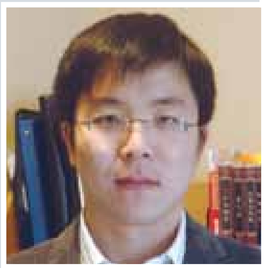
Fuzzy approach to a sticky problem



Liang Jing

Bing Chen

Baiyu Zhang

Pu Li

Jing, Chen, Zhang and Li suggest a unique mathematical approach to optimizing oil spill clean-up operations, and illustrate their approach by means of a hypothetical case study.

Who should read this paper?

Spill response organizations, oil industry executives, environmental protection agencies and any others with a need to better understand the complex interactions between technical, environmental and logical factors at play during oil spill clean-up operations.

Why is it important?

Clean-up of an offshore oil spill is a dynamic, multifaceted operation that is subject to many variables and constraints. The objective is to quickly respond and complete the clean-up within the shortest time period to minimize environmental impacts and the cost of the operation. However, uncertainties in the decision-making process may arise from subjective judgments regarding what type of clean-up equipment to deploy (skimmers, centrifugal separators, vacuum trucks, incineration barges, etc.) and when, and how to adapt the response activities to changing environmental and spill conditions. In an effort to simultaneously address these different types of uncertainty, the authors have applied the rigour of mathematics to the vagueness inherent in the decision-making process. A combination of fuzzy set theory, probability theory, and interval analysis are combined in an effort to provide decision makers with a better understanding of the impact of their decisions. The advantage of using a case study is that many scenarios can easily and quickly be tested. In this case, no less than 1,000 groups of decision variables were included in the analysis.

Results of this work suggest that a mathematical tool, or set of tools, could be developed for use by oil spill response organizations to allocate limited resources with higher confidence in the shortest period of time during oil spill clean-up operations.

About the authors

Liang Jing is a PhD candidate in Civil Engineering at Memorial University of Newfoundland (MUN). His research is focused on the development of an integrated simulation-optimization system for marine oily wastewater management. Bing Chen is an Associate Professor of Civil Engineering and leader of the Northern Region Persistent Organic Pollution Control Laboratory at MUN. His research interests revolve around oil spill response and mitigation and coastal/marine pollution modelling and control. Baiyu Zhang is an Assistant Professor of Civil Engineering at MUN with research interests in offshore/onshore oil spill control, wastewater treatment and northern environmental studies. Pu Li is a PhD Candidate in Civil Engineering at MUN. His research focuses on integrated decision support systems for offshore oil spill response in harsh environments.

A STOCHASTIC SIMULATION-BASED HYBRID INTERVAL FUZZY PROGRAMMING APPROACH FOR OPTIMIZING THE TREATMENT OF RECOVERED OILY WATER

Liang Jing, Bing Chen, Baiyu Zhang, Pu Li
Northern Region Persistent Organic Pollution Control Laboratory, Faculty of Engineering and Applied Science, Memorial University of Newfoundland, St. John's, NL, Canada

ABSTRACT

In this paper, a stochastic simulation-based hybrid interval fuzzy programming (SHIFP) approach is developed to aid the decision-making process by solving fuzzy linear optimization problems. Fuzzy set theory, probability theory, and interval analysis are integrated to take into account the effect of imprecise information, subjective judgment, and variable environmental conditions. A case study related to oily water treatment during offshore oil spill clean-up operations is conducted to demonstrate the applicability of the proposed approach. The results suggest that producing a random sequence of triangular fuzzy numbers in a given interval is equivalent to a normal distribution when using the centroid defuzzification method. It also shows that the defuzzified optimal solutions follow the normal distribution and range from 3,000-3,700 tons, given the budget constraint (CAD 110,000-150,000). The normality seems to be able to propagate throughout the optimization process, yet this interesting finding deserves more in-depth study and needs more rigorous mathematical proof to validate its applicability and feasibility. In addition, the optimal decision variables can be categorized into several groups with different probability such that decision makers can wisely allocate limited resources with higher confidence in a short period of time. This study is expected to advise the industries and authorities on how to distribute resources and maximize the treatment efficiency of oily water in a short period of time, particularly in the context of harsh environments.

