Coupling of Multi-agent Based Simulation and Particle Swarm Optimization for Environmental Planning and Decision Making

by

© Xudong Ye

A thesis submitted to the

School of Graduate Studies

In partial fulfillment of the requirements for the degree of

Master of Engineering

Civil Engineering

Faculty of Engineering and Applied Science

Memorial University of Newfoundland

October 2017

St. John's Newfoundland and Labrador

ABSTRACT

Environmental design making modeling is a vital part in environmental decision making process to help to conclude which decisions should be made and how to find alternatives for each decision. However, the complicated circumstances, massive data, uncertainties and multiple criteria standards make the decision-making process sophisticated and hard to realize.

This research focused on developing new environmental modelling methods by dynamic coupling of agent based modelling (ABM) and a multi-agent system (MAS) with PSO optimization algorithm and other kinds of traditional environmental simulation models for supporting environmental engineering decision making.

Firstly, a novel multi-agent hybrid particle swarm optimization (MAHPSO) approach was developed for a wastewater treatment plant network design. A hybrid particle swarm optimization module was proposed to account for both continuous and binary variables, and then integrated with the concept of multi-agent to enhance solution convergence and stability. The feasibility and effectiveness of method was tested and demonstrated by a case based on the wastewater treatment plants network of the city of St. John's, Canada. The results were compared with those of the traditional GA approach and the HPSO method. The proposed MAHPSO approach was approved to be capable of significantly enhancing solution convergence without sacraficing the computation time/efficiency, and of providing optimal results with high accuracy and repeatability. The approach could be used

as an effective evolutionary algorithm for complex system optimization and planning problems in environmental and other fields.

Secondly, a simulation-based multi-agent particle swarm optimization (SA-PSO) approach was developed for supporting dynamic decision making in offshore oil spill responses. The ABM as an emerging simulation method was introduced into oil spill responses in the first time to simulate the response actions with consideration of dynamic interactions among individual devices and/or response centre. A PSO method was further adopted to optimize the allocation of response devices/vessels among spill sites and warehouses with minimal total cost and time. Through a hypothetical oil spill case, the proposed SA-PSO approach showed strong capability and efficiency in reducing response time and optimizing responses. The results indicated that the proposed SA-PSO approach could efficently decrease the total response time, and dynamically optimize the allocation of response equipment. It had the strong potential to be applied to decision making problems in environmental and other fields.

This research developed two new modeling methods for supporting WWTP network designs and oil spill responses, respectively. The results of two case studies demonstrated the value of the integration of emerging artificial intelligence approaches with traditional environmental simulation models for facilitating environmental engineering and management.

ACKNOWLEDGEMENTS

Foremost**,** I would like to express my sincere gratitude to my supervisor, Dr. Bing Chen, for providing me the valuable opportunity to pursue my master study, for his extremely patient guidance, support and encouragement throughout my study and for his great inculcation on life and work.

I also gratefully appreciate the Northern Region Persistent Organic Pollution Control (NRPOP) Laboratory, the Faculty of Engineering and Applied Science, and the Memorial University for their financial support.

In addition, I would like to give acknowledgements to Dr. Baiyu Zhang for her kind advices, as well as the members of our research group, including Dr. Liang Jing, Dr. Pu Li, Xing Song, Fuqiang Fan, Tong Cao, Qinghong Cai, Zhiwen Zhu, Khoshrooz Kazemi, Jisi Zheng, Bo Liu, He Zhang, Weiyun Lin, Dr. Yinchen Ma, Zelin Li, Dr. Hongjing Wu, Ze Lv, Kedong Zhang, and Xiao Zheng for their assistance, helpful advices and suggestions during my study.

Last but not least, I would like to thank my parents and family for their great love, encouragement, care and support. Without the aforementioned help and care, I cannot imagine how I lived and studied for these valuable years.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS AND SYMBOLS

ABBREVIATIONS

ABM	Agent based modelling
BDI	Belief-desire-intention
BOD	Biological oxygen demand
BPSO	Binary particle swarm optimization
DSS	Decision supporting systems
EA	Evolutionary algorithms
GA	Genetic algorithm
GA-NN	Genetic algorithm-based neural network
GMU	George mason university
HPSO	Hybrid particle swarm optimization
IBMs	Individual-based models
ITOPF	International tanker owners' pollution federation limited
MADM	Multi-agent decision making
MAHPSO	Multi-agent hybrid particle swarm optimization

MAOP	Multi-agent optimization problem
MAS	Multi-agent system
MBR	Membrane bioreactor
MIDO	Mixed-integer dynamic optimization
MILP	Multi-period mixed-integer linear programming
MINLP	Non-convex mixed-integer nonlinear program
MSINP	Mixed integer nonlinear programming
NGO	Non-governmental organizations
NRPOP	Northern region persistent organic pollution control laboratory
O&M	Operation and maintenance
OD	Oxidation ditch
PSO	Particle swarm optimization
RO	Reverse osmosis
RSM	Response surface methodology
SA-PSO	Simulation-based multi-agent particle swarm optimization approach

SBR	Sequencing batch reactor
SDS	Shortest distance selection
SO	Simulation and optimization
SPC	Sludge process center
ST	Slick thickness
TS	Total solids
WUTN	Optimal water usage and treatment network
WWRN	Wastewater reuse network
WWTPs	Wastewater treatment plants

SYMBOLS

A	Area of spill k
$A_{i,j}$	Coordinates of agent A
AR(t)	Annual increase rate of O&M cost
Asph	Asphaltenes
BOD_{MBR}	Biological oxygen demand
c_1 and c_2	Two acceleration constants called cognitive factor and social factor
CDj	Compost demand
Ci	Capital cost
CP	Compost price
D	Distance
Dj	Distance between city j and the landfill
d	d-th dimension of a particle
(%)Dis	Percentage dispersed oil
Djk	Distance between city j and city k
DV	Dispersed oil

$(\%)Ev$	Percentage evaporated oil
EL	Annual equipment loss rate
$exchange\left(x_{id}(t)\right)$	Value changes from 0 to 1 or vice versa
F_{emul}	Fractional water content
F_{emul}^{final}	Maximum water volume that can be incorporated in the emulsion
$f_{ORR_{sk,i,t}}$	Net oil recovery rate of skimmer i at time t
$iter_{max}$	Maximum number of iteration
FD	Dispersion rate
FE	Evaporation rate
FR	Flow rate
FV	Evaporated oil
gBest	Global best particle position among all the particles in the group
i	Index of a particle
$iter_{current}$	Current number of iteration
IR	Annual interest rate

k	Mooney constant
M	Molecular weight
$N_{i,j}$	Neighbors of A_{ij}
Oi	O&M cost
ORR_{sk}	Amount of recovered oil per hour
P^{sat}	Vapor pressure
pBest	Previous local best position of a particle
p_{gd}	Group gbest
Pj	Population
p_{id}	Particle pbest
R	Gas constant
r_1 and r_2	Uniform random values
rand ()	A uniform random value between 0 and 1
RRP	Reclaimed wastewater reuse percentage
S_t	Interface tension between oil and water
RWi	Reclaimed water reusing benefit
$S'(v_{id})$	Modified sigmoid probability distribution

Si	Sludge generation rate
$\text{Sigmoid}(v_{id})$	A sigmoid probability distribution transformation
SKi	Skimmer i
SPCC	Sludge processing centre capital cost
SPCO	Sludge processing centre operating cost
$ST_{k,t}$	Slick thickness of spill k at time t
SWR	Sludge weight reduction rate
t	Time index
T	Transportation cost (Chapter 3)
T	Total time span (Chapter 4)
$TS_{SBR}/TS_{Oxidation\ ditch}$	Total solid
TV_t	Total recovered oil in each stage t
U	Wind velocity
v_{id}	Particle velocity
$V_{0,k}$	Initial volume of spill k

V_{sk}	Total recovered oil amount by all skimmers during the response time period
w	Inertia weight factor
Wax	Waxes contents
w_{ini} and w_{end}	Upper and lower boundaries of inertia weigh
WG	Wastewater generation rate
x_{id}	Particle position
xij	Binary decision variables indicating whether to build a type i WWTP in city j
Xsize and Ysize	Integer number of max coordinates
yj	Binary decision variables indicating whether to build the SPC in city j
zj	Sludge transported from city j to the SPC
μ	Dynamic viscosity of the oil
μ_0	Initial dynamic viscosity of the oil
ρ^{sat}	Oil density

CHAPTER 1: INTRODUCTION

1.1 Background

Nowadays, computer models have been extensively developed and used by environmental researchers. Decision supporting systems (DSS), which have been around since the 1950/60s, are sophisticated (Bulling, 2014) and, to some extent, intelligent systems that support people in their decision making by providing integrated simulation, optimization and info-analysis functions (Schmolke et al., 2010; Stillman et al., 2016). Intelligent agents are intelligent software or computer system that contain essential properties such as learning, social ability, reactivity and pro-activeness and perform a series of complex tasks autonomously (Kumar et al., 2016). Due to the fundamental requirement for DSS to achieve the objectives autonomously, interactively, and dynamically, an intelligent agent could be a potential aspect to realize this. Agent based modeling (ABM) is formed from agents that interact within an environment. Agents could be not only individual computer programs, but also, more generally, unique portions of a program indicating social actors, such as, the individuals, organizations, or bodies (Gilbert,2008). Agents are autonomous, goal-oriented and pro-active. Decision making models with agents have a wide application range from classical utility maximization in the presence of complete and static information to complex dynamic planning problems particularly in the areas of business and management (Bulling,2014). Under general terms, an agent does not work individually, interaction is also a vital characteristic for an agent. It interacts with environmental conditions and other agents situated in the same environment. Multi-agent systems (MAS) are systems comprised of multiple, self-interested agents (Timm et al., 2006). Multi-agent decision making (MADM) with the consideration of multiple agents in a decision making system has a key characteristic that the actions and decisions of agents are autonomous but interactive, and the goals of agents are possibly different, even contradictory (Yu et al., 2012). Outcomes and behaviors from MADM, reflected by complex interactions, could be unpredictable and unforeseen, but may be relatively close to the results from real-world experiments. The process of good decisions is not easy and requires agents to act strategically and follow given rules (Chennaoui et al., 2014). The behaviors of agents are based on their specific strategies. A strategy is a methodology which the agent implements to achieve its goals while following the basic rules (Ilieva, G., 2011). Agents need to take self-control mechanisms, inter-judgement conditions of communication, cooperation and competition into consideration. The number of required skills is vast and so is the number of tools and techniques relevant to MADM (Yuan et al., 2015). The flowchart, integrated with Bulling (2014)'s study, indicates a general overview for agent-based and multi-agent decision making (Fig. 1.1). Due to the strengths of agent based modeling and multi-agent systems on decision making systems, they have a vast potential to be applied to environmental problems, although such applications are rarely reported (Wong, et al., 2012; Lim, et al., 2013; Chao, et al., 2015)

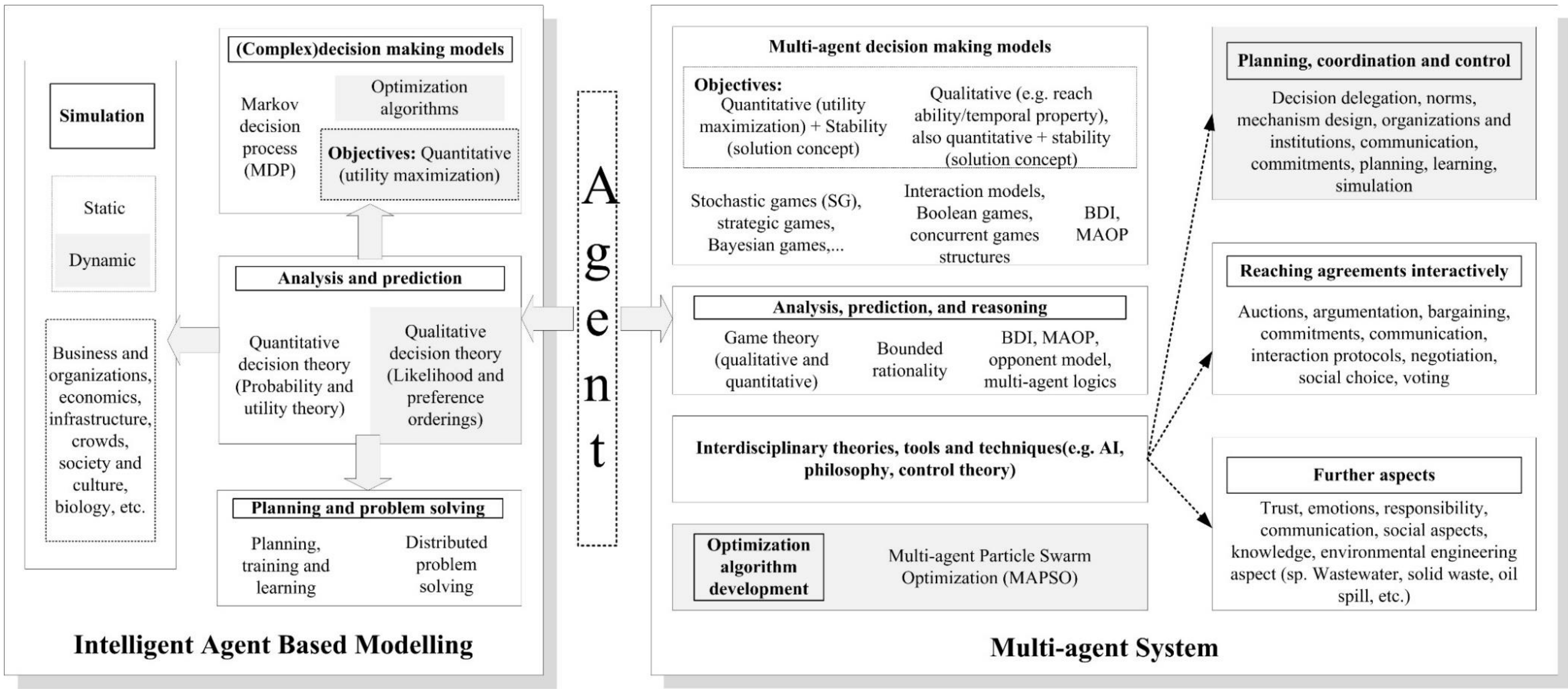


Figure 1.1 Overview of aspects relevant to agent based and multi-agent based decision making (Bulling, N., 2014).

The accelerating pace of industrialization, urbanization and population growth, which our planet has faced over the last one hundred years, has considerably increased environmental pollution and habitat destruction, and negatively affected water, air and soil quality. The pollution and contaminated sites threaten human health, animal and plant life on land and in the ocean. Further, it would cause a variety of unforeseen negative impacts, risks and liabilities to the environment and society (Depellegrin et al., 2013). Wastewater disposition and offshore oil spill contamination response are two of the most intractable environmental problems. They also present two different but representative types of environmental decision making. This research chose them as case studies for methods testing and demonstration. The following provides discussions on these two types of environmental decision making, and the associated challenges as well as the opportunities for application of agent based DSS methods.

In Canada, a high proportion of about 90% population is served by a wastewater collection and treatment system. The range of treatment level is from no treatment to very sophisticated and thorough treatment (Environment Canada, 2012). A mature and efficient wastewater treatment system could reduce the environmental and health impacts (Luciano et al., 2012). These impacts can include negative effects on fish and wildlife populations, oxygen depletion, beach closures and other restrictions on recreational water use, restrictions on fish and shellfish harvesting and consumption and restriction on drinking water (Spellman, 2009; Rivas et al., 2011). Therefore, decision support for treatment network planning and treatment technique selection has been an effective approach to wastewater management and environmental protection. The previous wastewater treatment decision making studies mainly focused on the following three aspects: (1) Process simulation and cost analysis: Simulate the main processes of a wastewater treatment plant and integrate a standardized cost estimation, in order to analyze and optimize the treating cost under multiple scenarios. Further, design and control optimization could be included in some cases (Gillot et al., 1999; Moles et al., 2001; Zhang, B., 2015). (2) Process analysis and efficiency in optimization: Most researchers applied diverse optimization approaches with experiments. The fitting function was usually under specified cost constraints. For example, response surface methodology (RSM) is a common method used for this kind of problems (Kaksonen et al., 2003; Körbahti, 2006; Wang et al., 2007). (3) Treatment system optimization: The objective functions usually consider capital and operational costs during a certain period of concern. The aim is to optimize the entire treatment/reuse system and its performance. The formulated constraints could include the water quality indicators (such as COD/BOD, TN, and TP) as the standards (Feng et al., 2004; Ponce-Ortega et al., 2009).

In general, most of previous studies focused on individual treatment unit or system. The integrated consideration of the entire wastewater treatment network in a city or even among cities would have great values in efficiency improvement and cost reduction from municipalities and regions. However, limited efforts have been reported in the literature. It is worth of asking: Is it possible to develop an effective and efficient network planning associated with multiple wastewater treatment plants using different selections of treatment techniques to achieve both environmental and economic goals for a long-term operation? This triggered the presented research by developing a new agent based optimization method for WWTP planning and design.

Offshore oil spill accidents are commonly considered as one of the most harmful environmental disasters in terms of severe biological and socioeconomic consequences. Major accidental oil spills can cause catastrophic impact on oceans and shorelines around the world, constituting a major challenge for operational management, strategic contingency planning, and response decision making (Wirtz et al., 2006). For instance, the Exxon Valdes oil spill in 1989 cost 2,259 billion U.S. dollars for clean-up operations (Exxon Valdes oil spill trustee council, 2001). The spill caused serious damage and threatened the ecological system including commercial and recreational fishing, tourism and other enterprises linked with natural resources (Gill et al., 2012). The Arabian Gulf has a long history of oil spill since 1967, especially, the 1991 *Al-Ahmadi* oil spill releasing 0.5-1.0 million tonnes of oil (Danish, 2010). The Prestige oil spill in 2003 on the Galician coasts affected 1,000 km of vulnerable coast and 745 beaches with 70 million U.S. dollars in economic losses from direct income and $108 million U.S. dollars in clean-up operations (Garza-Gil et al., 2006; Sanctuary et al., 2006). The BP oil spill in 2010 were the most ecologically damaging release of oil in North American history. An estimated 171 million gallons of oil had leaked into the highly productive and biodiverse Gulf of Mexico (Dickey et al., 2012; Gill et al., 2012). Contingency management thus aims to simply keep the drifting oil away from sensible coastal areas (Liu et al, 2005; Fingas, 2011). Due to the complex features of the marine and coastal, dynamic meteorological and oceanic conditions system, and different ecological and economic values of coastal areas under risk, decision making during a oil spill response has been reported as a critical but challenging task. Even if not in the response process itself, at least in the aftermath and during the political evaluation of the response strategy, in which various interested groups such as primate and public organizations, NGOs, scientific institutions and local communities are involved. How to time-effectively and collectively consider interest from diverse stakeholder, capacity of response systems, and complex conditions of environment into spill response decision making has been promptly reloaded as critical and necessary but challenging.

Most of the previous offshore oil spill decision making studies mainly focused on the following three aspects: (1) Risk-based decision making approach: Add risk assessment algorithms into the decision-making models, in order to minimize risks from spilled oil to ecosystem services. Most studies used static models or statistical models to analyze data from previous spill accidents or hypothetic scenarios as a case study with risk assessment algorithms to examine model responses (Carriger, et al., 2011; Psarros, et al., 2011). But these types of models could not fully reflect the consequences from the accidents, and hard to realize the real-time decision making and modify the scenarios with given uncertainties constantly. ABM, as a dynamic model, could analyze the model scenarios timely, and consider the risk impacts from the complicated and interacted marine ecosystem. (2) Simulation-based decision making approach: mainly focus on applying process simulation with response fate and transport modeling to optimize the scenarios by minimizing the response time and total cost This type of models Simulate the trajectory of oil spills based on historical data; developing what-if scenario models with uncertainty to improve the pre-accident planning; review and simulate the models with experimental equations to shed light on the political, technical, and financial issues that have influenced the decision-making process and are likely to influence new approach application, mainly on chemical dispersant. (Etkin, D.S., 1998; Li et al., (2012, 2014); Boufadel, et al., 2014; Leschien, et al., 2014). Two main challenges indicated that firstly, models hard to coupling simulation models with optimizing decision making models dynamically. Secondly, current models showed the weakness on the realization of complicated high-interacted simulation situations. Agent based modeling coupling with PSO optimization can, to some extent, solve the problems.

Furthermore, few studies on offshore oil spill emergency response considered the role of dynamic decision making system and the response on a harsh environment, such as North Atlantic Ocean, Canada. It would be valuable to develop a dynamic decision making system to deal with the cleanup response for the offshore oil spill accidents on harsh marine environments, and generate a novel approach by coupling simulation model and optimization algorithms for making an information-exchanging decision making system.

1.2 Objectives

To help address the above challenges, this research aimed to develop novel agent based simulation and optimization approaches for environmental planning and decision making. The developed approaches will be applied for two typical environmental problems, wastewater treatment plants network design and offshore oil spill response decision making. The major research tasks are as follows:

(1) To develop a new hybrid particle swarm optimization version (HPSO) method to deal with non-linear problems with both continuous and discrete variables; to integrate HPSO with MAS into a new multi-agent based hybrid particle swarm optimization (MAHPSO) approach to enhance the solution convergence and stability; and to exam the practicability and efficiency of the proposed approach through wastewater treatment network planning case study simplified in Newfoundland and Labrador from the real system in the city of St. John's, and comparison with genetic algorithm (GA) and HPSO method;

(2) To develop a new simulation-based multi-agent particle swarm optimization (SA-PSO) approach to facilitate the simulation and optimization coupling environmental decision making; and to apply the proposed approach for a hypothetical offshore oil spill case in North Atlantic Ocean to test its feasibility and capability along with a competition with the traditional short distance selection (SDS) method, which was operated by choosing nearest spills closed to skimmer-ships.

1.3 Structure of the Thesis

This thesis consists of five chapters. Chapter 1 outlines the general research background and scopes, research objectives and thesis structure. Chapter 2 provides the literature reviews of the relevant topics including (1) current development and application of agent based approaches, (2) relevant applied environmental optimization methods and applications of wastewater treatment system design and network planning, (3) decision making methods and applications for offshore oil spill emergency responses. Chapter 3 presents the development of MAHPSO approach. Chapter 4 describes the SA-PSO approach and supporting a case study on dynamic decision making for offshore oil spill responses. Finally, Chapter 5 draws conclusions of this research with recommendations for future work. The structure of the thesis is illustrated in Figure 1.2.

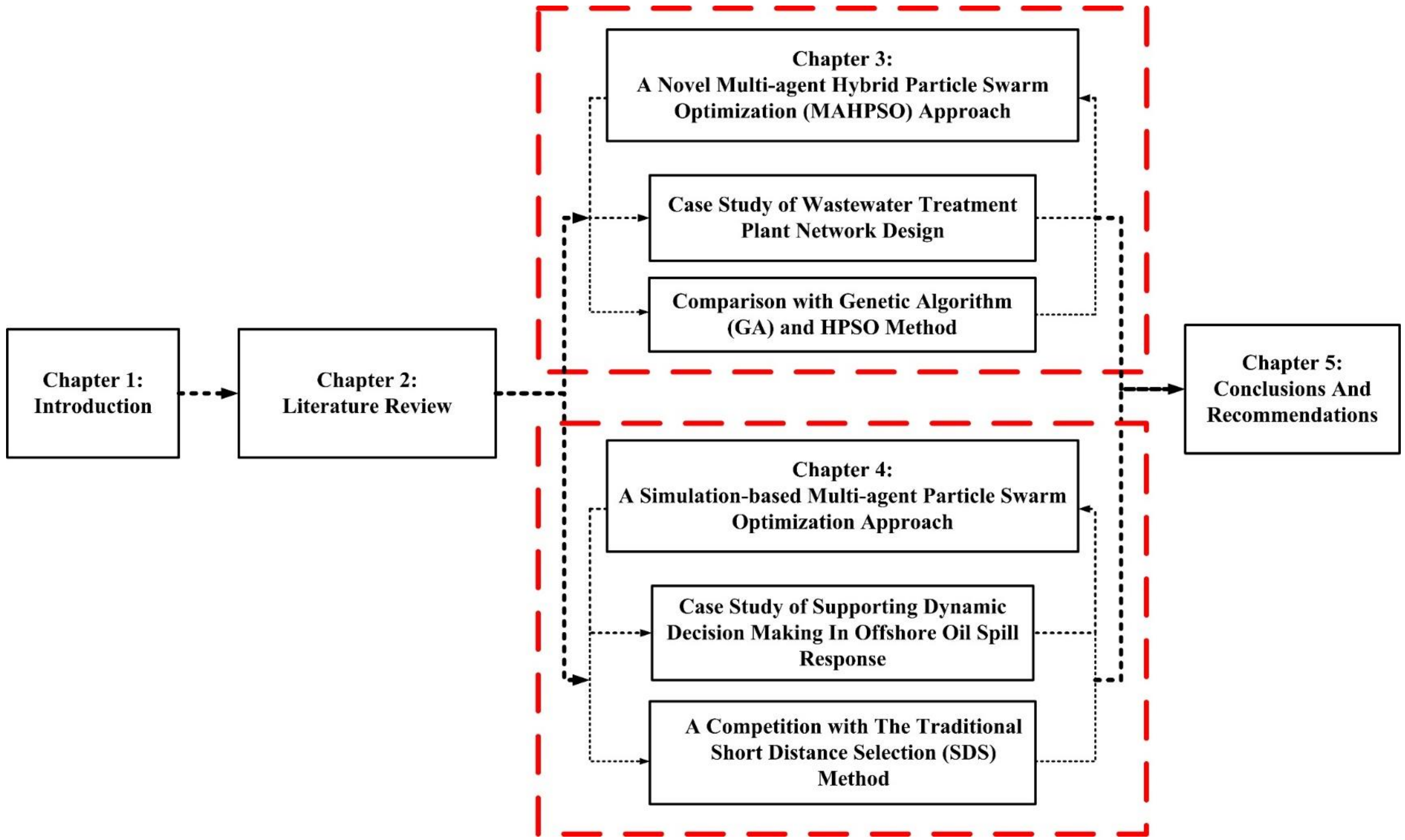


Figure 1.2 Roadmap of the research

CHAPTER 2: LITERATURE REVIEW

2.1 Agent Based Approach

2.1.1 What is an agent?

Intelligence implies a certain degree of autonomy, which in turn, requires that ability to make independent decisions. Truly, intelligent agents could be an effective means to make such decisions. An agent is an entity that functions continuously and autonomously in an environment in which other processes take place and other agents exist. In most dynamic domains, a designer cannot possibly foresee all situations that an agent might encounter, and therefore, the agent needs the ability to learn from and adapt to new environments. This is especially valid for multi-agent systems, where complexity increases with the number of agents acting in the environment (Kudenko et al, 2003).

From a practical modeling standpoint, a traditional intelligent agent would possess the following general characteristics (Fig 2.1) (Jeusfeld, 2003; Macal et al., 2008; Springer, 2016):

- **Self-identification:** An agent is an identifiable, discrete, or modular, individual with a set of characteristics and rules governing its behaviors and decision-making capability. Agents are self-contained. The discreteness requirement implies that an agent has a boundary and one can easily determine whether something is part of an agent or not, or is a shared environment characteristic.

- **Autonomy:** An agent is autonomous and self-directed. Agents operate without direct intervention from the user, and have some sort of control over their actions. An agent can function independently in its environment and in its interactions with other agents for the limited range of situations that are of interest.

- **Reactivity:** Agents perceive their environment and respond to changes, which is also called learning behavior. An agent can learn and adapt its behaviors based on experience. It can get information from the environment or other agents, so that it can use this kind of information to update its situation.

- **Pro-activeness:** agents not only react in response to the environment, but also exhibit goal-directed behaviors. An agent, which is goal-directed, has goals to achieve with respect to its behaviors. This allows an agent to compare the outcome of its behavior to the goals that it is trying to achieve.

- **"Social" ability:** An agent is social, interacting with other agents. It is located in an external environment in which the agent can interact with other agents. Agents have protocols for interaction with other agents, and can recognize and distinguish the traits of other agents.

In environmental planning and decision making problems, high level of interactions and complicated decision-making rules are usually required. Interactions between individuals often cause nonlinear effects in a tremendous population level. Agent-based modelling is the only way that allows for the explicit modelling of social interaction and the social networks that result from it (Klabunde & Willekens, 2016). In agent-based modelling, the focus is on individual agents, their decision processes, their interactions with other agents, and the effects of that interaction on decision processes. Differences between individuals can be illustrated easily because agent-based models can act as microsimulation models at their core.

This represents a huge opportunity for environmental modelling, as networks shape of the environmental planning and decision. Information on optimization candidates, simulation particles, response decision making center is transmitted through these networks. As shown in Figure 2.1, agents can have different attributes, behavioural rules, decision making rules, and can react and reflect with the environment with their specific characteristics. Then agents can acquire and store useful information to help update their behaviors and decision makings. Thus, an environmental planning and decision making model with nonlinear decision making and complicated simulation situations can be realized through a series of basic simple rules and autonomic agents.

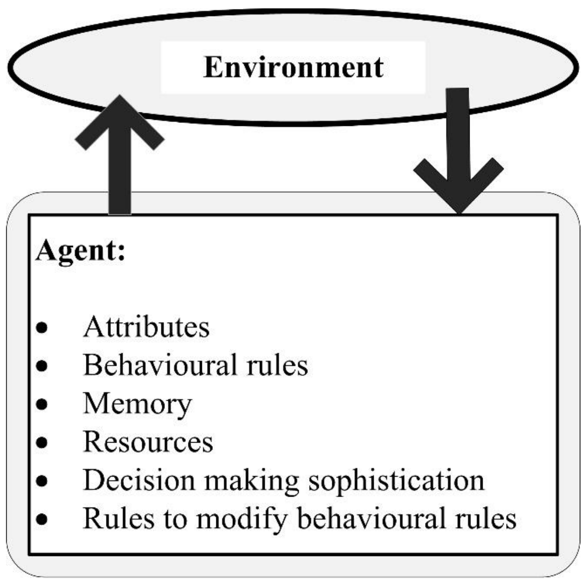


Figure 2.1 Basic characteristics and behaviors of agents (Macal et al., 2008)

Based on the objective need, agents would undertake very different tasks, and exhibit various behaviors. Due to previous research, a great number of agent types have been indicated as follows (Fig 2.2), for example, the mobile agent, autonomous agent goal-based agent, reactive agent, and some other types. Each agent could have more than one property, and have multiple tasks in the system.

