; k_a is the sum of the values for all wavelengths of sunlight absorbed by the PAH; PAH_d is the concentration of dissolved PAH, mg/L; Q_s is the total absorption capacity by sediment, m^3; C_{0e} is the oil concentration after absorption balance; d_s is the sediment particle diameter, mm; K_p, and K_{ab} are absorption parameters; $\vec{V}$ is the advection or drift velocity, m/s; α_w is the wind drift factor; $\overrightarrow{V_w}$ is the wind velocity, m/s; α_c is the current drift factor; $\overrightarrow{V_c}$ is the depth-averaged current velocity, m/s; $\overrightarrow{V_0}$ is the turbulent fluctuation of the drift velocity/s; ΔV_b is the volume of beached oil reenter to the sea, m^3; V_b is the volume of oil on the shoreline, m^3; λ_h is the half-life, hour; Q_{max} is the maximum capacity of a beach for oil, m^3; L_s, W_s, and D_s are the length, width, and depth of sediments on the beach, m; and η_{eff} is the effective porosity of the sediments.

2.2.5 Cleanup process simulation and control modeling

For oil spills, the cleanup process simulation and control include a series of simulation processes of response process techniques (e.g., booming, in-situ burning, skimming, dispersion, and bioremediation) related to oil spill simulation models, as well as maintaining and controlling the response output within the desired range by mechanisms and algorithms. A clear understanding of the mechanisms of response processes can assist in quantifying the direct relationships among the inputs (e.g., number and types of skimmers) and outputs (e.g., recovery rate), as well as the indirect relationships, such as the time-series correlation (Jing et al., 2015). Models of oil behavior, effects and fate, and the influence of spill response measures (e.g., skimming or dispersant) have been treated as an essential part of successful process control strategies (Li et al., 2014b). Many transformation processes occur when oil is spilled. Parts of these processes are referred to as oil behaviors. The first section is weathering, a series of processes whereby the physical and chemical properties of the oil change after a spill happens. The most critical processes are evaporation and emulsification. A second section is related to the movement of oil in the marine environment. Weathering and movement processes can overlap. Weathering process can strongly affect the oil movement and vice versa. The type of spilled oil and weather conditions can influence spill fates during and after the spill.

A simulation-control-based response model can provide the decision-makers with a hypothetical means to predict and optimize the consequence of different combinations of oil spill recovery and cleanup operations. Especially, a real-time aid of process simulation and control tool can promote the response efficiency and effectiveness and minimize the overall time and cost during spill response action. Fast and accurate spill estimates to deal with timely and effective decisions in deploying skimmers, applying dispersants, or conducting other response activities before, during and after the spill event is always a key element in a successful oil spill response process. However, complexity and dynamic variations from the fate and transport of spilled oil, weathering and oceanic conditions, equipment operations, and their interactions accumulate the response decision-making into a high-challenging issue. Traditional physics-based spill models are weak in providing a good solution. Numerical simulations with dynamic changes with a couple of system optimization are a possible approach to enhance the performance for decisions and planning (Chen et al., 2019b). Nonetheless, when incorporating different cleanup techniques (i.e., booming, skimming, in situ burning, dispersant application and bioremediation) into a synthesis system, a problem of limited background data, high nonlinearity and various uncertainties of oil properties and weather conditions still need to be conquered.

Cold and harsh environmental conditions must be considered to deal with the accidents that occurred in northern Canada and the Arctic. Due to a wide range of wind speed and direction, limited visibility, low temperature, rough water surface, ice coverage, etc., it is potentially a substantial challenge for oil spill cleanup process simulation and control (Li et al., 2014b). Till now, even though cleanup process simulation and control research had a significant development, several knowledge gaps exist on the fate and behavior of oil in water in ice conditions (solid, slush and frazil ice) and during active periods of formation and breakup of annual and multi-year ice as the impacts on ecosystems. Consequently, coupling with different response methods under Arctic conditions is still challenging to predict and manage in a timely, eco-friendly, and cost-effective way.

2.2.6 Response operation and decision-making optimization

The oil spill response process is a dynamic, time-sensitive, multifaceted, and complex process suffering various constraints and challenges. Quantity and properties of the spilled oil, spill locations, environmental and weather conditions and the resource status of available response techniques are the factors that affect the consequence of responses (Ornitz and Champ, 2002). Response operations usually suffer a limited time window and improper decisions, which may compromise oil recovery efficiency and waste resources. Developing and implementing an optimized strategy becomes highly desirable to better coordinate different types of operations.

From previous studies, a sort of decision making, emergency and optimization models are developed to promote decision support under changing environmental conditions. While numerous studies focused on resource allocation and/or spatial conditions, only a few studies considered the impacts of continuously changed factors (e.g., oil weathering process and removal efficiency of different devices) on the response optimization. The studies from 2005 to 2021 are summarized in Figure 2.2. Liu and Wirtz (2005) demonstrated a multi-agent system with three different negotiation protocols by cooperation and competition to analyze the impact of outcomes from oil spill response decision-making. Wirtz and Liu (2006) represented an oil spill decision model approach with the integration of a spill contingency simulation model, environmental GIS data as well as multi-criteria analysis methods. The model efficiency was examined by the 2002 Prestige accident with the rank of different response actions to spills. You and Leyffer (2011b) demonstrated a mixed-integer programming model to provide an optimization means to predict the oil trajectory, response procedures and coastal protection planning by the integrated consideration of response operation and oil fate and transport processes. Zhong and You (2011) developed a bi-criterion, multiperiod mixed-integer linear programming model to provide the optimal oil spill response plans by integrating weathering modeling, and multi-objective optimization. Li et al. (2012) proposed a multiple-stage simulation-based mixed-integer nonlinear programming method to evaluate recovery efficiency and provide optimal decisions for spill cleanup with skimmers in harsh environments. Azevedo et al. (2014) integrated hydrodynamic, transport and oil weathering modules to develop an Eulerian-Lagrange 2D/3D oil spill model to support the management of oil spill accidents. Li et al. (2014b) developed a Monte Carlo simulation-based oil recovery and devices allocation model with dynamic mixed-integer nonlinear programming, followed by an agent-based simulation and optimization coupling approach. Passos et al. (2014) developed a multi-criteria approach by integrating the methods of an interactive and multi-criteria decision model and fuzzy synthetic evaluation to provide efficient contingency plans for spill accidents. Davies and Hope (2015) reviewed the use of Bayesian networks (BNs) in ecology, environmental management, oil spill contingency planning and post-incident analysis and proposed a BNs-based framework for a real-time decision support system for oil spill responses. Jin et al. (2015) represented a scheduling optimization approach to enhance the efficiency of marine oil spill disposal with the integration of navigation systems, wireless network and spill monitoring methods. Leschine et al. (2015) indicated a what-if scenario analysis module to aid in selecting a spill contingency plan. Li et al. (2016b) introduced an agent-based simulation and optimization coupling approach for device combination and allocation during marine oil spill recovery. Garrett et al. (2017) proposed a dynamic network module to improve the performance of oil spill responses for energy exploration in the Arctic by using mixed-integer linear programming. Grubesic et al. (2017) indicated a tactical approach and evaluation framework by the combined spill simulation and spatial optimization model to provide the optimal allocation scenarios of response crews and equipment for marine oil spill response. Balogun et al. (2018) utilized the analytic hierarchy process model to perform tradeoffs in determining the most significant resources for emergency spill response operations. Ha (2018) indicated risk-based modeling of allocating recovery capacity for regional oil spills considering environmental and economic factors with the Analytic Hierarchy Process. Li et al. (2018) developed a multi-objective optimization model of site selection and resource allocation to generate optimal configuration plans for an oil spill rescue base in the Bohai Sea region. Amir-Heidari and Raie (2019) proposed a decision-supporting system for passive and active response planning in the Persian Gulf pre/post-spill stages based on a fast Lagrangian oil spill model

(GNOME). Grubesic et al. (2019) indicated a strategic planning modeling of response resource allocation with the geographic information system to protect environmentally sensitive coastlines. Ye et al. (2019b) developed a dynamic spill response decision-making module with agent-based simulation and particle swarm optimization. Li et al. (2019) presented a dispatching optimization model of emergency materials for large-scale marine oil spill responses. Ye et al. (2020) used human factor analysis and fuzzy preference evaluation to develop an integrated offshore oil spill response decision-making model. Hu et al. (2020) developed a fuzzy-based decision tree tool to select oil spill response methods by enhancing linear regression models. Liu and Callies (2020) proposed a Bayesian network for decision-making on chemical dispersants for oil spills in the German Bight. Bi et al. (2021) developed a decision tree considering oil collectability, shoreline character, types and amounts of oil and cleanup requirements to evaluate and select shoreline surface washing agents. Wu et al. (2021) proposed a quantitative decision-making model for early emergency response for spills from ships with the considerations of identified alternatives and influenced factors in accidents and responses. Ye et al. (2021a) developed an emergency response system with the integration of dynamic spill weathering simulation and system optimization with an enhanced particle swarm optimization with multi-agent theory and evolutionary population dynamics

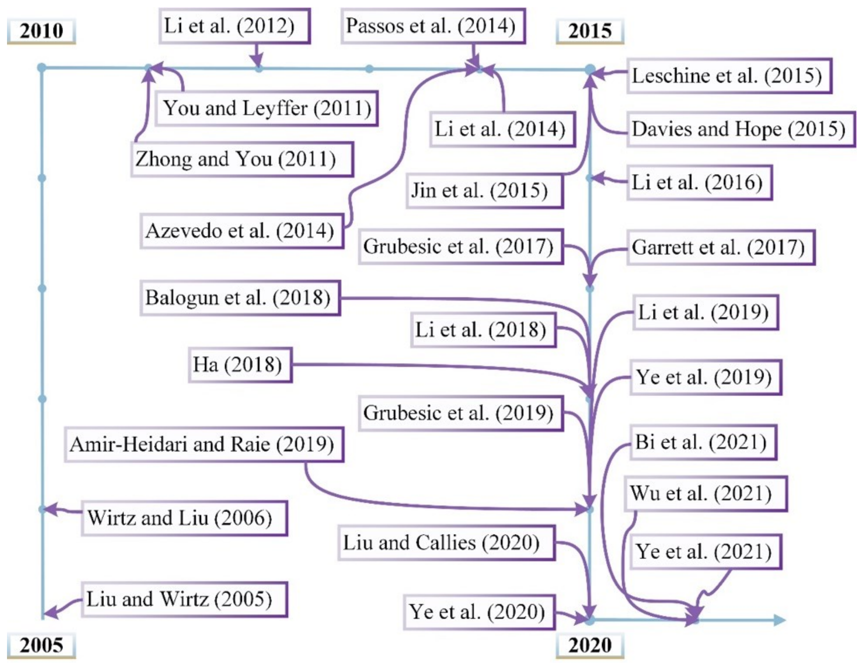


Figure 2.2 The timeline of the relative studies of marine oil spill decision making and planning (Year 2005-2021)

Most studies focused on resource allocation and/or spatial conditions. However, a few studies considered the impact of other factors (e.g., oil weathering process and removal efficiency of different devices) in the response optimization. However, limited studies have attempted to realize dynamic spill simulation and response optimization in decision-making models. Furthermore, harsh oceanic circumstances (e.g., rough seas, cold water, sea ice) tend to make an emergency response to oil spills even more challenging due to the dramatic changes of oil properties and operational conditions, which will inevitably hinder and affect the efficiency of response actions (e.g., booming, skimming, dispersion, and in-situ burning) (Afenyo et al., 2016; Beegle-Krause et al., 2017; Lee et al., 2015a; Li et al., 2014a). Therefore, a comprehensive emergency response system of these issues into the response simulation and decision-making system is urgently desired.

2.3. Agent Based Approach

2.3.1 Agent

Agent-based theory generates a series of powerful simulation modeling techniques for the applications to real-world complicated systemic problems and also a set of principles with a high capacity to integrate with traditional techniques (e.g., optimization algorithm and simulation modeling) for performance enhancement (Macal and North, 2009; Ye et al., 2019a). In agent-based modeling, a system is established and modeled as a collection of autonomous decision-making entities called agents. Agents individually assess their information on situations and decisions according to a set of rules (Bonabeau, 2002). They are an entity that operates continuously and autonomously in a modeling environment existing with multiple processes and agents (Chen, 2012). They imply a certain degree of autonomy and learning abilities that can be used as an effective means for independent decision-making (Bonabeau, 2002; Jackson et al., 2017). From a practical modeling perspective, traditional intelligent agents have the following general characteristics (Figure 2.3), as shown in the following (Macal, 2016; Ye et al., 2019a).

- ***Self-identification:*** Agents are identifiable, discrete, self-controlled individuals with a set of characteristics and rules that control their behaviors and decision-making capability. They have boundaries and easily determine the situations and share a certain of information.

- ***Autonomy:*** Agents are independent and self-directed with the non-intervened operations in their environment and interactions with other agents.
- ***Reactivity:*** Agents have the "learning behavior" to perceive their environment and respond to changes. They are informative to learn and adapt the behaviors based on experience, environmental circumstances, and other agents' situations.
- ***Pro-activeness:*** Agents are goal-directed to achieve concerning their behaviors with the comparisons of outcomes.
- ***"Social" ability:*** Agents are in an external environment with the protocols to identify, distinguish and interact with other agents.

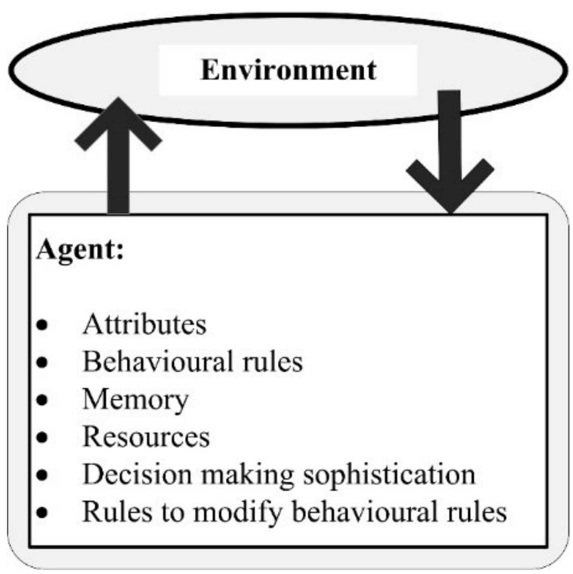


Figure 2.3 Basic characteristics and behaviors of agents

Generally, an agent-based model contains (a) Numerous agents designated at various scales, dimensions, or types. (b) Heuristics for decision-making, planning or system control or support. (c) Learning rules, adaptive processes, thresholds, or restrictions. (d) An interaction topology. And (e) A global environment. According to objective needs, agents perform different types to undertake various tasks and behaviors. Each agent can have single or multiple properties and types (Figure 2.4) (e.g., mobile agent, goal-based agent, and reactive agent) and have multiple tasks in a system.

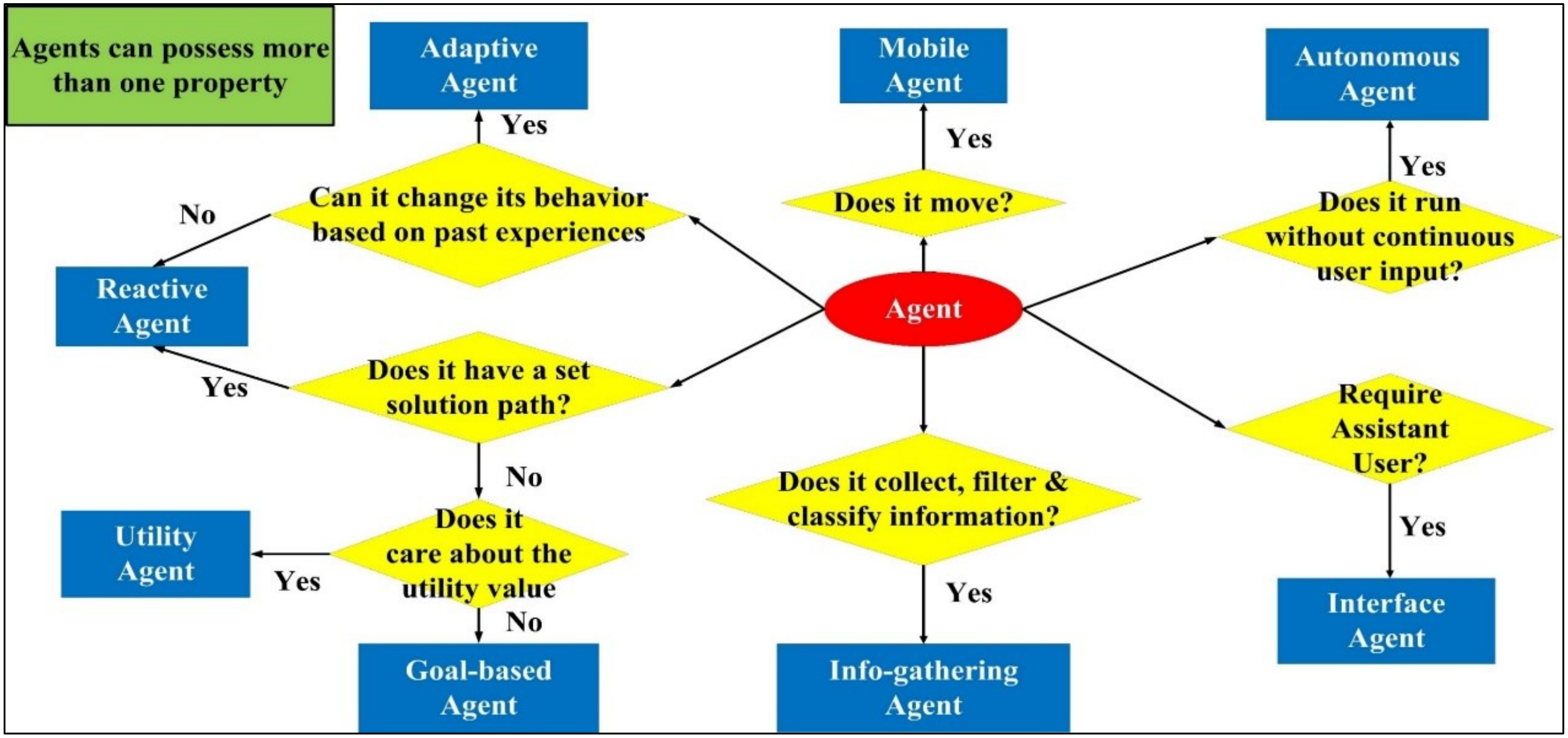


Figure 2.4 The types of agents

2.3.2 Two main agent-based approaches

Agent-based modeling (ABM) and multi-agent system (MAS) are two main and typical approaches for intelligent agents based on different application purposes. Agent-based modeling (ABM) is hereby introduced to achieve a dynamic, high-freedom, and interactive simulation approach. It is a kind of microscale models to simulate the actions and interactions of agents with a certain degree of autonomous characteristics (Orsi, 2019). It combined the elements of game theory, a complex system as well as evolutionary programming, which made it accessible to cooperate with optimization processes (Casado-Vara et al., 2018; Paulin et al., 2018). In ABM, agents can individually assess their environmental conditions and make decisions based on a set of rules. It is a class of computing models used to simulate behaviors and interactions of autonomous entities, including individuals and collective entities (e.g., organizations or groups), to evaluate their impacts on the system (Figure. 2.5). A unique feature of ABM is the repetitive competitive interactions between different agents with the support of high-performance computers to explore dynamics out of the reach of pure mathematical methods. A basic ABM model can contain a system of agents and the pre-set relationships of agents. Through repetitive emulations, even a simple ABM model can realize complex behavior patterns and provide valuable information on dynamic changes in a real-world system (Bonabeau, 2002). With its capacity for evolution and self-learning, ABM allows unpredictable behaviors to emerge. Unexpected outcomes correspond to the role and influence of uncertain factors in the real world. It is mainly used in non-computing related scientific fields, including biology, ecology and social sciences (Niazi and Hussain, 2011).

In contrast, a multi-agent system is modeled as a collection of agents to reflect and analyze the relationships between agents. It can solve complex or impossible problems for an individual agent-based or a monolithic system to deal with. MAS is a core research area of contemporary artificial intelligence. A MAS model consists of multiple decision-making agents, which interact in an information-sharing environment to achieve common or contradictory targets or goals (DeAngelis and Diaz, 2019). It is a computerized system composed of multiple interactive intelligent agents in an environment and may include some methodic, functional, procedural approach, algorithmic search, or reinforcement learning. Current studies on MAS mainly focus on online trading, disaster response and social structure modeling (Sabater and Sierra, 2002; Schurr et al., 2005; Vereshchaka and Dong, 2019). Sophisticated ABM or MAS models can incorporate different learning techniques (e.g., neural networks, evolutionary algorithms) to allow practical learning and adaptation. Till now, a few studies on ABM and MAS have been applied to the environmental decision-making problems (Ding et al., 2016; Groeneveld et al., 2017; Ye et al., 2019a; Ye et al., 2019b). The flowchart, integrated with Bulling (2014)'s study, indicates a general overview of agent-based and multi-agent decision making (Figure 2.6). Due to the strengths of agent-based modeling and multi-agent systems in decision-making systems, they have a vast potential to be applied to environmental problems.

Agent-based models (e.g., ABM and MAS) are mindsets more than technologies (Bonabeau, 2002). The mindsets describe a system from the perspective of its constituent units. However, agent-based models do not conflict with traditional differential equation modeling. The set of differential equations and empirical rules provides constituent units of dynamic systems by ABM and MAS. The synonym of ABM and MAS would be microscopic modeling because both starts to mimic the social systems from simple and minor components. However, an alternative would be macroscopic modeling. Both agent-based modeling and multi-agent system are based on the concepts of agents, which represent a computational entity (e.g., numerical module, software programs, or robots) that can perform perceptions and actions upon its environment and evolve its behavior autonomously, at least partially relying on its own experience (Weiss, 1999). The benefits of Agent-based modeling over other modeling techniques can be reflected in the captures of emergent phenomena, systems' natural description, and flexibility. The main difference is that ABM generally implements a small number of highly complex agents with the main features considering their capacities to deal with tasks. On the other hand, MAS typically contains many simple agents, focusing on the emergency of new phenomena from social interactions. Using a loose analogy in network theory, it is as if ABM is the nodes of a small network, while MAS is the links of an extensive network. In some cases, there is no clear threshold to distinguish them.

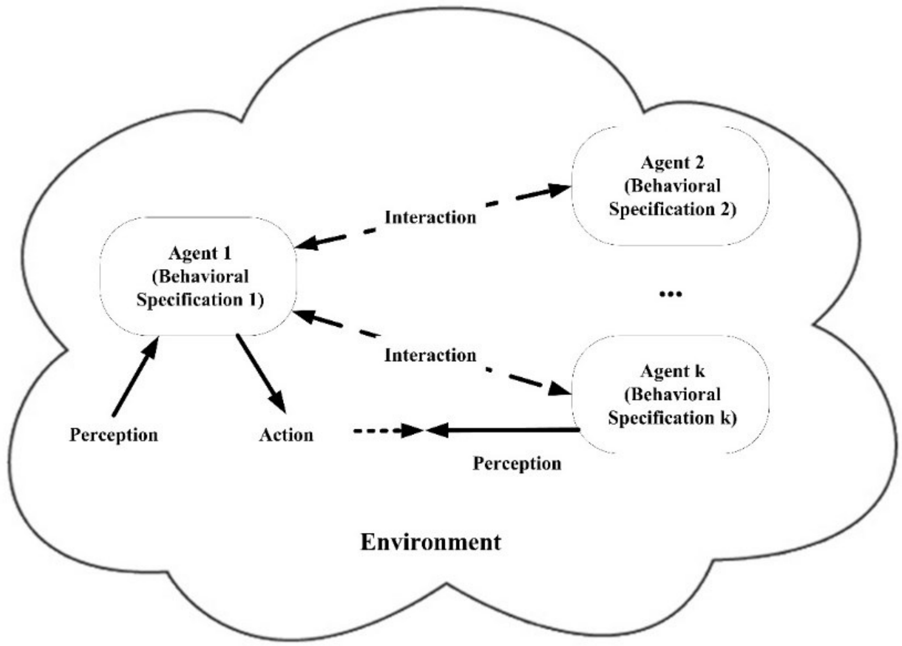


Figure 2.5 An abstract model scheme for agent-based modeling approach

(Bandini et al., 2009)

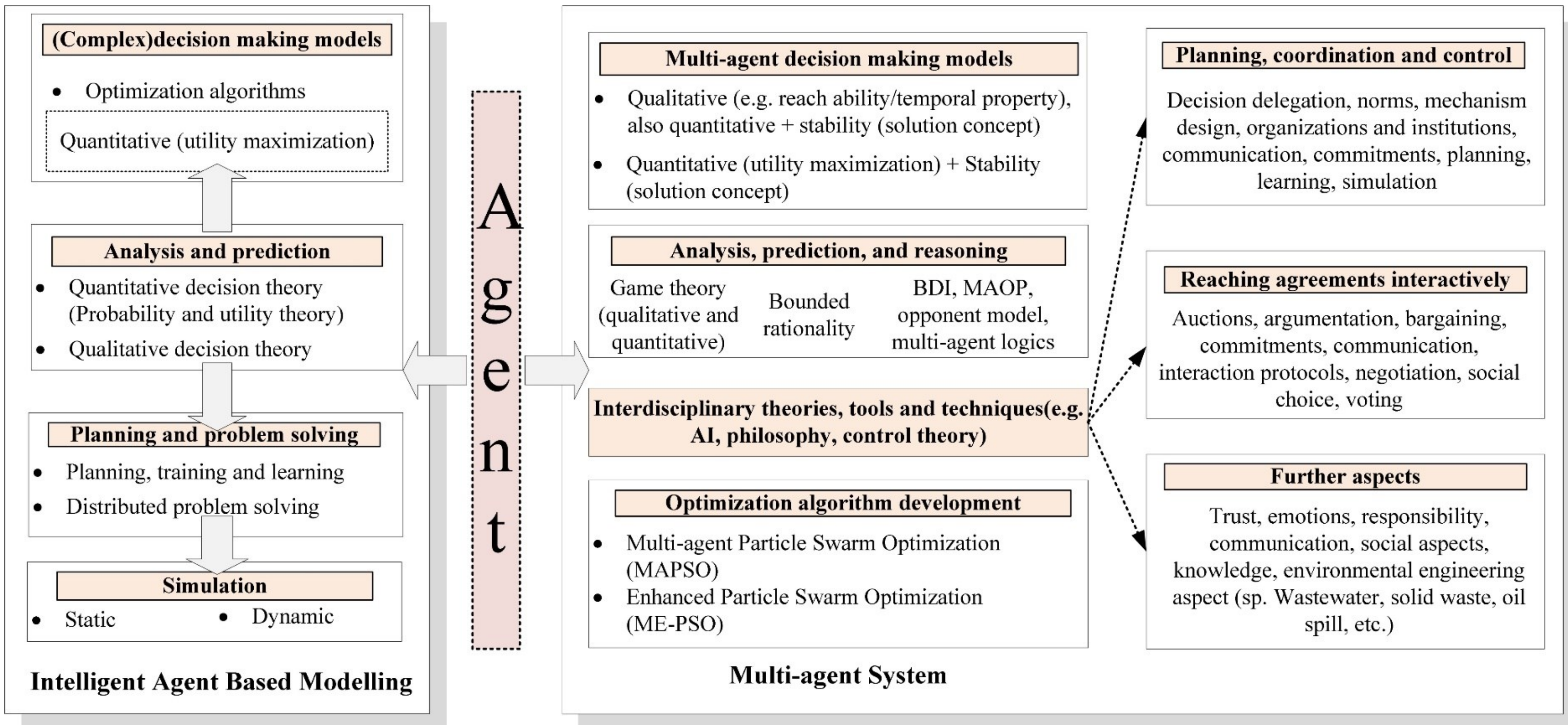


Figure 2.6 Overview of aspects relevant to agent-based and multi-agent-based decision making

In MAS, the actions or communications of agents commonly serve in two types: blackboard communication and directed communication (Figure 2.7). Blackboard communication, as the most common way of communication, represents that, through the interactions via the shared environment, agent actions cause perceivable and interpretable effects by other agents. Directed communication is the other type used to access information from different agents via message passing. The information is transferred from one agent to another. The environment is used only as a means of transportation without interactions.

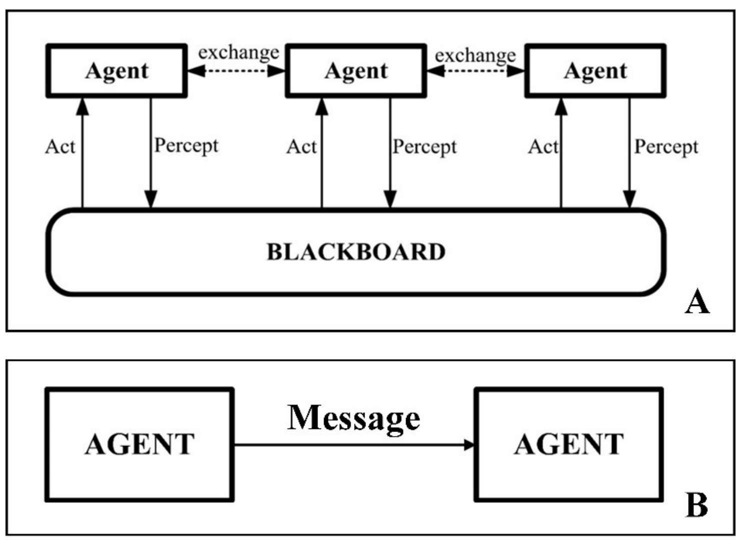


Figure 2.7 Blackboard communication (A) and Directed communication (B)

Agents in a multi-agent system have the following characteristics (Zhao et al., 2005): a) stay and act in an environment with given boundaries; b) impact its local environment and interact with other agents; c) are at least partially independent, self-aware, sociable, and autonomous; d) achieve particular goals or tasks; e) respond to changes in time according to their learning ability. It is necessary to develop institutional coordination through reusable structures to provide flexible system behavior in such large-scale MAS systems. Four typical structures are star (centralized), ring (decentralized), chain (hierarchy), and network (democratic) (Figure 2.8). The structures in MAS are characterized by three aspects: capacity, duration, and decision-making (Kirn et al., 2006). Capacity is the ability to provide solutions to the same set of problems on a large scale or in a short time. Duration represents remaining an unchanged structure for MAS modeling throughout the entire life cycle. The duration type could be short, medium, long, static, or dynamic. Decision-making stands for selecting appropriate levels to provide proper decisions or management according to the balance of flexibility and coordination efficacy.

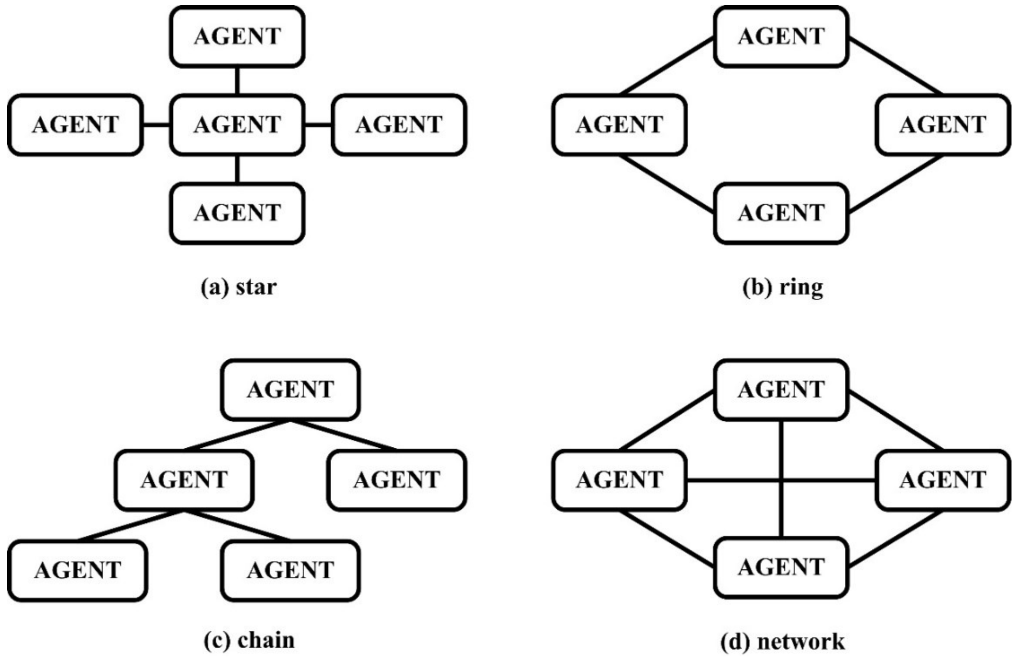


Figure 2.8 Interaction structure of multi-agent system

2.3.3 Agent-based simulation software tools

In recent years, the utilization of agent-based software tools for research in different fields related to agent-based modeling and the multi-agent system has grown. ABM platforms, software implementation frameworks, and simulation tools are also developed. Several reviews have been done to analyze and discuss the studies and potentials in different areas, including policy evaluation (Castro et al., 2020; Kremmydas et al., 2018), disease (Li et al., 2016c; Nianogo and Arah, 2015), stream diffusion (Kiesling et al., 2012), building and construction (Berger and Mahdavi, 2020; Ding et al., 2018), flood (Simmonds et al., 2020), resource planning and management (Berglund, 2015), social conflict and violence (Groff et al., 2019; Lemos et al., 2013), public health (Retzlaff et al., 2021; Tracy et al., 2018), and optimization (Barbati et al., 2012). Some of the reviews reviewed the developed software and platforms for agent-based studies. Chen (2012) reviewed the platforms of Swarm®, Repast®, StarLogo®, and Netlogo® with the background and foundational information and briefly discussed the potential for urban and architectural research. Table 2.3 indicates the summary and comparison of various software and modeling tools to deal with agent-based or multi-agent problems. With the rapid development in recent years of computer technologies (e.g., CPUs or graphic cards), operating systems (e.g., Windows, Linux, or Mac OS), and programming languages (e.g., C++, Java, or Python), a number of these tools gradually become unavailable and outdated, which cannot be used as an efficient agent-based software anymore. Software should be updated frequently to keep up with the improving speed of hardware and system. Old software tools are replaced even though they may have outstanding performance at that time. Table 2.3 summarizes the recent information based on the software list of Abar et al. (2017), which can help scientists and engineers quickly assess and choose the proper tool for their research applications. However, some tools have no continuous update and maintenance (20 of 85 tools) after the Year 2010, which cannot be further used as the foundation for new research. Furthermore, some tools also have essential improvements after the study of Abar et al. (2017). Thus, the table summarizes up-to-date information on current powerful ABM platforms and tools with the most fundamental properties, including software name, programming language, development difficulty, model scalability level, operating system, year of the latest update, the number of available resources (e.g., manuals, example modules, training videos, online courses, and technical forum), and latest website for resource and download. Software for agent-based simulation and modeling can be undertaken on various operating systems (i.e., Windows, Linux, Unix, Mac OS X, and browsers). Additionally, ABM and MAS modeling can be realized with general-purposed programming languages (e.g., C++, Java, or Python) or specially designed languages (e.g., StarLogo, EntendSim, or SmallTalk). As agent-based modeling is a kind of objective-oriented and population-based techniques, the scalability of agent size is a vital element for applications, which are defined as small-scale (< 100 agents), medium-scale (100-1,000 agents), large-scale (1,000-10,000 agents), and extreme-scale (> 10,000 agents). The development difficulty is related to users' programming experience (from "friendly to non-programmer" to "professional programmer"). Some of the available tools are developed for specific projects (e.g., Agent Cell, GALATEA, JAS), the updating frequency of these tools may decrease after the completion of projects, making them out-of-date after the next several years. The general-purpose agent-based tools (e.g., Netlogo, Repast, MASON, Mathematics, MATSim, SimEvents) should be the first choice to be utilized as the modeling platforms for the development of new studies.

According to previous studies and the author's experience, current platforms still contain obstacles for research purposes (Railsback et al., 2006). First, there are difficulties in model compatibility and a lack of specific mathematical algorithms (i.e., optimization toolbox and calculus calculation programs). Second, there is a lack of training programs and required software skills in many research areas to use ABM or MAS. Third, the limitations of software functions and unoptimized memory usage cannot meet the needs of some research purposes. The shortcomings limit the application of the agent-based model, but the software version updates and extensions can partially alleviate the shortcomings.

Table 2.3 Summary and comparison of agent-based software tools

No.	Software Tool	Programming language	Development Difficulty	Model Scalability Level	Operating System	Year of Latest Update	Resource
1	Agent Cell	C++, Java	Hard	Large-scale	L	2013	Little
		https://sourceforge.net/p/agentcell/wiki/Home/					
2	AgentCubes (AgentSheets)	Java	Simple	Small-scale	W,M,L,U,B	2021	Adequate
		https://agentsheets.com/					
3	AgentScript	Java	Simple	Small-scale	W,M,L,U,B	2021	Some
		http://agentscript.org/					
4	Altreva Adaptive Modeler	Microsoft.Net	Simple	Large-scale	W	2020	Adequate
		https://www.altreva.com/technology.html					
5	AnyLogic	Java	Moderate	Large-scale	W,M,L	2021	Adequate
		https://www.anylogic.com/					
6	Ascape	Java	Moderate	Large-scale	W,M,L,U	2010	Little

		http://ascape.sourceforge.net/					
7	Breve	C++, Pathon	Moderate	Medium-scale	M	2015	Little
		http://www.spiderland.org/s/					
8	BSim	Java	Hard	Large-scale	W,M,L	2017	Some
		http://bsim-bccs.sourceforge.net/					
9	CloudSim	Java	Moderate	Large-scale	W,M,L	2019	Some
		http://www.cloudbus.org/cloudsim/					
10	Cormas	SmallTalk	Moderate	Medium-scale	W,M,L	2021	Some
		http://cormas.cirad.fr/					
11	CRAFTY	Java	Moderate	Large-scale	W,M,L	2015	Little
		http://crafty-abm.sourceforge.net/					
12	DigiHive	C++	Hard	Medium-scale	W	2019	Little
		http://digihive.pl/					
13	EcoLab	C++	Hard	Large-scale	W	2021	Little
		http://ecolab.sourceforge.net/					

14	Envision	C++	Moderate	Medium-scale	W	2015	Little
		http://envision.bioe.orst.edu/					
15	Eve	Java	Moderate	Medium-scale	W,M,L,U	2015	Little
		https://eve.almende.com/					
16	ExtendSim	EntendSim Model Language	Moderate	Medium-scale	W,M	2021	Adequate
		https://extendsim.com/					
17	FLAME	C	Moderate	Large-scale	W,M,L	2016	Some
		http://flame.ac.uk/					
18	FLAME GPU	C for CUDA	Hard	Large-scale	W,M,L	2021	Some
		https://flamegpu.com/					
19	FlexSim	Microsoft. NET Framework	Simple	Medium-scale	W	2021	Adequate
		https://www.flexsim.com/					
20	Framsticks	Java	Simple	Small-scale	W,M,L	2021	Some

		http://www.framsticks.com/						
21	GAMA	Java	Moderate	Small-scale	W,M,L	2021	Adequate
		https://gama-platform.github.io/					
22	GALATEA	Java	Moderate	Medium-scale	W,M,L	2021	Little
		https://sourceforge.net/projects/galatea/					
23	GridABM	Java	Hard	Large-scale	W,L	2013	Little
		https://sourceforge.net/projects/gridabm/					
24	GROWLab	Java	Moderate	Medium-scaale	W,M,L	2018	Some
		https://icr.ethz.ch/research/growlab/					
25	HLA-RePast	Java	Hard	Large-scale	L,U	2021	Little
		https://github.com/HLA-RePast					
26	Insight Maker	Java	Moderate	Medium-scale	W,M,L	2021	Adequate
		https://insightmaker.com/					
27	Jamel	Java	Simple	Small-scale	W,M,L,U	2018	Some

		http://p.seppecher.free.fr/jamel/						
28	JAMSIM	Java	Moderate	Medium-scale	W,M,L,U	2017	Little
		https://github.com/compassresearchcentre/jamsim					
29	JAS	Java	Simple	Medium-scale	W,M,L,U	2006	Some
		http://jaslibrary.sourceforge.net/					
30	JASA	Java	Moderate	Medium-scale	W,M,L,U	2016	Little
		https://jasa.sourceforge.io/					
31	JAS-mine	Java	Moderate	Medium-scale	W,M,L,U	2021	Some
		http://www.microsimulation.ac.uk/jas-mine/					
32	JCASim	Java	Simple	Small-scale	W,M,L,U,B	2009	Some
		http://www.jcasim.de/					
33	jES	Java	Simple	Small-scale	W,M,L,U	2016	Little
		https://terna.to.it/jes/					
34	LSD	C++	Moderate	Large-scale	W,M,L,U	2020	Little
		https://www.labsimdev.org/wp/					

35	MASON	Java	Hard	Large-scale	W,M,L,U	2021	Adequate
		https://cs.gmu.edu/~eclab/projects/mason/					
36	MASS	Java	Moderate	Large-scale	W,M,L	2014	Some
		http://mas.cs.umass.edu/research_old/mass/					
37	MASyV	C	Hard	Medium-scale	M,L,U	2008	Some
		http://masyv.sourceforge.net/					
38	Mathematics® (Wolfram)	Wolfram Language, C/C++, Java, Mathematica	Moderate	Medium-scale	W,M,L	2021	Adequate
		https://www.wolfram.com/mathematica/?source=nav					
39	MATSim	Java	Hard	Extreme-scale	W,M,L,U	2021	Adequate
		https://matsim.org/					
40	Mesa	Python 3+	Moderate	Medium-scale	W,M,L,U	2021	Some
		https://pypi.org/project/Mesa/					
41	MIMOSA	Java	Moderate	Medium-scale	W,L	2021	Little

		https://sourceforge.net/projects/mimosa/					
42	Mobility Testbed	Java	Moderate	Medium-scale	W,M,L,U	2014	Little
		https://github.com/agents4its/mobilitytestbed					
43	Modgen	Microsoft Visual Studio	Moderate	Medium-scale	W	2017	Some
		https://www.statcan.gc.ca/eng/microsimulation/modgen/modgen					
44	Netlogo	Starlogo	Moderate	Large-scale	W,M,L,U,B	2021	Adequate
		https://ccl.northwestern.edu/netlogo/					
45	Pandora	C++, Phthon, Cassandra, Microsoft.NET Framework	Moderate	Large-scale	W	2018	Little
		https://xrubio.github.io/pandora/					
46	PDES-MAS	C++	Hard	Extreme-scale	L,U	2020	Little
		https://pdes-mas.github.io/					
47	PedSim Pro	C++	Easy	Small-scale	W,M,L	2021	Adequate

		https://www.pedsim.net/					
48	Repast HPC	C++	Hard	Extreme-scale	W,M,L,U	2021	Adequate
		https://repast.github.io/repast_hpc.html					
49	Repast Simphony	Java	Hard	Large-scale	W,M,L,U	2021	Adequate
		https://repast.github.io/repast_simphony.html					
50	Scratch	Squeak	Easy	Small-scale	W,M,B	2021	Adequate
		https://scratch.mit.edu/					
51	SEAS	C++	Moderate	Small-scale	W	2021	Some
		https://teamseas.com/					
52	SimAgentMPI	Python	Hard	Large-scale	W,M,L,U	2020	Some
		https://tylerbanks.net/SimAgentMPI/					
53	SimBioSys	C++	Moderate	Large-scale	W,M,L	2021	Some
		https://www.simbiosys.com/					
54		C, C++, MATLAB code language	Moderate	Large-scale	M,M,L	2021	Adequate

	SimEvents (with MATLAB®, Simulink®)	https://www.mathworks.com/products/simevents.html					
55	SIMIO	C	Moderate	Large-scale	W	2021	Adequate
		https://www.simio.com/software/					
56	Simjr	Java	Simple	Small-scale	W,M,L	2010	Little
		https://code.google.com/archive/p/simjr/					
57	SimSketch	Java	Simple	Small-scale	W,M,L,B	2013	Little
		http://modeldrawing.eu/our-software/simsketch/					
58	Simul8	Visual Logic Code	Moderate	Large-scale	W,M	2021	Adequate
		https://www.simul8.com/					
59	StarLogo Nova	Java	Simple	Small-scale	W,M,B	2018	Some
		https://www.slnova.org/					
60	StarLogo TNG	OpenGL programming	Simple	Small-scale	W,M	2021	Some
		https://education.mit.edu/starlogo-tng-download/					

61	Sugarscape	Java	Simple	Small-scale	W,M,L,U,B	2013	Little
		https://sourceforge.net/projects/sugarscape/					
62	Swarm	Java, C	Hard	Extreme-scale	W,M,L	2020	Some
		https://www.swarm.org/wiki/Main_Page					
63	TerraME	C++/Lua	Moderate	Large-scale	W,M,L	2020	Some
		http://www.terrame.org/doku.php					
64	UrbanSim	Python	Moderate	Large-scale	W,M,L	2021	Adequate
		https://urbansim.com/					
65	Xholon	Java	Moderate	Medium-scale	W,M,L,U	2021	Adequate
		http://www.primordion.com/Xholon/					

(**Note:** B: work in the browser, L: Linux, M: Mac OS X, U: Unix, W: Windows)

(The information is updated to July 2021)

2.3.4 Application in environmental field

In recent years, agent, as a novel dynamic modeling and decision-making approach, has been applied in all fields. Due to the capacities of dynamics and self-learning by ABM and MAS, the agent-based techniques could efficiently deal with environmental problems. In the environmental field, previous studies focus on the issues of climate changes and policies (Castro et al., 2020; Chappin et al., 2017; Entwisle et al., 2016; Gerst et al., 2013; Gubareva and Gomes, 2019; Hailegiorgis et al., 2018; Lamperti et al., 2016; Patt and Siebenhüner, 2005; Pons et al., 2014; Wang et al., 2013b), urban water supply (Ali et al., 2017), water consumption (Soboll and Schmude, 2011), flooding (Du et al., 2017; Haer et al., 2020; Jenkins et al., 2017), water resource planning and management (Akhbari and Grigg, 2013; Berglund, 2015; Darbandsari et al., 2017; Darbandsari et al., 2020; Ding et al., 2021; Galán et al., 2009; Kanta and Berglund, 2015; Lin et al., 2020; Xiao et al., 2018; Zechman, 2007, 2011, 2013), water pollution (Shafiee and Zechman, 2011), groundwater management (Arasteh and Farjami, 2021), water reuse (Kandiah et al., 2019), oil spill response management (Han et al., 2019a; Li et al., 2016b), risk assessment and damage evaluation (Hansen et al., 2015; Hyun et al., 2019; Skov et al., 2021; Topping and Lagisz, 2012), air quality and pollution (David and Don, 2012; Dragomir, 2014; Gurram et al., 2019; Hülsmann et al., 2011), wastewater treatment and management (Aulinas et al., 2008; Berglund, 2015; Jing et al., 2018; Oliva-Felipe et al., 2021; Polaków and Metzger, 2012;

Sànchez-Marrè et al., 2008; Schuler et al., 2011). According to the previous studies, few studies focus on marine oil spill pollution and response management. The simulation and decision-making of marine oil spills is a complex process related to dynamic simulations of multiple stages and oil-related changes and the assignment and allocation of different response options and resources. Agent-based modeling and the multi-agent system could be high-potential approaches for coupling dynamic simulation modules and manifold system control and management.

2.4 Environmental Optimization Methods

In most model-based research fields, mathematical optimizations aim to perform the selection of a best-concerned element (regarding specific criteria) from some available alternatives (Snyman and Wilke, 2018). In most cases, optimization problems dig out the maximum or minimum of one or some objective functions with a systematical selection of values of input factors and parameters from defined ranges. The generalization of formulas by optimization theory and techniques covers a wide range of applied mathematics. More generally, optimization issues involve finding "best available" values of some objective functions given a followed domain (or input). The optimization problems can include various types of objective functions and domains. The objective functions would adjust their available domain range through the constraints within iterations or updates (Kallrath, 2013).

In my research on decision-making and emergency response management, optimization methods are an essential aspect of improving the efficiency of the target system and reducing budget and operation costs. To select appropriate response resources by balancing response time, costs, and even environmental impacts. Additionally, appropriate adjustments to process parameters can significantly increase the cleanup rates of spilled oil. Due to the fast computation speed, the high compatibility with agent-based modeling, and the large capacity of variants, particle swarm optimization (PSO) is chosen as the main optimization algorithm in the following chapters. The traditional PSO has the benefits of simple implementation, quick-adjust with a few parameters and short computation time. However, the convergence could be premature and easily trapped into a local minimum, especially with complex problems (Abdmouleh et al., 2017a). To overcome the shortcomings, my research focuses on improving the capacity and efficiency of PSO with the integration of advanced updating thoughts (e.g., multi-agent system, evolutionary population dynamics) to develop better PSO versions to serve the optimization problems related to marine oil spill responses.

In addition, the genetic algorithm (GA) is a traditional meta-heuristic approach that has been extensively developed in computer science and operations research (Mirjalili, 2019). According to the strengths of high efficiency and high stability, it was used as a benchmark to compare different developed optimization algorithms for testing their efficiencies. Section 3 developed with the integration of PSO with agent-based simulation modeling for supporting dynamic decision-making in marine oil spill response. In Section 4, an improved PSO version was integrated with the multi-agent system and evolutionary population dynamic (EPD). In Section 6, a comparative particle swarm optimization (C-PSO) was further developed by comparing 12 hybrid PSO variants and 16 inertia weighting coefficient functions. The foundational knowledge of optimization algorithms is shown in the following aspects.

2.4.1 Particle swarm optimization

Particle swarm optimization is a computational method to improve candidate solutions (also called particles) through iterations and moves particles in the multi-dimensional search space according to position and velocity updates (Olsson, 2010). It is an evolutionary algorithm that solves the optimization problems with nonlinear, constrained/unconstrained, or non-differentiable multimodal functions (Eberhart and Kennedy, 1995b). PSO is a stochastic, population-based computer algorithm based on swarm intelligence. Swarm intelligence is based on the principles of social psychology, provides insights into social behavior, and contributes to engineering applications (Lin et al., 2015). Each particle's movement is influenced by its current position, its local known position and is also affected by the global best-known position, which is updated as better positions are found with the interaction of other particles (Figure 2.9) (Eberhart and Kennedy, 1995a; Wang et al., 2010). PSO uses iterative updates from a population of candidate solutions to improve its optima, like a genetic algorithm. It has an outstanding optimization performance, such as a high computational efficiency with a low memory space requirement and CPU speed (Khare and Rangnekar, 2013). PSO variants add more parameter adjustments to improve their optimization performances. The basic PSO is usually applied for problems with continuous variables. The discrete binary PSO was provided to deal with discrete design variables (e.g., selections of technology types and quantities) first developed by Kennedy and Eberhart in 1997 (Kennedy and Eberhart, 1997).

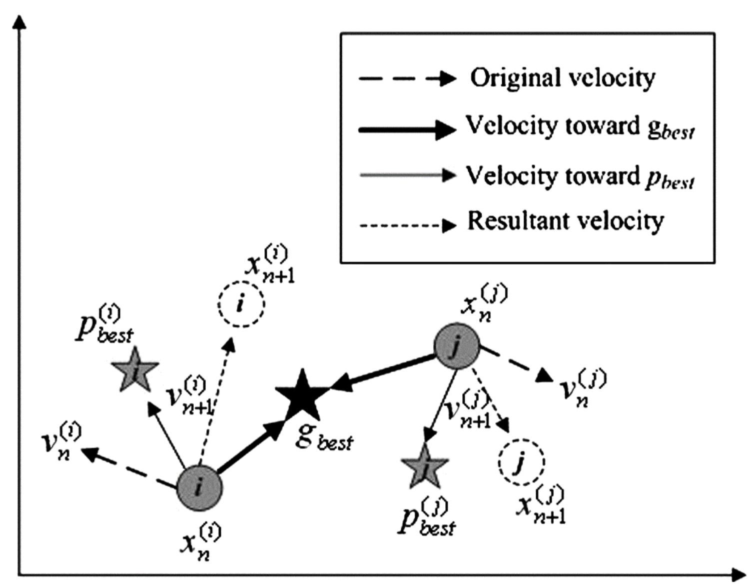


Figure 2.9 The basic flowchart of update process for PSO

PSO is a stochastic population heuristic optimization approach developed by Eberhart and Kennedy (1995a) for continuous nonlinear function optimization problems. It stimulates the movement of birds in a flock of birds that share information (Acan and Gunay, 2005), and their interaction is defined by topology. A candidate solution, as a point in a multi-dimensional search space, imitates the behaviour of birds to adjust its position and velocity for better coordinates with the experience of itself and other birds. PSO is a meta-heuristic algorithm because it has almost no assumptions or any assumptions about the problem to be optimized, and it can search for candidate solutions. PSO is relatively straightforward to be implemented for solving scheduling problems because of its simplicity, high convergence and short computation time (Ye et al., 2019a). However, the traditional PSO algorithm still has its shortcomings. It is easy to fall into the local optimum in the high-dimensional space, and the convergence speed is low in the iterative process. A set of PSO variants have been developed to overcome this limitation.

In the traditional PSO, each particle represents a solution to the problem and searches for a global minimum or maximum in the search space. Particles update their positions by flying around in the multi-dimensional search space until a relatively stable position is selected or the stopping criteria are satisfied (Del Valle et al., 2008). Each particle is allocated in a multi-dimensional space according to the number of variables or requirements, and a particle owns two characteristics: coordinates (position) and its corresponding flight speed (velocity). Each particle's position represents a candidate for an optimal solution in available value ranges. During the initial process, the positions and velocities of particles are valued randomly. During each iteration, the previous local best position of a particle is recorded and indicated as *pBest*, and the global best particle position among all the particles in the group is denoted as *gBest*. Each particle updates its velocity and location based on the interaction with its own experience, local best position and global best position. The acceleration of movement towards the best location of an individual and the group is weighted randomly. Therefore, the particle travels to a new position depending on its updated velocity. According to the most standard PSO version (Shi and Eberhart, 1998), the essential feature is adjusting positions and velocity with Eq 1 and 2. Each particle represents a candidate solution to the problem, containing a position vector (x) and a velocity vector (v). The vectors include the information from the *d-th* dimensional search space. The position vectors record the coordinates of particles as $x_i = [x_{i1}, x_{i2}, \dots, x_{id}]$. The velocity vectors control the adjustment speed of particles' positions as $v_i = [v_{i1}, v_{i2}, \dots, v_{id}]$. They integrate the updated information from its present velocity (v_{id}), the individual best solution of themselves so far (p_{id}), and the global best solution of all particles (p_{gd}). The inertia weight (w) controls the contribution of the current velocity. It can be a positive constant, a linear or nonlinear function with the iteration number (Shi and Eberhart, 1998). A proper inertia weight can coordinate the effects of the velocity and particle interactions to prevent local optima. c_1 and c_2 are two acceleration factors, called cognitive factor and social factor. Thus, acceleration factors equal to 2 in most studies, which have an average value of 1 (Khare and Rangnekar, 2013). They are desired that they should have the same significance for velocity update. r_1 and r_2 are two different random numbers within the range of [0,1].

$$v_{id} = w \cdot v_{id} + c_1 \cdot r_1 \cdot (p_{id} - x_{id}) + c_2 \cdot r_2 \cdot (p_{gd} - x_{id}) \tag{2.1}$$

$$x'_{id} = x_{id} + v_{id} \tag{2.2}$$

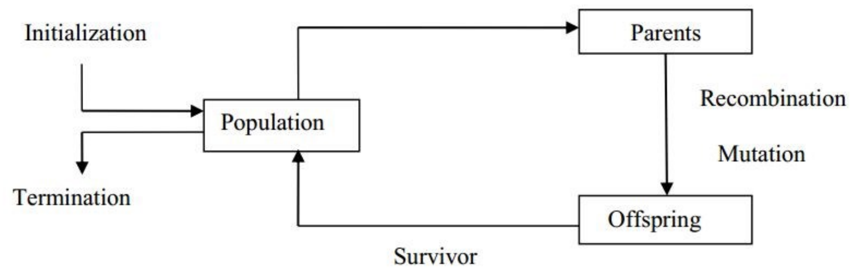
where, v_{id} is particle velocity, x_{id} is particle position, i is the index of a particle, d is the d-*th* dimension of a particle, w is the inertia weight factor, c_1 and c_2 are two acceleration constants called cognitive factor and social factor, respectively. r_1 and r_2 are uniform random values in the range of [0, 1], p_{id} is particle *pBest*, p_{gd} is group *gBest*.

Particle swarm optimization (PSO), proposed by Kennedy and Eberhart, is a widespread evolutionary algorithm method (Kennedy and Eberhart, 1995). The algorithm is inspired by swarm intelligence and the social behavior of birds. PSO is a meta-heuristic algorithm to deal with complex mathematical problems in engineering (He and Wang, 2007). Iteratively attempts to improve candidate solutions (i.e., particles) and move particles around a multi-dimensional searching space based on a simple mathematical formula of particle position and velocity (Parsopoulos and Vrahatis, 2010). Their current position influences the movements of particles, their best-known position, and the global best-known position to figure out better positions with the interactions (Zhao et al., 2011). Particle swarm optimization (PSO) is a robust evolutionary algorithm that has been widely used to solve optimization problems (Cheng and Jin, 2015). The basic version of PSO has a simple update formula and no assumptions, which is easy to implement for most optimization problems. It proceeds with a large search space for solutions. However, it may fall into a local optimum with a low convergence speed in complex problems (Bongirwar et al., 2018). The developed PSO variants are reviewed for their improved optimization performance (Engelbrecht, 2016; Fang et al., 2010; Garcia-Gonzalo and Fernandez-Martinez, 2012; ping Tian, 2013; Song and Gu, 2004) or and application in electrical and power engineering (Jordehi, 2015; Niazi and Lalwani, 2017), shipping (Kanović et al., 2014), mechanical engineering (Kulkarni et al., 2015), geotechnical engineering (Andrab et al., 2017; Hajihassani et al., 2018) and data analysis (Esmin et al., 2015; Ghorpade-Aher and Bagdiya, 2014). Marine oil spill decision-making problems are complicated with the requirements of variable types (i.e., integer variables for design quantity selection and continuous variables for process parameter adjustment), process simulation models (e.g., empirical equations of treatment, agent-based simulation, artificial neural network, marine oil spill simulation software), multiple objectives (e.g., minimum of cost, energy, time and ecological impact). PSO has been widely used as a robust optimization approach to deal with these problems.

In marine oil spill studies, PSO and its variants have been applied to the studies about response scheduling (Huang et al., 2020b), oil spill detection and monitoring (Fan et al., 2014; Sheta et al., 2018), oil spill mapping (Ball et al., 2017; Odonkor et al., 2019) and oil slick classification (Ozkan et al., 2012). However, a few studies utilized PSO to optimize response planning for marine oil spills (Ye et al., 2019b). Particle swarm optimization has the advantages of easy implementation, fewer adjusted parameters, higher robustness, and shorter computational time than other evolutionary optimization approaches (Abdmouleh et al., 2017b). However, the efficiency of PSO is also limited by premature convergence with local minima, especially when encountering complex problems. In order to overcome the limitations, several PSO variants were developed (Cheng and Jin, 2015; Taherkhani and Safabakhsh, 2016; Wang et al., 2011). Multi-agent theory is a proficient approach to enlarging convergence searching areas and improving the interactions between different solution candidates (Chen et al., 2019b). However, it has the shortcomings of slow convergence speed, high calculation cost and large population size. Evolutionary population dynamics (EPD) improves the performance of meta-heuristics by selecting a better median fitness of the whole population by removing weak solutions (Saremi et al., 2015). With the combination of EPD with multi-agent PSO, the new variants have the potential to improve optimization efficiency.

2.4.2 Genetic algorithm

In operations research based on computer science and models, the genetic algorithm (GA) is a meta-heuristic method inspired by the process of natural selection and belongs to an advanced evolutionary algorithm (EA). Genetic algorithms are often used to generate high-quality solutions to solve optimization and search problems that rely on biologically inspired operators (such as mutation, crossover, and selection) (Katoch et al., 2021; Mitchell et al., 1996). As shown in Figure 2.11, the main steps are population generation, fitness function discovery, application of genetic operators and population evaluation (Johar et al., 2016). In genetic algorithms, a set of candidate solutions for the best problem (called individual, biological or phenotype) are all developed toward a better solution. Each candidate solution has a set of characteristics (its chromosome or genotype) that can be mutated and changed. Traditionally, the solution is represented as a string of 0 and 1 in binary form, but other encodings are also possible (Whitley, 1994). A typical genetic algorithm requires two basic rules: 1) the genetic representation of the solution domains (constraints); 2) the fitness functions (objective functions) to evaluate the scope of the solution.



Pseudo –code
Begin
INITIALISE population with random candidate solution
EVALUATE each candidate.
REPEAT UNTILL (termination condition) is satisfied DO
1. SELECT Parents
2. RECOMBINE Pairs of parents
3. MUTATE the resulting offspring.
4. SELECT individuals or the next generation.
END

Figure 2.10 General scheme of evolutionary process

Three leading genetic operators are used to find the best solution: reproduction (selection), crossing, and mutation. 1) *Reproduction (selection):* An individual is copied to let the fitness function values make more copies of a better string in a population 2) *Cross*: After reproduction, the string of the mating pool is required for crossover. The crossover is the procedure that combines two strings to generate a better string. 3) *Mutation*: new strings and information are added randomly to the genetic search process and prevent an irrecoverable loss of potentially useful information, which reproduction and crossover can cause (Johar et al., 2016; Sivaraj and Ravichandran, 2011).

Although GA is a popular optimization method to solve most operational problems, it still has limitations compared with alternative optimization algorithms. First, GA is usually limited to complex problem breakdowns with repeated fitness function evaluations. For complex high-dimensional multi-modal problems with complex fitness functions, finding the best solution becomes difficult (Nicolas, 2017). Second, GA cannot expand a large number of elements well, and these elements need to be mutated in a vast space. Protecting well-represented solutions from further destructive mutations is a problem (Sivaraj and Ravichandran, 2011). Third, GA may tend to converge to local optima or even arbitrary points rather than to global optima in many problems (Rudolph, 1994). That means the model cannot determine how to sacrifice a good short-term solution to get a better long-term solution. Due to these limitations, traditional genetic algorithms can be used to check the efficiency of innovatively developed optimization methods, and it is possible to use variants of genetic algorithms to modify specific problems.

2.5 Human Factor Analysis

The Human Factor Analysis and Classification System (HFACS) was developed by Shappell and Wiegmann (2000). It is a broad framework of human error, initially used by the U.S. Air Force to investigate and analyze human factors in aviation (Wiegmann et al., 2005). HFACS is mainly based on James Reason's Swiss cheese model (Reason, 1990). The HFACS framework provides tools to assist in the investigation process with training and prevention. Researchers can systematically identify active and latent failures in the organization that led to the eventual accident. The purpose of HFACS is to understand the potential cause and effect of the accident rather than to blame. The HFACS framework (shown in Figure 2.12) describes human error at each of the four failure levels: 1) Unsafe acts of operators, 2) Preconditions for unsafe acts, 3) Unsafe supervision, and 4) Organizational influences. In each level of HFACS, causal categories are established to identify active and potential failures that occur. In theory, at least one failure will occur at each level, leading to adverse events. If one of the faults is corrected at any time that caused the adverse event, the adverse event can be prevented (Shappell and Wiegmann, 2001).

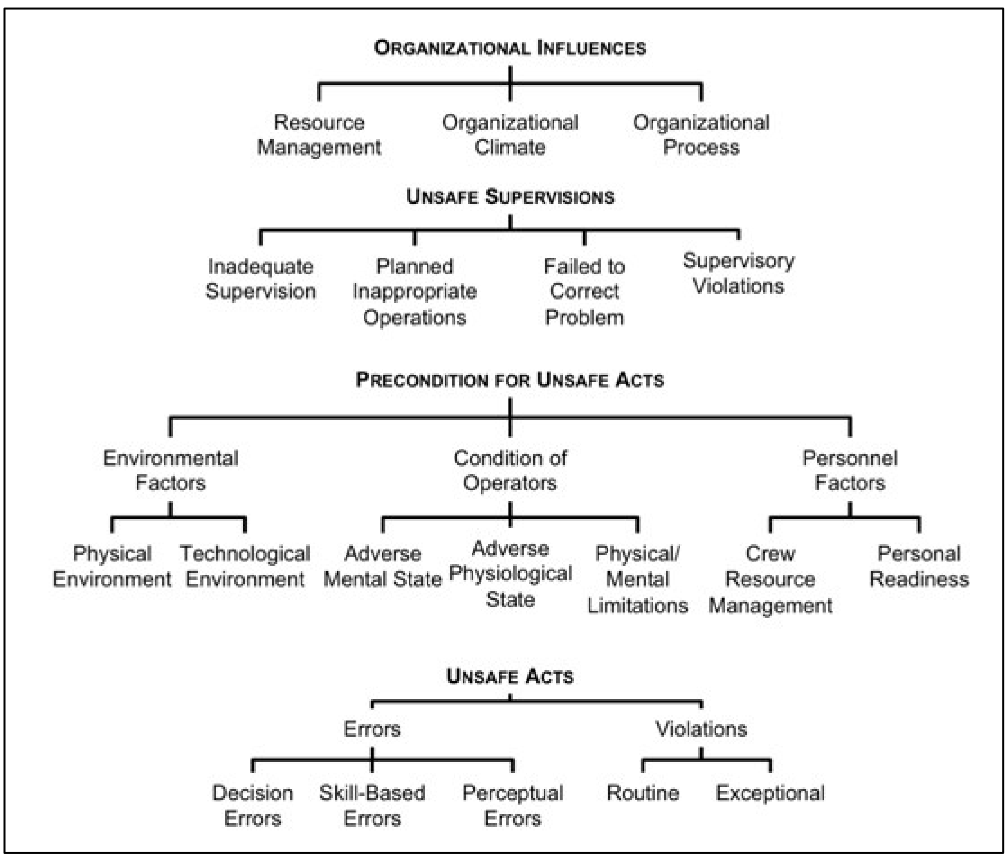


Figure 2.11 The HFACS framework

2.5.1 HFACS level 1: unsafe acts

The Unsafe Acts level is divided into two categories-errors and violations-and then these two categories are divided into sub-categories. Errors are unintentional actions, while violations are actions that deliberately ignore rules and regulations.