KEY WORDS

Simulation-based hybrid interval fuzzy programming; Fuzzy linear optimization; Oil spill clean-up; Recovered oily water

NOMENCLATURE

$\overline{Z}$ = value of the fuzzy objective function (total daily treatment capacity in tons/day)

$\overline{c}_j$ = fuzzy objective function coefficients (hourly treatment capacities of each facility in tons/hour)

$\overline{X}_j$ = fuzzy decision variables (daily operation hours of each facility in hours)

M_j = upper bounds of decision variables (maximum daily operation hours of each facility in hours)

N_j = total numbers of each facility

$\overline{a}_j$ = fuzzy operation and maintenance costs of each facility (CAD/hr)

$\overline{d}_j$ = fuzzy transportation costs of each facility (CAD/ton)

$\overline{e}_i$ = fuzzy selling prices of recovered bunker oil from each facility (CAD/ton)

$\overline{b}$ = fuzzy maximum daily total budget (CAD)

j = facility sequence

Random = random numbers for the left, right, and vertex points of and

$\overline{a}_{ij}$ = fuzzy constraint coefficients

$\overline{b}_i$ = fuzzy right-hand sides of constraints

min = minimum bounds of and

max = maximum bounds of and

$\overline{w}$ = fuzzy number

$\mu_{\overline{w}}$ = membership function of

a = minimum bounds of

c = maximum bounds of

urnd = Sobol quasi-random numbers of uniform distribution

$\overline{Z}^*$ = corresponding value of the fuzzy objective function

$\overline{Z}^1$ = current best fuzzy objective function

INTRODUCTION

An offshore oil spill is defined as the discharge or release of petroleum hydrocarbons into the ocean or coastal waters. It may be due to the collision and/or grounding of oil tankers, accidental spill or leakage from offshore platforms and drilling rigs, and natural disasters such as typhoons and earthquakes that can cause huge damage to sea-based facilities and tankers. Crude oil, refined petroleum products and their by-products, bunker fuel, and waste oil have long been identified as the major contributors to marine oil pollution. They can constitute a direct hazard to marine ecosystems and human health through a variety of pathways, including digestion of oil, oiling of feathers and skins, avoidance of oil habitat, inhalation or dermal contact, and indirect threats to seafood safety and mental health [Boehm et al., 2008]. Less than 1% of the oil-soaked animals can survive and the residual contamination is believed to chronically affect wildlife and human health even for decades. The clean-up of offshore oil spills is usually subject to many constraints such as the type of oil, the oil-water volume fraction, and the temperature. The most commonly used methods include booming and skimming, chemical dispersants, biodegradation, in situ burning, and use of sorbants. Each method has its own advantages and disadvantages while skimming is one of the most environmentally friendly oil removal techniques [Pezeshki et al., 2000; You and Leyffer, 2011]. Oil skimmers can float across the top of the slick contained within the boom and suck or scoop the oils of different viscosities into storage tanks without adding chemicals. It is worth noting that most crude oils and intermediate to heavy products can emulsify and form so-called water-in-oil-emulsions when spilled at sea. Therefore, the recovered mixture usually contains not only oil but also water and needs to be further treated before discharge [Gaaseidnes and Turbeville, 1999; Maguire-Boyle and Barron, 2011].