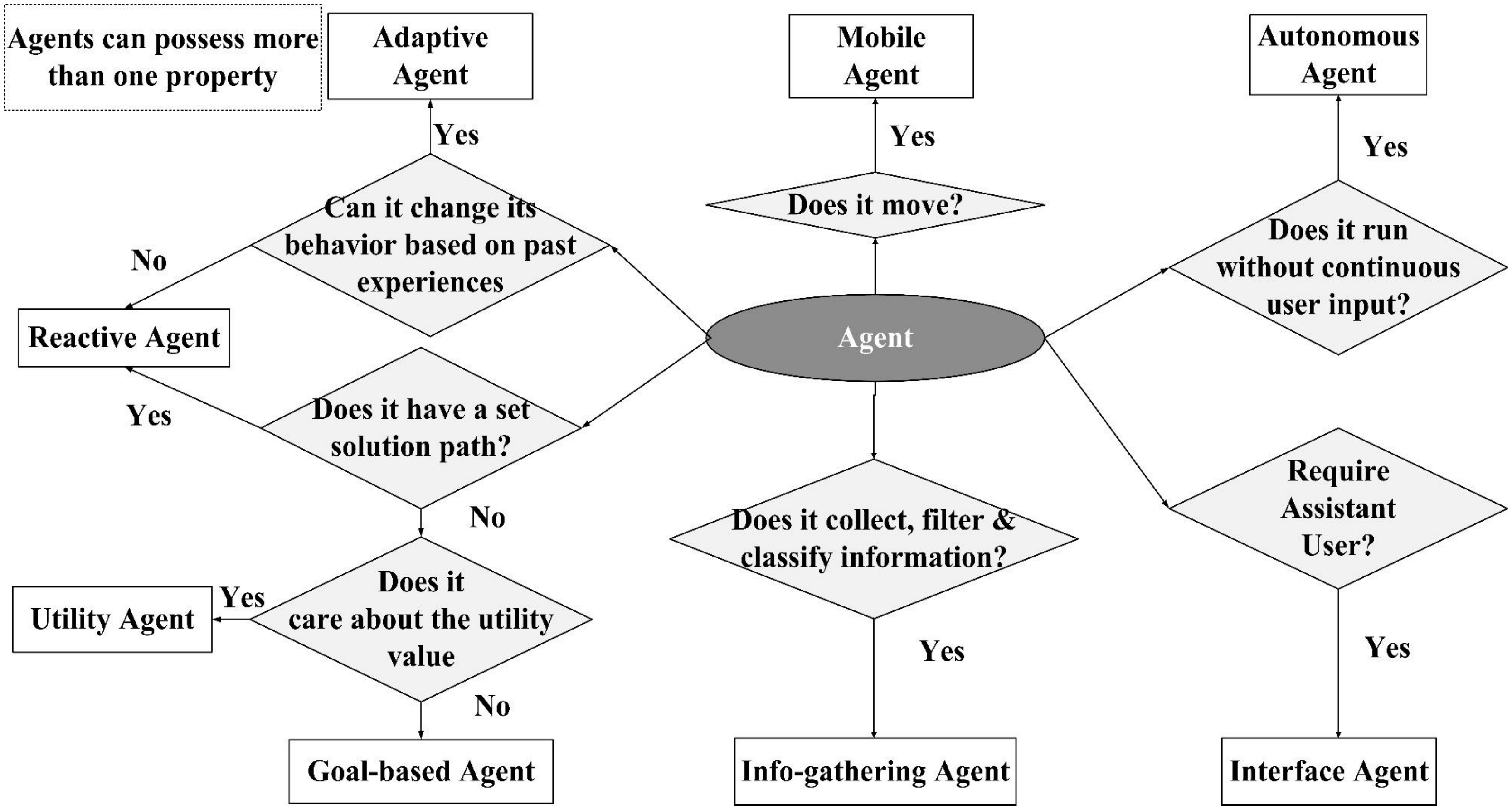


Figure 2.2 The types of agents

2.1.2 Two main agent based approaches

Two main categories for intelligent agents can be indicated as agent based modelling (ABM) and multi-agent system (MAS), based on different application targets. ABM is where agents individually assess its situation in the environment and make decisions on the basis of a set of rules. It is mainly used on non-computing related scientific domains including biology, ecology and social science (Niazi et al, 2011). Comparatively, MAS is a system modeled as a collection of agents. It reflects and analyzes the relationships between agents. MAS is a computerized system composed of multiple interacting intelligent agents within an environment. The current research on MAS mainly focuses on the aspects of online trading, disaster response, and modelling social structure (Schurr, et al., 2005; Rogers et al., 2007; Genc et al., 2013). Until now, rare studies on ABM and MAS have been applied to the environmental decision making problems.

An agent-based model (ABM) is a diverse research area concerned with the building of intelligent software based on the concept of "agent" (Niazi et al., 2011). It is one of a class of computational models for simulating the actions and interactions of autonomous agents (both individual and collective entities such as organizations or groups) with a view to assessing their effects on the system. As shown in Fig 2.3, each agent has individual behaviors, social interaction, and learning capacity from others and environment. An agent could be a representation of an interacting social component of a large system used to explore emergent global behavior in a simulation (Gilbert et al., 2005; Niazi et al., 2011).

Agent based models are also called individual-based models (IBMs) particularly in ecology fields (Grimm et al, 2005; Cohen et al, 2014). The applications of ABMs or IBMs for research and management are growing rapidly in a number of fields. Based on the literature review, ABMs are used on not only non-computing related scientific fields including biology, ecology, and social science (Niazi et al, 2011), but also dynamic-computing related academic domains for economy, business, and even earth science and environmental science (Gazda, 2012; Baptista et al, 2014; Blanchart et al, 2009; Banitz et al, 2015). Even though there is considerable overlap, agent based modelling is related to, but still different from, the concept of multi-agent systems (MASs) or multi-agent simulation (Fig. 2.4) in that, the goal of ABM is to look for explanatory insight into the collective behavior of agents obeying simple rules, typically in natural systems. But MAS is more focusing on solving specific practical or engineering problems (Niazi, 2011). The terminology of ABM is used more often in the sciences group behaviors simulation (Niazi, 2011), MAS research may point at an appropriate approach in engineering including online trading, disaster response, and modelling social structures (Rogers et al., 2007; Schurr et al., 2005; Sun et al., 2004). The general characteristics of several general ABM model platforms that can be used for solving environmental problems shown in Table 2.1. With the development of software. Nowadays, most of the platforms can deal with ABM and MAS, respectively.

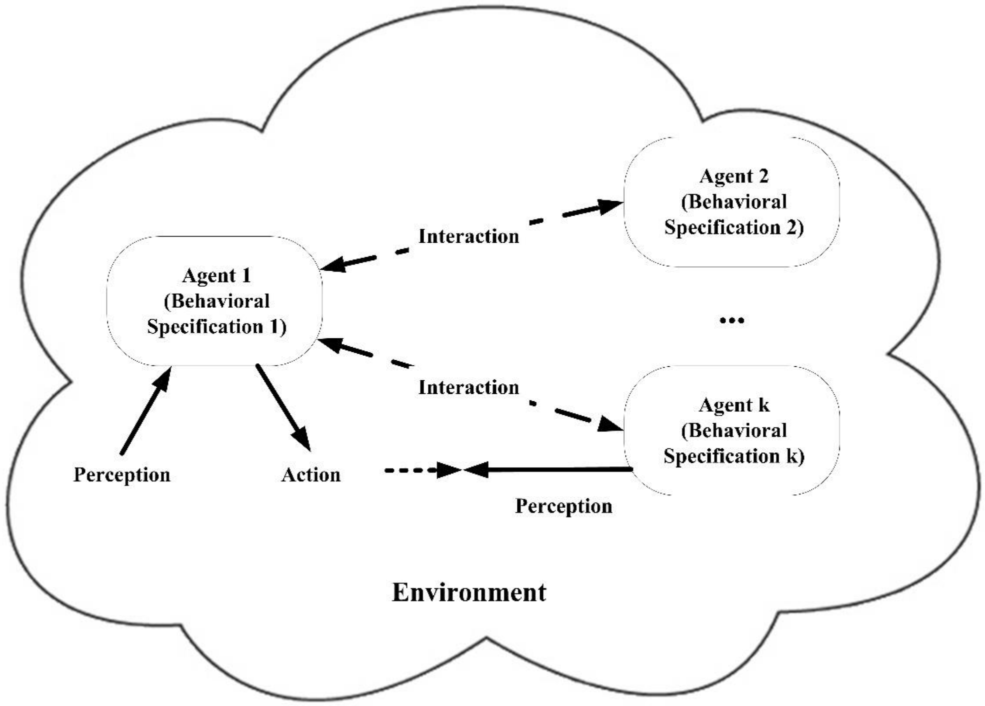


Figure 2.3 An abstract model scheme for agent based modeling approach

(Bandini et al., 2009)

Intelligent agents can be used as autonomous, flexible problem-solving entities which operate in a specific environment. Agents meeting in the environment may interact and cooperate, and thus form a multi-agent system (MAS). MAS is defined as consisting of heterogeneous agents that are generally self-motivated and act to fulfill internal goals, but may also share tasks with others. No global or centralized control mechanism exists in the system (Kirn, S. et al., 2006). Agents must reason to coordinate their actions, plans, and knowledge. Agents, in the systems, can cope with situations in a way involving inconsistent knowledge about the environment (i.e., world, other agents), partial domain representation, and changing, overlapping plans resulting from the need to interact with other agents (Krin. et al., 2006).

A multi-agent system (MAS) is a computerized system composed of multiple interacting intelligent agents within an environment. Multi-agent systems can be used for problems that are difficult or impossible for an individual agent or a monolithic system to solve. Some examples are shown in Fig 2.4. Which reflect intelligence in MAS may include some methodic, functional, procedural approach, algorithmic search or reinforcement learning. Based on Zhao et al. (2005), the agents in a multi-agent system have the following characteristics:

a. Agents live and act in a given bounded environment.

b. Agents are able to impact its local environment, and to interact with other agents in its local environment.

c. Agents are at least partially independent, self-aware, sociable, and autonomous.

d. Agents attempt to achieve particular goals or perform particular tasks.

e. Agents are able to respond in a timely manner to changes that occur in them according to their learning ability.

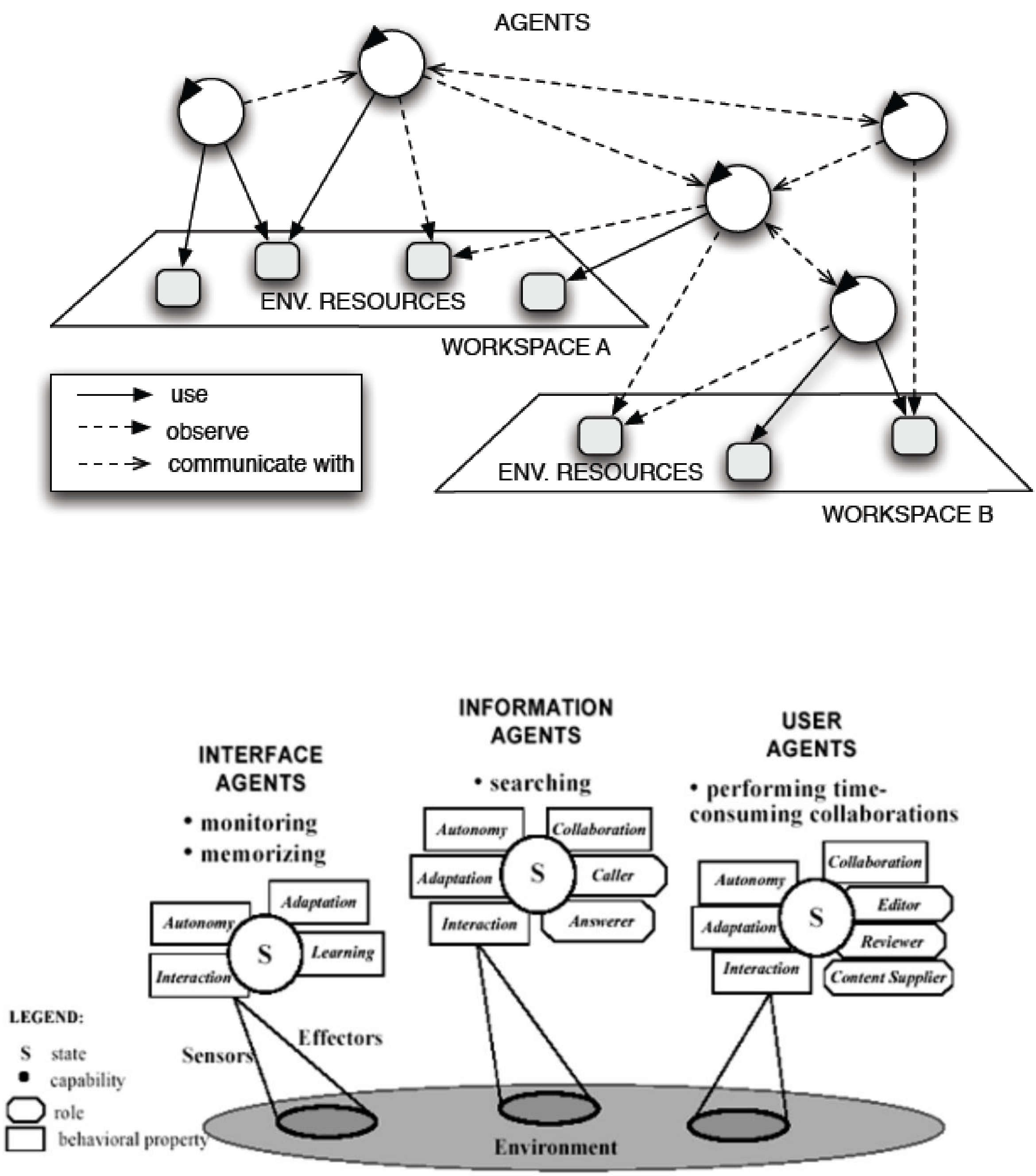


Figure 2.4 Examples of the model schemes for multi-agent system

(Source: http://jacamo.sourceforge.net/?page_id=40, Garcia et al., 2002)

The implementation of an operational behavior with MAS requires the interaction between agents. Krin et al. (2006) identifies that the presence of agents should be capable to act and /or communicate, the constructions can serve as a meeting point for agents, and dynamic elements allow for local and temporary relationships between agents. Two basic types of communication are shown as follows (Krin et al., 2006):

- **Blackboard Communication:** It is the most general approach for communication, which is interaction via the environment where an action of an agent causes an effect which is perceivable and interpretable by other agents (Fig. 2.5). By exchanging information, agents in environmental planning and decision making issues update their behaviors by learning from other agents in order to better fit the requirements decision making rules and meet the limitation from the living environment.

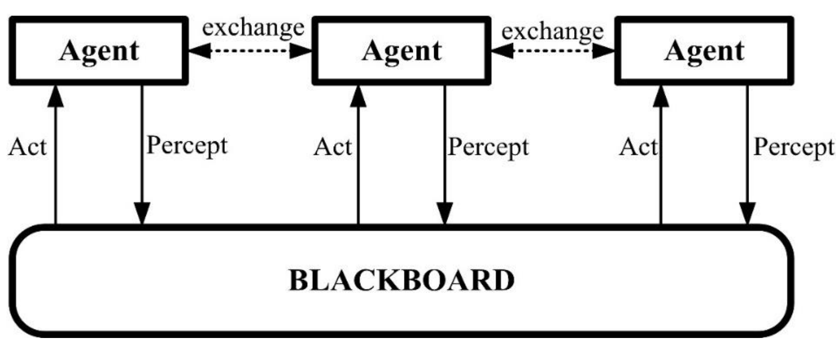


Figure 2.5 The blackboard architecture

- **Message Passing:** Communication based on varying access rights influenced by the information provider for accessing information within the system is called directed communication. Directed communication in MAS is performed by message passing, where a message is sent from one agent to another, and the environment is used only as a means of transportation (Fig 2.6)

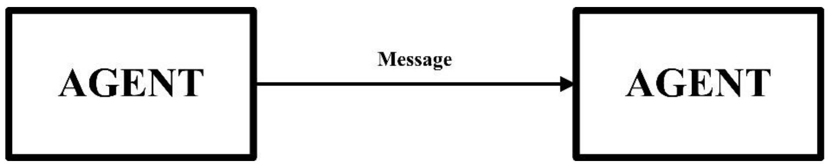


Figure 2.6 Message passing

In such large-scale MAS systems, it is necessary to develop institutionalized coordination through reusable structures, providing for flexible system behavior. Four basic types of structure inferred by Krin et al. (2006) are indicated as follows: Star (centralized), ring (decentralized), chain (hierarchy), and network (democratic) (Fig. 2.7). The structures in MAS are characterized by three aspects: capacity, duration, and decision-making (Krin et al., 2006).

a) **Capacity:** Enable to provide a solution of the same problem sets at a large scale or in a shorter period;

b) **Duration:** Structures should persist over the complete life time of MAS. According the goals, the duration could be short to mid to long term, static or dynamic.

c) **Decision-making**: The scope ranges from decision makers appointed at design time to democratic selection algorithms during run-time. The main criteria of decision-making is for choosing an appropriate level of decision making capabilities as well as capability management depends on the balance of flexibility and coordination efficiency.

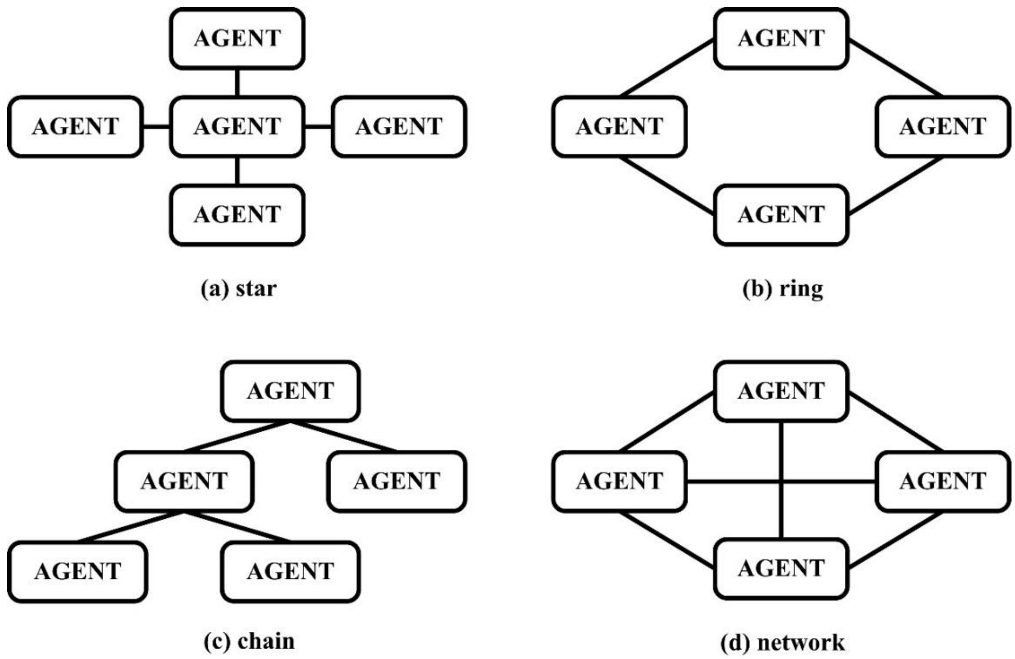


Figure 2.7 Interaction structure of multi-agent system

2.1.3 Agent based simulation software tools

During recent years, as the use of agent based models for research in different fields is growing, the number of available modelling software platforms increases. Numerous ABM platforms, along with a set of software implementing frameworks and simulation tools, are developed (Railsback et al., 2006). However, due to the characteristics of high interactions, large transported information and huge variable population, environmental ABM models need some specific ABM software platform in order to enhance modelling computing speed and behaviors. But each software has its own scope of applications. Therefore, first thing is to find the pros and cons of current ABM software platform, and choose one proper software to use. Based on the manual descriptions and previous studies, only a few tools have the potential to be applied in the decision making for environmental problems. Table 2.1 shows the general characteristics of several powerful ABM platforms

The first ABM software is called Swarm (http://www.swarm.org). Swarm is a collection of open-source libraries, that were originally developed at the Santa Fe' Institute in New Mexico. The code is written in Objective-C, but now also available for simulations in Java. The architecture of Swarm enables the implementation of models in a large variety of research fields. Perrone (2005) discussed general principles of the agent based platforms of StarLogo (the precursor to NetLogo), Repast, Ascape, and Swarm. Swarm was seemingly evaluated as the most powerful one, but also mentioned as the most difficult to learn. Swarm stopped updating the program from around 2010, and started the update again recently in 2016.

Repast (http://repast.sourceforge.net) was started as a Java implementation of Swarm, but nowadays, it has diverged significantly from Swarm to become an independent platform for agent. It was originally developed at the University of Chicago and is now especially used for research in social science. Repast has numerous good tutorials and a mailing list which helps individuals start easily. However, the background knowledge of

Java is required. There are two main software components including Repast Simphony 2.3.1 and Repast for High Performance Computing 2.1, both released in 2015. First component is a richly interactive and easy to learn Java-based modeling system that is designed for use on workstations and small computing clusters. The other one is a lean and expert-focused C++-based modeling system that is designed for use on large computing clusters and supercomputers. The environment also includes flowcharts, graphing tools, and automated connections to external tools.

MASON (http://cs.gmu.edu/~eclab/projects/mason/), is developed as a relatively new Java platform, mainly for MASs, which is a discrete-event multi-agent simulation library core focusing on high execution speed. This library was developed by the George Mason University's (GMU) evolutionary computation laboratory and the GMU center for social complexity. MASON is designed to be the foundation for large custom-purpose Java simulation obtaining with an optional suite of visualization tools in 2D and 3D. In addition to Java and Objective-C software, the Logo family of platforms has followed quite a different evolution. MASON and Repast has a faster execution speed, especially dealing with complex models (Railsback et al., 2006).

NetLogo (http://ccl.northwestern.edu/netlogo/) is a multi-agent programmable modeling environment. The primary purpose of NetLogo was used to provide a high-level platform that allows even elementary school students to build and learn from simple ABMs. NetLogo has been used by tens of thousands of students, teachers and researchers worldwide. And it also powered HubNet participatory simulations, which can link the program with personal terminal device (i.e., a networked computer or Texas Instruments graphing calculator) to realize the simulations in the class and let students take part in enacting the behavior of a system. However, NetLogo, now, contains many sophisticated capabilities (behaviors, agent lists, links, graphical interfaces, etc.). Moreover, the new version obtains both 2D and 3D platforms and is available for multi-scenario runs with the function of BehaviorSpace. NetLogo has become a relatively mature ABM and MAS software platform with specific primitives developed from StarlogoT. Besides, NetLogo includes multiple types of extensions, in order to meet the requirements of costumers to accomplish their goals. Unlike the previously mentioned tools, NetLogo models are not object-oriented, but programmed procedurally. Railsback et al. (2006) reviewed the feasibility and execution speed of MASON, NetLogo, Repast, and Swarm. NetLogo was indicated to be the most professional platform in its appearance and documentation. And it could have the widest application scope compared with other platforms. Although its execution speed for complex models is relatively weak, the authors declare that it is not a significant limitation for most applications. Netlogo could be the easiest-to-use software platform of all. Bergen-Hill et al. (2007) gave a suggestion of the choice of a toolkit during the different stages: to use a simple programming software, like NetLogo, which allowed fast development for prototyping models; and later used a system capable of distributed batch-runs, such as Repast.

Except these four ABM platforms, there are still have a number of ABM platforms, including, ADK, AnyLogic, AOR Simulationused, iGen, JADE, SeSAm, etc., that can be used for other research purposes, such as large scale distributed applications, discrete events, human performance modeling, embeddable cognitive agents, graph theory, etc.

Table 2.1 General characteristics of several powerful ABM platforms

Platform	Primary Domain	Programming Language	GIS	3D	User Support
Swarm	General purpose agent based	Java; Objective-C	-	-	Wiki; tutorials; examples; documentation; FAQ; selected publications; mailing lists
MASON	General purpose; social complexity, physical modeling, abstract modeling, AI/machine learning	Java	Yes	Yes	Mailing list; documentation; Tutorials; third party extensions; reference papers; API
Repast	Social sciences	Java (RepastS, RepastJ); Python (RepastPy); Visual Basic, .Net, C++, J#, C# (Repast.net)	Yes	Yes	Documentation; mailing list; defect list; reference papers; external tools; tutorials; FAQ; examples
NetLogo	Social and natural sciences; Teaching and training purpose models	NetLogo	Yes	Yes	Documentation; FAQ; selected references; tutorials; third party extensions; defect list; mailing lists

Due to the short period of development, ABMs and MASs software platforms still contain obstacles for the purposes of researchers. Based on previous studies and the author's experience, the problems mainly result in three aspects.

- First, the difficulty of model compatibility, and the lack of specific mathematic algorithms (i.e. optimization toolbox and calculus calculation programs);

- Second, an absence of training in software skills in the education of researchers in many fields that use ABMs and the short of essential computer and programming skills needed for developing ABMs (Railsback et al., 2006);

- Third, the limitation of software functions and un-optimized memory usage cannot satisfy the demands for a portion of research purposes.

The shortcomings limit the application of agent based models, but the software version updates and extension developments provided by developing organizations could partly relieve the defects.

In my master study, I developed my own optimization programs for two studies. In my first study, I developed the program by Matlab in order to satisfy the requirement of the coupling of complicated functions, constraints and developed PSO version. Because the new version of MAHPSO was developed by myself and no current program can be applied. For the second study, based on the specific advantages of NetLogo, which were fast calculation speed for general complex models, easy to learn, powerful model compiling capacity, and good expandability, the second study program was developed with

Netlogo in Starlogo language. The whole program was developed by myself including the simulation and optimization sections.

2.1.4 Application in environmental field

In recent year, agent, as a novel dynamic modeling and decision making approach, has been applied in all fields. In the environmental field, Balbi et al. (2013) represented a spatial agent based model for assessing strategies of adaptation to climate and tourism demand changes demonstrated in a winter tourism socio-ecosystem of Auronzo di Cadore. Multiple future scenarios including snow cover, temperature, tourist conditions, and market competitions are considered. Villamor et al. (2014) developed an agent based model for the social-ecological system of rubber agroforests builds on LUDAS framework. The proposed model demonstrated to reduce carbon emission effectively, and test to improve net returns of local rubber agroforest farmers. Further, Biodiversity performance measures can be designed to make payments for agro-biodiversity schemes conditional. Tang et al. (2015) proposed a multi-agent based model for carbon emissions trading (CET) in China with multiple CET simulated designs to find an appropriate policy, the impacts of CET on the economy and environment were analyzed. The results confirmed the effectiveness of the proposed model and gave helpful insights into CET design.

2.2 Environmental Optimization Methods

In most model-based research fields, mathematical optimization is the selection of a best element (with regard to some criterion) from some sets of available alternatives. In the majority of cases, an optimization problem consists of maximizing or minimizing an objective function by systematically choosing input values from within a defined set and computing the value of the function. The generalization of optimization theory and techniques to other formulations comprise a large area of applied mathematics. More generally, optimization includes finding "best available" values of some objective functions given a followed domain (or input). A variety of different types of objective functions and different types of domains would be included in the optimization problem. With the function of constraints, the objective functions would adjust their available domain range within iterations or updates.

In my studies of decision making and planning systems, optimization methods acted as a vital section to increase the efficiency and decrease the budget and operation costs for the target system. Due to the advantages of fast computation speed, high compatibility with agent based modeling, and high capacity of variants, particle swarm optimization (PSO) was chosen as the main optimization algorithm for two studies in the later chapters. In addition, genetic algorithm (GA) was a traditional meta-heuristic approach, which has been developed widely in computer science and operations research. According to the strengths of high efficiency and high stability, GA was used to test the efficiency of the developed MAHPSO approach in section 3. The foundational knowledge of these two optimization algorithms are shown in the following aspects.

2.2.1 Particle swarm optimization

Particle swarm optimization is a computational method to optimize a complicated problem by iteratively trying to improve a candidate solution, which is also called particles, and moving the particles around the multi-dimensional searching space according to simple mathematical formula over the particle's position and velocity (Parsopoulos et al, 2010; Olsson, 2011). The PSO is a stochastic, population-based computer algorithm modeled on swarm intelligence. Swarm intelligence is based on social-psychological principles and provides insights into social behavior, as well as contributing to engineering applications (Olsson, 2011; Lin et al, 2015). Each particle's movement is influenced by its current position, its local known position and is also affected by global best known position, which are updated as better positions are found with the interaction of other particles (Fig. 2.8) (Eberhart et al, 1995; Kennedy et al, 1997; Zhao et al, 2005). In PSO, each particle represents a potential optimal candidate. They work together in order to enhance the capacity to reach the optimal result through interactions.

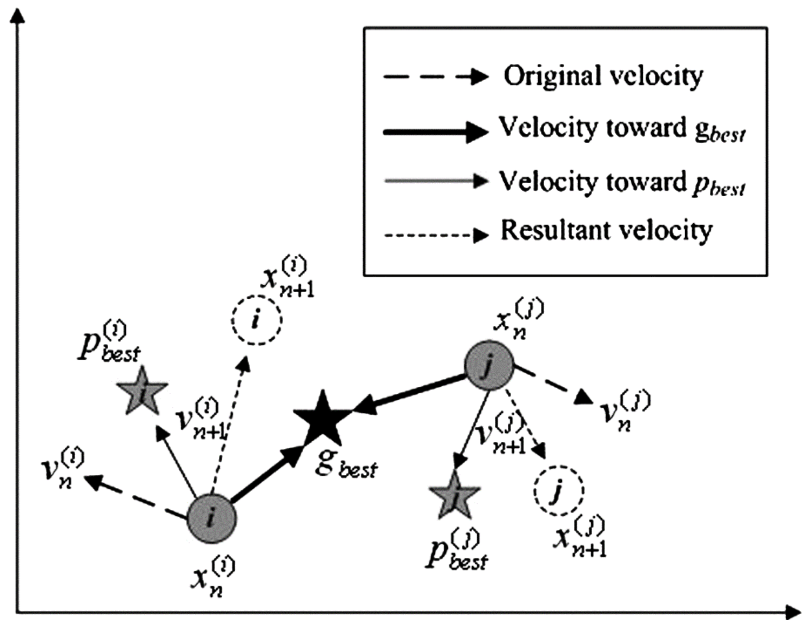


Figure 2.8 The basic flowchart of update process for PSO (Wang et al., 2010)

PSO was originally developed by Eberhart and Kennedy in 1995, and was first intended for simulating social behaviour. It mimics the movement of birds in a flock sharing information with each other (Acan et al., 2005), and the way they interact with each other is defined by topology. PSO is a meta-heuristic as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solution. The basic update algorithms and the detailed optimized process steps are shown as follows. However, the traditional PSO algorithm still has its own disadvantages, which indicates that it is easy to fall into local optimum in high-dimensional space and has a low convergence rate in the iterative process (Aote et al, 2013; Li et al., 2014). In order to conquer this limitation, a set of PSO variations has been developed. Numerous variants based on a basic PSO algorithm are possible.