Errors***: 1) Skill-based errors*****:** Operator errors when performing routine, highly practiced tasks related to procedures, training, or proficiency, resulting in unsafe conditions (for example, failure to prioritize attention, list errors, bad habits). ***2) Decision errors:*** Errors that occur when the operator's actions or actions proceed as expected and the selected plan proves to be insufficient to achieve the desired end state and result in an unsafe situation (for example, excess capacity, rule-based error, inappropriate Procedures). ***3) Perceptual errors:*** Errors occur when the operator's sensory input drops and makes decisions based on incorrect information. **Violation:** ***1) Routine violation:*** The errors are a habitual action on the part of the operator and are tolerated by the regulatory agency. ***2) Exceptional violations:*** Violations are behaviors that are isolated from authority. They are neither typical personal behaviors nor behaviors tolerated by management. (Celik and Cebi, 2009; Shappell and Wiegmann, 2001)

2.5.2 HFACS level 2: preconditions for unsafe acts

The Preconditions for Unsafe Acts level is divided into three categories:

environmental factors, condition of operators, and personnel factors. These three categories are further divided into sub-categories. Environmental factors refer to physical and technical factors that affect individual behavior, conditions, and behaviors and cause human errors or unsafe conditions. The condition of the operators refers to a bad mental or physical state and physical/psychological limiting factors, which may affect the operation, condition or behavior of the individual, and lead to human error or unsafe conditions. Personal factors refer to the factors of crew resource management and personal readiness. These factors will affect personal practices, conditions or behaviors, and lead to human errors or unsafe conditions.

- **Environmental factors:** ***1) Physical environment:*** Refers to factors that include both operational settings (for example, weather, altitude, terrain) and the surrounding environment (for example, heat, vibration, light, toxins). ***2) Technical environment***: Refers to factors including various design and automation issues, including device and control design, display/interface characteristics, list layout, task factors, and automation.

- **Conditions of operators:** ***1) Adverse mental state***: Refers to factors including mental conditions (such as stress, mental fatigue, motivation) that affect work performance. ***2) Adverse physiological state:*** Refers to factors that include those medical or physiological conditions that affect performance (for example, medical illness, physical fatigue, hypoxia). ***3) Physical/mental limitations:*** Refers to the situation where the operator lacks the physical or mental ability to cope with the situation, thereby affecting performance (for example, visual limitation, insufficient reaction time).

- **Personnel factors:** ***1) Crew Resource Management***: Refers to factors including communication, coordination, planning and teamwork issues. ***2) Personal readiness***: Refers to the off-duty activities required to achieve the best job performance, such as compliance with crew rest requirements, alcoholic beverage restrictions and other off-duty requirements. (Diller et al., 2014; Shappell and Wiegmann, 2001)

2.5.3 HFACS level 3: unsafe supervision

The Unsafe Supervision level is divided into four categories. **1) Inadequate supervision**: The responsibility of any supervisor is to provide employees with opportunities for success. They must provide guidance, training, leadership, supervision, or incentives to ensure the safe and effective execution of tasks. **2) Plan Inappropriate Operation**: Refers to those operations that are acceptable and different in emergencies but are not acceptable during normal operations (for example, risk management, personnel pairing, operating rhythm). **3) Fail to Correct Known Problem**: Refers to the situation where the supervisor knows the known defects but allows them to continue to mitigate (for example, report unsafe trends, take corrective actions and correct safety hazards). **4) Supervisory Violation**: Refers to the situation where the regulator deliberately ignores the current rules and regulations (for example, the implementation of the rules and regulations, unnecessary dangers, insufficient documentation).

2.5.4 HFACS level 4: organizational influences

The organizational Influences level is divided into three categories. **1) Resource management:** Refers to organizational-level decisions related to allocating and maintaining organizational assets (such as human resources, money/budget resources, equipment/facility resources). **2) Organizational climate:** Refers to the working atmosphere within the organization (for example, structure, policy, culture). **3) Operational process:** Refers to the organizational decisions and rules governing the daily activities (for example, operations, procedures, and supervision) within the organization.

2.5.5 Application of HFACS in marine problems

According to the previous research, HFACS has been successfully utilized in many different disciplines, such as accidents in aviation (Daramola, 2014; Li and Harris, 2006), mining (Patterson and Shappell, 2010; Zhang et al., 2019c), shipping (Chauvin et al., 2013; Chen et al., 2013), railway (Madigan et al., 2016; Zhan et al., 2017), oil and gas industry (Theophilus et al., 2017), construction (Xia et al., 2018), and hazardous chemicals (Zhou et al., 2018) as well as the issues of health care (Hsieh et al., 2018) and fire prevention (Soner et al., 2015).

In recent years, several studies of HFACS have been published on the prevention or analysis of offshore accidents, mainly marine transportation accidents. Celik and Cebi (2009) identified human errors in shipping accidents by HFACS and a fuzzy analytical hierarchy process. Xi et al. (2010) developed an HFACS-based data mining modeling to analyze the occurrence of human factors in marine accidents. Chauvin et al. (2013) investigated the contributory factors involved in 39 marine collision incidents with HFACS. Chen et al. (2013) developed a dedicated human and organizational factors framework for maritime accident investigation and analysis based on HFACS. Zhang et al. (2019b) used the HFACS and fault tree model to review the risk factors of ship collision accidents between an assisted ship and an icebreaker. While an oil-related study was proposed to improve the traditional HFACS for the oil and gas industry considering regulatory deficiencies and emerging violation issues (Theophilus et al., 2017), there are few studies directly related to the prevention, control, response or analysis of oil spills. Wu and Peng (2016) developed an extended grey relational analysis modeling for oil spill emergency management by TOPSIS and a group consensus facilitation method. Koseoglu et al. (2018) determined the optimal site for an oil spill response center in the Marmara Sea using the analytic hierarchy process and TOPSIS. Golbarg et al. (2018) analyzed the risk factors and severity of oil pipelines in Shadegan International wetland by Delphi and MCDM techniques. Akyuz and Celik (2018) proposed a quantitative risk analysis of an oil spill incident using interval type-2 fuzzy sets with the failure model and effect analysis.

CHAPTER 3 A SIMULATION-BASED MULTI-AGENT PARTICLE SWARM OPTIMIZATION APPROACH FOR SUPPORTING DYNAMIC DECISION MAKING IN MARINE OIL SPILL RESPONSES*

* This chapter is mainly based on the following referred publication:
Ye XD, Chen B., Li P., Jing L., Zeng G. (2019). A simulation-based multi-agent particle swarm optimization approach for supporting dynamic decision making in marine oil spill responses. Ocean & Coastal Management, 172, 128-136. https://doi.org/10.1016/j.ocecoaman.2019.02.003
Contributions: Ye XD, conceptualization, methodology, modeling, validation, formal analysis, writing - original draft; Chen B, conceptualization, writing-revision and editing; Li P, modeling, data collection; Jing L, writing-revision; Zeng G, writing-revision.

3.1 Introduction

A marine oil spill is defined as an accidental release or discharge of petroleum hydrocarbons at seas caused by human errors or natural disasters (Beyer et al., 2016; Li et al., 2014a). With the growing operations in marine shipping and marine petroleum industries, the increased risk of oil spills has gained significant attention (Li et al., 2016a; Liu et al., 2015; Pezeshki et al., 2000; Piatt et al., 1990; Powers et al., 2017). Although the statistics indicate a declining number of oil spills due to the technical advancement and more stringent regulations, major spills still frequently, occur leading to significant negative impacts on the environment and economy (Burgherr, 2007; Etkin, 1999; Farrow et al., 2016; Fingas, 2016; Huijer, 2005). Spilled oil may persist and contaminate the marine environment during and after the accident for decades, causing billions of dollars in damages and response/recovery (Kingston, 2002; Smith et al., 2011). A recent example is the BP Deepwater Horizon Oil Spill in 2010, which was released with a total cleanup cost of over $14 billion (Lee et al., 2015a; Ramseur and Hagerty, 2013). This event created a strong shockwave globally in the industry, government, and the public, as well as the research community. Consequently, a tremendous amount of research efforts have been made in the areas of contingency planning, oil fate and transport modeling, risk and impact assessment, and response technique development. (Barron, 2012; Bence et al., 1996; Daly et al., 2016; Kujawinski et al., 2011; Maki, 1991; Peterson et al., 2003). In comparison, limited studies have been reported on the development and implementation of process optimization and decisionmaking in marine oil spill responses. Therefore, how to avail of advanced modeling tools to improve the efficiency of response operation and decision-making with consideration in dynamic changes of oil spills has been recognized as a vital and urgent task in the field (Boufadel et al., 2016; Esler and Iverson, 2010; Perring et al., 2011; Socolofsky et al., 2011; Sylves and Comfort, 2012). Furthermore, limited studies have attempted to realize dynamic spill simulation and response optimization in decision-making models. Harsh oceanic circumstances (e.g., rough seas, cold water, sea ice) tend to make emergency response to oil spills even more challenging due to the dramatic changes in oil properties and operational conditions, which will inevitably hinder and affect the efficiency of response actions (e.g., booming, skimming, dispersion, and in-situ burning) (Afenyo et al., 2016; Beegle-Krause et al., 2017; Lee et al., 2015a; Li et al., 2014a). Therefore, comprehensive considerations of these issues into the response simulation and decision-making system is urgently desired.

To fill this gap, this study aimed to develop a simulation-based multi-agent particle swarm optimization approach to support dynamic decision-making in marine oil spill response. In the developed system, agent-based modeling (ABM) was hereby introduced to achieve a dynamic, high-freedom, and interactive simulation approach. Particle swarm optimization (PSO) was used as the means to optimize the result from simulation to desire a better decision-making result. Multi-agent system (MAS) finally composed the whole frame for the system to make the system work smoothly and successfully, to control and transmit results from ABM and PSO aspects. The study outcomes were expected to facilitate a more effective and efficient tool for emergency oil spill response under highly dynamic conditions.

3.2 Methodology

3.2.1 Agent based modeling for oil spill simulation

The simulation-based multi-agent particle swarm optimization (SA-PSO) approach considered ABM for simulation, PSO for optimization and MAS for system integration to realize the information transportation and dynamic decision-making. Specifically, agent-based modeling was responsible for the dynamic simulation process, including oil response operations and oil weathering. It was a computer modeling process comprised of multiple types of autonomous and heterogeneous agents. Agents were given specific rules for behavior simulation (i.e., weathering oil or oil response) as well as for interactions with other agents (i.e., the skimming process for oil recovery). ABM was bottom-up modeling to reflect the behaviors or interactions from the lowest micro-level, making it suitable for complex simulations and decision-making. Oil spill trajectory will be considered in future studies. PSO provided feedback and adjusted the current decisions by comparing the scenarios' allocation plans and clean-up efficiency.

3.2.2 Marine oil spill cleanup and recovery response simulation

In marine oil spill cleanup response, the net oil recovery rate of skimmer mainly depends on slick thickness (*ST*). The function (Eq. 3.1) between ORR_{sk} and ST is defined as follows:

$$ORR_{sk} = \alpha \times ST^2 + \beta \times ST \qquad \text{(Eq. 3.1)}$$

where ORR_{sk} is defined as the amount of recovered oil per hour (m^3/hr), α and β are empirical coefficients obtained from experimental tests (Li et al., 2014a). Accordingly, the objective function of the marine oil spill recovery response by skimmers (Eq. 3.2) can be generated as follows:

$$V_{sk} = \sum_{t=1}^{t} \sum_{i=1}^{i} f_{ORR_{sk,i,t}(ST_{k,t})} \qquad \text{(Eq. 3.2)}$$

where V_{sk} is the total recovered oil amount by all skimmers during the response time period (m^3), *t* is the response time period (*hr*), *i* is the index number of skimmers, *k* is the number of spills, $f_{ORR_{sk,i,t}}$ represents the net oil recovery rate of skimmer i at time t, and $ST_{k,t}$ shows the slick thickness of spill k at time t.

The slick thickness (Eq. 3.3) can be calculated by the equation shown as follows:

$$ST_{k,t} = \frac{V_{0,k} - \sum_{t=1}^{t-1} V_{loss,k,t}}{A_{k,t}} \qquad \text{(Eq. 3.3)}$$

where $V_{0,k}$ is the initial volume of spill k, $A_{k,t}$ is the area of spill k at time t, and $V_{loss,k,t}$ is the oil loss at time t through oil response and natural weathering processes.

As *ST* is dynamically related with the spilled oil volume, and skimmers may move among several spills to improve the efficacy of recovery rate or shorten the response time. Therefore, the problem becomes dynamic and non-linear, and cannot be easily solved.

In the practical applications of marine oil spill response, the process of oil weathering is crucial in affecting recovery performance (Albaigés, 2014; Fingas, 2016; Li et al., 2014b). Evaporation, dispersion, and emulsification are selected as the main weathering processes in the ABM simulation section to identify the interaction of changing oil properties with timely cleanup.

According to Fingas (2016), the empirical equation of evaporation for oil (Eq. 3.4) is as follows:

$$FE = \frac{c + d \times (T - 273.15) \times Ln(t)}{100} \qquad \text{(Eq. 3.4)}$$

where, c and d are empirical parameters for specific oil, FE is the evaporation rate ($m^3/hour \cdot m^3 of\ oil$), T is temperature (*K*), t is time (*minute*), and Ln() is natural logarithm.

Moreover, the equation for the dispersion process (Eq. 3.5) developed by Mackay et al. (1980a) is indicated as follows:

$$FD = \frac{0.11 \times (U+1)^2}{1 + 50 \times \mu^{0.5} \times ST \times s_t} \qquad \text{(Eq. 3.5)}$$

where *FD* is the dispersion rate ($m^3/(s \cdot m^3\ of\ oil)$), μ is the dynamic viscosity of the oil (*cP*), U is the wind speed (m/s), and S_t is the interface tension between oil and water (dyne/m).

Furthermore, the equation for the emulsification proposed by Rasmussen (1985) is shown as follows:

$$\frac{dF_{emul}}{dt} = R_1 - R_2 \qquad \text{(Eq. 3.6)}$$

$$R_1 = \frac{K_1}{\mu_0} \times (1 + U)^2 \times (F_{emul}^{final} - F_{emul}) \tag{Eq. 3.7}$$

$$R_2 = \frac{K_2}{Asph \times Wax \times \mu_0} F_{emul} \tag{Eq. 3.8}$$

where F_{emul} is the fractional water content; F_{emul}^{final} is the maximum water volume that can be incorporated in the emulsion, *U* is wind velocity, K_1 and K_2 are empirical dimensionless constants; Asph and Wax are percentages of asphaltenes and waxes contents, and μ_0 is the initial dynamic viscosity of the oil.

Kirstein and Redding (1987) represented a relatively simple empirical dependence in the form of the equation to illustrate the relationship between viscosity and water content (Eq. 3.9).

$$\mu = \mu_0 \times \exp\left(\frac{2.5 \times F_{emul}}{1 - k \times F_{emul}}\right) \tag{Eq. 3.9}$$

where μ is the resulting viscosity, μ_0 is the starting oil viscosity, and k is the Mooney constant which is 0.62-0.65, and F_{emul} is the fractional water content.

When considering the simulation of the oil cleanup response efficiency, along with the weathering processes, the objective function for the skimmer cleanup response (Eq. 3.10) can be formulated as follows:

$$\text{Max V} = \sum_{t=1}^{t}\sum_{i=1}^{i} f_{ORR_{sk,i,t}(ST_{k,t})} \tag{Eq. 3.10}$$

s.t.

$$ST_{k,t} = \frac{V_0 - \sum_{t=1}^{t-1}(SV_t + FV_t + DV_t)}{A_{k,t}} \tag{Eq. 3.11}$$

$$FD_t = f_{FD}\left(ST_{k,t}\right) \tag{Eq. 3.12}$$

$$FV_t = FE_{t-1} \times (V_0 - \sum_{t=1}^{t-1}(SV_t + FV_t + DV_t)) \tag{Eq. 3.13}$$

$$DV_t = FD_{t-1} \times (V_0 - \sum_{t=1}^{t-1}(V_t + FV_t + DV_t)) \tag{Eq. 3.14}$$

where SV is the removed oil by skimmers (m^3), *FV* is the evaporated oil (m^3) and *DV* is the dispersed oil (m^3).

3.2.3 Particle swarm optimization algorithm

This study presented the first attempt at introducing the PSO method into oil spill response decision makings. In the proposed SA-PSO system, PSO played a role as the tool to receive the outputs from ABM section, after optimizing the device locations and checking with the stop criteria, outputs from PSO would be decided to send back to ABM for the next iteration or as the final decision for the problem.

Each particle i updates its velocity and position values by evaluating positional information from the selected global leader and its own personal best, as indicated in Eq. 3.15 and 3.16.

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot \left(x_{pbest_i} - x_i(t)\right) + c_2 \cdot r_2 \cdot \left(x_{gbest_i} - x_i(t)\right) \quad \text{(Eq. 3.15)}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad \text{(Eq. 3.16)}$$

Where *i* is the iteration number; *w* is the inert weight 0.8; c_1 and c_2 are two learning factors from the personal and global best particles respectively, 2.0 is the reasonable value for learning factors (i.e., c_1 and c_2) based on trial results, r_1 and r_2 are two random numbers generated uniformly in the range [0, 1].

3.2.4 An integrated multi-agent system and the SA-PSO framework

In multi-agent systems, agents obtain the information (e.g., user model, spill data, location) and processing approaches (e.g., preference-elicitation methods, negotiation strategies, time-series analyzers) (Khan et al., 2018; Winoto, 2003). MAS divides a large system into small, interactive, communicable, and manageable systems. All agents (including agents for simulation, optimization, and database) in MAS can transfer information from an agent to other agents. One key element of MAS is information sharing, essential in an application-oriented domain. The structure of MAS would be varied based on research areas and topics (Goran, 2011). The framework of the proposed SA-PSO system was shown in Figure 3.1.

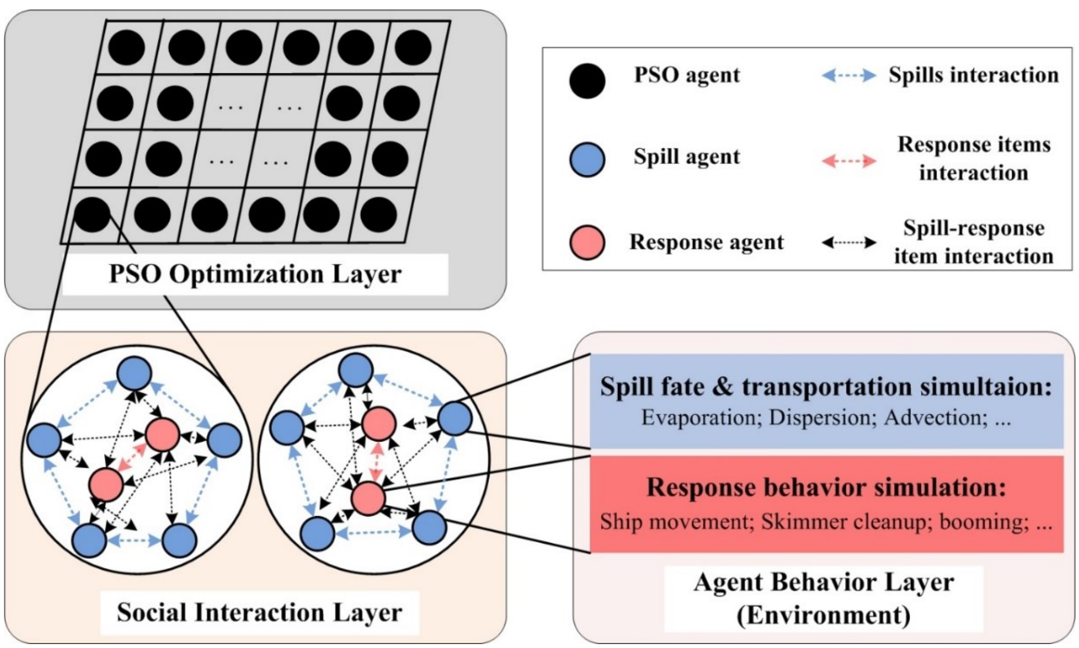


Figure 3.1 The multi-agent system (MAS) structure of the simulation-based multi-agent particle swarm optimization (SA-PSO) approach

MAS could contain more than one layer so that each layer can have a different function. In the proposed structure, 3 layers, PSO optimization layer (POL), social interaction layer (SIL), and agent behavior layer (ABL), worked collectively. First, POL plays as the optimization environment for particle swarm optimization algorithm. Each black point was a PSO agent, which is a candidate solution containing all the information and functions from the other two layers. SIL and ABL are used for simulation processes. SIL reflects the interaction characteristics between different agents. In SA-PSO model, the performance of a response item (i.e., a skimmer) is interacted by the behaviors of other response items as well as oil spill characteristics. For example, when a skimmer shipped to a spill, the skimmer would collect oil on that spill, it would affect the evaporated and dispersed oil rates, density, viscosity, and water content of the spill. Moreover, when more than one skimmer moved on the same spill, they would have a competition behavior for oil collection. ABL provides a platform for all agents to continuously update their behaviors followed by the specific rules, spill weathering modeling, spill response modules, etc. For example, the properties of oil spills are calculated by weathering models with consideration of evaporation, dispersion, and emulsification. Further, skimmers obey the rules for oil collection and movement. With the contribution of MAS, ABM simulation and PSO optimization, the proposed SA-PSO system can work as a dynamic system with complicated inner and external interactions. Moreover, the data from different sections could transmit and reflect smoothly and successfully. Thus, the proposed system has the potential to be used for decision support systems (DSS) of marine oil spill accidents.

The framework of the SA-PSO approach is shown in Figure 3.2. The approach can utilize the global objective as the goal for agents and dynamically adjust the planning setting according to the results from the simulation and optimization sections in each iteration. In the system, the information of equipment location, response performance and oil spill fate and transport can be simulated by ABM with spill modeling and database support. PSO can further generate the optimal choices for the next iteration. Predicted outcomes and related decision-making under different scenarios can be provided and compared. Variant dynamic simulation and optimization systems can be further updated from the proposed framework according to the specific purposes and requirements.

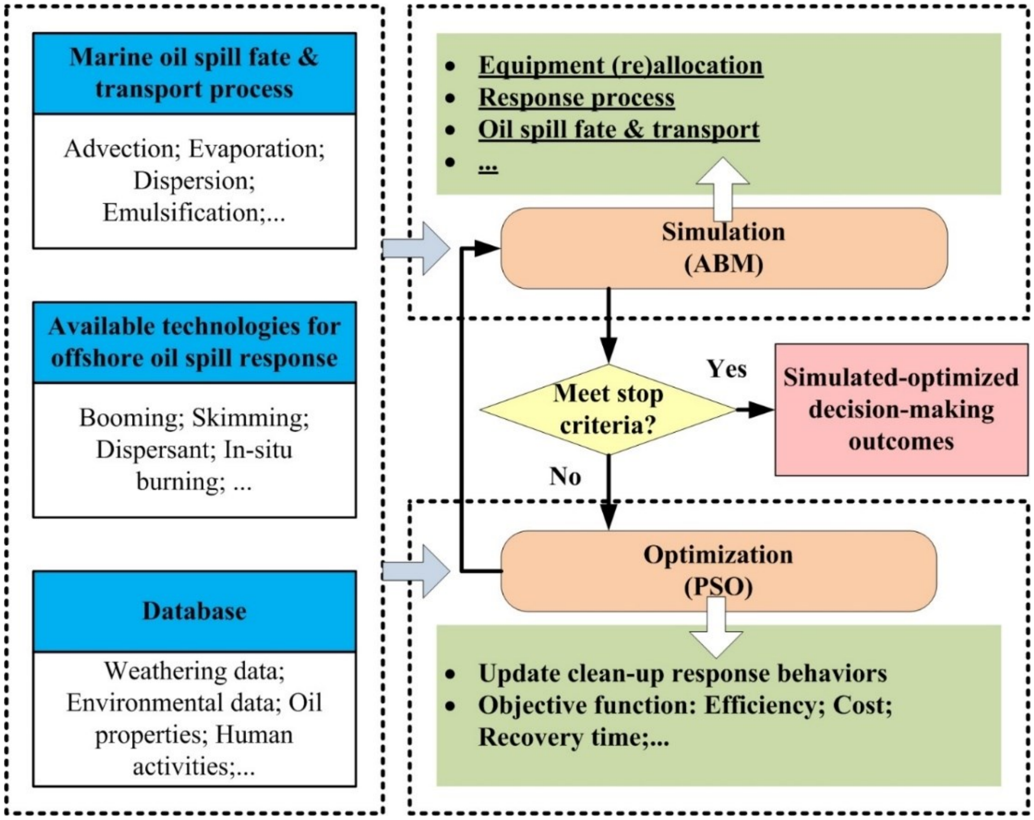


Figure 3.2 Framework of the simulation-based multi-agent particle swarm optimization (SA-PSO) approach

The modeling operational platform supporting the proposed system is NetLogo®, which is a popular multi-agent programmable modeling environment, which is developed by Uri Wilensky in 1999, and has been utilized as an efficient tool for ABM and MAS modeling by a great number of researchers (Banitz et al., 2015; Carbo et al., 2018; Dickerson, 2014). Therefore, NetLogo® is used as the foundation programming platform for the SA-PSO model.

3.3 Case Study

3.3.1 Case description

A hypothetic case study was considered for testing the efficiency of the SA-PSO method. The case indicated a marine oil spill accident of Arabian Light crude oil in the North Atlantic area with a total amount of 5,000 m^3. With the effects of advection and spreading, the spilled oil was split into 10 slicks within a 50 km by 50 km area. Table 3.1 illustrates the oil volumes and coordinates of these oil slicks. In marine oil spill response management, response organizations always regard time as the top priority. The faster the oil can be recovered; the less damage can be caused to the marine environment. Therefore, this study's main objective is to optimize the response operation with the simulation of oil fate and response behaviors to achieve the shortest response time.

Table 3.1 Oil volume and site coordinates of oil slicks

Slick	Oil Volume (m^3)	Coordinate	
		X(km)	Y(km)
1	619.69	40.03	47.35
2	532.44	35.97	43.74
3	332.03	32.03	40.88
4	802.76	17.92	35.01
5	879.86	25.33	27.42
6	913.84	26.49	32.38
7	319.37	42.61	20.84
8	232.82	43.25	15.72
9	186.12	39.80	8.46
10	181.07	37.44	5.03

The ship-mounted skimmers belonging to three different spill response teams (Team A, B, and C) were the only available nearby cleanup means that can be applied in this area. In the scenarios, the skimmers from the three teams had different cleanup efficiencies. Three teams were berthed at three different ship docks, and a specific transportation time was needed for allocation. It was assumed that all teams had enough storage space for removed oil. The detailed location relationships of response ships and oil slicks were indicated in Table 3.2 and Figure 3.3.

Table 3.2 The location information about three ship docks

Ship	X(km)	Y(km)
A	15.00	0
B	0	15.00
C	80.00	0

e

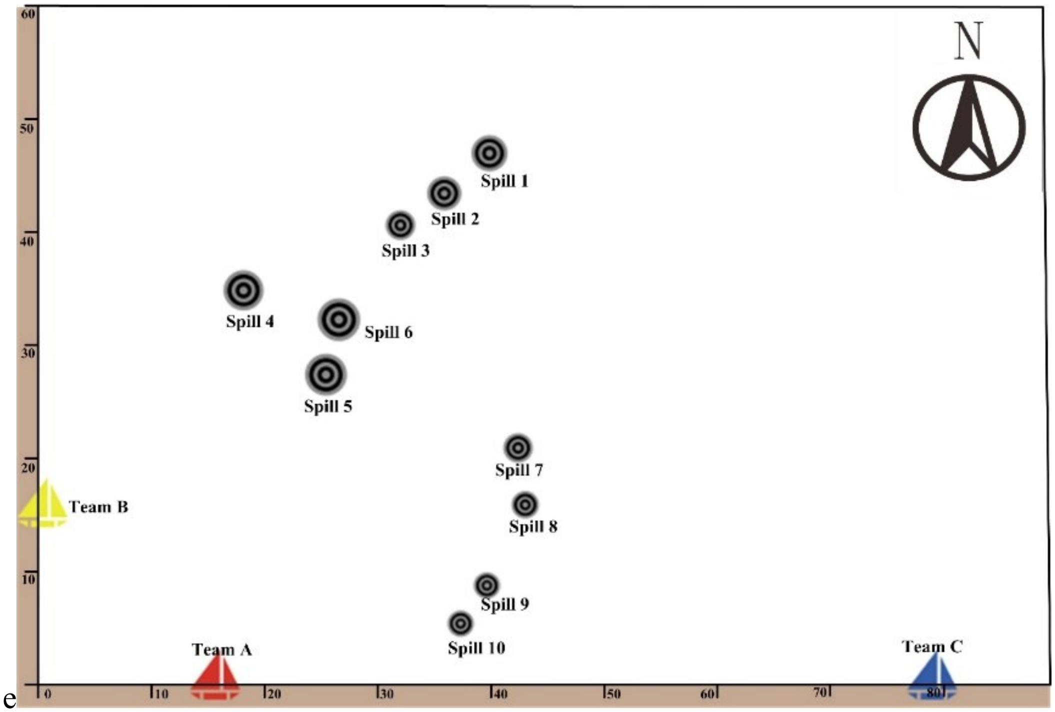


Figure 3.3 Location relationships of response ships and oil slicks

3.3.2 Oil weathering process simulation

Significant and dynamic interactions existed between response operations and oil weathering processes. For example, the skimming process can directly change the volume and thickness of oil slicks, which affected diverse weathering processes such as evaporation and dispersion. On the other hand, the changed oil properties due to weathering can in turn affect skimming operations (e.g., oil thickness and viscosity are key factors in selecting skimmers and adjusting operational parameters). Thus, it was critically important to integrate the response decision-making model with oil weathering simulation. The major weathering processes, evaporation, natural dispersion, and emulsification were discussed in this hypothetic case for oil weathering processes. Table 3.3 illustrated the inputs for the oil spill weathering processes.

Table 3.3 Arabian Light crude oil characteristics for the weathering processes

Parameter	**Value**	**Unit**	**Parameter**	**Value**	**Unit**
Temperature (T)	278.15	K	Wind speed (U)	10	m/s
Vapor pressure (P^{sat})	10.40	Pa	Water content (F_{emul})	0.10	%
Oil density (ρ^{sat})	8.78×10^{-1}	g/L	Gas constant (R)	8.314	$m^3 \cdot Pa \cdot k^{-1} \cdot mol^{-1}$
Oil viscosity (μ)	31	cP	Interface tension (S_t)	1.68×10^3	dyne/m
Emulsion formation viscosity (0% Evaporation)				2.30×10^4	cP

*The parameter values are from data in 0°C.

Based on Fingas (2016), the empirical equation for predicting evaporation for Arabian Light crude oil (Eq. 3.17) was shown as follows:

$$(\%)Ev = (2.4 + 0.045(\mathrm{T} - 273.15))\ln(\mathrm{t}) \qquad \text{(Eq. 3.17)}$$

where, $(\%)Ev$ was percentage evaporated oil, *T* was temperature (℃), and *t* was the time (minute).

For the parameters of dispersion and emulsification processes, based on Mackay et al. (1980a), Rasmussen (1985), and Azevedo et al. (2014) studies, the data was achieved for $K_1 = 3.0 \times 10^{-9}\ kg/m^3$, and $K_2 = 3.5 \times 10^{-7}\ kg/m \cdot s^2$ with a maximum water content of F_{emul}^{final} closed to 90%. In addition, Fingas (2016) indicated that the asphaltenes and waxes contents of crude oil were 4.0% and 7.0%, respectively.

The parameters in oil weathering simulation procedures were considered as constant, which included temperature, wind speed, oil density, and interface tension. Besides, no wind directions were considered in this hypothetic case, due to the beforehand processes of advection and spreading. Oil movement was not considered during the oil simulation. The effect of emulsification on the volume of oil was neglected in the study.

3.3.3 Oil recovery simulation

The recovery simulation modules of ship-mounted skimmers were based on the studies of Li et al. (2012b and 2014a). The detailed information about empirical coefficients used for three skimmers was shown in Table 3.4. As slick thickness was the key element leading to the oil recovery efficiency of skimmers, Figure 3.4 indicated the relationships between slick thickness and different skimmers.

Table 3.4 Model coefficients for the net oil recovery rate of three ship-mounted skimmers

Types of skimmers	**Empirical coefficients**	
	$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$
SK_1 (Team A)	0.01437	0.01602
SK_2 (Team B)	-0.00791	0.84975
SK_3 (Team C)	-0.01591	1.54975

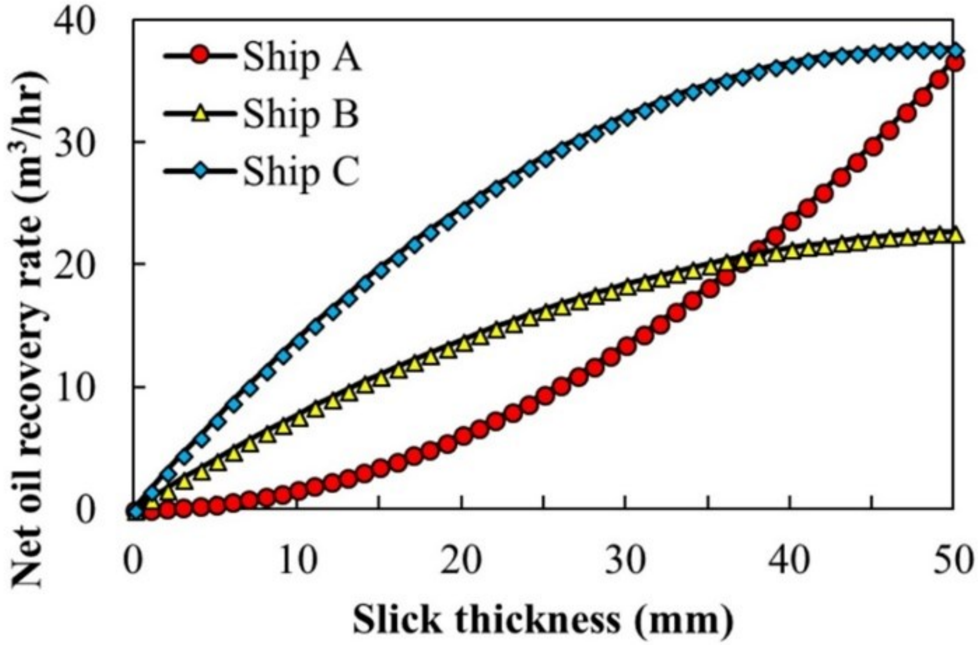


Figure 3.4 The relationships between slick thickness and net oil recovery rates of ship-mounted skimmers (Li et al., 2012b and 2014a)

The goal of the contingency plan was to achieve an overall removal rate of 90% by considering both the natural weathering process and human-introduced cleanup processes (e.g., skimming). According to the previous information and the algorithms of SA-PSO, a global optimization function can be generated as follows:

Objective function: $\boldsymbol{Min\ t}$

s.t.

$$\sum_{t=1}^{t} TV_t \geq 90\% \times total\ oil\ volume \quad \text{(Eq. 3.18)}$$

$$TV_t = SV_t + FV_t + DV_t \quad \text{(Eq. 3.19)}$$

where *t* is the response period (hr); TV_t was the total recovered oil in time t (m^3); SV_t is the removed oil (m^3) by skimmers at time t, FV_t is the evaporated oil (m^3) at time t and DV_t is the dispersed oil (m^3) at time t.

3.3.4 PSO setting and SA-PSO computing environment

In the optimization section, PSO was implemented to find the optimal solution. The model was written in NetLogo®. For PSO settings, the particle size was 256, 200 repeating runs were carried out with 50 iterations per time tick.

3.3.5 Comparison with other approaches

The shortest distance selection approach (SDS) method was applied to the case study to compare and examine the efficiency of the SA-PSO approach. By comparison, the SA-PSO approach was tested to see whether the developed approach can show better robustness and efficiency than others.

SDS was the ordinary and straightforward approach used in marine oil spill emergency response. The approach indicated a process which allowed a response team to choose the nearest oil slicks as the target for oil recovery, after ships met the requirement for cleanup on those slicks, then chose the second nearest oil slicks near them to continue. The judgement criteria were the distance between two spills. No interaction between multiple skips and cleanup efficacy was considered in this approach, but it was the simplest and quickest-responding method. Therefore, SDS was used to examine the developed SA-PSO efficacy.

3.4 Results and Discussion

3.4.1 Decision making with weathering process simulation

The modeling results indicated that considering oil weathering processes, the operation time for achieving an oil recovery rate of 90% was 83 hours based on the optimal vessel routes determined by the SA-PSO modeling.

The weathering agent-based simulation model section in SA-PSO reflected the dynamic relationship of oil volumes between spills and time. As illustrated above, three vital weathering processes were possessed in the model: evaporation, dispersion, and emulsification. The evaporation of the specific oil type was affected by time at a constant temperature. The dispersion process was influenced by wind speed, viscosity and interface tension between oil and water. Moreover, viscosity was dynamically impacted by an emulsification procedure. Further, emulsification led to the variation of water volume with time and then influenced the viscosity value simultaneously. However, the impacts of water content change on oil volume were neglected.

Table 3.5 showed the decision-making results of SA-PSO and SDS approaches under the weathering processes. SA-PSO plan can reduce the time by 11 hours compared to the SDS one, increasing 11.7% recovery speed in the spill incidents. A shorter response time can decrease the amount of weathered oil, which can mitigate damage to the marine environment and reduce the risk to humans. In SA-PSO, team C was the one that had the highest amount of recovered oil, which was about 400 m^3 higher than the amount of team C in the SDS scenario. As the skimmer utilized on team C had the highest collective efficiency (Figure 3.5), the SA-PSO decision tried to lead team C to keep having a high efficacy for high-thickness spills during the entire procedure.

Table 3.5 Decision-making results of SA-PSO and SDS in the weathering scenario

	SA-PSO	SDS
Operation time (hr)	83	94
Recovered oil (Team A) (m^3)	680.80	1045.57
Recovered oil (Team B) (m^3)	880.33	899.24
Recovered oil (Team C) (m^3)	1706.12	1310.90
Total recovered oil (%)	65.35	65.11
Evaporated oil (%)	26.14	26.36
Dispersed oil (%)	0.6025	0.64
Remain oil (%)	7.91	7.89

Figure 3.5 and Figure 3.6 indicated the amount of oil recovered from each team by two approaches. The curves of SA-PSO were much smoother than those of SDS, due to the main effect of slick thickness on recovery rate. The SA-PSO plan can optimize the recovery rate related to the change of slick thickness of each spill to save the operation time. While the SDS always cleaned up one spill before moving to the other, which would hinder the cleanup efficiency with the decrease of oil volume and the effect of weathering. Figure 3.7 and Figure 3.8 illustrated the variations of oil volumes by each spill in the SA-PSO and SDS scenarios with weathering process during the entire procedure. The SA-PSO decision intended to balance oil volume level for all spills by optimizing the time cost of

movement and cleanup efficiency. The SDS was easy to set up and operated for decision makers. However, the results indicated that SDS produced a relatively long response time, causing more environmental damage. In addition, the SDS scenario ignored the spill sites far away from the current skimmers (e.g., Spills 1 and 2) leading to the reduced overall efficiency of the skimming operation.

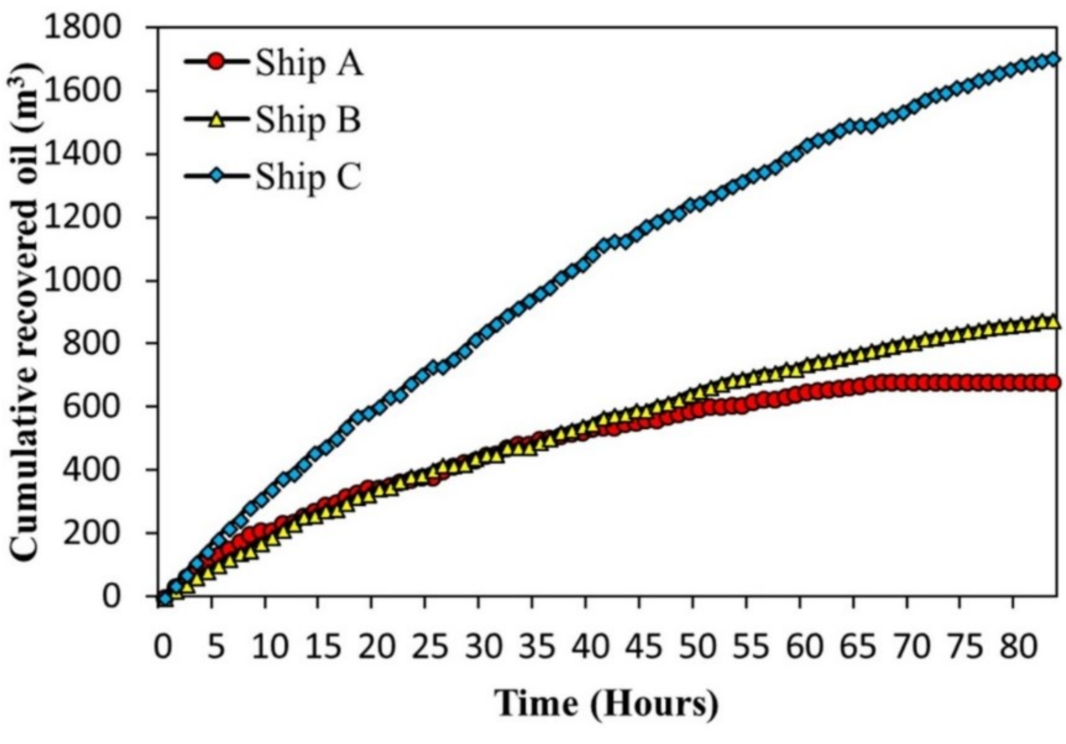


Figure 3.5 Cumulated oil recovery by each ship in SA-PSO scenario with oil weathering process

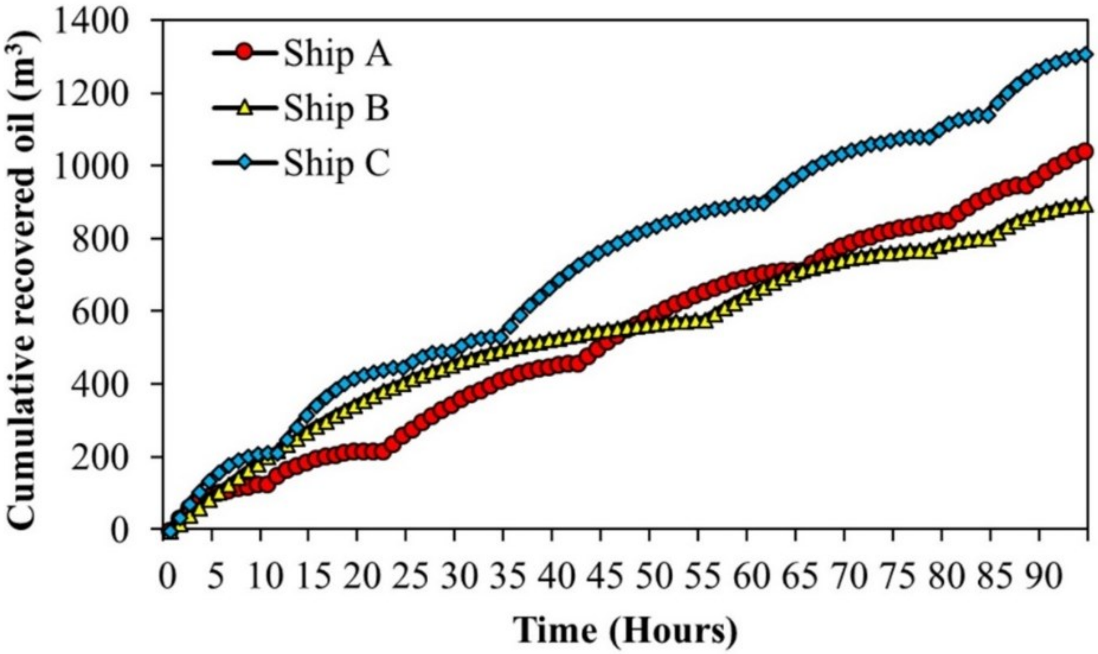


Figure 3.6 Cumulated oil recovery by each ship in SDS scenario with oil weathering process

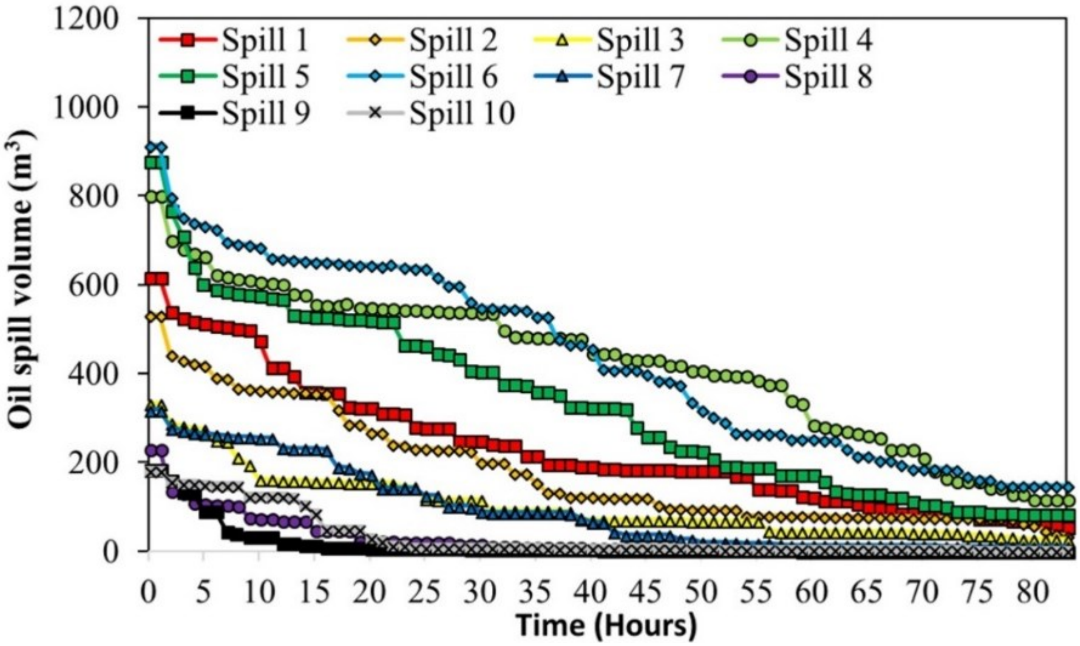


Figure 3.7 Oil volumes by each spill in SA-PSO scenario with weathering process

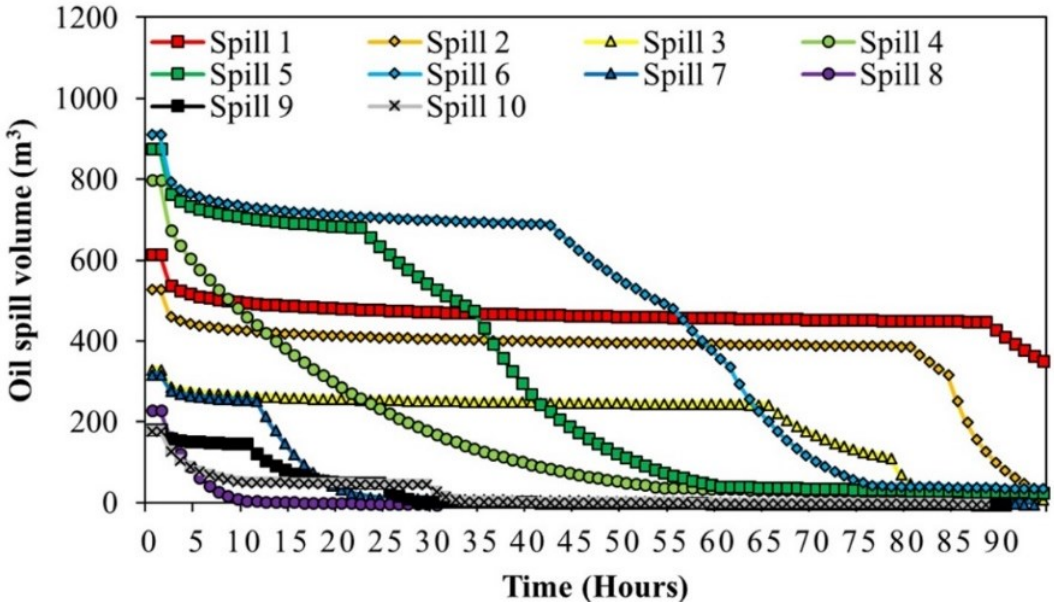


Figure 3.8 Oil volumes by each spill in SDS scenario with weathering process

3.4.2 Decision making without weathering process simulation

The models without weathering processes were also considered as a scenario to examine the efficiency of the proposed approach. As shown in Table 3.6, the results from the two methods were similar. The SA-PSO result was 3 hours shorter than the other. According to the figures (Figure 3.9-3.10), the SA-PSO decision preferred to cooperate the effort on multiple spills together and tried to move back and forth on nearby spills to keep a high collective efficiency with high slick thickness. Furthermore, the collective amounts from ships were close in two approaches. Even though the operation times in the non-weathering scenarios were close, the SA-PSO had a significant advantage compared to the other in the weathering ones. In addition, the operation time of weathering cases was much longer than non-weathering ones, which indicated that weathering processes can complicate the situation. For example, the evaporation process can decrease the oil volume rapidly in the early stage, which would decrease the slick thickness. Thus, the difficulty of skimmer collection would increase. Therefore, the complicated weathering processes and uncertainties in the circumstances can improve the contribution of SA-PSO to decision making system of marine oil spill accidents. Oil weathering processes during spill responses, which largely reduced the cleanup efficiency, should be considered as important roles in spill accident contingency planning and response.

Table 3.6 Decision-making results of SA-PSO and SDS in the non-weathering scenario

	SA-PSO	SDS
Operation time (hr)	48	51
Recovered oil (Team A) (m^3)	1762.85	1773.03
Recovered oil (Team B) (m^3)	1090.20	1058.34
Recovered oil (Team C) (m^3)	1810.20	1823.34
Total recovered oil (m^3)	4663.25	4654.71
Remain oil (%)	6.74	6.91

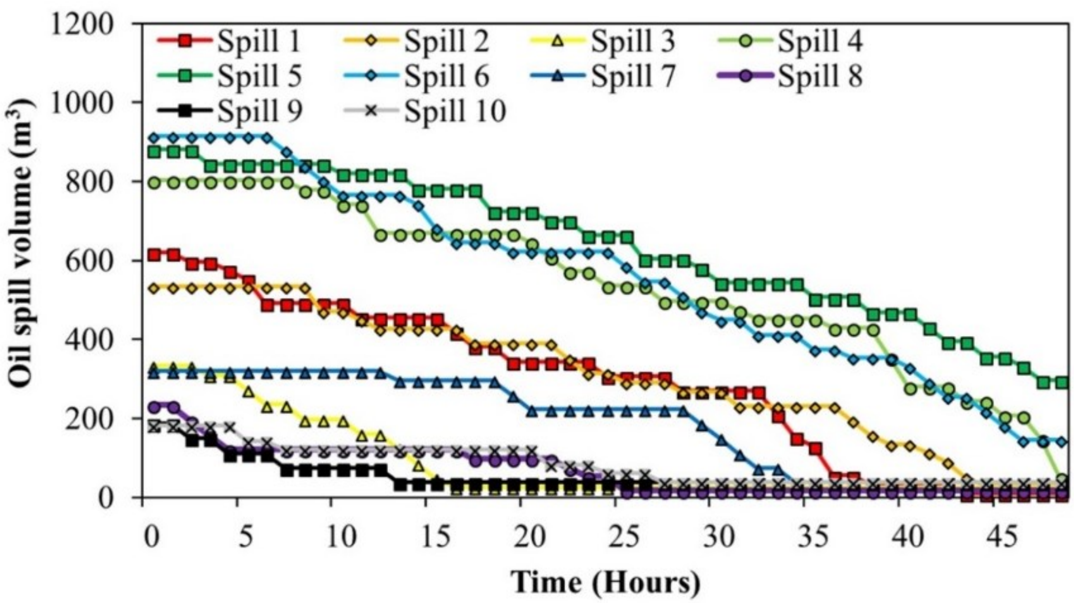


Figure 3.9 Oil volumes by each spill in SA-PSO scenario without weathering process

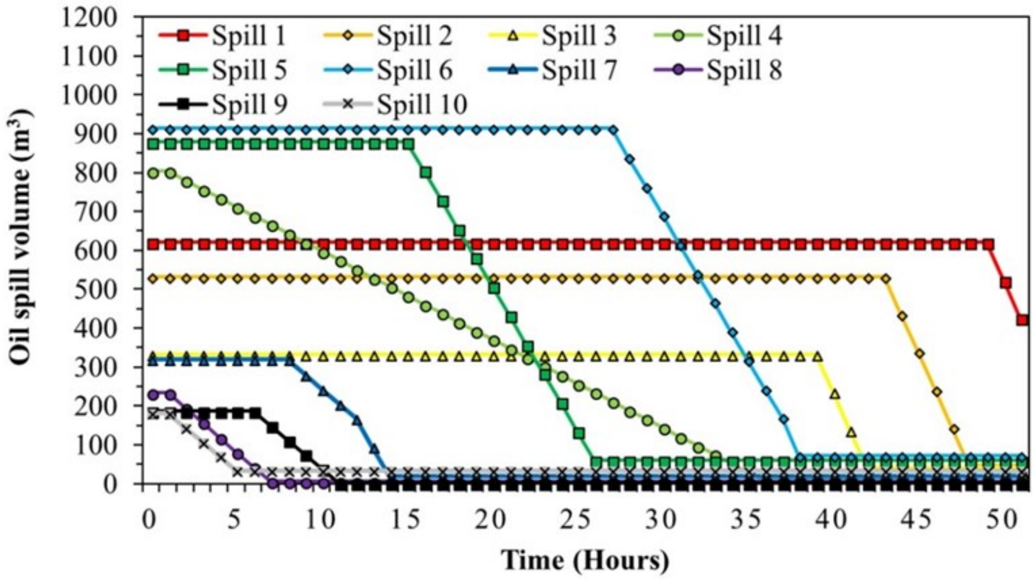


Figure 3.10 Oil volumes by each spill in SDS scenario without weathering process

3.5 Summary

A proper decision-making method can be an efficient and effective tool to support the cleanup processes in marine oil spill responses by minimizing the response time and costs. The SA-PSO method has been developed combining the advantages of agent-based modeling, particle swarm optimization, and a multi-agent system. The proposed method was tested by a hypothetical case study with Arabian Light crude oil in the North Atlantic Ocean. Weathering processes including evaporation, dispersion, and emulsification were considered in the simulation, along with the skimming response process in the harsh environment.

In the case study, the developed approach was applied to optimize the allocation of 3 spill response teams for 10 different locations of oil slicks after spreading and advection processes. In the weathering scenario, the modeling results indicated that the optimal routes of vessels could lead to a minimum response time within 83 hours to achieve the 90% oil recovery rate, including man-made skimmer cleanup and natural attenuation process. The developed SA-PSO approach significantly improved the response efficiency compared to the traditional SDS method by saving about 11.7 % of response time (i.e., 11 hours). In the non-weathering scenario, the SA-PSO approach could also improve efficiency by saving 5.9% of response time (i.e., 3 hours.). The consideration of weathering processes further complicated the decision-making process. However, the results demonstrated that the proposed approach could timely and effectively provide optimal decisions for allocating devices and managing operations in a dynamic condition with improved performance.

Through the application of the proposed methods, a shorter response time could be achieved, leading to a decrease in the existence and amount of oil in the marine environment and consequently reduced environmental impact and human health risk. Even though the case study was applied in supporting the oil recovery process, the developed SA-PSO has the potential to dynamically and systematically support multiple cleanup techniques concerning in-situ burning, skimmers, sorbents, surfactant, and biodegradation. The complex problem and high-level intent of interactions could enlarge the advantages of SA-PSO. In future studies, hydrodynamic simulation of oil spill trajectory and more complicated weathering processes will be considered to explore the application range of SA-PSO further. In addition, the consideration of uncertainties and risk assessment will be concerned with the decision supporting objectives.

CHAPTER 4 AN IMPROVED SIMULATION-OPTIMIZATION EMERGENCY RESPONSE SYSTEM FOR MARINE OIL SPILL DYNAMIC RESPONSE *†

* This chapter is mainly based on the following referred publications:

Ye, X., Chen, B., Lee, K., Storesund, R., Li, P., Kang, Q., & Zhang, B. (2021). An emergency response system by dynamic simulation and enhanced particle swarm optimization and application for a marine oil spill accident. Journal of Cleaner Production, 297, 126591. https://doi.org/10.1016/j.jclepro.2021.126591

Contributions: Ye XD, methodology, software, validation, formal analysis, writing- original draft; Chen B, conceptualization, writing-revision and editing, supervision; Lee K, conceptualization, writing-review and editing. Storesund R, writing-revision and editing; Li P, methodology; Kang Q, writing-revision and editing; Zhang BY, formal analysis.

Ye, X., Chen, B., Jing, L., Zhang, B., & Liu, Y. (2019). Multi-agent hybrid particle swarm optimization (MAHPSO) for wastewater treatment network planning. Journal of environmental management, 234, 525-536. https://doi.org/10.1016/j.jenvman.2019.01.023

Contributions*:* Ye XD, conceptualization, methodology, modeling, validation, formal analysis, writing-original draft and revision; Chen B, conceptualization, writing-revision and editing, supervision; Jing, L, methodology, writing-revision; Zhang B, formal analysis; Liu Y, writing revision.

4.1 Introduction

Anthropogenic and natural disasters, such as oil spills and earthquakes, often cause significant negative impacts on our society and the natural environment. An emergency response system (ERS) to such disasters becomes vital for mitigating the associated harmful effects in a timely and effective manner (Iazeolla et al., 2016). The effectiveness of responses can be ensured by optimizing the operation and especially the implementation of resources available for response operations. Due to the limiting factors (e.g., time, locations, and resources in both quality and quantities), an optimal schedule and plan for assigning and allocating resources to the affected areas should be worked out and executed (Fiedrich et al., 2000). The implementation of an optimal ERS can effectively save time, resources, and human efforts and reduce damage. As a typical disaster, marine oil spills are considered one of the most severe environmental perturbations to the marine ecosystem (Li et al., 2016a). Billions of dollars can be spent during and after oil spills on the response and restoration operations (Lee et al., 2015b). For example, the BP oil spill disaster, spilled out more than 210 million gallons of crude oil into the ocean and caused 11 workers died and 17 workers injured. The spill and the cleanup had an impact on the environment (Harrison, 2020). The Sanchi oil spill, caused by the collision of oil tanker Sanchi collided with a cargo vessel, caused fire, explosions and sinking, killing all 32 crew members, spilling or burning more than 100,000 tons of petroleum products (Wan and Chen, 2018).

The oil pollution (e.g., condensate and bunker oil) evaporated and formed an oil slick resulting in terrible damage to air quality, marine inhabitants, coastal waters and beaches, and maritime economic industries (Chen et al., 2020). Thus, the importance of emergency preparedness and response for oil spills has been widely recognized worldwide to minimize adverse impacts and save time, life and cost (García-Garrido et al., 2016). An effective emergency response system cooperating knowledge and resources (i.e., the availability of spill response options and required logistical support) is needed. Optimization algorithms are an important tool, used for the selection and distribution of emergency materials in response operations (Qian et al., 2020). Particle swarm optimization (PSO) is a powerful and robust evolutionary algorithm for system control and optimization (Cheng and Jin, 2015).

Emergency response is a dynamic and complex management process that requires consideration of multiple stages, phases, goals, and options. The emergency strategy for the selections of technologies and resources should be dynamically adjusted according to the continuous changes in corresponding information (Han et al., 2019b). Additionally, the objectives need to correspond to the relevant models in time or stage. Different combinations of response manners will affect overall emergency outcomes. Furthermore, it is important to achieve the best state of the entire emergency response system through the appropriate combination of practical modules. Optimization algorithms are an important tool, which are commonly used for the selection and distribution of emergency materials in response operations (Qian et al., 2020). Particle swarm optimization (PSO) is powerful and robust evolutionary algorithm for system control and optimization (Cheng and Jin, 2015). Compared with other evolutionary optimization methods, the advantages of PSO are that it is easy to implement and has fewer adjustment parameters, higher robustness and shorter calculation time (Abdmouleh et al., 2017b). However, PSO efficiency is limited by premature convergence with local minima, especially when encountering complex problems. The combination of EPD and multi-agent PSO has the potential to improve optimization efficiency.

This study describes the development and evaluation of an emergency response management modeling system integrating dynamic process simulation and system optimization. An enhanced particle swarm optimization algorithm (ME-PSO) is also developed with the strengths of multi-agent theory and EPD. The developed ERS and ME-PSO algorithm are further applied to optimize the contingency planning of marine oil spill response optimization. The structure of this paper is organized as follows. Section 4.2 describes the design of the ERS framework and the development of an enhanced particle swarm optimization algorithm (ME-PSO). Section 4.3 demonstrates the application of the proposed methodologies to an offshore oil spill response case with the consideration of resource dispatching, oil weathering processes and removal efficiency of different technologies. Section 4.4 presents the analysis of results of marine oil spill response and optimization performance of the ME-PSO, discussions, and recommendations. Section 4.5 provides conclusions from this study.

4.2 Methodology

4.2.1 Improved emergency response system (i-ERS)

An emergency response system was developed to provide an enhanced framework to support response operations following accidents or unexpected events. It provided a dynamic response management system on the basis of optimized cost or time planning. As shown in Figure 4.1, the ERS integrated the results of multiple simulations, an efficient system optimization module and information pertaining to the accident, including available response options. This information on accident location and response capacities was added to the resource allocation simulation modules, including resource allocation and transportation, human resource deployment, response resource loading/unloading and preparation status. Weathering conditions (e.g., temperature and wind speed) and waste residue status (e.g., types, volumes, and areas) were used as inputs to calculate the weathering effects on residues/wastes and the changes in waste/residue characteristics. The simulated response efficiencies were interactively determined by the quantities and types of response resources and the status of waste/residues. The simulation results for response allocation and waste/residue status were further transferred to the optimization module to continuously improve response planning with optimal cost/time management for resource allocation. The optimization module used in this study was the newly developed ME-PSO algorithm. Detailed descriptions and evaluations are presented in the next section.

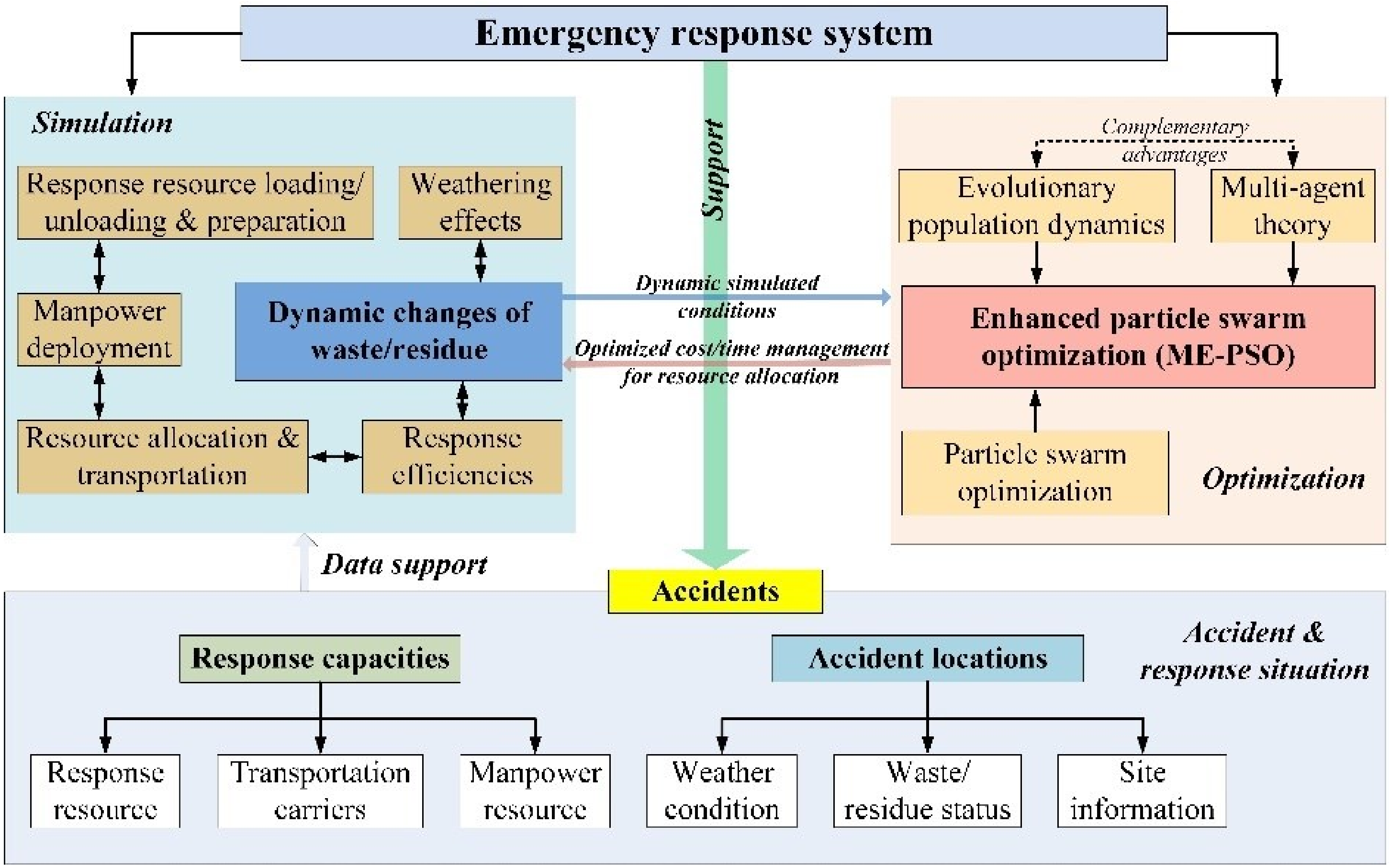


Figure 4.1 The framework of the improved simulation-optimization emergency response system

4.2.2 Enhanced particle swarm optimization

4.2.2.1. Particle swarm optimization (PSO)

PSO is a well-regarded population-based stochastic evolutionary algorithm for optimization solving (Eberhart and Kennedy, 1995b). It is used as the base algorithm for optimization method development. See Chapter 3 for details. The inertia weight factor (w) is set as descending (Eq. 4.1) (Ye et al., 2019a).

$$w_t = \frac{w_{ini} - w_{end}}{iter_{max}} (iter_{max} - iter_t) + w_{end} \quad \text{(Eq. 4.1)}$$

4.2.2.2 Evolutionary population dynamics

Evolutionary population dynamics (EPD) aims to improve optimization performance by replacing the poor solutions in the population with new ones closer to the best solutions (Saremi et al., 2015). EPD-PSO assumes that a candidate solution that is worse than the median of the whole population is not likely to achieve an optimal result (Saremi and Mirjalili, 2019). The poor solutions are relocated to new positions around the best solutions (Eq. 4.2 or 4.3) or random re-initialization (Eq. 4.4). The renewed solutions around the best solutions (G_{best} and P_{best}) enhance the convergence speed and the median of all solutions. Re-initialized solutions increase exploration and local solution avoidance.

$$x_i^{t+1} = G_{best} \pm [(ub - lb) \cdot r + lb] \quad \text{(Eq. 4.2)}$$

$$x_i^{t+1} = P_{best} \pm [(ub - lb) \cdot r + lb] \quad \text{(Eq. 4.3)}$$

$$x_i^{t+1} = [(ub - lb) \cdot r + lb] \quad \text{(Eq. 4.4)}$$

where, ub and lb indicate the upper and lower bound of multi-dimensional parameters in positions.