The simplest treatment is nothing more than using a series of large holding tanks to allow water and oil to be separated under the action of gravity alone. In addition to that, centrifugal separators are known in which the oily mixture is forced to rotate at extremely high angular velocities thereby causing the separation of oil and water by density [Krebs et al., 2012]. Other management options such as destruction by incineration and direct disposal to landfill have also been implemented in some areas to accommodate the limited storage or processing capacity. However, a rich body of literature indicated that the transportation and treatment of recovered oily water usually requires a large number of personnel and equipment [Dollhopf and Durno, 2011]. This may, if not properly planned, significantly increase the cost and time of clean-up and pose a variety of technical challenges, particularly in the context of harsh environments where cold water, low temperature, dynamic/strong wave and current can significantly affect the applicability of these measures [Jing et al., 2012]. While an optimized contingency plan can make all relevant units orderly, the scheduled tasks should be completed within the shortest time period to minimize costs and associated environmental impacts. To deal with this, the application of system optimization approaches for supporting environmental decision-making processes could be a promising solution [Krohling and Campanharo, 2011; Wandera et al., 2011].

Precise information is difficult to obtain due to imperfect knowledge, measurement error, limited data accessibility, and variations of parameters which are inherent to the environment. System optimization problems, therefore, are usually subject to various uncertainties and complex interactions among technical, environmental and managerial factors. As one of the traditional optimization approaches, fuzzy linear programming (FLP) has long been investigated and advanced since the early stage of fuzzy set theory which allows the representation of uncertainties due to human impreciseness in the form of membership functions [Bellman and Zadeh, 1970; Maleki et al., 2000; Zhang et al., 2003; Veeramani et al., 2011]. It can be used to effectively reflect known possibilities and formulate the vagueness inherent in decision-making processes in an efficient way. Many attempts have been reported in the literature to use FLP in environmental decision-making [Chen et al., 2003; Xu et al., 2009; Li and Chen, 2011; Tan et al., 2011]. On the other hand, stochastic methods also have been widely used to tackle uncertainties with known probability distribution functions especially for objective and constraint coefficients. Review of the existing studies suggests that the most rigorous method of fitting a probability distribution is using the normal distribution [Kiemele et al., 1997; Dunn and Clark, 2009]. However, the central limit theorem defines that a normal distribution can only be approximated with a sufficiently large sample size which is often impractical under normal circumstances [Liu et al., 2010]. Most of the parameters and decision variables are usually unknown or replaced with interval estimates based on references or experts' opinions [Chen, 2005a; 2005b; Li et al., 2006; He et al., 2009; Cao et al., 2011]. Although various types of uncertainty have been discussed in the literature, there has been no study investigating the feasibility of handling both types of fuzzy, probabilistic and interval inputs in system optimization problems. The interval-based FLP, uniform distribution, and Monte Carlo simulation would be integrated to simultaneously communicate fuzzy, interval, and stochastic uncertainties caused by imprecise information, subjective judgment, and variable environmental conditions into the optimization process. Therefore, in this paper, a stochastic simulation-based hybrid interval fuzzy programming (SHIFP) approach is developed to aid the decision-making process by solving fuzzy linear optimization problems. Fuzzy set theory, probability theory, and interval analysis are combined to provide decision makers with a better understanding of the impact of their decisions. A case study related to recovered oily water treatment during offshore oil spill clean-up operations is conducted to illustrate the feasibility of the SHIFP approach.

METHODOLOGY

In a decision process using the traditional FLP model, coefficients and variables may be fuzzy, instead of precisely given numbers as in crisp linear programming models. Consider the following FLP problem with fuzzy variables and fuzzy constraints:

$$\max_{\overline{X_j}} \overline{Z} = \sum_{j=1}^{n} \overline{c_j}\,\overline{X_j} \quad (1)$$

subject to:

$$\sum_{j=1}^{n} \overline{a_{ij}}\,\overline{X_j} \le \overline{b_i} \quad 1 \le i \le m \quad (2)$$