In the traditional PSO, each particle represents a solution to the problem and travels the search space looking for the global minimum or maximum. Particles update their positions by flying around in a multi-dimensional search space until a relatively stable position has been selected or the stop criteria has been satisfied (Shumugalatha et al., 2008). To environmental planning and decision making problems, the traditional PSO cannot solve the problem with mixed variables (continuous and discrete) and cannot have a good accuracy for high non-linear optimization problems. To address the shortcomings, first, I developed a hybrid PSO to fix the problem with mixed variables. Second, adding MAS in updating step to increase the converge and accuracy of the proposed optimization method. Each particle allocates 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 optimal solution in available value ranges. At 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 individual and the group is weighted randomly. Therefore, the particle travels to the new position depending on its new velocity. The updating equations for particle velocity and position are shown in Eq. 2.1 and Eq. 2.2 as follows:

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

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

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*.

2.2.2 Binary particle swarm optimization

For the sake of solving binary and discrete variable problems, Kennedy et al. developed a binary particle swarm optimization approach to fill this gap in 1997. For binary particle swarm optimization (BPSO) version, trajectories travel with the judgement by probability distribution that a position will take on a zero or one value (Kennedy et al., 1997; Hossein et al., 2008). In a BPSO search space, a particle moves to nearer and farther corners of the hypercube by flipping various numbers of bits. Velocity is converted into the range of [0, 1] by probability distribution, so that a particle can move in a state space restricted to 0 and 1 in each dimension. Kennedy et al. (1997) indicated to consider a sigmoid function transformation in Eq. 2.3, the position will be updated according to Eq. 2.4.

$$\mathrm{Sigmoid}(v_{id}) = \frac{1}{1+e^{-v_{id}}} \tag{2.3}$$

$$\text{if rand}() < \mathrm{S}\big(v_{id}(\mathrm{t}+1)\big), \text{then } \mathrm{x}_{id}(\mathrm{t}+1) = 1$$

$$\text{else } \mathrm{x}_{id}(\mathrm{t}+1) = 0 \tag{2.4}$$

where $\mathrm{Sigmoid}(v_{id})$ is a sigmoid probability distribution transformation and rand () is a uniform random value between 0 and 1.

However, on the basis of previous research, BPSO still has several disadvantages:

First, asymmetry distribution in the sigmoid function (Eq. 2.3, Fig. 2.9) leads the probability up to 1 in positive direction, but down to 0 in negative position. The original sigmoid function neglects the importance of changes in the negative direction.

Second, the position updating equation (Eq. 2.4) modifies particle position without considering particle's previous statement. The results would fall into a local optimum without the leading force of previous statement.

Therefore, a developed BPSO is necessary to improve the efficacy.

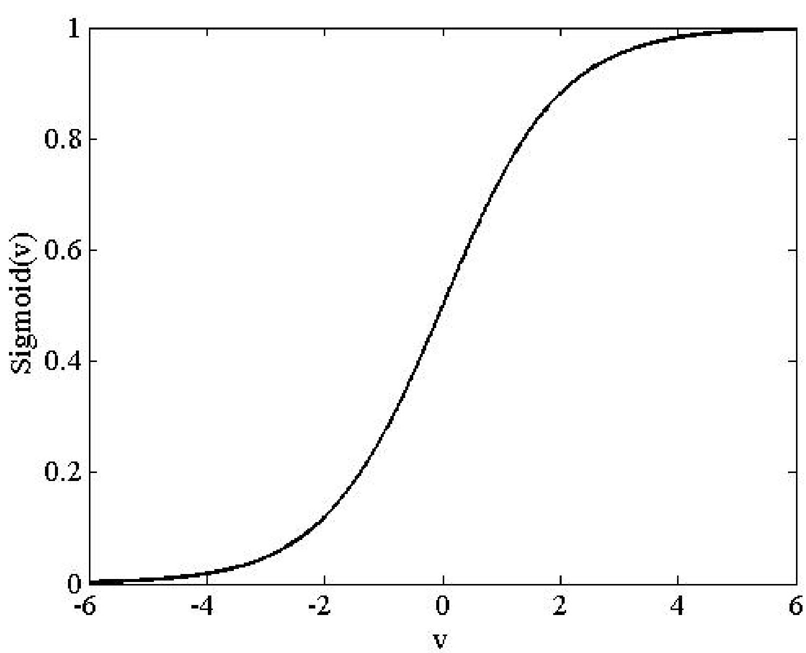
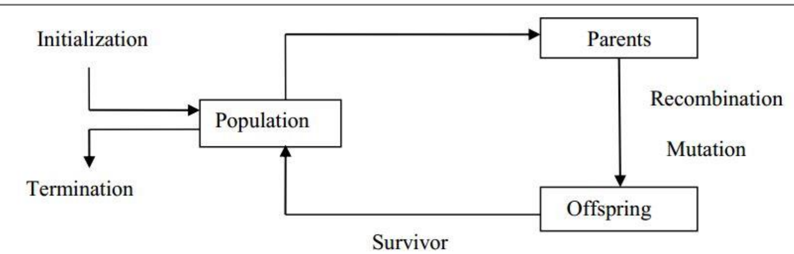


Figure 2.9 The distribution plots of sigmoid function

PSO and BPSO have been a powerful and high-developed capacity evolutionary optimization technique, and been used in a number of research fields, including: social behavior, computer, electricity, geology, energy, etc. (Eberhart et al., 1995; Kennedy et al., 1997; Zhao et al., 2005). But few studies have been done on environmental problems, and it has a high potential for such complicated problems. In my study, PSO was used as the foundation for optimization tool, to be specific, the original PSO algorithm has been developed with multi-agent system theory in order to enhance solution capacity and efficiency and integrate with decision making supporting system. Moreover, original PSO was combined with binary PSO into a hybrid PSO version with the capacity to deal with the complicated non-linear wastewater treatment plants (WWTPs) planning problems with multiple types of variables, including continuous variables for sludge and wastewater amount control, and binary and discrete variables for site and treatment techniques selection. In addition, PSO was used as the optimization procedure to couple with agent based simulation modeling and multi-agent system, in order to generate a simulation-based multi-agent particle swarm optimization decision making system in section 4. The detailed results shown in the following chapter indicates that the developed PSO versions provide a great performance for environmental problems.

2.2.3 Genetic algorithm

In computer science and model based operations research, genetic algorithm (GA) is a meta-heuristic inspired by the process of natural selection that belongs to the upper class of evolutionary algorithms (EA). GA is commonly used to generate high-quality solutions to optimization and search problems by relying on bio-inspired operators such as mutation, crossover and selection (Mitchell, 1996). It has been widely used as a powerful optimization tool in the environmental field such as in water distribution network design , (Zheng et al., 2011; Mora-Melia et al., 2013). The major steps are generation of population, finding the fitness function, and application of genetic operator and evaluation of population as shown in Fig 2.10 (Johar et al., 2016).



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 (Johar et al., 2016)

In a genetic algorithm, a population of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0 and 1, but other encodings are also possible (Whitley, 1994). A typical genetic algorithm needs two basic rules:

a) A genetic representation of the solution domain (constraints).

b) A fitness function to evaluate the solution domain (objective function).

So as to find the optimal solutions, three main genetic operators, reproduction (Selection), crossover, and mutation, are needed.

a) **Reproduction (selection)**: It is a process, in which an individual is copied, considering their fitness function values to make more copies of a better string in a population (Sivaraj et al., 2011; Johar et al., 2016).

b) **Crossover:** After reproduction, the string of the mating pool is required for crossover. A crossover is the procedure that combines two strings to hope generating a better string (Sivaraj et al., 2011; Johar et al., 2016).

c) **Mutation**: Add new strings and information within a random way to the genetic search process and prevent an irrecoverable loss of potentially useful information which reproduction and crossover can cause (Sivaraj et al., 2011; Johar et al., 2016).

Even though GA is a popular optimization for solving most operation problems, limitations still exist, when compared with alternative optimization algorithms.

First, GA is often limited to segment for complex problems with repeated fitness function evaluation. It will be difficult to find the optimal solution to complex high-dimensional, multimodal problems with complex fitness functions.

Second, GA cannot scale well with a great number of elements, which need to mutate within a huge space size. The protection for good represented solutions from further destructive mutations is a problem (Sivaraj et al., 2011).

Third, in a number of problems, GA may have a tendency to converge toward local optima or even arbitrary points rather than the global optimum of the problem (Rudolph, 1994). Which means the model cannot make out how to sacrifice good short-term solution to obtain a better long-term solution.

Due to the limitations, traditional GA can be used to examine the efficiency of innovative developed optimization approach and has the potential to be altered with GA variants for specific problems.

2.2.4 Application for Wastewater Treatment Systems and Network Planning

The planning of regional wastewater treatment systems is a traditional and classic type of optimization problems. Generally, this kind of planning optimization problems could be summarized into several aspects: to define the characteristics of the treatment and transport system in a region or water basin, which assures compliance with given pollution control criteria and with minimum economic cost, and/or with appropriate technical skills and price policy, etc. (Melo et al, 1994; Zeng et al., 2007). In addition, Tyteca et al. (1977), Gakan et al. (1998) and Melo et al. (2007) indicated that researchers may try to satisfy other goals, which render the problem multi-objective:

- To minimize the environmental impact.
- To maximize system reliability.
- To maximize system flexibility under uncertain conditions.
- To assure equity among users of the system.
- To maximize benefits from reuse of treated effluent.
- To minimize the concentration of contaminants of concern.
- To optimize the selection of secondary wastewater treatment system techniques followed by cost-efficiency or treatment efficacy.

The optimized outcomes of the problems should include the identification of a system composed by several treatment plants, each one treating effluents from one or more polluting plants, as well as the layout of the necessary transport systems. Due to the negative environmental impacts of excess sludge production or unsettled sludge (Wei et al., 2003; Alvarez, et al., 2002), current wastewater treatment systems optimization should carefully consider the treatment and transportation of sludge and marketing distribution of sludge production.

Based on the views of Tang et al. (1987), Zhao et al. (2005) and Melo et al. (2007) and the author's opinion, the major difficulties for the optimization of regional wastewater treatment systems are shown as follows:

- Nearly all objectives are difficult to quantify and even to define accurately.
- The number of potential solutions grows exponentially with problem size, creating the need to use computerized optimization techniques;
- The assumptions and simplifications of real-world conditions influence the reasonableness and practice of optimal results and decision making plans;
- Cost functions are robustly non-linear and concave, seriously limiting the application of most common optimization methods.
- Most wastewater treatment system planning models are hard to be verified.
- Current models are difficult to realize the coupling of dynamic treatment process simulation model and system optimization models. Uncertainties could be obtained, but still have some defects.

Moreover, the practical applications of optimization models have several additional problems.

First, such a model should be compatible with existing institutional water resources management procedures (Melo et al, 1994), in the other words, the developed models should have practical significance to the real-world treatment systems development.

Second, environmental engineering projects are usually designed by engineers and politicians not familiar, and indeed suspicious, of mathematical models. Which is the reason why such models are seldom used in common practice (Melo et al, 1994).

Third, the real-world circumstance is too complicated to be simulated. Therefore, assumptions and simplifications are necessary and vital to be used into models. However, that also increases the risks of the application in sensitive and fragile scenarios.

A series of studies have been done on the wastewater network optimization issues. Galan and Grossmann (1998) developed a model to optimize the design of a distributed wastewater network, which embodied apparatus in multicomponent streams in order to decrease the concentrations of some contaminants. Huang et al. (1999) developed an optimal water usage and treatment network (WUTN) to be used in any chemical plant in order to use less fresh water consumption and/or the reduction of wastewater treatment capacity. Yang and Huang (2000) illustrated a wastewater reuse network (WWRN) for minimizing wastewater. Yang et al. (2000) developed a mathematical approach for solving optimization problems by a nonlinear programming method, in order to frame a wastewater reuse network (WWRN) considering water streams with multiple pollutants. Chang et al. (2001) indicated a genetic algorithm-based neural network (GA-NN) for the optimization of intelligent controller design of wastewater treatment plants. Saif et al. (2008) described a nonconvex mixed-integer nonlinear mathematical modelling program (MINLP) with an efficient branch-and-bound algorithm for the global optimization of the reverse osmosis (RO) design network of water and wastewater streams including pumps, turbines, and RO stages. Brand and Ostfeld (2011) applied a genetic algorithm (GA) model to optimize regional wastewater systems design, where transmission gravitational and pumping sewer pipelines, decentralized treatment plants, and final reused ways of reclaimed wastewater were considered in the mathematical modelling. Ahmetović and Grossmann (2011) developed a global optimization for integrated process water networks considering multiple sources of water, water-using processes, wastewater treatment, and pre-treatment operations by using mixed integer nonlinear programing (MINLP).

2.2.5 Application for Offshore Oil Spill Response Decision Making

Major oil spills attract the attention of both the public and the media. In the past years, the attention generated a global awareness of the risks of oil spills and the damage they can do to the environment (Fingas, 2011). Oil is a necessity in our industrial society and a major element of our lifestyle. Even though innovative energy has been a breakthrough to the environmental impacts brought from traditional energy sources, most of the energy used in transportation runs on oil and petroleum products. Offshore oil spills can lead to significantly negative impacts on socio-economy and constitute a direct hazard to the marine environment and human health. The response to an oil spill usually consists of a series of dynamic, time-sensitive, multifaceted and complex processes subject to various constraints and challenges (Li, 2014). An offshore oil spill, where oil is released into the ocean or coastal waters, is the release of a liquid petroleum hydrocarbon into the environment, especially into marine areas. Due to human activity, a series of pollution endanger the safety of the environment. 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, or the spill of any oily refuse or waste oil (Fingas, 2011). Oil spills can have disastrous consequences for society; economically, environmentally, and socially. As a result, oil spill accidents have initiated intense media attention and political uproar, and brought a political struggle concerning government response to oil spills for what actions can best prevent them from happening (Fingas, 2011 and 2013; Li, 2014; Broekema, 2016).

Offshore oil spill cleanup response is the study and practice of reducing the number of oil or hazardous substances that release into the environment and limiting the amount released during those incidents. Generally, the techniques shown in Fig 2.11 are the traditional and major methods for offshore oil spill cleanup processes. 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.

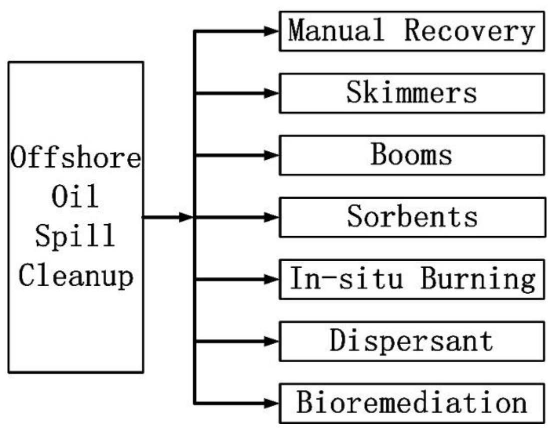


Figure 2.11 The schematic of offshore oil spill cleanup methods (Fingas, 2011 & 2013; Li, P, 2014)

The brief background is shown as follows:

- **Manual Recovery:** Manual recovery method, the basic way for costal oil cleanup, mainly uses cleanup tools to physically remove oil stained on shorelines, including oil and debris removal, and cleaning and scrubbing. (Street, 2011a; Fingas, 2013; Henry, 2014).

- **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 (Fingas, 2011). They are usually used together with the booms. (Muizis, 2013). The effectiveness of a skimmer is rated according to the amount of oil that it recovers as well as the amount of water picked up with the oil (Fingas, 2013; Li, 2014). The performance of most skimmers operates best, when the oil slick is relatively thick and most perform not efficiently on thin slicks (Fingas, 2013).

- **Booms:** Booms are mechanical barriers that protect natural resources from spreading of crude oil. They serve in water areas mainly as a technology to contain the oil spill to facilitate further cleaning steps (ITOPF, 2013; Henry, 2014).

- **Sorbents:** Sorbents are materials that soak up oil from the water. Sorbents play an important 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 very small spills; and work as a passive technique of cleanup (Fingas, 2013).

- **In-situ Burning:** In-situ burning, or ISB is a typical oil spill cleanup technique that involves controlled burning of the oil at or near the spill site (Street, 2011; Fingas, 2013). When conducted properly, in-situ burning could significantly reduce the amount of oil on the water and minimize the adverse effect of the oil on the environment (Faksness et al., 2012; Fingas, 2011; Li, 2014; Van Gelderen et al., 2015).

- **Dispersant:** Dispersant is used to label chemical spill treating agents that promote the formation of small droplets of oil that "disperse" throughout the top layer of the water column (Fingas, 2011). The main aim of dispersants application is to break down the oil slicks into small droplets, which submerge into the depth and become rapidly diluted (Muizis, 2013; ITOPF, 2014).

- **Bioremediation:** Bioremediation is an oil spill treatment option that will enhance the efficacy of the natural biodegradation process of the ocean (Walther, 2014). It is the process that uses decomposers and green plants, or their enzymes, to improve the condition of contaminated environment due to hydrocarbons (Atlas et al, 2011).

In recent decades, many researchers have studied the transport and fate of oil spills based on the trajectory method and mass balance approach (Huang, 1983; Delvigne, 1994; Fingas, 2011 and 2013). But more than that, prompt response to oil spills has been recognized as a critical issue based on the results from those simulation models. Developing an effective and efficient tool for oil spill emergency decision supporting system (DSS) has already grown to be an urgent and necessary target for current research. Liu et al. (2005) employed three different negotiation protocols, one shot, ultimatum and alternating offer, with a multi-agent system theory for cooperation and competition, to examine the impact of choosing different protocols on the outcome about oil spill response decision-making. Wirtz et al. (2006) addressed an oil-spill DSS model approach integrated with economy, ecology and uncertainty by the contingency simulation system OSCAR with wind and current forecasts, environmental GIS data and multi-criteria analysis techniques. The DSS is able to rank different response actions to a chemical or oil spill. And the proposed approach was tested with the Prestige accident off the coast of Spain in 2002. Li et al. (2012) developed a multiple-stage simulation based mixed integer nonlinear programming (MSINP) approach to provide sound decisions for skimming spilled oil in a fast, dynamic and cost-efficient manner, which is especially helpful to harsh environments. Aderson et al. (2014) introduced a multi-criteria method (TODIM-FSE) for solving classification problems. The model is envisaged as embedded within SISNOLEO (a Portuguese acronym for An Information System for Oil Spill Planning), aiming at helping potential users to decide upon suitable contingency plans for oil spill situations.

Except offshore oil spill simulation, optimization is also desired to provide decision supporting under changing environmental conditions. You and Leyffer (2011) proposed the mixed-integer dynamic optimization (MIDO) model to simultaneously predict the time trajectories of the oil volume and slick area, the response cleanup schedule and coastal protection plan, by taking into account the time-dependent oil physiochemical properties, spilled amount, hydrodynamics, weather conditions, facility availability, performance degradation, cleanup operational window, and regulatory constraints. Zhong and You (2011) developed a bi-criterion, multi-period mixed-integer linear programming (MILP) model to simultaneously predict the optimal time trajectories of oil volume and slick area, transportation profile, response resource utilization levels, cleanup schedule, and coastal protection plan. The epsilon-constraint method was used as the optimization method and a

Pareto optimal curve was produced to reveal how the optimal total cost and response operations change under different specifications of responsiveness. Jin et al. (2015) developed a whole set of operation scheduling scheme of marine oil spill emergency vessels following the characteristics of marine oil spill emergency disposal environment and the requirements for emergency vessel scheduling by integrating the ENC, GPS, AIS, wireless network and oil spill monitoring technologies, in order to improve the capacity of marine oil spill disposal.

In addition, dynamic simulation has been considered from previous studies, harsh oceanic circumstances tend to make emergency response to oil spills even more challenging by changing the fate and properties of oil dramatically within a short period, which will inevitably hinder and affect the efficiencies of recovery and cleanup processes (Brandvik et al, 2006; Bjerkemo, 2011; Li et al, 2014). Till now, few studies have been carried out specifically focusing on the solutions of this issue.

2.3 Summary

In this chapter, section 2.1 reviewed the basic background of agent, agent based modeling and multi-agent systems, and discussed the characteristics and advantages of agent based approach on environmental problems. ABM and MAS, two main agent-based approaches, had similarities, but can work as different aspects in the sophisticated problems. Section 2.1.3 specifically reviewed the applications of traditional agent based simulation software tools, and compared the advantages and disadvantages of them. And selected proper software, NetLogo, as the platform for the studies.

Section 2.2 reviewed on the topics of environmental optimization methods, in which three important algorithms, particle swarm optimization, binary particle swarm optimization, and genetic algorithm, were illustrated. PSO and BPSO were applied as the fundamental algorithms on the studies in section 3 and 4. GA acted as the tool for examining the efficiency of the novel multi-agent hybrid particle swarm optimization in section 3.

Section 2.3 and 2.3 gave a review on optimization models for regional wastewater treatment systems and network planning, and decision making models for offshore oil spill emergency problems. Section 2.3 introduced the background of WWTPs planning research, current studying processes, brief reviews on publications in the past few decades, and existing research gaps in this field. Section 2.4 indicated the background of offshore oil spills, a brief introduction to traditional offshore oil spill cleanup procedures, and reviews on offshore oil spill models related with decision making mentioned from the studies in the recent years. To date, no developed PSO version can solve the mixed-type sophisticated problem, and few studies integrate such a developed PSO version with MAS for improving convergence. In addition, little research on dynamic decision-making system models combined simulation and optimization for offshore oil spill accident response. And few studies integrated an agent based approach for solving environmental problems and developing simulation and optimization algorithms.

CHAPTER 3: A NOVEL MULTI-AGENT BASED HYBRID PARTICLE SWARM OPTIMIZATION (MAHPSO) APPROACH FOR WASTEWATER TREATMENT PLANTS NETWORK DESIGN

[1]

[1] The chapter was extracted from the following journal paper under preparation: A novel multi-agent based hybrid particle swarm optimization (MAHPSO) approach for wastewater treatment plants network design.

3.1 Introduction

Owing to the rapid development of civilization and population growth, the annual amount of municipal wastewater disposal becomes higher with the increase of population. Municipal wastewater usually contains grit, debris, suspended solids, disease-causing pathogens, decaying organic waste, nutrients and many other chemicals (Agidi et al., 2013). It needs to be properly treated to reduce the concentrations of various pollutants and to meet environmental regulations and standards prior to discharge (Gao et al., 2012; Margot et al., 2013). To alleviate the pollution burden of natural water bodies, wastewater treatment plants (WWTPs) are widely used to process domestic and industrial waste streams (Friedler et al., 2006; Pai et al., 2011). However, not all wastewater can be properly treated due to the lack of infrastructure and poor facility development. Around 70% of wastewater on average is treated in high-income countries, 38% in upper-middle-income countries as follows, 28% in lower-middle-income countries, and low-income countries can only treat 8% wastewater (Sato et al., 2013). Design optimization therefore has been recognized as an important tool for improving the efficiency and reducing the associated costs of WWTPs from a long-term perspective. However, according to the literature reviews in section 2, most of the previous studies have not taken the planning of WWTP network across large city clusters containing multiple cities into account. The rapid urbanization has led to the formation of large city clusters where their infrastructure, such as WWTPs, are often planned and developed through collaborations between local governments and key stakeholders as a network instead of individually. Solving such network problems, PSO is a good method as the optimization approach.

With the advantages of rapid convergence speed, easy implementation, short computation time, fewer parameters to be adjusted and easy development, PSO and its variations have become a kind of popular optimization methods for solving such network nonlinear problems (Zhao et al., 2005; Shumugalatha et al., 2008; Wang et al., 2014). In addition, for network problems with integer or binary variables, binary PSO (BPSO) is a good method for that (Kennedy et al., 1997; Hossein et al., 2008). However, few researches and PSO variations can solve the optimization problems including continuous and binary variables simultaneously, but which is a common and important type of network problems for wastewater treatment plants designs. Moreover, for nonlinear optimization problems, PSO and BPSO may be trapped by a local optimum. In response to such technical gaps, this paper presented a novel multi-agent hybrid particle swarm optimization (MAHPSO) approach. The hybrid particle swarm optimization module (HPSO) was developed to account for both continuous and binary variables, while the concept of multi-agent system (MAS) was adopted to enhance solution convergence. A real-world case study in regard to the planning of a WWTP and sludge processing network was carried out to examine the efficacy of the proposed approach.

3.2 Methodology

Most of the WWTPs network design problems contains multiple types of variables and hard to get an outstanding optimal result. In order to deal with these problems, the proposed method should be capable to handle multiple types of variables and have the high-stability and good convergence. In the novel MAHPSO algorithms, the original PSO and

BPSO, as the fundamental algorithms, have been updated into hybrid PSO (HPSO) through coupling together to realize the calculation with continuous and discrete variables simultaneously. On the basis of HPSO, MAS was integrated in the system with the purpose of improving the capacity of convergence and prevent the optima from being trapped by a local optimum. The details for the developed method are indicated in the following aspects:

3.2.1 Hybrid particle swarm optimization

In the previous studies, few considered mixed-variables nonlinear problems. For solving mixed-variable optimization problems, different evaluation processes are needed for continuous and binary variables. In order to deal with these problems automatically and successfully, PSO and BPSO are necessary to be integrated into one hybrid PSO approach. The background and basic knowledge about PSO and BPSO have been illustrated in the previous chapter. Here to skip this part and only indicate the achievements for the development of the algorithms. In this study, a developed hybrid particle swarm optimization (HPSO) was made.

For PSO updating equations for particle velocity and position, the original equations were used as shown in Eq. 3.1 and Eq. 3.2.

$$v_{id} = w \cdot v_{id} + c_1 \cdot r_1 \cdot (p_{id} - x_{id}) + c_2 \cdot r_2 \cdot \left(p_{gd} - x_{id}\right) \tag{3.1}$$

$$x'_{id} = x_{id} + v_{id} \tag{3.2}$$

According to literature review, c_1 and c_2 generally equal to 2, 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*.

The selection of inertia weight factor w can improve the convergence in non-linear problems by controlling the balance between self-adjustment and interactions. In order to increase the model accuracy when particles move close to the optimum, adaptive linear decreasing weight is developed according to the following equation (Eq.3.3). As shown in Fig 3.1, with the increase the iteration, particles will move closed to the optimum. On the basis of the reduction of the effect of self-control, particles will have more efforts from other particles. Thus, particles have more opportunities to find a better optimum rather than trapped by local optimum.

$$w_{current} = \frac{w_{ini} - w_{end}}{iter_{max}} \cdot (iter_{max} - iter_{current}) + w_{end} \tag{3.3}$$

where, w_{ini} and w_{end} are the upper and lower boundaries of inertia weight, equals to 0.9 and 0.4 during the run, respectively, $iter_{max}$ is the maximum number of iteration, and $iter_{current}$ is the current number of iteration.

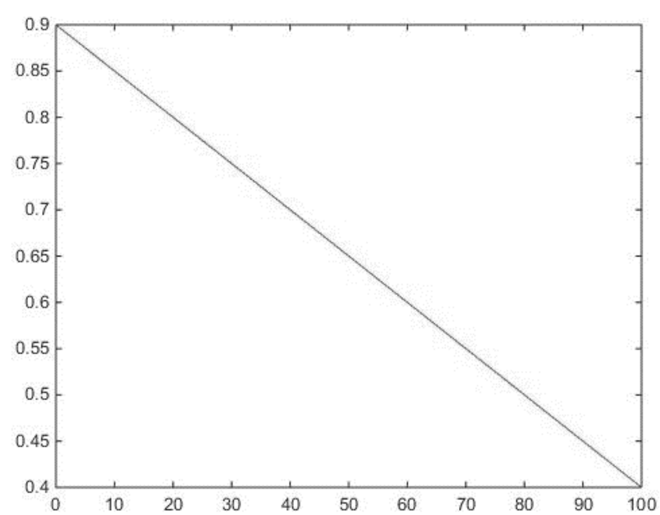


Figure 3.1 Adaptive linear decreasing weight for PSO

For the section on BPSO update equations, according to previous researches, they still have several disadvantages indicated in section 2. Based on previous studies, a modified BPSO probability function and position updating equation, developed by Hossein et al. (2008), were applied, in order to overcome the disadvantages of the original BPSO, and made the distribution symmetrical for velocities in both positive and negative directions. It integrated particle's previous statements into updating criteria. Further, the tests in his paper showed a much better performance with the developed equation rather than the traditional one. The new BPSO equations and the modified sigmoid distribution are shown as follows:

$$S'(v_{id}) = 2\times|Sigmoid(v_{id}) - 0.5| \tag{3.4}$$

$$\text{if rand}() < S'\big(v_{id}(t+1)\big), then\ x_{id}(t+1) = exchange\big(x_{id}(t)\big)$$

$$\text{else } x_{id}(t+1) = x_{id}(t) \tag{3.5}$$

where $S'(v_{id})$ represents the modified sigmoid probability distribution and $exchange\big(x_{id}(t)\big)$ shows that the value changes from 0 to 1 or vice versa.

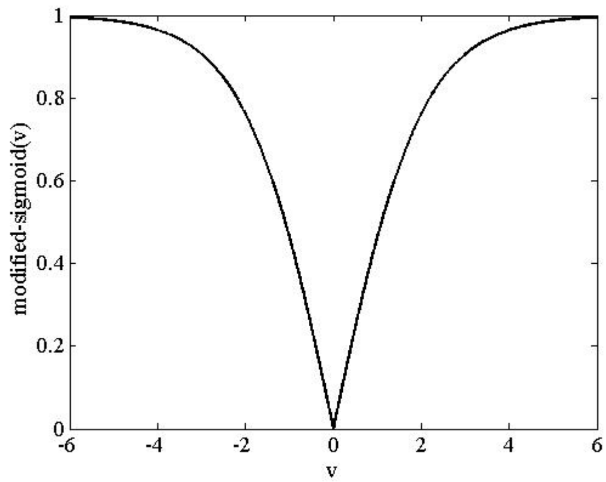


Figure 3.2 The distribution plots of modified sigmoid function

By the combination of PSO and BPSO velocity and position update equations, the hybrid PSO could achieve the advantages of methods to figure out mixed variables. During the evaluation process of, particles should calculate the updated velocity by Eq. 3.1 with Eq. 3.3 as adaptive nonlinear decreasing weight. After the aforementioned steps, variables should check whether the variables themselves are continuous, if yes, then Eq. 3.2 is defined to update position; Else, Eq. 3.4 and 3.5 would be applied for position update. Afterwards, variables are integrated to calculate fitting values by objective functions.