4.2.2.3. Multi-agent theory (MA)[5]

The multi-agent system (MAS) represents a computational system for the interactions or collaborations of agents to achieve goals (Zhao et al., 2005). When adding MA to improve the interactive ability of PSO, Agents can not only operate autonomously and independently but also cooperate or compete to achieve their own individual targets as well as share information with others. (McArthur et al., 2007; Nedic and Ozdaglar, 2009; Sabater and Sierra, 2002). Due to the similar interaction strategy as the basic philosophy of PSO, MAS can be integrated as a part of an optimized approach by developing PSO into a version of multi-agent PSO (MAPSO) to enlarge the scope of exploration, enhance the influences from other solutions and prevent the candidate solutions from trapping into local optima. Four vital points are considered when combining MAS into the current PSO for optimization:

1) Each agent represents its independent performance and target.
2) All agents are allocated in a global environment with boundaries.
3) Each agent has a fixed coordinate related to its local environment and neighbours.

** Multi-agent PSO was developed by Ye et.al. (2019) in the article, Multi-agent hybrid particle swarm optimization (MAHPSO) for wastewater treatment network planning. The proposed method can be used for both continuous and discrete variables. The MAPSO is the part for continuous variable, which was used in this study.

4) Agents update their performances by the rules, including fitting function, competition and cooperation strategies and position updating standards.

In MAPSO, an agent is not only a candidate of MAS but also a particle of PSO. To define the location of agents, a lattice-like environment shown in Figure 4.2 is proposed as the global environment. Figure 4.3 shows the interactive relation between the and global environment. Agents (or particles) are allocated in the global environment with their unique coordinates. They competed and cooperated with their neighbours to speed the convergence as well as prevent from trapping by local optimums by learning from the sharing information in every iteration. In addition, high-quality optimal solutions can also be updated from previous self-learning experience. The stepwise procedure for implementing the MAPSO model on a MATLAB® platform is summarized as follows (Figure 4.4):

Step 1. **Representation:** Define the nonlinear problems, including objective function, decision variables, input parameters, constraints, boundaries, and total iteration number. Each agent obtains a fitness value for the problem. The purpose of agents is to minimize/maximize the fitness with the requirements of boundaries and constraints.

Step 2. **Environment generation:** A lattice-like environment is constructed. In the global environment, each agent is settled as a point on a lattice-like environment in Figure 4.2. Each circle indicates an agent with its own velocity and position information. The environment size is $X_m \cdot Y_n$, where X_m and Y_n are integers. The number of lattices also represents the population size in PSO. Each agent has its own local environment (Figure 4.3) with neighbouring agents in MAS to affect the interaction and improve the model performance. Suppose agent $\alpha_{i,j}$ has four neighbouring agents $N_{i,j}$ from four directions representing as $[\alpha_{i^L,j}, \alpha_{i^R,j}, \alpha_{i,j^L}, \alpha_{i,j^R}]$, where,

$$i^L = \begin{cases} i-1 & i \neq 1 \\ X_m & i = 1 \end{cases} \quad \text{(Eq. 4.5a)}$$

$$j^L = \begin{cases} i-1 & j \neq 1 \\ Y_n & j = 1 \end{cases} \quad \text{(Eq. 4.5b)}$$

$$i^R = \begin{cases} i+1 & i \neq X_m \\ 1 & i = X_m \end{cases} \quad \text{(Eq. 4.5c)}$$

$$j^R = \begin{cases} j+1 & i \neq Y_n \\ 1 & i = Y_n \end{cases} \quad \text{(Eq. 4.5d)}$$

$$i = 1, 2, \dots, X_m; j = 1, 2, \dots, Y_n \quad \text{(Eq. 4.5e)}$$

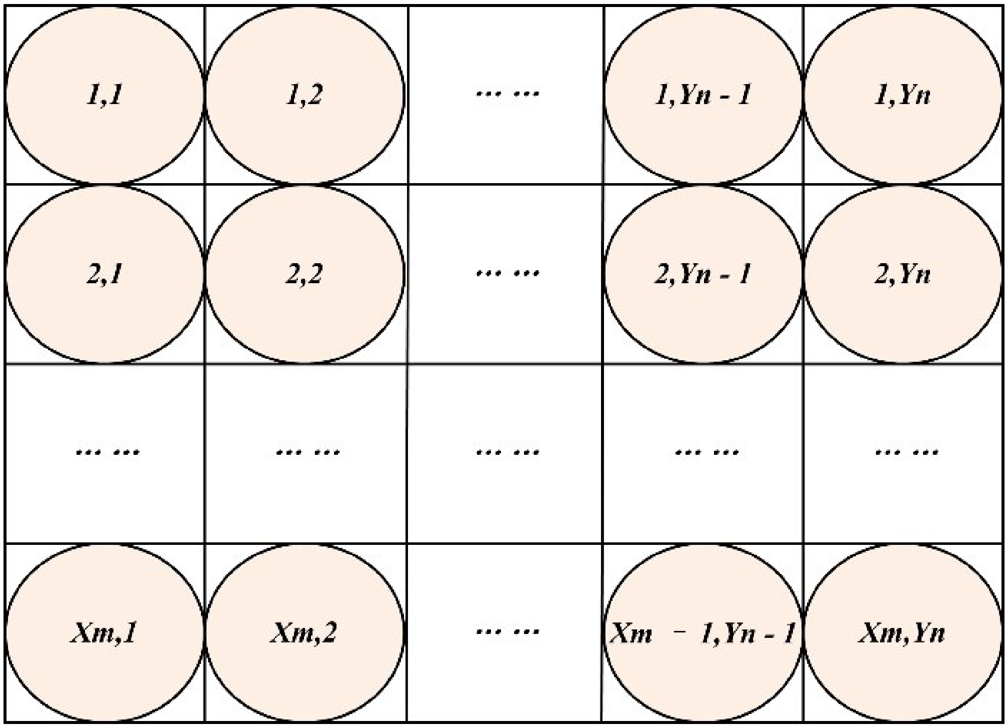


Figure 4.2 The structure of the global environment

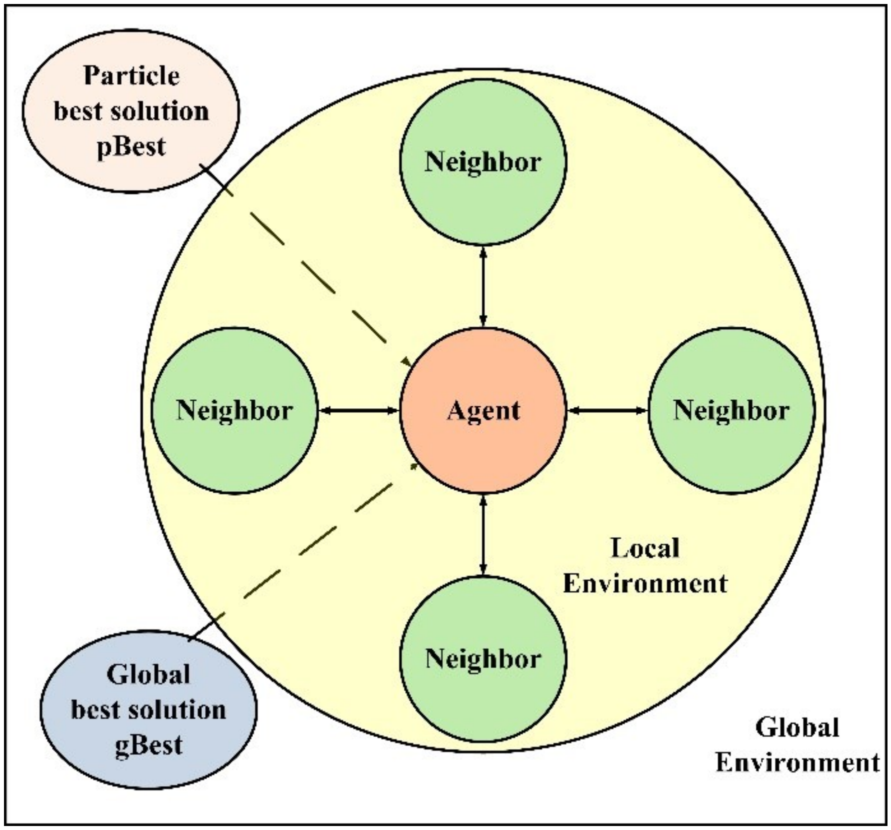


Figure 4.3 The interactive communication of an agent

Step 3. **Initialization:** All position values of agents are set randomly, and the initial velocity is set as zero. Ensure all variables satisfy the requirement of constraints and boundaries.

Step 4. **PSO evaluation:** Evaluate the fitness values of agents by using objective functions as well as finding out their *pBest* and *gBest* in each iteration.

Step 5. **PSO update:** Particle velocity and position are updated. After that, ensure the updated position satisfies the requirement of boundaries and constraints.

Step 6. **MAS evaluation:** Calculate the fitness values of agents with objective functions. Check whether the new optimal solution meets the stop criteria required by objective functions. If yes, then stop; otherwise, then continue.

Step 7. **MAS competition and cooperation:** Perform the neighbours for each agent, generate neighbor best solution N_{best} for each local environment. To be specific, suppose the optimal fitness value among an agent_{ij} and its four neighbors were represented as $N_{best,ij}$. If $f(\text{agent}_{ij}) \leq f\ (N_{best,ij})$, agent_{ij} is a winner in the competition, its position remains unchanged. Otherwise, it is a loser, then, agent_{ij} is replaced by a new agent with modified position statement following a crossover-like procedure of *Eq. 4.6*, in order to ensure that the new agent blends with the benefits of the loser agent and its neighbor best solution.

$$x'_{ij} = N_{best,ij} + rand() \times (N_{best,ij} - x_{ij}) \qquad \text{(Eq. 4.6)}$$

Where, *rand ()* represents a uniform random number in the interval of (0,1). Ensure the updated position satisfies the requirement of variables boundaries.

Step 8. **Update the iteration counter** $t = t + 1$, and go to step 4.

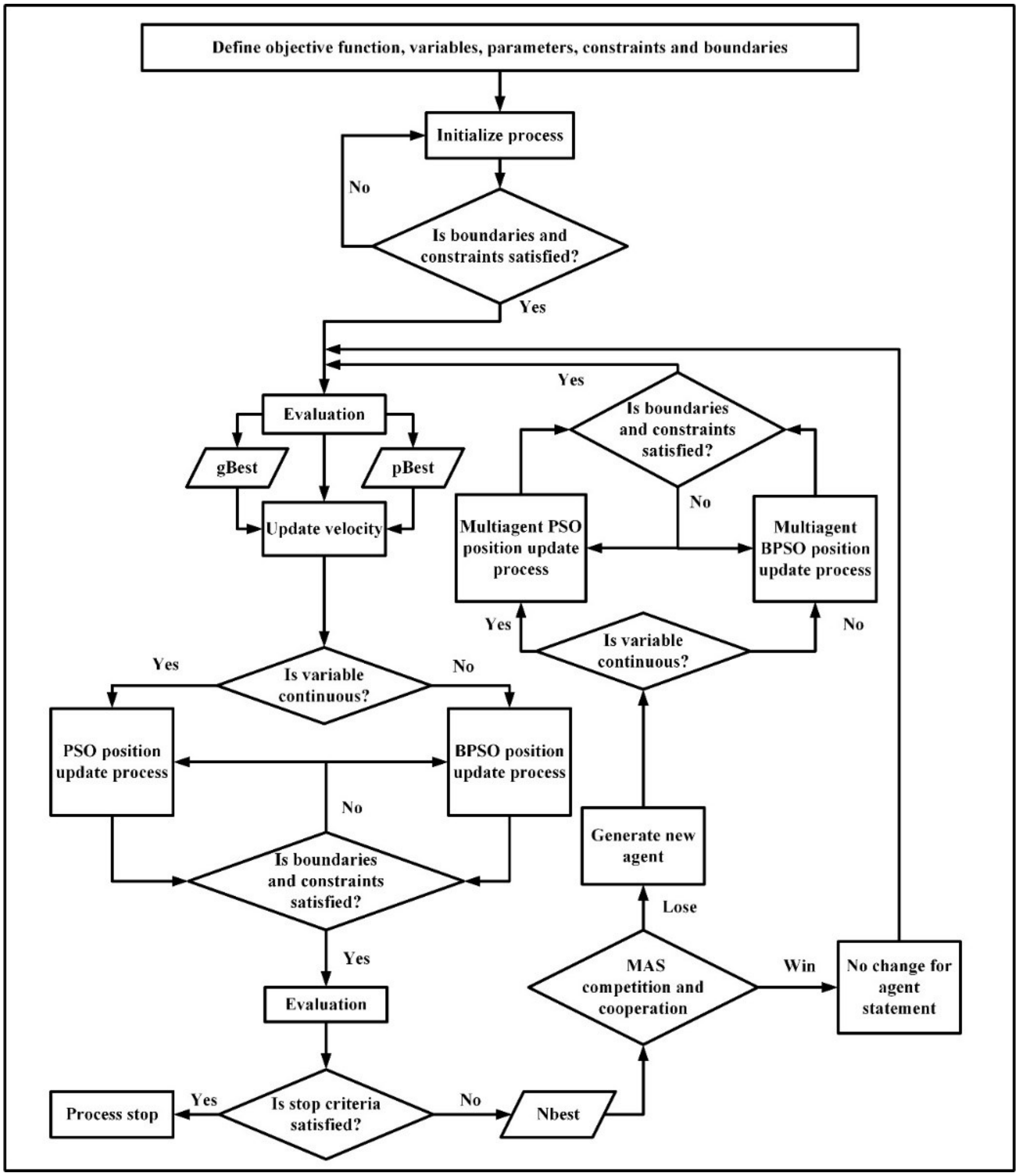


Figure 4.4 The framework of the multi-agent particle swarm optimization

4.2.3 Improvement of the enhanced particle swarm optimization algorithm (ME-PSO)

Multi-agent theory (MA) can help expand the search by interacting with nearby solution candidates. It prevents results from obtaining local optimal results. However, the enlarged range increases the computation time and makes it challenging to find the best results with a few iterations. Evolutionary population dynamics (EPD) relocates weak solutions based on the current best solutions. It is efficient for unimodal and some multi-modal problems. One potential approach to improve the performance of evolutionary algorithms is to hybridize or combine different update operators. In the proposed PSO version, ME-PSO combines the advantages of its parents (i.e., MA-PSO and EPD-PSO) to help overcome the parents' deficiencies. ME-PSO inherits the strong points which speed up the convergence and reduce the calculation time, while expanding the search range. The pseudocodes of the proposed method are shown in Appendix **A**. In this version, agents (also known as particles) enhance their solutions with multi-agent algorithms, which expand search ranges and social interactions in all three iterations. High-frequent updates with MA may not lead to good solutions under a relatively low population size. While in the other two iterations, EPD algorithms update agents for weak solutions.

4.3. Application for Marine Oil Spill Accidents

4.3.1 Case description

The proposed ERS framework can be applied for the support and optimization of the response strategies with the linkages of dynamic simulations of site conditions and response performance, system optimization and control as well as corresponding information. A hypothetic case study was conducted to test the developed ERS and ME-PSO efficiency for a marine oil spill incident. An oil recovery operation's ultimate goal is to collect as much oil as possible on a reasonable and economic basis (Ye et al., 2020). A successful recovery system must overcome the interconnected issues associated with large volumes of oil, changing oil characteristics during weathering, and deployment of recovery units and subsequent pumps and storage units (Li et al., 2016a). Optimized response planning can significantly reduce time and cost (Ye et al., 2019b).

The case study was centered on a 5,000 m^3 spill of Arabian Light crude oil in the North Atlantic Ocean. The primary response technique of many government authorities was the mechanical recovery using booms to concentrate the spilt oil and skimmers to selectively recover and pump the oil to storage tanks (ITOPF, 2014b). Thus, booming and skimming were considered as the leading oil recovery process in this case study. Three response centers with different response resources were available to perform response operations. After boom deployment, the spill area was assumed to be confined to 100,000 m^2. The oil recovered by skimmers was removed from the sea, transported to the inlet side of a pumping system, and then transferred to the storage units.

4.3.2 Oil recovery simulation module

Oil spill emergency resources should be operated in a proper procedure at the accident scene. The supplied length of oil containment booms should be longer than the perimeter of the spills to control the oil from further diffusion. The skimmers, unloaded pumps, temporary internal tanks, and storage vessels should be arranged in pairs and operations coordinated to achieve high recovery performance. Ships from ports or response centers were assigned as emergency response vessels for oil recovery (with limited storage capacity), oil waste storage and transport to shore (Li et al., 2019). Response efficiency was often limited by the proficiency of the available response equipment (e.g., booms, skimmers, and pumps). In this case study, each of the three response centers (RCs) provided skimmers with a different net oil recovery rate using Eq. 4.7-4.8 and Table 4.1 (Li et al., 2014b; Ye et al., 2019b). Dispatch time for the exercise was defined as the loading time plus the travel time of each vessel to the response site. The information about recovery materials is presented in Table 4.2.

$$ORR_{sk} = \alpha \times ST^2 + \beta \times ST \qquad \text{(Eq. 4.7)}$$

$$ST_{k,t} = \frac{V_{0,k} - \sum_{t=1}^{t-1} V_{loss,k,t}}{A_{k,t}} \qquad \text{(Eq. 4.8)}$$

where ORR_{sk} is defined as the amount of recovered oil per hour (m^3/hr), α and β are empirical coefficients obtained from experimental tests. $ST_{k,t}$ shows the slick thickness of spill k at time t (mm). $V_{0,k}$ is the initial volume of spill k, $A_{k,t}$ is the area of spill k at time t, and $V_{loss,k,t}$ is the oil loss at time t through oil response and natural weathering processes.

Table 4.1 Model coefficients for the net oil recovery rate of three ship-mounted skimmers

Types of skimmers	Empirical coefficients	
	α	β
SK_1 (Team A)	0.00737	0.00702
SK_2 (Team B)	-0.00791	0.62975
SK_3 (Team C)	-0.01591	1.14975

Table 4.2 The matrix of emergency materials for oil spills at different response centers

Response centers (RCs)		Storage volume (m^3)					
		Boom (100 m/unit)	**Skimmer Type-1**	**Skimmer Type-2**	**Skimmer Type-3**	**Pump-1 (10 m^3/hr)**	**Pump-2 (50 m^3/hr)**
	1	45	15	10	17	10	40
	2	50	15	10	17	10	40
	3	55	15	10	17	10	40
		Available quantity (*unit*)					
	1	5	3	3	2	10	5
	2	8	3	2	4	15	7
	3	7	1	3	1	12	5
		Vessel dispatch time (*hour*)				**Available vessel quantity (*unit*)**	
		Disposal vessels (200 m^3)		**Disposal vessels (400 m^3)**			
	1	3		3		1	1
	2	3		3		2	1
	3	3		3		1	1

4.3.3 Oil weathering simulation module

The dynamic changes of the remaining oil volume after its accidental release at sea significantly affected the oil spill response efficiency. Oil weathering processes can directly change the oil volume and thickness over time. The major weathering processes, evaporation, natural dispersion, and emulsification were considered in this hypothetic case. The evaporation of Arabian Light crude oil was shown in Eq. 4.9 (Fingas, 2016). Eq. 4.10 was the equation for the dispersion process developed by Mackay et al. (1980a). Furthermore, the equations for emulsification proposed by Rasmussen (1985) were represented in Eq. 4.11-4.13. Kirstein and Redding (1987) proposed a relatively simple empirical equation for the illustration of the relationship between viscosity and water content (Eq. 4.14). The parameter values for oil weathering simulation were shown in Table 4.3 (Azevedo et al., 2014; Li et al., 2014a; Mackay et al., 1980b; Rasmussen, 1985; Ye et al., 2019b). The parameters for oil weathering processes simulation (i.e., temperature, wind speed, oil density and interface tension) were assumed to be constant. Wind direction and oil movement were not considered in this hypothetic case since advection and spreading were not considered. The effect of emulsification on oil volume was neglected in the study. However, the changes of viscosity and water content by emulsification was considered to affect oil dispersion process.

$$(\%)Ev = (2.4 + 0.045(\mathrm{T} - 273.15))\ln(\mathrm{t}) \qquad \text{(Eq. 4.9)}$$

$$FD = \frac{0.11\times(U+1)^2}{1+50\times\mu^{0.5}\times ST\times S_t} \quad \text{(Eq. 4.10)}$$

$$\frac{dF_{emul}}{dt} = R_1 - R_2 \quad \text{(Eq. 4.11)}$$

$$R_1 = \frac{K_1}{\mu_0}\times(1+U)^2\times(F_{emul}^{final} - F_{emul}) \quad \text{(Eq. 4.12)}$$

$$R_2 = \frac{K_2}{Asph\times Wax\times\mu_0}F_{emul} \quad \text{(Eq. 4.13)}$$

$$\mu = \mu_0 \times \exp\left(\frac{2.5\times F_{emul}}{1-k\times F_{emul}}\right) \quad \text{(Eq. 4.14)}$$

where, $(\%)Ev$ was percentage evaporated oil, *T* was temperature (℃), and *t* was the time (minute); *FD* was the dispersion rate ($\mathrm{m}^3/(\mathrm{s}\cdot\mathrm{m}^3$ of oil)), U was the wind speed (m/s), μ was the dynamic viscosity of the oil, and S_t was the interface tension between oil and water; F_{emul} was the fractional water content; F_{emul}^{final} was the maximum water volume that can be incorporated in the emulsion, K_1 and K_2 were empirical dimensionless constants; Asph and Wax were percentages of asphaltenes and waxes contents, and μ_0 was the initial dynamic viscosity of the oil.

Table 4.3 The parameters for Arabian Light crude oil weathering processes

Parameter	Value	Unit	Parameter	Value	Unit
Temperature (T)	278.15	K	Wind speed (U)	10	m/s
Initial oil viscosity (μ_0)	55	cP	Interface tension (S_t)	1.68×10^{3}	dyne/m
Empirical dimensionless constant (K_1)	3.0×10^{-9}	kg/m^3	Empirical dimensionless constant (K_2)	3.0×10^{-7}	kg/m·s^2
Asphaltenes	4.0	%	Waxes contents	2.9	%
Maximum water content (F_{emul}^{final})	90	%	Initial water content (F_{emul}^{ini})	0.10	%
Mooney constant (*k*)	0.65				

4.3.4. Dynamic response optimization module

The optimization problem in the case study was developed with dynamic mixed integer nonlinear programming. It considered the dispatch of emergency booms, skimmers, and pumps by vessels with proper loading storages, nonlinear oil recovery efficiency and oil weathering simulation. The objective of the case study was to determine the optimal plan with limited resources to maximize the collected oil volume within the first 48-hour period. The dispatch time for each voyage was 3 hours. The time scale was set to hours. According to the above information, a general optimization model can be generated as follows:

- ***Variable categories:*** the variables in the case included the dispatched quantities (Eq. 4.15) of all types of skimmers (x), pumps (y), boom (z) and vessels (v) from the different response centers. The detailed variable matrices were shown in Appendix B. The parameters with capital letters

$$X = \{x_{ijmn}, y_{ijmn}, z_{jmn}, v_{jmn}\} \qquad \text{(Eq. 4.15)}$$

where, i is the types of resources. Specifically, the case considered three types of skimmers, two types of pumps and two types of disposal vessel; j is the response centers ($j = 3$); m is the vessel type used to allocate resources ($m = 2$); n is *nth* voyage of disposal vessels ($n = 2$). The parameters with capital letters (i.e., I, J, M, N) represent the maximum numbers of resources. In this case, two voyages were taken for resource allocation.

- ***Objective functions:*** the objective function was to maximize the total recovered oil within 48 hours (Eq. 4.16) with consideration of operational skimmers (Eq. 4.17-4.19), operational pumps (Eq. 4.20-4.21), dynamic recovered oil by skimmers (Eq. 4.23), real-time slick thickness (Eq. 4.25), remaining oil (Eq. 4.26), evaporated oil (Eq. 4.27), dispersed oil (Eq. 4.28), fraction water content (Eq. 4.29) and dynamic viscosity (Eq. 4.30). Meanwhile, the oil recovery procedures can only start after the setup of booms (Eq. 4.22). If the booms could be set up after the first voyage, then recovery could be implemented after the first 3 hours. If the setup of booms was completed after the second voyage, then the recovery operation could start after the first 6 hours. If the setup was not completed within two voyages, the recovery would be treated as failure. The recovery rate of skimmers should be less than the pumping rate of all pumps (Eq. 4.24), so that the skimmed oil can be fully transferred to storage tanks and vessels.

$$Max\ V_{recovered\ oil} = \sum_{t=t_0}^{48} f_2(t) \quad \text{(Eq. 4.16)}$$

$$Skimmer_1 = \sum_{i=1}^{1} \sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{n=1}^{N} x_{ijmn} \quad \text{(Eq. 4.17)}$$

$$Skimmer_2 = \sum_{i=2}^{2} \sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{n=1}^{N} x_{ijmn} \quad \text{(Eq. 4.18)}$$

$$Skimmer_3 = \sum_{i=3}^{3} \sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{n=1}^{N} x_{ijmn} \quad \text{(Eq. 4.19)}$$

$$Pump_1 = \sum_{i=1}^{1} \sum_{j=1}^{J} \sum_{m=1}^{N} \sum_{n=1}^{N} y_{ijmn} \quad \text{(Eq. 4.20)}$$

$$Pump_2 = \sum_{i=2}^{2} \sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{n=1}^{N} y_{ijmn} \quad \text{(Eq. 4.21)}$$

$$if\ \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{n=1}^{N} z_{jmn} \times L_j \geq Spill\ perimeter, then\ t_0 = 6hr$$

$$if\ \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{n=1}^{1} z_{jmn} \times L_j \geq Spill\ perimeter, then\ t_0 = 3hr$$

$$if\ \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{n=1}^{N} z_{jmn} \times L_j \leq Spill\ perimeter, then\ failed, V_{recovered\ oil} = 0$$

(Eq. 4.22)

$$f_1(t) = \sum_{sk=1}^{SK} Skimmer_{sk} \times ORR_{sk}(f_3(t-1)) \qquad \text{(Eq. 4.23)}$$

$$f_2(t) = \min\left(f_1(t), \sum_{p=1}^{P} Pump_p \times eff_p\right) \qquad \text{(Eq. 4.24)}$$

$$f_3(t) = f_4(t-1)/A \qquad \text{(Eq. 4.25)}$$

$$f_4(t) = Oil_{ini} - \sum_{t=t_0}^{t-1} f_2(t-1) - f_5(t-1) - \sum_{t=1}^{t-1} f_6(t-1) \qquad \text{(Eq. 4.26)}$$

$$f_5(t) = \left(2.4 + 0.045 \times (T - 273.15)\right) \times \frac{ln(60t)}{100} \times Oil_{ini} \qquad \text{(Eq. 4.27)}$$

$$f_6(t) = \frac{0.11 \times (U+1)^2}{1 + 50 \times f_8(t-1)^{0.5} \times f_3(t-1) \times S_t} \qquad \text{(Eq. 4.28)}$$

$$f_7(t) = f_7(t-1) + [\frac{K_1}{\mu_0} \times (1+U)^2 \times \left(F_{emul}^{final} - f_7(t-1)\right) - \frac{K_2}{Asph \times Wax \times \mu_0} f_7(t-1)]$$

$$f_7(0) = F_{emul}^{ini} \qquad \text{(Eq. 4.29)}$$

$$f_8(t) = \mu_0 \times \exp\left(\frac{2.5 \times f_7(t-1)}{1 - k \times f_7(t-1)}\right) \quad \text{(Eq. 4.30)}$$

where, L is the unit length of boom at response center j; sk is the type of skimmer; ORR is skimming rate; p is the type of pump; eff_p is the pumping efficiency; A is the spill area; Oil_{ini} is the initial volume of spilled oil; the parameters with capital letters (i.e., SK, P) represent the maximum numbers of resources

- ***Constraints:*** The constraints were used to restrict the demand for response resources (i.e., skimmers, pumps, and boom) to meet the supplies from each response centers (Eq. 4.31-4.33). The resources carried on each vessel during a single voyage were less than the maximum storage of vessels (Eq. 4.34).

$$0 \leq \sum_{m=1}^{M} \sum_{n=1}^{N} x_{ijmn} \leq x_{ij,max} \quad \text{(Eq. 4.31)}$$

$$0 \leq \sum_{m=1}^{M} \sum_{n=1}^{N} y_{ijmn} \leq y_{ij,max} \quad \text{(Eq. 4.32)}$$

$$0 \leq \sum_{m=1}^{M} \sum_{n=1}^{N} z_{jmn} \leq z_{ij,max} \quad \text{(Eq. 4.33)}$$

$$0 \leq \sum_{i=1}^{I} x_{ijmn} \times SV_{x_{ij}} + \sum_{i=1}^{J} y_{ijmn} \times SV_{y_{ij}} + z_{jmn} \times SV_{z_j} \leq SV_{v_{jmn}} \quad \text{(Eq. 4.34)}$$

where, $x_{ij,max}$ are the available quantities of resources supplied by response centers; SV is the storage volumes in Table 4.2.

4.4. Results and Discussions

4.4.1. Results of marine oil spill response system

The case presented an optimal response plan for a marine oil spill accident with the dispatchment and selection of different response resources. The modeling results indicated that the optimal response plan for the simulated marine oil spill resulted in approximately 80.28% of the spilled oil being recovered within the first 48 hours of the response. Figures 4.5 and 4.6 showed that there were enough booms to block and concentrate the oil to a required area, transported by the vessels during their first voyage. After setting the booms to prevent oil from spreading and dispersing, operators could start the recovery in the fourth hour. From the fourth hour to the sixth hour, after meeting the critical capacity of booms, a total of six type-1 skimmers, three type-2 skimmers, four type-3 skimmers, 12 type-1 pumps and five type-2 pumps were transferred for oil recovery. A total of five type-2 skimmers, three type-3 skimmers and three type-2 pumps were further transferred during the second voyage to increase the recovery efficiency. The discharge rate of pumps could satisfy the needs for transferring all skimmed oil to the oil storage or tanks. All types of skimmers perform a good recovery efficiency at the beginning. The type-2 skimmers have a weaker performance for a low-thickness slick than other types. Thus, they have a low recovery volume after 20 hours. As the remaining oil on the sea decreased, the thickness of the floating oil became too thin to use the skimmers. After 30 hours, very little oil was recovered. After 34 hours, the recovery process was completed. The remaining oil evaporated or dispersed due to weathering processes or remained in seawater. Figure 4.7 indicates that the average space for carrying equipment of vessel transportation was 43.09%. The 400 m^3 disposal vessel from Response Center 1 was not used for the second voyage for cost savings. But some trips had low transportation efficiency. For example, only 5.00% space of the 400 m^3 disposal vessel from Response Center 3 was utilized during the 2nd voyage. Thus, the response plan could be further optimized by considering the operational costs of coordinated transportation from the multiple response centers. Figure 4.8 shows that Response Center 1 transported all skimmers and 80.00% of its booms. Response Center 2 shipped all its skimmers, 42.86% of its type-2 pumps and all booms. Response Center 3 provided all type-2 and 3 skimmers, all its pumps and 57.14% booms.

The proposed ERS system solved the allocation of response resources for marine oil spill accidents under the consideration of dynamic simulations and changing accident conditions. It can select appropriate resources to initiate response procedures quickly. For example, in the first voyage, the vessels focused on handling the booms to prevent the spill from spreading first. It can ensure that oil can be cleaned up simultaneously when the vessels took the second voyage. Additionally, selecting the appropriate quantity and types of booms can leave more space to transport skimmers and pumps. Generally, the thicker the oil layer is, the higher efficiency the skimmer will have. Removing more oil at the early stage can also leave less oil to be evaporated. In the further transportation and response stages, the choice of skimmers and pumps is optimized to let all recovered oil be transferred to the temporary tank and ensure no redundant devices are transferred with the waste of time and cost. The recovery efficiency in the hypothetical case might be higher than the ones in the actual applications. Since the assumptions of the properties of oil and weathering conditions were constant and there were no considerations of efforts from in-situ situations (e.g., wave, wind, and precipitation), human errors, system risks and uncertainties, the recovery efficiency in the actual situations will be decreased dramatically.

However, these factors will evenly affect the outcomes of all plans. Thus, a plan with a high recovery rate under hypothetical situations also has a high potential to comparatively improve the recovery efficiency of the real applications. The modules of simulation and optimization in the ERS framework can be updated based on the specific requirements to realize practical applications for the response procedures to other accidents and disasters.

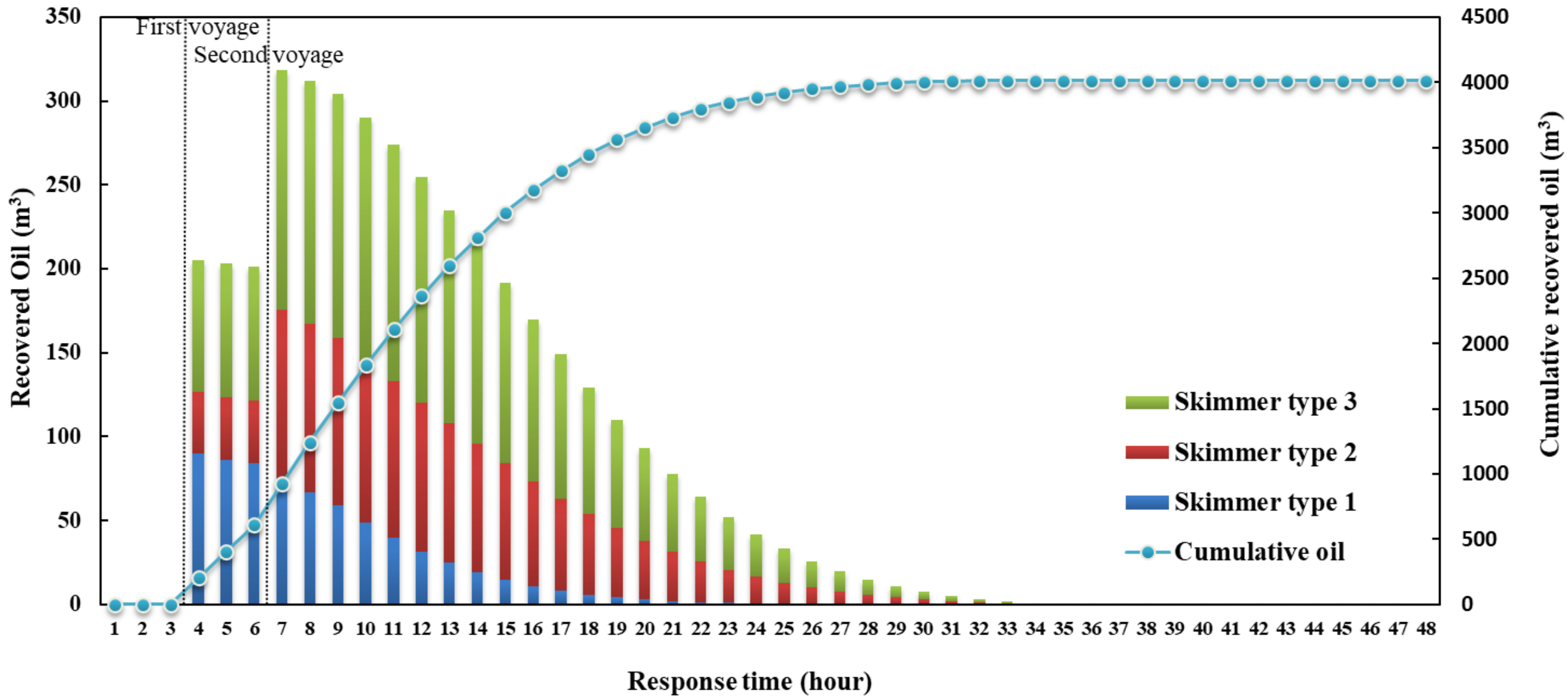


Figure 4.5 The recovered and cumulative volume of spilled oil by skimmers

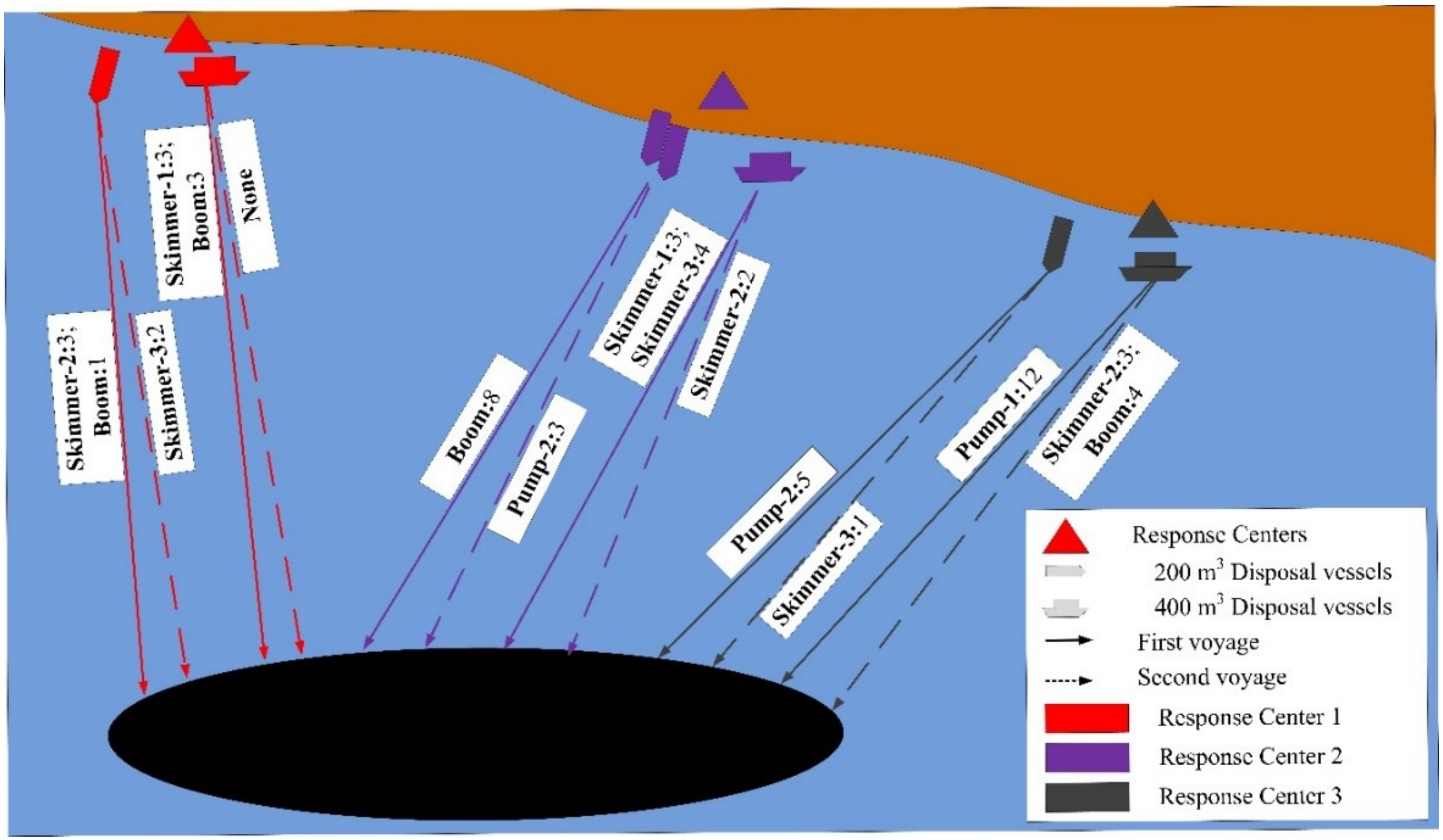


Figure 4.6 The dispatch map of response resources

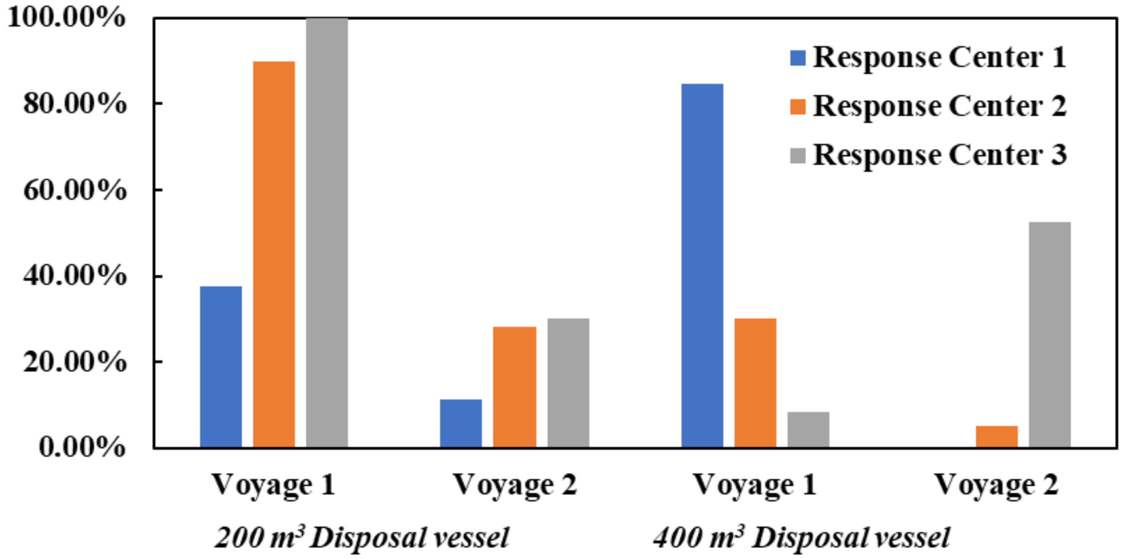


Figure 4.7 The space for carrying equipment of vessel transportations.

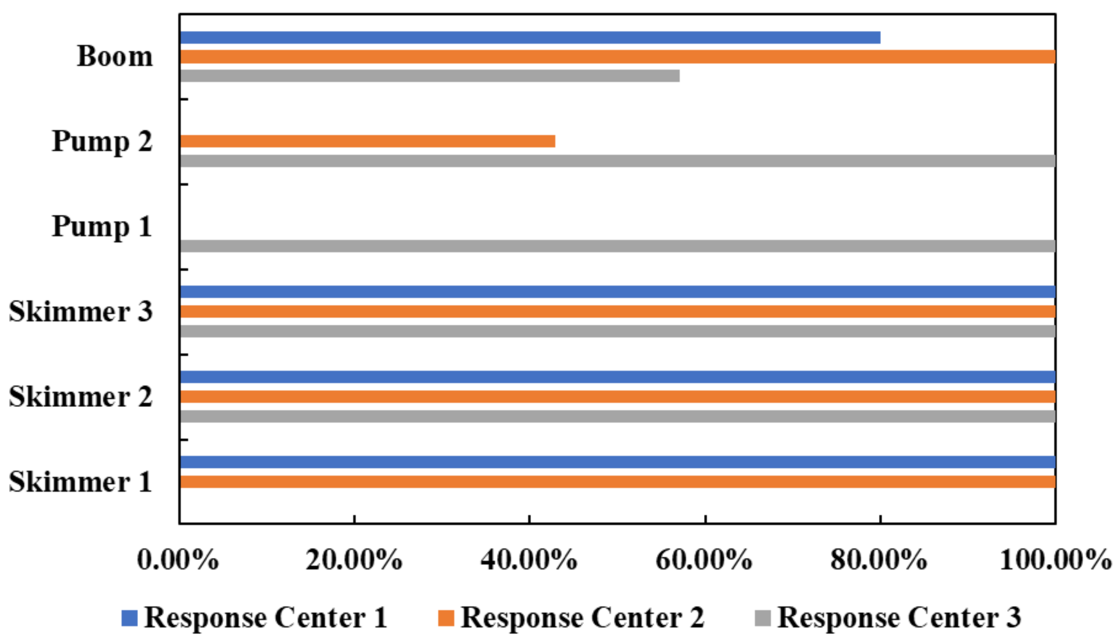


Figure 4.8 The resource utilization from response centers

4.4.2. Optimization performance evaluation of ME-PSO

4.4.2.1. Performance evaluation with benchmark functions

The performance of the proposed ME-PSO algorithm was evaluated by comparison with traditional PSO versions (i.e., PSO, MA-PSO and EPD-PSO). The capacities of exploitation and exploration were examined using 13 uni-modal and multi-modal benchmarked functions, which were updated based on Saremi and Mirjalili (2020), shown in Appendix C. For a relatively comprehensive analysis of the proposed algorithms, a total of 624 scenarios with four PSO versions were calculated. To be specific, the population size was tested at 8 levels (i.e., 50, 100, 150, 200, 300, 400, 500 and 1,000). The maximum number of iterations was tested at 6 levels (i.e., 50, 100, 200, 300, 400, and 500). The average values of functions under each scenario were calculated using 100 runs. The proposed models were written in Matlab 2019® on a desktop computer with Intel 4770K CPU and 32 G RAM. Figure 4.9 showed the overall optimization results of four PSO versions, with the result set from every 48 scenarios with different selections of population sizes and maximum numbers of iterations, to benchmark functions. The ME-PSO results were used as the baseline to compare with the other PSO results. The bars above the horizontal axis represent that the number of results inferiors to ME-PSO. The bars below the horizontal axis are the ones superior to ME-PSO. The figure indicated that ME-PSO had a more outstanding performance than PSO and MA-PSO for both uni- and multi-modal functions. ME-PSO had a similar performance to EPD-PSO. But each performed better on different functions. The detailed results are shown as heating maps in Appendix D. EPD-PSO had good outcomes with fewer iterations, but ME-PSO could find more optimized results with relatively larger iterations. The results were also analyzed through response surfaces. Figure 4.10 showed some examples. Full figures are presented in Appendix E. Generally, the minimum values became lower with the maximum population and maximum iteration increase. For uni-modal functions, maximum the population took more effort than maximum iteration. For multi-modal functions, the functions needed more iterations to reach the best result and maximum iteration took more effort than the maximum population. For most functions, large populations (e.g., 800 or 1,000) did not enhance performance. The average computation time of algorithms in one run ranged from 2.42 and 2.73 seconds (PSO and EPD-PSO) to 4.51 and 4,96 seconds (MA-PSO and ME-PSO). Searching time and computation cost were optimized with maximum populations around 200 to 400.

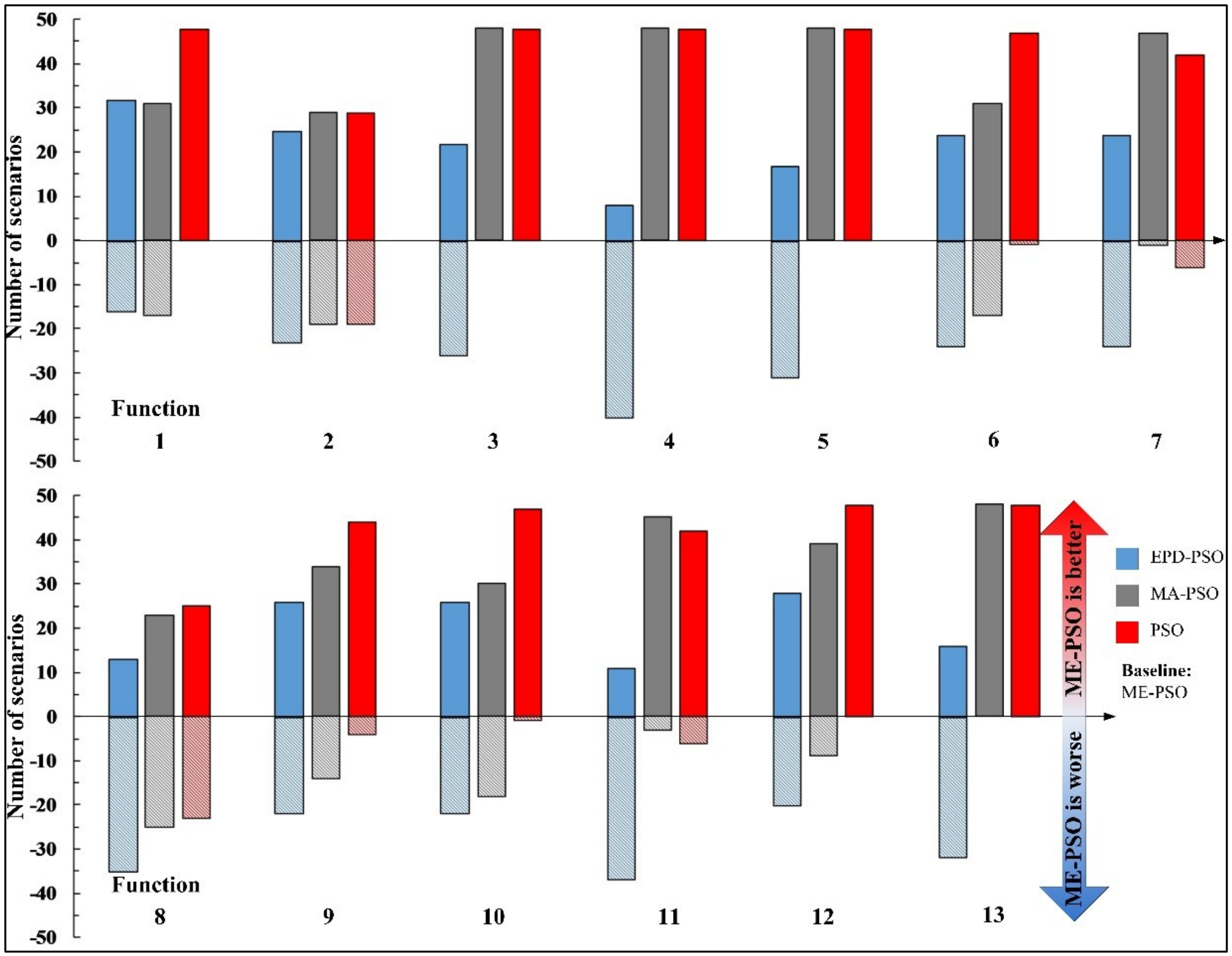


Figure 4.9 The overall optimization results of PSOs on benchmark functions under different scenarios

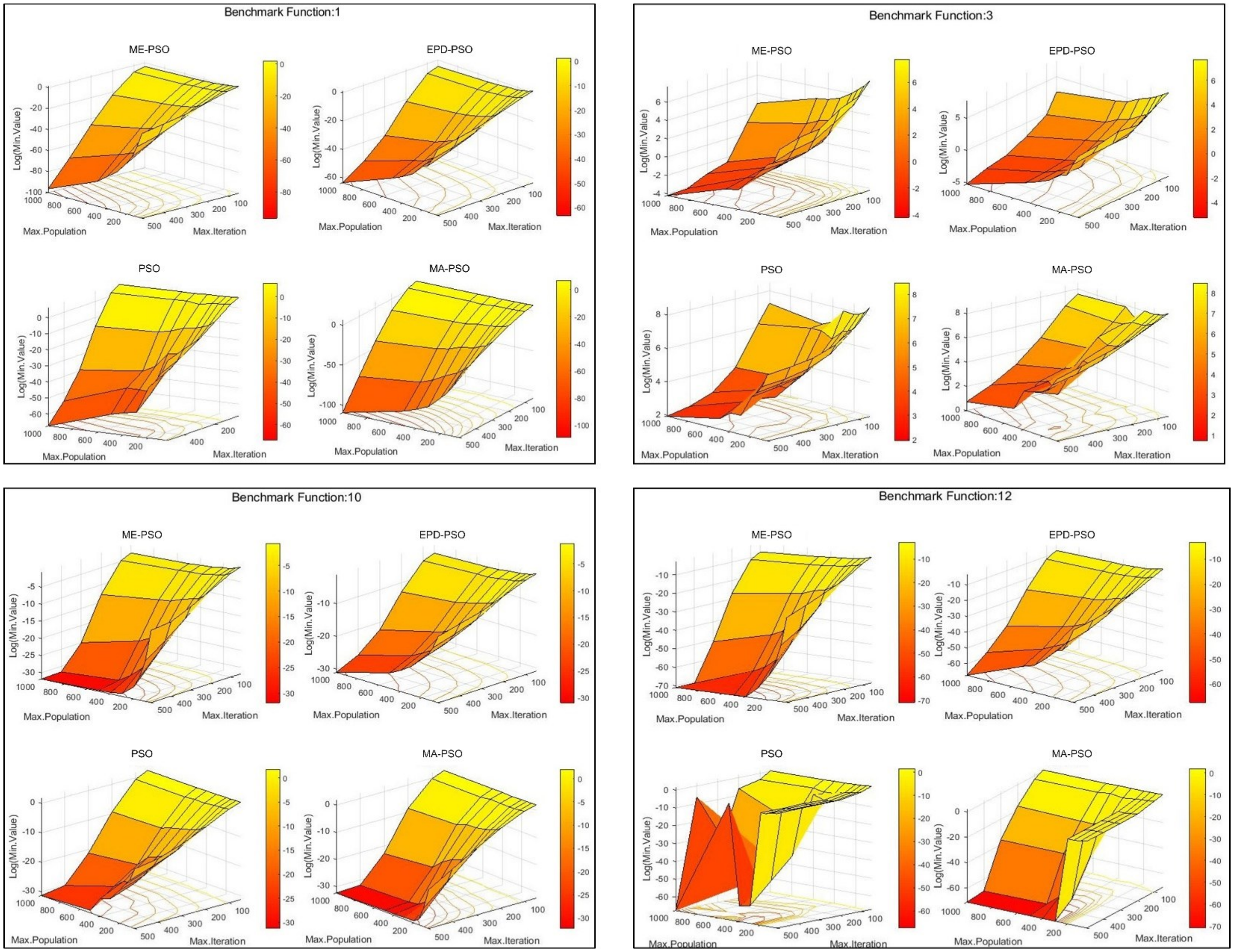


Figure 4.10 Examples of response surfaces of PSOs to benchmark functions

The performances of the compared PSO algorithms (i.e., ME-PSO, EPD-PSO, MA-PSO and PSO) were further assessed by ranking them with the Holm-Bonferroni procedure (Aydilek, 2018; Cheng and Jin, 2015). The Holm-Bonferroni procedure ranked the PSOs on the basis of their average performance calculated over the 13 test functions**.** Specifically, a score R_i was assigned for $i = 1, \cdots, N_A$ (where N_A was the number of optimization algorithms under analysis, $N_A = 4$ in the case). For each testing function, the highest score of $N_A$was assigned to the PSO algorithm with the best performance, the second highest score of $N_A - 1$was assigned to the second-best algorithm, until to the worst-performed algorithm with a score of 1. The PSO algorithms were ranked based on the mean score averaged over all the benchmark functions. According to the ranked R_i values, the algorithm with the highest value was further considered as the reference of R_0 to calculate the value Z_j with the Eq. 4.35. According to the Z_j values, the corresponding cumulative normal distribution values P_j were calculated in comparison with the thresholds θ_j with the confidence level δ (set to 0.05 in the case) as $\theta_j = \delta/(N_A - j)$. If $p_j < \theta_j$, the null hypothesis - no significant difference between the performance of two algorithms - was rejected, denoted as $h = 1$. Otherwise, the null hypothesis was accepted denoted as $h = 0$. The detailed ranking results were shown in Appendix F. The proposed ME-PSO had the same outstanding performance as the parent version of EPD-PSO for optimization under different iteration numbers and population sizes, except very few iterations of 50 and 100. Figure 4.11 showed that ME-PSO had a better performance than others at higher numbers of iterations and while MA-PSO performed better as the number of iterations increased. ME-PSO and EPD-PSO outperformed the others when considering population size.

Through a comprehensive analysis of the above aspects, ME-PSO showed an outstanding performance in solving complex optimization problems.

$$Z_j = \frac{R_j - R_0}{\sqrt{\frac{N_A(N_A+1)}{6N_p}}} \quad \text{(Eq. 4.35)}$$

where, N_p is the number of test functions, N_A is the number of optimization algorithms, R_0 is the rank value of the reference algorithm, R_j, for $j = 1, \cdots, N_A - 1$, is the rank values of the rest of the algorithms.

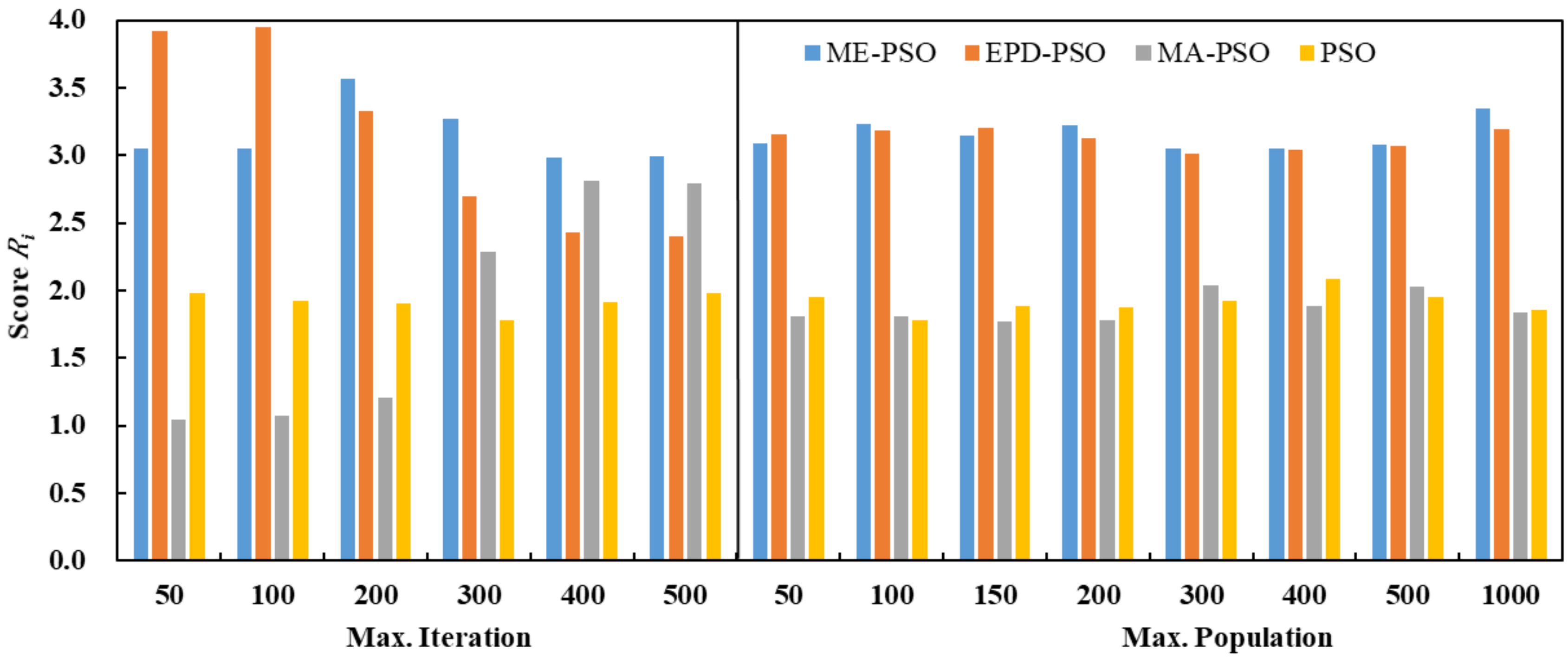


Figure 4.11 Ranking score (R) of PSOs with consideration of maximum number of iterations

4.4.2.2. Performance evaluation with the case study of marine oil spill accidents

The optimization performance of the ME-PSO to practical applications was evaluated by the proposed case study presented in Section 4.3. The maximum iteration number and population size were chosen as 300 and 300, respectively. Under the selected model factor, the cooperated efforts of EPD and MA could be realized to enhance the algorithm convergence. The model was programmed by MATLAB 2019®. A total of 1000 runs were taken to analyze the distribution of the optimized recovered oil and figure out the best optimized response plan. The results are shown in Figure 4.12. The average recovery rate within 48 hours was 79.38%. The standard deviation was 25.99. 123 runs achieved an optimized recovery rate over 80.00%. 803 runs achieved a recovery rate over 79.00%. The lowest recovery rate was 78.03%. These results confirmed that ME-PSO provided a stable and efficient computation performance.

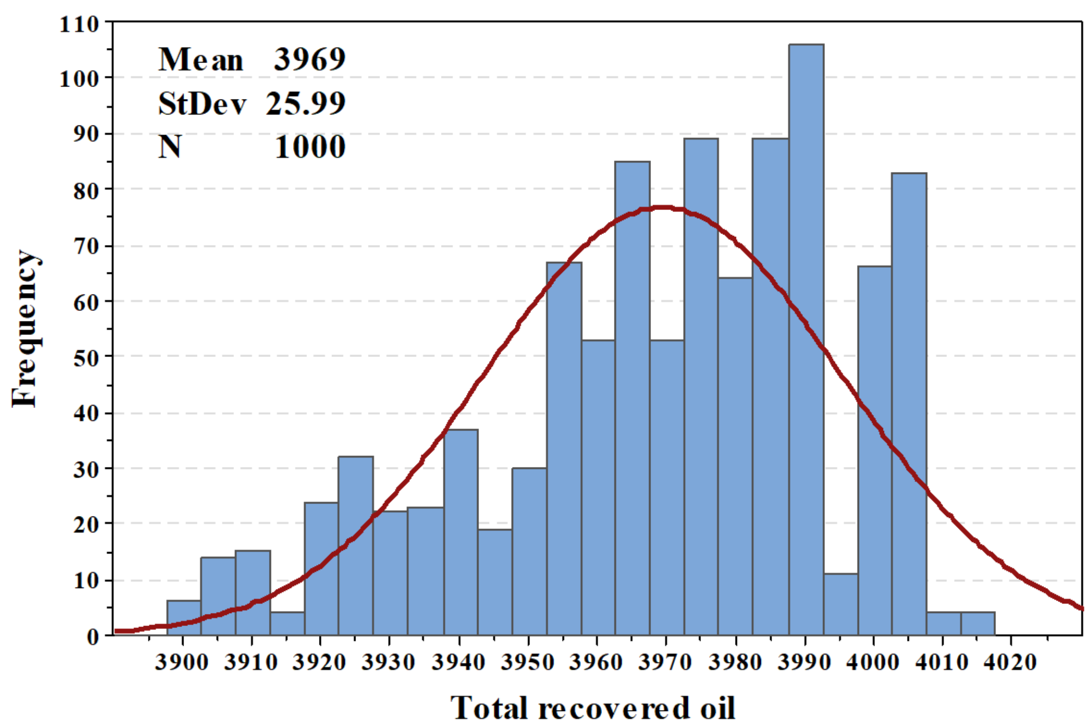


Figure 4.12 The distribution of optimized results under 200 runs

4.4.3 Future research challenges

The proposed improved emergency response system (i-ERS) and enhanced particle swarm optimization (ME-PSO) provide a framework for marine oil spill emergency response. In future practical applications, the oil spill response community can adopt and use the developed models with the adjustment of spill simulation parameters, response technologies, resource types and quantities, and response targets according to the specific requirements. Despite of the above theoretical and practical implications, this study still had several limitations which need to be resolved in future research. Recommendations include:

1) Multi-objective optimization modeling could be an appropriate approach to deal with emergency response problems. Although the fastest response time with the highest recovery rate is the most essential goal of a marine oil spill, how to organize human and equipment resources to improve response efficiency, reduce the relative annual response cost and minimize the environmental impacts on sensitive and coastal zones is another issue that needs to be solved. A multi-objective optimization based ERS is currently under development to address this issue.

2) Since the emergency response process is a complex system, the impact of remaining uncertainties on the overall efficiency needs to be further considered. Monte Carlo simulation may be a typical and efficient approach. The uncertainty analysis could further benefit the development of a trade-off module for response system optimization, which will be included in future studies.

3) Humans, as operators, are involved in all response procedures. Human errors or mistakes may affect response efficiency. For example, a wrong choice of the available

response options could highly reduce response efficiency. In addition, the case study did not consider the need for break time for operators. It assumed that sufficient human resources were deployed to complete the recovery task as soon as possible. However, in most cases, operators or laborers do not work at night. The influence of human limitations will be considered in future studies.

4) The oily water recovered from spills contains a large amount of liquid and solid waste. However, some empirical formulas regard this part as oil, which may cause the simulation efficiency to be much higher than the actual efficiency. In addition, some empirical oil weathering equations do not consider the influence of the booms, which will prevent oil from spreading. The restriction of the booms could affect the change in oil area, oil thickness, density, evaporation, dispersion, and emulsification. These limitations will reduce the practicality of the optimization model for marine spill response planning. Further experimental analysis should be carried out. Decanting (oil-water separation) systems including the use of demulsifier and other ship-mounted wastewater treatment devices can greatly reduce the volume of oily water transferred back to shore. The presence and efficiency of decanting systems could be considered in future studies.

5) The efficiency of the proposed ME-PSO should be further evaluated through different optimization approaches (e.g., genetic algorithm) and other problems related to decision making or planning, rather than PSO and typical mathematical optimization problems.

4.5. Summary

A sound emergency response system can provide effective support to shorten the response time for an accident and reduce the harmful effects. The research developed an emergency response system by integrating dynamic simulation of multiple response processes, response system optimization and site-specific information including available response options. Furthermore, an ME-PSO algorithm was developed by combining the advantages of MA and EPD. The ME-PSO could accelerate the convergence speed and reduce the calculation time, while expanding the search range for better results. A representative case of marine oil spill response was applied to demonstrate and evaluate the performance of the developed ERS and ME-PSO algorithm. An optimized oil spill response plan was generated considering the optimal allocation and deployment of response resources (e.g., booms, skimmers, pumps, and vessels) from three response centers were optimized. The system considered dynamic simulations of oil weathering and recovery performance, as well as the ME-PSO optimization. The results indicated the optimal response plan recovered approximately 80.28% of the spilled oil within the first 48 response hours. Allocation of resources, recovery behaviors of skimmers, space for carrying equipment of vessel transportations and resource utilization from response centers were also analyzed. The efficiency rate from the case might be higher than real cases due to the simplification of assumptions as constants and no considerations of effects from in-situ conditions (e.g., wave, wind and precipitation), human errors, system risks and uncertainties. Since these factors will evenly affect the planning outcomes, a plan with a high recovery rate under the hypothetical situations can comparatively improve the recovery efficiency of the real applications with high potential.