$$0 \le \overline{X_j} \le M_j \quad 1 \le j \le n \quad (3)$$

where $\overline{Z}$ is the value of the objective function; $\overline{c_j}$ are the objective function coefficients; $\overline{X_j}$ are the decision variables; $\overline{a_{ij}}$ are the constraint coefficients; $\overline{b_i}$ are the right-hand sides of the constraints; and M_j,which are real numbers, are the upper bounds of decision variables. A basic assumption is that $\overline{c_j}, \overline{X_j}, \overline{a_{ij}}$ and $\overline{b_i}$ are all triangular fuzzy numbers. Note that $\overline{b_i}$ and M_j are usually given by literature data or subjective experience. On the other hand, $\overline{a_{ij}}$ and $\overline{c_j}$, such as machine hours, labour force, required materials, and operational cost are usually imprecise due to incomplete information and the lack of complete understanding. Their minimum and maximum bounds can be determined based on literature review or expert survey. To account for imprecise knowledge and to model the uncertainty, triangular fuzzy numbers with regard to $\overline{a_{ij}}, \overline{c_j}$ and the corresponding $\overline{X_j}$ are randomly generated using Monte Carlo simulation within given intervals such that the left spread, right spread, and vertex values are assumed to have uniform distributions. The uniform distribution is commonly used where one can specify only the minimum and maximum possible values for the input variable. Subsequently, the constraints are examined to verify if any of them has been violated. If all constraints are satisfied, $\overline{X_j}$ are determined to be feasible and a corresponding value of the objective function $\overline{Z}^*$ can be calculated. If $\overline{Z}^1$ is the current best and $\overline{Z}^* \ge \overline{Z}^1$, then $\overline{Z}^1$ should be replaced with $\overline{Z}^*$, otherwise $\overline{Z}^*$ is discarded. Repeat the above procedure for a preset number of replications;

the optimization results can be obtained as a probability distribution. The detailed algorithm can be summarized as follows:

Step 1: Assign triangular fuzzy numbers to $\overline{b}_i$ and crisp values to M_j based on literature review or subjective opinions. It is noted that M_j are treated as real numbers because the intervals $[0,\ \ M_j]$ are used to generate random fuzzy numbers.

Step 2: Review literature and collect expert opinions about the values of constraint and objective function coefficients which can be either intervals or discrete numbers. Set the minimum and maximum bounds for each coefficient such that uniform distributions can be assumed within the bounds.

Step 3: Sobol quasi-random numbers of uniform distribution are generated in sets of three (i.e., left spread, right spread, and vertex point) and bounded between 0 and 1. Equation 4 is then applied to convert the random numbers from unit interval [0, 1] to the preset intervals of each coefficient (i.e., $\overline{a}_{ij}$ and $\overline{c}_j$). It should be satisfied that left spread ≤ vertex ≤ right spread to ensure the triangular shape.

$$Random = min + urnd(\max - min) \tag{4}$$

where *Random* represents the random numbers for the left, right, and vertex points of $\overline{a}_{ij}$ and $\overline{c}_j$; *min* and *max* are the minimum and maximum bounds determined in Step 2, respectively; and *urnd* are Sobol quasi-random numbers of uniform distribution.

Step 4: As with Step 3, for each specific set of $\overline{a}_{ij}$ and $\overline{c}_j$, random triangular fuzzy numbers are generated for $\overline{X}_j$ and bounded between 0 and M_j.

Step 5: Examine the constraints to ensure the validity of $\overline{X}_j$. If any constraint is not satisfied, then $\overline{X}_j$ need to be regenerated.

Step 6: The objective function is calculated as $\overline{Z}^*$ using feasible $\overline{X}_j$ and further compared with the current best value $\overline{Z}^1$. If $\overline{Z}^* \geq \overline{Z}^1$, then $\overline{Z}^1$ should be replaced with $\overline{Z}^*$, otherwise $\overline{Z}^*$ is discarded.

Step 7: Repeat Steps 4 through 6 for a preset number of replications (e.g., 1,000, 5,000) to obtain the maximum objective function as a triangular fuzzy number in terms of each set of $\overline{a}_{ij}$ and $\overline{c}_j$. The centre of gravity method is used to defuzzify the fuzzy objective function into a crisp value [Van Broekhoven and De Baets, 2006].

$$COG(\overline{w}) = \frac{\int_a^c x\mu_{\overline{w}}(x)dx}{\int_a^c \mu_{\overline{w}}(x)dx} \tag{5}$$

where *a* and *c* are the minimum and maximum bounds of fuzzy number $\overline{w}$; and $\mu_{\overline{w}}$ is the membership function.