3.2.2 Multi-agent based particle swarm optimization

In accordance with the advantages indicated in the previous chapter. MAS approach can be used to compute and optimize complicated problems. Agents in MAS do not only act autonomous and independent, but also cooperate or compete to achieve their own individual goals as well as sharing information with others. The strategy of cooperation and competition fits the goal of basic theory of PSO and BPSO. In this paper, MAS was treated as a part of optimized approach to develop a new optimal algorithm with better performance. As shown before, PSO methods still have the limitation of convergence. Hence, due to the addition of MAS, the interaction ability of the new PSO approach has been enhanced. This can help reinforce the ability of convergence for avoiding dropping into a local optimal.

In this study, on the basis of HPSO, MAS were integrated to generate the proposed MAHPSO approach for dealing with WWTPs network design problems. An agent was not only a candidate of MAS, but also a particle for HPSO method. To confirm the location of agents, a lattice-like environment shown in Fig. 3.3 was constructed as the global environment. Each agent (or particle) was settled in the environment with their own coordinates. In order to obtain optimal solution quickly, each agent competed and cooperated with their neighbours for sharing information purpose in every iteration. In addition, agents can evolve high-quality optimal solution with previous experience by self-learning.

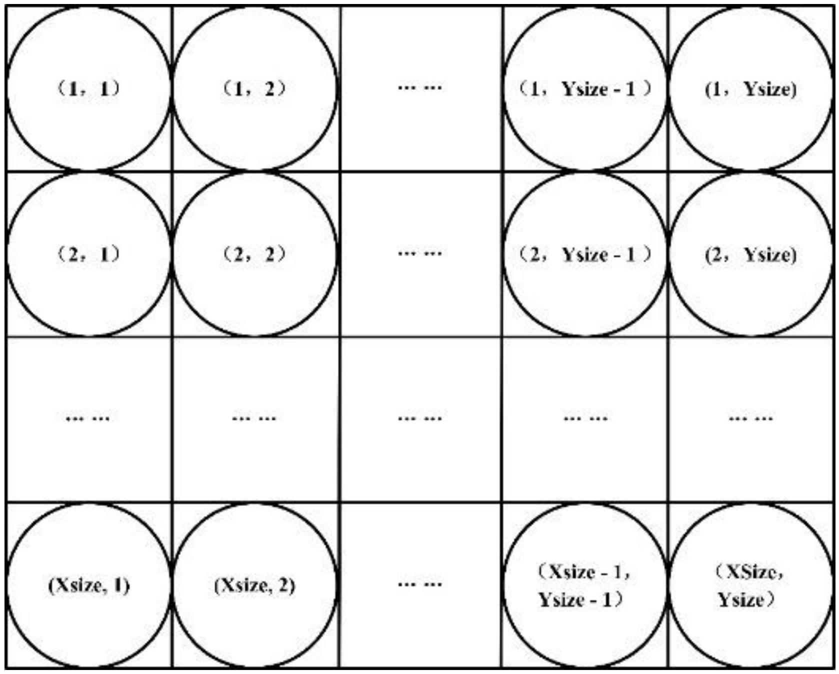


Figure 3.3 The structure of the global environment

The proposed MAHPSO can realize the optimization approach with the following steps:

1) **Definition and goal of agent:** In MAHPSO, an agent represented a candidate solution to the optimization problem, and it also treated as a particle for HPSO. Each agent obtained a fitness value to the problem. For WWTPs network design problems, agents in the system contained the total cost for the design. The purpose of agents was to minimize the total cost and satisfy the requirements of boundaries and constraints, such as, wastewater treatment volume, sludge recycle demand, the capacity of WWTP, etc. Each agent possessed all control variables to be optimized, each agent's position and velocity involved all variable values and all variations of variable values at every iteration.

2) **Definition of the global environment:** In MAHPSO, a lattice-like environment was constructed. In the global environment, each agent was settled as a particle on a lattice-like point in Fig. 3.3. Each circle represented an agent composed with two properties: particle current velocity and position statement. The size of the lattice-like environment was *Xsize* × *Ysize*, where *Xsize* and *Ysize* were integer. The number of lattice also indicated the swarm population which was the total number of particles in HPSO.

3) **Definition of the local environment:** As an agent can sense its local environment in MAS, the interaction can be applied for the improvement of the proposed method. In this paper, it was defined that agent A located at (i, j) was denoted as $A_{i,j}$, where $i = 1,2, \dots, Xsize$; $j = 1,2, \dots, Ysize$, thus, four neighbours of A_{ij} from its four direction $N_{i,j}$, were defined as follows:

$$N_{i,j} = \{A_{i^L,j}, A_{i^R,j}, A_{i,j^L}, A_{i,j^R}\} \tag{3.6}$$

where,

$$i^L = \begin{cases} i-1 & i \neq 1 \\ Xsize & i = 1 \end{cases} \qquad j^L = \begin{cases} i-1 & j \neq 1 \\ Ysize & j = 1 \end{cases}$$

$$i^R = \begin{cases} i+1 & i \neq Xsize \\ 1 & i = Xsize \end{cases} \qquad j^R = \begin{cases} j+1 & i \neq Ysize \\ 1 & i = Ysize \end{cases}$$

In this way, the interactive communication of an agent from the local and global environment can be illustrated in Fig. 3.4.

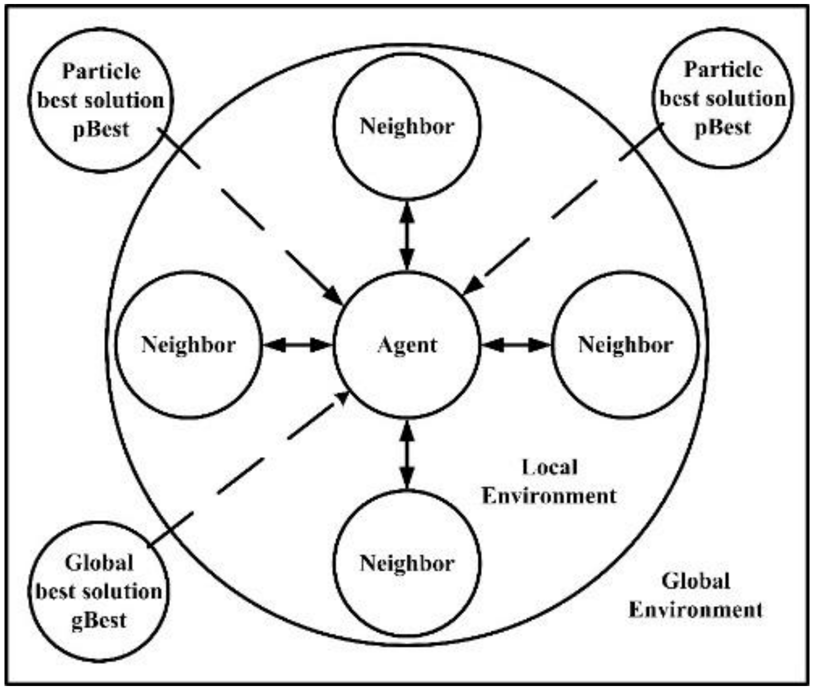


Figure 3.4 The interactive communication of an agent

4) **Definition of agent behavior rules:** In order to quickly and accurately achieve the purpose of agents, each agent possessed several behavior rules. First, in the aforementioned illustration, an agent (i.e. agent A) represented a candidate solution, which had a fitness values calculated by the optimization problem fitness functions. For WWTPs network design problems, the fitting values were generally considered about the minimal total cost of the whole system composed with capital, and operation and maintenance (O&M) cost. The fitness function can be indicated as follows:

$$f(A) = F\_min\ (Cost) \tag{3.7}$$

In MAHPSO, the difference from traditional PSO variations was that the competition and cooperation with neighbors in the local environment were concerned, in order to share useful information and combine the basic evolution mechanism of HPSO. Hence, the proposed MAHPSO can accelerate the convergence speed and avoid the appearance of local optimization scenarios. The detail of competition and cooperation strategy was shown as follows:

Supposed that the minimal fitness value among an agent α and its neighbors were represented as $Nbest^{\alpha}$, and the variables for $f\ (Nbest^{\alpha}) = f(N_1^{\alpha}, N_2^{\alpha}, \ldots, N_n^{\alpha})$ were located in the solution space. If agent α satisfied the following criteria:

$$f(\alpha) \leq f\ (Nbest^{\alpha}) \tag{3.8}$$

Then, agent α can be treated as a winner, thus, its position remained unchanged. Otherwise, it was a loser, and agent α would be replaced by a new agent with modified position statement. From Eq. 3.9 and Eq. 3.10, sort of heuristic crossover in evolutionary algorithms were used to ensure the new agent blends with the benefits of the loser agent and neighbor best solution.

If the variables were continuous:

$$\alpha_k' = Nbest_k^{\alpha} + rand(0,1)\times(Nbest_k^{\alpha} - \alpha_k) \tag{3.9}$$

If the variables were binary:

$$F = 1 + Nbest_k^{\alpha} - rand(0,1)\times(\alpha_k + 1) \tag{3.10}$$

$$If\ F \leq \frac{1+2*Nbest_k^{\alpha}-\alpha_k}{2}, then\ \alpha_k' = \alpha_k;$$

$$else\ \alpha_k' = exchange\ (\alpha_k)$$

where *rand (0,1)* represents a uniform random number in the interval of (0,1). Besides, all variable should ensure the movement in the solution space. Thus, if $\alpha_k' < x_{k,min}$, then $\alpha_k' = x_{k,min}$; and if $\alpha_k' > x_{k,max}$, then $\alpha_k' = x_{k,max}$. In the algorithm, $x_{min} = (x_{1,min}, \ldots, x_{k,min}, \ldots, x_{n,min})$ and $x_{max} = (x_{1,max}, \ldots, x_{k,max}, \ldots, x_{n,max})$ indicates the lower and upper boundaries of variables respectively.

In MAHPSO, many different optimization approaches were applied for the realization of purposes. The proposed method absorbed the advantages of MAS and HPSO to solve the mixed-variable WWTP network design problems with speedy and accurate convergence. Fig 3.5 illustrated the framework of the proposed MAHPSO approach. To be specific, the procedure of the overall method was illustrated in the following steps:

Step 1: Define the problem and system composed with objective function decision variables, input parameters, constraints, boundaries, and total iteration number.

Step 2: Generate a lattice-like environment, initialize each agent position statement randomly, set initial velocity equals to zero and make sure that all variables satisfy the requirement of constraints and boundaries. If $\alpha_k < x_{k,min}$, then $\alpha_k = x_{k,min}$; and if $\alpha_k > x_{k,max}$, then $\alpha_k = x_{k,max}$.

Step 3: Evaluate the fitness values of each agent using objective functions. And find out the local best value *pBest* and global best value *gBest*.

Step 4: Update velocity and particle position. Specifically, the velocity is developed by Eq. 3.1, continuous and binary variables will be evolved with PSO and BPSO position update formula (Eq. 3.2, Eq. 3.4 and 3.5) respectively. Then, ensure that the updated position satisfies the requirement of boundaries and constraints.

Step 5: Evaluate the fitness values of each agent using objective functions. And check if the new optimal solution meets the stop criteria. If yes, then stop; otherwise, then continue.

Step 6: Perform the neighbours for each agent, generate neighbor best solution *Nbest* for each local environment.

Step 7: Execute the competition and cooperation strategy and further adjust the position statement in search space on each agent according to Eq. 3.9 and Eq. 3.10 for continuous and binary variables respectively. And ensure that the new agents from loser agents satisfy the requirement of boundaries and constraints.

Step 8: Update the iteration counter $\mathrm{t} = \mathrm{t} + 1$, and go to step 3.

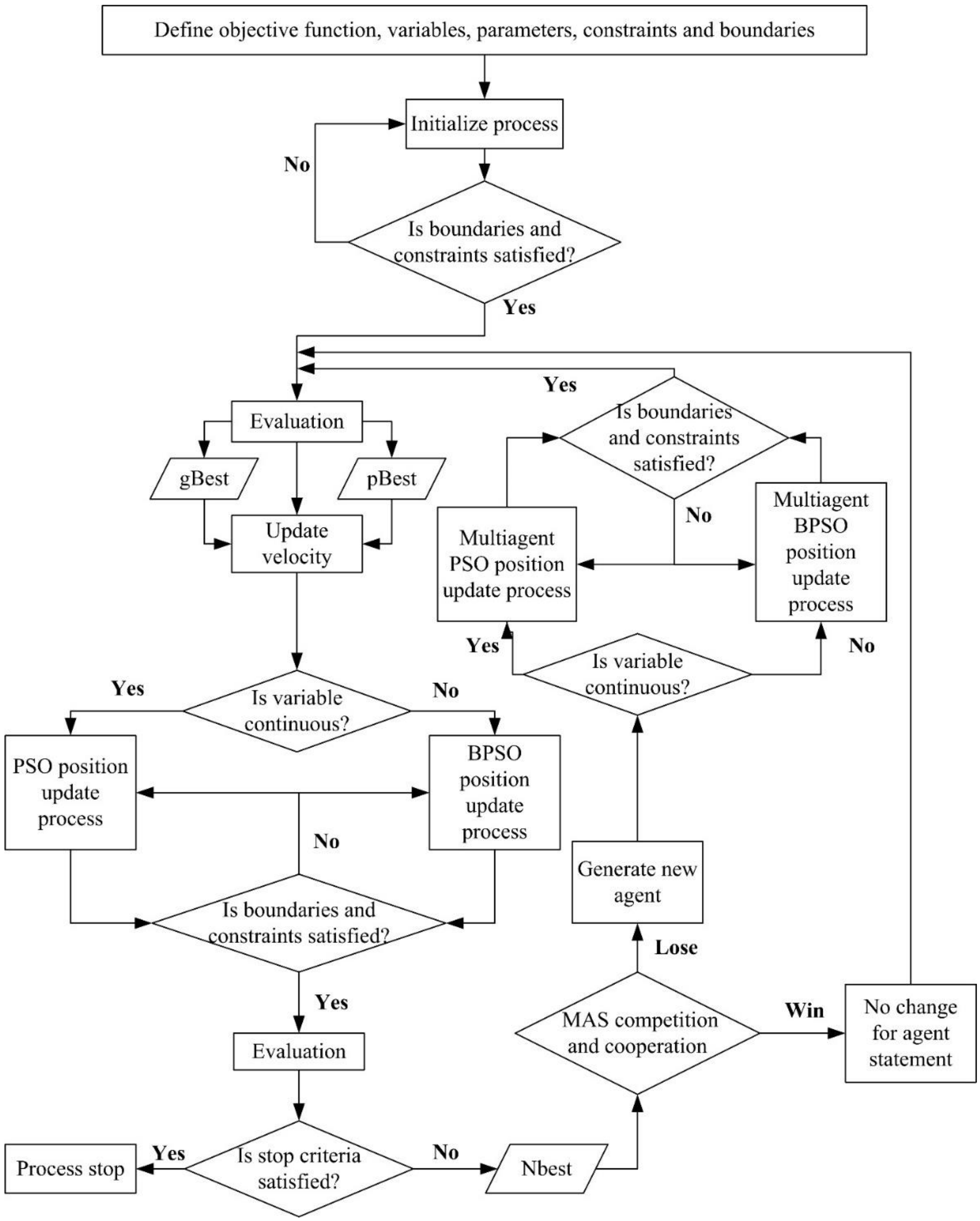


Figure 3.5 The framework of the multi-agent hybrid particle swarm optimization (MAHPSO) approach

3.3 Case Study

3.3.1 Case description

For the sake of solving the decision planning problems of wastewater treatment plants networking through multiple cities. The developed methodology was applied to optimize the design of a WWTP network in the metropolitan area of St John's, Newfoundland, Canada (Fig. 3.6). Although the case study was hypothetical, it closely reflected a real scenario based on published data sources. In this study, each of the seven cities planned to construct a WWTP for water quality improvement, whereas only one sludge process center (SPC) was allowed to be built in one of the seven cities (Fig. 3.7). Aside from the clarifiers, the most distinguishable attribute of a WWTP was usually the secondary treatment option where biological contents of the sewage can be degraded. How to choose the most appropriate secondary treatment technique has therefore been regarded as a crucial factor to the successful design and implementation of WWTPs (Garrido-Baserba et al., 2012). Therefore, in the current study, three types of secondary WWTP, namely sequencing batch reactor (SBR), oxidation ditch (OD), and membrane bioreactor (MBR) were available to be chosen. The daily inflows of wastewater were set according to the populations and the wastewater generation rates in each city. Wastewater quality in terms of total solids (TS) and biological oxygen demand (BOD) were predefined. The capital and O&M costs of each type of WWTP were determined by the piecewise functions shown in Table 3.1 (U.S. EPA, 1983; DeCarolis et al., 2007). The planning horizon was 20 years. A 3.2% annual interest rate and a 2% annual equipment loss rate were considered in O&M for long-term cost prediction. Treated effluent could be reused for numerous purposes and the benefits were associated with the secondary treatment options. Sludge was set to be generated from each type of WWTP with predefined rates. After dewatering with pre-set weight reduction rates, sludge could be transported to a SPC or the existing landfill in the city of St. John's where the transportation cost was proportional to distance (Table 3.2). The capital and O&M costs of the SPC were predefined. Sludge transported to the SPC was composted and sold back at pre-set prices to meet each city's annual demand of 500 tonnes in total, whereas the excessive sludge at the SPC was redirected to the landfill. All the parameter values listed in Table 3.3 were provided by references (U.S. EPA, 1999a, 1999b, 1999c; Government of Newfoundland and Labrador, 2005a, 2005b; CCME, 2008a, 2008b, 2009) to solve the problem.

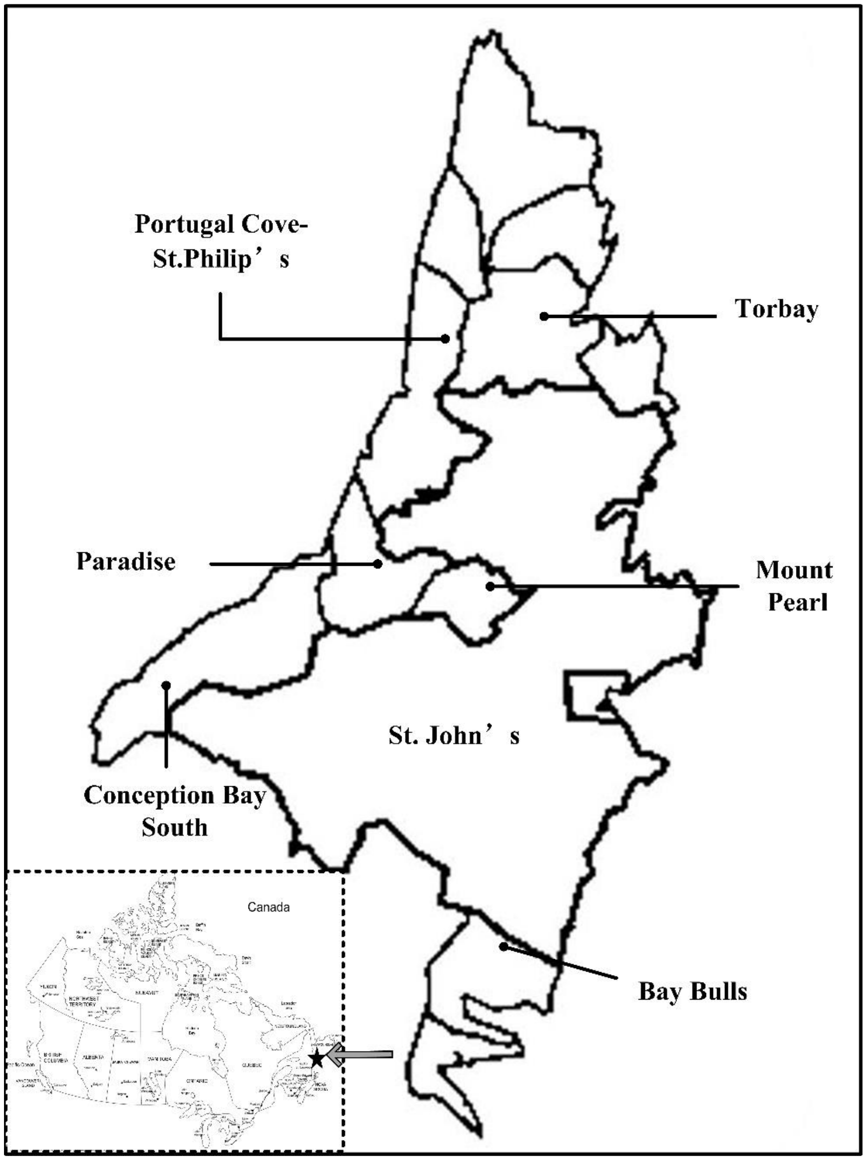


Figure 3.6 The map of metropolitan area of St John's, Newfoundland, Canada

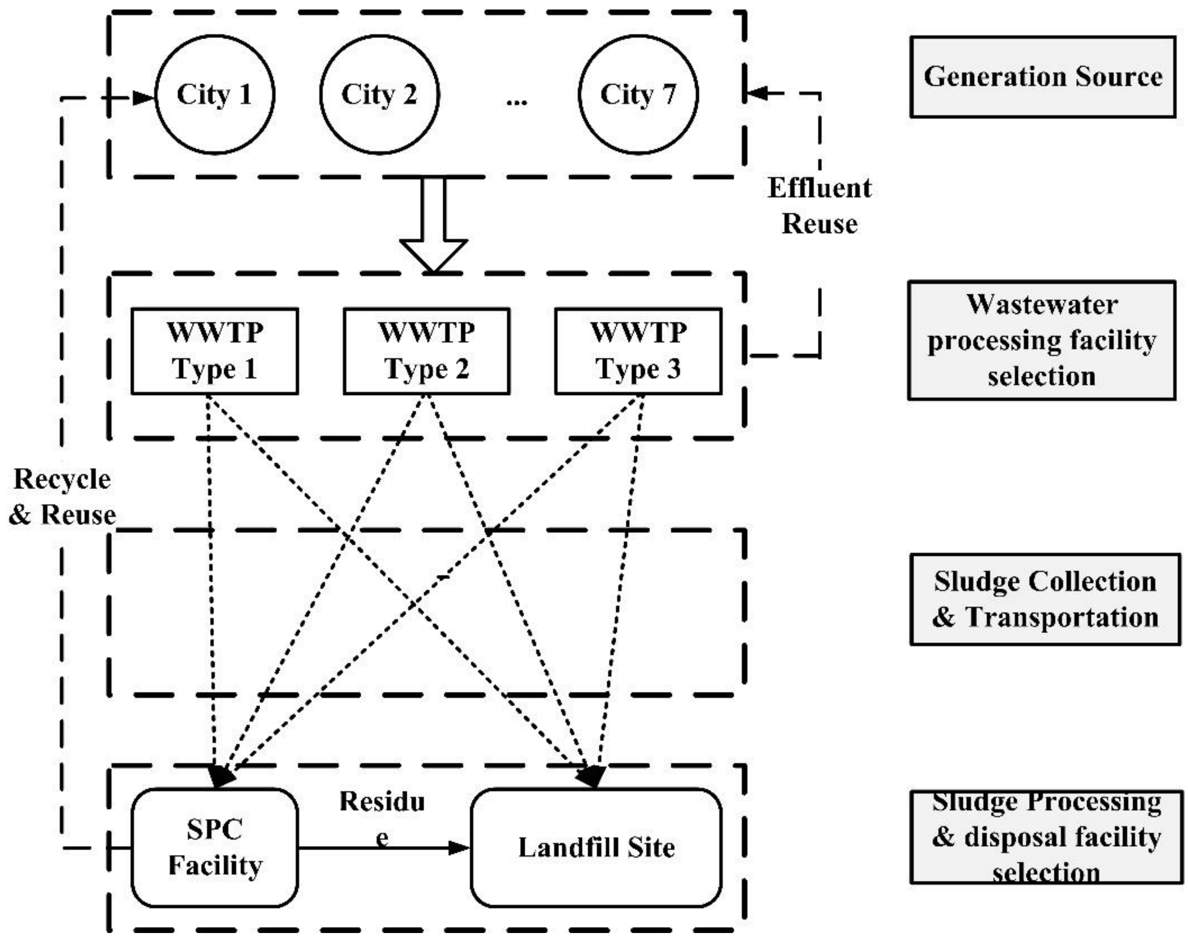


Figure 3.7 Wastewater treatment stream flow network

Table 3.1 Capital and O&M costs piecewise distributions

Cost ($)	$\boldsymbol{FR}$ $(\boldsymbol{m^3/day})$	**SBR**	**Oxidation Ditch**	**MBR**
Ci	$\leq 2 \cdot 10^3$	$1.38 \times FR + 348000$	$1.77 \times FR + 592000$	$1.97 \times FR + 1210000$
	$> 2 \cdot 10^3$	$0.99 \times FR + 1128000$	$0.82 \times FR + 2492000$	$0.58 \times FR + 3990000$
Oi	$\leq 2 \cdot 10^3$	$0.20 \times FR + 20000$	$0.22 \times FR + 12000$	$0.056 \times FR + 87600$
	$> 2 \cdot 10^3$	$0.054 \times FR + 312000$	$0.064 \times FR + 324000$	$0.058 \times FR + 83600$

(U.S. EPA, 1999a, 1999b, 1999c)

Table 3.2 Distance (D) among all cities and the landfill

j	**Distance (km)**	**St. John's**	**Torbay**	**Mount Pearl**	**Portugal-St. Philips**	**Paradise**	**Conception Bay South**	**Bay Bulls**	**Landfill**
1	St. John's	0	12.2	10.7	12.1	14.1	25.9	35.3	6.1
2	Torbay	12.2	0	23.9	19.7	21.7	34.2	50.5	9.1
3	Mount Pearl	10.7	23.9	0	12.4	5.4	15.7	25.3	20.4
4	Portugal Cove-St. Philip's	12.1	19.7	12.4	0	10.2	21.9	40.7	16.3
5	Paradise	14.1	21.7	5.4	10.2	0	11.3	33.8	18.9
6	Conception Bay South	25.9	34.2	15.7	21.9	11.3	0	38.8	29
7	Bay Bulls	35.3	50.5	25.3	40.7	33.8	38.8	0	47.4

Table 3.3 The most likely values of the parameters

Parameter	Description	Category	Value	Unit
$\boldsymbol{S_i}$	Sludge generation rate	S_1: SBR	0.6	$\mathrm{kg/(kg \cdot TS)}$
		S_2: Oxidation ditch	0.65	$\mathrm{kg/(kg \cdot TS)}$
		S_3: MBR	0.5	$\mathrm{kg/(kg \cdot BOD)}$
$\boldsymbol{RW_i}$	Reclaimed water reusing benefit	RW_1: SBR	0.0004	$/L
		RW_2: Oxidation ditch	0.0002	
		RW_3: MBR	0.0001	
$\boldsymbol{P_j}$	Population	P_1: St. John's	102,500	-
		P_2: Torbay	7,397	
		P_3: Mount Pearl	24,284	
		P_4: Portugal Cove-St. Philip's	1,500	
		P_5: Paradise	19,500	
		P_6: Conception Bay South	19,265	
		P_7: Bay Bulls	1,283	
WG	Wastewater generation rate	-	265	$\mathrm{L/(day \cdot capita)}$
$\boldsymbol{RRP}$	Reclaimed wastewater reuse percentage	-	15	%
$\boldsymbol{TS_{SBR} / TS_{Oxidation\ ditch}}$	Total solid	-	250	mg/L

$\boldsymbol{BOD_{MBR}}$	Biological oxygen demand	-	220	mg/L
SPCC	Sludge processing centre capital cost	-	2.5	$\$/(\text{kg} \cdot \text{day})$
SPCO	Sludge processing centre operating cost	-	0.0005	\$/kg
CP	Compost price	-	1	\$/kg
$\boldsymbol{CD_j}$	Compost demand	CD_1: St. John's	300	ton/year
		CD_2: Torbay	100	
		CD_3: Mount Pearl	320	
		CD_4: Portugal Cove St. Philip's	25	
		CD_5: Paradise	200	
		CD_6: Conception Bay South	20	
		CD_7: Bay Bulls	35	
SWR	Sludge weight reduction rate	-	40	%
T	Transportation cost	-	0.5	$\$/(\text{ton} \cdot \text{km})$

Note: the costs have been updated with the ENR construction cost index (ENR = 5916)

3.3.2 Objective functions

The objective function was to minimize the total cost (Eq. 3.11) by considering the capital and O&M costs of the WWTPs (Eq. 3.12) and the SPC (Eq. 3.13), transportation cost of sending sludge from cities directly to the SPC and the landfill (Eq. 3.14), transportation cost of compost from the SPC to the cities (Eq. 3.15), transportation cost of excessive sludge from the SPC to the landfill (Eq. 3.16), treated wastewater reusing benefits (Eq. 3.17), and compost sales benefits (Eq. 3.18) over a 20-year span.

$$\text{Min } f = \sum_1^T f_1(t) + f_2(t) + f_3(t) + f_4(t) + f_5(t) - f_6(t) - f_7(t) \quad (3.11)$$

$$f_1(t) = \sum_{j=1}^{7} \sum_{i=1}^{3} FR_j \cdot x_{ij} \cdot (C_i(FR) + O_i(FR) \cdot AR(t)) \quad (3.12)$$

$$f_2(t) = \sum_{j=1}^{7} CD_j \cdot 1000 \cdot (SPCC \cdot 365 + SPCO(t) \cdot AR(t)) \quad (3.13)$$

$$f_3(t) = \sum_{j=1}^{7} \left[|y_j - 1| \cdot z_j \cdot \left(\sum_{k=1}^{7} |y_j - y_k| \cdot D_{jk} \right) + \left(\sum_{i=1}^{3} WG \cdot P_j \cdot x_{ij} \cdot S_i \cdot (TS \text{ or } BOD) \cdot SWR \cdot 365 \cdot 10^{-9} - z_j \right) \cdot D_j \right] \cdot T \cdot AR(t) \quad (3.14)$$

$$f_4(t) = \sum_{j=1}^{7} |y_j - 1| \cdot \left(\sum_{k=1}^{7} |y_j - y_k| \cdot D_{jk} \right) \cdot CD_j \cdot T \cdot AR(t) \quad (3.15)$$

$$f_5 = \left(\sum_{j=1}^{7} z_j - \sum_{j=1}^{7} CD_j \right) \cdot \left(\sum_{j=1}^{7} y_j \cdot D_j \right) \cdot T \cdot AR(t) \quad (3.16)$$

$$f_6 = \sum_{j=1}^{7} WG \cdot P_j \cdot RRP \cdot \left(\sum_{i=1}^{3} RW_i \cdot x_{ij} \right) \cdot 365 \cdot AR(t) \quad (3.17)$$

$$f_7 = \sum_{j=1}^{7} CD_j \cdot 1000 \cdot CP \cdot AR(t) \quad (3.18)$$

$$FR_j = WG \cdot P_j \quad (3.19)$$

$$AR(t) = (1 + IR)^t \cdot (1 + EL)^t \tag{3.20}$$

where x_{ij} were the binary decision variables indicating whether to build a type i WWTP in city j; y_j were the binary decision variables indicating whether to build the SPC in city j; z_j were the sludge transported from city j to the SPC (tonnes/year); FR_j indicated the daily flowrate in each city; t was the time index (year); T was the total time span which is 20 years; $AR(t)$ was the annual increase rate of O&M cost; IR (3.2%) and EL (2%) were the annual interest and annual equipment loss rates, respectively; D_{jk} stood for the distance between city j and city k (km); and D_j was the distance between city j and the landfill (km). The distance between the SPC and the city where the SPC located was assumed to be 0. The weight of sludge used for composting equaled to the weight of compost product. The capital and O&M costs of each type of WWTP generally were assumed to be dependent on daily inflow rate (Table 3.1). In this case, the costs were assumed to be piecewise distributions based on the recommendations from U.S. EPA (1983) and DeCarolis et al. (2007).