The ERS presented an effective strategy to maximize the benefits with the minimal response time. The optimization performance of the proposed ME-PSO was evaluated with three PSO algorithms (i.e., PSO, MA-PSO and EPD-PSO) with 13 uni/multi-modal benchmark functions under different parameter selections (i.e., 8-level population size and 6-level maximum numbers of iterations) and the practical case. The results indicated that the ME-PSO had the best and most stable performance with a faster convergence speed.

Challenges and recommendations for future research in multi-objective optimization, uncertainties, human factors, response technologies and optimization performance were discussed. Complex problems and high-level interactive processes can benefit the advantages offered by the ERS and ME-PSO. Although the developed ERS and ME-PSO were tested for a marine oil spill case, they can also be applied for other emergency management cases by updating the simulation modules and accident-specific information. Beside the scientific improvement on the simulation-optimization coupling and optimization algorithm, the proposed system presents a great potential of being a powerful tool for emergency response planning and decision making in many fields worldwide.

CHAPTER 5 AN INTEGRATED OFFSHORE OIL SPILL RESPONSE DECISION MAKING APPROACH BY HUMAN FACTOR ANALYSIS AND FUZZY PREFERENCE EVALUATION*

* This chapter is mainly based on the following referred publication

Ye, X., Chen, B., Lee, K., Storesund, R., & Zhang, B. (2020). An integrated offshore oil spill response decision making approach by human factor analysis and fuzzy preference evaluation. Environmental Pollution, 262, 114294. https://doi.org/10.1016/j.envpol.2020.114294

Contributions: Ye XD, methodology, software, validation, formal analysis, writing-original draft; Chen B, conceptualization, writing-revision and editing, supervision; Lee K, writing-revision and editing; Storesund R, conceptualization, writing-revision and editing; Zhang BY, writing-revision & editing

5.1. Introduction

Human errors and mistakes, as wrong actions made at an inappropriate time and an unsafe place, are one of the significant factors in the accidents and incidents within complex systems, such as marine oil exploration and spill response systems (Schorsch et al., 2017). As a necessary condition for the accident, every human error figures prominently in casualty situations in the marine system (Rothblum, 2000). Ishak et al. (2020) declared that human errors are a significant factor of oil spills. Human errors can be related to communication, task assignments, mental or physical fatigue, knowledge or understanding, training levels, working years and experience (Ishak et al., 2020; Von Zharen, 1994). The offshore oil spill prevention and response operations cover multiple stages, including spill occurrence, spill monitoring, decision making/contingency planning and spill response. Human errors can be divided into two categories as active and latent human errors (Chiu and Hsieh, 2016). Active human errors directly lead to an accident. The impacts are immediately apparent and easily recorded in incident reports or logs. Latent errors result in accidents indirectly, and their adverse consequences could be dormant for a long time in the system, they only become apparent following interactions with other causal factors that enable it to break through the defenses of the system. They are common, important, highly related, but often neglected. Under significant achievements in the studies of human factor analysis, the recognition has now been given to the theory and modelling of human factor analysis (Reason, 1990; Shappell and Wiegmann, 2000).

Human factors analysis and classification system (HFACS), derived from Reason's Swiss cheese model, is a broad human error organizational framework for accident analysis. The framework of a typical HFACS system is shown in Figure 2.12 at Chapter 2. It assists investigators in systematically identifying active and latent human factors in organizations to accidents. HFACS does not aim to attribute blame but to understand the underlying causal factors to enhance the efforts of investigation, target training and prevention (Chauvin et al., 2013). According to the previous research, HFACS has been successfully utilized in many different disciplines, such as accidents of aviation (Daramola, 2014; Li and Harris, 2006), mining (Patterson and Shappell, 2010; Zhang et al., 2019c), shipping (Chauvin et al., 2013; Chen et al., 2013), railway (Madigan et al., 2016; Zhan et al., 2017), oil and gas industry (Theophilus et al., 2017), construction (Xia et al., 2018), and hazardous chemicals (Zhou et al., 2018) as well as the issues of health care (Hsieh et al., 2018) and fire prevention (Soner et al., 2015).

Multi-criteria decision-making (MCDM) has been used effectively to rank the importance of error factors based on the classification outcomes from HFACS. It can further help provide improved strategies to decrease the impacts and risks of human errors (Zabeo et al., 2011). Various MCDM methodologies have been developed to evaluate multiple conflicting criteria in decision making, such as analytic hierarchy process (Balsara et al., 2019), analytic network process (Zhang et al., 2016), simple multi-attribute rating technique (Siregar et al., 2017), technique for the order of prioritization by similarity to ideal solution (Biswas et al., 2016; Şengül et al., 2015). The advantage of using MCDM is its ability to analyze an accident based on different criteria. The multiple levels of complexity, among different decision makers or tradeoff factors with environmental, social or economic considerations, make the conclusions of MCDM analysis more reliable and credible (Govindan et al., 2015).

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), proposed by Hwang (1981), is the well-known MCDM approach to analyze the performances of alternatives under multiple criteria. It evaluates the chosen alternatives based on the concept of the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal solution (Tzeng and Huang, 2011). It has been widely applied to solve decision-making problems in the research field of selection (Guo and Zhao, 2015; Karim and Karmaker, 2016), water quality assessment (Xu et al., 2019), risk assessment (Wang and Elhag, 2006), system ranking and evaluation (Lima-Junior and Carpinetti, 2016; Şengül et al., 2015), planning and management (Ervural et al., 2018). The TOPSIS is easy to make full use of attribute information to provide a cardinal ranking of alternatives. It does not require attribute preferences to be independent. However, to most information on offshore oil spills, human judgements or preferences are expressed by vague descriptive words (e.g., high, low, very low) (Madi et al., 2016). TOPSIS is limited by its inability to resolve the vagueness or ambiguity issues in decision making (Chiu and Hsieh, 2016). Fuzzy set analysis can be coupled to overcome the shortcoming to allow unquantifiable, incomplete, non-obtainable information or partially uncertain facts to be involved in decisions (Kim et al., 2014). It transfers linguistic preferences into exact numerical form for TOPSIS. Several oil spill-relevant studies have been published, highlighting the strength of MCDM and TOPSIS. But few studies considered the efforts of fuzzy-based TOPSIS for the response decision making or human factor analysis to offshore oil spill accidents.

This study focused on developing an enhanced and feasible human factor-based multi-criteria decision-making approach to fill the gaps of offshore oil spill decision making and accident analysis. The proposed approach integrated a specific HFACS model for offshore oil spill accidents (HFACS-OS) with a fuzzy-based TOPSIS (Fuzzy-TOPSIS) method. The human error factors within the stages of spill occurrence, monitoring, decision making/contingency planning and responses were classified and evaluated to help generate an efficient improved strategy for decision-makers to reduce the risks and probabilities of accidents or failures. Furthermore, the efficiency of the proposed approach was subsequently validated with a case study taking into account priority evaluation, sensitivity analysis and other implications. The historical spill cases and records were used to analyze the human-factor based causal factors with different complexities and further evaluate them with the relative priorities to determine the leading causes of the accident. This research enhanced the depth and broadness of the methodology of human error analysis, improved system reliability and provided support for accident response.

5.2. Methodology

5.2.1 Human factors analysis and classification system

The human factor analysis and classification system (HFACS) is a comprehensive approach for the analysis of the impacts of human factors and mistakes to catastrophic events, accidents, hazards, or regular operations. It was initially developed from the Swiss Cheese Model by Reason (1990). Both active and latent human errors are investigated from four levels, which are unsafe acts of operators, preconditions for unsafe acts, unsafe supervision, and organization influences (Shappell and Wiegmann, 2000, 2001). The HFACS has the strengths of diagnosis, reliability and comprehensiveness, especially in large-scale and complex accidents (Ye et al., 2018). It is an efficient approach to systematically analyzing the human factors that existed in spill accidents. The HFACS is initially developed for aviation, and an improved version for offshore oil spill systems is needed.

The level of "Unsafe acts" focuses on the representation of accidents. Failures at this level can be further divided into two sub-categories, errors, and violations. At this level, the actions in oil spills that deviated from a generally recognized safe way or specified method with increased accident potential, are analyzed (Entailing et al., 2017). The unsafe acts could be a consequence of errors by omission with a disregard of required actions or errors by a commission with the incorrect actions (Theophilus et al., 2017). The "Preconditions for unsafe acts" level considers the psychological precursors of the active human errors analyzed in "Unsafe acts" and the latent errors formed in accidents (Chiu and Hsieh, 2016). The considered human factors are classified into three sub-categories: environmental factors, condition of the operators, and personnel factors. The level of "Unsafe supervision" analyzes the latent human errors made by first-line supervisors, which may produce the causes of unsafe acts. Four sub-categories, inadequate supervision, planned inappropriate operations, failed to correct problems, and supervisory violations, are included in "Unsafe supervision" (Shappell and Wiegmann, 2000). The level of "Organizational influences" classifies the latent errors and causal factors of wrong decisions from the aspect of organizational management, which can directly affect supervisory practices. It contains three sub-categories of resource management, organizational climate and organization process (Zhan et al., 2017).

5.2.2 Fuzzy TOPSIS

5.2.2.1 Fuzzy set theory and fuzzy number

The expressions of perception, preference and judgement are influenced by vagueness, uncertainty and subjective thoughts (Jing et al., 2013; Li et al., 2011). The fuzzy set theory is developed to deal with problems with the uncertainty of human judgement (Chen et al., 2017; López et al., 2008). The linguistic values are applied to represent the preference of decision makers and then converted into fuzzy numbers for strategies. A fuzzy set $\tilde{A}$ can be illustrated by a triangular membership function $x_{\tilde{A}}(t)$ with three parameters (a, b, c). Using triangular fuzzy numbers (TFN) can help handle any linguistic uncertainty which may exist in the preferences of decision makers. $x_{\tilde{A}}(t)$ is defined in Eq. 5.1 as:

- $a \rightarrow b$: an increase function.
- $b \rightarrow c$: a decrease function.
- $a < b < c$

$$x_{\tilde{A}}(t) = \begin{cases} 0, & t < a;\ t > c \\ \frac{t-a}{b-a}, & a \leq t < b \\ \frac{c-t}{c-b}, & b \leq t < c \end{cases} \qquad \text{(Eq. 5.1)}$$

5.2.2.2 Fuzzy TOPSIS

The Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) was developed by Hwang and Yoon in 1981 (Tzeng and Huang, 2011) and extended with fuzzy numbers (FNs) by Chen in 2000 (Chen, 2000). TOPSIS is the most well-known method to determine the best alternative for MCDM problems (Nădăban et al., 2016; Wang et al., 2009). Its primary objective is to choose the options with the shortest distance to Positive Ideal Solution (PIS) (the solution with the minimal cost criteria and the maximal benefit criteria) and the farthest distance to Negative Ideal Solution (NIS) (the solution with the maximal cost criteria and the minimal benefit criteria) and then generate a ranking of all alternatives (Chiu and Hsieh, 2016; Wang and Elhag, 2006). The best option should be closest to PIS and farthest from NIS. The procedure of fuzzy TOPSIS is shown in Appendix F (Chen, 2000; Şengül et al., 2015; Shen et al., 2018).

5.2.3 The coupling analysis and decision supporting system for accidents

A coupling system between HFACS and Fuzzy TOPSIS is fully integrated to implement the accident problems to provide human factor-based analysis and decision support. The complexities and interactions of human errors in multiple related stages (e.g., marine oil spill accidents include spill occurrence, monitoring, decision making, and response) should be not only considered but also kept out of repetition and overlap. The selected stages are essential in occurrence and response management. The human factors in these stages can, to some extent, represent the factors existing in the entire system. Therefore, it is necessary to make a cooperator tool to collect and combine fragmentary information from spill-related stages as a summarized result for each item in the HFACS framework. That can make the outcomes from HFACS more systematic and comprehensive, which are convenient to be analyzed and ranked by TOPSIS. Fault tree analysis (FTA), initially developed by Bell Telephone Laboratory, is a top-down failure analysis approach by Boolean logic. It combines a series of lower-level events to reflect the failure condition of the top event objectively (Sherwin et al., 2016). FTA is efficient in combining response factors of human errors (e.g., probabilities or impact index) from different spill-related stages to higher-level categories in HFACS.

The flowchart of the proposed system is shown in Figure 5.1. First, the information about human/casual factors is collected through surveys or specific databases after determining the stages. Second, in order to decrease the cost of calculations, FTA further combines the collected information from different considered stages. The lower-level or minor factors are combined into an overall impact level (e.g., high, medium, low), which are further structured by HFACS as categorized failure factors for the priority analysis.

Third, the fuzzy set further translates the linguistic levels into triangular fuzzy numbers and TOPSIS goes ahead for the evaluation of alternatives with a prioritized list with multiple criteria, such as different decision-making organizations (e.g., the government, response organizations, industries, non-governmental organizations and universities) or response factors (e.g., total recovery time, environmental impacts, and economic costs).

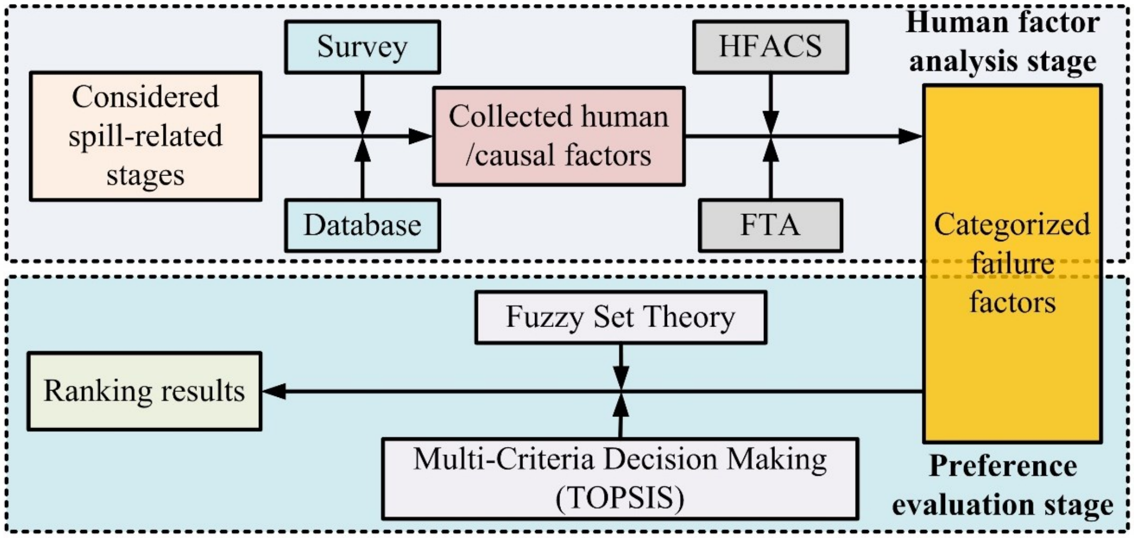


Figure 5.1 The flowchart of the proposed offshore oil spill accident analysis and decision supporting system.

5.3. Application for Marine Oil Spill Accidents

In this section, the efficiency of the proposed method was examined by a hypothetical case study. In the case, four considered spill-related stages, oil spill occurrence, spill monitoring, decision making/contingency planning, and spill response, were considered as the target processes for human and causal factor analysis (Zhang et al., 2019a). In the spill occurrence stage, the accidents of platform spills and tanker & barge spills were the main sources in this case. The monitoring and detection behaviors of spills were categorized into spill monitoring. After the accidents, the meetings and activities for making decisions and contingency plans, such as the planning meeting, tactics meeting and operational period briefing, induced by Incident Command System (2012), were classified into the third stage, decision making/contingency planning. The correlated supervisory and operational activities to spill responses and countermeasures (e.g., booming, skimming, in-situ burning, dispersant spreading) were considered in the stage of spill response (Chen et al., 2019a; Li et al., 2016a). The detailed procedures of operating the human factor analysis based on the human factor analysis and classification system for offshore oil spill accidents (HFACS-OS) and preference evaluation according to fuzzy-based TOPSIS (Fuzzy-TOPSIS) were shown in the following sections.

5.3.1 Human factor analysis stage

The preparedness and classification of the human factor list were covered under this stage. The human and organization factors were collected from the marine accident-related journal papers, reports, databases, as well as the suggestions from experts and decision-makers (BSEE, 2019; Cai et al., 2013; Musharraf et al., 2013; NAS, 2018; Ramzali et al., 2015; Wang et al., 2013a; Yuhua and Datao, 2005). These factors were further summarized into main categories and related sub-categories following the HFACS framework provided by Shappell and Wiegmann (2001) and the results were illustrated in Table 5.1. Since the causal information under one minor sub-category may come from multiple spill-related stages. For example, task overload, associated with skill-based error (A1) under error-unsafe acts, could occur at all spill stages from the occurrence to response. Thus, the interactions among the accident casual factors were further quantitatively demonstrated with the logical framework built by fault tree analysis. That can help generate an integral risk level for each sub-category and reduce the extra workload. With the consideration of uncertainties, the values of probabilities were further represented in five ranking levels, very low (0-0.2), low (0.2-0.4), medium (0.4-0.6), high (0.6-0.8), and very high (0.8-1.0), which were used as the fundamental inputs to Fuzzy-TOPSIS.

Table 5.1 The human factors in spill occurrence and response based on HFACS-OS framework

Unsafe acts of workers: Errors (A)	A1. Skill-based errors A2. Decision errors A3. Perceptual errors
Unsafe acts of workers: Violations (B)	B1. Routine violation B2. Exceptional violation
Precondition for unsafe acts: Condition of operator (C)	C1. Adverse mental states C2. Adverse physiological states C3. Physical/mental limitations
Preconditions for unsafe acts: Personnel factors (D)	D1. Crew resource management D2. Personal Readiness
Preconditions for unsafe acts: Environmental factors (E)	E1. Physical environment E2. Technical environment
Unsafe supervision and monitoring (F-I)	F. inadequate supervision G. Planned inappropriate operations H. Failed to correct a known problem I. Supervisory violations
Adverse organizational influence: Resource management (J)	J1. Human resources J2. Monetary/Budget resource J3. Equipment/facility resources
Adverse organizational influence: Organizational climate (K)	K1. Structure K2. Policies

	K3. Culture
Adverse organizational influence: Organizational process (L)	L1. Operations L2. Procedures L3. Oversight

5.3.2. Preference evaluation stage

The Fuzzy-TOPSIS was further applied to select the critical factors in accumulated human factors in the four categories of HFACS-OS. First, multiple criteria were identified. Different decision-making organizations (e.g., the government departments, industries, response organizations and NGOs) or end-point factors (e.g., total response time, total cost and ecological impact) could identify the criteria for the safety of operation and response. In this case, it was assumed that three groups, including 15 experts from five different organizations, related to oil production or spill response, joined to evaluate the impact of human factors on spills. Their responses were shown in Figure 5.2 by using the linguistic variables. The triangular fuzzy number of rank levels were shown in Appendix G. The weights of organizations for human factor analysis associated with their priorities to operation and response were represented in Table 5.2. The fuzzy decision matrix was further constructed and normalized with the weights of criteria and linguistic response matrices. The distances of the considered human factors from the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) of related criteria (Table 5.2) were calculated to find their closeness to the FPIS and remoteness to the FNIS. Based on the results of the closeness coefficient, CC_i, the ranks of the essential error factors were provided in Table 5.3.

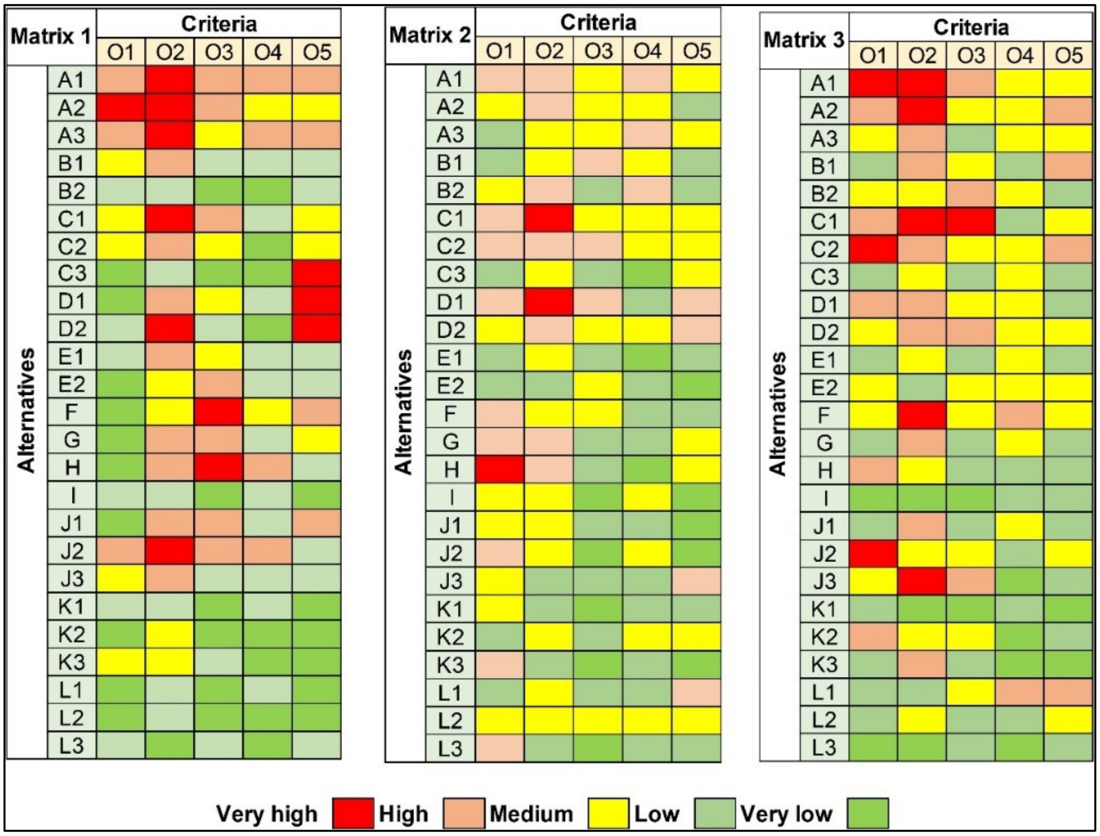


Figure 5.2 Linguistic response matrices of 15 experts from five different organizations.

Table 5.2 The weights, FPIS and FNIS of five organizations to the human factor evaluation

Organization (O)	Linguistic term of rank	Triangular FN	FPIS	FNIS
O1	High	(7,9,10)	(1.40, 3.86, 10.00)	(0.70, 0.96, 1.43)
O2	High	(7,9,10)	(1.40, 5.400, 10.00)	(0.70, 0.90, 1.11)
O3	Medium	(3,5,7)	(1.00, 5.00, 7.00)	(0.30, 0.63, 2.33)
O4	Low	(1,3,5)	(0.20, 1.29, 5.00)	(0.10, 0.39, 1.67)
O5	Very Low	(1,1,3)	(0.33, 1.00, 3.00)	(0.10, 0.13, 1.00)

Table 5.3 The distances, closeness coefficient and ranks of considered human-factor categories

	d^*	d^-	CC_i	Rank		d^*	d^-	CC_i	Rank
A1	17.79	0.22	0.01	25	**G**	9.76	10.98	0.53	16
A2	15.89	2.66	0.14	24	**H**	9.31	12.03	0.56	15
A3	11.46	8.98	0.44	19	**I**	4.15	16.33	0.80	**4**
B1	8.58	12.11	0.56	13	**J1**	8.20	12.18	0.60	12
B2	6.34	15.94	0.72	8	**J2**	12.95	7.10	0.35	22
C1	15.17	3.10	0.17	23	**J3**	9.30	12.20	0.57	14
C2	12.33	7.20	0.37	21	**K1**	2.14	17.31	0.89	**1**
C3	4.13	16.40	0.80	**3**	**K2**	7.87	12.30	0.61	11
D1	11.49	8.33	0.42	20	**K3**	5.57	16.31	0.75	7
D2	10.59	9.82	0.48	17	**L1**	4.57	16.30	0.78	**5**
E1	7.68	12.27	0.62	10	**L2**	5.03	16.15	0.76	6
E2	6.59	13.50	0.67	9	**L3**	3.46	16.85	0.83	**2**
F	10.38	9.43	0.48	18					

5.4. Results and Discussions

5.4.1 Results of HFACS-OS and Fuzzy-TOPSIS

The study analyzed the 104 human factors under 25 sub-categories in 4-level HFACS-OS. Fuzzy-TOPSIS further revealed the leading factors. As shown in Table 5.3 and Figure 5.3, the identified human factors are ranked by their closeness coefficients. The leading factors related to the spill occurrences and responses within the whole system, as well as each main category of the HFACS framework, can be observed in the meantime. The top five leading causal factors found by the proposed approach were K1 (structure) under "organizational climate"; L1 (operations) and L3 (oversight) under "organizational process"; C3 (physical/mental limitations) under "condition of operator" and I (supervisory violations). The human factors from unsafe supervision and organizational levels are more dangerous to the safety of the entire system. In addition, to the level of "unsafe acts of workers", the factors in "violations" (B) are in the second quarter of the list, and the factors in "errors" (A) are evaluated in the second half. The causal factors and human errors in the level of "unsafe acts" are distinct and directly related to accidents and failures, but their influences decreased if considering both active and latent human errors, especially the factors in the levels of "unsafe supervision and monitoring" and "adverse organizational influence". 1/4 factors under "unsafe supervision" were classified in the first quarter, and the rest factors were listed in the third quarter. 7/9 factors under the "organizational influence" were represented in the first half priorities. Based on the outcomes, the analysis and assessments of causal factors and human errors could be further evaluated with considerations of impacts from groups and organizations.

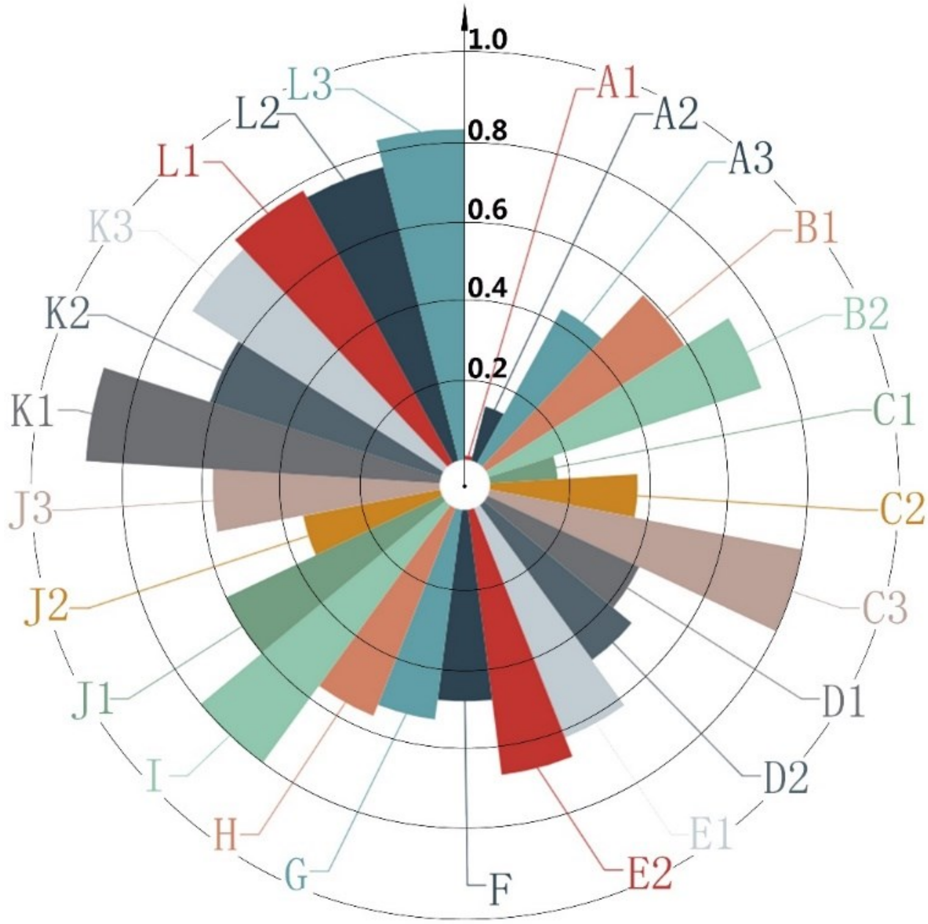


Figure 5.3 The priority of 25 human factor categories

5.4.2 Sensitivity analysis

A sensitivity analysis was conducted to test the robustness of the evaluated results. It analyzed the responses of human factors under different criteria weights. The intention of sensitivity analysis was assessed with multiple scenarios with different criteria weights. The sensitivity analysis figured out the possible range of human factor categories and evaluated the system robustness under different scenarios. In this study, the criteria weights of the original scenario were further exchanged with one another to generate a total of 60 combinations of weights non-repeatedly. The details of the combinations were shown in

Appendix H. For each combination, the closeness coefficient of human factors was calculated. The results were summarized with mean and medium in Figure 5.4.

According to Figure 5.4, the top 5 human factors with the highest closeness coefficient values among all combinations are K1 (structure) and K3 (Culture) under “organizational climate”, I (Supervisory violations), L3 (oversight) under “organizational process” as well as C3 (physical/mental limitations) under “condition of operator”. The consequences were similar to the results from the original scenario. It showed that the results had high robustness. Fuzzy-TOPSIS can be an efficient approach to combine the responses from multiple decision makers and generate a robust priority list. The closeness coefficient values in Figure 5.4 showed that the human factors from “unsafe supervision” and “organizational influence” took relatively higher values than the other HFACS levels, which meant the latent human factors in the systems should be attached importance. The safety management for oil spill accidents should be further developed from a group- or organization-scale perspective. Even though the active human factors were superficially the direct reason leading to an accident or failure in system operations, the latent factors should be further explored and consciously prevented.

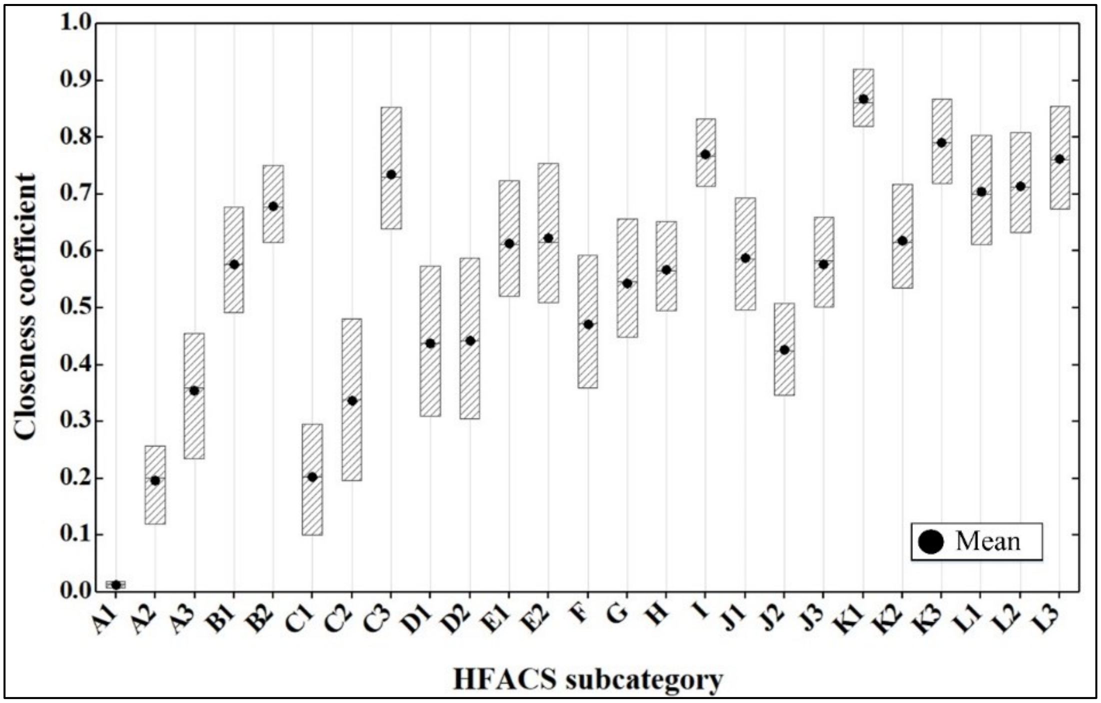


Figure 5.4 The closeness coefficients of 25 categories of human factors under 60 combinations of criteria weights

5.4.3 Theoretical and practical implications

This research contributed to a systematic analysis of accident causations of offshore oil spill accidents and safety performances of follow-up response processes. The results addressed gaps in the limited research on the underlying causes or antecedents of marine oil spill accidents and responses with consideration of human factors. The proposed HFACS-OS classified the causal factors and related human factors with an in-depth intervention to the root causes in different spill-related stages. The factors considered included the behaviors of diverse operators, workers, managers, stockholders, decision makers. The factors of society, economy, environment, and ecosystem as well as the organizational influences (e.g., working environment, legislation and enforcement). An overall picture of the underlying causes of safety performance was generated for offshore oil spill accidents and responses.

The incorporation of Fuzzy-TOPSIS with the HFACS-OS after that analyzed and forecasted the safety performances in oil-related operation and accident response with the contribution of the establishment of leading factors. The proposed module systematically evaluated human factors through multi-levels and multi-facets to diagnose the most sensitive risk factors related to project safety failures. In addition, the study provided an integrated approach to spill accident analysis with qualitative analysis (HFACS-OS) and quantitative analysis (Fuzzy-TOPSIS) to identify the core safety risk factors.

5.4.4 Limitations and future research perspectives

Despite the above theoretical and practical implications, this study still had several limitations, which need to be resolved in future research. Recommendations include:

1) Surveys with a large number of samples should be considered. The information should be gathered from experts, stockholders, operators, researchers, decision-makers from different organizations with their unique perspectives and experience. In addition, actual accident records could be further collected under confidential agreements to generate the risk index to reflect the probabilities of occurrence through a human-factor aspect. Thus, a knowledge base can be built up by merging surveys and historical data. It improves the efficiency of the proposed method for solving actual accidents and the accuracy of analyzing the causal factors of accidents. Knowledgebase development is working on for further study.

2) The analysis of the interactions of different factors at the same level (e.g., organization influence) or among different levels (e.g., unsafe acts and unsafe supervision) should be considered in the HFACS-OS methodology. The factors and categories applied in current HFACS versions were almost independent. That was efficient, but several accidental reasons had to be categorized into more than one HFACS item, which could be overlapped and decrease the system accuracy. Thus, if adding the interaction analysis, the influence relationships in HFACS can be closer, and the developed HFACS-OS could be more systematic and comprehensive. Moreover, cognitive biases were inevitably involved. Suitable investigation approaches should be considered to avoid biases. An improved HFACS-OS system is under development for the following study.

3) Multiple methods of optimization and evaluation should be further applied to evaluate the HFACS outcomes from different aspects. The current HFACS-OS is only integrated with Fuzzy-TOPSIS. Comparing with different evaluation approaches can

make the decisions for offshore oil spill responses more robust and comprehensive. The optimization methods can figure out the most suitable plans according to the needs of real-world situations.

4) The risk factors and non-human factors can be involved to enrich the current HFACS-OS version to analyze all possible causation factors.

5) A human factor-based simulation system should be developed to help decision-makers predict, compare and analyze the accidents under different conditions (e.g., response techs, weather conditions, oil types, onshore/offshore).

5.5. Summary

This study provided an improved qualitative and quantitative analysis approach to detect the human factors related to offshore oil spill occurrences and responses. A refined HFACS-OS hierarchical framework and comprehensive classifications based on the original version of HFACS with the historical spill cases and records were used to analyze the human-factor based causal factors with different complexities. The Fuzzy-TOPSIS method was applied to evaluate the relative priorities of identified HFACS categories to determine the leading causes of the accident. With the application of the Fuzzy-TOPSIS, the establishment of the knowledge base, with the support of experts, accidental records, refereed journals and reports, became crucial. It became evident that the knowledge base was not merely a collection of information, but the response of a synergistic group with multi-faceted knowledge of the decision-making problem at hand. To a certain extent, the multiple experts reduced the bias of subjective judgements. The results from the case study showed the priorities of human factors under 25 sub-categories of the four-level HFACS framework. The analysis and assessment of causal factors and human errors not only considered active causal or human factors but also paid attention to the impacts of groups and organizations. According to the ranking of casual and human factors, point-to-point prevention measures can be presented by decision-makers in case of the recurrence of similar accidents.

In a spill accident decision-making process, the decision makers and responders had different academic training and social-economic background, and some members may take a more critical position than others. A sensitivity analysis was performed to explore the influence of variations in individual judgement on final priorities and to evaluate the robustness of the system. It prevented outcomes from distorting perceptions and ensured to consider all responses from different members. The results with 60 non-repeated combinations of criteria weights showed high robustness to the system. In addition, theoretical and practical implications of the proposed approach were further discussed, and the limitations and future research perspectives associated with the development of data collection, HFACS and optimal evaluations were also analyzed. In summary, the proposed system from this study can apply to both incidents and safety systems. It helped to address knowledge gaps regarding the influence of human factors on the oil spill accidents and response operations and provided an improved support tool for subsequent decision-making.

CHAPTER 6 A MULTI-CRITERIA RESPONSE SYSTEM FOR MARINE OIL SPILL ACCIDENTS BY COMPARATIVE PARTICLE SWARM OPTIMIZATION*

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* This chapter is based on the following paper:

Ye XD, Chen B, Li P, Lee K, Storesund R, & Zhang BY. (2022). A multi-criteria response system for marine oil spill accidents by comparative particle swarm optimization. Ready for submission.

Contributions: Ye XD, Conceptualization, methodology, software, validation, formal analysis, writing-original draft; Chen B, conceptualization, writing-revision and editing, supervision; Li P, methodology, writing-revision; Lee K, writing-revision and editing; Storesund R, conceptualization, writing-revision and editing; Zhang BY, writing-revision & editing

6.1 Introduction

With the rapid development of human activities such as offshore oil exploration and tanker transportation in the marine environment, the growing interests and increased potential risks make the preparation and response to marine oil spill accidents inevitable (Garrett et al., 2017). With the occurrence of a large-scale oil spill, coordinating numerous resources to formulate appropriate response plans for the emergency responses becomes challenging and tricky due to the considerable need for urgency, uncertainty, resource constraints, costs, environmental impacts, and potential consequences (Huang et al., 2020b; Zhang et al., 2021). Selecting an appropriate oil spill response scheme can reduce adverse environmental impacts of spilled oil, maximize the total oil cleaning efficiency in a limited time, and minimize the total cost and wastes generated during the response process (Ye et al., 2021a). Despite utilizing proactive precautions, a large-scale oil spill may still occur. For example, the Deepwater Horizon oil spill in 2010 was an industrial disaster with catastrophic damages to the coastal areas, with a total cleanup cost of more than $14 billion (Beyer et al., 2016). During the post-accident response, more than 39,000 personnel, 5,000 vessels and 110 aircraft were dispatched, over 700 km of oil booms were deployed, 275 controlled burns were performed, skimmers recovered approximately 27 million gallons of the oil-water mixture, and more than 1.5 million gallons of dispersants were used. However, improper decision-making on emergency resource allocation usually results in a waste of manpower and budget (Summerhayes, 2011; Zhang et al., 2021). A large-scale spill usually has disastrous consequences for human society. It is essential to involve developed computational methods (e.g., simulation, optimization, and artificial intelligence modules) in emergency response processes for post-accident management, which can coordinate depletable resources to address dynamic changes of spilled oil (e.g., oil weathering and trajectory) (Mohammadiun et al., 2021).

In the thesis, three studies have been addressed to develop emergency response systems for large-scale spills. Chapter 3 focused on realizing the establishment of dynamic simulation modules related to spilled oil characteristics (i.e., oil weathering) and cleanup techniques (i.e., skimmers), and the coupling of simulation modules with a traditional evolution algorithm (i.e., particle swarm optimization) (Ye et al., 2019b). Based on Chapter 3, Chapter 4 improved the optimization algorithm by integrating multi-agent theory and evolutionary population dynamics (i.e., ME-PSO) and enriching the dynamic response module by adding the behaviors of booms, pumps, and vessels (Ye et al., 2021a). Chapter 5 addressed a developed HFACS model (i.e., HFACS-OS) for marine oil spill accidents with the Fuzzy-TOPSIS multi-criteria decision-making method to realize an enhanced and feasible human factor-based evaluation and decision support system. However, there are still some improvements and challenges that can be considered.

First, the total response time/total oil cleaning efficiency was considered as the core target for system optimization in previous studies (Ye et al., 2021a). Decision-makers would prefer to reduce the expenditures and environmental impacts simultaneously with a trade-off of a relatively low response time or high cleaning efficiency (You and Leyffer, 2011a). However, a few studies developed a system for marine oil spill response. Thus, multi-criteria or multi-objective optimization should be the next stage for developing the response system. Traditional multi-objective optimization outcomes can provide pairs of Pareto optimal solutions in a Pareto curve, which is helpful but not very suitable to deal with an optimized response preparation within a time-limit tactics meeting (Deb, 2014).

No time can be spent on filtering from hundreds of optimized solutions. Finding a unique solution with a priority list of different criteria (e.g., response time: high level, cost: medium level and impacts: medium level) from decision-makers could be a better approach. A weighted multi-objective function should be developed to overcome the problems of uneven data dimensions and weights from time, cost, and impact simulation results.

Second, the outstanding optimization performance of ME-PSO with the integration of PSO, MA and EPD has been evaluated in Chapter 4 (Ye et al., 2021a; Ye et al., 2019b). The hybrid with other updating approaches can further improve the performance of ME-PSO. Barebone PSO is an improved PSO variant by using Gaussian distribution of iteratively best solutions ($P_{best}\ and\ G_{best}$) to update candidate solutions, which removes the contribution of inertia weight section in the original PSO variant (Yao and Han, 2013). On the other hand, the inertia weight is an essential element to control the convergence of solutions in most PSO variants (Rathore and Sharma, 2017). Different selections of inertia weight function can greatly promote or hinder optimization performance (Han et al., 2010). Descending inertia weight is the only function tested. More inertia weight functions should be tested and compared to prove or replace the descending inertia weight of the ME-PSO.

Therefore, to fill the mentioned gaps, this study describes the development and evaluation of an emergency response management modeling system with the integration of dynamic process simulation and weighted multi-criteria system optimization. Total response time, response cost and environmental impacts are regarded as multiple optimization goals. An improved weighted sum optimization function was developed to unify the scaling and proportion of different goals. A comparative PSO is also developed in combination with various algorithm improving methods and the best-performing inertia weight function. The developed response system and PSO algorithm are further applied to optimize the contingency planning of marine oil spill response optimization. The structure of this chapter is organized as follows. Section 2 describes the design of the multi-criteria emergency response framework (MC-ERS). Section 3 indicates the comparison and evaluation of the developed comparative PSO algorithm (C-PSO). Section 4 demonstrates the application of the proposed methodologies to a marine oil spill response case considering resource dispatching, oil weathering process and removal efficiency of different technologies. Section 5 presents the analysis of marine oil spill response results, system uncertainties with human factors, sensitivity analysis, discussions, and recommendations. Section 6 provides conclusions from this study.

6.2 Multi-criteria Emergency Response System

After an accident occurs, an emergency response system can provide a plan to help manage the allocation and dispatch of response resources and achieve efficient use of time and cost and protect the environment (Deqi et al., 2012). For accidents involving the release of highly toxic and fast-spreading pollutants (e.g., spilled oil, chemicals), maximizing the oil cleaning efficiency in a limited time to control the dangerous situation is the top priority (Gai et al., 2017; Liu et al., 2018). On the basis of ensuring a high response efficiency, reducing response cost and environmental impacts is usually the follow-up priority (Depellegrin et al., 2017; Huang et al., 2020b). Multi-objective optimization (MOO) can provide a set of matching solutions with a Pareto curve to show the possible combinations in different scenarios (Caramia and Dell'Olmo, 2020). However, due to the limited time for making decisions on emergency pollutant accidents, such implied and multifarious results decrease the practicability of MOO for emergency response in the real world. Providing the most suitable optimal plan based on the need and preferences of decision-makers is the most appropriate way for utilizing MOO (Miljković et al., 2017).

The weighted sum model (WSM) is an efficient multi-criteria decision analysis method for evaluating some alternatives in terms of several decision criteria (Kaddani et al., 2017). It scales all the multi-objective functions into one goal by multiplying each objective by a user-supplied weight (Eq. 6.1). The weight given to one objective is usually proportional to the relative importance of the objective in the problem, and the sum of weights equals one (Marler and Arora, 2010). There are two issues with utilizing a WSM for ERS planning. First, the selected objectives for accident responses stand for different aspects. The magnitude of the results from objective functions may vary significantly. A direct combination into a WSM-based function can heavily affect the influence of small numbers on the final result. For example, the response time (e.g., 50 hours) is small relative to the cost (e.g., $\$10^7$). Even though a considerable weight is given to the response time, the controlling force of response time to the WSM-based objective function is reduced substantially. Thus, a normalization conversion should be performed. Second, the maximum and minimum values are indispensable to normalize the data. Unlike the normalization process for data preparation, there are no clear minimum and maximum values for objectives. An inappropriate selection of boundary values can also mislead optimization results.

To overcome the challenges and find the appropriate values for normalization, the objective function $f_m(x)$ for a minimum value achieves its lower boundary $f_m^{lb}(x)$ by finding the minimum value in the optimization with objective function $f_m(x)$ with 500 runs. The function achieves its upper boundary $f_m^{ub}(x)$ by finding the absolute value of the maximum value in the optimization with objective function -$f_m(x)$ with 500 runs.

Eq. 6.3 further normalizes the function results for the WSM-based objective function (Eq. 6.1). The main advantages of the WSM are that it is easier to understand and can be effectively handled by a decision-maker. Moreover, the workload for optimization calculations can be greatly reduced and the strength of single-objective optimization in a direct search for the "best" solution can be revealed (Mahrach et al., 2020). The proposed approach for selecting $f_m^{ub}(x)$ and $f_m^{lb}(x)$ can set the values into a wide but reasonable range so that the changes in results of functions can affect the total optimized solution.

$$\min \ F(x) = \sum_{m=1}^{M} w_m \cdot f_m^n(x) \qquad \text{(Eq. 6.1)}$$

$$\sum_{i=1}^{M} w_i = 1, \ \ w_i \in (0,1) \qquad \text{(Eq. 6.2)}$$

For $f_m(x)$ for a minimum value,

$$f_m^n(x) = \frac{f_m(x) - f_m^{lb}(x)}{f_m^{up}(x) - f_m^{lb}(x)}$$

For $f_m(x)$ for a minimum value,

$$f_m^n(x) = \frac{f_m^{up}(x) - f_m(x)}{f_m^{up}(x) - f_m^{lb}(x)}$$

(Eq. 6.3)

where, $F(x)$ is the final objective function by weighted sum method to combine weight coefficients w_m and normalized objective functions $f_m^n(x)$, m = 1, 2, …, M. $f_m^{up}(x)$ and $f_m^{lb}(x)$ are the upper boundary and lower boundary for the single-objective optimization of $f_m(x)$.

The multi-criteria emergency response system (MC-ERS) is developed to provide an efficient framework to support response decisions and operations following incidents or unexpected events. As shown in Figure 6.1, the framework is a time-step approach integrating dynamic simulation modelling and an improved WSM-based multi-criteria optimization. The dynamic simulation results of pollution behavior, environment condition and response performance are further composed as the elements to generate the objection functions for optimization. The decision-makers set the decision preference as the weighting levels for objective functions based on the requirements, demands and standards/regulations, such as very high, medium, or low. The linguistic levels are gathered to convert to proportional values with a sum of 1 as weight coefficients for the WSM-based function. This study uses a comparative PSO (C-PSO) as the optimization method to find the optimal solution for response resource allocation and scheduling. The details of C-PSO are illustrated in Section 6.3.

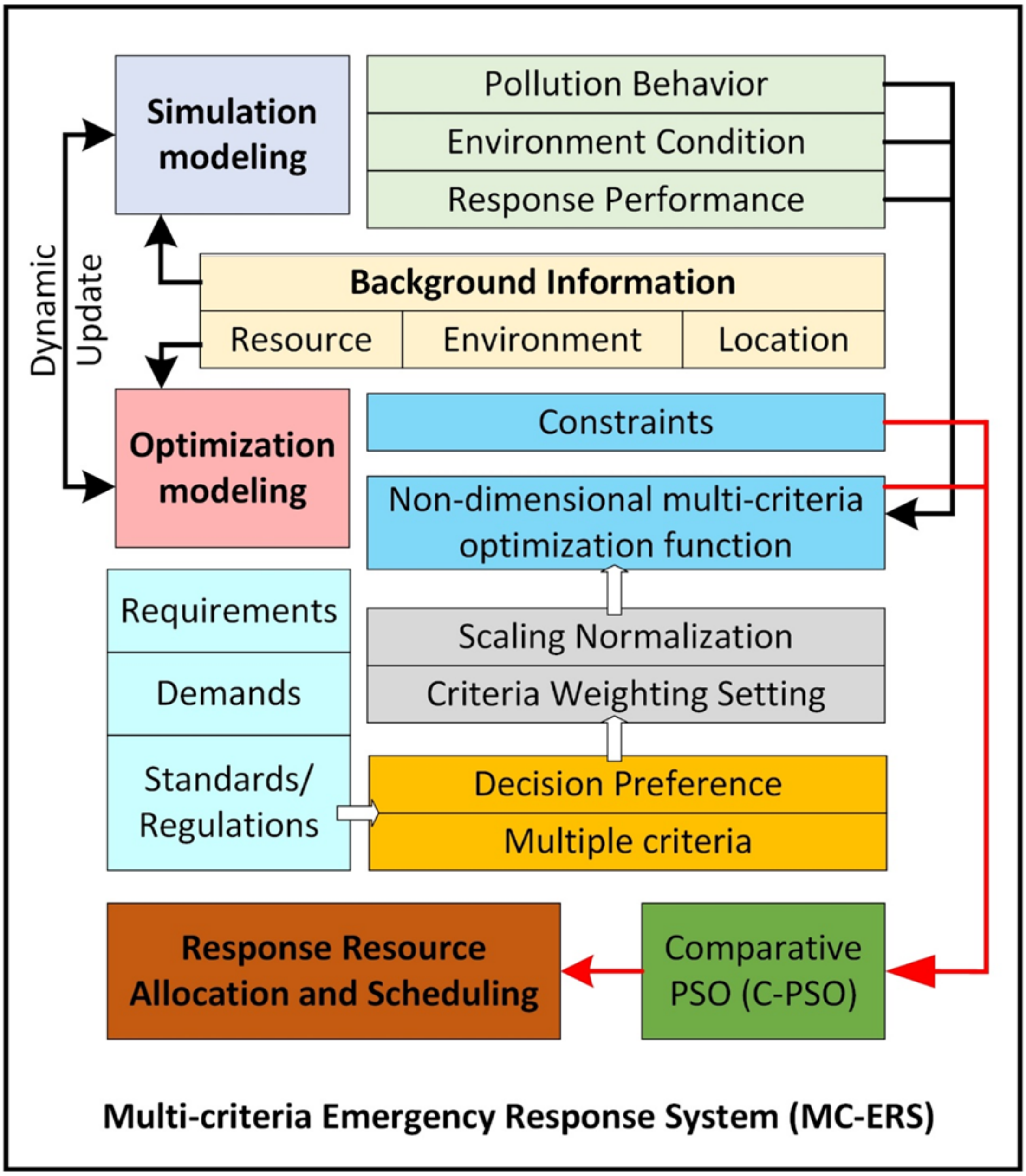


Figure 6.1 The framework of the Multi-criteria Emergency Response System

6.3 Comparative Particle Swarm Optimization

6.3.1 Framework of comparative particle swarm optimization

Particle swarm optimization is an evolutionary algorithm that improves optimized solutions through the learning behaviors of self, previous experience, and social information (Cheng and Jin, 2015). It is a stochastic and population-based computational method to guide particles in the multi-dimensional search space according to position and velocity updates through iterations (Eberhart and Kennedy, 1995b). The study in Chapter 4 has developed a ME-PSO variant by integrating the strengths of multi-agent theory (MA) and evolutionary population dynamics (EPD) to compensate for the limitation of the original PSO on optimal prematurity and the dependency of long update iterations. The ME-PSO has been evaluated as having excellent convergency performance and shortening the number of iterations to reach the best solution (Ye et al., 2021a). By comparing with other combinations with algorithm improvement strategies, the capacity of ME-PSO is further proved or improved. Moreover, inertia weight is a crucial element to improve the solution capability of PSO (Bansal et al., 2011). The descending inertia weight method is the only strategy used in the previous study (Ye et al., 2021a). A comparison of multiple inertia weight strategies also helps improve optimization performance.

Figure 6.2 indicates the selection procedure of comparative particle swarm optimization (C-PSO). Three algorithm improvement strategies, including multi-agent theory (MA), evolutionary population dynamic (EPD), and barebones theory (BB), are selected to generate 12 PSO variants, as shown in Table 6.1. The detailed illustration of strategies is shown in the following section. Barebones PSO is a powerful PSO variant proposed by Kennedy (2003), in which each particle only has a position vector and eliminates the velocity vector. The new position is updated by Gaussian distribution based on particles and overall best solutions in the current iteration (Yao and Han, 2013). Thus, the barebones theory is used as a candidate variant (BBPSO), and the position update through Gaussian distribution in the BBPSO also provides a new trial for neighbor agents' updates by MA (MABBPSO). In the stage of algorithm strategies, the hybrid PSO variants are tested by 13 uni-modal and multi-modal benchmarked functions (Appendix C). The maximum iteration number is set as 500 to let all variants do their best to find the best solution. Fast convergence is an advantage, but better results are preferable in most situations than quick results. With the advance of technologies, computation speed has no longer become a limitation. For all tests, all scenarios run 100 times for an average result and three population size levels are selected, which are 100, 300, and 500. Eq 6.4 further summarizes the results from benchmarked functions for an overall score to evaluate the performance of variants. The scores use the result of the original PSO variant as the baseline. The results are compared through optimization performance. The variant with the lowest score was screened out for second-stage comparison of inertia weight strategies. Table 6.2 indicates 16 selected inertia weight strategies under three categories, iteration-based strategy (10), random or constant strategy (5), and best result-based strategy (1). To keep the strategies comparative, the values for initial and end weights are selected as the same as 0.90 and 0.40. The PSO variants with 16 weighting strategies were evaluated by 13 benchmarked functions and summarized by Eq. 6.4 for result comparisons. The results by the constant inertia weight (No. 1), as the earliest weighting equation, are used as the baseline for the comparison.

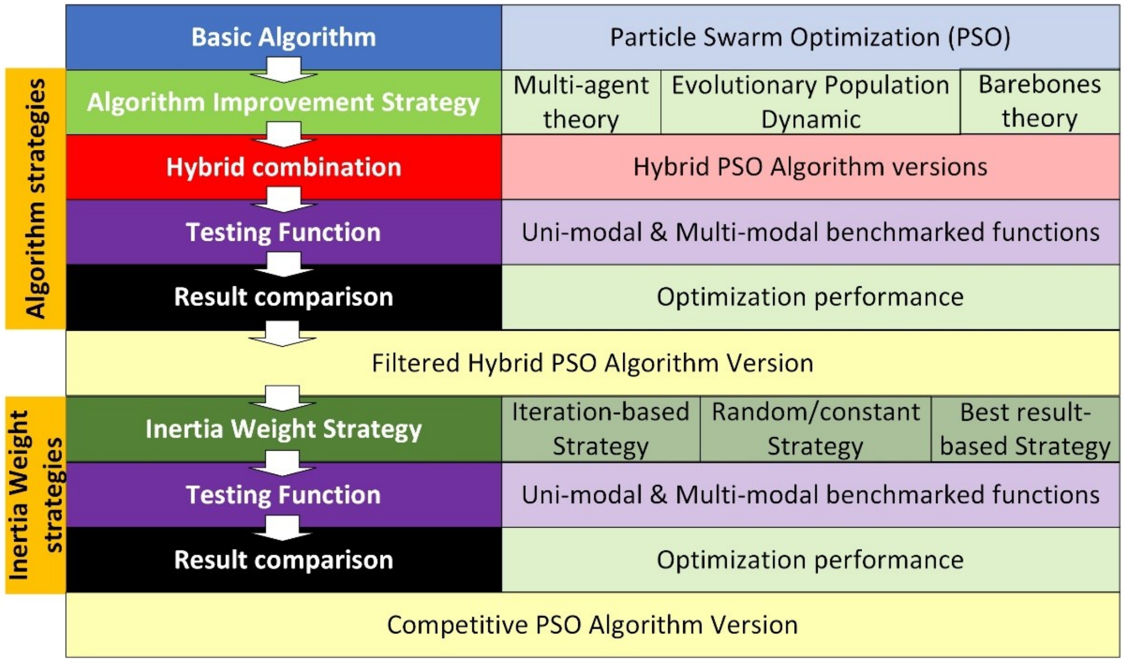


Figure 6.2 The selection procedure of comparative particle swarm optimization

Table 6.1 The list of hybrid PSO variants

No.	Name	Algorithm Improvement Strategy
V1	PSO	None
V2	MAPSO	MA
V3	MABBPSO	MA, BB
V4	BBPSO	BB
V5	BBMAPSO	BB, MA
V6	BBMABBPSO	BB, MA
V7	EPDPSO	EPD
V8	EPDMAPSO	EPD, MA
V9	EPDMABBPSO	EPD, MA, BB
V10	EPDBBPSO	EPD, BB
V11	EPDBBMAPSO	EPD, BB, MA
V12	EPDBBMABBPSO	EPD, BB, MA

$$F_{score}^{Variant} = \prod_{i=1}^{Nb} R_i^{Vairant} \Big/ R_i^{PSO} \qquad \text{(Eq. 6.4)}$$

where, $F_{score}^{Variant}$ is the overall score of a PSO variant, Nb is the number of benchmarked functions, $R_i^{Vairant}$ is the result of a PSO variant to ith benchmarked function, R_i^{PSO} is the result of the original PSO to ith benchmarked function. If the R value is zero, such values will be discussed separately.

Table 6.2 Inertia weight strategies for comparative PSO variants

No.	Name of Inertia Weight	Formula of Inertia Weight	Parameter Values	Ref.
1	Constant inertia weight	$w = \frac{(w_{ini} - w_{end})}{2}$		(Shi and Eberhart, 1998)
2	Logarithm decreasing inertia weight	$w = w_{ini} + (w_{end} - w_{ini}) \cdot log_{10}(a + \frac{10 \cdot iter_t}{iter_{max}})$	$a = 1.0$	(Gao et al., 2008)
3	Exponent decreasing inertia weight	$w = (w_{ini} - w_{end} - d_1) \cdot \exp(\frac{1}{1 + \frac{d_2 \cdot iter_t}{iter_{max}}})$	$d_1 = 0.2$ $d_2 = 7.0$	(Li and Gao, 2009)
4	Natural exponent inertia weight strategy	$w = w_{end} + (w_{ini} - w_{end}) \cdot \exp(-(\frac{4 \cdot iter_t}{iter_{max}})^2)$		(Chen et al., 2006)
5	Global-local best inertia weight	$w = (1.1 - \frac{gbest_i}{pbest_i})$		(Arumugam and Rao, 2006)
6	Chaotic random inertia weight	$z = rand(0,1)$ $w = 0.5 \cdot rand(0,1) + 0.5 \cdot (4 \cdot z \cdot (1 - z))$		(Feng et al., 2007)
7	The Chaotic inertia weight	$z = rand(0,1)$		(Feng et al., 2007)

		$w = (w_{ini} - w_{end}) \cdot \left(\frac{iter_{max} - iter_t}{iter_{max}}\right) + w_{end} \cdot (4 \cdot z \cdot (1 - z))$		
8	Linear decreasing inertia weight	$w = w_{ini} - (w_{ini} - w_{end}) \cdot (\frac{iter_t}{iter_{max}})$		(Xin et al., 2009)
9	Random inertia weight	$w = 0.5 + 0.5 \cdot rand(0,1)$		(Eberhart and Shi, 2001)
10	Decreasing exponential function inertia weight (DEFIW)	$w = {iter_t}^{-(\sqrt[iter_t]{iter_t})}$		(Arasomwan and Adewumi, 2013)
11	Fixed inertia weight (FIW)	$w = \frac{1}{2 \cdot \ln{(2)}}$		(Hsieh et al., 2008)
12	Decreasing inertia weight (DIW)	$w = w_{ini} \cdot u^{-iter_t}$	$u = 1.00002$	(Jiao et al., 2008)
13	Double exponential	$w = \exp\left(-\exp\left(\frac{iter_t - iter_{max}}{iter_{max}}\right)\right)$		(Chauhan et al., 2013)

	dynamic inertia weight			
14	Nonlinear decreasing inertia weight inertia weight (NDIW)	$w = (w_{ini} - w_{end}) \cdot \left(\frac{iter_{max} - iter_t}{iter_{max}}\right)^n + w_{end}$	$n = 1.2$	(Chatterjee and Siarry, 2006)
15	Linear or non-linear decreasing inertia weight	$w = (2/iter_t)^{0.3}$		(Fan and Chiu, 2007)
16	Descending inertia weight	$w = w_{end} + (w_{ini} - w_{end}) \cdot (\frac{iter_{max} - iter_t}{iter_{max}})$		(Adewumi and Arasomwan, 2016)

$\boldsymbol{w_{ini}}$: ***the initial weighting value*, 0.90**; $\boldsymbol{w_{end}}$: ***the end weighting value*, 0.40**; $\boldsymbol{iter_t}$: ***current iteration***; $\boldsymbol{iter_{max}}$: ***maximum iteration***

6.3.2 Particle swarm optimization algorithm improvement strategy

6.3.2.1 Particle swarm optimization

PSO is a well-regarded population-based stochastic evolutionary algorithm for optimization solving (Eberhart and Kennedy, 1995b). It is inspired by social-psychological principles with interactions to improve the quality of problem solutions iteratively. Each candidate solution (particle) has two characteristics: position (x) and velocity (v). The characteristics represent the values of multi-dimensional parameters (i.e., x_i) and variation ranges of positions (i.e., v_i). In each iteration, the velocity is updated based on Eq. 6.5 and the position will be further updated with the new velocity (Eq. 6.6). Descending inertia weight (Eq. 6.7) is selected as the coefficient function in the first comparison stage.

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot \left(P_{best,i} - x_i^t\right) + c_2 \cdot r_2 \cdot (G_{best} - x_i^t) \tag{Eq. 6.5}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{Eq. 6.6}$$

$$w_t = \frac{w_{ini} - w_{end}}{iter_{max}}(iter_{max} - iter_t) + w_{end} \tag{Eq. 6.7}$$

where, t refers the current iteration, i indicates the ith particle, w is the inertia weight factor (Eq. 6.3), c_1 and c_2 are two acceleration constants called cognitive factor and social factor ($c_1, c_2 = 2$), r_1 and r_2 are uniform random values in [0,1], $P_{best,i}$ is the best solution of ith particle so far, and G_{best} is the best solution of all particles. w_{ini} and w_{end}, equal to 0.9 and 0.4, respectively, are the upper and lower boundaries of the inertia weight. $iter_{max}$ and $iter_t$ are the maximum number and current number of iterations, respectively.

6.3.2.2 Multi-agent system

MA represents a computational system for the interactions or collaborations of agents to achieve goals (Zhao et al., 2005). When adding MA to improve the interactive ability of PSO, agents represent candidate solutions of PSO located in a lattice-like environment. Each $agent_\alpha$ has four neighbour agents (N_α) from different directions. The neighbour agents elect the agent with the best solution, $N_{\alpha,best}$, to compete with the solution of $agent_\alpha$. If $f(agent_\alpha) \leq f(N_\alpha)$, $agent_\alpha$ is the winner without changes. Otherwise, the position of $agent_\alpha$ will be replaced based on the following equation (Eq. 6.8). The details of MA-based PSO can be found in Ye et al. (2019a). The integration of MA with PSO expands the scope of exploration, enhances the influence of other solutions, and prevents the candidate solutions from being stopped by local optima.

$$\mathrm{x}_{i,new}^{t} = N_{best,i}^{t} + r \cdot (N_{best,i}^{t} - \mathrm{x}_{i}^{t}) \quad \text{(Eq. 6.8)}$$

6.3.2.3 Evolutionary population dynamics

EPD aims to improve the optimization performance by replacing the poor solutions in the population with new ones closer to the best solutions (Saremi et al., 2015). In EPD-PSO, it assumes that a candidate solution that is worse than the median of the whole population is not likely to achieve an optimal result (Saremi and Mirjalili, 2019). The poor solutions are relocated to new positions around the best solutions (Eq. 6.9 or 6.10) or by random re-initialization (Eq. 6.11). The renewed solutions around the best solutions (G_{best} and P_{best}) enhance the convergence speed and the median of all solutions. Re-initialized solutions increase exploration and local solution avoidance.

$$x_i^{t+1} = G_{best} \pm [(ub - lb) \cdot r + lb] \quad \text{(Eq. 6.9)}$$

$$x_i^{t+1} = P_{best} \pm [(ub - lb) \cdot r + lb] \quad \text{(Eq. 6.10)}$$

$$x_i^{t+1} = [(ub - lb) \cdot r + lb] \quad \text{(Eq. 6.11)}$$

where, ub and lb indicate the upper and lower bound of multi-dimensional parameters in positions.

6.3.2.4 Barebones theory

Barebones PSO (BBPSO) is a simple but very powerful optimization (Al-Rifaie and Blackwell, 2012). It relies on removing velocity update (Eq. 6.5) and updates position information of candidate solutions by sampling from a Gaussian distribution. The barebones theory makes the PSO variant without the parameters $w, c_1, and\ c_2$ (Zhang et al., 2015). A new position is updated by Eq. 6.12. Empirical research shows that the performance of BBPSO can be competitive with the original and some improved PSO algorithms (Yao and Han, 2013). Inspired by the idea of barebones, Eq. 6.12 can also be used to generate new position information for the replaced "loser" agents in the multi-agent neighbor comparison process (i.e., Eq. 6.8). Thus, four hybrid PSO algorithms are generated: MABBPSO, BBMABBPSO, EPDMABBPSO, and EPDBBMABBPSO. Specifically, four algorithms used the barebone theory to replace PSO location and velocity update equations (i.e., MABBPSO, EPDMABBPSO) or both PSO update equations and MA neighbor comparison update equation (BBMABBPSO, EPDBBMABBPSO).

$$x_i^{t+1} = N(\frac{G_{best}^t + P_{best,i}^t}{2}, \left|G_{best}^t - P_{best,i}^t\right|) \qquad \text{(Eq. 6.12)}$$

where, $N()$ indicates a Gaussian distribution with a mean of $\frac{G_{best}^t + P_{best,i}^t}{2}$ and a standard deviation of $\left|G_{best}^t - P_{best,i}^t\right|$.