Step 8: Repeat Steps 3 through 7 for a preset number of replications (e.g., 1,000, 5,000). The defuzzified maximum objective function can be obtained as a probability distribution function in order to reflect the inherent uncertainty in the optimization process.

CASE STUDY

The objective of this case study is to examine the effectiveness of the proposed SHIFP approach in handling various uncertainties in the system optimization process. A hypothetic case of oil spill was assumed to occur in the North Atlantic nearshore of Newfoundland and Labrador. An estimated total of 50,000 tons of bunker oil was accidentally spilled and needed to be cleaned up. Numerous weir skimmers and drum skimmers were employed to collect spilled oil which was more or less blended with seawater. The local authority had a number of incineration barges, vacuum trucks, centrifugal separators, and temporary storage facilities to treat the recovered oily water. The objective was to maximize the treatment capacity of recovered oily water on a daily basis in order to reduce environmental risks. The main constraint was associated with the costs encountered in the treatment processes such that the total net cost should not exceed a given limit. The decision variables were chosen as the daily operation hours of each treatment facility by which decision makers could arrange the schedule for clean-up action.

$$\max_{\overline{X_j}} \overline{Z} = \sum_{j=1}^{4} \overline{c_j}\,\overline{X_j} N_j \tag{6}$$

subject to:

$$\sum_{j=1}^{4} \overline{a_j}\,\overline{X_j} N_j + \sum_{j=1}^{4} \overline{c_j}\,\overline{d_j}\,\overline{X_j} N_j - \sum_{j=1}^{4} \overline{c_j}\,\overline{e_j}\,\overline{X_j} N_j \le \overline{b} \tag{7}$$

$$0 \le \overline{X_j} \le M_j \quad j = 1,2,3,4 \tag{8}$$

where $\overline{Z}$ is the total daily treatment capacity which needs to be maximized (tons/day); $\overline{c_j}$ are the hourly treatment capacities of each facility; $\overline{X_j}$ and N_j are the daily operation hours and the total numbers of each facility, respectively; $\overline{a_j}$ and $\overline{d_j}$ are the operation and maintenance (O&M) and transportation costs, respectively; $\overline{e_j}$ are the selling prices of recovered bunker oil from each facility; $\overline{b}$ is the maximum daily total budget (in CAD) which was set by the local authority as (110,000 130,000 150,000); and M_j are the maximum daily operation hours of each facility, in other words, the upper bounds of each decision variable. Various intervals and point values were collected by reviewing literature on previously identified databases, referring to existing contingency plans, and consulting experts. The corresponding lower and upper bounds of the coefficients and decision variables were either assumed for computational simplicity or determined by choosing the maximum and minimum values of these source data (Table 1). It should be noted that the number of Monte Carlo iterations used for this case study was determined as 1,000 by taking time constraints and the efficiency of convergence into account.

Facilities	Sequence	Total number	Daily hours (hr)	O&M cost (CAD/hr)	Transportation cost (CAD/ton)	Hourly capacity (tons/hr)	Recovered oil price (CAD/ton)
	j	N_j	$\overline{X_j}$	$\overline{a_j}$	$\overline{d_j}$	$\overline{c_j}$	$\overline{e_j}$
Incineration barge	1	6	[0, 12]	[100, 500]	[4.5, 6]	[0.15, 0.25]	0
Vacuum truck	2	20	[0, 24]	[200, 300]	[20, 30]	[3, 5]	[26, 35]
Centrifugal separator	3	10	[0, 20]	[100, 250]	[20, 30]	[8, 11]	[30, 50]
Temporary storage	4	5	[0, 16]	[20, 60]	[33, 40]	[4, 5.5]	[18, 24]

Table 1: Detailed description of treatment facilities of recovered oily water.