3.3.3 Constraints

The constraints (Eq. 3.21 and Eq. 3.22) were used to restrict the selection of WWTP and SPC quantities in each city. Only one type of WWTP can be chosen for each city and only one SPC was needed to be built for sludge processing among 7 cities. The SPC should be fully loaded at 1000 tonnes per year (Eq. 3.23), and the sludge amount transferred from each city into the SPC should not be higher than their sludge generation amount (Eq. 3.24).

$$\sum_{i=1}^{3} x_{ij} = 1 \tag{3.21}$$

$\forall j$:

$$\sum_{j=1}^{7} y_j = 1 \tag{3.22}$$

$$\sum_{j=1}^{7} z_j \geq 1000 \tag{3.23}$$

$$x_{ij}, y_j \in binary$$

$$0 \leq z_j \leq \min_i WG \cdot P_j \cdot x_{ij} \cdot S_i \cdot (TS \text{ or } BOD) \cdot SWR \cdot 365 \cdot 10^{-9} \tag{3.24}$$

3.3.4 MAHPSO settings

The proposed MAHPSO approach was implemented to find the optimal solution. The model was written in Matlab 2014b® and operated on an intel i7 4770K computer with 8 G RAM. For the MAHPSO test, 200 runs were carried out with 50 iterations with each run. The number of particles was chosen to be 256.

3.3.5 Sensitivity analysis

To understand which parameters in this case study contributed the most to the optimization results, sensitivity analysis was conducted by adjusting all the parameters in Table 3.5 and evaluating their impacts on the 20-year overall cost. Based on the assumption of independent interrelationship, each parameter was individually adjusted by ±5%, ±15%, and ±30% while keeping others at their initial values (adjustment of each parameter was made to all land covers at one time).

3.3.6 Comparison with GA and HPSO

In addition, the HPSO and a traditional GA (Liang et al., 2014 and 2015) approaches were also implemented for comparison in terms of the total cost and total running time. The optimal results from 200 runs were summarized to find the best, worst, average optimal total cost ($), and average execution time for one run (sec). For these two comparison tests, the conditions including generation number, iteration number and particle number were set as the same as the MAHPSO test.

3.4 Results and Discussion

3.4.1 Optimization results

Table 3.4 presented the optimization results obtained from the proposed MAHPSO approach. The total cost over the 20-year planning horizon was minimized to $\$\ 5.074\times10^{8}$. Five cities were assigned MBR, while two were assigned SBR and OD, respectively, due to the sludge demand and treatment cost concerned. MBR was the best choice for the cities with a large population and large daily flow rate, such as St. John’s and Mount Pearl. However, the cities only had less than 2,000 people, the cost of SBR and OD were much lower for cities with small daily wastewater generation rates, such as Portugal Cove-St. Philip's and Bay Bulls (Table 3.4). In addition, over the planning horizon, sludge transported into the sludge processing center was mainly from St John's (286.15 tonne/yr), Mount pearl (317.47 tonne/yr) and Bay Bulls (333.33 tonne/yr). After composting treatment at the SPC, 372.37 tonnes of excessive compost had to be transported to landfill, due to the balance among the benefits, the transportation cost and demands of cities. Moreover, St John's and Mount Pearl were two cities with the highest sludge amount and both closed to the SPC, and the sludge from Bay Bulls can save half of the cost rather than tranfering to the landfill. The SPC was set up at Mount Pearl, compared with the contribution of the other cost, sludge transported to SPC was only a small amount in annual sludge generated from 7 cities, and Mount Pearl was the central city among 7 cities, and nearby St John's, excess sludge could be easy sent to the landfill site in St John's. This planning can reduce the transportation cost for SPC to the whole system.

The results indicated that, in MAHPSO, the nonlinear wastewater treatment network planning problems can be solved with a satisfied optimal result. The most significant contribution of the MAHPSO approach lied in that it represents a new effective attempt to deal with multiple types of variables including continuous ones and binary ones. Moreover, the real-world data based application was a new study by combining WWTP type selection, SPC location selection, and resource recycle and reuse processes into an integrated framework, which could provide a cost-effective decision making supporting for water resources stewardship in Newfoundland. With the above-motioned strengths, the complicated wastewater treatment plant network planning problems associated with multiple variable types could be effectively reflected through the developed MAHPSO approach.

Table 3.4 Optimal results for WWTP network case study

City	WWTP type	Annual sludge transported to the SPC (tonne/year)
St John's	M	286.15
Torbay	M	118.43
Mount Pearl	M	317.47
Portugal Cove-St. Philip's	S	24.32
Paradise	M	266.67
Conception Bay South	M	26
Bay Bulls	O	333.33
SPC Location		Mount Pearl
Total cost (10^8\$/20 yrs)		5.074

(S: SBR, O: Oxidation ditch, M: MBR)

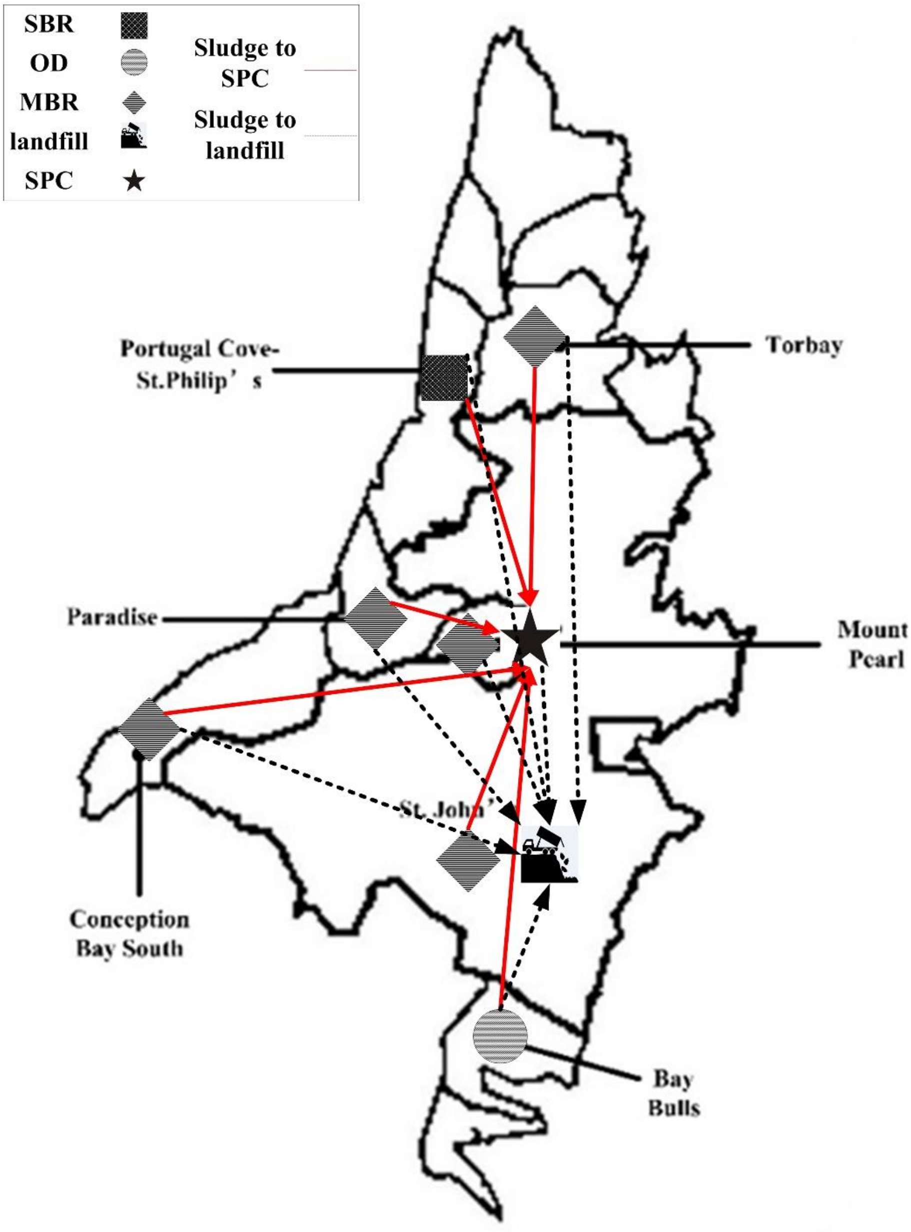


Figure 3.8 The framework of MAHPSO planning scenario

3.4.2 Sensitivity analysis results

To evaluate the significance of each parameter, a sensitivity analysis was performed to rank input parameters based on their influence on the optimization results (Table 3.5). According to the assumption of independent interrelationship, each parameter was individually varied by ±15, ±30, and ±50% while keeping others constant, and evaluated its significance based on the variation of the total cost. As shown in Table 3.5, the results indicated that sludge processing centre operating cost, total compost demand, wastewater generation rate, O&M costs of MBR and population were determined as the most five significant parameters. Sludge processing centre operational cost was most influential parameter with the variation of total cost changed from -45.16% to +43.74% within the analysis range from the -50% level to +50% level. Due to the vital effort of SPC and the large demand of sludge product to reduce the impact of sludge and increase the recycling capacity, SPC operational cost controlled the effect of both the variation of flow rate and sludge produced from 7 areas. The SPC operational cost was based on the daily amount of sludge transported from 7 cities. A high amount the sludge could lead a high overall cost. Total compost demand from 7 cities was the second most sensitive parameter, which varied the total cost with a -42.74% to +41.64% range by the analysis range from the -50% to +50% level. This indicated that the total compost demand had a balance between transportation cost and sludge benefit. Even though compost, as a product, had a good benefit for soil improvement and agriculture purposes, a large amount of sludge might not bring a better benefit to the city. The wastewater generation rate was the third most influential one as the variation of total cost changed from -12.77% to +10.94% by varying wastewater generation from the -50% level to the +50% level. Because the amount of wastewater was a key element for the whole study, specifically, it was a main factor to the capital and operating costs of a WWTP, it also affected the benefit for reused water and transportation costs. The O&M cost of MBR technology was the fourth significant parameter with a -10.41% to +6.7% through the range of sensitivity analysis, because the MBR was the highest rate technique chosen in MAHPSO planning scenarios (5/7), due to the benefit of low capital and operational costs of MBR for large population cities compared with other two techniques. Thus, the high demands of MBR led to a high O&M cost during 20 years as discussed in the case, which drove it to be a significant parameter in the system. The fifth most sensitive parameters were population in each city. The variation of total cost changed from -12.98% to +10.25% by varying these two parameters from the -50% level to the +50% level. Because a low population meant a low daily wastewater generation flow and vice versa. Thus, the choices for wastewater treatment technologies would be much different, which would lead to a various total cost for capital and O&M. Therefore, population is also a vital parameter in the system.

Table 3.5 Sensitivity analysis of optimization case parameters

One factor a time (OFAT)		50%↓	30%↓	15%↓	15%↑	30%↑	50%↑
Parameter	**Unit**	**Variation of total cost (%)**					
C_1	$/(L · day)	-1.49	-1.33	-0.63	-0.20	-1.23	-1.23
C_2		-1.30	-1.57	-0.69	-0.15	-1.55	-1.55
C_3		-5.07	-3.61	-1.65	0.35	2.34	2.34
O_1		-6.16	-1.66	-0.35	-1.32	-1.12	-1.12
O_2		-4.40	-1.27	-0.99	-1.25	-0.23	-0.23
O_3		-10.41	-7.74	-4.45	2.03	4.56	4.56
S_1	kg/(kg · TS)	-0.40	-1.44	-0.18	-0.62	-1.39	-1.39
S_2		-1.24	-1.53	-1.09	0.41	-0.98	-0.98
S_3		-1.23	-0.01	-1.01	-1.06	-0.05	-0.05
RW_1	$/L	-0.69	-1.43	-0.15	-0.76	-0.22	-0.22
RW_2		-0.18	-1.45	-1.36	-1.41	-1.38	-1.38
RW_3		-0.69	-0.31	-1.30	-0.72	-1.63	-1.63
WG	L/(day · capita)	-12.77	-7.79	-3.61	2.03	6.08	6.08
RRP	%	-0.05	-0.85	-1.03	-0.95	-1.60	-1.60
P		-12.98	-7.20	-3.94	2.31	5.77	5.77
TS_{SBR}	mg/L	-0.81	-0.24	-0.63	-1.49	-1.30	-1.30
$TS_{Oxidation\ ditch}$		-1.08	-1.25	-1.40	0.15	-0.94	-0.94
BOD_{MBR}		-1.36	-0.42	-1.07	-1.30	-1.29	-1.29
SPCC	$/(kg · day)	-45.16	-27.48	-14.65	11.82	26.25	26.25
SPCO	$/kg	-0.75	-0.33	-0.96	-0.18	-0.73	-0.73
CP		0.15	0.28	-0.76	-1.95	-1.04	-1.04

CD_j	ton/year	-42.74	-26.54	-12.93	11.61	24.48	24.48
SWR	%	-0.61	-1.20	-1.07	-0.74	-0.89	-0.89
T	$\$/(\mathrm{ton} \cdot \mathrm{km})$	-0.60	-0.60	-0.16	-1.01	-1.30	-1.30

3.4.3 Comparison with GA and HPSO

The best and worst 20 year-span scenarios found by MAHPSO and other two comparison methods were indicated in Table 3.6 and Fig 3.8-3.12. For MAHPSO, optimization results indicated that the overall cost was minimized to \$5.0740×10^8 in 38.04 sec per run. For comparison purposes, the result obtained from the GA was \$6.3610×10^8 in 19.43 sec, while the hybrid PSO without multi-agent system acquired \$5.0856 ×10^8 in 16.04 sec for the best result. It was illustrated the proposed MAHPSO approach can significantly enhance solution convergence as compared to GA and HPSO. Moreover, MAHPSO showed good consistency and stability by keeping the difference between the best and worst scenarios within a 0.5% range, while GA had the worst consistency among all three methods. As shown in Fig 3.9-3.11, even though there are still some outliers out of 200 runs, more than 75% optimum can narrow down and reach the best optimum in the algorithm. HPSO only had about 2% results that can obtain the best result of \$5.0856 ×10^8, most of the optimum indicated in a scattered zone from \$5.1000 ×10^8 to 5.3500 ×10^8, and the results varied in a ± 3% from the avarage value. The results from HPSO illustrated that, it has the potential to work as a quick calculation method for planning or predition to obtain a preliminary result, but for further improving the accuracy, MAHPSO could be the follow-up algorithm. GA, even as a traditional optimization approach, obtained the worst result among all approaches. Even though the results from GA were stable, and can reach the best optimum each time, the optimum values were much higher than the other two methods to the value of \$$6.3610\times10^8$. As shown in Table 3.6, MAHPSO had to sacrifice the computation speed in order to ensure more optimal solution as compared to GA and HPSO. Thus, the optimization results showed that MAHPSO outperformed HPSO and GA, and could be competent for the practice of WWTP network decision making problems with mixed variables. With the application of MAS to enhance the communication among particles, MAHPSO can reach the optimum faster than HPSO and provent *pBest and gBest* results from trapping by a local optimum. The cooperation and compitition with neighbors particles can enlarge the adjustment range of particles when they were close to local optimums. Besides, although MAHPSO takes the longest calculation time for each run, MAHPSO could have the best performance to convenge into the best optimial results by setting the stop cretira to the number of times reaching the optimal solution Therefore, MAHPSO could obtain a better convergency proformance than the original HPSO.

Table 3.6 Comparison of optimal total cost for different Methods (Min f)

	Optimal total cost (E+08$)			Average execution time (sec/run)
	Best	Worst	Average	
GA	6.3610	6.3610	6.3610	19.43
HPSO	5.0856	5.3298	5.2138	16.04
MAHPSO	5.0740	5.1032	5.0817	38.04

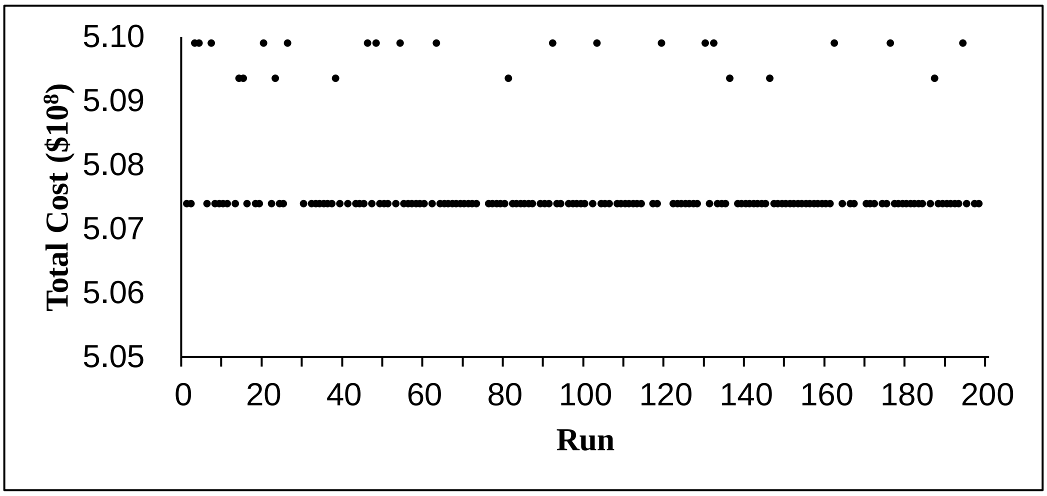


Figure 3.9 The distribution of optimum from MAHPSO for 200 runs

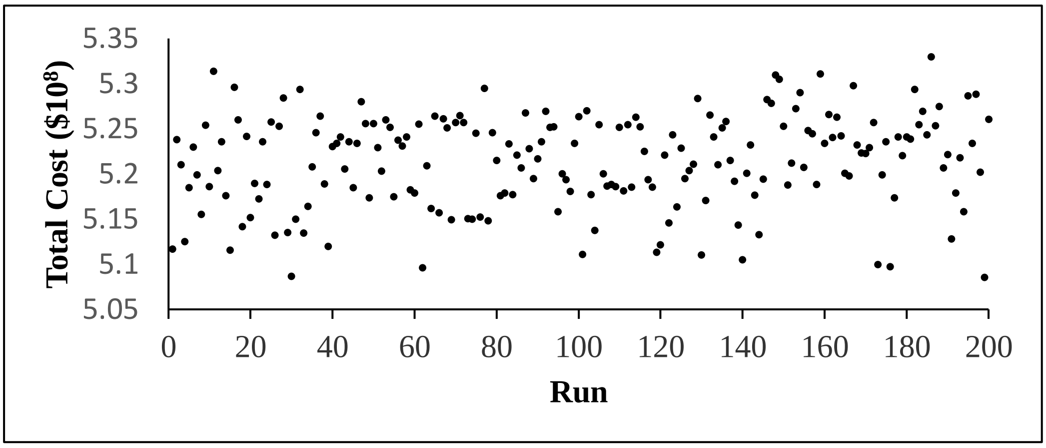


Figure 3.10 The distribution of optimum from HPSO for 200 runs

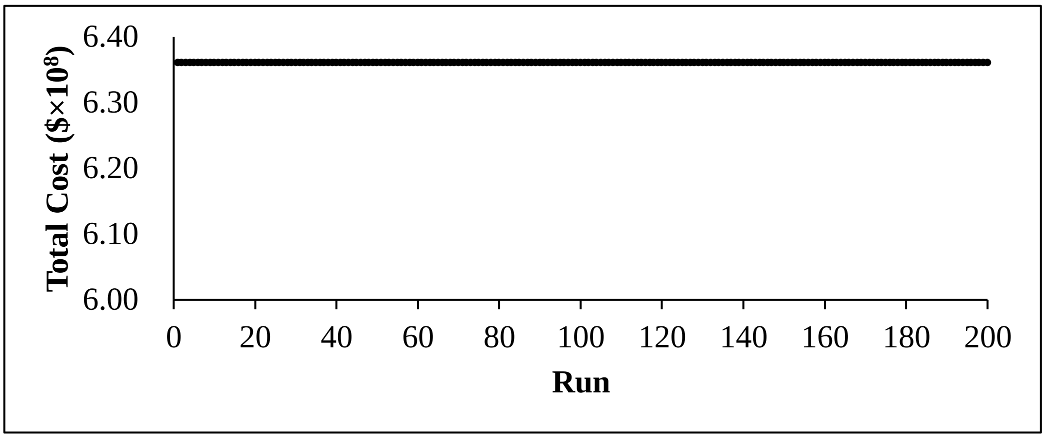


Figure 3.11 The distribution of optimum from GA for 200 runs

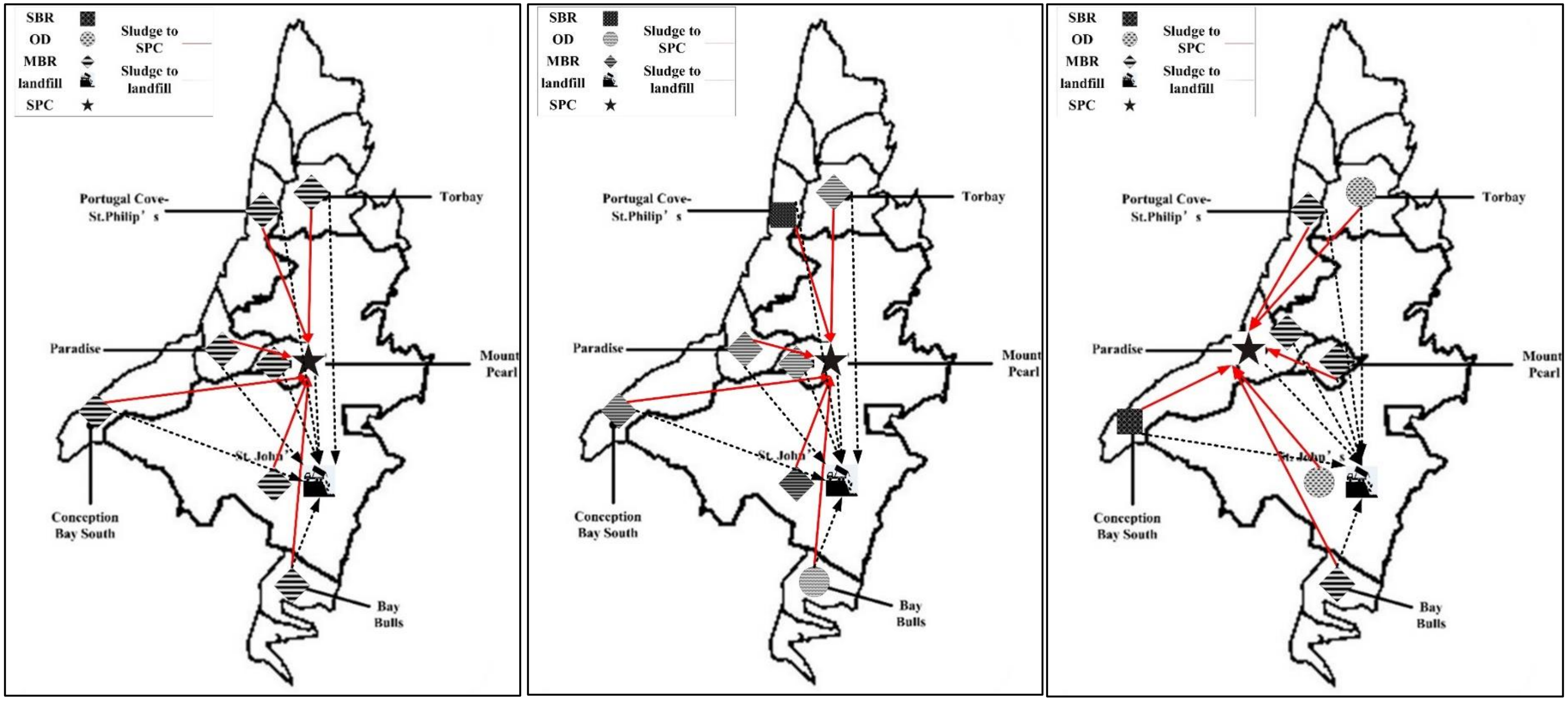


Figure 3.12 The frameworks for HPSO (Left), MAHPSO (Mid) and GA (Right)

3.5 Summary

A MAHPSO method has been developed for WWTP network decision making problems with mixed variables. The proposed method had the characteristics of multi-agent system, which had the environment of the agent lattice and the behaviors of agent, such that competition and cooperation could be operated in each iteration process, and further adjusted its position in the search space according to HPSO for continuous and binary variables, respectively. Thus, each agent could diffuse and share its useful knowledge to the global environment quickly, and all agents could learn and evolve after a process of interaction. Owing to the three distinct operators, the MAHPSO method was capable to find high quality solutions with an outstanding convergence property in a minimum iteration count. The performance of the proposed method demonstrated through the optimization of a real-world WWTP network design case in St. John's area in Canada. Optimization resulted indicated that the overall cost was minimized to $\$5.0740\times10^{8}$. Sensitivity analysis showed that sludge processing centre operating cost, total compost demand, wastewater generation rate, O&M costs of MBR and population were the five most important parameters for the study. For comparison purposes, the best results obtained was $\$6.1279\times10^{8}$ from a traditional GA and $\$6.3610\times10^{8}$ from HPSO. It was illustrated the proposed MAHPSO approach, as compared to traditional GA and HPSO, can significantly enhance solution convergence without sacraficing the running speed. The proposed MAHPSO approach can be used as an inexpensive and effective evolutionary algorithm for other complex environmental optimization problems.

CHAPTER 4: A SIMULATION-BASED MULTI-AGENT PARTICLE SWARM OPTIMIZATION (SA-PSO) APPROACH FOR SUPPORTING DYNAMIC DECISION MAKING IN OFFSHORE OIL SPILL RESPONSES[2]

[2] The chapter was extracted from the following journal paper under preparation:

4.1 Introduction

With the increasing contamination of water bodies in oceans by oil spills, offshore oil pollution has received particular attention over past years by researchers and governmental officials. The minimization of the economic and environmental impacts of oil spills in oceanic circumstances is a major concern worldwide (Azevedo, et al., 2014). Offshore oil spill is defined as an accidental release or discharge of petroleum hydrocarbons due to human operations or natural disasters (Li, et al., 2014). According to ITOPF (2008) report, 85% of the spills are smaller than 7 tons. Fingas (2011) indicated that worldwide oil spillage rates have decreased dramatically since the 1960s and 1970s, from about 635,000 tons annually to about 300,000 tons per year from all sources. However, large spills still frequently occur every year and have major environmental and economic negative impacts to the world. In recent decades, two of the most remarkable disasters are the Exxon Valdez Oil Spill in 1989 and the BP Deepwater Horizon Oil Spill in 2010. A great number of studies around their outcomes, including simulation modeling, decision making planning, economic analysis, and cleanup technology development, etc., have been published in the past few years. Due to spills having led to both tremendous economic losses and durable social-environmental impacts. For which, the inefficient decision support system tools coupling with simulation models and optimization approach during the emergency response were one of the vital issues that needed to be conquered. (Anchorage, 1992; Esler et al., 2010; Perring et al, 2011; Scocolofsky et al., 2011; Sylves et al., 2012; Boufadel et al., 2016).

In recent decades, according to the literature reviews of offshore oil spill models indicated in section 2, many researchers have done research about developing an effective and efficient tool for oil spill emergency decision supporting system (DSS) and adding optimization approaches into the system to provide decision supporting under changing environmental conditions. Further, several studies have attempted to realize dynamic simulation in the models. However, harsh oceanic circumstances tend to make emergency response to oil spills even more challenging by changing the fate and properties of oil dramatically within a short period of time, which will inevitably hinder and affect the efficiencies of recovery and cleanup processes (Brandvik et al, 2006; Bjerkemo, 2011; Li et al, 2014). Till now, few studies have been carried out specifically focusing on the solutions of this issue. Therefore, a real-time dynamically simulated and optimized decision supporting system taking into account the restrictions of devices and the enhancement of response efficiency is urgently desired.

To fill this gap, this study aimed at developing a simulation-based multi-agent particle swarm optimization approach for supporting dynamic decision making in offshore oil spill responses. In the developed system, agent based modeling (ABM), a dynamic, high-freedom, and interactive simulation approach, was hereby proposed to render a certain degree of autonomous characteristics to the system, achieve a better simulation of the process and make it accessible to cooperate with optimization processes. Particle swarm optimization (PSO), an effective optimization algorithm, 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 in order to make the system can work smoothly and successful, to control and transmit the result from ABM and PSO aspects. The outcomes of the study were expected to facilitate a more effective and efficient tool for emergency oil spill response under highly dynamic conditions.