6.3.3 Performance comparison

6.3.3.1 Algorithm comparison

Table 6.3 represents the results of 12 PSO variants with the conversion by Eq. 6.4. The algorithms are compared based on average, minimum, range (Range=Max-Min), and standard deviation from 13 benchmarked functions over 100 runs. The original results are shown in Appendix J. The results show that the algorithms V2 (MAPSO), V3 (MABBPSO), V7(EPDPSO), V8 (EPDMAPSO), and V9(EPDMABBPSO) have better optimization performances than other variant algorithms. The EPDPSO variant has the best optimization performance with small population size (i.e., 100). However, with the increase in population, the promoted efforts from MA neighbor comparison make EPDMAPSO the best algorithm. Large population sizes can make the PSO have a better search range and competition for better outcomes. The scores of "average result", "minimum result", "range" and "standard deviation" become lower by increasing the population size. The algorithms with barebones (V3 and V9) can achieve good results, but those are worse than MAPSO and MAEPDPSO. It indicates that barebones can enhance PSO optimization performance but updating replaced solutions with neighbor solutions' results can promote optimization performance effectively.

Table 6.3 Summarized results of PSO variants by benchmarked functions

		Average result	Minimum result	range	Standard deviation
Population: 100	V1	1	1	1	1
	V2	2.4616E-27	4.3361E-44	2.7192E-22	1.9113E-23
	V3	1.0236E+00	1.1912E-06	5.8101E+03	6.0920E+02
	V4	6.4765E+33	4.3801E+34	9.1861E+29	5.4215E+29
	V5	4.4028E+33	1.6617E+33	2.4446E+30	5.2411E+29
	V6	1.0587E+34	1.0017E+34	3.2444E+30	1.0268E+30
	V7	1.9682E-31	2.3505E-64	6.0256E-25	5.6427E-26
	V8	1.3407E-18	4.4072E-53	3.1443E-14	1.3319E-14
	V9	2.0052E-12	1.6097E-51	4.6598E-08	1.5442E-08
	V10	6.2910E+33	1.4950E+34	1.2529E+30	5.9920E+29
	V11	8.1238E+34	2.1319E+34	2.3465E+31	1.2728E+31
	V12	4.6529E+33	1.7557E+34	2.3255E+29	2.2022E+29
Population: 300		**Average result**	**Minimum result**	**range**	**Standard deviation**
	V1	1	1	1	1
	V2	1.3557E-38	9.2204E-53*	9.0574E-37	9.5829E-37
	V3	1.4636E-11	4.5921E-23	5.1447E-11	3.9796E-11
	V4	3.1193E+28	9.5494E+24	7.8345E+24	5.4606E+24
	V5	2.0409E+29	9.0604E+24	1.4918E+26	9.8828E+25
	V6	2.5002E+28	5.5222E+24	1.6190E+24	3.0959E+24
	V7	8.5994E-45	2.5331E-74	9.4300E-40	2.1699E-40
	V8	1.0625E-64	4.9192E-85*	7.2659E-58	7.2847E-59

	V9	6.6082E-44	1.5470E-74	1.7160E-38	7.8560E-39
	V10	1.1653E+29	3.3971E+26	3.7559E+26	1.4174E+26
	V11	1.0200E+29	6.9627E+22	4.6152E+26	2.4648E+26
	V12	4.4021E+28	1.4700E+26	8.1292E+24	9.0914E+24
Population: 500		**Average result**	**Minimum result**	**range**	**Standard deviation**
	V1	1	1	1	1
	V2	3.1286E-41	3.7903E-62*	5.8832E-42	2.3707E-41
	V3	5.8179E-13	4.9972E-30	1.0161E-15	2.4563E-15
	V4	9.6686E+28	5.9535E+18	3.7740E+24	3.0326E+24
	V5	6.8284E+28	5.3412E+19	1.7309E+25	9.1907E+24
	V6	3.0287E+28	2.4031E+18	1.3313E+24	1.9433E+24
	V7	1.7584E-51	1.0032E-76	4.4035E-47	1.4878E-47
	V8	3.1092E-83	6.6462E-107*	8.2679E-78	2.5725E-78
	V9	2.8496E-59	4.0061E-93*	9.9862E-54	1.7782E-54
	V10	4.7726E+28	1.4948E+18	4.9920E+24	8.5424E+24
	V11	3.2293E+27	4.7864E+15	1.0814E+24	7.0826E+23
	V12	2.6402E+28	3.0490E+20	3.6667E+23	3.7674E+23

* The minimal value of $R_i^{Vairant}$ is zero.

6.3.3.2 Weight inertia comparison

Based on the results from Table 6.3, the EPDMAPSO was selected as the filtered PSO variant for the weight inertia comparison. Table 6.4 indicates the results of the comparison by 16 weight inertia equations. The original results are shown in Appendix K. It shows that the No.4 function has the best coordinate performance with EPDMAPSO to reach a better optimal solution. Thus, the developed C-PSO indicates the strengths of EPD for filtering poor solutions, MA for competing between solutions, and natural exponent inertia weight strategy for controlling the convergence speed.

Table 6.4 The total score of optimized performance of MAEPDPSO with 16 inertia weight function

	Average Value				Minimal Value			
	Population	100	300	500	Population	100	300	500
Inertia weight function	**1**	1	1	1	**1**	1	1	1
	2	2.304E-55	2.622E-32	4.081E-29	**2**	2.304E-55	5.935E-49	1.15E-28
	3	2.558E-67	1.133E-45	3.973E-08	**3**	2.558E-67	4.84E-86	1.12E-07
	4	**6.46E-107**	**5.302E-97**	**4.056E-93**	**4**	**6.46E-107**	**1.42E-96**	**4.17E-106**
	5	5.547E-13	1.437E-42	2.849E-29	**5**	2.107E-28	8.679E-42	8.03E-29
	6	6.712E-18	9.069E-27	4.017E-31	**6**	9.283E-19	2.091E-40	1.132E-30
	7	1.544E-25	2.327E-08	1.68E-37	**7**	6.745E-37	1.406E-07	4.736E-37
	8	1.363E-65	4.098E-16	2.247E-61	**8**	1.363E-65	2.475E-15	6.333E-61
	9	1.985E-66	3.198E-31	5.754E-41	**9**	1.985E-66	1.931E-30	1.622E-40
	10	3.422E-19	6.143E-41	3.03E-75	**10**	3.422E-19	3.71E-40	3.163E-88
	11	2.386E-32	1.001E-69	4.798E-78	**11**	2.386E-32	6.048E-69	1.352E-77
	12	6.934E-41	6.035E-23	3.516E-51	**12**	6.934E-41	3.645E-22	2.649E-63
	13	8.41E-18	4.874E-38	2.22E-15	**13**	8.41E-18	2.944E-37	2.257E-16

	14	8.528E-25	2.552E-52	7.683E-35	**14**	8.528E-25	1.179E-51	2.166E-34
	15	4.062E-45	1.504E-09	1.498E-41	**15**	4.062E-45	9.081E-09	4.224E-41
	16	8.828E-46	5.009E-16	1.154E-89	**16**	8.828E-46	3.025E-15	3.252E-89

6.4 Application for Marine Oil Spill Accidents

6.4.1 Case description

The proposed MC-ERS framework and C-PSO algorithm are further applied for supporting and optimizing the response strategies with the linkages of response efficiency, operation cost and environmental impact. A hypothetical case study is conducted to evaluate the efficiency of the proposed modeling for a marine oil spill incident. Spill oil cleanup operation aims to collect as much oil as possible reasonably and economically. The case considers dynamic simulations of oil weathering and response performance, resource dispatching, system optimization and control. The case study focuses on responding to a 10,000 m^3 spill of Arabian Light crude oil in the North Atlantic Ocean. The primary response techniques are chosen as booms and skimmers for oil concentration and recovery due to their comprehensive utilization by countries (Ye et al., 2021a). As shown in Figure 6.3, emergency supplies from five onshore resource storages (ORSs) can be transported by highway transportation using less-than-truckload (LTL) and full-truckload (FTL) trucks to two coastal emergency response centers (CERCs) and ports for transshipment. The resources to the spill accident point for response operations are then delivered with 200-m^3 and 400-m^3 load vessels by waterway transportation. The following assumptions are defined to make the model closer to the actual situation:

1) The predicted location information of the accident point for the arrival is known. Large-scale oil spill emergency response requires time to prepare, plan, set up, and transport. During this period, the oil plume will continuously drift due to the influence of sea wind and currents. The predicted location of the plume is assumed as the known information predicted by oil trajectory modeling.

2) The start time of response is set to load resources of the first-round transportation from ORSs.
3) The inventory condition of emergency materials, trucks and vessels provided by resource centers and ports is known.
4) The distances between ORSs and CERCs, and the distances between CERSs and the spill point are known.
5) It is assumed that the carrying space of vehicles and vessels is limited by volumes rather than weights of emergency materials. The maximum carrying space is restricted to 80% and 90% cargo space of trucks and vessels.
6) The maximal round of transportation of each truck and vessel is two. Trucks and vessels must return to their departure place for second-round transportation.
7) The first-round vessel transshipment can only be started after the first-round truck transportation of emergency materials is completed.
8) Due to more cargo space of trucks than vessels, a part of resources by the first-round highway transportation can be temporarily stored at CERCs and shipped by the second-round water transportation. Such an alternative can save costs and time and improve transportation efficiency.
9) The periods of truck loading/unloading, transshipment and boom setup are set as constants.
10) The oil removal process must be started after using booms to contain the spilled oil.
11) The sea conditions are known and remain unchanged during the response period.
12) After boom deployment, the spill area was assumed to be confined to 200,000 m^2. And the contaminated area will not expand any more

13) Evaporation, dispersion, and emulsification are the major weathering processes in the dynamic simulations that affect oil properties and volume.

14) The oil recovered by skimmers was removed from the sea, transported to the inlet side of a pumping system, and then transferred to the storage units. The response assumes that the storage units are sufficient. Oil skimming rates and pumping rates restrict the recovery efficiency.

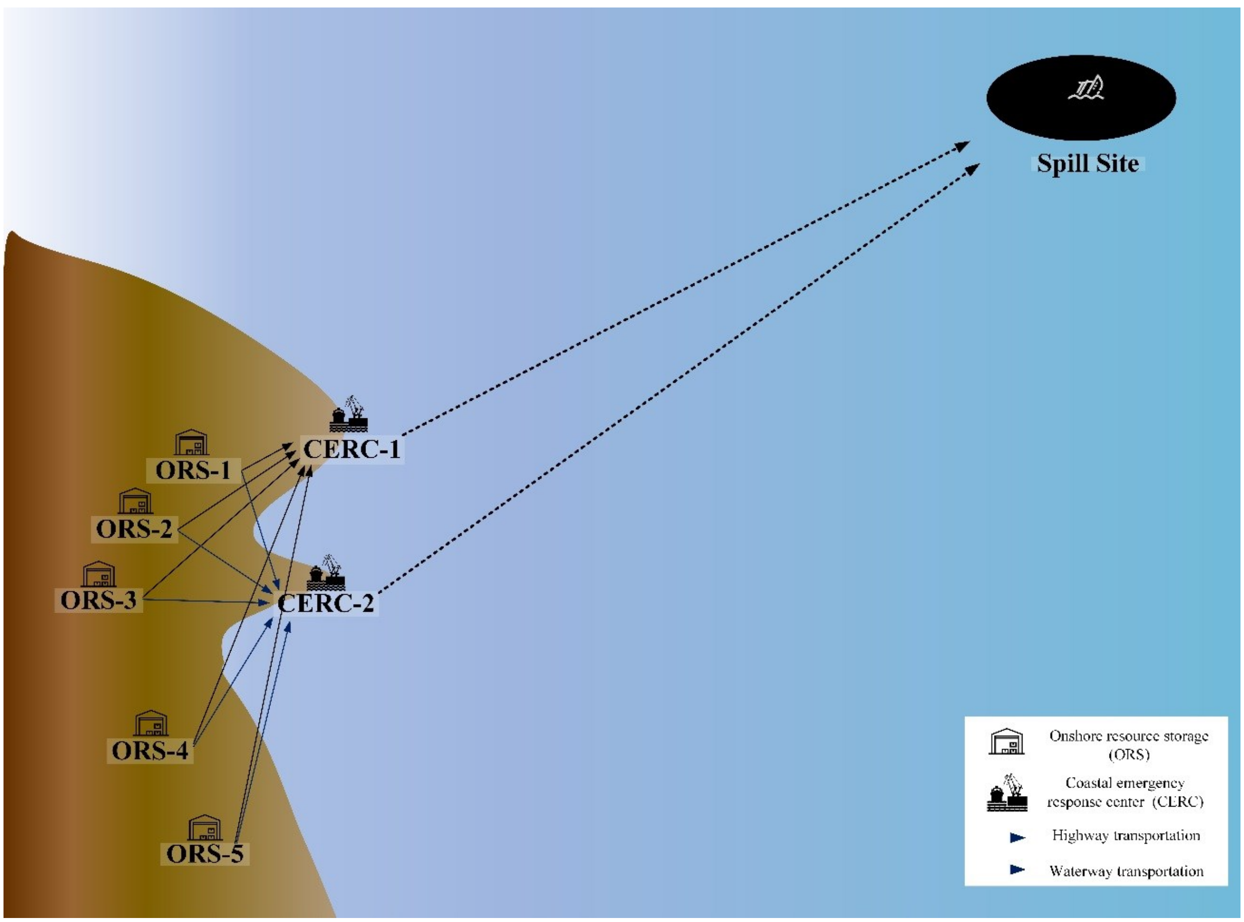


Figure 6.3 Schematic diagram of emergency resource dispatch

6.4.2 Optimization modeling of multi-criteria emergency response system

Symbolic Explanation

I: Set of ORSs, $I = \{1,2, \ldots, i, \ldots\}$;

J: Set of CERCs, $J = \{1,2, \ldots, j, \ldots\}$;

K: Type of skimmers, $K = \{1,2, \ldots, k, \ldots\}$;

L: Type of pumps, $L = \{1,2, \ldots, l, \ldots\}$;

M: Type of trucks, $m = 1\ is\ LTL\ type, m = 2\ is\ FTL\ type$;

N: Type of vessels, $n = 1\ is\ 200m^3\ type, n = 2\ is\ 400m^3\ type$;

O: Round of transportation, $o = 1\ and\ 2$ are two rounds of highway transportations, $o = 3\ and\ 4$ are two rounds of waterway transportations,

B: Unit of booms;

Sk^k: Unit of type k skimmers;

P^l: Unit of type l pump;

$Q^{m,o}$: Unit of type m trucks used in highway transportations;

$R^{n,o}$: Unit of type n vessels used in waterway transportations;

C: Cost;

EL: Environmental Loss;

t: Time;

RE: Response Efficiency

z: Resource transportation

$$z_{ijo} = \begin{cases} 1, & from\ ORS\ i\ to\ CERC\ j\ by\ round\ o\ transportation \\ 0, & otherwise \end{cases};$$

$$z_{jo} = \begin{cases} 1, & from\ CERC\ j\ to\ the\ spill\ point\ by\ round\ o\ transportation \\ 0, & otherwise \end{cases};$$

Objective function (1): Maximize the total response efficiency

Marine oil spill response is a complex and time-bound process. Improving efficiency and cleaning up as much oil as possible is always the top priority. The objective function (1) is to maximize the total recovered oil within the first five days after a large-scale spill occurred. As shown in Figure 6.4, the process includes resource selection from ORSs, dispatching time by highway and waterway transportation, judgement of response start time, dynamic simulation of oil cleanup and oil weathering simulation. The resource selection includes selecting six types of emergency materials and two types of carrying trucks in five onshore response storages (ORSs), two coastal emergency response centers (CERCs) for transshipping, two types of vessels for marine transportations, and the sequence of material transportation to ensure an early start of spill response. The dispatching time includes three stages of transportation: from ORSs to CERCs, transshipment at CERCs, and from CERCs to the spilled point. Trucks and vessels can transport materials up to two rounds. The materials sent to CERCs by the first-round highway transportation can be transported to the accident site by the first-round or second-round waterway transportation. The judgement requires that the oil cleanup process with skimmers and pumps can only be approved when the supplied length of oil containment booms at the spilled point is sufficient (i.e., length of boom > perimeter of the spill plume) to control the oil from further diffusion and the setup of the boom is completed. The efficiency of oil spill response is significantly affected by dynamic changes in the remaining oil after its accidental release at sea. The weathering can directly change oil volume and properties over time. The dynamic simulations consider the response performance of three types of skimmers and oil weathering behaviors with the timely changes in oil volume and properties. The case contains three major weathering processes, evaporation, natural dispersion, and emulsification.

- ***Dispatch Time of Emergency Resource***

The dispatch time of emergency resources controls the beginning of the oil cleanup response at the spilled site. In each transportation round, the time for the last material reaching the accident site is the shortest dispatch time. Thus, as shown in Eq. 6.13, the maximum time of all paths taken from ORSs to CERCs to the spill site represents the shortest time of the entire system According to the boom requirement to control the spreading of spilled oil, the quantity of boom judges the response time t_0 arrived at the spill site by two rounds of transportations. Table 6.5 indicates the traveling time of resource dispatching to the spill site. In this case, the waterway transportation and unloading time in two rounds (i.e., t_3, t_5) is set as the same. Due to the weight reduction of vessels, the transportation speed returning to CERCs is adjusted from 12 knots to 15 knots. The time of boom setup (t_6) is set as 30 minutes. Due to the time scale of weathering and response simulations is an hour, the $t_0$should be further transferred from minutes to the nearest integer hour greater than or equal to the value.

$If\ B_{o=3} \cdot length/unit\ \geq\ Boom\ requirement$:

$$t_0 = \max\,[t_{1,ij} \cdot z_{ij,o=1} + (t_{2,j} + t_{3,j}) \cdot z_{j,o=3}] +\ t_6$$

$If\ B_{o=3} \cdot length/unit\ <\ Boom\ requirement$ & $\sum_{o=3}^{4} B_o \cdot length/unit\ \geq$ $Boom\ requirement$:

$$t_0 = \max\,[t_{1,ij} \cdot z_{ij,o=1} + (t_{2,j} + t_{3,j} + t_{5,j}) \cdot z_{j,o=3} + (t_{2,j} + t_{3,j}) \cdot z_{j,o=4}] +\ t_6 \quad (6.13)$$

Table 6.5 Traveling time of resource dispatching to the spill site (*minute*)

	Highway Travelling and Loading/Unloading Time (t_1)					Transshipment
	ORS_1	ORS_2	ORS_3	ORS_4	ORS_5	(t_2)
CERC-1	79	90	102	116	107	60
CERC-2	102	166	163	168	189	60

	Waterway Traveling and Unloading Time (t_3, t_5)	Waterway Traveling back to CERCs (t_4)
CERC-1	661	495
CERC-2	634	472

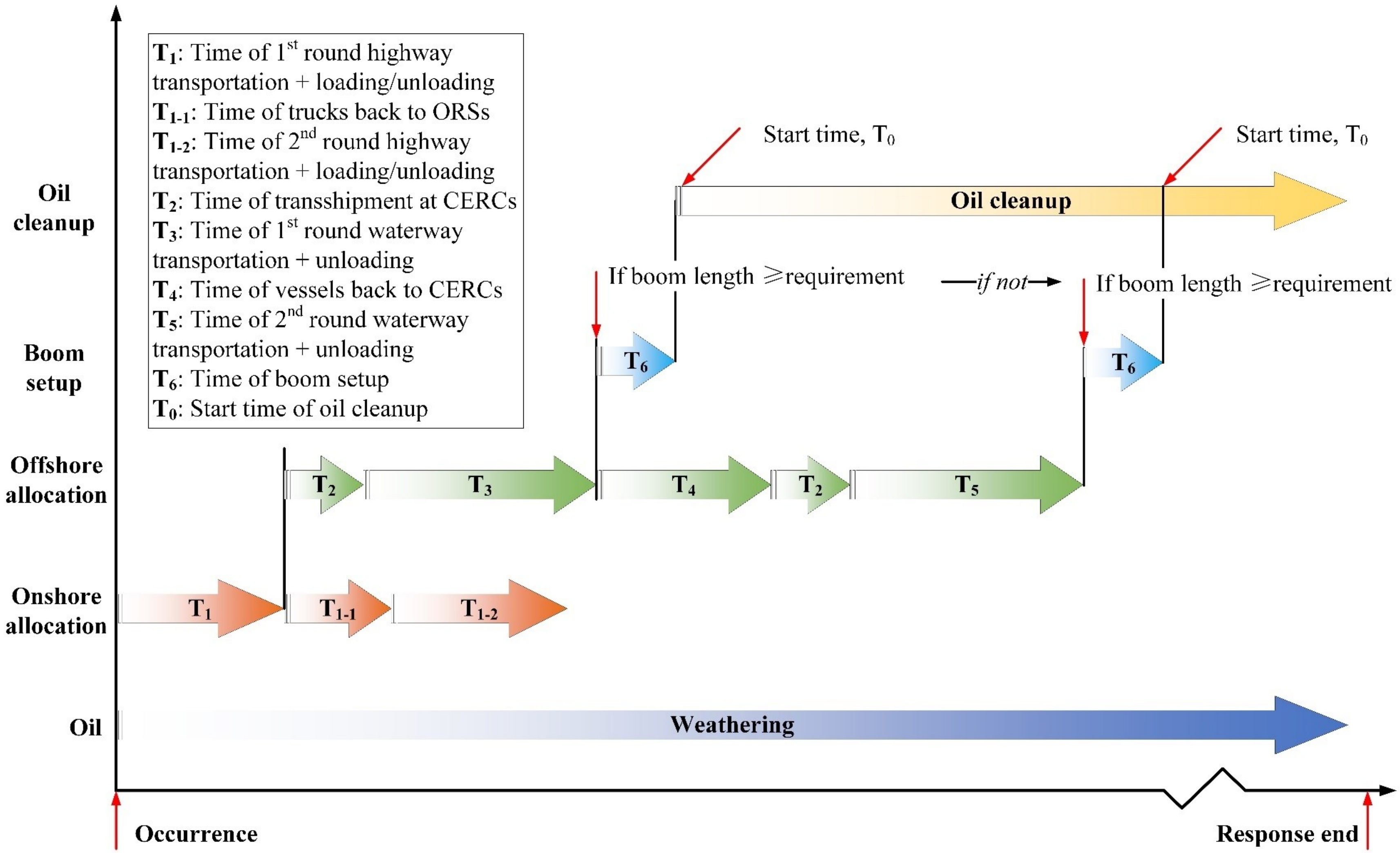


Figure 6.4 Timeline of resource allocation and oil emergency response

- ***Oil Weathering Simulation Module***

The dynamic changes of remaining oil volume and oil slick thickness affect the response efficiency of skimmers. Oil weathering processes can directly change the oil volume and thickness over time. The major weathering processes, evaporation, natural dispersion, and emulsification were considered in this hypothetical case. The evaporation of Arabian Light crude oil is shown in Eq. 6.14 (Fingas, 2016). Eq. 6.15 is the equation for the dispersion process developed by Mackay et al. (1980a). Furthermore, the equations for emulsification proposed by Rasmussen (1985) are represented in Eq. 6.16-6.18. Kirstein and Redding (1987) proposed a relatively simple empirical equation to illustrate the relationship between viscosity and water content (Eq. 6.19). The parameter values for oil weathering simulation are shown in Table 4.3 (Azevedo et al., 2014; Li et al., 2014a; Mackay et al., 1980b; Rasmussen, 1985; Ye et al., 2019b). The parameters for oil weathering processes simulation (i.e., temperature, wind speed, oil density and interface tension) were assumed to be constant. Wind direction and oil movement were not considered in this hypothetical case since advection and spreading were not considered. The effect of emulsification on oil volume was neglected in the study.

$$(\%)Ev(t) = (2.4 + 0.045(\mathrm{T} - 273.15))\ln(\mathrm{t}) \qquad \text{(Eq. 6.14)}$$

$$FD = \frac{0.11 \times (U+1)^2}{1+50 \times \mu^{0.5} \times ST \times S_t} \qquad \text{(Eq. 6.15)}$$

$$\frac{dF_{emul}}{dt} = R_1 - R_2 \qquad \text{(Eq. 6.16)}$$

$$R_1 = \frac{K_1}{\mu_0} \times (1+U)^2 \times (F_{emul}^{final} - F_{emul}) \quad \text{(Eq. 6.17)}$$

$$R_2 = \frac{K_2}{Asph \times Wax \times \mu_0} F_{emul} \quad \text{(Eq. 6.18)}$$

$$\mu = \mu_0 \times \exp\left(\frac{2.5 \times F_{emul}}{1 - k \times F_{emul}}\right) \quad \text{(Eq. 6.19)}$$

where, $(\%)Ev$ is percentage evaporated oil, T is temperature (°C), and t is the time (minute); FD is the dispersion rate $(\mathrm{m}^3/(\mathrm{s} \cdot \mathrm{m}^3 \text{ of oil}))$, U is the wind speed (m/s), μ is the dynamic viscosity of the oil, and S_t is the interface tension between oil and water; F_{emul} is the fractional water content; F_{emul}^{final} is the maximum water volume that can be incorporated in the emulsion, U is wind velocity, K_1 and K_2 are empirical dimensionless constants; Asph and Wax are percentages of asphaltenes and waxes content, and μ_0 is the initial dynamic viscosity of the oil.

- ***Oil recovery simulation module***

Oil spill emergency resources should be operated in a proper procedure at the accident scene (Chen et al., 2019c). The skimmers, unloaded pumps, temporary internal tanks, and storage vessels should be arranged in pairs and operations coordinated to achieve high recovery performance. Ships tasked from ports or response centers include emergency response vessels for oil recovery (with limited storage capacity), oil waste storage and transportation back to shore (Li et al., 2019). Response efficiency is often limited by the proficiency of the available response equipment (e.g., booms, skimmers, and pumps). In this case study, three types of skimmers are provided by ORSs with a different net oil recovery rating (illustrated in Eq. 6.20-6.21 and Table

6.6 (Li et al., 2014b; Ye et al., 2019b). In practical applications, the efficiency of skimmers is reduced due to various uncertain factors and long-term use. A time-related descending factor is included to reflect the situation roughly (Eq. 6.23). The confined efficiency (Eq. 22) is assumed as 70% of the theoretical efficiency, and it will continuously decrease with the increase in usage. The timely recovered oil is constrained by a mutual effect of skimmed oil and pumped oil. A low slick thickness ($\leq 1mm$) is assumed to make the failure of skimmers.

$$ORR_{k,t} = \alpha_k \times {ST_t}^2 + \beta_k \times ST_t \quad \text{(Eq. 6.20)}$$

$$ST_t = \frac{V_0 - \sum_{t=1}^{t-1} V_{loss,t}}{A_t} \quad \text{(Eq. 6.21)}$$

$$ORR'_{k,t} = ORR_{k,t} \cdot Df_t \quad \text{(Eq. 6.22)}$$

$$Df_t = 0.7 - 0.6 \cdot (t - t_0)/t_{end} \quad \text{(Eq. 6.23)}$$

$$Recovered\ oil_t = min\,(\textstyle\sum_{k=1}^{3} ORR'_{k,t} \cdot Sk_{spill,t}^{k}, \sum_{l=1}^{2} pump\ eff_l \cdot p_{spill,t}^{l}) \quad \text{(Eq. 6.24)}$$

where, $ORR_{k,t}$ is defined as the amount of recovered oil per hour (m^3/hr) of a type k skimmer at time t, α and β are empirical coefficients obtained from experimental tests. ST_t shows the slick thickness at time t (mm). V_0 is the initial volume of the spill, A_t is the spill area at time t, and $V_{loss,t}$

is the oil loss at time t through oil response and natural weathering processes. $ORR'_{sk,t}$ is the confined skimmer efficiency by the descending factor Df_t. t_0 and t_{end} are the response start time and end time. $Sk^k_{spill,t}$ is the quantity of type k skimmer at the spill site at time t. $p^l_{spill,t}$ is the quantity of type l pump at the spill site at time t. $pump\ eff_l$ is the pumping efficiency of a type l pump.

Table 6.6 Model coefficients for the net oil recovery rate of three ship-mounted skimmers

Types of skimmers	Empirical coefficients	
	α	β
1	0.00737	0.00702
2	-0.00791	0.62975
3	-0.01591	1.14975

- ***Oil response efficiency optimization module***

The objective function of oil response efficiency aims to maximize the total recovered oil within 120 hours (5 days) after a large-scale spill occurred, as shown in Eq. 6.25. The time step is set in hours. The remained oil at time t (Eq. 6.26) corresponds to the recovered oil from the start time t_0 to time *t-1*(Eq. 6.20-6.24) and the weathered oil from the occurrence to time *t-1* (Eq. 6.14-6.19). The oil area is assumed as a constant during the response process. Thus, the change of slick thickness is related to the remaining oil volume (Eq. 6.27). The constraints restrict the quantity of transferred resources to meet the supplied from ORSs and maximum carrying space of trucks and vessels. The information of resources and vehicles provided by ORSs and CERCs is shown in

Table 6.7. All types of resources transferred by two rounds of highway transportation to CERCs should be lower than the inventories at ORSs (Eq. 6.28). The resource transferred to the CERCs and the spilled site should be lower than the available carrying space of trucks and vessels (Eq. 6.29 and 6.30)

$$Max\ (V_{recovered\ oil}) = \sum_{t=t_0}^{120} Recovered\ oil_t \qquad \text{(Eq. 6.25)}$$

$$V_{remained\ oil}(t) = V_{initial\ oil} - \sum_{t=t_0}^{t-1} Recovered\ oil_t - \sum_{t=1}^{t-1} Weathered\ oil_t \qquad \text{(Eq. 6.26)}$$

$$ST_t = V_{remained\ oil}(t-1)/A \qquad \text{(Eq. 6.27)}$$

Constraints:

$$0 \le \sum_{o=1}^{2}\sum_{j=1}^{2} resource_{j,o} \le resource_j^{inventory};$$

$$resource = \{B, Sk^1, Sk^2, Sk^3, P^1, P^2\} \qquad \text{(Eq. 6.28)}$$

$$0 \le B_{i,j,o} \cdot B_{volume} + \sum_{k=1}^{3} Sk_{i,j,o}^{k} \cdot Sk_{volume}^{k} + \sum_{l=1}^{2} Sk_{i,j,o}^{l} \cdot P_{volume}^{l} \le \sum_{m=1}^{2} Q_{i,j}^{m,o} \cdot Q_{Space}^{m} \cdot SR_{truck};\ i = \{1,2,\dots,5\}, j = \{1,2\}, o = \{1,2\} \qquad \text{(Eq. 6.29)}$$

$$0 \le B_{j,o} \cdot B_{volume} + \sum_{k=1}^{3} Sk_{j,o}^{k} \cdot Sk_{volume}^{k} + \sum_{l=1}^{2} Sk_{j,o}^{l} \cdot P_{volume}^{l} \le \sum_{n=1}^{2} R_j^{n,o} \cdot R_{Space}^{n} \cdot SR_{vessel};$$

$$j = \{1,2\}, o = \{3,4\} \qquad \text{(Eq. 6.30)}$$

where, A is the spilled area (m^2), *resource* represent the types of emergency materials, B_{volume}, Sk_{volume}^{k}, P_{volume}^{l} are the unit volume of materials ($m^3/unit$), Q_{Space}^{m} and R_{Space}^{n} are the unit carrying space of trucks and vessels($m^3/unit$), SR_{truck} and SR_{vessel} are the space restriction factors of trucks (80%) and vessels (90%).

Table 6.7 The matrix of emergency materials for emergency response at ORSs and CERCs.

	Boom (100 m/unit)	Type-1 Skimmer	Type-2 Skimmer	Type-3 Skimmer	Type-1 Pump (10 m^3/hr)	Type-2 Pump (50 m^3/hr)	LTL type truck	FTL type truck
Volume/Space (m^3)	50	15	10	17	10	40	55	115
ORS-1*	3	5	3	3	16	8	4	3
ORS-2*	8	0	4	5	12	8	5	2
ORS-3*	7	3	5	2	14	12	5	2
ORS-4*	2	4	0	7	10	5	3	3
ORS-5*	15	6	0	5	14	12	7	3

	Type-1 Vessel (200 m^3)	Type-2 Vessel (400 m^3)		Type-1 Vessel (200 m^3)	Type-2 Vessel (400 m^3)
CERC-1*	3	2	CERC-2*	4	1

Note:

ORS: onshore response storage; CERC: Coastal emergency response center.

*Quantity of resource

Objective function (2): Minimize the total response cost

With the ongoing oil emergency response, the response cost is increasingly incurred. The total cost (Eq. 6.31) includes resource transportation and response operation costs. The operating expenses of highway transportation (Eq. 6.32) and waterway transportation (Eq. 6.33) are calculated based on the fixed vehicle costs, including a labor cost of loading and unloading and the quantity of trucks and vessels used in a transportation process. Table 6.8 indicates the unit costs of highway transportation by two types of trucks (i.e., LTL trucks and FTL trucks) from 5 ORSs to 2 CERCs. The trucking costs are generated based on the information of Endres (2021) and Henry (2020) with multiple factors (e.g., Driver compensation, fuel, equipment financing, maintenance, and insurance) and travel distances. The unit cost in a voyage is set as 1,500 and 2,500 for a 200-m^3 and 400-m^3 vessel, respectively. The operation of boom setup is assumed as U.S.$300. The operation cost of spill response by skimmers is corresponded to the volume of recovered oil ($V_{recovered\ oil}$) by a unit cost of U.S.$94.50/$m^3$·oil.

$$Min(C_{total}) = C_{highway} + C_{waterway} + C_{boom-setup} + C_{response} \quad \text{(Eq. 6.31)}$$

$$C_{highway} = C_{i,j}^{m} \cdot Q_{i,j}^{m,o} \quad \text{(Eq. 6.32)}$$

$$C_{waterway} = C_{j}^{n} \cdot R_{j}^{n,o} \quad \text{(Eq. 6.33)}$$

where, C_{total} is the total response cost, $C_{highway}$ is the cost of highway transportation, $C_{i,j}^{m}$ is the unit cost of a type *m* truck from ORS *i* to CERC *j*, $Q_{i,j}^{m,o}$ is the quantity of type *m* truck in round o, $C_{waterway}$ is the cost of waterway transportation, C_j^n and $R_j^{n,o}$ are the unit cost and quantity of type n vessels from CERC j to the spill site, $C_{boom-setup}$ is the operation cost of boom setup, $C_{response}$ is the operation cost of spill response by skimmers.

Table 6.8 The unit cost of highway transportation from ORSs to CERCs (U.S.$/truck)

	LTL to CERC 1	LTL to CERC 2	FTL to CERC 1	LTL to CERC 2
ORS 1	31	111	51	185
ORS 2	56	129	84	193
ORS 3	71	137	98	191
ORS 4	72	131	123	224
ORS 5	61	134	94	206

Objective function (3): Minimize the total environmental impact

The environmental impact or ecological loss caused by oil spill pollution is also a vital objective function in the MC-ERS. A higher response efficiency for controlling and cleaning the spilled oil can reduce the environmental impact. A formula (Eq. 6.34) revised based on natural resource damage assessment (NRDA) for the natural resource damage caused by a coastal spill is used to calculate the total environmental impact considering an average impact from the spilled oil and a cumulative impact from response operation (Faass, 2010). SMA, AD and ETS values are set as 1, U.S.$2/ft^2, *and* U.S.$10,000. The value of AC is calculated by 20 staff with a wage of U.S.$25/hour.

$$Min\ (Environmental\ impact) = \frac{\sum_{t=1}^{120}[(B \cdot V_{remained\ oil}(t) \cdot L \cdot SMA) + (AD \cdot A \cdot SMA)] \cdot PC + ETS}{120} + \sum_{t=t_0}^{120} AC \quad \text{(Eq. 6.34)}$$

where, B is the base rate (U.S.$1.00), $V_{remained\ oil}(t)$ is the volume of remained oil (gallons), L is the local factor (8 = inshore; 5 = nearshore; 1 = offshore), SMA is the factor of the special management area (2 = yes; 1 = no), *AD* is the additive dollar amount for impacted habitat (range from U.S.$10.00 to U.S.$0.05 per square foot), *A* is the spilled area (square feet), *PC* is type of pollutant (8 = heavy oils; 4 = midweight oils; 1 = light oils), *ETS* is the endangered/threatened species (U.S.$10,000 and U.S.$5,000, respectively), *AC* is the administrative costs (charged hourly, based on wage).

WSM-based objective function

The WSM-based objective function (Eq. 6.1) converts a multi-objective problem to a single-objective problem by enhancing the optimization performance and increasing the subjective judgement of decision-makers. It (Eq. 6.35) consists of the objective functions of spill response efficiency, response cost and environmental impact by the normalization process of their upper and lower boundary (Eq. 6.3). The values of upper and lower boundary values are summarized according to the results of 500 runs with a single objective function, which are 7,935 m^3 and 0 m^3 for recovered oil, U.S.$770,455 and U.S.$0 for response cost, and U.S.$25,645,051and U.S.$20,005,369 for environmental impacts. Response efficiency or response time is always the primary concern. How to reduce the environmental losses and operation costs can be further considered under a relatively quick response. Thus, the weights are selected as 0.6, 0.2, 0.2 for three functions, respectively (Eq. 6.2). More scenarios with different weight combinations were analyzed in Section 6.5.2. Detailed results were also shown in Appendix J.

$$\min \ F(x) = w_1 \cdot f^n_{V_{recovered\ oil}}(x) + w_2 \cdot f^n_{C_{total}}(x) + w_3 \cdot f^n_{Environmental\ impact}(x) \quad \text{(Eq. 6.35)}$$

6.5 Results and Discussions

6.5.1 The results of MC-ERC system

The results of the MC-ERC system presented an optimal response plan for a marine oil spill accident with multiple criteria, locations for resource dispatching and phase simulations. They showed that the WSM-based objective function *F(x)* could be minimized to 0.2568 with the scores of 0.0069 for response efficiency, 0.1931 for response cost and 0.0568 for environmental impacts, which indicated that 76.50% of the spilled oil was cleaned within the first five days with a total cost of U.S.$ 743,874, and the accident and response cause an ecological loss of U.S.$ 21,607,039. At the expense of a high operation cost, the solution can have a higher response efficiency and a relatively low environmental loss. In actual situations, due to the complex influences of human features, environmental conditions and uncertain factors, the recovery rates of response equipment would be much lower than the rates in the hypothetical case. Since these factors and features would equally affect all planning scenarios, the MC-ERC system's optimized plan still had a high application value and the potential for further development. Figure 6.5 indicated the changes in oil volume during the response process. Oil weathering, especially evaporation, has a significant effort on the volume of remaining oil significantly after the occurrence of the spill. After receiving enough boom material to contain the spilled area, the cleanup process started at the 16th hour. As the response operates, the remaining oil volume and slick thickness become lower, resulting in a decrease in the recovery rates of the skimmers.

Further supplies of response devices by the second-round waterway transportation help maintain a similar hourly response efficiency as before for a long period.

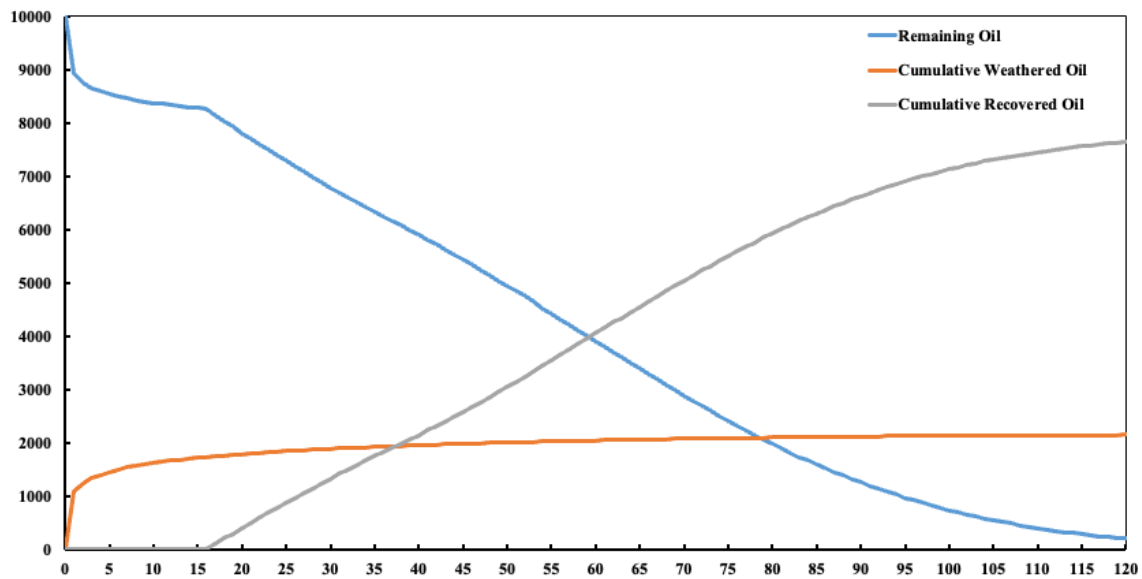


Figure 6.5 The changes of oil volume in the response process

Figure 6.6 showed the utilization of resources at five ORSs. ORS-4 provided the most resource (90%) to the site, and other ORSs provided similar proportions of resources (47% - 60%). ORS-1 provided all boom, about 53% skimmers and 44% pumps. ORS-2 provided 38% boom, all type-2 skimmers, 20% type-3 skimmers and 37.5% pumps. ORS-3 provided 57% boom, all type-1 and type-3 skimmers, 60% type-2 skimmers and 19% pumps. ORS-4 provided all booms, type-3 skimmers and pumps, and half type-1 skimmers. ORS-5 provided 27% boom, 17% type-1 skimmers, all type-3 skimmers, and about 78% pumps.

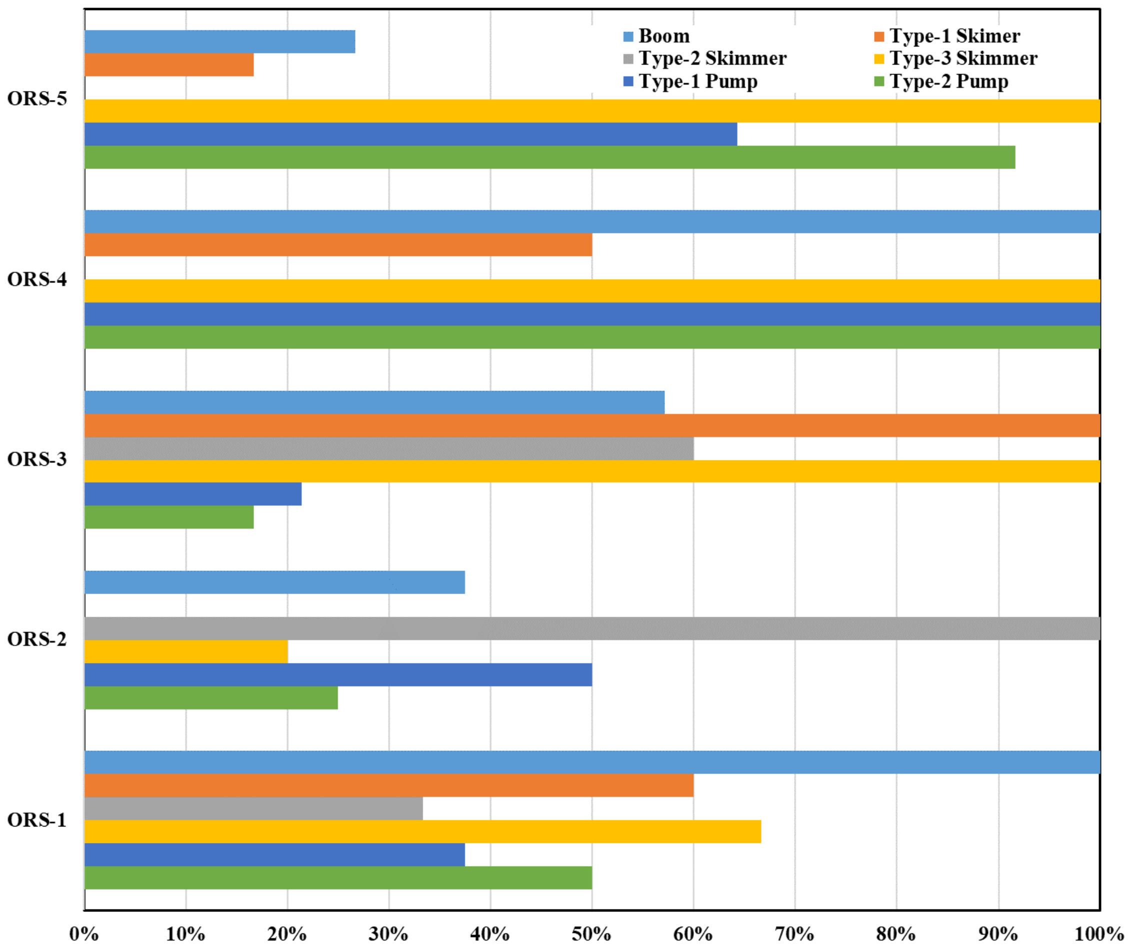


Figure 6.6 The utilization condition of resources at ORSs.

Figures 6.7 and 6.8 illustrated the use of trucks and vessels in resource transportation. Almost all trucks were used in the first-round highway transportation to achieve the purpose of efficient use of space usage and a reduction of trucks used for the second-round transportation. All type-2 vessels were used to undertake most of the resource transportation tasks in terms of vessel use. 75% and 50% of type-1 vessels were used at CERC-2 for the first- and second-round waterway transportations.

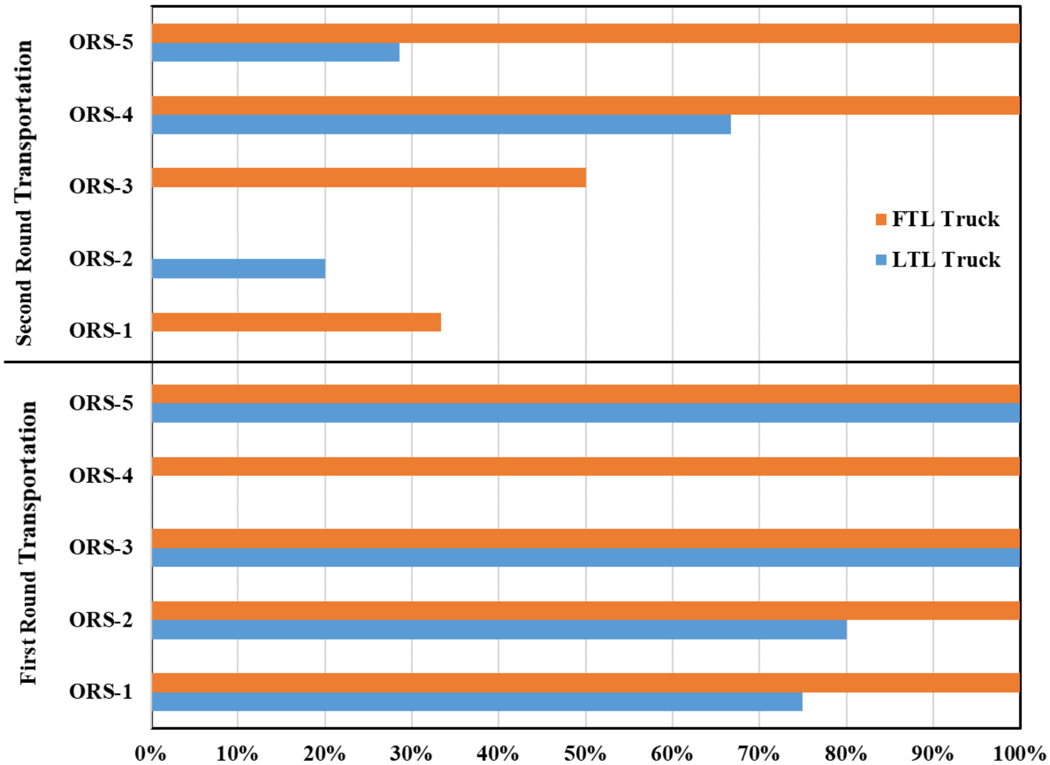


Figure 6.7 The usage condition of trucks for highway transportation

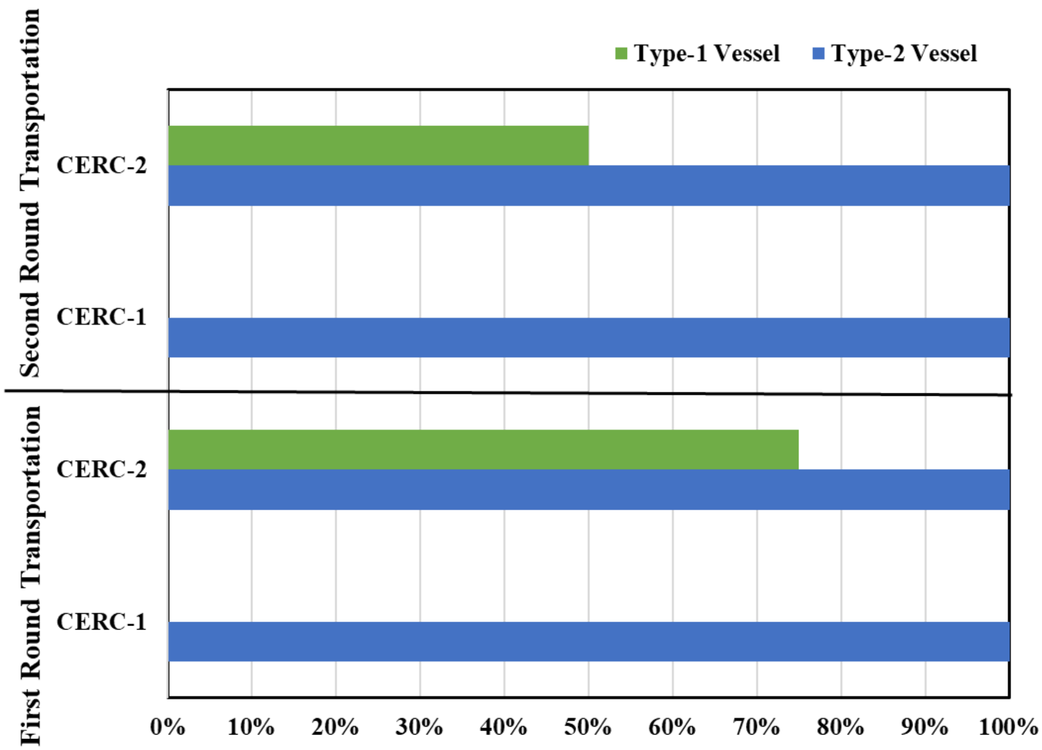
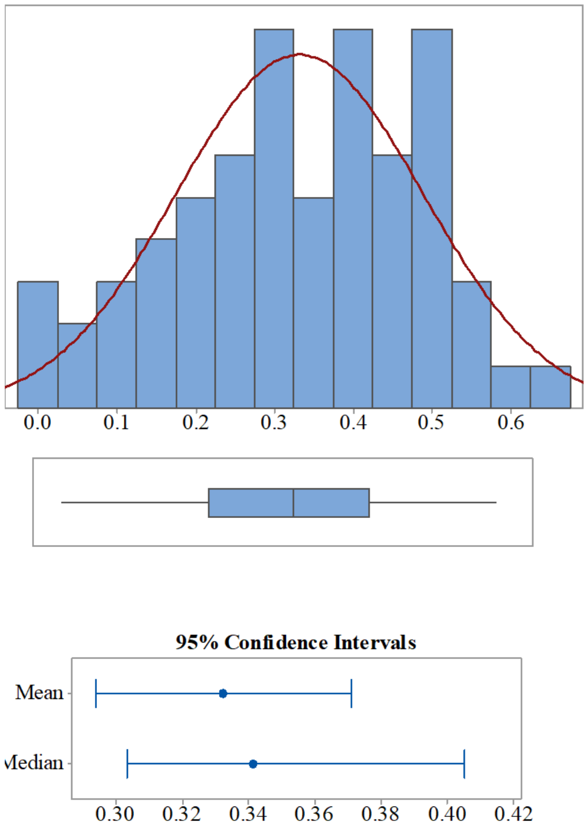


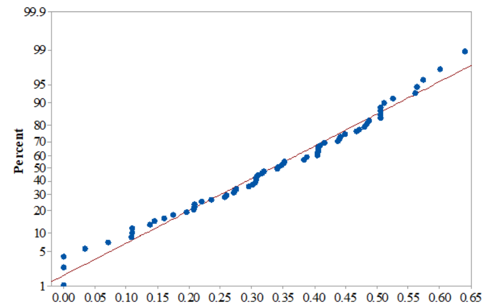
Figure 6.8 The usage condition of vessels for waterway transportation

The proposed MC-ERS system solved the emergency response problems of optimizing resource allocation for marine oil spill accidents considering response efficiency, cost, and environmental impacts. An early oil cleaning operation can be realized by selecting resource types and quantities appropriately. More cleanup materials can be delivered in the first-round water transportation after meeting the boom requirements with an optimized plan. Under satisfying the concerns of cost and environmental loss, more materials were further transported to enhance recovery efficiency. According to the proposed approaches, decision-makers can combine the optimized plans and their actual management experience to make scientific and high-efficient decisions on the dynamic dispatching and scheduling of response materials for marine oil spill incidents in a short preparation period. With the collaboration of expert experience and the assistance of MC-ERS, the speed and performance of resource allocation and oil cleanup can be improved. The spilled oil was also prevented from further contamination and spread. The modules (e.g., simulation and optimization) in the MC-ERS framework can be further revised based on the specific requirements and demands to realize practical applications for response procedures for other types of accidents and disasters.

6.5.2 Performance analysis of weighting effort

A series of weight value combinations were used for system optimization to analyze the performance of the proposed MC-ERS modeling. The value interval was selected as 0.1. The value of each weight changed from 0 to 1. A total of 66 scenarios with different weight combinations were generated. The outcome of a scenario was the minimal value among 500 runs. The detailed results were shown in Appendix L. As shown in Figure 6.9, the results had an average value of 0.3370. When considering only one criterion (e.g., w_1=1, w_1=0, w_1=0), the results reached the lowest optimized value of 0. The 95% confidence interval for the average value is from 0.2936 to 0.3708. The 95% confidence interval for the medium is 0.3031 to 0.4052. According to the Anderson-Darling Normal Test result, the distribution of the result met the requirement of a normal distribution (P-Value > 0.05). Thus, when decision-makers used the MC-ERS modeling to optimize a resource allocation plan and response operation, the generated results can be quickly evaluated with mean and standard deviation values through normal distribution formulas to analyze the quality of the optimized plan.





Anderson-Darling Normality Test	
A-Squared	0.39
P-Value	0.383
Mean	0.33219
StDev	0.15688
Variance	0.02461
Skewness	-0.323092
Kurtosis	-0.514597
N	66
Minimum	0.00000
1st Quartile	0.21716
Median	0.34117
3rd Quartile	0.45337
Maximum	0.63968
95% Confidence Interval for Mean	
0.29362	0.37075
95% Confidence Interval for Median	
0.30314	0.40517
95% Confidence Interval for StDev	
0.13394	0.18938

Figure 6.9 Normality Test and Result analysis of weight effort results

6.5.3 Future research challenges

The proposed MC-ERS and C-PSO provided a multi-criteria decision-making framework and an efficient system optimization approach for marine oil spill emergency responses. Despite the above theoretical and practical implications, this research still has some limitations and challenges which should be resolved in future research. Recommendations include:

1) System uncertainty is one of the challenges in models of simulation and decision-making. It is a vital research area for modeling. How to reasonably consider uncertainty in the system is a problem that needs to be solved in future research. Fuzzy theory, Bayesian networks, Monte Carlo simulations, and other types of stochastic modeling based on the event relationships and historical data are available approaches to be involved.
2) The current resource transportation model, to some extent, is still based on a stage-based algorithm. For example, trucks at one ORS simultaneously act as a team to the same destination. This is the limitation of top-down modeling and algorithm-based optimization. With the increase of system autonomy and feasibility, the entire system can be further optimized. For example, each vehicle independently selects the delivery destination, resource type and quantity, departure time. Such a challenge in complex systems could be solved by considering some bottom-up or rule-based models, such as agent-based modeling.
3) The performance simulation modeling of oil cleanup techniques is still insufficient, which hinders the practices of the proposed decision support systems. How to use existing data resources to develop some accurate simulation models through the

combination of intelligence learning approaches and other data statistics methods is an urgent challenge to be solved. Moreover, there are often obvious efficiency losses or performance differences in response tools or monitoring results from laboratories to actual on-site situations. Such a difference should be further concerned in simulation modeling.

4) Humans, as operators and decision-makers, participate in all response processes. Human errors or mistakes may affect the entire response process. Thus, the influence of human behaviors and performance should be further emphasized as an essential element in the analysis of system efficiency and stability.

6.6 Summary

An efficient emergency response system can shorten response time, reduce operating cost and the harmful impacts of pollutants on the environment This study developed a multi-criteria emergency response system comprehensively considering total response efficiency, cost, and environmental loss. The proposed MC-ERS system integrated dynamic simulations of multiple processes related to oil weathering and cleanup and optimized resource allocation by multiple transportation modes. A developed weight-sum model was also be involved in converting multi-objective optimization problems to single-objective optimizations to achieve a targeted optimization and performance improvement. Furthermore, a C-PSO algorithm was developed through a competition of 12 PSO variants with three algorithm improvement strategies (i.e., MA, EPD, BB) by 13 uni-modal and multi-modal benchmarked function as well as a further competition with 16 selected inertia weight strategies. The C-PSO algorithm performed better outcomes than other variants by combining MA and EPD strategies with the natural exponent inertia weight strategy.

A representative case of emergency response for a marine oil spill response was applied to demonstrate and evaluate the performance of the developed MC-ERS and C-PSO algorithm. An optimized oil spill response plan was generated considering the optimal allocation and deployment of response resources from five onshore response storages to two coastal emergency response centers for transshipment and further to the spilled site. The results indicated the optimal response plan recovered 96.50% of the spilled oil within the first five days with a total cost of U.S.$ 743,874, and the accident and response caused an ecological loss of U.S.$ 21,607,039. The efficiency rate might become higher than the actual case due to the simplification and the assumptions and no concerns of environmental uncertainties, human errors, and system failures. Since these factors would uniformly affect the planning results, a plan with a high recovery rate under the hypothetical situations can relatively improve the response efficiency in a practical application with high potential. Performance evaluation of weighing values by 66 scenarios of different weight value combinations. The results indicated an average value of 0.3370 with a standard deviation of 0.1569. The distribution of results conformed to the normal distribution. An optimized plan generated by the decision-maker can quickly evaluate its quality by the normal distribution formulas.

Besides the scientific improvement on the simulation optimization coupling and optimization algorithm, the proposed system presents a great potential of being a powerful tool for emergency response planning and decision making in many fields worldwide.

CHAPTER 7 CONCLUSIONS AND RECOMMENDATIONS

7.1 Summary

Marine oil spills have been concerned as a major source of pollutants in the marine environment. The short-time and long-time effects of spilled oil can significantly negatively impact marine lives, the economy, and humans. Approximately 1.25 million tons of oil have annually entered the global marine environment due to ocean-based activities. Emergency or disaster response systems rely on the cooperation and collaboration of various agencies to effectively minimize negative impacts. Improving marine oil spill response efficiency to minimize environmental and socioeconomic impacts has been recognized as a growing, critical need worldwide in both scientific and practical fields. The desired overall system performance is influenced by effective resource allocation and dynamic changes in accident site conditions, which is critical for emergency response management. Meanwhile, human factors/errors (such as inappropriate actions by operators and unsafe supervision by organizations) should be emphasized as a primary cause of oil spill incidents.

To help fill the gaps, this dissertation research has developed an improved emergency response decision support system for supporting offshore oil spill responses. Such a system consists of novel concepts and modeling approaches, including 1) a new simulation-based multi-agent particle swarm optimization approach for supporting marine spill decision-making through the integrated simulation and optimization of response device allocation and process control. 2) an improved emergency response system based on dynamic process simulation and resource allocation optimization techniques. 3) an integrated offshore oil spill response decision-making approach using human factor analysis and fuzzy preference evaluation. 4) A multi-criteria response system for marine oil spill accidents by a comparison-based particle swarm optimization.

A comprehensive review has been done for marine oil spill decision support and system optimization. It includes current mechanical, chemical, and biological techniques of marine oil cleanup and response, current procedure and protocols for emergency response system and decision support system from early warning and monitoring, response technology screening and evaluation, to NEBA, related developments of simulation and optimization modeling. The novel techniques applied or developed in the thesis are reviewed, such as agent-based modeling, environmental optimization methods, and human factor analysis. Previous studies of such techniques in spill response and decision making have also been reviewed and summarized. Current 65 available agent-based software tools are also collected into a list with categories of programming language, development difficulty, model scalability level, operating system, and maintenance condition.

Targeting the disclosed knowledge gaps and technological needs, Agent-based modeling as an emerging simulation method is first applied to simulate oil spill fate and response. The particle swarm optimization method is further adopted to optimize response device/vessel allocation and performance with a minimal cost and time. A multi-agent system finally controls and transmits the results from agent-based modeling and particle swarm optimization as a dynamic and interactive system. A new simulation-based multi-agent particle swarm optimization approach is developed. The proposed method is tested by a hypothetical case study with Arabian Light crude oil in the North Atlantic Ocean. Weathering processes including evaporation, dispersion, and emulsification are considered in the simulation, along with the skimming response process in a harsh environment. By applying the proposed methods, a shorter response time could be achieved, leading to a decrease in the existence and amount of oil in the marine environment and consequently reduced environmental impact and human health risk.

Furthermore, an emergency response system is developed by integrating dynamic simulation of multiple response processes, response system optimization, and site-specific information, including available response options. Furthermore, a ME-PSO algorithm was developed by combining the advantages of MA and EPD. The ME-PSO could accelerate the convergence speed and reduce the calculation time while expanding the search range for better results. A representative case of marine oil spill response was applied to demonstrate and evaluate the performance of the developed ERS and ME-PSO algorithm. An optimized oil spill response plan was generated considering the optimal allocation and deployment of response resources (e.g., booms, skimmers, pumps, and vessels) from three response centers were optimized. The system considered dynamic simulations of oil weathering and recovery performance, as well as the ME-PSO optimization.

In order to investigate the influences of active operational failures and unsafe latent factors in the marine oil spill accidents, an improved qualitative and quantitative analysis approach is developed to detect the human factors related to offshore oil spill occurrences and responses. A refined HFACS-OS hierarchical framework and comprehensive classifications based on the original version of HFACS with the historical spill cases and records were used to analyze the human-factor-based causal factors with different complexities. The Fuzzy-TOPSIS method was applied to evaluate the relative priorities of identified HFACS categories to determine the leading causes of the accident. With the application of the Fuzzy-TOPSIS, the establishment of the knowledge base, with the support of experts, accidental records, refereed journals and reports, became crucial. It became evident that the knowledge base was not merely a collection of information but the response of a synergistic group with multi-faceted knowledge of the decision-making problem at hand. The multiple experts, to a certain extent, reduced the bias of subjective judgements. The results from the case study showed the priorities of human factors under 25 sub-categories of the four-level HFACS framework. The analysis and assessment of causal factors and human errors considered active causal or human factors and paid attention to the impacts of groups and organizations. According to the ranking of casual and human factors, point-to-point prevention measures can be presented by decision-makers in case of the recurrence of similar accidents.

Additionally, an emergency response management modeling system was developed with the integration of dynamic process simulation and weighted multi-criteria system optimization. Total response time, response cost and environmental impacts are regarded as multiple optimization goals. An improved weighted sum optimization function was developed to unify the scaling and proportion of different goals. A comparative PSO is also developed by comparison to a variety of algorithm-improving methods and the best-performing inertia weight function. The developed response system and PSO algorithm are further applied to optimize the contingency planning of marine oil spill response optimization.

7.2 Research Contributions

This research has led to the following major contributions:

1) A novel approach was developed to support the decision-making of offshore oil spill responses. The SA-PSO method has been developed by combining the advantages of agent-based modeling, particle swarm optimization, and multi-agent system. Dynamic optimization was coupled with the simulation of oil weathering processes. An offshore oil spill case was applied to evaluate the approach under scenarios. Sound decisions were provided in a dynamic and time-efficient manner.
2) An improved emergency response system (i-ERS) with a dynamic system simulation-optimization was proposed. A ME-PSO with the integration of multi-agent and evolutionary population dynamics was developed. Benchmark functions and PSO variants evaluated the optimization performance of ME-PSO. The performance of proposed i-ERS was employed with a case study in marine oil spill dynamic response
3) A qualitative-quantitative evaluation system of unsafe human factors and causal errors in offshore oil spill accidents was proposed. An enhanced HFACS for offshore oil spills with multi-stage analysis was developed. The multi-criteria decision-making (Fuzzy TOPSIS) was employed for analysis. The significance of human factors/errors on oil spill accidents and response operations was improved. The proposed system can be a decision-making support tool for accident responses.
4) A multi-criteria-based emergency response management modeling system with the integration of dynamic process simulation is developed. Total response time, response cost and environmental impacts are regarded as multiple optimization goals. An improved weighted sum optimization function was developed to unify the scaling and proportion of different goals. A comparative PSO (C-PSO) is also developed by comparing 12 hybrid PSO algorithms and 16 inertia weight functions to improve the

optimization performance. The C-PSO integrates the strengths of EPD, MA, and the natural exponent inertia weight strategy. The developed response system and C-PSO algorithm are further applied to optimize the contingency planning of marine oil spill response optimization.

5) The developed approaches and DSS modeling are the first to date targeting marine oil spill responses. These methods are particularly suitable for accident responses in the marine environment of the North Atlantic Ocean. The research also promotes the understanding of the process of marine oil spill response, system optimization, dynamic simulation and agent-based modeling, and human factor impacts. The developed methodologies can provide modeling tools for other related areas that require timely and effective decisions under complicated conditions and multi-aspect concerns.

7.3 List of Publications

7.3.1. Refereed journal publications

- First author

My contributions:

Conceptualization, Methodology, Modeling and software, Formal analysis, Investigation, Data Collection and management, Writing-original draft, review and editing.

1) **Ye XD,** Zhu ZW, Merlin F, Yang M, Chen B, Lee, K, Zhang B (2021). Ecological Impact of Dispersants and Decision Making. *Journal of Environmental Informatics Letters*. https://doi.org/10.3808/jeil.202100058.

2) **Ye XD**, Chen B, Storesund R, Lee K, Li P, Zhang BY, Kang Q (2021). Environmental response management strategies with an enhanced particle swarm optimization – a case study in marine oil spill dynamic response planning. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2021.126591 (IF=9.297).