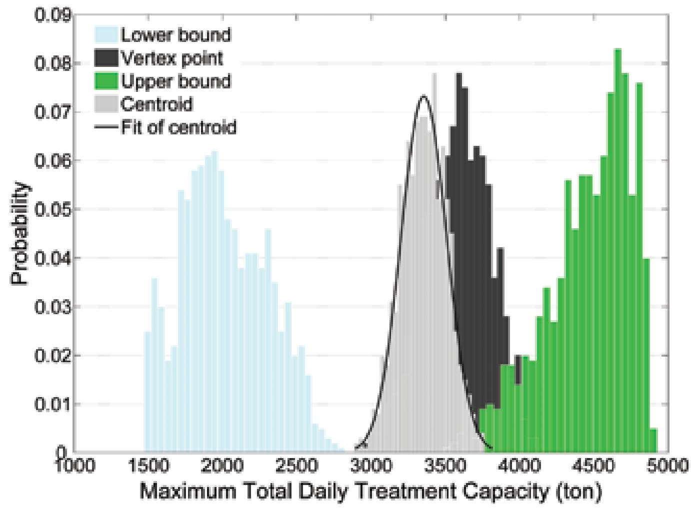


Figure 1: Probability distributions of the lower bound, vertex point, upper bound, and defuzzified centroid of the objective function.

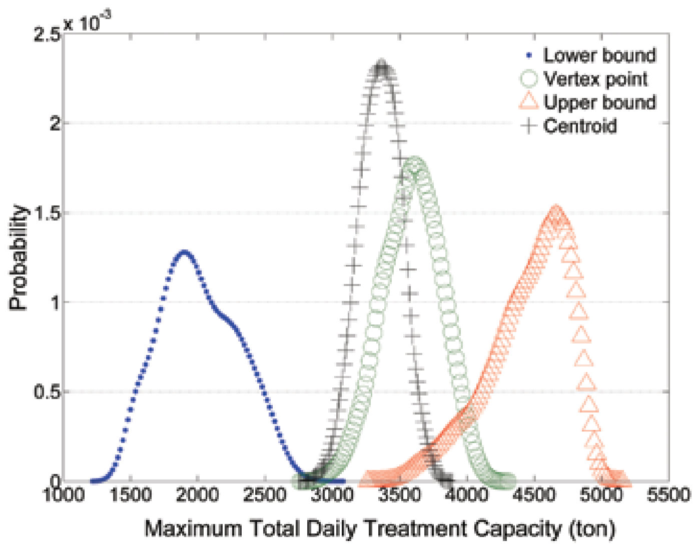


Figure 2: Probability density estimates of the lower bound, vertex point, upper bound, and defuzzified centroid of the objective function.

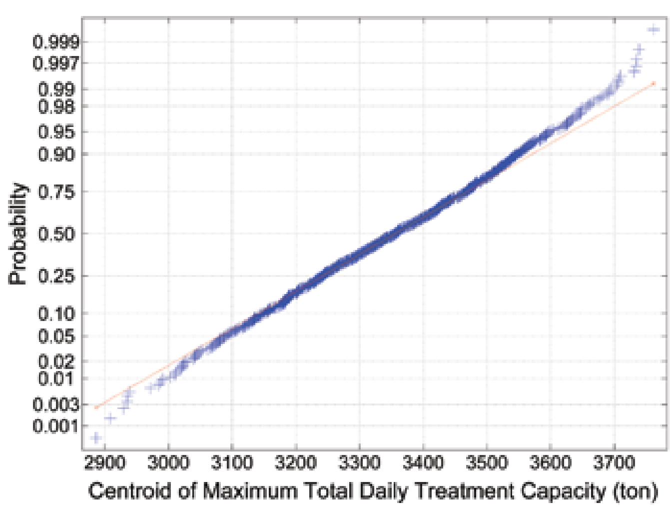


Figure 3: Normal probability plot of the centroid of the objective function.