4.2 Methodology

4.2.1 Agent based modeling for oil spill simulation

The SA-PSO approach considered the ABM for simulation, PSO for optimization and MAS for integration of the system to realize the information transportation and dynamic decision making. Specifically, agent based modelling was responsible for the dynamic simulation process including the behaviors of oil cleanup and recovery response and oil spill weathering simulation. 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.

4.2.1.1 Offshore oil spill cleanup and recovery response simulation

In offshore oil spill cleanup response, the net oil recovery rate of skimmer mainly depends on slick thickness (ST). The function (Eq. 4.1) between ORR_{sk} and ST is defined as follows:

$$ORR_{sk} = \alpha \times ST^2 + \beta \times ST \tag{4.1}$$

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, 2014). Accordingly, the objective function of the offshore oil spill recovery response by skimmers (Eq. 4.2) can be voiced as follows:

$$V_{sk} = \sum_{t=1}^{t} \sum_{i=1}^{i} f_{ORR_{sk,i,t}(ST_{k,t})} \tag{4.2}$$

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 (4.3) can be calculated by the equation shown as follows:

$$ST_{k,t} = \frac{V_{0,k} - \sum_{t=1}^{t-1} V_{loss,k,t}}{A_t} \tag{4.3}$$

where $V_{0,k}$ is the initial volume of spill k, A is the area of spill k, 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 in order 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.

4.2.1.2 Offshore oil spill weathering simulation

In real-world practices, oil recovery is significantly affected by the weathering processes, such as spreading and drift, evaporation, natural dispersion, emulsification, biodegradation, etc. (Fingas, 2011 and 2013). In most of spill cases, the recovery and cleanup processes are required to be done within a short period. Evaporation, dispersion, and emulsification could play vital roles in oil weathering. Therefore, these processes will also be taken into account in the ABM simulation section.

According to Fingas (2011), the empirical equation of evaporation for oil (Eq. 4.4) is as follows:

$$FE = \frac{c + d \times (T - 273.15) \times Ln(t)}{100} \tag{4.4}$$

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*), and t is time (*minute*).

Moreover, the equation for the dispersion process (Eq. 4.5) developed by Mackay et al. (1980) is indicated as follows:

$$FD = \frac{0.11 \times (U+1)^2}{1 + 50 \times \mu^{0.5} \times ST \times s_t} \tag{4.5}$$

Where FD is the dispersion rate ($m^3/(s \cdot m^3\ of\ oil)$), μ is the dynamic viscosity of the oil (cP), 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:

$$\frac{dF_{emul}}{dt} = R_1 - R_2 \tag{4.6}$$

$$R_1 = \frac{K_1}{\mu_0} \times (1 + U)^2 \times (F_{emul}^{final} - F_{emul}) \tag{4.7}$$

$$R_2 = \frac{K_2}{Asph \times Wax \times \mu_0} F_{emul} \tag{4.8}$$

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 the wind velocity, K_1 and K_2 are empirical dimentsionless constants; Asph and Wax are percentages of asphaltenes and waxes contents and μ_0 is the initial dynamic viscosity of the oil.

Kirstein et al. (1988) published a relatively simple empirical dependence in the form of the equation to illustrate the relationship between viscosity and water content (Eq. 4.9).

$$\mu = \mu_0 \times \exp(\frac{2.5 \times F_{emul}}{1 - k \times F_{emul}}) \tag{4.9}$$

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. 4.10) can be formulated as follows:

$$\text{Max V} = \sum_{t=1}^{t} \sum_{i=1}^{i} f_{ORR_{sk,i,t}(ST_{k,t})} \tag{4.10}$$

s.t.

$$ORR_{nis,t} = f_{ORR_{ni,t}}\left(\frac{V_0 - \sum_{t=1}^{t-1}(V_t + FV_t + DV_t)}{A}\right) \tag{4.11}$$

$$FD_t = f_{FD}(ST_{t-1}) = f_{FD}(\frac{V_0 - \sum_{t=1}^{t-1}(V_t + FV_t + DV_t)}{A}) \tag{4.12}$$

$$FV_t = FE_{t-1} \times (V_0 - \sum_{t=1}^{t-1}(V_t + FV_t + DV_t)) \tag{4.13}$$

$$DV_t = FD_{t-1} \times (V_0 - \sum_{t=1}^{t-1}(V_t + FV_t + DV_t)) \tag{4.14}$$

Where *FV* is the evaporated oil (m^3) and *DV* is the dispersed oil (m^3).

4.2.2 Particle swarm optimization algorithm

PSO is a stochastic population heuristic optimization approach first developed by Eberhart and Kennedy (1995) for continuous non-linear function optimization. PSO is currently applied in various scheduling problems because of its simplicity and efficiency. However, PSO is a new application as an optimization tool for solving offshore oil spill accidents decision supporting problems with devices allocations. In the proposed SA-PSO system, PSO played the role as the tool to receive the outputs from ABM section, after optimized the device locations and checked 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* is evolved by exploiting positional information from the selected global leader and its own personal best to update its velocity and position values, as indicated in Eq.4.15 and 4.16. The detailed background of PSO has been illustrated in section 2.2.1

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot \left(x_{pbest_i} - x_i(t)\right) + c_2 \cdot r_2 \cdot \left(x_{gbest_i} - x_i(t)\right) \tag{4.15}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{4.16}$$

Where i is the iteration number, w is the inert weight, c_1 and c_2 are two learning factors from the personal and global best particles respectively, r_1 and r_2 are two random numbers generated uniformly in the range [0, 1].

4.2.3 An integrated multi-agent system and a SA-PSO framework

In multi-agent systems (MAS), agents' knowledge includes information (e.g. user model, heuristics, financial data, etc.) and object classes for retrieving or processing it (e.g. preference-elicitation methods, negotiation strategies, time-series analyzers, etc.) (Winoto, 2003). One key element of MAS is the information sharing, which is important in application oriented domain. The structure of MAS would be varied based on research areas and topics (Rodrigues, 2011). In the proposed SA-PSO system, the system mode used was shown in Fig. 4.1. 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, the PSO optimization player played as the optimization environment for particle swarm optimization algorithm. Each black point was a PSO agent, which was a candidate solution containing all the information and functions from the other two layers. SIL and ABL were used for simulation processes. The social interaction layer reflected the interaction characteristics between different agents. In SA-PSO model, skimmers had interactions with other skimmers' behaviors and oil spill characteristics. When a skimmer shipped to a spill, the skimmer would collect oil on the spill, it would affect the evaporated, dispersed oil rate, density, viscosity and water content for spills. Moreover, when more than one skimmer moved on a spill, they would have a competition behavior for oil collection. For the last layer, the environment or agent behavior layer provided a platform for all agents to continuously update their behaviors followed by their specific rules. For example, oil spills followed weathering processes including evaporation, dispersion, and emulsification. Further, skimmers obeyed the rules for oil collection and movement. With the contribution of MAS, ABM simulation and PSO optimization can work as a dynamic system with the complicated inner and external interactions. Moreover, the data from different sections could transmit and reflect smoothly and successfully.

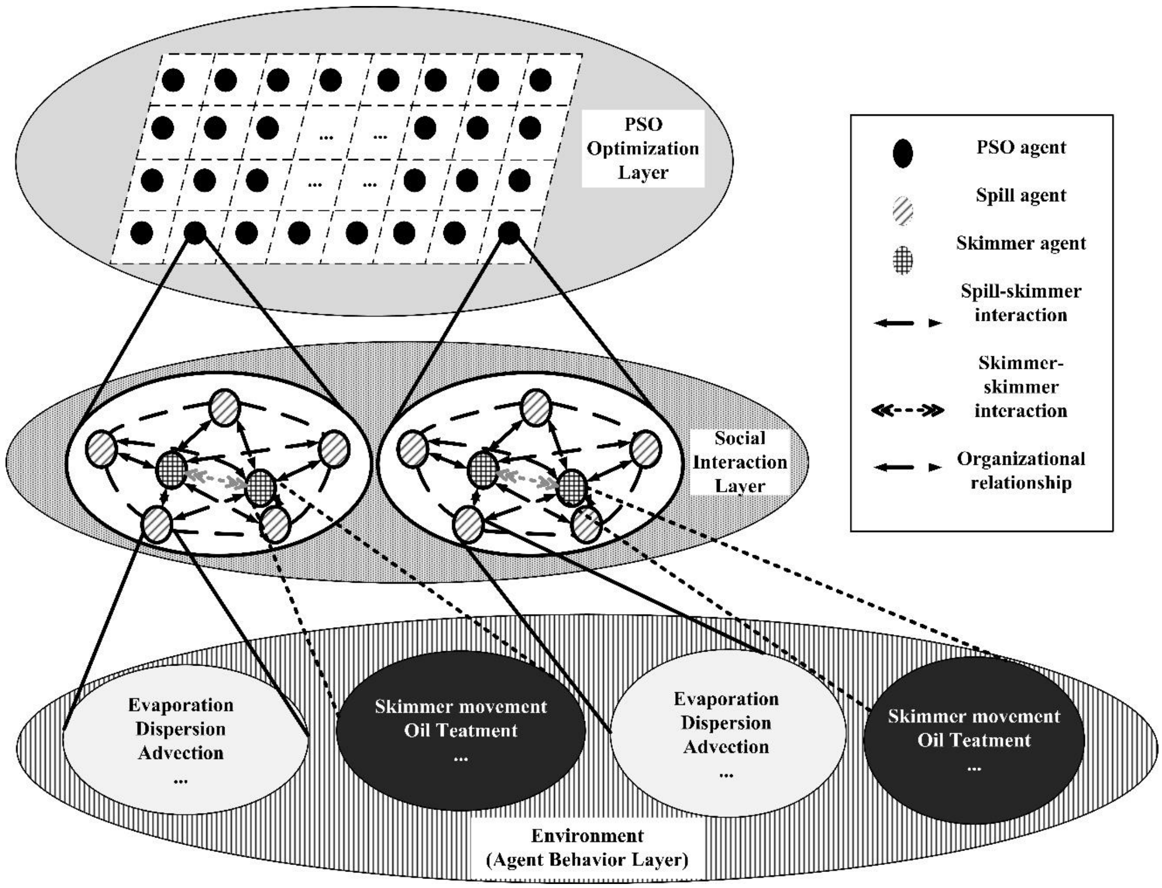


Figure 4.1 The multi-agent system (MAS) structure of the simulation-based multi-agent particle swarm optimization (SA-PSO) approach

By the cooperation of ABM, MAS, and PSO, the simulation-based multi-agent particle swarm optimization system could be treated as a novel developed system that have the potential to be used for decision supporting system (DSS) of offshore oil spill accidents. The framework of the SA-PSO approach is shown in Fig. 4.2 The approach can utilize the global objective as the goal for agents and dynamically adjust the planning setting according to the results from simulation and optimization sections in each iteration. The modelling operational platform supporting the proposed system is call NetLogo®. It is a popular multi-agent programmable modelling 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 (Dickerson, 2014; Banitz, et al., 2015; Arayhi et al, 2016). Therefore, NetLogo® is used as the foundation platform for the SA-PSO model.

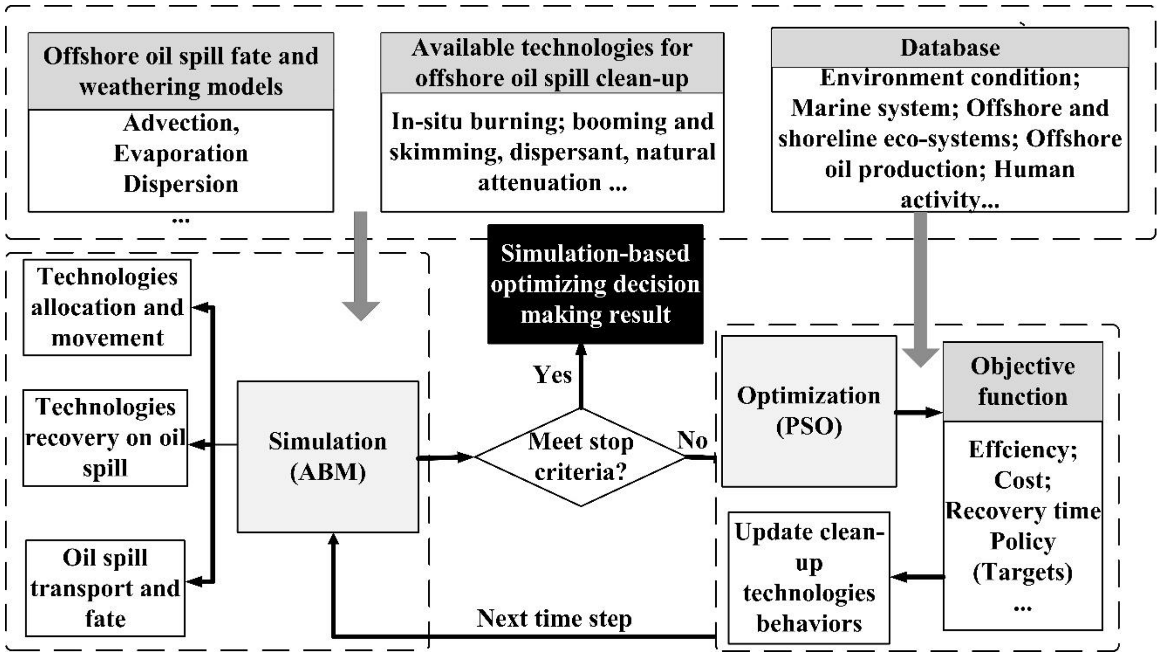


Figure 4.2 Framework of the simulation-based multi-agent particle swarm optimization (SA-PSO) approach

4.3 Case Study

4.3.1 Case description

A hypothetic case study was considered to test the efficiency of SA-PSO method. The case indicated an offshore 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 4.1 illustrated the oil volumes and coordinates of these oil slicks.

Table 4.1 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

Three different ship-mounted skimmers, which were installed on three ships (ship A, B, and C), were the only available nearby cleanup tools that can be applied in this area to collect the spilled oil at this scenario. Three ships were berthed at three different ship docks and a specific transportation time period was needed for allocation. The detailed location relationships of response ships and oil slicks were indicated in Figure 4.3 and Table 4.2.

Table 4.2 The location information about three ship docks

Ship	X(km)	Y(km)
A	15	0
B	0	15
C	80	0

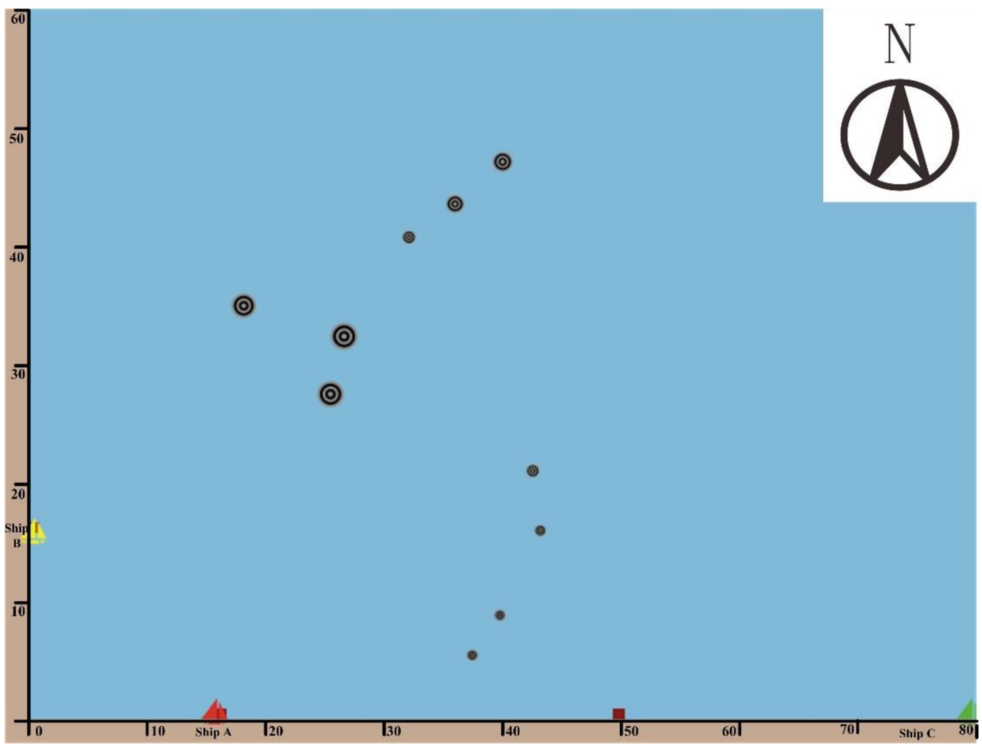


Figure 4.3 Location relationships of response ships and oil slicks

4.3.2 Oil weathering process simulation

The oil weathering processes included evaporation, emulsification, natural dispersion, dissolution, sedimentation, etc.(Fingas, 2011). The major weathering processes, evaporation, natural dispersion and emulsification, were discussed in this hypothetic case for oil weathering processes. Table 4.3 illustrated the inputs for the oil spill weathering processes.

Table 4.3 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})	10.4	Pa	Water content (F_{emul})	0.1	%
Oil density (ρ^{sat})	0.8781	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)	1680	dyne/m
Emulsion formation viscosity (0% Evaporation)				23000	cP

*The parameter values are from data in 0℃.

Based on Fingas (2011), the empirical equation for predicting evaporation for Terra Nova crude oil (Eq. 4.17) was shown as follows:

$$(\%)Ev = (2.4 + 0.045(\mathrm{T} - 273.15))\ln(\mathrm{t}) \tag{4.17}$$

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

According to Mackay et al. (1980), the simulation equation for natural dispersion process (Eq. 4.18) was shown as follows:

$$(\%)Dis = \frac{0.11 \times (U+1)^2}{1 + 50 \times \mu^{0.5} \times ST \times S_t} \tag{4.18}$$

where, $(\%)Dis$ was percentage dispersed oil, U was wind speed in m/s, μ was the dynamic oil viscosity in unit of cP, ST was oil slick thickness in mm, and S_t, was interface tension between oil and water in unit of dyne/m.

Based on Mackay et al. (1980), Rasmussen (1985), and Azevedo et al. (2014) studies, the data was achieved for $K_1 = 3.0\times10^{-9}\ kg/m^3$, and $K_2 = 3.5\times10^{-7}\ kg/m \cdot s^2$ with a maximum water content of F_{emul}^{final} closed to 90%. In addition, Fingas et al. (2004) indicated that the asphaltenes and waxes contents of Terra Nova crude oil were 4% and 7%, respectively.

In the oil weathering simulation part, some parameters values were considered as constant, which include, 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. No oil movement processes were taken into account during the oil dynamic simulation. Emulsification did not affect the spill volumes.

4.3.3 Oil recovery simulation

Three ships with three types of ship-mounted skimmers were applied as the recovery technology for oil spills. The empirical equation for the net oil recovery rate of skimmers was illustrated as follows (Li et al., 2012, 2014):

$$ORR = a \times ST^2 + b \times ST \quad (4.19)$$

where, ORR was the net oil recovery rate in unit of $m^3 \cdot oil/hr$, a and b were empirical coefficients obtained from experimental tests, and ST was oil slick thickness in mm.

The detailed information about empirical coefficients used for three skimmers were shown in Table 4.4. As slick thickness was the key element leading to the oil recovery efficiency of skimmers, Figure 4.4 indicated the relationships between slick thickened and different skimmers.

Table 4.4 Model coefficients for net oil recovery rate of three ship-mounted skimmers

Types of skimmers	Empirical coefficients	
	a	b
SK_1 (Ship A)	0.01437	0.01602
SK_2 (Ship B)	-0.00791	0.84975
SK_3 (Ship C)	-0.01591	1.54975

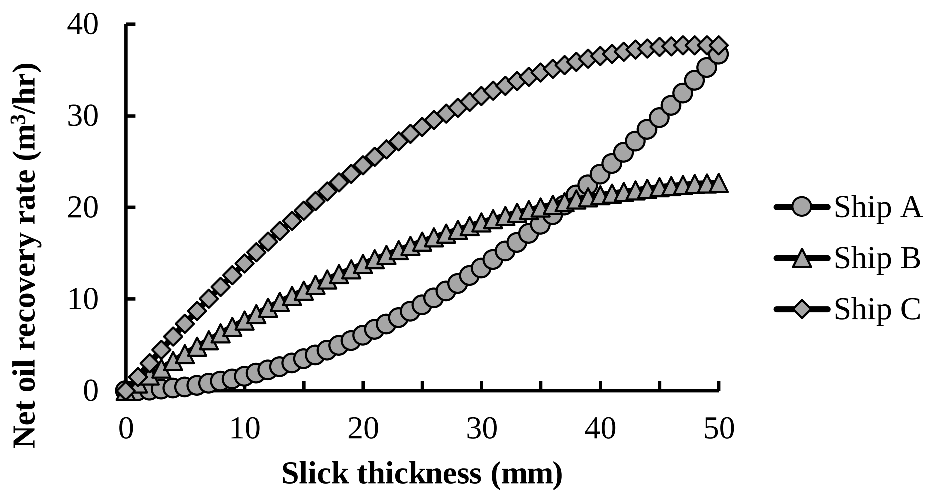


Figure 4.4 The relationships between slick thickness and net oil recovery rates of ship-mounted skimmers

Due to the inconvenient conditions in the harsh environment, no other skimmers and vessels were ready for the emergency response. The objective of the response in the case was to achieve the decision making plan for 90% of oil recovery, including natural attenuation and man-made cleanup processes, within a minimum response time. According to the previous information and the algorithms of SA-PSO, a global optimization function can be generated as follows:

$\boldsymbol{Min\ T}$

s.t.

$$\sum_{t=1}^{T} TV_t \geq 90\% \times total\ oil\ volume \tag{4.20}$$

$$TV_t = f_t(Ship_i, ST_{ik}) \tag{4.21}$$

$$\forall t = 1, \cdots, T; i = a, b, c; k = 1, \cdots, 7$$

Where T was the time scale of operation (hour); t was the indicator of stage; TV_t was the total recovered oil in each stage (m^3); and $TV_t = f_t(Ship_i, ST_{ik})$ was the simulation objective function at time tick t; ST_{ik} was the slick thickness of each slick k at stage t (mm).

4.3.4 PSO settings and SAPSO computing environment

In the optimization section, PSO was implemented to find the optimal solution. The model was written in NetLogo® and operated on an intel i7 4770K computer with RAM. For PSO settings, the particle size was 256, 200 repeating runs were carried out with 50 iterations per time tick.

4.3.5 Comparison with other approaches

The shortest distance selection approach (SDS) method was applied into the case study in order to compare and examine the efficiency of SA-PSO approach. By comparison, SA-PSO approach was testing if the developed approach can show a better robustness and efficiency than others.

SDS was the common and simple approach used in offshore oil spill emergency response. The approach indicated a process which allowed skimmer-ships to choose the closest oil slicks near them to be the target for oil recovery, after ships met the requirement for cleanup on those slicks, then chose the second closest oil slicks near them to continue to work. The only judgement criteria was 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 SAPSO efficacy.

4.4 Results and Discussion

4.4.1 Decision making with weathering process simulation

The modeling results indicated that with consideration of 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 SAPSO modeling.

The weather agent based simulation model section in SAPSO reflected the dynamic relationship of oil volumes of spills and time. As the above illustration, three vital weathering processes possessed in the model, which were evaporation, dispersion, and emulsification. The evaporation of the specific oil type was affected by time with a constant temperature. The dispersion process was under the influence of wind speed, viscosity and interface tension between oil and water. In this case, wind speed and interface tension were assumed as constants. And viscosity was dynamically impacted by an emulsification procedure. Further, the emulsification led to the variation of water volume with time and then influenced the value of viscosity simultaneously. However, the impacts from the change of water content on oil volume was neglect.

Table 4.5 showed the decision-making results of SAPSO and SDS approaches under the weathering processes. SAPSO plan can reduce the time by 11 hours compared to the

SDS one, which can increase 11.7% recovery speed in the spill incident. In SAPSO, ship C was the one that had the highest amount of recovered oil, which was about 400 m^3 higher than the amount of ship C in SDS scenario. As the skimmer mounted on ship C had the highest collective efficiency (Fig 4.4), the SAPSO decision tried to lead ship C to keep having a high efficacy during the entire procedure. Fig 4.5 and Fig 4.6 indicated the amount of oil recovered by each ship at each stage by two approaches. The curves of SAPSO were much smoother than the ones of SDS, according to the main effect of slick thickness to recovery rate. The SAPSO plan can optimize the recovery rate related to the change of slick thickness of each spill, in order 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. Fig 4.7 and Fig 4.8 illustrated the variations of oil volumes by each spill in the SAPSO and SDS scenarios with weathering process during the entire procedure. The SAPSO decision intended to keep a balance of oil volume level for all spills by optimizing the time cost of movement and cleanup efficiency. However, the SDS scenario ignored the large spills, such as spill 1 and 2. Fig 4.9 and Fig 4.10 indicated the transport and fate of spilled oil of both methods during the operational period. It can be seen that evaporation led to a vital force at the early stage, and dispersed oil had a little effect to the weathering process compared with evaporation.

Table 4.5 Decision making results of SAPSO and SDS approaches

	SAPSO	**SDS**
Operation time (hr)	83	94
Recovered oil (Ship A) (m^3)	680.80	1045
Recovered oil (Ship B) (m^3)	880.33	899
Recovered oil (Ship C) (m^3)	1706.12	1310
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

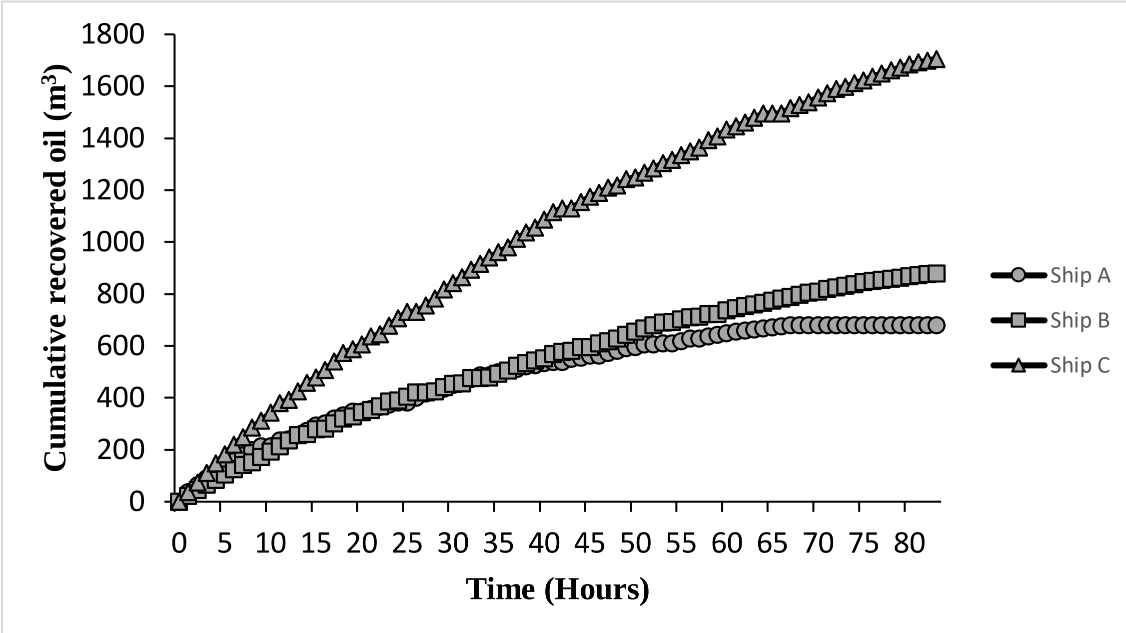


Figure 4.5 Cumulated oil recovery by each ship in SAPSO scenario with oil weathering process

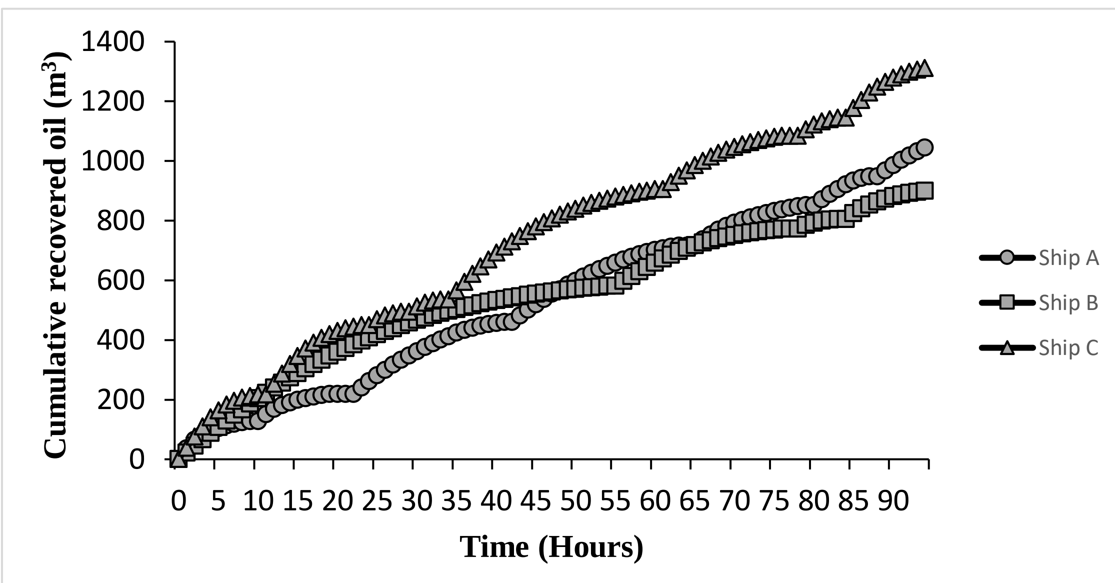


Figure 4.6 Cumulated oil recovery by each ship in SDS scenario with oil weathering process