3) **Ye XD,** Chen B, Lee K, Storesund R, Zhang BY (2020). An Integrated Offshore Oil Spill Response Decision Making Approach by Human Factor Analysis and Fuzzy Preference Evaluation. *Environmental Pollution.* https://doi.org/10.1016/j.envpol.2020.114294 (IF=8.071)

4) **Ye XD**, Chen B, Li P, Jing L, Zeng GN (2019). A simulation-based multi-agent particle swarm optimization approach for supporting dynamic decision making in marine oil spill responses. *Ocean and Coastal Management*. https://doi.org/10.1016/j.ocecoaman.2019.02.003 (IF=3.284)

5) **Ye XD**, Chen B, Jing L, Zhang BY, Liu Y (2019). Multi-agent hybrid particle swarm optimization (MAHPSO) for wastewater treatment network planning. *Journal of Environmental Management*. https://doi.org/10.1016/j.jenvman.2019.01.023 (IF=6.789)

- Co-author

My contributions:

Modeling development, Experiments, Result analysis, Writing-original draft, review and editing.

6) Song X, Chen B, Liu B, Lye L, **Ye XD,** Nyantekyi-Kwakye, B, Zhang BY (2021). Impacts of Frazil Ice on the Effectiveness of Oil Dispersion and Migration of

Dispersed Oil. *Environmental Science & Technology*. https://doi.org/10.1021/acs.est.1c04014 (IF= 9.028).

7) Wu HJ, Chen B, **Ye XD**, Guo HC, Meng XY, Zhang BY. (2021). An improved calibration and uncertainty analysis approach using a multicriteria sequential algorithm for hydrological modeling. *Nature: Scientific Reports*. https://doi.org/10.1038/s41598-021-96250-6 (IF= 5.134).

8) Kang Q, Song X, Xin XY, Chen B, Chen YZ**, Ye XD**, Zhang, BY. (2021). Machine Learning–Aided Causal Inference Framework for Environmental Data Analysis: A COVID-19 Case Study. *Environmental Science & Technology.* https://doi.org/10.1021/acs.est.1c02204 (IF= 9.028).

9) Chen YF, Chen B, Song X, Kang Q, **Ye XD,** Zhang B (2021). A data-driven binary-classification framework for oil fingerprinting analysis. *Environmental Research.* https://doi.org/10.1016/j.envres.2021.111454 (IF=6.498).

10) Hu JH, Luo J, Zhu ZW, Chen B, **Ye XD,** Zhu P, Zhang BY (2021). Multi-scale Biosurfactant Production by Bacillus subtilis Using Tuna Fish Waste as Substrate. *Catalysts*. https://doi.org/10.3390/catal11040456 (IF=4.146).

11) Song X, Jing L, Chen B, Zhu ZW, Cai QH, **Ye XD**, Zheng X, Hill SJ, Zhang BY (2021). The Effect of Pressure Variation on Droplet Size Distribution of Dispersed Oil under Simulated Deep-water Conditions. *Heliyon.* https://doi.org/10.1016/j.heliyon.2021.e06291 (IF=0.455).

12) Lin WY, Zhang BY, **Ye XD**, Hawboldt K (2020). Sulfate Removal Using Colloid-Enhanced Ultrafiltration: Performance Evaluation and Adsorption Studies.

Environmental Science and Pollution Research. https://doi.org/10.1007/s11356-020-10884-z (IF=4.306)

13) Cao YQ, Zhang BY, Dong GH, Cai QH, Song X, **Ye XD**, Zhu ZW, Chen B. (2020). Microbial Eco-physiological Strategies for Salinity-mediated Crude Oil Biodegradation. *Science of the Total Environment*. https://doi.org/10.1016/j.scitotenv.2020.138723 (IF=7.963)

14) Data AR, Kang Q, Chen B, **Ye XD** (2018). Fate and transport modelling of emerging pollutants from watersheds to oceans: a review. Advances in Marine Biology. https://doi.org/10.1016/bs.amb.2018.09.002 (IF = 5.143)

15) Li ZL, Chen B, Wu HJ, Zhang H, **Ye XD**, Zhang KD. (2018). Parameterization study for modeling biosurfactant-enhanced aquifer remediation processes based on flow cell experiments. ASCE's Journal of Environmental Engineering. https://doi.org/10.1061/(ASCE)EE.1943-7870.0001310 (IF=1.746)

16) Li ZL, Chen B, Wu HJ, **Ye XD,** Zhang BY (2018). A design of experiment aided stochastic parameterization method for modeling aquifer NAPL contamination. Environmental Modelling and Software. https://doi.org/10.1016/j.envsoft.2017.12.014 (IF=5.288)

17) Jing L, Chen B, Zhang BY, **Ye XD** (2017). Modeling marine oily wastewater treatment by a probabilistic agent-based approach. Marine Pollution Bulletin. https://doi.org/10.1016/j.marpolbul.2017.12.004 (IF= 5.553)

18) Cai QH, **Ye XD,** Chen B, Zhang BY (2017). Complete genome sequence of Exiguobacterium sp. strain N4-1P, a psychrophilic bioemulsifier producer isolated

from a cold marine environment in North Atlantic Canada. Genome Announcements 5:e01248-17. https://doi.org/10.1128/genomeA.01248-17 (IF = 1.181)

19) Jing L, Chen B, **Ye XD**, Zhang BY (2017). Wastewater treatment plant network design using a multi-scale two-stage mixed integer stochastic (MSTMIS) model. Environmental Engineering Science. https://doi.org/10.1089/ees.2017.0100 (IF=1.907)

7.3.2. Published Peer-Reviewed Book Chapters:

My contribution as the first author:

Methodology, Modeling, Formal analysis, Data Collection and management, Writing-original draft, review and editing.

My contribution as a co-author:

Formal analysis, Data Collection and management, Writing-original draft, review and editing.

1) **Ye XD,** Chen B, Storesund R, Zhang B (2021). System control and optimization in wastewater treatment: a particle swarm optimization (PSO) approach. Soft Computing Techniques in Solid Waste and Waste Water Engineering. Elsevier. http://dx.doi.org/10.1016/B978-0-12-824463-0.00027-6
2) Zhang BY, Matchinski EJ, Chen B, **Ye XD**, Jing L, Lee K (2019). Marine oil spills—oil pollution, sources and effects. In World Seas: An Environmental Evaluation (pp. 391-406). Academic Press. https://doi.org/10.1016/B978-0-12-805052-1.00024-3

3) Chen B, **Ye XD**, Zhang BY, Jing L, Lee K (2019). Marine Oil Spills—Preparedness and Countermeasures. In World Seas: An Environmental Evaluation (pp. 407-426). Academic Press. https://doi.org/10.1016/B978-0-12-805052-1.00025-5

7.3.3. Conference publications and presentations

- Conference proceedings

1) **Ye XD,** Chen B, Zheng JS, Liu B, Zhang BY (2019). An agent-based stochastic-probability simulation modeling for chemical reactions in advanced oxidation processes. 2019 Canadian Society for Civil Engineering (CSCE) Annual Conference proceeding.

- Conference Abstracts and Presentations

1) **Ye XD,** Chen B, Lee K, Storesund R, Zhang BY. (2021). Multi-agent evolutionary population dynamics particle swarm optimization approach for supporting marine oil spill response. The International Chemical Congress of Pacific Basin Societies 2021, December 16-21, 2021, virtual. (Oral presentation).

2) **Ye XD,** Chen B, Lee K, Storesund R, Song X, Zhang B. (2021). An integrated modeling system of Bayesian Network and agent-based modeling for marine oil spill responses. The MPRI Student Research Forum 2021, September 23-24, 2021, virtual. (Oral presentation).

3) **Ye XD,** Chen B, Lee K, Storesund R, Song X, Zhang B. (2021). A marine oil spill response support system by Bayesian Network and agent-based modeling. The

LEADERS & PEOPLE 2021 Symposium on Environmental Research and Career Training, July 20-22, 2021, virtual. (Oral presentation).

4) **Ye XD,** Chen B, Lee K, Storesund R. (2021). A Simulation-based Contingency Planning Tool for Offshore Oil Spill Response. The 2021 International Oil Spill Conference, May 11-14, 2021, virtual. (Poster presentation).

5) **Ye XD**, Chen, B, Lee, K, Storesund, R, Zhang, B. (2020). An oil waste removal planning approach by using dynamic simulations and enhanced particle swarm optimization. The 2020 Multi Partner Research Initiative (MPRI) Student Forum, Nov. 13, 20 and Dec. 4, virtual. (Oral presentation).

6) **Ye XD**, Chen B, Lee K, Storesund R, Zhang B (2020). An Enhanced Simulation and Optimization Coupling Approach for Supporting Marine Oil Spill Responses. The 2020 PEOPLE Network symposium, August 30-31, 2020. (Oral presentation).

7) **Ye XD**, Chen B, Lee K, Storesund R, Zhang B (2020). A multi-agent based multi-objective particle swarm optimization (MMPSO) for the optimal planning of offshore oil decanting system. The 2020 Gulf of Mexico Oil Spill & Ecosystem Science Conference, February 3-6, 2020. (Poster presentation).

8) **Ye XD**, Chen B, Storesund R, Lee K, Zhang B (2019). An Agent-based Simulation Approach for Scaling-up Design of Wastewater Treatment System and A Case Study on Chemical Surfactant Removal. The PEOPLE 2019 symposium, October 17, 2019. (Oral presentation).

9) **Ye XD,** Chen B, Zheng JS, Liu B, Zhang B (2019). An agent-based stochastic-probability simulation modeling for chemical reactions in advanced oxidation processes. The 2019 Canadian Society for Civil Engineering (CSCE) Annual Conference, June 12-15, 2019. (Oral presentation).

10) Liu B, Chen B, Song X, Matchinski EJ, **Ye XD**, Talimi V, Thodi PN, Brown R (2019). A Preliminary Study of Air Bubble Assisted Oil Skimming Process and Decantation in Cold Water. The 42nd AMOP Technical Seminar on Environmental Contamination and Response, June 4-6, 2019.

11) **Ye XD,** Chen B, Storesund R, Lee K (2019). A New Offshore Oil Spill Response Decision Making Method Based on Human Factor Analysis and Fuzzy Preference Evaluation. The 42nd AMOP Technical Seminar on Environmental Contamination and Response, June 4-6, 2019. (Oral presentation).

12) **Ye XD,** Chen B, Wu HJ, Storesund R, Lee K (2019). Cause factor analysis for occurrence of offshore oil spill accidents. The 2019 Gulf of Mexico Oil Spill and Ecosystem Conference, February 6, 2019. (Poster presentation).

13) **Ye XD**, Chen B, Storesund R, Lee K (2018). A New Risk-Human Factor Analysis Method for Oil Spill Response Decision Making. The 41st AMOP Technical Seminar on Environmental Contamination and Response, October 2-4, 2018. (Oral presentation).

14) **Ye XD**, Chen B, Storesund R (2017). A new risk-human factors analysis method for marine oil spill decision making. The PEOPLE 2017 symposium, October 17, 2017. (Oral presentation).

15) **Ye XD**, Chen B, Jing L, Zhang BY (2017). A new optimization-based wastewater treatment network design approach. The 2017 NWWC National Water & Wastewater Conference, November 5-8, 2017. (Poster presentation).

16) **Ye XD,** Chen B, Jing L, Li P (2016). A simulation-based multi-agent particle swarm optimization approach for supporting dynamic decision making in offshore oil spill response. The 39th AMOP Technical Seminar on Environmental Contamination and Response, June 7 to 9, 2016. (Oral presentation).

17) **Ye XD**, Jing L, Chen B, Zhang B (2016). Optimal design of municipal wastewater treatment plant networks under uncertainty. The CWWA National Water and Wastewater Conference, November 13-16, 2016. (Poster presentation).

7.3.4. Recommendations for Future Research

1) For the modeling of emergency response system, the involvement of current commercial or open-source simulation software (e.g., Gnome, Oscar) can be considered as the simulation tool for oil plume trajectory, weathering, and even response techniques. Their comprehensive database can help calibrate, validate, and verify the simulation modeling to make the simulated outcome closer to the actual situation. However, how to couple with optimization model is a challenge. Additionally, expert experience can be added as an essential index rather than provide weighting values in Chapter 6. It could become an improvement by collecting such experience as "storable" information for decision evaluations. Furthermore, marine oil spill accidents are a kind of "unknown" accidents. Every case is unique. Accidents have differences

in location, oil type, occurrence cause, environmental condition, human activity, etc. It is hard to find same accidents. Thus, predicting the occurrence of the next accident or validating the developed models always becomes a challenge. Because the developed system always considers different or more things than the historical case. Thus, developing or finding an interactive or internal validation way could be a possible approach.

2) For the modeling for system optimization, the developed optimization algorithms (MA-PSO, ME-PSO and C-PSO) have been evaluated to show outstanding optimization performance. However, current evaluations only consider the comparisons of other PSO variants and GA. More types of optimization algorithms and optimization problems should be considered to test performances. System optimization has a high potential to cooperate with other decision-making approaches, such as multi-criteria decision making (MCDM) or net environmental benefit analysis (NEBA). The optimization algorithms can help make the trade-offs more efficient.

3) For the modeling of human factor analysis, surveys should be considered. The information should be gathered from experts, stockholders, operators, researchers, decision-makers from different organizations with their unique perspectives and experience. In addition, the analysis of the interactions of different factors at the same level (e.g., organization influence) or among different levels (e.g., unsafe acts and unsafe supervision) should be considered in the HFACS-OS methodology. The factors and categories applied in current HFACS versions were almost independent. That was efficient, but several accidental reasons had to be categorized into more than one HFACS item, which could be overlapped and decrease the system accuracy. Moreover,

cognitive biases were inevitably involved. Suitable investigation approaches should be considered to avoid biases. Besides, the risk factors and non-human factors can be involved to enrich current HFACS-OS version to analyze all possible causation factors.

4) The probability-based methods (e.g., Bayesian network, fault tree analysis, or event tree analysis) could be a kind of efficient approach to improve the performance of current developed emergency response systems. Such methods have the capacity to link different factors (e.g., human factors) into a systemic and logical structure.

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APPENDIX

A. The pseudocodes of the ME-PSO method

- ***Initialization***

Initialize the population, objective function, variables, input parameters, constraints, boundaries, and total iteration.

Calculate the fitness of each search agent

Find G_{best} and P_{best}

- ***Iteration***

```
While (t < Maximum iteration)
    for each search agent
        if mod(t,3)==0
            Compare through multi-agent algorithm
            if f(agent_α) > f(N_α),
                Update the position with Eq. 4.4-4.5
            end
        else
            if bad solution > median_group
                Generate a number from [1,2,3]
                    Update the position of the bad solution with number 1 →
                    Eq. 4.6, number 2 → Eq. 4.7, number 3 → Eq. 4.8
            end
        end
    end
Update w, velocity, fitness value, G_best and P_best with Eq. 4.1-4.3
t=t+1
end
Return G_best
```

B. Variable matrices for dispatch quantities

a) Skimmers

$$\begin{array}{ccc} Skimmer\ type\ 1 & Skimmer\ type\ 2 & Skimmer\ type\ 3 \\ \begin{bmatrix} x_{1111} & x_{1211} & x_{1311} \\ x_{1121} & x_{1221} & x_{1321} \\ x_{1112} & x_{1212} & x_{1312} \\ x_{1122} & x_{1222} & x_{1322} \end{bmatrix} & \begin{bmatrix} x_{2111} & x_{2211} & x_{2311} \\ x_{2121} & x_{2221} & x_{2321} \\ x_{2112} & x_{2212} & x_{2312} \\ x_{2122} & x_{2222} & x_{2322} \end{bmatrix} & \begin{bmatrix} x_{3111} & x_{3211} & x_{3311} \\ x_{3121} & x_{3221} & x_{3321} \\ x_{3112} & x_{3212} & x_{3312} \\ x_{3122} & x_{3222} & x_{3322} \end{bmatrix} \end{array}$$

b) Pumps

$$\begin{array}{cc} Pump\ type\ 1 & Pump\ type\ 1 \\ \begin{bmatrix} y_{1111} & y_{1211} & y_{1311} \\ y_{1121} & y_{1221} & y_{1321} \\ y_{1112} & y_{1212} & y_{1312} \\ y_{1122} & y_{1222} & y_{1322} \end{bmatrix} & \begin{bmatrix} y_{2111} & y_{2211} & y_{2311} \\ y_{2121} & y_{2221} & y_{2321} \\ y_{2112} & y_{2212} & y_{2312} \\ y_{2122} & y_{2222} & y_{2322} \end{bmatrix} \end{array}$$

c) Boom

$$\begin{array}{c} Boom \\ \begin{bmatrix} z_{111} & z_{211} & z_{311} \\ z_{121} & z_{221} & z_{321} \\ z_{112} & z_{212} & z_{312} \\ z_{122} & z_{222} & z_{322} \end{bmatrix} \end{array}$$

d) Vessel

$$\begin{array}{cc} Vessel\ type\ 1 & Vessel\ type\ 2 \\ \begin{bmatrix} v_{111} & v_{211} & v_{311} \\ v_{112} & v_{212} & v_{312} \end{bmatrix} & \begin{bmatrix} v_{121} & v_{221} & v_{321} \\ v_{122} & v_{222} & v_{322} \end{bmatrix} \end{array}$$

C. The unimodal and multi-modal benchmark functions for ME-PSO

Unimodal Function	Dimension	Variable range	f_{min}
$f_1(x)=\sum_{i=1}^{n} x_i^2$	30	[-100, 100]	0
$f_2(x)=\sum_{i=1}^{n} \lvert x_i\rvert+\prod_{i=1}^{n} \lvert x_i\rvert$	30	[-10, 10]	0
$f_3(x)=\sum_{i=1}^{n} (\sum_{j=1}^{i} x_j)^2$	30	[-100, 100]	0
$f_4(x)=\max_i\{\lvert x_i\rvert, 1\le i\le n\}$	30	[-100, 100]	0
$f_5(x)=\sum_{i=1}^{n} [100(x_{i+1}-x_i^2)^2+(x_i-1)^2]$	30	[-30, 30]	0
$f_6(x)=\sum_{i=1}^{n} (x_i+0.5)^2$	30	[-100, 100]	0
$f_7(x)=\sum_{i=1}^{n} (ix_i^4+random[0,1])$	30	[-1.28, 1.28]	0

Multi-modal Function	Dimension	Variable range	f_{min}
$f_8(x)=\sum_{i=1}^{n} (-x_i \sin(\sqrt{\lvert x_i\rvert}))^2$	30	[-500, 500]	0
$f_9(x)=\sum_{i=1}^{n} [x_i^2-10\cos(x_i)+10]$	30	[-5.12, 5.12]	0
$f_{10}(x)=-20e^{-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}}-e^{\frac{1}{n}\sum_{i=1}^{n}\cos(x_i)}+20+e$	30	[-32, 32]	0
$f_{11}(x)=\frac{1}{4000}\sum_{i=1}^{n} x_i^2-\prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	30	[-600, 600]	0
$f_{12}(x)=\frac{\pi}{n}\left\{100\sin^2(\pi y_1)+\sum_{i=1}^{n-1}(y_i-1)^2[1+10\sin^2(\pi y_{i+1})]+(y_n-1)^2\right\}+\sum_{i=1}^{n} u(x_i,10,100,4)$ $y_i=1+\frac{x_i+1}{4}$ $u(x,a,k,m)=\begin{cases} k(x-a)^m & if\ x>a \\ 0 & if\ -a<x<a \\ k(-x-a)^m & if\ x<-a \end{cases}$	30	[-30, 30]	0

$f_{13}(x) = 0.1\left\{sin^2(3\pi x_1) + \sum_{i=1}^{n}(x_i - 1)^2[1 + sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + sin^2(2\pi x_n)]\right\} + \sum_{i=1}^{n}u(x_i, 5,100,4)$	30	[-100, 100]	0

D. Comprehensive optimization results of PSOs on 13 benchmark functions under different scenarios

Function 1 Iter.	Popu.	ME-PSO	EPD-PSO	PSO	MA-PSO
50	50	6.5289E+00	3.9350E+00	5.7859E+02	9.9246E+02
50	100	2.0557E+00	7.1789E-01	4.8723E+02	7.4645E+02
50	150	1.4480E+00	4.7973E-01	4.0990E+02	6.3512E+02
50	200	7.7843E-01	1.7925E-01	3.7639E+02	5.7442E+02
50	300	2.3307E-01	1.1762E-01	3.7365E+02	3.9038E+02
50	400	1.5384E-01	5.5539E-02	2.4382E+02	4.8657E+02
50	500	9.2759E-02	3.5260E-02	2.9787E+02	3.9648E+02
50	1000	3.1319E-02	1.0602E-02	2.5115E+02	3.4275E+02
100	50	1.0270E+00	4.5199E-01	5.3932E+01	1.1420E+02
100	100	2.4779E-01	1.2551E-01	3.3397E+01	6.1880E+01
100	150	1.0159E-01	5.2586E-02	2.4914E+01	4.9168E+01
100	200	6.5382E-02	2.3589E-02	2.0795E+01	4.2010E+01
100	300	2.8111E-02	1.0239E-02	4.0348E+00	3.3031E+01
100	400	2.0752E-02	5.1438E-03	1.4404E+01	6.8782E+00
100	500	7.5110E-03	2.7218E-03	1.1589E+01	1.6619E+01
100	1000	2.3781E-03	1.0148E-03	7.2590E+00	1.2082E+01
200	50	2.5729E-03	3.0785E-03	3.0035E-02	7.7212E-02
200	100	6.6231E-05	1.2068E-04	1.8288E-03	6.5776E-03
200	150	7.4645E-06	9.1086E-06	4.1901E-04	1.6273E-03
200	200	1.1787E-06	4.5632E-06	1.3473E-04	5.7686E-04
200	300	1.8220E-07	3.6778E-07	4.3420E-05	2.0914E-04
200	400	3.9034E-08	6.9230E-08	3.1527E-06	1.3455E-05
200	500	1.5864E-08	2.2769E-08	5.7870E-07	7.0310E-06
200	1000	1.3730E-10	4.1155E-10	1.8767E-07	7.3726E-07
300	50	7.3827E-06	2.3081E-05	1.7285E-05	6.9311E-06
300	100	7.2981E-09	7.6013E-08	1.8363E-07	1.2590E-08
300	150	1.4461E-10	1.2524E-09	5.5631E-09	1.1117E-09
300	200	5.5665E-12	1.6490E-10	4.1102E-10	3.0840E-11
300	300	2.1940E-14	1.8712E-12	1.7705E-10	4.5923E-12
300	400	1.7495E-15	1.0700E-13	2.2019E-14	1.6016E-14
300	500	1.5266E-16	5.7641E-15	4.5835E-16	6.7616E-16
300	1000	1.0732E-20	2.8713E-18	8.9115E-18	7.4709E-19
400	50	1.6980E-07	1.0361E-06	7.8660E-07	2.9306E-10
400	100	1.1796E-12	5.0987E-10	4.0503E-10	6.9824E-15
400	150	2.3707E-15	4.8636E-12	2.4825E-12	1.3996E-17
400	200	9.2329E-18	3.7851E-13	7.8699E-14	5.4915E-20
400	300	7.4342E-22	2.0376E-15	1.9603E-19	5.2801E-23
400	400	1.3448E-23	1.5029E-17	3.3591E-19	1.1245E-26
400	500	3.9294E-25	2.1942E-18	3.7940E-19	2.5799E-29
400	1000	3.9050E-32	6.4331E-24	9.3678E-25	2.4903E-33
500	50	3.9954E-09	4.2809E-08	2.0878E-08	5.3023E-15
500	100	3.5416E-15	1.6952E-11	6.4113E-12	4.4329E-21
500	150	8.7409E-20	3.3396E-14	1.5881E-14	1.8603E-25
500	200	6.3005E-23	1.0865E-14	2.9286E-16	8.7784E-29
500	300	1.0531E-27	3.1474E-18	1.7713E-23	6.8010E-35
500	400	8.4514E-31	4.7409E-20	5.5415E-24	8.6451E-38
500	500	5.9186E-34	1.3435E-21	8.7453E-25	3.0454E-40
500	1000	1.3559E-42	3.1533E-28	5.3492E-30	3.5019E-48
		(+/-)	32/16	48/0	31/17

Function 2 Iter.	Popu.	ME-PSO	EPD-PSO	PSO	MA-PSO
50	50	1.1717E+00	7.7007E-01	1.0287E+01	1.3277E+01
50	100	5.8292E-01	4.2922E-01	9.0156E+00	1.1322E+01
50	150	4.1159E-01	2.4365E-01	8.5409E+00	1.0863E+01
50	200	2.6877E-01	1.9377E-01	8.1037E+00	1.0181E+01
50	300	1.9626E-01	1.1807E-01	7.9135E+00	8.8117E+00
50	400	1.3566E-01	1.0844E-01	8.0628E+00	7.7035E+00
50	500	1.3317E-01	8.3847E-02	8.0345E+00	9.5257E+00
50	1000	6.3654E-02	3.6144E-02	6.5173E+00	7.6505E+00
100	50	3.4357E-01	2.2004E-01	2.3894E+00	3.5689E+00
100	100	1.6949E-01	9.2172E-02	1.9465E+00	2.8329E+00
100	150	1.0235E-01	6.5015E-02	1.6581E+00	2.4718E+00
100	200	7.5366E-02	4.8424E-02	1.4875E+00	2.1916E+00
100	300	5.2107E-02	2.8953E-02	9.0065E-01	1.9332E+00
100	400	4.0143E-02	2.2497E-02	1.3300E+00	2.0961E+00
100	500	2.7603E-02	1.7096E-02	9.2090E-01	1.5114E+00
100	1000	1.3128E-02	9.6043E-03	8.5812E-01	1.1950E+00
200	50	1.0714E-02	9.2758E-03	2.8663E-02	4.1601E-02
200	100	1.0389E-03	1.5374E-03	5.8967E-03	1.2934E-02
200	150	4.2350E-04	4.2710E-04	2.1072E-03	5.5743E-03
200	200	1.6021E-04	2.0141E-04	1.0961E-03	3.4356E-03
200	300	3.7427E-05	7.0190E-05	1.2278E-04	1.5683E-03
200	400	1.7674E-05	3.0349E-05	1.5277E-04	1.8252E-03
200	500	1.1615E-05	1.3162E-05	6.5644E-05	5.7525E-04
200	1000	1.0216E-06	1.8423E-06	2.7245E-05	1.2529E-04
300	50	2.5081E-03	3.6914E-03	2.0081E-03	4.3911E-04
300	100	7.2926E-05	1.0305E-04	3.6068E-05	8.6978E-06
300	150	1.0535E-05	3.8135E-06	1.5953E-06	1.6649E-06
300	200	3.2977E-07	7.8496E-07	1.6509E-07	3.0327E-07
300	300	1.4330E-08	6.1737E-08	7.8285E-09	1.4650E-08
300	400	1.1032E-09	5.6506E-09	4.8678E-10	6.6083E-09
300	500	4.4819E-10	4.0929E-10	7.4683E-11	1.6176E-10
300	1000	8.4960E-13	2.3372E-12	2.0040E-12	2.6825E-11
400	50	2.1823E-03	2.9265E-03	6.7989E-04	4.9182E-06
400	100	9.6864E-06	7.6885E-05	6.9300E-05	6.6356E-08
400	150	9.2790E-06	3.2752E-07	2.3323E-09	3.7855E-10
400	200	2.9356E-08	4.1781E-08	8.7499E-11	1.3694E-11
400	300	1.4499E-10	7.0755E-11	2.3270E-13	3.6554E-14
400	400	7.5960E-13	4.6167E-13	8.1097E-15	4.5230E-15
400	500	1.7733E-15	6.9726E-14	1.1625E-14	1.8519E-15
400	1000	1.1086E-19	1.6161E-17	2.2804E-19	4.5123E-19
500	50	1.3163E-03	3.1943E-03	5.1926E-04	1.1699E-07
500	100	2.1323E-05	4.4824E-05	5.6140E-07	1.2339E-11
500	150	1.1124E-07	1.2696E-07	2.2357E-11	5.8998E-14
500	200	9.5081E-10	3.6840E-10	8.9731E-14	1.8865E-15
500	300	9.8054E-14	5.3456E-13	7.2612E-18	1.4922E-20
500	400	3.1428E-16	2.6548E-15	1.1833E-18	8.0179E-20
500	500	1.7400E-19	1.2583E-17	2.2733E-20	9.1254E-24
500	1000	8.5831E-27	4.2820E-22	6.8097E-25	3.2840E-27
		(+/-)	25/23	29/19	29/19

Function 3 Iter.	Popu.	ME-PSO	EPD-PSO	PSO	MA-PSO
50	50	2.2708E+03	2.2027E+03	4.8413E+03	4.8546E+03
50	100	1.1339E+03	1.2467E+03	3.3331E+03	3.7605E+03
50	150	6.8887E+02	7.0035E+02	2.7747E+03	3.3572E+03
50	200	4.0747E+02	4.3623E+02	2.5386E+03	3.0170E+03
50	300	1.8739E+02	2.1179E+02	2.6672E+03	3.0171E+03
50	400	1.2570E+02	8.0075E+01	1.1878E+03	1.2958E+03
50	500	1.0849E+02	5.4533E+01	8.8270E+02	2.5616E+03
50	1000	1.8501E+01	1.4577E+01	1.4090E+03	1.9222E+03
100	50	6.4023E+02	8.7834E+02	2.2058E+03	2.9909E+03
100	100	2.0754E+02	2.5283E+02	1.4242E+03	2.1052E+03
100	150	1.2575E+02	8.6634E+01	1.1803E+03	1.8012E+03
100	200	6.5994E+01	5.4659E+01	1.0703E+03	1.5687E+03
100	300	2.3518E+01	1.8290E+01	5.8371E+02	1.5198E+03
100	400	1.6897E+01	1.0306E+01	8.1899E+02	1.0051E+03
100	500	9.6860E+00	4.0152E+00	8.1633E+02	9.1306E+02
100	1000	3.1470E+00	8.3632E-01	4.8286E+02	9.2300E+02
200	50	2.7552E+02	1.2209E+02	8.3834E+02	1.1051E+03
200	100	5.2353E+01	3.8336E+01	4.5044E+02	7.1004E+02
200	150	1.2228E+01	1.0754E+01	3.4415E+02	5.1889E+02
200	200	5.1645E+00	7.1294E+00	2.5526E+02	4.2827E+02
200	300	1.8112E+00	2.9576E+00	1.2627E+02	3.5663E+02
200	400	1.2457E+00	1.5005E+00	7.2685E+01	5.3145E+02
200	500	5.4701E-01	1.0215E+00	5.6570E+01	1.6572E+02
200	1000	7.9819E-02	1.2318E-01	4.8851E+01	1.0411E+02
300	50	6.1910E+01	1.9496E+02	5.1709E+02	5.7711E+02
300	100	1.5224E+01	2.0804E+01	2.4972E+02	2.7599E+02
300	150	4.1345E+00	1.1012E+01	1.6086E+02	1.9284E+02
300	200	2.5379E+00	5.0528E+00	1.2185E+02	1.4709E+02
300	300	1.0564E+00	7.2311E-01	5.8928E+01	1.5355E+02
300	400	4.0407E-01	3.0226E-01	2.9330E+01	6.8124E+01
300	500	3.0372E-01	2.0154E-01	3.9618E+01	4.7026E+01
300	1000	4.3393E-02	2.7718E-02	1.5153E+01	1.7992E+01
400	50	4.7591E+01	9.8883E+01	4.2104E+02	3.0444E+02
400	100	1.0448E+01	1.9132E+01	1.8834E+02	1.4163E+02
400	150	3.3551E+00	8.6871E+00	1.3067E+02	1.0154E+02
400	200	1.8040E+00	1.3851E+00	9.3147E+01	7.3506E+01
400	300	6.6125E-01	5.2184E-01	1.1600E+02	1.5551E+01
400	400	2.9032E-01	2.5742E-01	3.6041E+01	3.4997E+01
400	500	1.8578E-01	1.2734E-01	2.5734E+01	2.5584E+01
400	1000	1.6465E-02	1.4552E-02	9.1766E+00	5.2656E+00
500	50	2.4365E+01	6.9004E+01	3.6267E+02	1.6564E+02
500	100	5.2175E+00	1.4220E+01	1.6668E+02	8.9044E+01
500	150	3.6146E+00	2.2117E+00	1.0652E+02	4.9776E+01
500	200	1.7071E+00	1.7378E+00	7.6290E+01	3.9506E+01
500	300	4.3530E-01	4.3357E-01	2.1899E+01	2.9539E+01
500	400	1.2379E-01	2.0034E-01	2.1296E+01	2.4201E+01
500	500	1.0729E-01	1.0183E-01	1.3160E+01	4.4883E+00
500	1000	1.4767E-02	5.3458E-03	6.9556E+00	2.0690E+00
		(+/-)	22/26	48/0	48/0

Function 4 Iter.	Popu.	ME-PSO	EPD-PSO	PSO	MA-PSO
50	50	3.4793E-01	1.8764E-01	1.3406E+01	1.6683E+01
50	100	1.4787E-01	9.2863E-02	1.1427E+01	1.4022E+01
50	150	9.2633E-02	7.3717E-02	1.0572E+01	1.3241E+01
50	200	8.0069E-02	3.6266E-02	1.0273E+01	1.2498E+01
50	300	5.6686E-02	2.9177E-02	7.1225E+00	1.3165E+01
50	400	4.1062E-02	2.2036E-02	1.0574E+01	1.1389E+01
50	500	3.5090E-02	1.7721E-02	8.0289E+00	1.0395E+01
50	1000	1.6001E-02	8.2261E-03	8.0536E+00	9.9661E+00
100	50	1.9544E-01	1.3651E-01	7.8908E+00	1.0647E+01
100	100	1.0394E-01	5.6922E-02	6.3167E+00	8.6542E+00
100	150	7.2548E-02	4.3120E-02	5.8066E+00	7.7123E+00
100	200	4.9604E-02	3.0733E-02	5.4953E+00	7.4840E+00
100	300	3.5498E-02	1.8385E-02	4.3198E+00	7.7766E+00
100	400	2.6036E-02	1.4222E-02	4.8958E+00	7.4797E+00
100	500	1.9352E-02	1.0931E-02	5.6846E+00	5.1206E+00
100	1000	1.0223E-02	5.0479E-03	3.5201E+00	4.9060E+00
200	50	8.2563E-02	1.4698E-01	4.6272E+00	6.0537E+00
200	100	5.1825E-02	8.7118E-02	3.2694E+00	4.1554E+00
200	150	3.1452E-02	6.6275E-02	2.7407E+00	3.2753E+00
200	200	2.1397E-02	3.6628E-02	2.4259E+00	2.8072E+00
200	300	1.3535E-02	2.4220E-02	1.4781E+00	2.2894E+00
200	400	1.0228E-02	1.8395E-02	1.7197E+00	2.1660E+00
200	500	8.3488E-03	1.4122E-02	1.7971E+00	1.3677E+00
200	1000	4.3046E-03	7.0271E-03	6.7917E-01	7.5199E-01
300	50	1.3645E-01	8.5922E-02	4.0354E+00	4.3344E+00
300	100	7.7586E-02	4.3749E-02	2.7765E+00	2.7163E+00
300	150	5.1350E-02	3.0103E-02	2.1176E+00	1.8087E+00
300	200	3.9178E-02	2.2288E-02	1.7956E+00	1.4896E+00
300	300	2.0944E-02	1.3043E-02	1.6499E+00	1.5713E+00
300	400	1.5758E-02	9.4639E-03	1.0273E+00	5.6470E-01
300	500	1.4606E-02	7.4337E-03	4.0873E-01	3.9601E-01
300	1000	7.0427E-03	3.3315E-03	3.8800E-01	1.4737E-01
400	50	1.2838E-01	8.3508E-02	3.6948E+00	3.3311E+00
400	100	6.4040E-02	4.5501E-02	2.5030E+00	1.7896E+00
400	150	4.4428E-02	2.4093E-02	1.9695E+00	1.2315E+00
400	200	2.8370E-02	2.4005E-02	1.5338E+00	1.0230E+00
400	300	2.0563E-02	1.5136E-02	1.1954E+00	9.7177E-01
400	400	1.5465E-02	8.4326E-03	9.7677E-01	1.4135E-01
400	500	1.3048E-02	7.9252E-03	5.5476E-01	1.5613E-01
400	1000	6.6036E-03	3.6371E-03	3.0038E-01	4.0881E-02
500	50	9.7857E-02	9.3819E-02	3.6599E+00	2.7320E+00
500	100	5.7718E-02	3.6233E-02	2.4942E+00	1.4484E+00
500	150	4.5369E-02	2.8768E-02	1.7553E+00	8.8255E-01
500	200	2.3820E-02	1.9065E-02	1.4730E+00	6.1519E-01
500	300	1.8953E-02	1.3459E-02	9.2764E-01	2.8686E-01
500	400	1.4046E-02	8.5261E-03	4.5123E-01	4.9526E-01
500	500	1.0605E-02	7.6491E-03	3.4564E-01	1.3282E-01
500	1000	5.9665E-03	3.2928E-03	2.4920E-01	1.3620E-02
		(+/-)	8/40	48/0	48/0

Function 5 Iter.	Popu.	ME-PSO	EPD-PSO	PSO	MA-PSO
50	50	3.1822E+01	1.3508E-01	3.7459E+04	9.9920E+04
50	100	1.0428E+01	5.0858E+00	2.5671E+04	5.6930E+04
50	150	5.8788E+00	3.2715E+00	1.9940E+04	4.6308E+04
50	200	3.2853E+00	1.4266E+00	1.7516E+04	3.7152E+04
50	300	2.3507E+00	1.0253E+00	1.6767E+04	5.0204E+04
50	400	1.2905E+00	6.8210E-01	7.5651E+03	5.0369E+04
50	500	9.8284E-01	2.2535E-01	7.0158E+03	1.1796E+04
50	1000	2.8583E-01	9.1505E-02	8.6120E+03	1.5991E+04
100	50	1.6438E+01	7.9684E+00	1.9049E+03	6.0012E+03
100	100	5.9235E+00	2.9955E+00	1.1513E+03	2.6027E+03
100	150	3.6373E+00	1.1268E+00	8.5816E+02	1.8378E+03
100	200	1.6949E+00	7.8750E-01	7.3228E+02	1.3216E+03
100	300	6.3865E-01	3.2592E-01	1.1424E+03	1.0968E+03
100	400	5.5580E-01	1.0571E-01	5.2191E+02	7.2141E+02
100	500	2.5858E-01	7.6122E-02	2.6387E+02	4.9198E+02
100	1000	5.7427E-02	3.1027E-02	2.8966E+02	5.3638E+02
200	50	4.0552E+00	6.6422E+00	1.1916E+02	1.1816E+02
200	100	3.6753E-01	5.1565E-01	8.9390E+01	7.8932E+01
200	150	1.0369E-01	1.7317E-01	7.4394E+01	6.7166E+01
200	200	4.7860E-02	7.1877E-02	5.9906E+01	6.0753E+01
200	300	7.6992E-03	1.3778E-02	3.0327E+01	2.0067E+01
200	400	3.3540E-03	6.6692E-03	8.0701E+01	2.8586E+01
200	500	1.6030E-03	1.7828E-03	2.2997E+01	1.7315E+01
200	1000	1.4305E-04	2.4447E-04	4.1027E+01	3.9966E+01
300	50	3.6627E+00	2.5614E+00	7.6675E+01	6.4165E+01
300	100	3.6785E-01	1.1972E-01	6.1388E+01	4.2882E+01
300	150	1.0312E-02	1.8101E-02	5.0645E+01	4.4210E+01
300	200	5.9571E-03	6.9924E-03	5.2156E+01	4.4636E+01
300	300	1.2840E-03	1.5336E-03	2.1308E+01	7.4470E+01
300	400	6.2031E-04	5.7271E-04	2.6783E+01	1.9987E+01
300	500	2.6783E-04	3.5380E-04	2.7126E+01	2.6213E+01
300	1000	7.6779E-05	3.2352E-05	4.2567E+01	3.6605E+01
400	50	3.7232E+00	1.1867E+00	7.2361E+01	5.2104E+01
400	100	4.3699E-01	5.5158E-02	5.8896E+01	3.8391E+01
400	150	1.5178E-02	9.6560E-03	4.8524E+01	4.0653E+01
400	200	2.8882E-03	3.2777E-03	4.4574E+01	4.0629E+01
400	300	6.5357E-04	4.0709E-04	2.6599E+01	2.2649E+01
400	400	3.8320E-04	2.1776E-04	2.7054E+01	4.3186E+00
400	500	3.0492E-04	2.4180E-04	2.6200E+01	2.5194E+01
400	1000	5.5337E-05	3.2886E-05	4.0339E+01	3.0821E+01
500	50	1.4671E+00	1.8497E+00	6.3169E+01	4.6363E+01
500	100	1.0687E-01	4.4547E-02	5.7720E+01	3.7066E+01
500	150	1.0143E-02	7.3250E-03	4.4036E+01	3.8105E+01
500	200	2.0484E-03	3.1572E-03	4.5629E+01	3.7801E+01
500	300	8.4433E-04	6.0807E-04	2.6353E+01	2.5256E+01
500	400	2.7010E-04	4.1103E-04	2.6420E+01	2.7841E+01
500	500	1.8729E-04	1.7116E-04	2.6083E+01	2.4796E+01
500	1000	1.7672E-05	5.0439E-05	4.0850E+01	3.3270E+01
		(+/-)	**17/31**	**48/0**	**48/0**

Function 6 Iter.	Popu.	ME-PSO	EPD-PSO	PSO	MA-PSO
50	50	7.9290E+00	2.4883E+00	5.7546E+02	9.9324E+02
50	100	2.2063E+00	9.9575E-01	4.9217E+02	7.3497E+02
50	150	1.3153E+00	4.1971E-01	4.1193E+02	6.3765E+02
50	200	5.3327E-01	1.9081E-01	3.8027E+02	5.9433E+02
50	300	2.4191E-01	1.1802E-01	3.0448E+02	3.9822E+02
50	400	1.3273E-01	4.3180E-02	3.4797E+02	4.0319E+02
50	500	8.5085E-02	3.9030E-02	1.9457E+02	3.6716E+02
50	1000	2.5374E-02	5.6002E-03	2.3784E+02	3.6080E+02
100	50	1.2265E+00	4.0191E-01	5.4469E+01	1.0884E+02
100	100	2.6123E-01	9.0600E-02	3.5380E+01	6.4977E+01
100	150	1.0542E-01	4.7251E-02	2.6393E+01	5.0884E+01
100	200	6.0483E-02	3.2055E-02	2.1153E+01	3.6964E+01
100	300	2.2281E-02	1.1353E-02	1.4858E+01	8.9022E+00
100	400	1.3249E-02	6.7224E-03	2.1001E+01	2.0548E+01
100	500	1.0031E-02	2.8265E-03	7.9054E+00	2.4640E+01
100	1000	2.4369E-03	7.8439E-04	6.2910E+00	1.2965E+01
200	50	2.8752E-03	1.8786E-03	3.2071E-02	6.9252E-02
200	100	8.8017E-05	7.8235E-05	2.5733E-03	6.4782E-03
200	150	7.9685E-06	6.0618E-06	3.2845E-04	1.8163E-03
200	200	2.1257E-06	1.2444E-06	1.3611E-04	6.1439E-04
200	300	4.0517E-07	1.4637E-07	3.2918E-05	1.1326E-04
200	400	7.8954E-08	4.0323E-08	4.4317E-06	1.6932E-05
200	500	2.1802E-08	1.6450E-08	3.1784E-06	1.3938E-06
200	1000	4.1375E-10	2.9818E-10	1.7117E-07	8.8604E-07
300	50	1.1823E-05	7.7288E-05	2.4724E-05	6.8240E-06
300	100	3.5867E-09	4.3917E-08	2.4827E-07	1.8225E-08
300	150	1.2612E-10	1.3239E-09	3.1353E-09	4.4785E-10
300	200	7.6831E-12	1.0860E-10	5.6163E-10	3.3169E-11
300	300	1.9363E-14	1.8754E-12	1.5090E-12	4.5319E-14
300	400	2.0315E-15	8.1613E-14	2.2513E-14	7.7316E-16
300	500	4.1869E-17	8.6620E-15	2.5138E-14	4.2010E-16
300	1000	7.9793E-21	3.4478E-18	1.8871E-17	5.2992E-19
400	50	2.2876E-07	4.0488E-06	8.7565E-07	1.9172E-10
400	100	2.5266E-13	4.8050E-10	2.5438E-10	1.1270E-14
400	150	1.3340E-15	3.4802E-12	2.4016E-12	1.0905E-17
400	200	3.4098E-18	4.1647E-13	3.8670E-14	9.7295E-20
400	300	2.7703E-21	6.1505E-16	3.1750E-17	1.7751E-23
400	400	1.1923E-23	2.1909E-17	9.8876E-18	1.2280E-25
400	500	1.0093E-25	6.2751E-19	2.1288E-20	3.5994E-28
400	1000	1.0098E-31	9.5717E-24	4.3523E-24	1.6332E-33
500	50	1.8241E-08	4.8466E-08	8.6534E-09	1.3912E-14
500	100	2.8649E-16	3.8951E-12	1.1698E-11	4.3205E-20
500	150	6.5643E-20	2.3953E-13	9.6262E-15	2.2166E-25
500	200	1.6624E-23	5.6897E-16	7.0547E-16	1.5038E-28
500	300	6.9820E-28	6.5690E-18	2.8572E-22	0.0000E+00
500	400	6.5889E-30	4.8064E-20	7.3187E-23	0.0000E+00
500	500	5.7624E-33	3.4857E-22	1.2598E-25	0.0000E+00
500	1000	0.0000E+00	6.7276E-27	4.7679E-30	0.0000E+00
		(+/-)	**24/24**	**47/1**	**31/17**

Function 7 Iter.	Popu.	ME-PSO	EPD-PSO	PSO	MA-PSO
50	50	1.0372E+01	1.0363E+01	1.1453E+01	1.1736E+01
50	100	1.0158E+01	1.0036E+01	1.0881E+01	1.1255E+01
50	150	9.9464E+00	9.9974E+00	1.0632E+01	1.0998E+01
50	200	9.8335E+00	9.9182E+00	1.0408E+01	1.0928E+01
50	300	9.6737E+00	9.6496E+00	9.6619E+00	1.1544E+01
50	400	9.5412E+00	9.4982E+00	1.0121E+01	1.0522E+01
50	500	9.5231E+00	9.4340E+00	9.4108E+00	9.9703E+00
50	1000	9.1631E+00	9.1883E+00	9.7891E+00	1.0151E+01
100	50	1.0036E+01	1.0061E+01	1.0820E+01	1.1172E+01
100	100	9.8362E+00	9.8271E+00	1.0203E+01	1.0773E+01
100	150	9.6533E+00	9.5854E+00	1.0074E+01	1.0409E+01
100	200	9.4804E+00	9.4792E+00	9.9335E+00	1.0158E+01
100	300	9.3029E+00	9.2804E+00	1.0502E+01	9.8969E+00
100	400	9.2156E+00	9.2207E+00	9.7879E+00	1.0818E+01
100	500	9.0760E+00	9.0880E+00	9.8956E+00	9.5918E+00
100	1000	8.9353E+00	8.8440E+00	9.2976E+00	9.6717E+00
200	50	9.6443E+00	9.6561E+00	1.0285E+01	1.0575E+01
200	100	9.3057E+00	9.3207E+00	9.8723E+00	1.0278E+01
200	150	9.2964E+00	9.2178E+00	9.7320E+00	9.9958E+00
200	200	9.0480E+00	9.1026E+00	9.5403E+00	9.8054E+00
200	300	8.8695E+00	8.9688E+00	9.5075E+00	8.4756E+00
200	400	8.9157E+00	8.8694E+00	8.6790E+00	9.3582E+00
200	500	8.8902E+00	8.8924E+00	9.0802E+00	9.7472E+00
200	1000	8.5639E+00	8.5675E+00	8.9563E+00	9.1751E+00
300	50	9.4096E+00	9.4843E+00	9.9812E+00	1.0325E+01
300	100	9.2460E+00	9.1131E+00	9.7405E+00	1.0028E+01
300	150	9.0976E+00	8.9891E+00	9.4941E+00	9.8857E+00
300	200	8.9851E+00	8.9656E+00	9.3698E+00	9.6862E+00
300	300	8.8160E+00	8.8128E+00	8.6769E+00	9.2187E+00
300	400	8.8349E+00	8.6907E+00	8.9649E+00	9.2502E+00
300	500	8.6979E+00	8.6288E+00	8.7263E+00	9.6342E+00
300	1000	8.3872E+00	8.4395E+00	8.7653E+00	8.9993E+00
400	50	9.2986E+00	9.3990E+00	9.7273E+00	1.0149E+01
400	100	9.0973E+00	9.0116E+00	9.6180E+00	9.7687E+00
400	150	8.8861E+00	8.9474E+00	9.3752E+00	9.6013E+00
400	200	8.8637E+00	8.7573E+00	9.2941E+00	9.4827E+00
400	300	8.6740E+00	8.7023E+00	9.2546E+00	8.7643E+00
400	400	8.6336E+00	8.6549E+00	9.1844E+00	8.9309E+00
400	500	8.4840E+00	8.5281E+00	8.9675E+00	9.4016E+00
400	1000	8.3039E+00	8.3530E+00	8.6621E+00	8.7190E+00
500	50	9.1995E+00	9.2517E+00	9.8027E+00	1.0102E+01
500	100	9.0122E+00	9.0570E+00	9.5291E+00	9.6390E+00
500	150	8.9127E+00	8.8528E+00	9.2917E+00	9.5179E+00
500	200	8.7783E+00	8.8097E+00	9.1619E+00	9.4684E+00
500	300	8.6295E+00	8.6385E+00	8.7828E+00	9.2889E+00
500	400	8.5534E+00	8.4780E+00	7.9917E+00	9.7076E+00
500	500	8.5149E+00	8.4538E+00	8.4431E+00	9.0370E+00
500	1000	8.2196E+00	8.2041E+00	8.5654E+00	8.8149E+00
		(+/-)	**24/24**	**42/6**	**47/1**

Function 8 Iter.	Popu.	ME-PSO	EPD-PSO	PSO	MA-PSO
50	50	6.5657E+00	3.7420E+00	1.8434E+04	2.8397E+04
50	100	1.6529E+00	1.3354E+00	1.2015E+04	2.1087E+04
50	150	1.2795E+00	2.3693E-01	1.1384E+04	1.6641E+04
50	200	6.9677E-01	1.4116E-01	1.0832E+04	1.6826E+04
50	300	2.0176E-01	5.2901E-02	7.7482E+03	7.2316E+03
50	400	9.0961E-02	4.3477E-02	5.1717E+03	2.1819E+04
50	500	6.2877E-02	1.4179E-02	6.4779E+03	1.5661E+04
50	1000	7.6235E-03	2.0901E-03	5.5317E+03	9.8602E+03
100	50	2.3466E+00	7.4578E-01	2.7573E+03	7.1731E+03
100	100	4.9995E-01	1.5985E-01	1.9736E+03	4.8204E+03
100	150	1.3523E-01	3.5244E-02	1.5654E+03	3.9514E+03
100	200	9.1425E-02	2.2890E-02	1.1215E+03	3.3806E+03
100	300	3.5376E-02	7.2139E-03	1.4133E+03	2.2932E+03
100	400	1.5749E-02	5.9548E-03	9.3585E+02	4.0573E+03
100	500	1.0772E-02	2.1723E-03	4.4801E+02	1.0021E+03
100	1000	1.8214E-03	5.0108E-04	4.7381E+02	1.2384E+03
200	50	1.1256E-01	1.7397E-01	1.5730E+01	4.6200E+01
200	100	7.6808E-03	6.5563E-02	2.3578E+00	9.3002E+00
200	150	6.4294E-03	2.2248E-02	8.7958E-01	1.3619E+00
200	200	2.2764E-03	1.0116E-02	2.7007E-01	1.1414E+00
200	300	1.0325E-03	3.1869E-03	9.6629E-02	3.1810E-03
200	400	1.2724E-04	7.2542E-04	1.3644E-03	1.5512E-02
200	500	1.8725E-04	5.7940E-04	9.2525E-05	3.9211E-05
200	1000	6.1001E-06	1.2951E-04	3.7485E-04	2.2812E-03
300	50	3.7420E-02	1.1249E-02	6.8590E-02	3.6340E-02
300	100	3.9948E-03	3.4980E-03	1.2252E-02	2.3583E-04
300	150	2.4065E-03	2.4077E-03	3.0203E-05	1.2977E-06
300	200	4.3065E-03	3.7011E-04	4.2456E-06	4.5021E-08
300	300	1.9833E-03	2.7646E-05	1.4082E-09	5.8857E-12
300	400	7.1044E-04	7.5594E-05	2.1514E-12	6.0064E-15
300	500	2.6278E-04	3.7672E-05	2.3428E-11	3.1247E-15
300	1000	3.2062E-05	2.9372E-06	2.9443E-13	5.8126E-16
400	50	1.7935E-02	3.8311E-02	1.7608E-03	6.3061E-05
400	100	8.0715E-03	8.4876E-03	8.8582E-05	2.3168E-11
400	150	1.4054E-03	5.4904E-04	1.9035E-08	1.7763E-13
400	200	7.9063E-04	1.9744E-04	1.7760E-09	3.4583E-16
400	300	4.2952E-04	4.3772E-05	3.7798E-12	2.6932E-21
400	400	1.2814E-04	3.0704E-05	5.0697E-17	1.7186E-25
400	500	3.5879E-04	1.1274E-05	2.9445E-15	1.1488E-26
400	1000	1.7297E-06	1.8678E-06	5.7445E-20	8.0040E-27
500	50	2.1694E-02	3.0275E-02	1.4486E-04	4.9599E-11
500	100	1.9903E-03	1.1271E-03	2.4866E-06	6.9495E-18
500	150	1.3506E-03	6.1839E-04	8.1243E-10	7.1838E-21
500	200	3.1356E-03	1.2501E-04	2.2151E-11	1.0535E-23
500	300	3.7964E-04	1.8865E-05	6.9655E-20	2.7158E-27
500	400	1.1943E-04	1.7058E-05	1.3926E-19	1.0461E-26
500	500	2.7282E-05	1.7147E-05	2.4700E-21	3.0679E-28
500	1000	2.3091E-06	8.1908E-07	7.6957E-24	1.0669E-26
		(+/-)	**13/35**	**25/23**	**23/25**

Function 9 Iter.	Popu.	ME-PSO	EPD-PSO	PSO	MA-PSO
50	50	9.9454E-02	5.2263E-02	8.8581E+00	1.5505E+01
50	100	3.0162E-02	9.5311E-03	7.1471E+00	1.1794E+01
50	150	1.6974E-02	5.1910E-03	6.3583E+00	9.9129E+00
50	200	7.2875E-03	3.5648E-03	5.9977E+00	9.0834E+00
50	300	3.9978E-03	1.4444E-03	4.5727E+00	9.5040E+00
50	400	1.6565E-03	6.8026E-04	4.9061E+00	9.0675E+00
50	500	1.0538E-03	4.2136E-04	2.5135E+00	8.9940E+00
50	1000	5.8779E-04	1.3137E-04	3.8422E+00	5.5145E+00
100	50	1.6729E-02	6.1695E-03	8.6826E-01	1.7341E+00
100	100	4.3107E-03	1.2325E-03	4.5969E-01	1.0551E+00
100	150	2.0314E-03	6.7849E-04	3.9051E-01	7.3669E-01
100	200	1.0866E-03	3.5348E-04	3.3581E-01	6.3197E-01
100	300	4.2259E-04	1.3257E-04	1.6324E-01	6.0451E-01
100	400	2.1116E-04	8.8038E-05	3.0497E-01	3.4180E-01
100	500	1.1957E-04	5.8181E-05	4.1916E-01	2.3623E-01
100	1000	4.1113E-05	1.0227E-05	1.0154E-01	1.7470E-01
200	50	5.6992E-05	2.8328E-05	5.3476E-04	1.0167E-03
200	100	1.5322E-06	9.8394E-07	4.1675E-05	1.0597E-04
200	150	1.7333E-07	2.2824E-07	8.7384E-06	1.9711E-05
200	200	3.0566E-08	4.7279E-08	2.2671E-06	9.3753E-06
200	300	4.7209E-09	2.8694E-09	1.9333E-07	5.5445E-07
200	400	5.5119E-10	6.9989E-10	2.2660E-08	1.9130E-06
200	500	1.9665E-10	1.7345E-10	1.0913E-09	3.7030E-08
200	1000	1.1656E-11	4.1167E-12	2.7115E-09	1.3858E-08
300	50	2.3022E-07	3.7166E-07	4.1768E-07	7.8609E-08
300	100	7.6497E-11	1.0057E-09	2.9174E-09	2.2640E-10
300	150	2.6891E-12	1.2969E-11	8.8567E-11	7.1631E-12
300	200	2.6006E-14	1.6853E-12	7.4314E-12	4.6485E-13
300	300	3.1797E-15	6.1231E-14	1.0658E-14	2.4869E-14
300	400	5.8620E-16	4.6896E-15	7.1054E-15	0.0000E+00
300	500	2.1316E-16	1.5277E-15	5.3291E-15	0.0000E+00
300	1000	0.0000E+00	0.0000E+00	3.5527E-17	0.0000E+00
400	50	9.4804E-08	2.2637E-08	5.2621E-09	5.8835E-12
400	100	4.8050E-14	8.0185E-12	8.2421E-12	3.1086E-15
400	150	2.3626E-15	2.6125E-13	8.4786E-14	7.9936E-16
400	200	6.5725E-16	1.2719E-14	9.0772E-15	1.9540E-16
400	300	1.4211E-16	1.2790E-15	0.0000E+00	0.0000E+00
400	400	5.3291E-17	1.7764E-16	0.0000E+00	0.0000E+00
400	500	0.0000E+00	3.5527E-17	0.0000E+00	0.0000E+00
400	1000	0.0000E+00	0.0000E+00	0.0000E+00	0.0000E+00
500	50	7.1809E-10	8.6251E-10	6.7879E-10	1.0516E-14
500	100	4.0323E-15	1.4440E-12	9.7842E-15	6.7502E-16
500	150	6.2172E-16	7.2120E-15	4.9205E-15	1.0658E-16
500	200	2.1316E-16	2.4158E-15	7.4607E-16	5.3291E-17
500	300	3.5527E-17	1.9540E-16	1.7764E-15	0.0000E+00
500	400	0.0000E+00	7.1054E-17	0.0000E+00	0.0000E+00
500	500	0.0000E+00	0.0000E+00	0.0000E+00	0.0000E+00
500	1000	0.0000E+00	0.0000E+00	0.0000E+00	0.0000E+00
		(+/-)	26/22	44/4	34/14

Function 10 Iter.	Popu.	ME-PSO	EPD-PSO	PSO	MA-PSO
50	50	5.1378E-01	3.0822E-01	6.0963E+00	7.4547E+00
50	100	2.5871E-01	1.5580E-01	5.4968E+00	6.8119E+00
50	150	1.5315E-01	1.1218E-01	5.0730E+00	6.3689E+00
50	200	1.3990E-01	8.0563E-02	4.9696E+00	6.0814E+00
50	300	8.2951E-02	5.9556E-02	4.4276E+00	4.9083E+00
50	400	6.7971E-02	3.6005E-02	4.5205E+00	5.9742E+00
50	500	5.0843E-02	2.8333E-02	4.0873E+00	5.5622E+00
50	1000	3.0328E-02	1.5309E-02	4.0359E+00	4.7811E+00
100	50	2.0640E-01	1.1985E-01	1.7227E+00	2.4828E+00
100	100	9.0565E-02	6.7665E-02	1.2878E+00	1.8686E+00
100	150	5.7053E-02	3.8246E-02	1.1581E+00	1.6400E+00
100	200	4.8081E-02	3.0420E-02	1.0232E+00	1.4974E+00
100	300	2.6622E-02	1.8147E-02	6.7959E-01	1.4743E+00
100	400	2.3276E-02	1.0824E-02	7.4158E-01	1.6876E+00
100	500	1.9149E-02	1.0365E-02	5.1347E-01	8.7691E-01
100	1000	8.8299E-03	4.3438E-03	5.8075E-01	7.9147E-01
200	50	9.6566E-03	8.4656E-03	3.2392E-02	5.0419E-02
200	100	1.5963E-03	1.1578E-03	9.8568E-03	1.5097E-02
200	150	4.4115E-04	4.1473E-04	4.1177E-03	7.9471E-03
200	200	2.6305E-04	2.0566E-04	2.4583E-03	4.6956E-03
200	300	1.1226E-04	7.6444E-05	9.6642E-04	2.1607E-03
200	400	3.1935E-05	3.4376E-05	4.0175E-04	1.8380E-03
200	500	2.2628E-05	1.4995E-05	1.1894E-04	4.4174E-04
200	1000	2.7075E-06	2.7898E-06	8.2422E-05	1.7832E-04
300	50	5.3075E-04	6.9631E-04	8.7512E-04	4.2517E-04
300	100	1.0731E-05	3.2923E-05	6.1477E-05	2.2528E-05
300	150	9.9936E-07	4.9363E-06	1.0015E-05	3.6129E-06
300	200	2.0833E-07	1.0294E-06	3.2593E-06	8.1288E-07
300	300	2.1176E-08	2.5283E-07	6.5032E-07	2.1196E-07
300	400	4.3270E-09	4.2451E-08	1.5331E-07	2.4133E-08
300	500	8.5222E-10	1.5541E-08	4.3038E-09	8.4091E-10
300	1000	1.3923E-11	2.0830E-10	5.9877E-10	1.2838E-10
400	50	4.0668E-05	1.2735E-04	5.8167E-05	2.5616E-06
400	100	1.1307E-07	3.1958E-06	2.7113E-06	1.5057E-08
400	150	3.5221E-09	2.6459E-07	3.6059E-07	5.9915E-10
400	200	2.1615E-10	4.5839E-08	2.8290E-08	3.9703E-11
400	300	8.5168E-12	3.7157E-09	5.5036E-10	6.1551E-13
400	400	5.0015E-13	5.1744E-10	4.5833E-10	5.0626E-14
400	500	5.9792E-14	8.9237E-11	2.3015E-11	2.9310E-14
400	1000	1.8368E-14	7.7648E-13	8.9315E-14	1.3429E-14
500	50	2.1644E-05	2.2107E-05	1.5574E-05	1.4451E-08
500	100	1.9169E-09	4.2210E-07	1.7869E-07	8.5932E-12
500	150	1.2461E-11	2.4756E-08	2.1795E-08	7.2973E-14
500	200	4.7628E-13	5.1024E-09	2.0175E-09	2.0819E-14
500	300	3.4461E-14	1.9934E-10	3.2601E-11	1.8652E-14
500	400	2.2098E-14	2.1516E-11	1.1117E-11	1.5099E-14
500	500	1.9504E-14	3.9474E-12	6.4837E-14	1.5099E-14
500	1000	1.4744E-14	3.4106E-14	2.5544E-14	9.3792E-15
		(+/-)	26/22	47/1	30/18

Function 11 Iter.	Popu.	ME-PSO	EPD-PSO	PSO	MA-PSO
50	50	9.2841E-01	6.4586E-01	6.2502E+00	9.7875E+00
50	100	6.6209E-01	4.4502E-01	5.2634E+00	7.3861E+00
50	150	5.1550E-01	3.0612E-01	4.6827E+00	6.7662E+00
50	200	4.0114E-01	2.1111E-01	4.4666E+00	6.3100E+00
50	300	2.6953E-01	1.5889E-01	5.4575E+00	5.1104E+00
50	400	1.9365E-01	7.8095E-02	4.7256E+00	4.8277E+00
50	500	1.4997E-01	6.3775E-02	3.2520E+00	3.2284E+00
50	1000	6.5907E-02	1.7669E-02	3.2278E+00	4.2545E+00
100	50	5.5245E-01	3.5850E-01	1.4769E+00	2.0095E+00
100	100	3.2064E-01	1.3830E-01	1.2776E+00	1.6047E+00
100	150	1.6782E-01	9.6365E-02	1.2286E+00	1.4301E+00
100	200	1.2495E-01	5.7143E-02	1.1803E+00	1.3625E+00
100	300	6.8151E-02	2.6221E-02	1.2832E+00	1.3808E+00
100	400	3.9031E-02	1.4396E-02	1.1145E+00	1.1836E+00
100	500	2.2010E-02	1.0722E-02	1.1000E+00	1.2604E+00
100	1000	6.4677E-03	1.6826E-03	1.0570E+00	1.1141E+00
200	50	1.7425E-02	1.3798E-02	8.3697E-02	1.3963E-01
200	100	5.5092E-03	1.3131E-02	1.7449E-02	2.8501E-02
200	150	6.1050E-03	8.6568E-04	1.2958E-02	1.7137E-02
200	200	4.3357E-03	4.3710E-03	1.2251E-02	1.0905E-02
200	300	1.2611E-03	4.9296E-07	7.4604E-06	3.4672E-02
200	400	1.3012E-03	2.9919E-07	2.6530E-06	2.2148E-02
200	500	2.7375E-04	7.8795E-04	9.8593E-03	2.5706E-02
200	1000	5.2030E-09	1.0989E-09	1.2395E-02	1.1033E-02
300	50	1.3013E-02	5.6443E-03	1.3039E-02	1.5346E-02
300	100	5.2935E-03	7.0393E-03	1.0457E-02	9.6657E-03
300	150	2.9535E-03	3.4821E-03	1.1075E-02	1.1652E-02
300	200	2.3995E-03	6.8905E-04	1.0954E-02	1.0788E-02
300	300	9.8558E-04	1.4161E-03	1.2316E-02	5.3557E-13
300	400	1.8849E-03	2.7158E-13	2.2151E-02	2.9498E-02
300	500	1.2022E-03	1.1221E-03	2.4610E-02	1.9690E-02
300	1000	0.0000E+00	2.9564E-04	1.1795E-02	1.1123E-02
400	50	6.3419E-03	5.2297E-03	1.1387E-02	1.1090E-02
400	100	8.7861E-03	4.3715E-03	1.1125E-02	1.0704E-02
400	150	3.7254E-03	2.3488E-03	1.0661E-02	1.0534E-02
400	200	1.6931E-03	1.3731E-03	1.2528E-02	9.8296E-03
400	300	2.0633E-03	1.3665E-03	7.7716E-16	0.0000E+00
400	400	2.5577E-03	2.9564E-04	0.0000E+00	2.2127E-02
400	500	1.9526E-03	1.6653E-17	0.0000E+00	7.3960E-03
400	1000	0.0000E+00	0.0000E+00	1.2102E-02	9.1464E-03
500	50	9.9320E-03	1.0796E-02	1.4479E-02	1.2427E-02
500	100	4.6473E-03	5.9282E-03	1.1071E-02	1.0457E-02
500	150	1.6015E-03	3.3275E-03	1.1586E-02	9.6972E-03
500	200	5.8758E-03	3.2331E-03	9.8844E-03	8.3194E-03
500	300	1.4765E-03	3.9400E-04	3.4492E-02	1.7226E-02
500	400	1.2276E-03	3.3307E-18	0.0000E+00	1.4780E-02
500	500	1.0737E-03	8.8012E-04	1.2321E-02	0.0000E+00
500	1000	3.9400E-04	0.0000E+00	1.5364E-02	8.7154E-03
		(+/-)	11/37	42/6	45/3

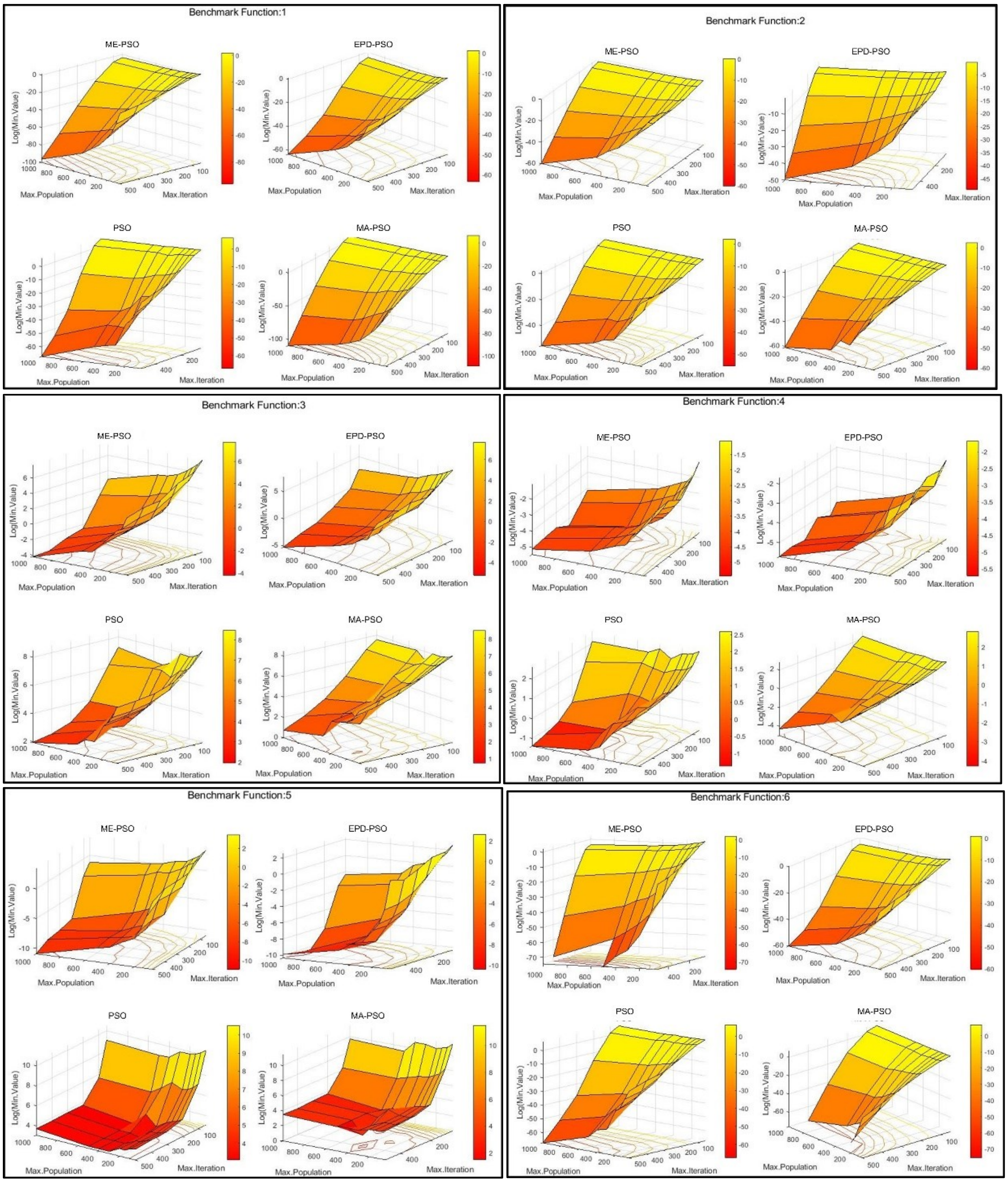
Function 12 Iter.	Popu.	ME-PSO	EPD-PSO	PSO	MA-PSO
50	50	6.2541E-02	3.9618E-02	4.8407E+00	7.8009E+00
50	100	2.0805E-02	1.6006E-02	3.4096E+00	5.7933E+00
50	150	1.2343E-02	7.7861E-03	2.8344E+00	4.9923E+00
50	200	7.5215E-03	3.7319E-03	2.6071E+00	4.5406E+00
50	300	4.2345E-03	1.9661E-03	1.8883E+00	4.3086E+00
50	400	3.0023E-03	1.0245E-03	2.0008E+00	4.3553E+00
50	500	1.6100E-03	9.5690E-04	1.6316E+00	2.8671E+00
50	1000	3.3895E-04	1.9560E-04	1.3803E+00	2.6081E+00
100	50	4.5790E-03	2.4713E-03	4.8292E-01	1.4696E+00
100	100	1.0576E-03	6.3211E-04	1.9902E-01	7.4927E-01
100	150	7.3194E-04	2.9401E-04	1.2802E-01	5.1173E-01
100	200	3.8934E-04	1.8295E-04	9.1895E-02	3.0646E-01
100	300	1.9983E-04	8.1303E-05	1.8389E-02	8.4229E-02
100	400	1.0784E-04	4.5179E-05	1.5577E-02	3.3647E-01
100	500	7.7056E-05	3.2447E-05	4.9717E-02	9.8998E-02
100	1000	1.6845E-05	8.1951E-06	3.1701E-02	6.5007E-02
200	50	6.4129E-06	9.0451E-06	6.3988E-02	6.9803E-02
200	100	3.8950E-07	3.9882E-07	2.3153E-02	3.7408E-02
200	150	6.9999E-08	3.4696E-08	1.3893E-02	1.7196E-02
200	200	1.2055E-08	2.3767E-08	1.2927E-02	2.5224E-02
200	300	2.9799E-09	1.2442E-09	1.0461E-01	2.4864E-07
200	400	3.0449E-10	2.9516E-10	1.5588E-09	1.6673E-08
200	500	1.2112E-10	1.5825E-10	1.6869E-09	1.8097E-08
200	1000	2.3424E-12	2.8725E-12	2.0927E-03	5.0085E-08
300	50	7.1731E-08	6.3569E-08	5.3301E-02	5.7374E-02
300	100	2.3346E-11	3.2369E-10	2.3188E-02	2.9273E-02
300	150	2.6163E-13	9.2861E-12	2.0913E-02	3.0310E-02
300	200	2.0906E-14	5.6190E-13	1.8821E-02	1.8824E-02
300	300	1.0363E-16	2.8175E-14	1.2842E-15	8.1212E-17
300	400	5.1222E-18	1.1897E-15	1.6061E-17	4.7434E-19
300	500	2.6937E-19	1.3235E-16	2.3724E-17	1.9737E-16
300	1000	8.6032E-23	2.4796E-20	4.9589E-18	1.8698E-16
400	50	8.3184E-10	2.6941E-09	4.4006E-02	5.6358E-02
400	100	1.5940E-15	1.6288E-12	2.1940E-02	4.7016E-02
400	150	1.6648E-17	5.9311E-14	2.0923E-02	3.5511E-02
400	200	2.3656E-20	1.6993E-15	1.1508E-02	1.7756E-02
400	300	2.0761E-23	8.6345E-18	1.2652E-20	5.4921E-27
400	400	1.4631E-25	2.8649E-19	1.9102E-23	3.7376E-27
400	500	7.4772E-27	8.8352E-21	5.4383E-22	1.5240E-30
400	1000	1.6116E-31	1.1305E-25	2.0923E-03	7.8310E-31
500	50	1.4260E-11	4.7817E-10	3.2402E-02	7.2095E-02
500	100	2.6137E-15	7.4050E-14	2.9282E-02	2.7162E-02
500	150	1.0352E-22	1.8697E-16	1.1508E-02	1.8812E-02
500	200	1.1178E-25	5.9398E-17	1.2554E-02	1.5664E-02
500	300	3.4359E-29	5.4868E-20	1.0305E-25	1.5705E-31
500	400	1.7463E-31	1.4654E-22	2.6795E-26	1.5705E-31
500	500	1.5869E-31	1.3090E-23	1.0461E-01	1.5705E-31
500	1000	1.5705E-31	5.4466E-30	4.7675E-30	1.5705E-31
		(+/-)	28/20	48/0	39/9

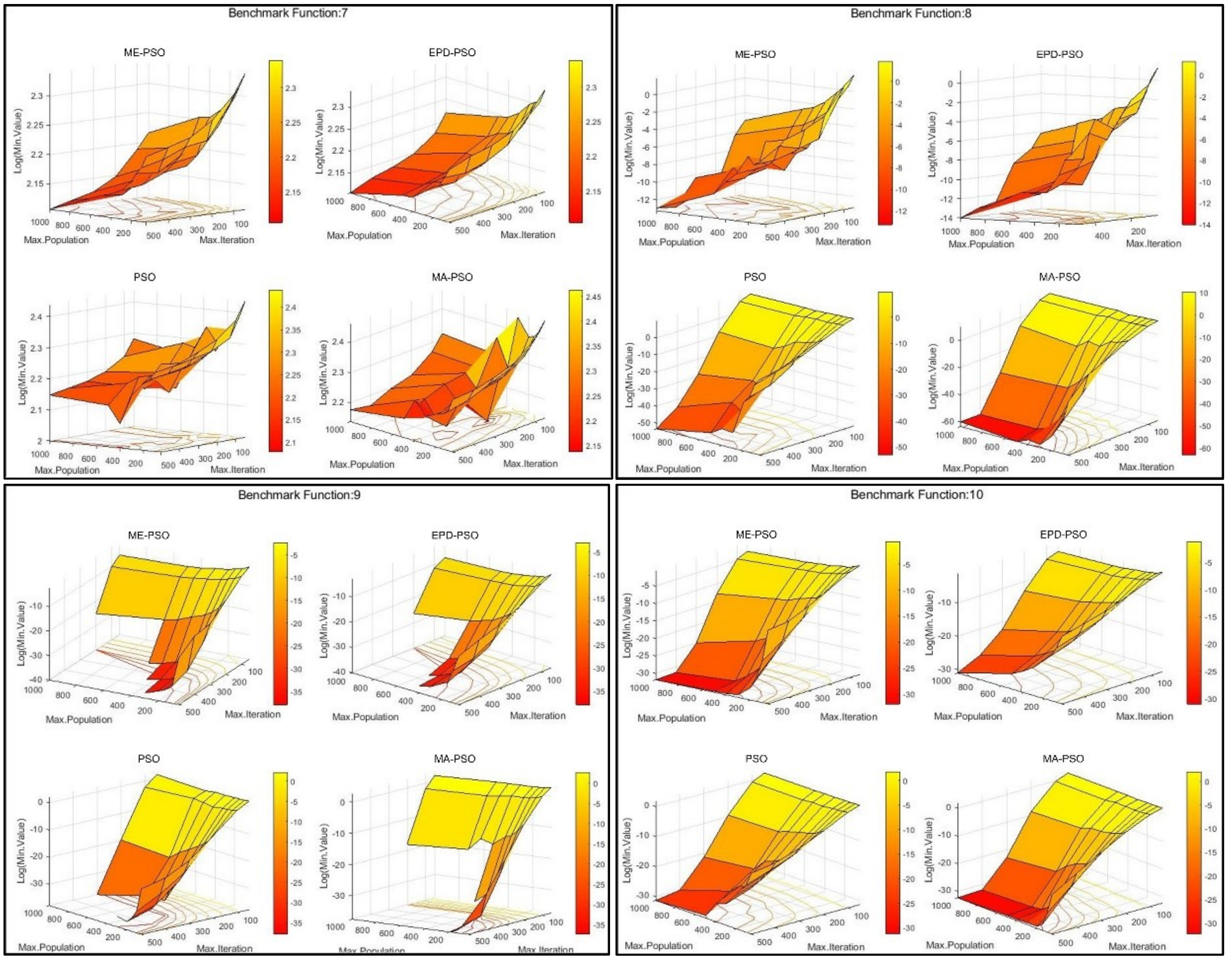
Function 13		ME-PSO	EPD-PSO	PSO	MA-PSO
Iter.	Popu.				
50	50	9.2361E-01	2.8147E-01	7.2111E+04	2.4119E+05
50	100	3.6640E-01	1.7928E-01	4.6989E+04	1.0744E+05
50	150	1.6637E-01	9.2155E-02	4.0356E+04	9.1588E+04
50	200	1.1677E-01	5.8716E-02	3.3354E+04	7.4745E+04
50	300	5.7338E-02	2.4751E-02	2.1432E+04	9.0826E+04
50	400	4.1391E-02	2.2525E-02	1.9447E+04	4.6868E+04
50	500	2.6859E-02	1.1869E-02	3.0836E+04	2.4567E+04
50	1000	1.1378E-02	3.3757E-03	1.4482E+04	3.5457E+04
100	50	2.3122E-01	1.1791E-01	4.5769E+03	1.7771E+04
100	100	9.5360E-02	4.3926E-02	2.6528E+03	1.1873E+04
100	150	4.5785E-02	2.0016E-02	1.4775E+03	7.7447E+03
100	200	2.0516E-02	1.4676E-02	1.4806E+03	8.1006E+03
100	300	1.1086E-02	7.1154E-03	6.0768E+02	6.2254E+03
100	400	7.1993E-03	4.9000E-03	8.7234E+02	1.5679E+03
100	500	4.6089E-03	1.9286E-03	2.9255E+02	2.6792E+03
100	1000	1.7721E-03	4.9481E-04	3.0866E+02	1.7481E+03
200	50	1.0692E-02	4.9218E-03	1.7440E+02	6.7376E+02
200	100	1.1631E-03	1.0133E-03	1.1729E+02	3.7027E+02
200	150	2.8044E-04	1.9812E-04	9.8838E+01	2.3171E+02
200	200	3.6308E-04	1.9166E-04	8.3194E+01	2.0910E+02
200	300	2.6365E-07	3.0950E-07	8.8092E+01	1.6915E+02
200	400	1.0031E-07	5.8864E-08	8.2430E+01	1.6097E+02
200	500	3.1922E-08	2.2958E-08	4.5478E+01	1.3141E+02
200	1000	6.3130E-10	8.4834E-10	2.4836E+01	9.2741E+01
300	50	8.4162E-03	2.8512E-03	1.1050E+02	1.5488E+02
300	100	9.7446E-04	5.5746E-04	7.1131E+01	1.0926E+02
300	150	1.8968E-04	4.1041E-09	5.4929E+01	9.3753E+01
300	200	2.4150E-12	1.2325E-10	4.1641E+01	8.2800E+01
300	300	9.2105E-15	3.1981E-12	9.0964E+00	1.0263E+02
300	400	1.9065E-15	6.5396E-14	2.8997E+01	4.3325E+01
300	500	4.4349E-17	1.3000E-14	2.8771E+01	4.1507E+01
300	1000	1.5023E-20	1.0849E-17	2.3385E+00	2.2868E+01
400	50	7.8229E-03	1.8186E-03	8.3982E+01	1.1153E+02
400	100	9.2500E-04	7.1193E-04	5.0557E+01	8.2790E+01
400	150	5.5737E-04	3.5596E-04	3.6172E+01	6.9938E+01
400	200	1.7798E-04	1.3579E-13	2.1116E+01	4.3111E+01
400	300	9.2954E-21	2.2651E-14	8.2584E-09	3.4812E-08
400	400	1.0790E-23	2.2573E-17	1.6833E-04	1.3849E-05
400	500	1.8744E-25	6.7903E-19	7.9222E+00	1.0277E-11
400	1000	4.1585E-32	8.3042E-24	4.4440E-01	7.8651E+00
500	50	4.7359E-03	1.1052E-03	7.5476E+01	1.0918E+02
500	100	9.0160E-04	5.9171E-12	4.0645E+01	6.6149E+01
500	150	1.8968E-04	2.8519E-14	2.5923E+01	4.6846E+01
500	200	3.2794E-23	6.2826E-16	1.6246E+01	3.1018E+01
500	300	9.6036E-28	1.4255E-17	4.6434E-01	9.2836E+01
500	400	2.5187E-30	1.4856E-19	1.9210E-02	2.8560E+01
500	500	2.0846E-32	3.5140E-21	6.6641E-02	6.5354E-01
500	1000	1.3498E-32	1.7180E-27	7.9616E-02	3.6451E+00
		(+/-)	16/32	48/0	48/0

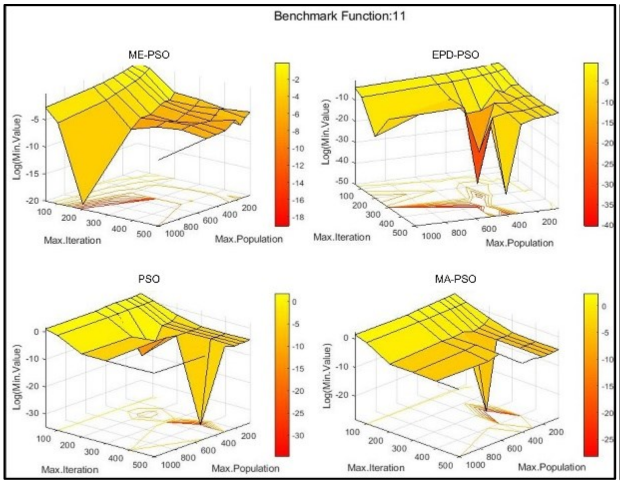
> 10	
8 ~ 10	
6 ~ 8	
4 ~ 6	
2 ~ 4	
1 ~ 2	
0.8 ~ 1	
0.6 ~ 0.8	
0.4 ~ 0.6	
0.2 ~ 0.4	
0 ~ 0.2	
0	
-0.2 ~ 0	
-0.4 ~ -0.2	
-0.6 ~ -0.4	
-0.8 ~ -0.6	
-1 ~ -0.8	
Other	

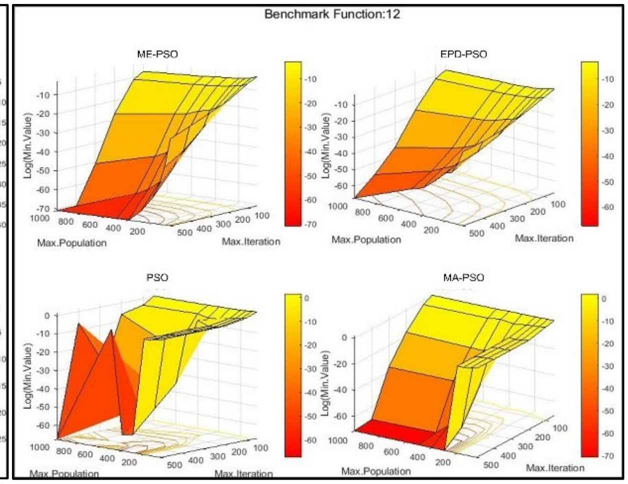
$$Index = \frac{PSO_i - PSO_{ME-PSO}}{PSO_{ME-PSO}}$$

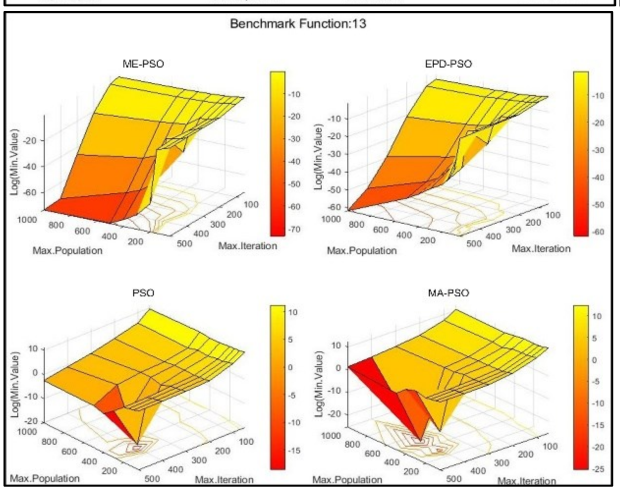
A. E. The response surfaces of PSOs to 13 benchmark functions




Benchmark Function:7
ME-PSO
EPD-PSO
PSO
MA-PSO
Benchmark Function:8
ME-PSO
EPD-PSO
PSO
MA-PSO
Benchmark Function:9
ME-PSO
EPD-PSO
PSO
MA-PSO
Benchmark Function:10
ME-PSO
EPD-PSO
PSO
MA-PSO
Log(Min.Value)
Max.Population
Max.Iteration







Note: The missing surface means that the results reach f_{min} ($f_{min} = 0$).

F. Ranking results based on Holm-Bonferroni procedure for the PSO algorithms with the consideration of maximum iteration (a) and population size (b)

(A)

Iter.	Rank	Algorithm	z	p	θ	h	Score
50	1	EPD-PSO	-	-	-	-	3.9231
	2	ME-PSO	-1.7280	4.1995E-02	0.0500	1	3.0481
	3	PSO	-3.8358	6.2600E-05	0.0250	1	1.9808
	4	MA-PSO	-5.6777	6.8600E-09	0.0167	1	1.0481
100	1	EPD-PSO	-	-	-	-	3.9519
	2	ME-PSO	-1.7850	3.7135E-02	0.0500	1	3.0481
	3	PSO	-4.0067	3.0800E-05	0.0250	1	1.9231
	4	MA-PSO	-5.6777	6.8600E-09	0.0167	1	1.0769
200	1	ME-PSO	-	-	-	-	3.5673
	2	EPD-PSO	-0.4747	3.1749E-01	0.0500	0	3.3269
	3	PSO	-3.2851	5.0970E-04	0.0250	1	1.9038
	4	MA-PSO	-4.6713	1.5000E-06	0.0167	1	1.2019
300	1	ME-PSO	-	-	-	-	3.2692
	2	EPD-PSO	-1.1393	1.2728E-01	0.0500	0	2.6923
	3	MA-PSO	-1.9369	2.6381E-02	0.0250	0	2.2885
	4	PSO	-2.9433	1.6200E-03	0.0167	1	1.7788
400	1	ME-PSO	-	-	-	-	2.9808
	2	MA-PSO	-0.3418	3.6625E-01	0.0500	0	2.8077
	3	EPD-PSO	-1.0824	1.3955E-01	0.0250	0	2.4327
	4	PSO	-2.1078	1.7500E-02	0.0167	0	1.9135

500	1	ME-PSO	-	-	-	-	2.9904
	2	MA-PSO	-0.3988	3.4503E-01	0.0500	0	2.7885
	3	EPD-PSO	-1.1583	1.2337E-01	0.0250	0	2.4038
	4	PSO	-1.9938	2.3100E-02	0.0167	0	1.9808

(B).

Popu.	Rank	Algorithm	z	p	θ	h	Score
50	1	EPD-PSO	-	-	-	-	3.153846
	2	ME-PSO	-0.12659	0.449632	0.05	0	3.089744
	3	PSO	-2.37994	0.008658	0.025	1	1.948718
	4	MA-PSO	-2.65844	3.93E-03	0.016667	1	1.807692
100	1	ME-PSO	-	-	-	-	3.230769
	2	EPD-PSO	-0.10127	0.459667	0.05	0	3.179487
	3	MA-PSO	-2.81035	0.0024744	0.025	1	1.807692
	4	PSO	-2.86099	2.11E-03	0.016667	1	1.782051
150	1	EPD-PSO	-	-	-	-	3.205128
	2	ME-PSO	-0.12659	0.449632	0.05	0	3.141026
	3	PSO	-2.6078	0.004556	0.025	1	1.884615
	4	MA-PSO	-2.83567	2.29E-03	0.016667	1	1.769231
200	1	ME-PSO	-	-	-	-	3.217949
	2	EPD-PSO	-0.17723	0.429664	0.05	0	3.128205
	3	PSO	-2.65844	0.003925	0.025	1	1.871795
	4	MA-PSO	-2.83567	2.29E-03	0.016667	1	1.782051
300	1	ME-PSO	-	-	-	-	3.051282

	2	EPD-PSO	-0.07596	0.469727	0.05	0	3.012821
	3	MA-PSO	-2.00016	0.022741	0.025	1	2.038462
	4	PSO	-2.22803	1.29E-02	0.016667	1	1.923077
400	1	ME-PSO	-	-	-	-	3.051282
	2	EPD-PSO	-0.02532	0.489901	0.05	0	3.038462
	3	PSO	-1.89889	0.02879	0.025	0	2.089744
	4	MA-PSO	-2.30398	0.010612	0.016667	1	1.884615
500	1	ME-PSO	-	-	-	-	3.076923
	2	EPD-PSO	-0.02532	0.489901	0.05	0	3.064103
	3	MA-PSO	-2.07612	0.018942	0.025	1	2.025641
	4	PSO	-2.22803	1.29E-02	0.016667	1	1.948718
1000	1	ME-PSO	-	-	-	-	3.346154
	2	EPD-PSO	-0.30382	0.380632	0.05	0	3.192308
	3	PSO	-2.93694	0.001657	0.025	1	1.858974
	4	MA-PSO	-2.98758	1.41E-03	0.016667	1	1.833333

G. The procedure of the fuzzy TOPSIS:

Step 1. Setup the representations of criteria and the alternatives.

In fuzzy TOPSIS, the fuzzy rating of k^{th}decision maker to i^{th} alternative A_i with j^{th}criteria C_j is represented as $\tilde{x}_{ij}^k = (a_{ij}^k, b_{ij}^k, c_{ij}^k)$ and the weight of criterion C_j is represented as $\widetilde{w}_j = (w_{j1}, w_{j2}, w_{j3})$.

Step 2. Construct the fuzzy matrix.

The fuzzy matrix $\widetilde{D}^k$ of decision maker k (Eq. 2) is clearly expressed as follows:

$$\widetilde{D}^k = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} \tilde{x}_{11}^k & \tilde{x}_{12}^k & \cdots & \tilde{x}_{1n}^k \\ \tilde{x}_{21}^k & \tilde{x}_{22}^k & \cdots & \tilde{x}_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1}^k & \tilde{x}_{m2}^k & \cdots & \tilde{x}_{mn}^k \end{bmatrix} \end{array} \qquad (2)$$

$$i = 1,2, \cdots m; j = 1,2, \cdots n; k = 1,2, \cdots K$$

The weighting matrix $\widetilde{W}$ for criteria (Eq. 3) is shown as follows:

$$\widetilde{W} = [\widetilde{w}_1 \quad \widetilde{w}_2 \quad \cdots \quad \widetilde{w}_j] \qquad (3)$$

Step 3. Combine decision matrices with aggregated fuzzy ratings for alternatives.

The fuzzy matrices from different decision makers (*k*) are further combined into one fuzzy matrix. The aggregated fuzzy rating of alternative A_i with criteria C_j, $\widetilde{x_{ij}} = (a_{ij}, b_{ij}, c_{ij})$ is calculated by Eq. 4:

$$a_{ij} = \min_k \{a_{ij}^k\}, b_{ij} = \frac{1}{k} \sum_1^k b_{ij}^k, c_{ij} = \max_k \{c_{ij}^k\} \qquad (4)$$

Step 4. Generate the normalized fuzzy decision matrix.

The normalized fuzzy decision matrix is represented as $\tilde{R} = [\tilde{r}_{ij}]$, the normalized formulas are shown in Eq 5 and 6:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), and\ c_j^* = \max_i\{c_{ij}\}; (benefit\ criteria) \qquad (5)$$

And,

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), and\ a_j^- = \min_i\{a_{ij}\}; (cost\ criteria) \qquad (6)$$

Step 5. Construct the weighted normalized fuzzy decision matrix.

The weighted normalized fuzzy decision matrix is constructed to consider the different importance of each criterion. It is denoted by $\tilde{V} = [\tilde{v}_{ij}]$, where

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j \qquad (7)$$

Step 6. Determine the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS).

The Fuzzy Positive Ideal Solution (FPIS, A^*) and Fuzzy Negative Ideal Solution (FNIS, A^-) can be defined as follows:

$$A^* = (\tilde{v}_1^*, \tilde{v}_2^*, \cdots, \tilde{v}_n^*), \text{where } \tilde{v}_j^* = \max_i\{v_{ij3}\} \qquad (8)$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \cdots, \tilde{v}_n^-), \text{where } \tilde{v}_j^- = \min_i\{v_{ij1}\} \qquad (9)$$

Step 7. Compute the distance from each alternative to the FPIS and FNIS.

The distance between two triangular FNs can be calculated by a vertex method (Chen, 2000). If there were two triangular FNs, $\tilde{x} = (a_1, b_1, c_1)$ and $\tilde{y} = (a_2, b_2, c_2)$, then the distance is:

$$\mathrm{d}(\tilde{x},\tilde{y}) = \sqrt{\frac{1}{3}[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]} \quad (10)$$

Thus, the distances (d_i^*, d_i^-) of each alternative between A^* or A^- can be obtained as follows:

$$d_i^* = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^*\right), d_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right) \quad (11)$$

Step 8. Demonstrate the closeness coefficient CC_i for each alternative to the ideal solution.

For each alternative A_i, the closeness coefficient CC_i can be calculated by Eq. 12 as follows:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*} \quad (12)$$

Step 9. Rank the alternatives.

The alternatives are ranked based on the relative closeness to the ideal solution. The ranking order of all alternatives was determined from the highest to the lowest based on the values of CC_i. The alternative with highest CC_i demonstrates the best alternative, which is the most efficient strategy to the MCDM problem.

H. Triangular fuzzy number (FN) for the importance of criteria

Linguistic term of rank	Triangular FN
Very high	(9,10,10)
High	(7,9,10)
Medium	(3,5,7)
Low	(1,3,5)
Very Low	(1,1,3)

I. Non-repeated combinations of criteria weights to sensitivity analysis

Scenario	Criteria weights				
	W_{O1}	W_{O2}	W_{O3}	W_{O4}	W_{O5}
1 (original)	H	H	M	L	VL
2	H	H	L	M	VL
3	H	H	L	VL	M
…	…	…	…	…	…
59	VL	M	H	L	H
60	VL	M	L	H	H

(Note: H, high; M, medium; L, low; VL, very low)

J. Original Results of PSO variants on algorithm comparison by benchmarked functions

No.	V1	V2	V3	V4	V5	V6
Name	PSO	MAPSO	MABBPSO	BBPSO	BBMAPSO	BBMABBPSO
No.	V7	V8	V9	V10	V11	V12
Name	EPDPSO	EPDMAPSO	EPDMABBPSO	EPDBBPSO	EPDBBMAPSO	EPDBBMABBPSO

Note: The values in the tables are the mean of results in 100 runs.

1) Average optimized results

	Benchmarked Function												
	Population Size: 100												
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	1.0227E-02	1.1634E-02	2.4699E+02	2.7421E+00	8.0129E+01	1.0624E-02	9.6074E+00	1.1383E+01	1.7153E-04	2.1665E-02	4.7472E-02	2.2120E-02	1.1036E+02
V2	7.6656E-08	1.2756E-05	2.7100E+02	1.7060E+00	4.7400E+01	3.6655E-08	9.8493E+00	2.4539E-03	6.4829E-10	3.4197E-05	1.0609E-02	2.4052E-02	1.5826E+02
V3	2.0620E-03	2.4219E-02	1.0569E+03	4.4895E+00	1.0205E+02	1.1015E-02	9.8028E+00	1.5267E+01	3.0500E-05	1.0157E-02	2.7729E-02	4.7029E-02	1.5165E+02
V4	1.4491E+02	1.3552E+01	3.5412E+03	2.2633E+01	6.7649E+03	1.3381E+02	9.9560E+00	1.3302E+03	2.1384E+00	3.3810E+00	2.1459E+00	3.5458E+00	6.3065E+04
V5	1.2698E+02	1.3227E+01	3.7648E+03	2.2921E+01	7.0817E+03	1.2609E+02	1.0041E+01	1.2678E+03	1.9525E+00	3.3550E+00	2.1285E+00	3.6788E+00	5.7715E+04
V6	1.3395E+02	1.3276E+01	3.4384E+03	2.2421E+01	8.9739E+03	1.3312E+02	9.9404E+00	1.3641E+03	2.7150E+00	3.5535E+00	2.1021E+00	3.4328E+00	6.5648E+04
V7	2.0477E-05	1.5027E-02	5.9248E-01	3.4500E-03	8.1963E-03	1.3808E-03	8.9664E+00	7.4054E-04	2.8754E-07	5.1362E-03	3.3566E-03	2.1877E-05	6.0377E-04
V8	6.7665E-09	8.0041E-02	1.4298E+01	2.1906E-02	3.2191E-01	4.6861E-02	8.8572E+00	7.8341E-03	5.9431E-04	3.2775E-02	1.0294E-01	6.8458E-04	1.1871E-02
V9	1.7274E-05	1.3695E-01	6.3551E+01	3.0828E-02	5.8650E-01	9.2843E-02	9.1384E+00	6.0534E-03	1.6202E-03	5.5954E-02	1.2671E-01	1.1242E-03	1.2803E-02
V10	1.5747E+02	1.3671E+01	3.4654E+03	2.2737E+01	6.5133E+03	1.2886E+02	1.0116E+01	1.6020E+03	1.8825E+00	3.5612E+00	2.2839E+00	3.1363E+00	5.8449E+04
V11	1.3358E+02	1.3358E+02	3.7627E+03	2.3065E+01	8.2347E+03	1.2755E+02	1.0110E+01	1.2868E+03	2.0303E+00	3.0511E+00	2.1909E+00	3.6618E+00	6.5461E+04
V12	1.3991E+02	1.3420E+01	3.5631E+03	2.2729E+01	6.3389E+03	1.1736E+02	1.0015E+01	1.1481E+03	2.2628E+00	3.2480E+00	2.2018E+00	3.5837E+00	6.4416E+04
	Population Size: 300												
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	9.7162E-04	2.9834E-03	1.2345E+02	1.6360E+00	6.1912E+01	8.1850E-04	9.0839E+00	2.6214E+00	1.3684E-05	5.6224E-03	1.6603E-02	1.1790E-03	5.5699E+01

V2	2.6725E-11	1.9550E-07	1.0216E+02	5.9460E-01	3.8910E+01	1.9149E-11	9.3065E+00	6.6157E-07	2.5205E-13	9.0185E-07	1.2153E-02	4.1846E-03	7.3484E+01
V3	1.0448E-06	9.7170E-05	4.4121E+02	2.3216E+00	6.0587E+01	1.4053E-06	9.3251E+00	4.2116E-02	1.8133E-08	1.8234E-04	1.0529E-02	2.7195E-02	1.0485E+02
V4	3.3248E+00	5.2683E+00	1.7144E+03	1.6522E+01	2.0184E+02	1.9398E+00	9.2226E+00	6.3925E+01	6.6937E-02	3.6383E-01	7.0433E-01	1.5144E+00	5.8095E+02
V5	3.7343E+00	5.4045E+00	1.7675E+03	1.6954E+01	2.3052E+02	3.7503E+00	9.3355E+00	1.0881E+02	6.3468E-02	3.5641E-01	7.3236E-01	1.4296E+00	7.6776E+02
V6	4.5802E+00	4.6645E+00	1.7769E+03	1.7333E+01	2.6140E+02	3.2811E+00	9.1920E+00	3.9040E+01	4.5565E-02	4.1904E-01	6.6804E-01	1.3649E+00	3.6563E+02
V7	5.1146E-07	1.5823E-04	9.4450E-02	1.7884E-03	8.2600E-04	1.0012E-06	8.6789E+00	3.4555E-05	5.1453E-09	2.3803E-04	7.0699E-06	3.1221E-09	6.8493E-05
V8	1.4461E-12	7.2207E-07	3.0988E+00	1.3149E-02	4.4059E-02	2.8738E-12	8.6344E+00	6.5769E-04	4.0997E-12	3.1590E-06	2.6713E-09	6.1614E-13	1.2737E-04
V9	5.0401E-09	1.3039E-05	1.5252E+01	2.2485E-02	5.3846E-02	1.9981E-09	8.7719E+00	3.5619E-04	6.6061E-11	1.6777E-03	4.9350E-04	3.5608E-11	2.4017E-03
V10	4.2169E+00	5.1030E+00	1.7197E+03	1.6743E+01	2.6344E+02	3.4934E+00	9.2149E+00	1.0602E+02	4.4302E-02	3.9971E-01	6.0872E-01	1.0764E+00	9.4719E+02
V11	4.6831E+00	4.6831E+00	1.7207E+03	1.6771E+01	2.4704E+02	3.2159E+00	9.2731E+00	9.2895E+01	6.7369E-02	4.0717E-01	6.3491E-01	1.2761E+00	4.9446E+02
V12	3.1944E+00	5.1625E+00	1.7265E+03	1.7575E+01	2.1162E+02	3.4277E+00	9.1958E+00	4.2355E+01	6.7330E-02	4.3441E-01	6.7435E-01	1.4817E+00	5.2766E+02
Population Size: 500													
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	2.9190E-04	1.6749E-03	9.0363E+01	1.1962E+00	5.6701E+01	3.2172E-04	8.8540E+00	6.6908E-01	5.2401E-06	3.2065E-03	1.4250E-02	6.9748E-06	3.5065E+01
V2	5.7791E-13	3.0500E-08	5.7926E+01	3.3983E-01	3.8830E+01	7.9791E-13	9.1654E+00	3.4886E-09	1.0179E-14	1.1848E-07	1.1345E-02	2.0923E-03	4.5365E+01
V3	3.3299E-08	9.9089E-06	2.9618E+02	1.7240E+00	4.4005E+01	4.3850E-08	9.1999E+00	6.9504E-04	5.3773E-10	2.7703E-05	1.2325E-02	2.5098E-02	7.3185E+01
V4	3.8471E-01	3.1531E+00	1.2926E+03	1.5123E+01	9.8579E+01	4.4249E-01	8.9304E+00	9.9131E+00	9.4012E-03	1.0560E-01	1.9725E-01	7.5437E-01	2.7109E+02
V5	4.5313E-01	3.1383E+00	1.3318E+03	1.4592E+01	1.0694E+02	4.4511E-01	8.9753E+00	9.5202E+00	6.3853E-03	1.1136E-01	1.6719E-01	7.2538E-01	2.7808E+02
V6	3.8642E-01	3.1626E+00	1.3559E+03	1.4848E+01	9.9081E+01	2.7052E-01	8.9179E+00	1.1125E+01	4.7957E-03	9.3644E-02	2.0489E-01	6.9936E-01	2.9688E+02
V7	9.5280E-08	2.0974E-05	9.8237E-03	1.8363E-03	5.1610E-04	8.7394E-08	8.5050E+00	3.4192E-06	1.6300E-09	4.7622E-05	2.2732E-07	2.0914E-10	4.4227E-08
V8	2.5245E-14	3.8219E-09	3.8096E-01	1.3896E-02	2.5799E-04	1.1927E-14	8.5779E+00	3.1492E-04	9.5923E-16	1.8764E-08	1.2787E-03	3.0331E-17	4.2430E-14
V9	8.6571E-11	4.6019E-07	4.6288E+00	1.9109E-02	2.0451E-03	1.0896E-10	8.7275E+00	1.1296E-04	1.0791E-12	1.5492E-06	5.8781E-03	2.0987E-13	5.2917E-11
V10	4.6125E-01	3.1068E+00	1.3968E+03	1.4490E+01	8.4590E+01	4.1645E-01	8.9497E+00	3.2932E+00	5.3084E-03	8.9580E-02	2.1003E-01	8.1945E-01	6.8268E+02
V11	2.7837E-01	2.7837E-01	1.3723E+03	1.4760E+01	9.2784E+01	4.2002E-01	9.0004E+00	1.7823E+01	2.8658E-03	1.1001E-01	1.7017E-01	7.7308E-01	3.0281E+02
V12	2.5608E-01	3.3003E+00	1.2926E+03	1.4883E+01	9.5572E+01	2.9924E-01	8.9830E+00	1.1637E+01	6.7283E-03	8.5316E-02	2.0933E-01	6.8928E-01	2.7421E+02

2) Minimal optimized results

	Benchmarked Function												
	Population Size: 100												
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	4.6834E-04	3.6065E-03	8.5074E+01	1.3433E+00	2.4427E+01	1.3582E-03	8.2566E+00	1.5224E-01	1.2608E-05	6.4174E-03	2.3845E-03	3.2378E-07	1.3206E+01
V2	9.4022E-10	1.8043E-06	7.2503E+01	6.0323E-01	5.7759E+00	1.5931E-10	8.6692E+00	2.2232E-07	1.3840E-11	6.4396E-06	8.6964E-10	1.5609E-12	1.8087E+01
V3	7.5687E-05	6.2641E-04	4.6442E+02	2.5129E+00	1.3347E+01	5.5795E-05	7.9234E+00	3.3718E-02	3.9499E-07	8.2083E-04	9.4123E-05	5.0388E-07	4.6729E+01
V4	1.2630E+01	5.4088E+00	1.8285E+03	1.5804E+01	4.3172E+02	1.0744E+01	8.5680E+00	4.0321E+01	2.6213E-01	7.5973E-01	1.0278E+00	9.6659E-01	4.6473E+02
V5	7.8189E+00	5.3485E+00	9.7408E+02	1.4516E+01	1.8452E+02	1.8649E+01	8.1907E+00	2.3177E+01	2.0288E-01	1.0707E+00	1.0978E+00	5.0954E-01	2.3506E+02
V6	1.1455E+01	4.4627E+00	1.6319E+03	1.1348E+01	3.9164E+02	1.2505E+01	7.2751E+00	4.3250E+01	1.9159E-01	7.9610E-01	1.1451E+00	5.5271E-01	4.7231E+02
V7	4.7812E-09	3.7874E-05	4.7887E-06	4.5071E-05	1.3087E-06	7.8017E-07	7.2181E+00	1.2465E-10	2.0778E-11	2.1101E-05	5.4503E-08	1.5377E-10	1.1830E-08
V8	7.1256E-13	2.6167E-04	8.1777E-04	5.7610E-05	7.1166E-06	1.6307E-07	6.3974E+00	8.8049E-09	1.8792E-08	3.2259E-04	3.0643E-05	2.8707E-09	9.5567E-07
V9	5.9017E-09	6.5874E-04	1.8502E-02	1.1849E-05	1.6713E-09	1.4023E-06	8.1966E+00	6.8698E-10	1.1678E-06	8.5251E-05	1.4232E-07	4.6937E-08	1.4289E-06
V10	2.0528E+01	5.2691E+00	1.5556E+03	1.2813E+01	5.0193E+02	1.4933E+01	8.2692E+00	4.1913E+01	1.0391E-01	7.4258E-01	1.1792E+00	5.4996E-01	3.5418E+02
V11	1.2428E+01	1.2428E+01	1.6803E+03	1.4677E+01	3.9604E+02	1.0418E+01	8.3405E+00	4.2591E+01	1.3119E-01	6.9286E-01	1.1079E+00	5.6978E-01	4.4187E+02
V12	1.4653E+01	5.3324E+00	1.4797E+03	1.4874E+01	2.6523E+02	1.0662E+01	8.0770E+00	6.5233E+01	2.9214E-01	8.3901E-01	1.0455E+00	5.6769E-01	3.1274E+02
	Population Size: 300												
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	6.8254E-05	8.6151E-04	4.5361E+01	8.0523E-01	1.8439E+01	6.8652E-05	7.8264E+00	2.3545E-03	9.8996E-07	1.5751E-03	3.8462E-04	4.2706E-08	2.0319E-01
V2	6.5031E-14	1.3900E-08	2.2930E+01	1.7878E-01	1.4361E+01	2.5167E-13	8.2231E+00	1.7112E-11	0.0000E+00	1.1834E-07	8.5598E-13	2.5472E-16	4.9938E-01
V3	1.8447E-08	6.4463E-06	1.2972E+02	1.3827E+00	1.2413E+01	1.6845E-08	8.1424E+00	1.4720E-05	2.0412E-10	1.5515E-05	5.9001E-08	1.4372E-11	8.3402E+00
V4	6.3411E-03	1.5257E+00	7.1461E+02	1.0518E+01	3.6728E+01	5.2379E-03	7.9551E+00	4.9636E-02	4.7483E-04	1.9137E-02	1.5237E-01	1.6704E-03	1.9491E+02
V5	3.1885E-02	2.0706E+00	6.4468E+02	8.9736E+00	2.2128E+01	7.4831E-03	8.2901E+00	1.3463E-02	3.5618E-04	1.0112E-02	4.1582E-02	1.4918E-02	1.4979E+02
V6	3.7915E-02	1.5714E+00	6.8074E+02	1.0832E+01	2.8582E+01	1.1951E-02	7.9395E+00	3.1969E-02	4.7706E-04	3.1110E-02	3.7443E-02	4.6264E-04	1.4704E+02
V7	5.2338E-11	1.3173E-06	5.5977E-05	9.9147E-06	1.9351E-10	4.5295E-11	7.7379E+00	1.1260E-11	1.9718E-13	4.3534E-06	6.9392E-10	2.8806E-13	1.3172E-09
V8	4.1787E-17	1.2465E-08	7.1213E-05	3.1208E-04	8.2773E-07	8.1018E-17	7.4594E+00	9.3319E-12	0.0000E+00	3.1662E-08	6.7724E-15	5.5057E-16	2.0308E-08
V9	4.1911E-13	1.1551E-07	4.3076E-03	1.1858E-04	1.4385E-07	2.6489E-13	7.7640E+00	1.5107E-09	4.9738E-14	7.1215E-05	2.7698E-11	5.4091E-15	6.8773E-10

V10	9.0598E-04	1.7533E+00	7.4142E+02	1.1383E+01	3.2879E+01	1.4072E-02	7.2537E+00	1.7773E-01	3.2920E-04	5.5909E-02	4.4465E-02	7.4027E-02	1.8283E+02
V11	1.9079E-02	1.9079E-02	9.2056E+02	9.7240E+00	3.1083E+01	9.7626E-03	7.8498E+00	3.7067E-02	1.8688E-04	1.9615E-02	3.1265E-02	2.7599E-03	1.9948E+02
V12	3.4953E-02	1.6762E+00	7.9031E+02	1.1799E+01	3.0855E+01	3.9468E-03	7.7871E+00	4.2696E-03	3.0295E-04	5.1084E-02	5.3776E-02	1.2683E-01	1.6417E+02
Population Size: 500													
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	1.1187E-05	2.9414E-04	2.1775E+01	5.5391E-01	2.3833E+00	9.9007E-06	6.7691E+00	6.3397E-03	2.3689E-07	6.1535E-04	4.7127E-05	1.2229E-08	4.1899E-03
V2	1.7779E-15	1.4238E-09	1.8051E+01	1.0307E-01	5.6316E+00	3.4900E-15	7.5982E+00	5.3153E-13	0.0000E+00	1.6963E-08	1.7653E-14	1.3545E-18	1.4930E-05
V3	2.4441E-10	2.8366E-07	1.1357E+02	8.0651E-01	2.5358E+00	2.1757E-10	7.9072E+00	5.0735E-07	4.6612E-12	4.8015E-06	4.7409E-10	2.1964E-12	2.1582E-01
V4	8.3810E-05	5.6425E-01	5.1461E+02	8.7460E+00	2.5023E+01	1.1601E-04	7.2851E+00	1.2550E-04	1.1135E-05	2.9235E-03	5.0202E-04	5.6032E-05	1.6283E+02
V5	7.7470E-05	1.1016E+00	6.6328E+02	9.4586E+00	1.2496E+01	2.2310E-04	7.4073E+00	1.6343E-03	1.4494E-06	1.9372E-03	1.0947E-03	8.3930E-05	1.6211E+02
V6	1.0820E-04	8.1941E-01	5.6308E+02	1.0624E+01	1.8693E+01	1.1475E-05	7.5728E+00	5.2429E-04	5.3227E-07	2.3757E-03	4.5767E-03	7.3543E-05	1.7684E+02
V7	1.0296E-10	4.9881E-07	1.0371E-06	9.6070E-07	1.8399E-09	7.6095E-11	6.6266E+00	1.9687E-14	2.4780E-12	9.0772E-07	3.6998E-11	1.6687E-13	1.0935E-13
V8	5.5839E-19	4.6097E-11	7.4642E-05	1.0327E-04	1.5335E-08	6.0404E-19	7.6105E+00	3.9307E-22	0.0000E+00	1.9843E-10	0.0000E+00	1.9454E-22	3.9682E-19
V9	6.9345E-15	5.6637E-10	2.4022E-06	1.0569E-05	3.3355E-09	5.8966E-14	7.5433E+00	3.2596E-18	0.0000E+00	1.5088E-08	1.1091E-13	7.6624E-17	3.8690E-15
V10	6.0449E-06	7.3871E-01	6.7613E+02	8.9337E+00	1.3047E+01	3.7677E-04	7.6723E+00	4.6336E-05	8.6819E-07	3.4154E-03	4.2245E-03	2.6498E-04	1.3516E+02
V11	1.1496E-04	1.1496E-04	4.5774E+02	1.0256E+01	2.0693E+01	6.1071E-05	7.8988E+00	1.9308E-03	3.8626E-06	1.6279E-03	8.6557E-04	6.1368E-05	1.6953E+02
V12	5.4340E-04	4.2516E-01	4.2903E+02	1.0114E+01	9.6721E+00	8.8104E-04	7.8276E+00	8.3815E-05	3.3408E-06	3.7394E-03	1.0944E-02	3.0217E-05	1.8629E+02

3) Range of optimized results

	Benchmarked Function												
Population Size: 100													
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	5.0904E-02	2.5332E-02	4.4487E+02	2.8698E+00	3.0915E+02	4.6009E-02	2.4664E+00	7.7785E+01	6.3035E-04	4.8006E-02	3.4753E-01	1.0557E-01	4.3190E+02
V2	2.7213E-06	1.0495E-04	8.5953E+02	2.6920E+00	1.5557E+02	4.6392E-07	2.2830E+00	1.1697E-01	6.4504E-09	1.1937E-04	4.1839E-02	4.1846E-01	3.4118E+03
V3	1.5004E-02	2.2267E-01	1.3773E+03	4.7041E+00	4.0748E+02	6.5128E-01	2.8680E+00	8.4059E+02	3.6190E-04	5.3203E-02	4.4660E-01	4.1849E-01	2.5114E+02
V4	5.8412E+02	1.9234E+01	3.7814E+03	1.7902E+01	5.8791E+04	4.3136E+02	3.8032E+00	6.4763E+03	8.5127E+00	8.0296E+00	5.0835E+00	1.3070E+01	9.1724E+05

V5	5.4102E+02	2.3278E+01	5.3265E+03	1.7530E+01	1.1538E+05	7.7745E+02	3.4176E+00	6.6512E+03	1.2263E+01	5.6007E+00	5.6307E+00	1.0205E+01	5.5655E+05
V6	8.5779E+02	2.4658E+01	4.4112E+03	1.9547E+01	6.5517E+04	4.8458E+02	4.7144E+00	7.0254E+03	3.4987E+01	6.0410E+00	4.0498E+00	9.6417E+00	4.4159E+05
V7	3.8472E-04	9.4972E-02	4.6928E+00	1.5813E-02	6.2578E-02	1.2727E-02	2.5204E+00	1.8835E-02	4.0065E-06	2.2445E-02	3.0059E-02	3.8923E-04	1.2035E-02
V8	1.3520E-07	3.1746E-01	6.8930E+01	1.4889E-01	4.6524E+00	4.7624E-01	3.3432E+00	1.5542E-01	4.0825E-03	1.4568E-01	6.7007E-01	3.9570E-03	8.4706E-02
V9	2.6598E-04	5.4801E-01	2.7380E+02	1.7394E-01	6.1984E+00	1.7779E+00	1.9125E+00	1.1818E-01	1.8391E-02	2.3591E-01	8.1709E-01	1.0430E-02	1.5700E-01
V10	5.7004E+02	2.8398E+01	4.1006E+03	1.7033E+01	6.9469E+04	7.7139E+02	3.5909E+00	8.4526E+03	7.7113E+00	6.8440E+00	7.3799E+00	8.9382E+00	4.2156E+05
V11	3.6997E+02	3.6997E+02	6.1937E+03	1.8334E+01	1.0343E+05	7.1431E+02	4.1421E+00	7.4834E+03	7.3456E+00	5.1144E+00	5.5324E+00	1.3533E+01	5.0485E+05
V12	4.1077E+02	2.2353E+01	4.3862E+03	1.7871E+01	3.8287E+04	5.2984E+02	3.9528E+00	1.0433E+04	7.8479E+00	6.2802E+00	4.5199E+00	7.6317E+00	4.8935E+05

Population Size: 300

	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	1.0253E-02	8.8198E-03	2.2168E+02	1.7248E+00	2.2767E+02	4.5874E-03	2.4447E+00	3.9669E+01	6.7209E-05	1.2564E-02	8.3092E-02	1.0461E-01	1.9083E+02
V2	9.2608E-10	8.1386E-07	2.9027E+02	1.2382E+00	7.0402E+01	3.9478E-10	2.1474E+00	2.8771E-05	1.7728E-12	4.2175E-06	5.6535E-02	1.0461E-01	2.1602E+02
V3	9.9219E-06	6.6231E-04	8.2695E+02	2.2997E+00	2.2434E+02	3.5663E-05	2.3104E+00	1.6917E+00	3.0255E-07	6.2172E-04	7.6010E-02	2.0828E-01	2.1688E+02
V4	3.5866E+01	1.9553E+01	2.3699E+03	1.2057E+01	1.6453E+03	1.5890E+01	2.7279E+00	6.1940E+02	4.4372E-01	1.4830E+00	1.1332E+00	5.9963E+00	9.7111E+03
V5	2.8040E+01	8.0115E+00	3.0141E+03	1.5048E+01	1.4651E+03	3.6237E+01	2.9176E+00	4.0557E+03	1.0857E+00	1.0680E+00	1.1847E+00	5.7181E+00	1.4556E+04
V6	7.5166E+01	8.2420E+00	2.5195E+03	1.2203E+01	2.5103E+03	2.5717E+01	2.9028E+00	6.2079E+02	2.5657E-01	1.4221E+00	1.2711E+00	4.8657E+00	1.5883E+03
V7	5.2623E-06	8.0970E-04	1.2987E+00	1.1261E-02	1.2004E-02	3.0078E-05	1.6817E+00	9.4006E-04	5.9437E-08	1.3204E-03	8.7553E-05	2.6858E-08	7.0478E-04
V8	3.0379E-11	5.0022E-06	2.0820E+01	5.8756E-02	4.5045E-01	7.8310E-11	1.8314E+00	1.7591E-02	6.3961E-11	1.8448E-05	2.4552E-07	1.2736E-11	4.5731E-03
V9	7.2924E-08	2.0736E-04	8.0458E+01	1.6649E-01	9.5841E-01	3.0477E-08	1.7048E+00	3.6489E-03	6.7384E-10	5.5661E-03	4.9238E-02	3.7990E-10	3.2602E-02
V10	3.6314E+01	9.0591E+00	2.1408E+03	1.0934E+01	2.3994E+03	3.6259E+01	3.4731E+00	4.0488E+03	6.2107E-01	2.0848E+00	1.2742E+00	2.9968E+00	3.9560E+04
V11	4.3753E+01	4.3753E+01	1.9686E+03	1.4693E+01	1.3288E+03	3.1412E+01	2.7239E+00	4.0751E+03	1.0720E+00	3.3862E+00	1.7218E+00	3.6400E+00	3.8795E+03
V12	1.8819E+01	1.0920E+01	2.3079E+03	1.5342E+01	8.3331E+02	2.6224E+01	2.8454E+00	5.7468E+02	5.3244E-01	3.2006E+00	1.2337E+00	7.7393E+00	9.4265E+03

Population Size: 500

	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	1.1187E-05	2.9414E-04	2.1775E+01	5.5391E-01	2.3833E+00	9.9007E-06	6.7691E+00	6.3397E-03	2.3689E-07	6.1535E-04	4.7127E-05	1.2229E-08	4.1899E-03
V2	1.7779E-15	1.4238E-09	1.8051E+01	1.0307E-01	5.6316E+00	3.4900E-15	7.5982E+00	5.3153E-13	0.0000E+00	1.6963E-08	1.7653E-14	1.3545E-18	1.4930E-05
V3	2.4441E-10	2.8366E-07	1.1357E+02	8.0651E-01	2.5358E+00	2.1757E-10	7.9072E+00	5.0735E-07	4.6612E-12	4.8015E-06	4.7409E-10	2.1964E-12	2.1582E-01

V4	8.3810E-05	5.6425E-01	5.1461E+02	8.7460E+00	2.5023E+01	1.1601E-04	7.2851E+00	1.2550E-04	1.1135E-05	2.9235E-03	5.0202E-04	5.6032E-05	1.6283E+02
V5	7.7470E-05	1.1016E+00	6.6328E+02	9.4586E+00	1.2496E+01	2.2310E-04	7.4073E+00	1.6343E-03	1.4494E-06	1.9372E-03	1.0947E-03	8.3930E-05	1.6211E+02
V6	1.0820E-04	8.1941E-01	5.6308E+02	1.0624E+01	1.8693E+01	1.1475E-05	7.5728E+00	5.2429E-04	5.3227E-07	2.3757E-03	4.5767E-03	7.3543E-05	1.7684E+02
V7	1.0296E-10	4.9881E-07	1.0371E-06	9.6070E-07	1.8399E-09	7.6095E-11	6.6266E+00	1.9687E-14	2.4780E-12	9.0772E-07	3.6998E-11	1.6687E-13	1.0935E-13
V8	5.5839E-19	4.6097E-11	7.4642E-05	1.0327E-04	1.5335E-08	6.0404E-19	7.6105E+00	3.9307E-22	0.0000E+00	1.9843E-10	0.0000E+00	1.9454E-22	3.9682E-19
V9	6.9345E-15	5.6637E-10	2.4022E-06	1.0569E-05	3.3355E-09	5.8966E-14	7.5433E+00	3.2596E-18	0.0000E+00	1.5088E-08	1.1091E-13	7.6624E-17	3.8690E-15
V10	6.0449E-06	7.3871E-01	6.7613E+02	8.9337E+00	1.3047E+01	3.7677E-04	7.6723E+00	4.6336E-05	8.6819E-07	3.4154E-03	4.2245E-03	2.6498E-04	1.3516E+02
V11	1.1496E-04	1.1496E-04	4.5774E+02	1.0256E+01	2.0693E+01	6.1071E-05	7.8988E+00	1.9308E-03	3.8626E-06	1.6279E-03	8.6557E-04	6.1368E-05	1.6953E+02
V12	5.4340E-04	4.2516E-01	4.2903E+02	1.0114E+01	9.6721E+00	8.8104E-04	7.8276E+00	8.3815E-05	3.3408E-06	3.7394E-03	1.0944E-02	3.0217E-05	1.8629E+02

4) Standard deviation of optimized results

	Benchmarked Function												
	Population Size: 100												
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	8.6756E-03	5.4823E-03	7.4589E+01	5.4978E-01	5.9960E+01	8.1116E-03	4.9960E-01	1.3989E+01	1.4591E-04	9.6170E-03	5.2502E-02	4.2782E-02	5.9488E+01
V2	2.8332E-07	1.4826E-05	1.5146E+02	5.4722E-01	3.2656E+01	6.2078E-08	4.9953E-01	1.2540E-02	1.0572E-09	2.3209E-05	1.0652E-02	5.9177E-02	3.4744E+02
V3	2.6989E-03	3.9888E-02	3.2563E+02	1.0080E+00	7.1268E+01	6.5773E-02	5.3120E-01	8.4585E+01	5.1931E-05	9.4173E-03	4.8326E-02	9.0667E-02	4.7488E+01
V4	1.1266E+02	4.0533E+00	9.7996E+02	3.2966E+00	8.5311E+03	9.0594E+01	7.6372E-01	1.3748E+03	1.6254E+00	1.5763E+00	8.4519E-01	2.1227E+00	1.2248E+05
V5	9.4572E+01	4.3173E+00	1.0291E+03	3.7238E+00	1.2456E+04	1.0112E+02	7.1152E-01	1.3837E+03	1.6564E+00	1.1210E+00	9.9801E-01	1.8094E+00	1.0015E+05
V6	1.2160E+02	4.3512E+00	1.0490E+03	3.4873E+00	1.1243E+04	8.6866E+01	7.8669E-01	1.2523E+03	4.4986E+00	1.3644E+00	7.5392E-01	1.7658E+00	8.3871E+04
V7	4.8720E-05	1.7051E-02	9.3455E-01	3.0269E-03	1.1578E-02	2.5269E-03	4.6554E-01	2.1157E-03	5.1479E-07	4.7668E-03	6.4755E-03	4.6239E-05	1.4099E-03
V8	1.9519E-08	7.0640E-02	1.5693E+01	2.2210E-02	6.8723E-01	8.2255E-02	5.2617E-01	2.0468E-02	8.8576E-04	3.2333E-02	1.4189E-01	7.9130E-04	1.7600E-02
V9	3.4517E-05	1.2321E-01	6.0406E+01	3.5102E-02	1.2013E+00	2.1713E-01	4.2955E-01	1.4565E-02	3.0623E-03	5.4159E-02	1.8414E-01	1.7676E-03	2.4164E-02
V10	1.2173E+02	4.2584E+00	1.0386E+03	3.3020E+00	9.0016E+03	1.1143E+02	6.8242E-01	1.7725E+03	1.5276E+00	1.4941E+00	1.1483E+00	1.5852E+00	8.3123E+04
V11	8.1514E+01	8.1514E+01	1.2127E+03	3.4540E+00	1.2112E+04	1.1243E+02	7.4090E-01	1.4913E+03	1.4684E+00	1.2999E+00	1.0434E+00	2.0312E+00	9.3398E+04
V12	9.6527E+01	4.2417E+00	1.0339E+03	3.7171E+00	6.8806E+03	9.4199E+01	7.3635E-01	1.3393E+03	1.5994E+00	1.4777E+00	8.2069E-01	1.5195E+00	9.2356E+04

Population Size: 300

	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	1.3628E-03	1.5518E-03	4.8675E+01	3.6546E-01	4.4515E+01	7.7625E-04	4.5274E-01	6.3267E+00	1.4322E-05	2.4605E-03	1.7322E-02	1.0512E-02	4.3236E+01
V2	9.8237E-11	1.4570E-07	5.6391E+01	2.4239E-01	2.3477E+01	4.4452E-11	4.9994E-01	3.5180E-06	3.5624E-13	6.7866E-07	1.3544E-02	2.0603E-02	4.0862E+01
V3	1.5462E-06	1.1503E-04	1.6083E+02	5.0449E-01	4.3797E+01	4.0820E-06	4.6310E-01	2.0275E-01	3.7732E-08	1.3354E-04	1.4941E-02	5.2711E-02	4.2765E+01
V4	5.5355E+00	2.4366E+00	5.5274E+02	2.6720E+00	1.8923E+02	2.4600E+00	5.0746E-01	1.4373E+02	8.8948E-02	2.9354E-01	2.9051E-01	9.7149E-01	1.1319E+03
V5	5.0795E+00	1.7296E+00	5.3651E+02	2.8732E+00	2.3755E+02	6.1145E+00	5.5342E-01	4.4081E+02	1.3059E-01	2.5090E-01	3.1831E-01	1.0205E+00	1.9990E+03
V6	1.1098E+01	1.7508E+00	5.1565E+02	2.8193E+00	3.2993E+02	4.6568E+00	5.5207E-01	9.4727E+01	5.4097E-02	3.3087E-01	3.1806E-01	1.0181E+00	2.4313E+02
V7	8.5187E-07	1.3310E-04	2.0814E-01	1.9989E-03	1.7652E-03	3.0958E-06	3.5800E-01	1.2181E-04	9.1267E-09	2.3051E-04	1.5037E-05	5.4113E-09	1.1648E-04
V8	4.3969E-12	9.4653E-07	3.7947E+00	1.3284E-02	7.2975E-02	8.5665E-12	3.8588E-01	2.1360E-03	1.0958E-11	3.5772E-06	2.4535E-08	1.4938E-12	4.8453E-04
V9	1.1511E-08	2.8021E-05	1.8368E+01	2.6337E-02	1.4594E-01	4.3378E-09	4.0761E-01	6.4019E-04	1.3544E-10	1.3538E-03	4.9237E-03	7.3571E-11	4.7403E-03
V10	6.3295E+00	1.9805E+00	4.9003E+02	2.3414E+00	3.0248E+02	5.4479E+00	5.7652E-01	4.2577E+02	8.5426E-02	3.3001E-01	3.3318E-01	6.6954E-01	4.0022E+03
V11	8.0998E+00	8.0998E+00	4.6991E+02	2.9995E+00	2.1683E+02	4.8790E+00	5.1005E-01	4.2002E+02	1.5825E-01	4.5976E-01	3.3487E-01	8.4439E-01	5.9057E+02
V12	4.2173E+00	1.7950E+00	5.0099E+02	3.0634E+00	1.6850E+02	5.2318E+00	5.0023E-01	1.0311E+02	9.6946E-02	4.4252E-01	3.1739E-01	1.2402E+00	1.0527E+03

Population Size: 500

	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	3.5987E-04	1.0673E-03	3.6495E+01	3.5988E-01	4.5504E+01	4.6449E-04	5.0817E-01	2.2496E+00	7.3278E-06	1.4381E-03	1.6457E-02	4.5968E-05	3.1470E+01
V2	1.2637E-12	2.9893E-08	3.3127E+01	1.8502E-01	2.4168E+01	2.4214E-12	5.3816E-01	9.7083E-09	1.9711E-14	9.3736E-08	1.2066E-02	1.4720E-02	3.1204E+01
V3	4.6208E-08	1.6019E-05	1.2451E+02	5.3870E-01	2.8942E+01	1.0964E-07	3.8937E-01	2.1870E-03	8.2227E-10	2.0743E-05	1.3549E-02	5.9670E-02	4.0600E+01
V4	7.6283E-01	1.6122E+00	3.8874E+02	2.4410E+00	9.4132E+01	1.2722E+00	4.5588E-01	5.7977E+01	2.5759E-02	1.2124E-01	2.2758E-01	7.0221E-01	5.0298E+01
V5	1.2474E+00	1.4505E+00	3.8225E+02	2.4998E+00	8.4043E+01	1.6529E+00	4.7812E-01	5.6268E+01	3.1089E-02	1.1773E-01	1.8006E-01	5.1366E-01	1.2847E+02
V6	9.0626E-01	1.4295E+00	4.2475E+02	2.3766E+00	6.8962E+01	1.1817E+00	5.2357E-01	5.8680E+01	9.1609E-03	9.7721E-02	2.1287E-01	6.2662E-01	1.5198E+02
V7	1.8231E-07	1.8389E-05	1.8630E-02	1.7769E-03	9.2242E-04	1.3506E-07	4.2587E-01	2.0760E-05	3.2111E-09	4.4244E-05	6.1736E-07	4.1450E-10	1.0237E-07
V8	8.4440E-14	4.6285E-09	6.7395E-01	1.5359E-02	4.1477E-04	2.3580E-14	3.4339E-01	1.2152E-03	2.0107E-15	2.0718E-08	7.9888E-03	5.4049E-17	2.6487E-13
V9	2.5810E-10	4.7034E-07	6.2045E+00	1.7798E-02	3.3203E-03	2.7682E-10	4.2034E-01	4.3636E-04	2.1706E-12	2.9975E-06	2.0155E-02	7.8962E-13	2.3237E-10
V10	1.3615E+00	1.3053E+00	3.5776E+02	2.5294E+00	4.7471E+01	1.3524E+00	6.0903E-01	5.3484E+00	1.3575E-02	8.6911E-02	2.2875E-01	7.1876E-01	4.0039E+03
V11	6.7632E-01	6.7632E-01	4.0530E+02	2.2515E+00	6.4639E+01	9.1019E-01	5.1230E-01	7.6915E+01	6.5199E-03	1.4156E-01	1.7193E-01	6.6587E-01	2.1181E+02