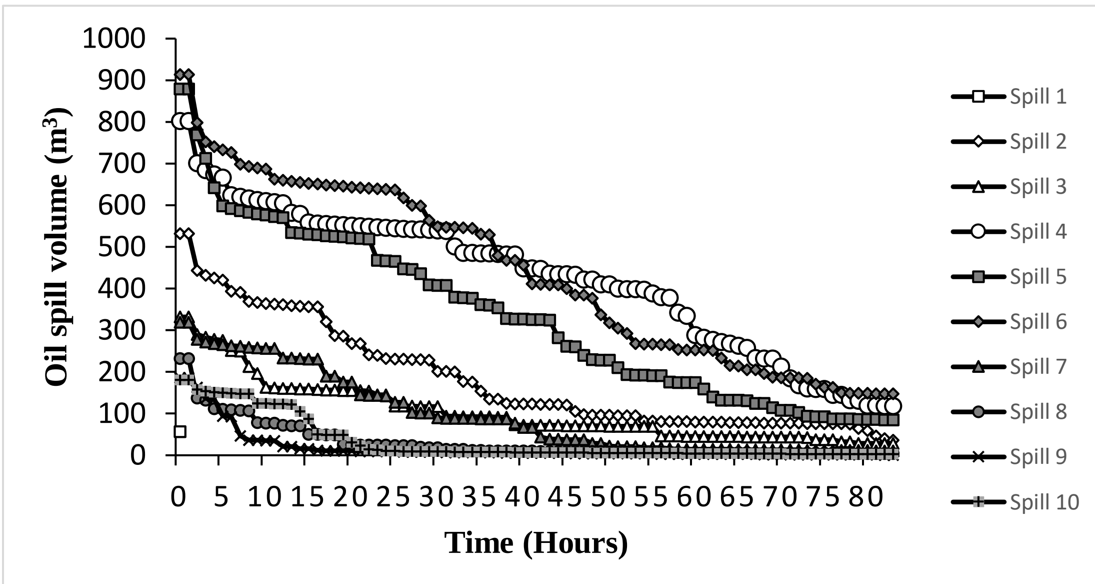


Figure 4.7. Oil volumes by each spill in SAPSO scenario with weathering process

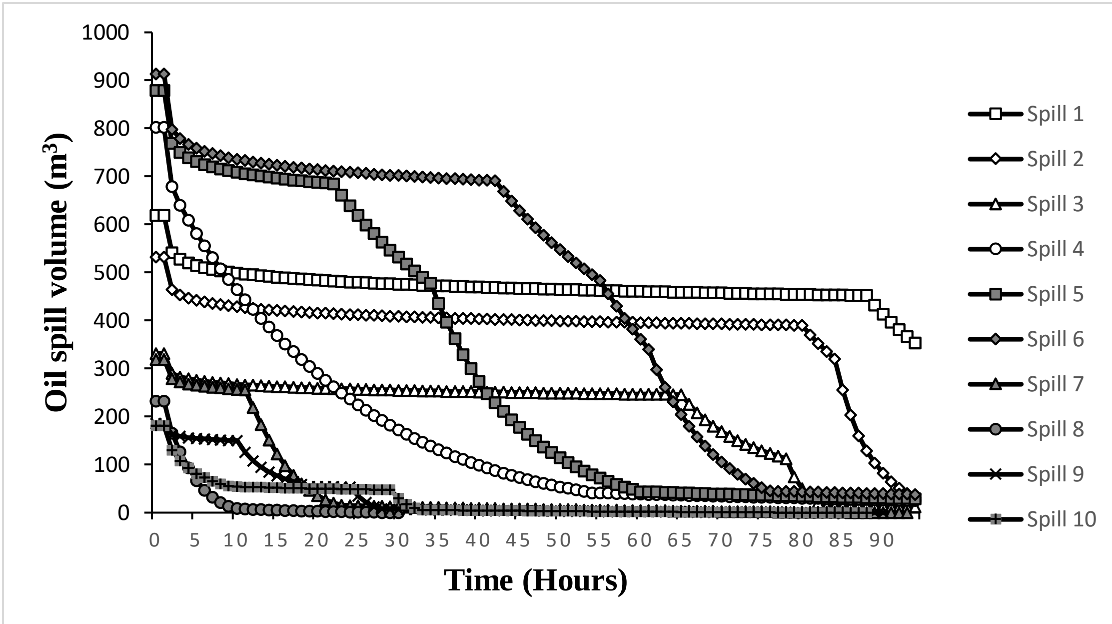


Figure 4.8 Oil volumes by each spill in SDS scenario with weathering process

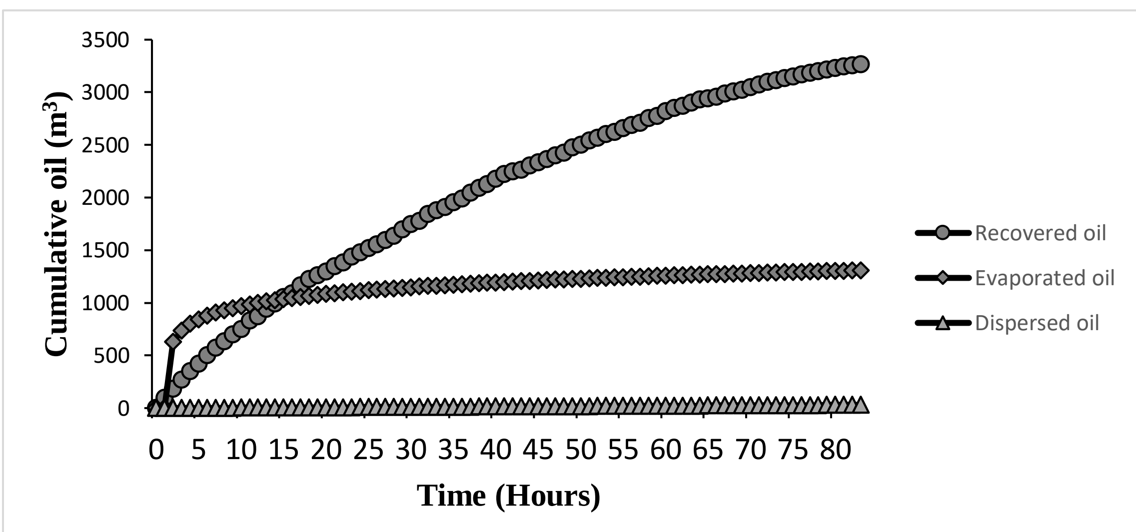


Figure 4.9 Transport and fate of spilled oil during the operational period in SAPSO scenario

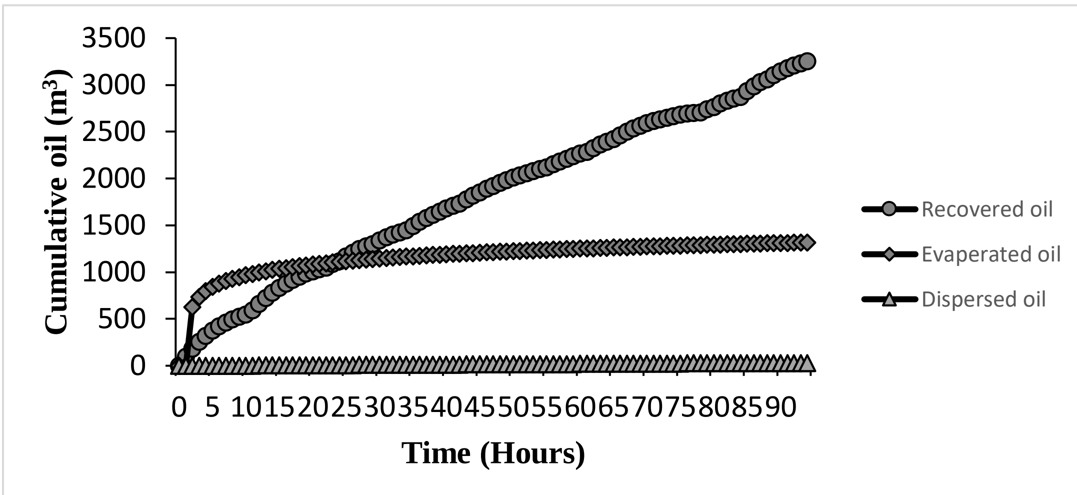


Figure 4.10 Transport and fate of spilled oil during the operational period in SDS scenario

4.4.2 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 the Table 4.6, the decisions from two methods were similar. The SAPSO result was 3 hours shorter than the other. According to the figures (Fig 4.11-4.14), the SAPSO decision preferred to cooperate the effort on all 10 spill together, tried to move back and forth on nearby spills to keep a high collective efficiency with a high slick thickness and decrease the total environmental impact systematically. As shown in Fig 4.11, from the SDS scenario, the oil spill volume remained if no skimmers worked on that spill. When ships operated, the volume decreased sharply. However, compared with SAPSO results, some spills with large amount of oil were not treated in time. For example, spill 1, 2 and 6 were not treated in first 30 hours. These large spills could cause a poor marine impact. Furthermore, the collective amounts of ships were close in two approaches. Ship A and C had almost the same curve shown in Fig 4.13 and 4.14. Even though the operation times in the non-weathering scenarios were close, in the weathering ones, the SAPSO had a significant advantage compared to the other. In addition, the operation time of weathering cases were much larger 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 SAPSO on offshore oil spill accident decision making system.

Table 4.6 Decision making results of SAPSO and SDS approaches

	SAPSO	SDS
Operation time (hr)	48	51
Recovered oil (Ship A) (m^3)	1762.85	1773.03
Recovered oil (Ship B) (m^3)	1090.20	1058.34
Recovered oil (Ship C) (m^3)	1810.20	1823.34
Total recovered oil (m^3)	4663.25	4654.71
Remain oil (%)	6.735	6.906

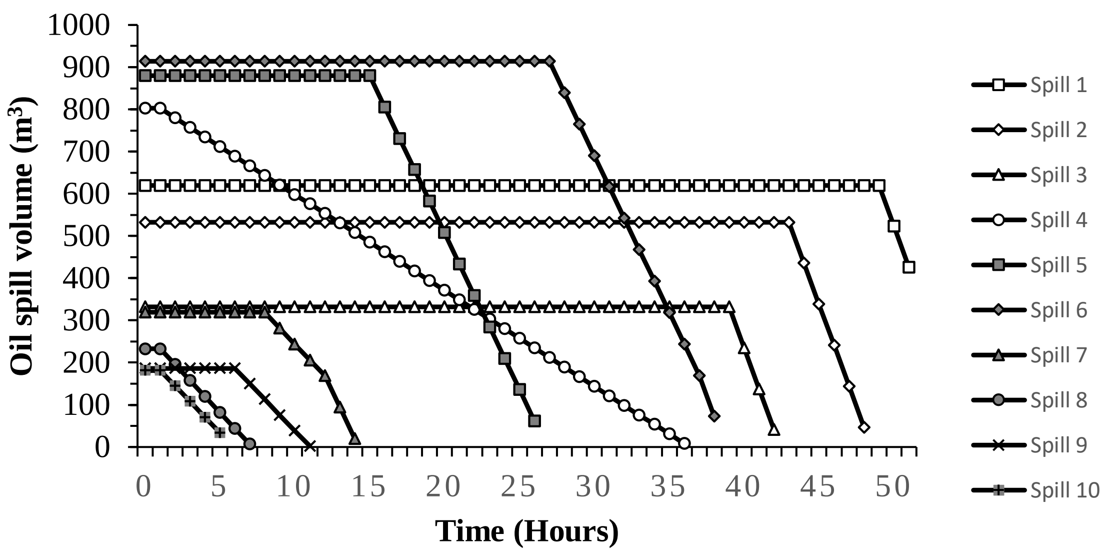


Figure 4.11. Oil volumes by each spill in SDS scenario without weathering process

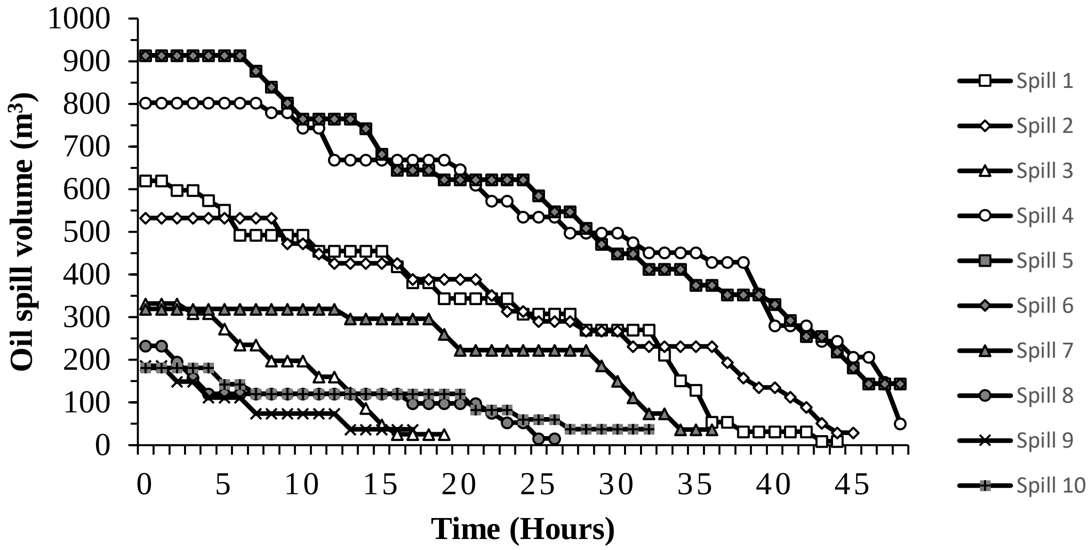


Figure 4.12 Oil volumes by each spill in SAPSO scenario without weathering process

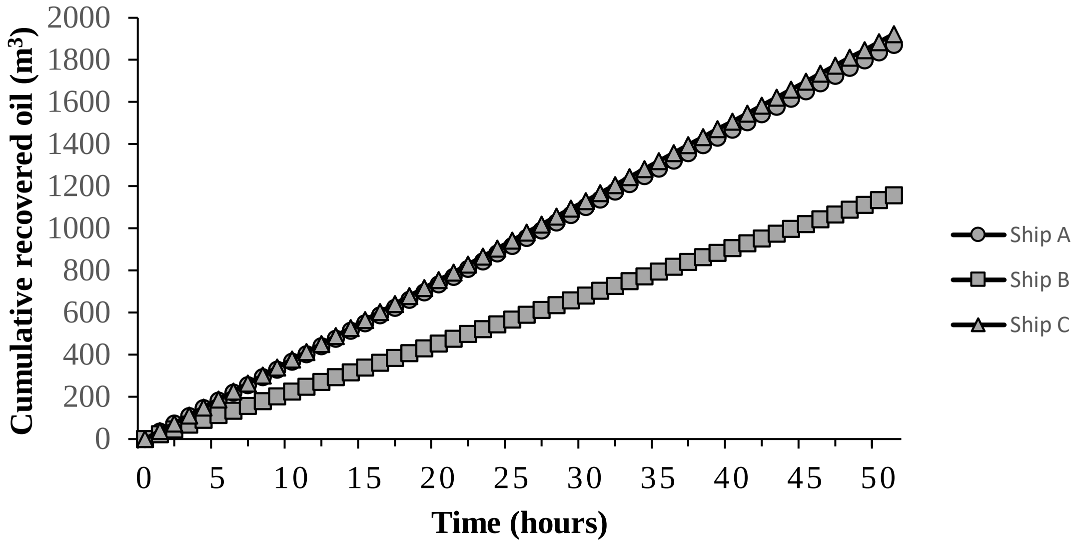


Figure 4.13 Cumulated oil recovery by each ship in SDS scenario without oil weathering process

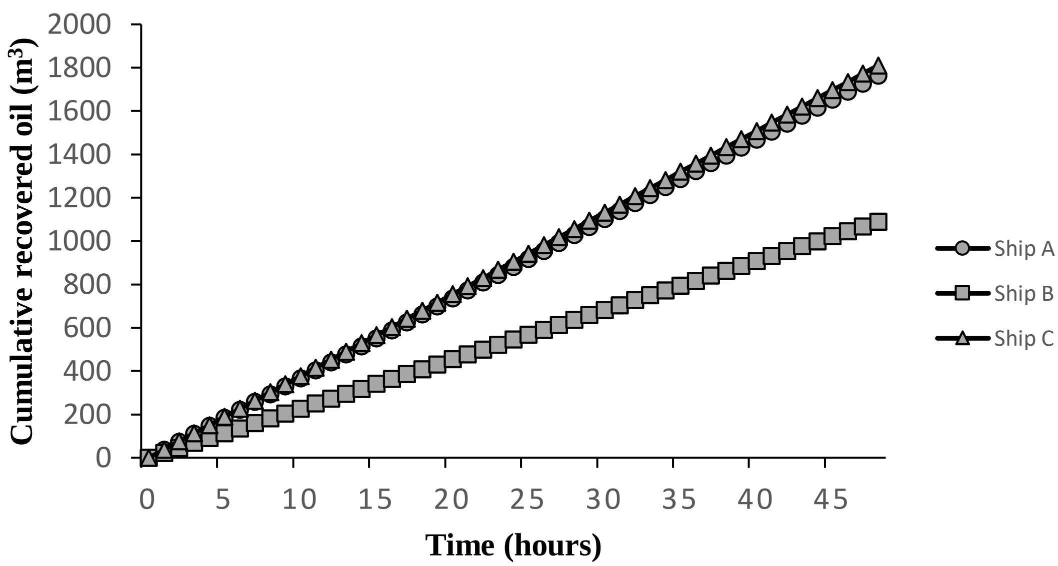


Figure 4.14 Cumulated oil recovery by each ship in SAPSO scenario without oil weathering process

4.5 Summary

The improvement of offshore oil spill response efficiency to minimize economic and environmental impacts has become a major need worldwide. This study proposed a new simulation-based multi-agent particle swarm optimization (SA-PSO) approach to facilitate a dynamic decision making at both levels simultaneously for response device allocation and control during offshore oil spill events considered. 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 booming and skimming operations in the harsh environment. The results demonstrated that the proposed approach can timely and effectively provide an optimal decision for the allocation of devices and control of operations in a dynamic condition.

Even though the case study was applied in supporting the oil recovery process, the developed SAPSO 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 SAPSO.

In future studies, hydrodynamic simulation of oil spill trajectory and more complicated weathering processes will be considered to further explore the application range of SAPSO. In addition the consideration of uncertainties and risk assessment will be concerned in the decision supporting objectives. Testing of the developed method through real-world application is considered with the collaboration with local government and companies.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In this research, the proposed MAHPSO approach, was approved by the integration of MAS theory with the interation among particles to be able to significantly enhance solution convergence without sacraficing the computation time/efficiency, and to provide optimal results with high accuracy and repeatability. From the real-world wastewater treatment plant network planning case in Newfoundland and Labrador, Canada. The results were compared with those of the traditional GA approach and the HPSO method. Optimization resulted indicated that the overall cost was minimized to $\$5.0740\times10^8$. For comparison purposes, the best results obtained was $\$6.1279\times10^8$ from a traditional GA and $\$6.3610\times10^8$ from HPSO. The results demonstrate the excellent performance of MAHPSO. The proposed approach could be used as an effective evolutionary algorithm for complex system optimization and planning problems in environmental and other fields.

Secondly, the proposed SAPSO approach could efficently decrease the total response time, and dynamically optimize the allocation of response equipment. In the hypothetic North Atlantic oil spill case study, the developed SAPSO approach was significantly improved from the traditional SDS method by saving about 11% time window (11 hours). With the analysis of weathering processes, the decision making became more complicated, and SAPSO showed an outstanding performance than SDS. The results indicated it had the strong potential to be applied to decision making problems in environmental and other fields.

5.2 Research Achievements

(1) In this study, a high-efficiency multi-agent based hybrid particle swarm optimization system was developed for dealing with complicated and distinct environmental issues. In order to solve the special problem of diversiform variables in environmental decision making models. HPSO approach was developed for the first time by integration of traditional particle swarm optimization and binary particle swarm optimization for dealing with non-linear problems with multiple types of variables (both continuous and discrete variables) to realize the performance of sophisticated environmental conditions; And then by introducing multi-agent system (MAS) concept, a multi-agent based hybrid particle swarm optimization (MAHPSO) approach was proposed in the first time to enhance the solution convergence by the consideration of individual and autonomous artificial intelligence theory. Furthermore, the research contributed to the advancement on the binary update equations in multi-agent criteria section. Moreover, through the examination by a wastewater treatment network

planning case study, and the comparison with the genetic algorithm (GA) and HPSO methods, the efficiency and feasibility were demonstrated. Besides, an optimized plan was valuable for future WWTPs network development in the city of St. John's, Canada. The WWTP network planning case showed the practicability of the MAHPSO system, and it could be used for not only other types of environmental decision making issues, but most optimization problems in other fields.

(2) This study developed a new simulation-based multi-agent particle swarm optimization (SA-PSO) system to facilitate the decision making at both simulation and optimization levels simultaneously. Agent based modeling is the first time to be applied in the offshore oil spill accident problems, and it is the first time that agent based simulation model coupled with a PSO optimization algorithm and integrated multi-agent system as the decision-making criteria to realize the dynamic process decision making. The proposed method was examined with a hypothetical case in the North Atlantic region showing the model efficiency and capability. The showed the practicability of the SA-PSO system to be applied for offshore oil spill accident responses, but it also provides a high-compatible and effective system for all types of simulation-based decision making problems.

Based on the research, two conference abstracts have been produced and six journal papers are-under review or preparation as follows:

a) Journal paper:

1) **Ye, X.**, Chen, B., Jing, L., and Zhang, B. A novel multi-agent based hybrid particle swarm optimization (MAHPSO) approach for wastewater treatment plants network design. (Under preparation). My duty is developing the proposed MAHPSO system, building the case study model, analyzing results and writing the whole paper.

2) Li, Z., Chen, B., Wu, H., and **Ye, X.** (2016). A hybrid stochastic – design of experiment aided parameterization method for modeling aquifer NAPL contaminations. Environmental Modelling and Software. (Under review). My duty is doing the experiments, and analyzing parts of result data.

3) Li, Z., Chen, B., Wu, H., Zhang, H., **Ye, X**., and Zhang, K. (2016). A parameterization study for modeling biosurfactant enhanced aquifer remediation processes based on flow cell experiments. ASCE's Journal of Environmental Engineering. (Under review). My duty is doing the experiments, and analyzing parts of result data.

4) Jing, L., Chen, B., **Ye, X.**, and Zhang, B. Wastewater treatment plant network design using a multi-scale two-stage mixed integer stochastic (MSTMIS) model. Environmental Engineering Science, in press. My duty is building the case study model and writing the introduction and sensitivity analysis parts of the final paper.

b) Conference abstract:

1) **Ye, X.**, Chen, B., Jing, L., and Li P. (2016). A simulation-based multi-agent particle swarm optimization approach for supporting dynamic decision making in offshore oil spill response. Abstract submission for 39th AMOP Technical Seminar on Environmental Contamination and Response, June 7 to 9, 2016. My duty is developing the whole SA-PSO system and presenting at AMOP.

2) **Ye, X**., Jing, L., Chen, B., and Zhang, B. (2016). Optimal design of municipal wastewater treatment plant networks under uncertainty. Abstract submission for The National Water and Wastewater Conference, November 13-16, 2016. My duty is developing the proposed method and making the poster for the conference.

5.3 Recommendations for Future Work

(1) The adoption of agent based approaches is recently emerging in environmental fields. This research proved the high potential of such methods in enhancing optimization and decision making. In future studies, ABM and MAS could be further integated into more traditional environmental simulation and optimization methods and tested by real world casesin order to test the capability and improve modeling performance. For example, the MAHPSO could be further used to replace current training processes of ANN (artificial nerual network) and ANFIS (adaptive network based fuzzy inference system). ANN and ANFIS need optimization method in its training step. To most ANN and ANFIS versions, GA is used as the tool. Based on the result in first study, MAHPSO has the high potential to enhance the current modeling performance. Moreover, MAHPSO can be further examimed with more sophicated cases such as considering multi-objective functions. In the HPSO, other optimization methods and concepts such as Markov decision process could be introduced and examined along with the MAHPSO.

(2) The cases used in this research were either simplified or hypothetical or semi-hypothetical. More real case studies are expected to test the applicability of developed

methods and understand their advantages and limitations for futher improvement to improve the authenticity and reliability for the developed methods.

(3) Agent based simulation has the potential for the simulation of complicated environmental processes, such as interior wastewater treatment processes, which has high interactions among different treatment stages and technologies, these could be considered in further research.

REFERENCES

Acan, A. and Gunay, A. (2005). Enhanced particle swarm optimization through external memory support. *In Proceedings of the Congress on Evolutionary Computation*, 2, 1875-1882.

Aderson, C.P., Marcello, G.T., Katia, C.G., Anelise, M.C., and Luiz, F.A.M.G. (2014). Using the TODIM-FSE method as a decision-making supporting methodology for oil spill response. *Computers & Operations Research,* 42, 40-48.

Agidi, S., Vedachalam, S., Mancl, K., and Lee, J. (2013). Effectiveness of onsite wastewater reuse system in reducing bacterial contaminants measured with human-specific IMS/ATP and qPCR. *Journal of Environmental Management,* 115, 167-174.

Ahmetović, E., and Grossmann, I. E. (2011). Global superstructure optimization for the design of integrated process water networks. *AIChE Journal, 57*(2), 434-457. doi:10.1002/aic.12276

Alireza, B. (2013). Waste management in the chemical and petroleum industries, *John Wiley & Sons Ltd,* Chapter 1, 1-24.

Alvarez, E.A., Mochon, M.C., Sanchez, J.C.J., and Rodriguez, M.T. (2002). Heavy metal extractable forms in sludge from wastewater treatment plants. *Chemosphere,* 47 (7), 765-775.

Anchorage, A. (1992). Exxon Valdez Oil Spill Restoration. E*xxon Valdez Oil Spill Trustee Council, State of Alaska Depts. of Fish & Game, Law, and Environmental Conservation, United States National Oceanic and Atomospheric Administration, Depts. of Agriculture and Interior in consultation with the Environmental Protection Agency*.

Aote, A. A., Raghuwanshi, M. M., and Malik, L. (2013). A brief review on particle swarm optimization: limitation & future directions. *International Journal of Computer Science Engineering (IJCSE),* 2(5), 196-200.

Araujo, G., Gras, P., Ginovart, M., and Moulton, V. (2016). INDISIM-Paracoccus, an individual-based and thermodynamic model for a denitrifying bacterium. *Journal of Theoretical Biology*, 403: 45-58.

Atlas, R.M. and Hazen, T.C. (2011). Oil biodegradation and bioremediation: a tale of the two worst spills in U.S. History. *Environmental Science & Technology*, 45(16), 6709-6715.

Azevedo, A., Oliveira, A., Fortunato, A.B., Zhang, J., and Baptista, A.M. (2014). A cross-scale numerical modeling system for management support of oil spill accidents. *Marine Pollution Bulletin*, 80, 132-147.

Baeza, J., Ganriel, D., and Lafuente, J. (2004). Effect of internal recycle on the nitrogen removal efficiency of an anaerobic/anoxic/oxic (A2/O) wastewater treatment plant (WWTP). *Process Biochemistry*, *39*(11), 1615-1624. doi:10.1016/S0032-9592(03)00300-5

Balbi, S., Giupponi, C., Perez, P., and Alberti, M. (2013). A spatial agent-based model for assessing strategies of adaptation to climate and tourism demand changes in an alpine tourism destination. *Environmental Modelling & Software*, 45, 29-51.

Bandini, S., Manzoni, S., and Vizzari, G. (2009). Agent based modeling and simulation: an informatics perspective. *Journal of Artificial Societies and Social Simulation*, 12(4).

Banitz, T., Gras, A., and Ginovart, M. (2015). Individual-based modelling of soil organic matter in NetLogo: Transparent, user-friendly, and open. *Environmental Modeling & Software*, 71, 39-45.

Baptista, M.L., Martinho, C., Lima, F., Santos, P.A., and Prendinger, H. (2014). A business simulation with an agent-based deliberative model of consumer behaviour. *Lecture Notes in Computer Science*. 8605, 215-223.

Beraud, B. (2010). Methodology for the optimization of wastewater treatment plant control laws based on modeling and multi-objective genetic algorithms. *Chemical and Process Engineering*.

Bjerkemo, O.K. (2011). Behaviour of oil and HNS spilled in Arctic waters – an Arctic Council Project. *The International Oil Spill Conference Proceedings (IOSC)*.

Blanchart, E., Marilleau, N., Chotte, J.L., Drogoul, A., Perrier, E., and Cambier, C. (2009). SWORM: an agent-based model to simulate the effect of earthworms on soil structure. *European Journal of Soil Science.* 60(1), 13-21.

Brand, N. and Ostfeld, A. (2011). Optimal design of regional wastewater pipelines and treatment plant systems. *Water Environment Research*, 83(1), 53-64.

Brandvik, P., Sorheim, K., Singsaas, I., and Reed, M. (2006). Short state-of-the –art report on oil spills in ice-infested waters: Oil behavior and response options: SINTEF.

Boufadel, M.C. and Geng, X.L. (2014). A new paradigm in oil spill modeling for decision making. *Environmental Research Letter*, 9 (8).

Boufadel, M.C., Geng, X.L., and Short, J. (2016). Bioremediation of the Exxon Valdez oil in Prince William Sound beaches. *Marine Pollution Bulletin*.

Bozkurt, H., Quaglia, A., Gernaey, K. V., and Sin, G. (2015). A mathematical programming framework for early stage design of wastewater treatment plants. *Environmental Modelling & Software,* 64, 164-176.

Broekema, W. (2016). Crisis-induced learning and issue politicization in the EU. *Public Administration,* 94(2), 381-398.

Bulling, N. (2014). A survey of multi-agent decision making. *Künstliche Intelligenz*, 28(3), 147-158.

Carpenter, S.R., Caraco, N.F., Correll, D.L., Howarth, R.W., Sharpley, A.N., and Smith, V.H. (1998). Nonpoint pollution of surface waters with phosphorus and nitrogen. *Ecological Applications*, 8, 559-568.

Carriger, J.F. and Barron, M.G. (2011). Minimizing risks from spilled oil to ecosystem services using influence diagrams: the Deepwater Horizon spill response. *Environmental science & technology*, 45 (18), 7631-7639.

CCME (Canadian Council of Ministers of the Environment). (2008a). Technical Supplement 1, Canada-wide Strategy for the Management of Municipal Wastewater Effluent, Economic Plan Supporting the Canada-wide Strategy for the Management of Municipal Wastewater Effluent. *Canadian Council of Ministers of the Environment*, *Winnipeg, Canada*.

CCME (Canadian Council of Ministers of the Environment). (2008b). Technical Supplement 2, Canada-wide Strategy for the Management of Municipal Wastewater Effluent, Environmental Risk Management: Framework and Guidance. *Canadian Council of Ministers of the Environment, Winnipeg, Canada.*

CCME (Canadian Council of Ministers of the Environment). (2009). Canada-wide strategy for the management of municipal wastewater effluent. *Canadian Council of Ministers of the Environment, Winnipeg, Canada.*

Chou, F.D. (2013). Particle swarm optimization with cocktail decoding method for hybrid flow shop scheduling problems with multiprocessor tasks. *Int. J. Production Economics*, 141, 137-145.