V12	4.3510E-01	1.5347E+00	3.8950E+02	2.2842E+00	7.3696E+01	5.7144E-01	4.0001E-01	5.7892E+01	2.4136E-02	9.2340E-02	2.1804E-01	6.1487E-01	6.6542E+01

5) Average computational time (second)

	Benchmarked Function												
	Population Size: 100												
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	8.1139E-01	8.1677E-01	1.6097E+00	8.0374E-01	1.2868E+00	8.1999E-01	1.4607E+00	9.4230E-01	8.3986E-01	9.1653E-01	1.3474E+00	1.6424E+00	1.4707E+00
V2	1.7750E+00	1.7853E+00	2.5642E+00	1.7528E+00	2.2487E+00	1.7899E+00	2.4173E+00	1.9121E+00	1.8228E+00	1.8897E+00	2.3189E+00	2.6562E+00	2.4256E+00
V3	1.7493E+00	1.7670E+00	2.6042E+00	1.7506E+00	2.2366E+00	1.7779E+00	2.4540E+00	1.8987E+00	1.8040E+00	1.8819E+00	2.2785E+00	2.5962E+00	2.4924E+00
V4	4.0955E-01	3.9898E-01	1.1644E+00	3.7719E-01	8.7313E-01	4.3192E-01	1.0206E+00	5.5385E-01	4.5455E-01	5.1592E-01	9.0830E-01	1.2079E+00	1.0516E+00
V5	1.3627E+00	1.3382E+00	2.1018E+00	1.2851E+00	1.8102E+00	1.3893E+00	1.9800E+00	1.4978E+00	1.4382E+00	1.4665E+00	1.8547E+00	2.1399E+00	2.0104E+00
V6	1.3729E+00	1.3763E+00	2.1338E+00	1.3001E+00	1.8319E+00	1.3971E+00	2.0198E+00	1.5071E+00	1.4183E+00	1.4778E+00	1.8794E+00	2.1658E+00	2.0112E+00
V7	8.3330E-01	8.7198E-01	1.6832E+00	8.6827E-01	1.3522E+00	8.7600E-01	1.5440E+00	1.0029E+00	8.7223E-01	9.8162E-01	1.4129E+00	1.7590E+00	1.5602E+00
V8	1.4726E+00	1.5028E+00	2.3528E+00	1.4932E+00	1.9884E+00	1.5056E+00	2.1611E+00	1.6471E+00	1.5449E+00	1.6167E+00	2.0383E+00	2.3909E+00	2.2157E+00
V9	1.4735E+00	1.4988E+00	2.3311E+00	1.4852E+00	1.9866E+00	1.5081E+00	2.1705E+00	1.6536E+00	1.5598E+00	1.6352E+00	2.0547E+00	2.4075E+00	2.2114E+00
V10	4.5438E-01	4.7760E-01	1.2540E+00	4.0381E-01	9.5221E-01	4.9967E-01	1.0950E+00	6.2816E-01	5.3400E-01	5.8869E-01	9.9401E-01	1.3072E+00	1.1379E+00
V11	1.0804E+00	1.0804E+00	1.8868E+00	1.0090E+00	1.5814E+00	1.1362E+00	1.7295E+00	1.2571E+00	1.1677E+00	1.2246E+00	1.6254E+00	1.9452E+00	1.7604E+00
V12	1.0837E+00	1.1228E+00	1.8926E+00	1.0111E+00	1.5835E+00	1.1286E+00	1.7266E+00	1.2609E+00	1.1712E+00	1.2246E+00	1.6387E+00	1.9412E+00	1.7608E+00
	Population Size: 300												
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	2.3480E+00	2.3690E+00	4.7182E+00	2.3191E+00	3.7475E+00	2.3654E+00	4.2764E+00	2.7316E+00	2.4261E+00	2.6647E+00	3.9402E+00	4.8607E+00	4.3041E+00
V2	5.2405E+00	5.3777E+00	7.5724E+00	5.1503E+00	6.6125E+00	5.2592E+00	7.1459E+00	5.6877E+00	5.3417E+00	5.5459E+00	6.8265E+00	7.9781E+00	7.1684E+00
V3	5.1571E+00	5.1924E+00	7.5807E+00	5.1363E+00	6.5729E+00	5.1863E+00	7.1770E+00	5.5341E+00	5.2682E+00	5.5071E+00	6.7276E+00	7.7868E+00	7.2276E+00
V4	1.1607E+00	1.1304E+00	3.3735E+00	1.0541E+00	2.5190E+00	1.1939E+00	2.9539E+00	1.5315E+00	1.2485E+00	1.4177E+00	2.5938E+00	3.5732E+00	3.0425E+00
V5	4.0006E+00	3.9386E+00	6.1825E+00	3.7827E+00	5.3083E+00	4.0520E+00	5.7411E+00	4.3423E+00	4.0801E+00	4.2372E+00	5.3956E+00	6.3444E+00	5.8446E+00
V6	4.0373E+00	3.9830E+00	6.2505E+00	3.7987E+00	5.3585E+00	4.0540E+00	5.9976E+00	4.3757E+00	4.0910E+00	4.2658E+00	5.4487E+00	6.3574E+00	5.9750E+00

V7	2.4109E+00	2.4975E+00	4.9668E+00	2.4518E+00	3.9639E+00	2.4933E+00	4.4745E+00	2.9117E+00	2.5163E+00	2.8760E+00	4.1083E+00	5.1583E+00	4.5800E+00
V8	4.3104E+00	4.3634E+00	6.8405E+00	4.3306E+00	5.8447E+00	4.3644E+00	6.3576E+00	4.8082E+00	4.5725E+00	4.6756E+00	5.9820E+00	6.9975E+00	6.4222E+00
V9	4.3393E+00	4.4972E+00	6.8705E+00	4.2737E+00	5.8342E+00	4.3694E+00	6.3812E+00	4.8267E+00	4.4730E+00	4.7586E+00	6.0477E+00	7.4890E+00	6.6116E+00
V10	1.2894E+00	1.3678E+00	3.6365E+00	1.1331E+00	2.7398E+00	1.3234E+00	3.1803E+00	1.7385E+00	1.4010E+00	1.6356E+00	2.8334E+00	3.8438E+00	3.2716E+00
V11	3.1546E+00	3.1546E+00	5.5191E+00	2.9256E+00	4.6280E+00	3.2049E+00	5.0608E+00	3.6236E+00	3.3520E+00	3.5203E+00	4.7092E+00	5.7694E+00	5.1887E+00
V12	3.1515E+00	3.2657E+00	5.5137E+00	2.9304E+00	4.6187E+00	3.1976E+00	5.0323E+00	3.6033E+00	3.3357E+00	3.5101E+00	4.7201E+00	5.6611E+00	5.1693E+00
Population Size: 500													
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	3.8669E+00	3.9197E+00	7.8889E+00	3.8362E+00	6.2461E+00	3.9132E+00	7.1259E+00	4.5335E+00	4.0121E+00	4.4380E+00	6.6170E+00	8.1082E+00	7.1165E+00
V2	8.7452E+00	8.7696E+00	1.2645E+01	8.5941E+00	1.1018E+01	8.7646E+00	1.1927E+01	9.3386E+00	8.9964E+00	9.2289E+00	1.1507E+01	1.3038E+01	1.1954E+01
V3	8.5523E+00	8.5976E+00	1.2610E+01	8.5636E+00	1.0948E+01	8.6353E+00	1.1976E+01	9.2074E+00	8.7549E+00	9.1244E+00	1.1207E+01	1.2781E+01	1.2010E+01
V4	1.9079E+00	1.8713E+00	5.7675E+00	1.7387E+00	4.1483E+00	1.9624E+00	4.8727E+00	2.5047E+00	2.0417E+00	2.3078E+00	4.2921E+00	5.8769E+00	5.0077E+00
V5	6.6418E+00	6.5906E+00	1.0321E+01	6.3092E+00	8.8154E+00	6.6895E+00	9.5386E+00	7.1962E+00	6.7649E+00	7.0029E+00	8.9843E+00	1.0487E+01	9.7057E+00
V6	6.6920E+00	6.6556E+00	1.0383E+01	6.3467E+00	8.9060E+00	6.7004E+00	9.9461E+00	7.2512E+00	6.7802E+00	7.0734E+00	9.0604E+00	1.0618E+01	9.8338E+00
V7	4.0039E+00	4.0444E+00	8.0987E+00	3.9704E+00	6.3976E+00	4.0627E+00	7.3155E+00	4.6600E+00	4.1791E+00	4.5332E+00	6.7205E+00	8.4119E+00	7.2754E+00
V8	7.3873E+00	7.2330E+00	1.1193E+01	7.1065E+00	9.5444E+00	7.3838E+00	1.0397E+01	7.8617E+00	7.3607E+00	7.6673E+00	9.8864E+00	1.2194E+01	1.0582E+01
V9	7.1949E+00	7.2444E+00	1.1244E+01	7.1014E+00	9.6235E+00	7.2003E+00	1.0471E+01	8.0228E+00	7.5967E+00	7.7653E+00	9.9260E+00	1.1629E+01	1.0776E+01
V10	2.1182E+00	2.0754E+00	5.8295E+00	1.8770E+00	4.3537E+00	2.1522E+00	5.0914E+00	2.7099E+00	2.2489E+00	2.4972E+00	4.5073E+00	6.1149E+00	5.2388E+00
V11	5.2423E+00	5.2423E+00	8.9789E+00	4.8542E+00	7.4870E+00	5.2980E+00	8.2218E+00	5.8492E+00	5.3753E+00	5.6225E+00	7.6359E+00	9.3104E+00	8.3816E+00
V12	5.2284E+00	5.1837E+00	9.0615E+00	4.8519E+00	7.4776E+00	5.2706E+00	8.2170E+00	5.8304E+00	5.3729E+00	5.6169E+00	7.6571E+00	9.3501E+00	8.3989E+00

6) Minimum Values of computation time (second)

	Benchmarked Function												
Population Size: 100													
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	7.9591E-01	8.0064E-01	1.5783E+00	7.9104E-01	1.2623E+00	8.0814E-01	1.4332E+00	9.2414E-01	8.2257E-01	8.9672E-01	1.3127E+00	1.6170E+00	1.4415E+00

V2	1.7518E+00	1.7590E+00	2.5108E+00	1.7200E+00	2.2037E+00	1.7627E+00	2.3837E+00	1.8753E+00	1.7985E+00	1.8519E+00	2.2679E+00	2.5736E+00	2.3827E+00
V3	1.7294E+00	1.7394E+00	2.5266E+00	1.7330E+00	2.2021E+00	1.7549E+00	2.4163E+00	1.8805E+00	1.7858E+00	1.8645E+00	2.2568E+00	2.5600E+00	2.4100E+00
V4	4.0131E-01	3.7324E-01	1.1237E+00	3.7061E-01	8.5907E-01	4.2320E-01	9.9683E-01	5.4471E-01	4.4391E-01	4.9765E-01	8.8214E-01	1.1903E+00	1.0007E+00
V5	1.3401E+00	1.2954E+00	2.0639E+00	1.2651E+00	1.7876E+00	1.3692E+00	1.9298E+00	1.4760E+00	1.3946E+00	1.4532E+00	1.8205E+00	2.1197E+00	1.9506E+00
V6	1.3545E+00	1.3181E+00	2.0969E+00	1.2775E+00	1.8085E+00	1.3770E+00	1.9553E+00	1.4860E+00	1.3994E+00	1.4611E+00	1.8556E+00	2.1415E+00	1.9652E+00
V7	8.1564E-01	8.5721E-01	1.6615E+00	8.5584E-01	1.3190E+00	8.6185E-01	1.5195E+00	9.8680E-01	8.5741E-01	9.5523E-01	1.3834E+00	1.7271E+00	1.5328E+00
V8	1.4515E+00	1.4783E+00	2.2777E+00	1.4656E+00	1.9627E+00	1.4859E+00	2.1367E+00	1.6308E+00	1.5188E+00	1.5889E+00	2.0045E+00	2.3364E+00	2.1483E+00
V9	1.4502E+00	1.4837E+00	2.2968E+00	1.4656E+00	1.9642E+00	1.4881E+00	2.1442E+00	1.6208E+00	1.5433E+00	1.6114E+00	2.0211E+00	2.3604E+00	2.1781E+00
V10	4.4342E-01	4.5832E-01	1.2265E+00	3.9503E-01	9.3428E-01	4.7500E-01	1.0812E+00	6.1612E-01	5.1820E-01	5.7593E-01	9.6389E-01	1.2721E+00	1.0939E+00
V11	1.0638E+00	1.0638E+00	1.8591E+00	9.9141E-01	1.5584E+00	1.1106E+00	1.7018E+00	1.2360E+00	1.1456E+00	1.2033E+00	1.6011E+00	1.9046E+00	1.7164E+00
V12	1.0606E+00	1.0673E+00	1.8572E+00	9.9131E-01	1.5583E+00	1.1000E+00	1.7005E+00	1.2427E+00	1.1513E+00	1.2089E+00	1.6090E+00	1.8998E+00	1.7156E+00
Population Size: 300													
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	2.3062E+00	2.3272E+00	4.6630E+00	2.2800E+00	3.7027E+00	2.3293E+00	4.2340E+00	2.6745E+00	2.3854E+00	2.6285E+00	3.8548E+00	4.7816E+00	4.2040E+00
V2	5.1641E+00	5.1902E+00	7.4503E+00	5.0897E+00	6.5067E+00	5.1995E+00	7.0391E+00	5.5381E+00	5.2733E+00	5.4828E+00	6.7230E+00	7.5893E+00	7.0472E+00
V3	5.1012E+00	5.1333E+00	7.4646E+00	5.0857E+00	6.5027E+00	5.1391E+00	7.1021E+00	5.4933E+00	5.2221E+00	5.4580E+00	6.6726E+00	7.5965E+00	7.1656E+00
V4	1.1451E+00	1.0793E+00	3.3167E+00	1.0348E+00	2.4578E+00	1.1750E+00	2.9159E+00	1.5126E+00	1.2340E+00	1.3932E+00	2.5584E+00	3.4981E+00	2.9203E+00
V5	3.9694E+00	3.8249E+00	6.0968E+00	3.7187E+00	5.2276E+00	3.9830E+00	5.6710E+00	4.2825E+00	4.0515E+00	4.2038E+00	5.3475E+00	6.2714E+00	5.6832E+00
V6	3.9927E+00	3.8572E+00	6.1820E+00	3.7454E+00	5.2991E+00	4.0135E+00	5.7365E+00	4.3429E+00	1.4205E+00	4.2302E+00	5.3881E+00	6.2929E+00	5.7504E+00
V7	2.3791E+00	2.4644E+00	4.9059E+00	2.4188E+00	3.9080E+00	2.4511E+00	4.4398E+00	2.8878E+00	2.4866E+00	2.7799E+00	4.0534E+00	5.0740E+00	4.5324E+00
V8	4.2460E+00	4.3099E+00	6.7472E+00	4.2680E+00	5.7887E+00	4.3169E+00	6.3018E+00	4.7572E+00	4.4316E+00	4.6217E+00	5.8809E+00	6.9137E+00	6.3406E+00
V9	4.3028E+00	4.3468E+00	6.8077E+00	4.2262E+00	5.7636E+00	4.3240E+00	6.3094E+00	4.7642E+00	4.4235E+00	4.7092E+00	5.9596E+00	6.9711E+00	6.4262E+00
V10	1.2715E+00	1.3025E+00	3.5897E+00	1.1097E+00	2.6974E+00	1.3089E+00	3.1391E+00	1.6784E+00	1.3754E+00	1.6092E+00	2.7920E+00	3.7339E+00	3.1229E+00
V11	3.1251E+00	3.1251E+00	5.4375E+00	2.8831E+00	4.5729E+00	3.1750E+00	5.0031E+00	3.5500E+00	3.3066E+00	3.4881E+00	4.6692E+00	5.6035E+00	5.0587E+00
V12	3.1101E+00	3.1133E+00	5.4483E+00	2.8762E+00	4.5776E+00	3.1564E+00	4.9819E+00	3.5358E+00	3.2628E+00	3.4745E+00	4.6805E+00	5.5680E+00	4.9756E+00
Population Size: 500													
	1	2	3	4	5	6	7	8	9	10	11	12	13

V1	3.8243E+00	3.8833E+00	7.7596E+00	3.7662E+00	6.1379E+00	3.8612E+00	7.0266E+00	4.4767E+00	3.9509E+00	4.3700E+00	6.4872E+00	7.9548E+00	6.9875E+00
V2	8.6597E+00	8.6703E+00	1.2517E+01	8.4947E+00	1.0873E+01	8.6774E+00	1.1779E+01	9.2480E+00	8.7865E+00	9.1043E+00	1.1185E+01	1.2728E+01	1.1789E+01
V3	8.4819E+00	8.4895E+00	1.2445E+01	8.4798E+00	1.0830E+01	8.5512E+00	1.1815E+01	9.1036E+00	8.6712E+00	9.0521E+00	1.1101E+01	1.2604E+01	1.1888E+01
V4	1.8832E+00	1.7723E+00	5.5047E+00	1.6894E+00	4.0610E+00	1.9275E+00	4.8170E+00	2.3368E+00	2.0179E+00	2.2818E+00	4.2285E+00	5.7916E+00	4.7878E+00
V5	6.5787E+00	6.3565E+00	1.0164E+01	6.1916E+00	8.7365E+00	6.6259E+00	9.4251E+00	7.0748E+00	6.6789E+00	6.9449E+00	8.8630E+00	1.0401E+01	9.4399E+00
V6	6.6352E+00	6.4230E+00	1.0271E+01	6.2236E+00	8.8005E+00	6.6388E+00	9.5387E+00	7.1554E+00	4.1310E+00	7.0109E+00	8.9755E+00	1.0479E+01	9.4944E+00
V7	3.9320E+00	4.0056E+00	8.0142E+00	3.9188E+00	6.2983E+00	4.0271E+00	7.2528E+00	4.6142E+00	4.1328E+00	4.4814E+00	6.6220E+00	8.2576E+00	7.1847E+00
V8	7.0990E+00	7.1460E+00	1.1041E+01	7.0231E+00	9.4209E+00	7.1472E+00	1.0320E+01	7.7610E+00	7.2906E+00	7.6002E+00	9.7418E+00	1.1368E+01	1.0303E+01
V9	7.1413E+00	7.1489E+00	1.1108E+01	7.0260E+00	9.4953E+00	7.1519E+00	1.0358E+01	7.7478E+00	7.3401E+00	7.6802E+00	9.8312E+00	1.1521E+01	1.0476E+01
V10	2.0909E+00	1.9854E+00	5.7387E+00	1.8230E+00	4.3069E+00	2.1258E+00	5.0528E+00	2.6420E+00	2.2213E+00	2.4580E+00	4.4360E+00	6.0697E+00	4.9491E+00
V11	5.1946E+00	5.1946E+00	8.8905E+00	4.7719E+00	7.4232E+00	5.2470E+00	8.1581E+00	5.8076E+00	5.3230E+00	5.5883E+00	7.5479E+00	9.1777E+00	8.1841E+00
V12	5.1649E+00	4.9543E+00	8.8587E+00	4.7821E+00	7.3994E+00	5.2246E+00	8.1546E+00	5.7819E+00	5.3219E+00	5.5532E+00	7.5708E+00	9.1339E+00	8.2110E+00

7) Range of computation time (second)

	Benchmarked Function												
	Population Size: 100												
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	8.4173E-02	2.8629E-02	2.8368E-01	2.4498E-02	2.3412E-01	2.2250E-02	2.5879E-01	3.0294E-02	2.7455E-02	3.2438E-02	3.8853E-01	5.9246E-02	6.8484E-02
V2	5.2953E-02	4.1865E-02	2.9043E-01	1.0309E-01	8.4141E-02	5.2768E-02	6.5016E-02	6.4309E-02	4.7042E-02	6.4780E-02	4.1529E-01	4.2890E+00	1.5462E-01
V3	1.0550E-01	5.9944E-02	3.9634E+00	4.4635E-02	3.3408E-01	7.8138E-02	6.4985E-01	4.2261E-02	3.4051E-02	3.6808E-02	4.8212E-02	5.6797E-01	3.9619E+00
V4	3.9110E-02	6.5488E-01	3.9321E-01	1.6519E-02	2.7999E-02	1.7655E-02	3.5191E-01	1.8750E-02	2.5519E-02	3.1928E-02	3.2911E-01	8.7063E-02	4.1639E-01
V5	1.5560E-01	8.7724E-02	3.9736E-01	4.1315E-02	4.1434E-02	4.0099E-02	3.0452E+00	1.1323E-01	2.9267E+00	4.7029E-02	6.2140E-02	5.0623E-02	7.0222E-01
V6	4.0750E-02	2.6055E+00	3.9727E-01	4.5925E-01	3.1717E-01	4.1794E-01	2.5695E-01	9.6874E-02	6.2919E-02	3.1802E-02	9.3045E-02	4.1474E-01	5.2041E-01
V7	7.3398E-02	2.3914E-02	1.0895E-01	9.2288E-02	5.4949E-02	2.6310E-02	2.5897E-01	2.9232E-02	3.5987E-02	3.8157E-02	2.7032E-01	2.9035E-01	4.5833E-02
V8	7.1578E-02	8.4821E-02	3.4448E+00	5.0720E-02	5.9070E-02	8.6010E-02	2.5642E-01	4.1212E-02	9.1564E-02	4.8245E-02	2.6233E-01	5.3932E-01	3.4610E+00
V9	1.0455E-01	3.6273E-02	3.1695E-01	3.6969E-02	2.3488E-01	5.1433E-02	8.4007E-02	1.5645E-01	3.3043E-02	9.2216E-02	6.0573E-02	4.7430E-01	6.1641E-02
V10	4.5425E-02	4.0331E-02	3.2073E-01	2.1735E-02	3.1772E-02	4.0270E-02	2.5227E-02	2.0318E-02	2.7443E-02	2.6221E-02	8.0729E-02	4.2232E-01	3.4379E-01

V11	7.8497E-02	7.8497E-02	3.2571E-01	3.4316E-02	4.2020E-02	4.5257E-02	2.7170E-01	5.1737E-02	3.4670E-02	3.3988E-02	4.6010E-02	4.3395E-01	5.9161E-01
V12	9.6587E-02	2.3696E+00	4.2064E-01	1.3276E-01	2.9644E-01	5.3257E-02	4.0488E-02	4.1061E-02	2.8465E-01	3.3025E-02	2.7913E-01	4.2488E-01	2.7654E-01

Population Size: 300

	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	9.9486E-02	1.6895E-01	1.2281E-01	6.5166E-02	9.0749E-02	6.1010E-02	3.5262E-01	9.0006E-02	6.3898E-02	6.5184E-02	7.2727E-01	1.2476E+00	1.1372E+00
V2	1.3829E-01	1.1511E+01	2.1666E-01	1.2431E-01	3.7801E-01	1.4587E-01	8.4675E-01	6.8974E+00	1.7695E-01	2.2330E-01	2.4295E-01	1.2884E+01	7.1694E-01
V3	1.1580E-01	1.2084E-01	8.3666E-01	1.4910E-01	1.8144E-01	1.5897E-01	3.4827E-01	2.0312E-01	2.5143E-01	6.1619E-01	6.6913E-01	1.2510E+01	6.8271E-01
V4	3.2820E-02	8.7413E-02	3.3039E-01	4.4328E-02	1.0335E+00	3.3427E-02	7.1692E-01	4.6943E-02	2.5899E-02	4.8718E-02	8.9495E-01	1.2402E+00	1.2024E+00
V5	1.0796E-01	1.9218E-01	3.8465E-01	8.4216E-01	1.0061E+00	8.8394E-01	2.0137E+00	1.0400E-01	7.0695E-02	1.4813E-01	6.3968E-01	1.5842E+00	1.0680E+00
V6	1.6545E-01	1.9616E-01	2.0769E-01	6.1888E-01	9.4507E-01	2.0986E-01	9.1321E+00	9.7846E-02	3.8069E+00	6.4531E-02	1.4017E+00	5.3872E-01	3.4611E+00
V7	1.0489E-01	1.6879E-01	2.1714E-01	5.2455E-02	8.2390E-01	7.6946E-02	1.4464E-01	1.1138E-01	5.3156E-02	5.8240E+00	5.4231E-01	7.1121E-01	9.0265E-01
V8	1.8025E-01	1.0799E-01	9.9724E-01	2.1391E-01	1.0514E+00	1.1214E-01	1.0363E+00	1.8366E-01	9.5419E+00	2.2017E-01	3.4058E-01	6.6597E-01	6.7881E-01
V9	1.8163E-01	9.4946E+00	1.1819E-01	8.8748E-02	1.9086E-01	3.4417E-01	7.9676E-01	2.9230E-01	2.0156E-01	1.8192E-01	8.8498E-01	1.1117E+01	1.0299E+01
V10	4.5382E-02	1.3421E-01	8.0966E-01	7.2850E-02	9.9193E-02	3.0963E-02	8.3428E-02	9.9788E-02	1.1142E-01	5.4024E-02	1.4766E-01	1.1978E+00	2.5295E-01
V11	5.9669E-02	5.9669E-02	6.8817E-01	1.4471E-01	8.9555E-02	1.3848E-01	1.7823E+00	1.6134E-01	2.0401E-01	1.2862E-01	9.7652E-02	1.6801E+00	8.2805E-01
V12	8.4489E-02	4.5433E+00	6.9981E-01	1.1892E-01	1.0759E-01	7.0774E-02	2.1340E-01	1.2657E-01	2.1089E-01	6.7708E-02	1.6815E-01	8.9153E-01	1.0478E+00

Population Size: 500

	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	9.0558E-02	7.6180E-02	6.3472E+00	1.0245E-01	1.6459E+00	9.0987E-02	1.3434E+00	1.5861E-01	1.6435E-01	3.1787E-01	4.9796E-01	2.9876E+00	2.1719E-01
V2	1.7449E-01	4.8879E-01	1.2261E+00	4.3126E-01	1.9844E+00	1.6242E-01	1.9452E+00	2.5956E-01	1.1372E+01	2.6278E-01	1.2025E+01	1.2695E+01	1.9142E+00
V3	3.4200E-01	2.3931E-01	3.3486E+00	3.6906E-01	1.9666E+00	5.4751E-01	3.0479E+00	1.0734E+00	6.2553E-01	2.1325E-01	1.2843E+00	2.2714E+00	1.2470E+00
V4	2.2380E-01	1.4852E-01	1.7509E+01	1.3276E-01	1.8663E+00	1.3039E-01	1.0214E+00	2.0210E-01	9.9891E-02	6.1295E-02	1.8257E+00	1.9528E+00	4.3900E-01
V5	1.7375E-01	3.9407E-01	3.7574E+00	1.8927E+00	1.5944E-01	6.2326E-01	1.6114E+00	3.9752E-01	6.7730E-01	1.7376E-01	1.6293E+00	2.5042E-01	2.6732E+00
V6	2.0647E-01	1.8759E+00	3.9583E-01	3.4377E+00	1.8736E+00	1.4751E-01	8.7008E+00	8.9075E-01	3.3592E+00	5.8249E-01	1.1163E+00	2.9643E+00	3.5041E+00
V7	1.3428E-01	1.8116E-01	4.6843E-01	9.4803E-02	3.6847E-01	7.0747E-02	1.6518E-01	1.6039E-01	1.5058E-01	1.7286E-01	1.2915E+00	2.5117E+00	9.7128E-01
V8	1.3453E+01	2.5108E-01	5.7921E-01	3.4959E-01	1.2702E+00	1.6098E+01	1.6039E-01	2.4366E-01	2.9258E-01	1.8010E-01	3.4401E+00	1.8753E+01	1.6665E+01
V9	2.6475E-01	1.6872E-01	4.2627E-01	3.0721E-01	1.5340E+00	1.2708E-01	1.6359E+00	1.5742E+01	1.6181E+01	1.6633E-01	1.4045E+00	1.2745E+00	1.7236E+01

V10	6.2549E-02	1.4367E-01	1.6359E-01	9.2695E-01	1.5895E-01	1.0006E-01	1.7617E-01	1.2190E-01	9.0230E-02	8.9345E-02	1.2770E-01	1.0565E-01	4.8499E-01
V11	1.8786E-01	1.8786E-01	2.1221E-01	2.6130E-01	2.9050E-01	4.8225E-01	2.6958E-01	1.7893E-01	1.8556E-01	8.4963E-02	1.9301E+00	2.7366E+00	1.4944E+00
V12	2.5041E-01	4.3750E-01	7.5991E+00	1.7793E-01	1.3972E-01	1.2971E-01	1.2405E+00	1.7122E-01	2.5638E-01	1.4910E-01	1.4303E+00	3.2109E+00	1.3377E+00

8) Standard deviation of computation time (second)

	Benchmarked Function												
	Population Size: 100												
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	9.6954E-03	5.5813E-03	3.8734E-02	4.8407E-03	2.4167E-02	4.6553E-03	2.4716E-02	5.3822E-03	5.7065E-03	5.5421E-03	5.3845E-02	1.0172E-02	1.3038E-02
V2	9.8463E-03	8.9227E-03	4.1336E-02	1.4452E-02	1.6118E-02	1.0905E-02	1.1805E-02	1.0004E-02	8.3413E-03	1.3650E-02	5.8529E-02	4.2685E-01	2.0694E-02
V3	1.2281E-02	8.6568E-03	3.9544E-01	7.8170E-03	3.2885E-02	9.3767E-03	7.7037E-02	8.5160E-03	7.1699E-03	7.2306E-03	9.6315E-03	7.8629E-02	3.9437E-01
V4	4.9480E-03	6.4061E-02	6.0451E-02	3.3054E-03	4.5133E-03	3.6492E-03	5.1274E-02	3.9024E-03	4.5423E-03	4.5973E-03	4.6921E-02	1.0843E-02	5.7810E-02
V5	1.5653E-02	1.8540E-02	6.0181E-02	8.6128E-03	9.0463E-03	6.6276E-03	3.0397E-01	1.3095E-02	2.9127E-01	7.0519E-03	1.4190E-02	9.7710E-03	7.9126E-02
V6	7.4245E-03	2.5770E-01	5.9269E-02	4.4595E-02	3.7657E-02	4.0609E-02	6.4475E-02	1.2081E-02	7.9926E-03	6.4129E-03	1.1107E-02	4.1093E-02	6.1020E-02
V7	8.8622E-03	4.8445E-03	1.5557E-02	1.0022E-02	9.4440E-03	5.3516E-03	2.6121E-02	5.5499E-03	5.9214E-03	6.1526E-03	2.8414E-02	3.7096E-02	7.5458E-03
V8	1.0645E-02	1.0834E-02	3.4355E-01	8.3195E-03	1.1330E-02	1.1202E-02	2.4712E-02	7.2669E-03	1.0984E-02	8.7061E-03	2.5735E-02	8.6265E-02	3.5678E-01
V9	1.5339E-02	6.3242E-03	4.3159E-02	7.6160E-03	2.3384E-02	9.3218E-03	1.0336E-02	1.8340E-02	6.9392E-03	1.3990E-02	1.0803E-02	7.3428E-02	1.2686E-02
V10	5.3659E-03	8.5144E-03	4.9383E-02	4.8246E-03	5.4852E-03	9.9111E-03	5.3688E-03	4.5370E-03	4.7674E-03	4.7371E-03	1.1774E-02	5.3924E-02	4.1852E-02
V11	9.9811E-03	9.9811E-03	5.2621E-02	7.5276E-03	6.7755E-03	9.8055E-03	3.4301E-02	7.5085E-03	5.6849E-03	6.3071E-03	1.1447E-02	6.5191E-02	5.8084E-02
V12	1.2973E-02	2.3411E-01	5.6449E-02	1.4098E-02	2.9333E-02	1.2082E-02	7.3408E-03	8.0396E-03	2.7468E-02	5.5403E-03	3.5856E-02	7.1001E-02	2.7266E-02
	Population Size: 300												
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	1.6156E-02	1.8917E-02	2.0705E-02	1.2602E-02	1.6016E-02	1.2054E-02	3.9822E-02	1.5447E-02	1.1373E-02	1.2736E-02	6.8268E-02	1.2032E-01	1.0940E-01
V2	2.3716E-02	1.1441E+00	3.6186E-02	2.6363E-02	4.5279E-02	2.7534E-02	8.0547E-02	6.8228E-01	2.9792E-02	3.2587E-02	3.3106E-02	1.7946E+00	8.0762E-02
V3	2.1079E-02	2.0363E-02	1.2771E-01	2.5885E-02	2.8715E-02	2.3477E-02	4.0849E-02	2.6791E-02	2.7604E-02	6.0627E-02	6.6887E-02	1.2459E+00	7.4580E-02
V4	7.3948E-03	1.9727E-02	3.4848E-02	8.6911E-03	9.9839E-02	7.1289E-03	9.3645E-02	7.6948E-03	6.5345E-03	8.6296E-03	8.7625E-02	1.9776E-01	1.1876E-01

V5	1.7820E-02	4.7654E-02	5.4990E-02	8.3740E-02	9.6671E-02	8.5079E-02	2.1482E-01	1.6888E-02	1.2586E-02	1.7867E-02	9.2133E-02	2.0156E-01	1.4094E-01
V6	2.0657E-02	3.9078E-02	3.4950E-02	6.1045E-02	9.1112E-02	2.2955E-02	9.2306E-01	1.7914E-02	3.0726E-01	1.3762E-02	1.3761E-01	5.3192E-02	3.9016E-01
V7	1.5724E-02	2.4170E-02	2.6744E-02	1.0021E-02	7.9852E-02	1.2917E-02	1.8707E-02	1.6755E-02	1.1026E-02	5.7871E-01	5.5829E-02	1.1713E-01	8.7801E-02
V8	2.5092E-02	1.7641E-02	9.7689E-02	2.6633E-02	1.0297E-01	2.1011E-02	1.0256E-01	2.1432E-02	9.5009E-01	2.4970E-02	4.7323E-02	1.0937E-01	6.7059E-02
V9	2.5072E-02	9.4412E-01	2.2475E-02	1.6826E-02	2.9397E-02	3.8676E-02	1.0000E-01	4.0502E-02	2.7844E-02	2.5857E-02	1.0897E-01	2.0599E+00	1.0250E+00
V10	7.2149E-03	2.3180E-02	7.9687E-02	1.4720E-02	1.4024E-02	6.3088E-03	1.4979E-02	2.5991E-02	1.8633E-02	1.0232E-02	1.8887E-02	2.0572E-01	4.8440E-02
V11	1.2042E-02	1.2042E-02	6.6703E-02	2.4145E-02	1.7812E-02	1.8599E-02	1.7616E-01	3.0691E-02	2.0794E-02	2.5407E-02	1.6740E-02	3.2127E-01	1.0238E-01
V12	1.3296E-02	4.4440E-01	6.8777E-02	2.1862E-02	1.9472E-02	1.2205E-02	2.3581E-02	3.0985E-02	3.1032E-02	1.4289E-02	2.2617E-02	8.6699E-02	1.5434E-01
Population Size: 500													
	1	2	3	4	5	6	7	8	9	10	11	12	13
V1	1.6808E-02	1.6682E-02	6.2954E-01	1.8362E-02	1.5845E-01	1.8891E-02	1.9783E-01	2.2957E-02	1.9307E-02	4.0113E-02	8.8377E-02	3.7044E-01	4.4023E-02
V2	3.5926E-02	5.4905E-02	1.1962E-01	5.1785E-02	1.9210E-01	3.5281E-02	2.1992E-01	4.3408E-02	1.1283E+00	4.6825E-02	1.1972E+00	1.2854E+00	2.4394E-01
V3	4.5979E-02	4.2739E-02	3.2825E-01	4.9494E-02	1.9530E-01	6.8411E-02	2.9411E-01	1.2392E-01	6.9410E-02	3.4076E-02	1.2885E-01	3.0531E-01	1.6740E-01
V4	2.2739E-02	2.4956E-02	1.7429E+00	2.0840E-02	1.8114E-01	1.6302E-02	9.9644E-02	2.1179E-02	1.3962E-02	1.1897E-02	2.1346E-01	1.9066E-01	8.4509E-02
V5	2.5572E-02	7.5247E-02	3.9038E-01	1.8729E-01	3.5313E-02	6.4120E-02	2.3987E-01	4.1456E-02	6.9115E-02	2.7750E-02	2.0863E-01	4.0893E-02	2.7592E-01
V6	2.9581E-02	1.7651E-01	6.5517E-02	3.4867E-01	2.2217E-01	2.2881E-02	1.0406E+00	8.6820E-02	2.7727E-01	5.9653E-02	1.3442E-01	2.8790E-01	4.4982E-01
V7	2.3975E-02	2.1556E-02	4.8372E-02	1.7623E-02	4.1959E-02	1.6485E-02	2.6678E-02	2.2979E-02	2.1624E-02	2.6444E-02	1.4063E-01	3.3192E-01	1.1548E-01
V8	1.5007E+00	3.4089E-02	6.9485E-02	4.3456E-02	1.2572E-01	1.6027E+00	3.6784E-02	3.8294E-02	4.3666E-02	3.1018E-02	3.6573E-01	3.6333E+00	1.6641E+00
V9	3.6796E-02	3.0273E-02	5.4525E-02	4.2366E-02	2.4372E-01	2.3415E-02	1.5892E-01	1.5705E+00	1.6094E+00	3.0883E-02	1.3603E-01	1.3332E-01	1.7175E+00
V10	1.1340E-02	3.0884E-02	2.9125E-02	9.2201E-02	2.0850E-02	1.3584E-02	2.2590E-02	1.6462E-02	1.3488E-02	1.4219E-02	2.4181E-02	2.1860E-02	8.3447E-02
V11	2.5538E-02	2.5538E-02	3.8724E-02	4.8515E-02	3.4398E-02	4.8292E-02	3.2524E-02	2.4002E-02	2.8696E-02	1.7720E-02	1.8903E-01	3.4679E-01	1.4951E-01
V12	2.9971E-02	6.7064E-02	7.6912E-01	3.6799E-02	2.6206E-02	2.2667E-02	1.2637E-01	2.7792E-02	3.7775E-02	2.2041E-02	1.6110E-01	4.8689E-01	1.9130E-01

K. Original Results of EPDMAPSO on inertia weighting comparison by benchmarked functions

Average result			Benchmarked Function												
			1	2	3	4	5	6	7	8	9	10	11	12	13
Inertia weight strategy	Population:100	1	5.8984E-01	1.4480E-01	1.4029E-02	1.7408E-03	2.6202E-01	7.8434E-01	6.8308E+00	2.0787E+00	4.5498E-01	1.9191E-01	2.6198E-02	1.2834E-01	1.7413E+00
		2	1.0455E-13	2.8971E-10	1.7087E-24	1.3064E-01	5.4251E-07	1.2657E-07	3.3913E+01	8.1719E+00	1.8818E-01	4.5989E-02	2.3131E-02	2.0472E-02	1.3598E+00
		3	2.3423E-01	9.3761E-05	9.3550E-02	6.4567E-15	6.8138E-24	9.0571E+00	8.7447E+00	8.4370E+00	1.8686E-02	1.6539E-03	5.3807E-14	2.0752E-03	3.8192E-15
		4	1.4550E-14	9.8400E-03	5.0661E-07	4.4036E-13	2.5578E-01	5.0875E-08	6.0086E-03	1.1366E-07	7.5951E-22	1.1414E-26	4.1213E-02	2.8649E-06	1.7064E-23
		5	1.8931E-01	1.5392E-07	2.9221E-03	3.2137E-02	2.3193E-02	3.1535E-03	6.5962E+00	1.2878E+00	9.8642E+00	2.8872E-02	1.2120E-02	9.1962E-03	3.1982E-02
		6	2.6084E-03	4.5987E-04	1.9758E-02	5.1288E-03	6.3065E-03	9.1307E+00	8.7352E+00	8.6224E+00	2.0790E-03	6.1848E-05	7.0749E-04	3.3846E-03	1.2867E-04
		7	1.6576E-04	1.2665E-02	9.5798E-03	1.1270E-02	2.0691E-02	7.7325E+00	4.0263E-02	1.3945E-04	1.3287E-05	7.4230E-05	4.6759E-03	2.3805E-04	2.1491E-03
		8	5.0322E-16	1.0604E-11	1.2131E-29	1.5073E-01	5.6948E-07	6.1014E-09	2.4234E+01	5.7742E+00	1.6127E-01	3.4636E-02	2.5304E-02	2.2923E-02	2.7598E+00
		9	1.9909E-01	6.1096E-05	1.4060E-01	1.9817E-19	2.0073E-29	8.9175E+00	8.5760E+00	8.5138E+00	2.8345E-02	3.1709E-03	2.9093E-05	2.5713E-03	2.0739E-13
		10	2.8469E-03	2.0238E-04	3.4217E-04	1.8460E-01	1.3733E-02	3.9261E-03	2.8613E-01	2.1470E-02	2.7813E-01	3.8817E-02	3.0261E-03	3.4263E-03	7.8913E-04
		11	8.3544E-05	9.8490E-04	1.6281E-03	5.9751E-04	1.9195E-04	9.2388E+00	8.5887E+00	8.5329E+00	7.0881E-05	1.9154E-06	2.5845E-06	8.6371E-06	2.3550E-06
		12	3.3313E-06	7.9603E-03	3.5396E-03	2.8730E-03	7.0986E-02	2.4878E-04	2.6446E-02	8.2891E-06	7.0322E-06	1.4163E-06	7.6609E-05	1.0263E-05	2.6391E-05
		13	3.7804E-04	6.9120E-06	3.9692E-06	1.0237E-01	1.1938E-03	1.1531E-04	8.9409E+00	1.3409E+00	2.6505E+00	6.7904E-02	1.9876E-02	1.6008E-02	2.6078E-01
		14	3.3620E-02	4.7176E-04	2.1626E-02	3.5460E-05	3.8334E-06	9.1388E+00	8.6943E+00	8.5326E+00	2.4917E-03	3.2185E-04	2.5945E-04	5.1078E-04	7.8990E-07
		15	8.2297E-08	5.9404E-03	2.3129E-03	3.4809E-04	4.2435E-02	1.3885E-04	1.3335E-04	5.8216E-04	9.7706E-07	1.2544E-08	1.1982E-02	1.7350E-04	2.7550E-06
		16	9.3012E-10	1.0328E-10	7.4894E-16	9.2045E-02	3.3209E-07	3.3380E-08	1.6620E+01	3.9809E+00	3.6254E-01	2.9900E-02	1.5542E-02	1.6100E-02	2.0852E-01
	Population:300	1	1.9674E-01	1.5133E-02	8.3051E-01	1.4688E-01	5.4372E-01	1.9306E-01	1.3190E+01	4.1834E+00	7.4427E-01	8.7589E-02	2.9633E-02	1.1152E-02	1.6197E+00
		2	5.6711E-02	1.4732E-05	2.1284E-02	1.3717E-03	4.0533E-08	8.9200E+00	8.6569E+00	8.5239E+00	1.6391E-02	2.4598E-04	8.2081E-04	8.2199E-04	1.0871E-12
		3	1.9011E-11	7.1146E-03	1.1104E-04	1.6675E-09	8.8308E-02	5.3964E-08	1.3970E+01	5.0339E-03	8.8852E-04	1.1933E-03	1.3849E-02	4.4253E-05	1.5255E-05
		4	2.1316E-15	5.0486E-03	1.7346E-05	1.3882E-08	8.4890E-02	5.5164E-06	6.3838E-16	7.4968E-04	4.0375E-12	1.4714E-16	7.0083E-05	1.9589E-04	8.2168E-15
		5	2.7751E-02	4.0784E-04	5.0510E-02	5.4596E-12	3.2935E-14	9.1221E+00	8.5553E+00	8.5811E+00	1.5612E-02	5.4859E-04	2.1728E-02	6.6405E-04	1.2400E-11
		6	7.2493E-09	3.3289E-03	5.0263E-07	1.0940E-01	1.7363E-03	2.6000E-05	4.4214E-03	3.1915E+00	6.0981E-01	2.4130E-02	1.0281E-02	2.0697E-02	2.5150E-01
		7	1.8979E-01	4.1808E-04	7.0567E-03	1.4724E-01	5.3158E-02	4.7374E-03	4.0106E+00	1.2195E+00	5.8872E+00	9.2421E-02	2.6543E-02	9.4583E-03	1.2315E-01
		8	4.5162E-03	1.9771E-03	2.4439E-01	2.3433E-02	7.0829E-03	9.1477E+00	8.8205E+00	8.4091E+00	4.0156E-03	1.2251E-04	2.8333E-04	5.6695E-03	1.5488E-04
		9	1.2222E-04	4.7024E-03	1.1700E-02	1.2721E-02	2.6333E-02	2.5892E-04	9.6494E-03	3.0622E-04	4.9509E-05	1.4843E-04	2.2687E-03	3.1400E-04	2.6017E-03
		10	3.5430E-01	6.4605E-04	2.6497E-01	5.9061E-10	2.4390E-15	9.0336E+00	8.4772E+00	8.7108E+00	1.3124E-02	3.1643E-04	3.4055E-04	4.7685E-03	1.1472E-11
		11	3.1723E-03	4.3958E-02	1.0909E-06	9.8428E-09	3.8814E-01	3.3415E-03	1.0905E-02	1.6605E-03	7.9467E-14	2.4832E-18	2.7428E-02	2.7362E-06	2.2758E-15
		12	6.0498E-04	4.3797E-03	2.5871E-05	3.7729E-03	2.9773E-03	3.2334E-03	1.4970E-01	4.0884E-03	4.7917E-03	2.9335E-03	1.6609E-03	4.5777E-04	4.9536E-04

	13	1.4389E-04	1.6450E-04	4.9717E-04	1.9836E-05	3.9192E-05	9.3045E+00	9.0095E+00	8.7192E+00	2.7017E-05	1.3477E-06	3.5036E-06	5.6342E-06	7.4442E-07
	14	5.5651E-07	4.5582E-04	1.2974E-03	5.7752E-04	3.1460E-04	2.5692E-05	4.4123E-05	1.8832E-05	1.1684E-06	6.8755E-07	1.3626E-04	1.0876E-05	1.2325E-05
	15	1.7295E-01	4.3626E-04	5.0001E-03	5.7249E-02	3.4079E-02	5.1212E-03	4.3990E+00	1.0702E+00	4.9738E+00	6.6171E-02	2.1622E-02	1.0329E-02	8.4615E-02
	16	3.7434E-03	1.3040E-03	1.7650E-01	1.8987E-02	4.4466E-03	9.1374E+00	8.8833E+00	8.5481E+00	3.3856E-03	2.3853E-04	1.8922E-03	2.1231E-03	2.2453E-04
Population:500	1	3.6113E-01	2.5778E-01	8.0634E-02	9.3687E-02	7.6830E-03	8.9607E+00	8.6767E+00	8.5675E+00	2.1575E-02	4.4027E-02	1.1749E-02	7.8188E-02	2.8736E-02
	2	4.4351E-05	4.9654E-03	9.9538E-03	1.0411E-02	4.7948E-02	2.6353E-04	1.0845E-02	2.0948E-04	2.8331E-05	4.4761E-05	4.0021E-03	3.7156E-04	2.9813E-03
	3	1.1347E-01	1.5934E-04	4.8750E-03	1.5889E-01	3.9272E-02	3.2732E-03	7.7154E+00	3.4191E-01	6.8154E+00	3.8687E-02	1.4105E-02	6.1038E-03	3.3262E-02
	4	3.1328E-03	4.7791E-02	1.4063E-08	8.4910E-14	3.1801E-01	3.1014E-14	1.3031E-02	8.1960E+00	3.2424E-18	5.0760E-28	8.7611E-02	9.4851E-04	1.4211E-14
	5	4.6088E-05	5.0688E-03	1.8143E-02	1.4169E-02	3.8232E-02	8.4363E-05	1.2013E-02	1.7431E-04	1.3630E-04	1.1171E-04	2.0245E-03	8.8938E-05	2.3120E-03
	6	1.7010E-06	6.2118E-10	5.2660E-10	9.6438E-02	2.9762E-05	2.9181E-07	1.9187E+01	2.2407E+00	5.3802E-01	8.5216E-02	1.9070E-02	1.2991E-02	1.5931E-01
	7	7.3780E-02	4.4275E-05	1.9587E-02	2.2980E-08	7.5273E-10	9.0878E+00	8.7445E+00	8.5105E+00	6.2295E-03	1.9915E-03	4.5439E-04	2.6179E-08	1.3726E-10
	8	1.1056E-11	1.0100E-02	1.2402E-04	4.9257E-06	8.3332E-02	1.1595E-07	3.9380E-03	4.7262E-04	9.3529E-10	4.0815E-12	1.2142E-02	1.4917E-04	2.3905E-09
	9	1.5709E-10	5.1854E-08	3.4353E-17	1.1771E-01	1.7517E-06	5.3809E-06	2.3420E+01	3.5334E+00	2.5464E-01	1.5685E-02	1.4442E-02	1.8107E-02	1.9353E-01
	10	4.4245E-07	4.3054E-03	1.4461E-06	1.8190E-09	1.1971E-01	1.7252E-06	7.3350E+00	7.7977E-04	8.5174E-14	5.9835E-19	1.8554E-02	4.2719E-04	1.1438E-16
	11	3.5062E-15	5.5907E-22	8.1072E-26	2.3261E-01	9.3286E-10	3.2800E-16	3.6583E+01	1.4112E+01	1.5597E-01	7.2176E-02	3.8338E-02	2.5670E-02	6.6933E+00
	12	1.1608E+00	3.1297E-04	3.8419E-01	2.3372E-15	3.2321E-25	8.9940E+00	8.6983E+00	8.4991E+00	1.2474E-02	1.8451E-03	3.3768E-11	5.8427E-03	9.9668E-04
	13	2.9157E-03	2.0395E-02	5.9711E-02	1.1923E-02	8.2099E-03	9.3603E+00	8.9514E+00	8.7730E+00	3.1574E-04	8.6033E-05	2.0387E-04	1.1855E-03	1.1946E-04
	14	4.8688E-09	4.0158E-07	1.2113E-14	1.1753E-01	1.1154E-05	1.9397E-05	1.2767E+01	2.3566E+00	3.5308E-01	2.0517E-02	1.1692E-02	1.5303E-02	2.9522E-01
	15	1.9073E-02	4.6998E-04	7.2862E-02	1.9403E-11	6.0839E-15	9.0226E+00	8.5475E+00	8.5826E+00	8.0403E-03	1.3591E-03	1.6150E-04	1.5455E-03	9.7158E-12
	16	9.7700E-16	6.5455E-03	7.8471E-06	1.4639E-08	7.2574E-02	3.4450E-06	3.8591E-14	6.0985E-04	8.8928E-12	2.8379E-16	1.8778E-02	9.6449E-05	5.2703E-14

Minimum Result			Benchmarked Function 1	2	3	4	5	6	7	8	9	10	11	12	13
Inertia weight strategy	Population:100	1	9.0500E-04	3.6565E-03	2.9940E-06	1.5099E-14	1.0406E-02	2.6983E-03	2.0987E-01	2.6458E-04	2.0446E-07	7.3347E-03	1.8374E-03	2.1450E-03	1.3498E-03
		2	9.3145E-18	2.3131E-11	1.0776E-27	2.9070E-04	1.0228E-09	9.3352E-16	3.3930E+00	1.8033E-03	8.1368E-05	4.2568E-29	7.0622E-04	4.2204E-10	1.8624E-04
		3	1.0050E-03	9.1381E-07	1.7079E-03	1.8416E-16	5.7938E-28	7.8752E+00	8.1049E+00	7.0671E+00	5.3261E-05	7.2243E-07	1.8827E-33	8.2018E-06	0.0000E+00
		4	0.0000E+00	3.9251E-08	1.2078E-08	1.5099E-14	4.3275E-08	0.0000E+00	0.0000E+00	1.5107E-13	9.7990E-26	1.5705E-31	3.5049E-05	2.2880E-17	0.0000E+00
		5	2.0682E-03	3.6896E-15	5.4835E-06	2.3749E-04	1.9992E-03	1.9983E-03	3.0673E-02	1.0454E-03	5.6008E-02	3.2048E-03	2.0580E-04	2.5511E-04	4.0292E-05
		6	1.6403E-05	6.3602E-05	2.2077E-05	3.3082E-06	2.0677E-06	8.3879E+00	3.3784E-11	7.6399E+00	1.4411E-08	2.1449E-08	1.9693E-09	5.8449E-07	1.0109E-10
		7	1.4233E-08	7.0272E-05	2.5775E-05	6.5024E-04	3.8511E-04	3.3360E-07	1.4311E-04	2.1668E-07	8.4080E-08	7.3137E-08	1.1787E-05	1.6344E-06	2.6759E-05
		8	2.8511E-19	1.6950E-29	4.1954E-34	1.3729E-04	4.1336E-11	4.5899E-19	4.0987E-01	8.6072E-02	1.5734E-03	1.1806E-03	1.0218E-03	2.3494E-04	3.1305E-03
		9	2.4604E-03	4.1746E-09	1.4855E-04	9.3949E-22	0.0000E+00	8.3111E+00	7.9077E+00	7.8365E+00	6.1979E-10	2.6763E-07	1.4238E-39	3.0163E-06	5.3291E-15
		10	6.8664E-05	5.7818E-07	7.5195E-08	6.4210E-03	6.2123E-04	1.9924E-04	1.3641E-04	1.2186E-04	7.8611E-06	9.3347E-04	8.5012E-05	2.3384E-04	6.3999E-07
		11	3.3383E-08	1.2993E-06	1.6350E-07	1.8241E-05	2.1508E-06	8.1622E+00	7.5441E+00	7.7058E+00	6.7056E-10	6.2803E-09	7.1738E-12	7.0133E-09	1.2705E-09
		12	3.7850E-08	1.2429E-03	4.0630E-04	1.0923E-04	1.4300E-09	1.1240E-12	1.0833E-05	2.6637E-08	2.7684E-10	4.3073E-09	1.7171E-08	8.5902E-08	3.1285E-09
		13	4.5949E-06	2.7854E-07	1.1436E-08	2.6250E-03	5.2795E-05	4.9003E-06	4.0715E-01	1.3485E-03	3.4324E-04	5.0066E-04	6.7349E-04	3.5177E-04	3.2483E-05
		14	1.1031E-06	3.4963E-06	9.9402E-05	2.3984E-08	2.9784E-08	8.0215E+00	7.8028E+00	7.5673E+00	2.0716E-10	2.7394E-07	4.3271E-12	7.7928E-08	2.6384E-08
		15	5.8400E-10	3.4127E-04	1.2049E-04	1.3021E-05	8.4726E-05	5.0215E-08	8.2465E-09	2.1261E-07	9.0407E-09	8.0787E-12	1.2527E-05	1.9554E-07	7.7180E-10
		16	5.7689E-12	3.3954E-18	1.0499E-18	3.8241E-03	1.2993E-08	8.2774E-12	1.7158E-01	5.2361E-02	5.6195E-04	2.5078E-04	2.8480E-04	5.2107E-04	5.7455E-03
	Population:300	1	2.3600E-02	5.6971E-03	1.3751E-01	2.8338E-03	1.7785E-04	5.4768E-02	1.2374E-01	1.1537E-02	1.5235E-02	1.5598E-02	2.7825E-03	2.5868E-03	3.9673E-03
		2	2.5628E-04	3.3204E-08	4.1697E-06	1.3812E-12	1.5088E-16	8.3191E+00	7.4987E+00	7.6525E+00	2.1878E-06	1.1173E-11	1.2064E-22	1.0424E-08	2.1316E-14
		3	2.6645E-16	6.0220E-16	1.4044E-05	1.8237E-11	3.1919E-05	3.6748E-14	5.6515E-02	1.0378E-03	2.9502E-13	6.2626E-19	4.3810E-05	7.1098E-07	2.1421E-16
		4	0.0000E+00	1.2874E-04	6.1711E-19	1.5175E-15	3.8313E-19	3.5781E-10	0.0000E+00	1.4554E-06	7.9839E-15	1.2499E-21	3.1488E-05	1.9332E-04	2.3928E-19
		5	5.0491E-06	9.8977E-07	1.0747E-04	8.5393E-15	3.0443E-17	7.6593E+00	7.8174E+00	7.4212E+00	1.2219E-06	6.9737E-08	1.4737E-21	6.0330E-07	2.8422E-14
		6	0.0000E+00	5.5628E-07	6.4483E-15	3.0732E-10	3.0927E-06	1.4958E-11	0.0000E+00	1.1650E-06	2.3792E-16	1.7296E-21	3.2476E-05	6.9917E-08	3.1361E-17
		7	2.0587E-04	2.1511E-07	5.8688E-07	1.1227E-03	2.1091E-03	3.1236E-03	1.0444E-05	3.5236E-04	3.5504E-02	1.6319E-03	4.6859E-04	7.5556E-04	1.1569E-04
		8	1.1578E-07	2.6184E-06	8.3244E-04	4.6434E-06	1.7893E-06	8.3454E+00	7.8819E+00	7.5783E+00	2.5096E-10	8.2125E-11	2.6228E-08	1.1671E-07	5.9375E-07
		9	2.7689E-09	1.1005E-04	1.2132E-04	6.4718E-04	9.2431E-06	1.6022E-07	9.0692E-07	4.3087E-06	1.3103E-08	2.6793E-07	1.6764E-05	1.8293E-06	7.7530E-06
		10	7.9820E-04	4.6521E-06	2.3092E-04	2.4403E-13	1.0154E-17	8.1683E+00	7.6825E+00	8.0368E+00	1.1406E-05	7.8886E-07	1.3392E-22	4.3695E-06	1.7764E-15
		11	0.0000E+00	4.2844E-03	2.6961E-08	7.7828E-10	1.6914E-05	3.3795E-13	0.0000E+00	2.9900E-06	1.1271E-15	1.6754E-19	5.6465E-04	9.5676E-11	2.1285E-18
		12	6.3718E-08	1.0662E-10	1.3852E-07	2.0630E-04	5.1545E-05	1.9744E-04	3.0018E-04	0.0000E+00	0.0000E+00	9.8227E-08	1.6429E-04	2.2887E-05	1.5981E-06

	13	6.9439E-08	8.9671E-08	1.6661E-06	6.1834E-08	2.2968E-08	7.8885E+00	7.6071E+00	8.0083E+00	9.0944E-10	1.0203E-13	6.0012E-10	2.4798E-09	5.9052E-09
	14	1.9453E-11	3.4856E-04	7.9936E-15	7.9936E-15	1.0818E-10	1.0668E-07	1.3120E-08	6.5460E-10	9.2508E-09	4.0124E-09	1.2964E-06	3.1696E-08	2.3864E-08
	15	5.6561E-04	1.1660E-05	9.3194E-05	4.9255E-03	8.6402E-04	4.1014E-03	9.0424E-03	2.4355E-05	9.8563E-04	4.0523E-03	2.5051E-03	1.5080E-05	5.6787E-05
	16	1.0272E-05	3.6939E-05	6.4708E-05	1.4083E-06	2.1949E-05	8.5509E+00	8.2381E+00	7.7731E+00	8.3053E-07	6.5122E-13	8.7127E-10	2.4121E-05	2.1677E-06
Population:500	1	4.7096E-02	2.5221E-02	2.8606E-02	1.7170E-02	3.2456E-03	8.0402E+00	8.1264E+00	8.0232E+00	1.2031E-03	1.0681E-02	2.0579E-03	1.4631E-03	1.0495E-07
	2	2.0081E-09	2.7115E-03	1.8380E-03	4.4850E-04	4.0460E-06	1.2392E-05	3.5532E-05	2.9239E-07	7.2851E-09	4.7166E-08	2.1537E-05	2.2634E-07	5.5378E-07
	3	7.4410E-06	1.1014E-05	3.9972E-08	3.3337E-05	6.8188E-05	1.1454E-03	1.7878E-02	6.9184E-05	9.1877E-08	5.1227E-04	9.2898E-11	5.6151E-05	2.7118E-08
	4	0.0000E+00	1.2097E-04	5.5460E-10	7.6778E-15	1.5620E-19	0.0000E+00	0.0000E+00	3.4253E-03	3.9369E-23	4.1134E-31	1.2512E-23	4.2132E-10	1.2398E-24
	5	7.8300E-08	2.2631E-04	8.2730E-04	5.2023E-04	1.7677E-04	2.8757E-06	1.3647E-05	2.4499E-06	2.2892E-07	1.4268E-07	5.6312E-07	3.0150E-06	2.3692E-06
	6	3.8896E-10	5.0550E-11	6.2969E-12	3.0729E-03	1.8439E-06	1.9829E-07	1.7065E+00	3.5278E-03	5.9668E-04	1.4765E-02	2.4711E-03	4.5571E-04	1.2686E-04
	7	8.9544E-07	1.4330E-07	2.7157E-06	6.7349E-10	4.2114E-12	7.5554E+00	8.2029E+00	7.5540E+00	1.8072E-08	3.2259E-07	1.7504E-14	6.3967E-11	1.1262E-12
	8	4.9738E-14	3.8508E-04	2.4299E-06	9.3011E-07	6.7300E-07	1.4231E-10	2.2331E-11	2.2239E-07	9.4760E-12	8.8469E-15	3.1973E-07	2.6083E-08	9.5490E-13
	9	3.9203E-12	1.1616E-16	1.6734E-19	3.4085E-03	3.4800E-08	8.9738E-12	5.1832E-01	2.7653E-03	1.0955E-03	7.0014E-05	6.9802E-04	3.0068E-04	1.5342E-05
	10	8.8818E-17	3.3854E-03	3.6338E-07	6.3801E-11	6.4354E-04	2.0484E-12	1.3531E-03	1.6533E-08	3.8578E-17	3.2379E-22	2.7337E-05	5.4349E-08	6.2959E-20
	11	3.8698E-19	3.8539E-25	3.1982E-28	3.5491E-03	5.9371E-12	9.4118E-17	1.8526E+00	1.0509E-02	1.4195E-03	3.6209E-03	2.9747E-03	1.2029E-03	2.5489E-04
	12	1.1125E-03	3.4604E-07	9.8142E-03	7.7548E-19	2.6106E-28	7.8062E+00	8.0130E+00	7.5542E+00	1.7840E-05	8.3406E-07	9.0298E-35	2.0336E-05	2.6645E-16
	13	0.0000E+00	7.3564E-04	4.9836E-04	7.9936E-15	5.8121E-04	8.6048E+00	0.0000E+00	2.3322E-05	2.9112E-11	2.0177E-08	2.3768E-06	1.2105E-11	5.8959E-29
	14	9.2737E-15	3.2135E-16	3.7953E-18	9.5026E-04	4.5114E-07	9.7683E-11	2.1127E-03	8.4340E-04	5.2375E-05	5.7283E-04	3.7416E-04	2.3657E-03	3.3142E-05
	15	1.5186E-05	6.9210E-09	1.2310E-04	3.9314E-13	2.6834E-18	7.7074E+00	7.3034E+00	7.7996E+00	9.3928E-07	2.1087E-10	1.8741E-19	4.9404E-06	1.7764E-15
	16	0.0000E+00	1.5511E-03	5.3369E-07	1.7134E-09	2.0598E-04	4.1323E-13	0.0000E+00	1.9180E-05	5.5796E-15	2.0998E-20	4.2469E-04	4.4126E-08	1.5089E-16

L. Detailed results of performance evaluation of weighting values

w_1	w_2	w_3	Result	w_1	w_2	w_3	Result
0	0	1	0.0000	0.1	0.6	0.3	0.4063
0	0.1	0.9	0.4410	0.1	0.7	0.2	0.3066
0	0.2	0.8	0.5110	0.1	0.8	0.1	0.2092
0	0.3	0.7	0.5605	0.1	0.9	0	0.1087
0	0.4	0.6	0.6006	0.2	0	0.8	0.2728
0	0.5	0.5	0.6397	0.2	0.1	0.7	0.3476
0	0.6	0.4	0.4054	0.2	0.2	0.6	0.4151
0	0.7	0.3	0.3072	0.2	0.3	0.5	0.4673
0	0.8	0.2	0.2083	0.2	0.4	0.4	0.5633
0	0.9	0.1	0.1078	0.2	0.5	0.3	0.5051
0	1	0	0.0000	0.2	0.6	0.2	0.4051
0.1	0	0.9	0.3103	0.2	0.7	0.1	0.3061
0.1	0.1	0.8	0.3825	0.2	0.8	0	0.2067
0.1	0.2	0.7	0.4846	0.3	0	0.7	0.2947
0.1	0.3	0.6	0.5244	0.3	0.1	0.6	0.3158
0.1	0.4	0.5	0.5739	0.3	0.2	0.5	0.3401
0.1	0.5	0.4	0.5053	0.3	0.3	0.4	0.4487
w_1	w_2	w_3	Result	w_1	w_2	w_3	Result
0.3	0.4	0.3	0.4792	0.5	0.5	0	0.4868
0.3	0.5	0.2	0.5057	0.6	0	0.4	0.2749
0.3	0.6	0.1	0.4044	0.6	0.1	0.3	0.2350
0.3	0.7	0	0.3048	0.6	0.2	0.2	0.2715
0.4	0	0.6	0.1748	0.6	0.3	0.1	0.3422
0.4	0.1	0.5	0.2563	0.6	0.4	0	0.4082
0.4	0.2	0.4	0.3507	0.7	0	0.3	0.1605
0.4	0.3	0.3	0.4395	0.7	0.1	0.2	0.1954
0.4	0.4	0.2	0.4712	0.7	0.2	0.1	0.3186
0.4	0.5	0.1	0.5050	0.7	0.3	0	0.3007
0.4	0.6	0	0.4055	0.8	0	0.2	0.0714
0.5	0	0.5	0.1451	0.8	0.1	0.1	0.1374
0.5	0.1	0.4	0.2590	0.8	0.2	0	0.2198
0.5	0.2	0.3	0.3524	0.9	0	0.1	0.0333
0.5	0.3	0.2	0.3870	0.9	0.1	0	0.1096
0.5	0.4	0.1	0.4370	1	0	0	0.0000