Cohen, E.B., Pearson, S.M., and Moore, F.R. (2014). Effects of landscape composition and configuration on migrating songbirds: inference from an individual-based model. *Ecological Applications*, 24(1), 169-180.

Chang, N., Chen W.C., and Shieh, W.K. (2001). Optimal control of wastewater treatment plants via integrated neural network and genetic algorithms. *Civil Engineering and Environmental Systems,* 18, 1-17.

Chao, D., Hashimoto, H., and Kondo, N. (2015). Dynamic impact of social stratification and social influence on smoking prevalence by gender: An agent-based model. *Social Science & Medicine*, 147, 280-287.

Chennaoui, A., and Paquet, M. (2014). Multi-Agent Decision-Making Support Model for the Management of Pre-Hospital Emergency Services. *International Journal of Machine Learning and Computing*, 4(2), 198-203.

Chu, Y. and You, F. (2013). Integrated scheduling and dynamic optimization of complex batch processes with general network structure using a generalized Benders decomposition approach. *Industrial & Engineering Chemistry Research*, 52(23), 7867-7885.

Danish, Ekram Y. (2010). Ecological impact from chemicals in the Arabian Gulf due to Gulf oil spill. *, 24(1), 65-73.*

Davis, M.L. and Cornwell, D.A. (2008). Introduction to environmental engineering, 4th edition. McGraw-Hill Higher Education, 420-422.

DeCarolis, J., Adham, S., Pearce, W.R., Hirani, Z., Lacy, S., and Stephenson, R. (2007). Cost trends of MBR systems for municipal wastewater treatment. *WEFTEC*, 3407-3418.

Delvigne, G.A.L. (1994). Natural and chemical dispersion of oil. J. Adv. *Marine Technol. Conf. Japan*, 11, 23-40.

Depellegrin, D. and Blazauskas, N. (2013). Integrating ecosystem service values into oil spill impact assessment. *Journal of Coastal Research*, 29(4), 836-846.

Dickerson, M. (2014). Multi-agent simulation, netlogo, and the recruitment of computer science majors. *Journal of Computing Sciences in Colleges*, 30(1), 131-139.

Dickey, R.W. (2012). FDA risk assessment of seafood contamination after the BP oil spill. *Environmental health perspectives*, 120(2), 54-55.

Eberhart, R. and Kennedy, J. (1995). A new optimizer using particle swarm theory. *Proceedings of the Sixth International Symposium on Micro Machine and Human Science*, 39-43.

El-Halwagi, M. and Manousiouthskis, V. (1989). Synthesis of mass exchange network. *AIChE Journal*, *35*(8), 1233-1244.

Environment Canada. (2012). Wastewater Systems Effluent Regulations (SOR/2012-139).

Esler, D. and Iverson, S.A. (2010). Female harlequin duck winter survival 11 to 14 years after the Exxon Valdez oil spill. *The Journal of Wildlife Management*, 74(3), 471-478.

Etkin, D.S. (1998). Factors in the dispersant use decision-making process: historical overview and look to the future. *Proceedings of the Twenty-First Arctic and Marine Oil spill Program Technical Seminar*: pp. 281-304.

Etkin, D.S. (1999) Estimating Cleanup Costs for Oil Spills. *International Oil Spill Conference Proceedings: March 1999*, 1999 (1), pp. 35-39.

Faksness, L.G., Hansen, B.H., Altin, D., and Brandvik, P.J. (2012). Chemical composition and acute toxicity in the water after in situ burning – a laboratory experiment. *Marine Pollution Bulletin*, 64(1), 49-55.

Feng, X. and Chu, K.H. (2004). Cost optimization of industrial wastewater reuse systems. *Process Safety and Environmental Protection,* 82(3), 249-255.

Fingas, M.F. (2011a). Oil spill science and technology: prevention, response, and cleanup. *Burlington, MA: Elsevier/Gulf Professional Pub.*

Fingas, M. (2011b). Oil spill science and technology. *Gulf Professional Publishing*.

Fingas, M. (2013). The basics of oil spill cleanup. *CRC Press,* 43-61, 79-38, 97-105, 131-141, 147-149.

Friedler, E., Lahav, O., Jizhaki, H., and Lahav, T. (2006). Study of urban population attitudes towards various wastewater reuse options: Israel as a case study. *Journal of Environmental Management,* 81, 360-370.

Galan, B. and Grossmann, I.E. (1998). Optimal design of distributed wastewater treatment networks. *Ind. Eng. Chem. Res.*, 1998, 37 (10), 4036–4048

Gao, P., Munir, M., and Xagoraraki, I. (2012). Correlation of tetracycline and sulfonamide antibiotics with corresponding resistance genes and resistant bacteria in a conventional municipal wastewater treatment plant. *Science of the Total Environment*, 421-422， 173-183.

Garrido-Baserba, M., Reif, R., Hernández, F., and Poch, M. (2012). Implementation of a knowledge-based methodology in a decision support system for the design of suitable wastewater treatment process flow diagrams. *Journal of environmental management,* 112, 384-391.

Garza-Gil, M., Suris-Regueiro, C., & Varela-Lafuente, M. (2006). Assessment of economic damages from the Prestige oil spill. *Marine Policy*, 30, 544-551.

Gazda, V., Grof, M., Horvath, J., Kubak, M., and Rosival, T. (2012). Agent based model of a simple economy. *Journal of Economic Interaction and Coordination*, 7(2), 209-221.

Gene, Z., Heidari, F., Oey, M.A., Splunter, S.V., and Brazier, F.M.T. (2013). Agent-based information infrastructure for disaster management. *Intelligent Systems for Crisis Management*, 349-355.

Gersberg, R., Elkins, B., Lyon, S., and Goldman, C. (1986). Role of aquatic plants in wastewater treatment by artificial wetlands. *Water Research, 20*(3), 363-368.

Gilber, N. and Troitzsch, K.G. (2005). Simulation for the social scientist. *McGraw Hill Education.*

Gilbert, N. (2009). Agent-based Models. *SAGE Publications.*1-5.

Gill, D.A., Picou, J.S., and Ritchie, L.A. (2012). The Exxon Valdez and BP Oil Spills. *American Behavioral Scientist*, 56(1), 3-23.

Gillot, S., Clercq, B.D., Defour, D., Simoens, F., Gernaey, K., and Vanrolleghem, P.A. (1999). Optimization of wastewater treatment plant design and operation using simulation and cost analysis.

Government of Newfoundland and Labrador. (2005a). Guidelines for the Design, Construction and Operation of Water and Sewerage Systems. *Department of Environment and Conservation, Water Resources Management Division, Government of Newfoundland and Labrador, St. John's, NL, Canada*.

Government of Newfoundland and Labrador. (2005b). Municipal Wastewater Management – Theory and Practices. *Department of Environment and Conservation,* *Government of Newfoundland and Labrador, St. John's, NL, Canada* (Accessed on March 30, 2015).

Grimm, V., and Railsback, S.F. (2005). Individual-based modeling and ecology., *Princeton University Press*, 485

Hashimoto, T., Onda, K., Nakamura, Y., Tada, K., Miya, A., and Murakami, T. (2007). Comparison of natural estrogen removal efficiency in the conventional activated sludge process and the oxidation ditch process. *Water Research, 41*(10), 2117-2126. doi:10.1016/j.watres.2007.02.029

Hossein, N., Majid, R., and Malihe, M. (2008). Binary particle swarm optimization: challenges and new solutions. *The Journal of Computer Society of Iran on Computer Science and Engineering*, 6, 21-32.

Huang, C.-H., Chang, C.-T., and Ling, H.-C. (1999). A Mathematical Programming Model for Water Usage and Treatment Network Design. *Industrial & Engineering Chemistry Research*(38), 2666-2679.

Huang, J.C. (1983). A review of the state-of-the art of oil spill fate/behavior models. *Proc., 1983 Oil Spill Conf., Washington, D.C.*, 313-322

Ilieva, G. (2011). Decision making methods in agent based modeling. *Proceeding s of the workshop on applications of software agents*, 8-11.

ITOPF. (2008). The international tanker owner pollution federation limited handbook.

ITOPF. (2013). Technical information paper, use of booms in oil pollution response.

ITOPF. (2014). Dispersants, how chemical dispersion works.

Jeusfeld, M.A. and Pastor, O. (Editors). (2003). Pattern for motivating an agent-based approach. *ER 2003 Workshops, LNCS 2814, Springer*, 229-240.

Jing, L., Chen, B., Zhang, B.Y., and Li, P. (2013a). A hybrid stochastic-interval analytic hierarchy process (SIAHP) approach for prioritizing the strategies of reusing treated wastewater. *Mathematical Problems in Engineering*, vol. 2013, Article ID 874805, 10 pages, doi:10.1155/2013/874805.

Jing, L., Chen, B., and Zhang, B.Y. (2013b). A hybrid fuzzy stochastic analytical hierarchy process (FSAHP) approach for evaluating ballast water treatment technologies. *Environmental Systems Research*, 2:10, doi:10.1186/2193-2697-2-10.

Jing, L., Chen, B., Zhang, B.Y., and Li, P. (2014). An integrated system planning and process control system for marine wastewater management. *The 2014 International Conference on Marine and Freshwater Environments.*

Jing, L., Chen, B., Zhang, B.Y., and Li, P. (2015). Process Simulation and Dynamic Control for Marine Oily Wastewater Treatment using UV Irradiation. *Water Research*.

Jing, W.W., An, W., Zhao, Y.P., Qiu, Z.Y., Li, J.W., and Song, S.S. (2015). Research on scheduling optimization of marine oil spill emergency vessels. *Aquatic Procedia*, 2, 35-40.

Johar, A., Jain, S.S., and Garg, P.K. (2016). Transit network design and scheduling using genetic algorithm – a review. *An International Journal of Optimization and Control: Theories & Applications*, 6(1), 9-22.

Judd, S. (2006). Principles and applications of membrane bioreactors in water and wastewater treatment. *Elsevier, Oxford*.

Kaksonen, A.H., Riekkola-Vanhanen, M-L., and Puhakka, J.A. Optimization of metal sulphide precipitation in fluidized-bed treatment of acidic wastewater. *Water Research,* 37 (2), 255-266.

Kennedy, J. and Eberhart, R. (1997). A discrete binary version of the particle swarm algorithm. *IEEE International Conference on Computational Cybernetics and Simulation*, 5, 4104-4108.

Kim, M., Guerra, P., Theocharides, M., Barclay, K., Smyth, S. A., and Alaee, M. (2013). Parameters affecting the occurrence and removal of polybrominated diphenyl ethers in twenty Canadian wastewater treatment plants. *Water research*, 47(7), 2213-2221.

Kirstein, B.E., and Redding, R.T. (1988). Ocean-ice oil-weathering computer program user's manual. *Outer Continental Shelf Environmental Assessment Program, 59. US Department of Commerce, National Oceanic and Atmospheric Administration and US Department of the Interior, Washington, DC*.

Klabunde, A., and Willekens, F. (2016). Decision-Making in Agent-Based Models of Migration: State of the Art and Challenges. *Eur J Popul*, 32: 73–97.

Körbahti, B.K. (2006). Response surface optimization of electrochemical treatment of textile dye wastewater. *Journal of Hazardous Materials*, 145 (1-2), 277-286.

Krin, S., Herzog, O., Lockemann, P., and Spaniol, O. (2006). Multiagent Engineering: Theory and Applications in Enterprises. *Berlin, Germany: Springer*, 71-177.

Kudenko, D., Kazakov, D., and Alonso, E. (2003). Chapter I: Machine learning for agents and multi-agent systems - Intelligent Agent Software Engineering. *Idea Group Inc*., 2-4.

Kumar, V. (2016). Research framework, strategies, and applications of intelligent agent technologies (IATs) in marketing. *Journal of the Academy of Marketing Science., 44(1), 24-45.*

Kuthambalayan, T. S., Mehta, P., and Shanker, K. (2014). Integrating operations and marketing decisions using delayed differentiation of products and guaranteed delivery time under stochastic demand. *European Journal of Operational Research*, 237(2), 617-627.

Lee, J. H. (2012). Energy Supply Chain Optimization: A Challenge for Control Engineers? In Eighth IFAC international symposium on advanced control of chemical processes, *International Federation of Automatic Control*, Furama Riverfront, Singapore (pp. 361-370).

Lehmann, A., Leibe, B., and Van Gool, L. (2011). Fast prism: Branch and bound hough transform for object class detection. *International journal of computer vision*, 94(2), 175-197.

Leschine, T.M., Pavia, R., Walker, A.H., Bostrom, A., and Starbird, K. (2015). What-if scenario modeling to support oil spill preparedness and response decision-making. *Human and Ecological Risk Assessment: An International Journal*, 21 (3).

Li, M., Du, W.Q., and Nian, F.Z. (2014). An adaptive particle swarm optimization algorithm based on directed weighted complex network. *Hindawi Publishing Corporation Mathematical Problems in Engineering*.

Li, P., Chen, B., Zhang, B.Y., Jing, L., and Zheng, J.S. (2012). A multiple-stage simulation-based mixed integer nonlinear programming approach for supporting offshore oil spill recovery with weathering processes. *Journal of Ocean Technology*, 7(4), 87-105.

Li, P., Chen, B., Li, Z.L., and Jing, L. (2014). An agent-based simulation-optimization coupling approach for device allocation and operation control in response to offshore oil spills with weathering. *The 2014 International Conference on Marine and Freshwater Environments.*

Li, P., Chen, B., Zhang, B.Y., Jing, L., and Zheng, J.S. (2014). Monte Carlo simulation-based dynamic mixed integer nonlinear programming for supporting oil recovery and devices allocation during offshore oil spill responses. *Ocean & Coastal Management*, 89, 58-70.

Li, P. (2014). Development of an integrated decision supporting system for supporting offshore oil spill response in harsh environments. (PhD's thesis), *Memorial University*.

Liao, Z., Mao, X., Hannam, P. M., and Zhao, T. (2012). Adaptation methodology of CBR for environmental emergency preparedness system based on an Improved Genetic Algorithm. *Expert Systems with Applications*, 39(8), 7029-7040.

Lin, M.K., Tan, K., and Leung, C.H. (2013). Using a multi-agent system to optimise resource utilisation in multi-site manufacturing facilities. *International Journal of Production Research*, 51(9), 2620-2638.

Lin, Q.Z., Li, J.Q., Du, Z.H., Chen, J.Y., and Ming, Z. (2015). A novel multi-objective particle swarm optimization with multiple search strategies. *European Journal of Operational Research*, 2012(1), 15-23.

Liu, X., and Wirtz, K.W. (2005). Sequential negotiation in multiagent systems for oil spill response decision-making. *Marine Pollution Bulletin*, 50(4), 469-474.

Linnhoff, B., and Hindemarsh, E. (1983). The Pinch Design Mehtod for Heat Exchanger Networks. *Chemical Engineering Science, 38*(5), 745-763. doi:10.1016/0009-2509(83)80185-7

Luciano, A., Viotti, P., Mancini, G., and Torretta, V. (2012). An integrated wastewater treatment system using a BAS reactor with biomass attached to tubular supports. *Journal of Environmental Management*, 113, 51-60.

Mackay, D., Buist, I.A., Mascarenhas, R., and Paterson, S. (1980). Oil spill processes and models. *Department of Chemical Engineering, University of Toronto, Toronto, Ontario, Environmental Service Publication*, No. EE-8.

Margot, J., Kienle, C., Marnet, A., Weil, M., Rossi, L., Alencastro, L. d., . . . Barry, D. (2013). Treatment of micropollutants in municipal wastewater: Ozone or powdered activated carbon? *Science of the Total Environment*(461-462), 480-498.

Melo, J.J. and Camara, A.S. (1994). Models for the optimization of regional wastewater treatment systems. *European Journal of Operational Research*, 73, 1-19.

Metcalf, and AECOM, E. I. (2014). Wastewater Engineering: Treatment and Resource Recovery, Fifth edition. *McGraw-Hill Education*.

Middlebrooks, E. (1982). Wastewater Stabilization Lagoon Design, Performance and Upgrading. *McMillan Publishing*.

Mitchcell, M. (1996). An introduction to genetic algorithms. *Cambridge, MA: MIT Press*.

Moles, C.G., Gutierrez, G., Alonso, A.A., and Banga, J.R. (2001). Integrated process design and control via global optimization: A wastewater treatment plant case study. *Proceedings of IEEE*, 4-7.

Mora-Melia, D., Iglesias-Rey, P., Martinez-Solano, F., Fuertes-Miquel, V. (2013). Design of water distribution networks using a pseudo-genetic algorithm and sensitivity of genetic operators. *Water Resources Management*, 27(12), 4149-4162.

Muizis, A. (2013). Evaluation of the methods for the oil spill response in the offshore arctic region. (Bachelor's thesis), *Helsinki Metropolia University of Applied Sciences*.

Nearchou, A.C. (2011). Maximizing production rate and workload smoothing in assembly lines using particle swarm optimization. *Int. J. Production Economics*, 129, 242-250.

Niazi, M., and Hussain, A. (2011). Agent-based computing from multi-agent systems to agent-based models: A visual survey. *Scientometrics*, 89(2), 479-499.

Olsson, A.E. (2011). Particle swarm optimization: theory, techniques and applications. *Hauppauge, US: Nova*.

Pai, T. Y., Yang, P. Y., Wang, S. C., Lo, M. H., Chiang, C. F., Kuo, J. L., and Chang, Y. H. (2011). Predicting effluent from the wastewater treatment plant of industrial park based on fuzzy network and influent quality. *Applied Mathematical Modelling*, 35(8), 3674-3684.

Pan, G., Qiu, S., Liu, X., and Hu, X. (2015). Estimating the economic damages from the Penglai 19-3 oil spill to the Yantai fisheries in the Bohai Sea of northeast China. *Maine Policy*, 62, 18-24.

Parsopoulos, K.E., and Vrahatis, M.N. (2010). Particle swarm optimization and intelligence: Advances and application. (pp. 1-328). *Hershey, PA: IGI Global.*

Perring, A.E., Schwarz, J.P., Spackman, J.R., Bahreini, R., De Gouw, J.A., Gao, R.S., Holloway, J.S., Lack, D.A., Langridge, J.M., Peischi, J. Middlebrook, A.M., Ryerson, T.B., Warneke, C., Watts, L.A., and Fahey, D.W. (2011). Characteristics of black carbon aerosol from a surface oil burn during the Deepwater Horizon oil spill. *Geophysical Research Letters*, 38(17).

Pie, H. and Mitchelmore, C. (2015). Acute toxicity of current and alternative oil spill chemical dispersants to early life stage blue crabs (Callinectes Sapidus). *Chemosphere*, 128, 14-20.

Ponce-Ortega, J. M., Hortua, A. C., El-Halwagi, M. and Jiménez-Gutiérrez, A. (2009), A property-based optimization of direct recycle networks and wastewater treatment processes. *AIChE J*., 55: 2329–2344.

Psarros, G., Skjong, R., and Vanem, E. (2011). Risk acceptance criterion for tanker oil spill risk reduction measures. *Marine Pollution Bulletin*, 62 (1), 116-127.

Qasim, S.R. (1985). Wastewater treatment plants: planning, design and operation. *Holt, Rinehart and Winston, New York*.

Rivas, A., Barcelo-Quintal, I., and Moeller, G.E. (2011). Pollutant removal in a multi-stage municipal wastewater treatment system comprised of constructed wetlands and a maturation pond, in a temperate climate. *Water science and technology: a journal of the International Association on Water Pollution Research*, 64(4), 980-987.

Rodrigues, D.M.S. (2011). Multi-agent-based simulation of university email communities. *IGI Global*, 273-291.

Rogers, A., David, E., Schiff, J., and Jennings, N.R. (2007). The effects of proxy bidding and minimum bid increments within eBay auctions. *ACM Transactions on the Web*, 1(2), 9-28.

Rojas, M. R., Leung, C., Bonk, F., Zhu, Y., Edwards, L., Arnold, R. G., Eduardo Sáez, A., and Klečka, G. (2013). Assessment of the effectiveness of secondary wastewater treatment technologies to remove trace chemicals of emerging concern. *Critical Reviews in Environmental Science and Technology*, 43(12), 1281-1314.

Rudolph, G. (1994). Convergence analysis of canonical genetic algorithms. *IEEE Transactions on Neural Networks*, 5(1), 96-101.

Saif,Y., Elkamel, A., and Pritzker, M. (2008). Global optimization of reverse osmosis network for wastewater treatment and minimization. *Industrial & Engineering Chemistry Research*, 47(9), 3060-3070.

Sanctuary, M. and Fejes, J. (2006). What's missing from measures of oil spill damage? a closer look at ecosystem valuation and policy responses. I*VL Report U2032. Stockholm: IVL Swedish Environmental Institute.*

Sato, T., Qadir, M., Yamamoto, S., Endo, T., and Zahoor, A. (2013). Global, regional, and country level need for data on wastewater generation, treatment, and use. *Agricultural Water Management*, 130, 1-13.

Schmolke, A., Thorbek, P., Deangelis, D.L., and Grimm, V. (2010). Ecological models supporting environmental decision making: a strategy for the future. *Trends in Ecology & Evolution*. 25(8), 479-486.

Schurr, N., Marechi, J., Tambe, M., Scerri, P., Kasinadhuni, N., and Lewis, J.P. (2005). The future of disaster response: humans working with multiagent teams using DEFACTO. *American Association for Artificial Intelligence*.

Shunmugalatha, A. and Slochanal, S.M.R. (2008). Application of hybrid multiagent-based particle swarm optimization to optimal reactive power dispatch. *Electric Power Components and Systems,* 36, 788-800.

Sivaraj, R. and Ravichandran, T. (2011). A review of selection methods in genetic algorithm. *International Journal of Engineering Science and Technology*, 3(5), 3792-3979.

Socolofsky, S.A., Adams, E.E., and Sherwood, C.R. (2011). Formation dynamics of subsurface hydrocarbon intrusions following the Deepwater Horizon blowout. *Geophysical Research Letters*, 38(9).

Spellman, F.R. (2009). Handbook of water and wastewater treatment plant operations. *Boca Raton: CRC Press/Talor & Francis.*

Sperling, M.V. (2007). Biological wastewater treatment series-volume one: wastewater characteristics, treatment and disposal. *IWA Publishing*, 2-150.

Springer. (2016). Agent and multi-agent systems: technology and applications. *The processing of 10th KES International Conference, KES-AMSTA 2016 Puerto de la Cruz, Tenerife, Spain*, 252-255.

Stawomir, B. (2007). Influence of temperature and water content on the rheological properties of polish honeys. *Polish Journal of Food and Nutrition Sciences.* 57(2A), 17-23.

Street, L.W. (2011). Offshore in-situ burn operations field guide (December).

Street, L.W. (2011a). Containment and recovery field guide: a geode to containment and recovery operations at sea (December).

Stillman, R.A., Wood, K.A., and Goss-Custard, J.D. (2016). Deriving simple predictions from complex models to support environmental decision-making. *Ecological Modelling*, 326, 134-141.

Su, X.Y., Tian, Y., Sun, Z.C., Lu, Y.B., and Li, Z.P. (2013). Performance of a combined system of microbial fuel cell and membrane bioreactor: wastewater treatment, sludge reduction, energy recovery and membrane fouling. *Biosensors and Bioelectronics*, 49, 92-98.

Sun, R. and Naveh, I. (2004). Simulating organizational decision-making using a cognitively realistic agent model. *Journal of Artificial Societies and Social Simulation*, 7(3).

Sylves, R.T. and Comfort, L.K. (2012). The Exxon Valdex and BP Deepwater Horizon Oil Spills. *American Behavioral Scientist*, 56(1), 76-103.

Tang, C.C., Brill, E.D., and Pfeffer, J.T. (1987). Optimization techniques for secondary wastewater treatment system. *Journal of Environmental Engineering*, 113(5), 935-951.

Tang, L., Wu, J., Yu, L., and Bao, Q. (2015). Carbon emissions trading scheme exploration in China: A multi-agent-based model. *Energy Policy*, 81, 152-169.

Timm, I.J., Scholz, T., Herzog, O., Krempels, K., and Spaniol, O (2006). Multiagent engineering: theory and application in neterprises. *Springer Berlin Heidelberg New York*, 35-53.

Turner, M., Skinner, J., Roberts, J., and Harvey, R. (2010). Review of Offshore Oil-spill Prevention and Remediation Requirements and Practices in Newfoundland and Labrador. *St. John's: Government of Newfoundland and Labrador*.

Tyrwca, D., Smeers, Y., Nyns, E., and Erickson, L.E. (1977). Mathematical modeling and economic optimization of wastewater treatment plants. CRC Crotoca; *Reviews in Environmental Control*, 8, 1-89.

U.S. EPA. (1983) An emerging technology sequencing batch reactors: A project assessment. *Office of Water, Washington D.C., U.S.*

U.S. EPA. (1999a). Wastewater Technology Fact Sheet: Sequencing Batch Reactors. *EPA 832-F-99-073, Office of Water, Washington D.C., U.S.*

U.S. EPA. (1999b). Wastewater Technology Fact Sheet: Aerated, Partial Mix Lagoons. *EPA 832-F-02-008, Office of Water, Washington D.C., U.S.*

U.S. EPA. (1999c). Wastewater Technology Fact Sheet: Oxidation Ditches. *EPA 832-F-00-013, Office of Water, Washington D.C., U.S.*

U.S. EPA. (2007). Wastewater management fact sheet: Membrane bioreactor. *EPA 832-F-99-073, Office of Water, Washington D.C., U.S.*

Van Galderen, L., Brogaad, N. L., Sorensen, M.X, Fritt-Rasmussen, Janne, Rangwala, A.S., and Jomaas, G. (2015). Importance of the slick thickness of effective in in-situ burning of crude oil. *Fire Safety Journal*, 78, 1-9.

Verl, A., Westkämper, E., Abele, E., Dietmair, A., Schlechtendahl, J., Friedrich, J., and Schrems, S. (2011). Architecture for multilevel monitoring and control of energy consumption. *Globalized Solutions for Sustainability in Manufacturing - Proceedings* *of the 18th CIRP International Conference on Life Cycle Engineering, Springer Berlin Heidelberg*, 347-352.

Villamor, G.B., Le, Q.B., Djanibekov, U., Noordwijk, M.V., and Vlek, P, L.G. (2014). Biodiversity in rubber agroforests, carbon emissions, and rural livelihoods: An agent-based model of land-use dynamics in lowland Sumatra. Environmental Modelling & Software, 61, 151-165.

Walther, Henry R. III. (2014). Clean up techniques used for coastal oil spills: an analysis of spills occurring in Santa Barbara, California, Prince William Sound, Alaska, the Sea of Japan, and the Gulf Coast". *Master's Projects*, 98-104.

Wang, J.P., Chen, Y.Z., Ge, X.W., and Yu, H.Q. (2007). Optimization of coagulation-flocculation process for a paper-recycling wastewater treatment using response surface methodology. *Colloids and Surface A: Physicochemical and Engineering Aspects*, 302 (1-3), 204-210.

Wang, X.Y., Wan, W.G., Zhang, X.Q., and Yu, X.Q. (2010). Annealed particle filter based on particle swarm optimization for articulated three-dimensional human motion tracking. *Opt. Eng*, 49(1).

Wang, Z., Xia, L., Wang, Y., and Liu, L. (2014). Multiagent and particle swarm optimization for ship integrated power system network reconfiguration. H*indawi Publishing Corporation Mathematical Problems in Engineering*, 2014, 1-7.

Wei, Y.S., Houten, R.T.V., Borger, A.R., Eikelboom, D.H., and Fan, Y.B. (2003). Minimization of excess sludge production for biological wastewater treatment. *Water Research,* 37(18), 4453-4467.

Whitley, D. (1994). A genetic algorithm tutorial. *Statistics and computing*. 4(2): 65-85.

Winoto, P. (2003). An investigation of the long-term impact of knowledge sharing on multi-agent system. *Proceedings of the IEEE/WIC International Conference on Intelligent Agent Technology (IAT'03)*.

Wirtz, K.W. and Liu, X. (2006). Integrating economy, ecology and uncertainty in an oil-spill DSS: the prestige accident in Spain, 2002. *Estuarine, Coastal and Shelf Science*, 70(4), 525-532.

Wong, T., Zhang, S., Wang, G., and Zhang, L. (2012). Integrated process planning and scheduling - Multi-agent system with two-stage ant colony optimisation algorithm. *International Journal of Production Research*, 50(21), 6188-6201.

Yang, Y. and Huang, Y. (2000). Synthesis of an optimal wastewater reuse network. *Waste Management* , *20*(4), 311-319.

You, F.Q. and Leyffer, S. (2011). Mixed-integer dynamic optimization for oil-spill response planning with integration of a dynamic oil weathering model. *R&D Notes*, 57(12), 3555-3564.

Yu, X., and Xu, Z. (2012). Graph-based multi-agent decision making. International Journal of Approximate Reasoning, 53(4), 502-512.

Yuan, K.F., Ma, S.H., He, B., and Gao, Y. (2015). Inventory decision-making models for a closed-loop supply chain system with different decision-making structures. *International Journal of Production Research*, 53(1), 183-219.

Yue, D. and You, F. (2013). Sustainable scheduling of batch processes under economic and environmental criteria with MINLP models and algorithms. *Computers & Chemical Engineering*, 54, 44-59.

Zeng, G.M., Jiang, R., Huang, G.H., Xu, M., and Li, J.B. (2007). Optimization of wastewater treatment alternative selection by hierarchy grey relational analysis. *Journal of Environmental Management*, 82, 2, 250-259.

Zhang, B. (2015). Optimization of a wastewater treatment plant expansion with flexible expansion time (Master's thesis, University of Toronto).

Zhao, B., Guo, C.X., and Cao, Y.J. (2005). A multiagent-based particle swarm optimization approach for optimal reactive power dispatch. *IEEE Transaction on Power Systems,* 20, 2, 1070-1078.

Zheng, F., Simpson, A., and Zecchin, A. (2011). Dynamically expanding choice-table approach to genetic algorithm optimization of water distribution systems. *Journal of Water Resources Planning and Management*, 137(6), pp.547-551.

Zhong, Z.X. and You, F.Q. (2011). Oil spill response planning with consideration of physicochemical evolution of the oil slick: A multiobjective optimization approach. *Computers and Chemical Engineering*, 35(8), 1614-1630.