RESULTS AND DISCUSSION

The histograms in Figure 1 depict that the distributions of the lower bounds, vertex points, and upper bounds of the maximized objective function were all close to the normal distribution. However, the results from the Lilliefors test, which is a two-sided goodness-of-fit test of normality, suggested that the null hypothesis of their normal distribution was rejected at a significance level of 5%. The offset of lower bounds and upper bounds towards the vertex points implies that the optimization results tended to concentrate in the range of 2,000-4,500 tons. These findings can be further demonstrated in Figure 2 by using the kernel-smoothing method to plot the probability density estimates. Another interesting finding is that the distribution of the defuzzified optimization results was well fitted by the normal distribution with a mean value of 3,352 tons and a standard deviation of 155.4 tons. The Lilliefors test cannot reject the null hypothesis that the centroid distribution was normal at a significance level of 5%. Its normality was further evaluated and confirmed by the normal probability plot as shown in Figure 3. In this case study, the results revealed that the maximum daily treatment capacity was likely to range from 3,000-3,700 tons given the budget constraint. In other words, from the technical perspective, it induces that oil skimmers are not recommended to operate if the amount of recovered oily water exceeds the treatment capacity unless other treatment or storage facilities are available.

Figures 4 and 5 show the lower bounds, upper bounds, vertex points, and centroids of the stochastically generated fuzzy numbers with regard to the coefficient of O&M cost of incineration barge. The lower and upper bounds mostly appeared at the edges of the predefined interval (100, 500), indicating that the support of random fuzzy numbers tended to be wider rather than concentrating around the middle value. Based on the Lilliefors test at the 5% significance level, its centroid distribution well fitted the normal distribution with a mean value of 299.8 CAD/hr and a standard deviation of 89.5 CAD/hr which are also reported in the corresponding normal probability plot (Figure 6). This finding elucidates that producing a random sequence of triangular fuzzy numbers in a given interval is equivalent to a normal distribution when using the centroid defuzzification method. It is worth noting that, if Figure 2 is compared with Figure 4, the centroids of both the random fuzzy coefficients and the fuzzy optimal solutions obey the normal distribution. The normality seems to be able to propagate throughout the optimization process, yet this interesting finding deserves more in-depth study and needs more rigorous mathematical proof to validate its applicability and feasibility.

Another interesting point to discuss is that the shapes of the fuzzy decision variables, corresponding to the maximized objective function, can be categorized into groups (Figure 7). For each set of the random coefficients, Monte Carlo simulation randomly generated fuzzy decision variables, validated the constraints, and found and recorded the particular group of decision variables that led to the maximum objective function. The above procedure was repeated 1,000 times such that 1,000 groups of decision variables were obtained. It should be noted that the optimal decision variables appeared repeatedly in

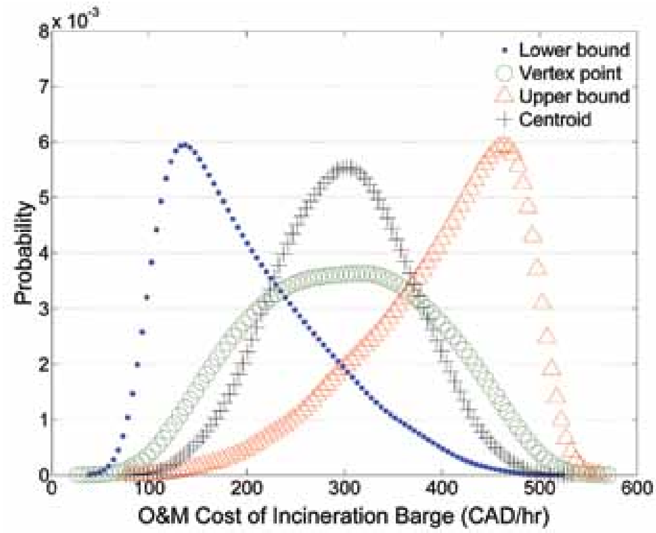


Figure 4: Probability density estimates of the lower bound, vertex point, upper bound, and defuzzified centroid of the O&M cost of incineration barge.

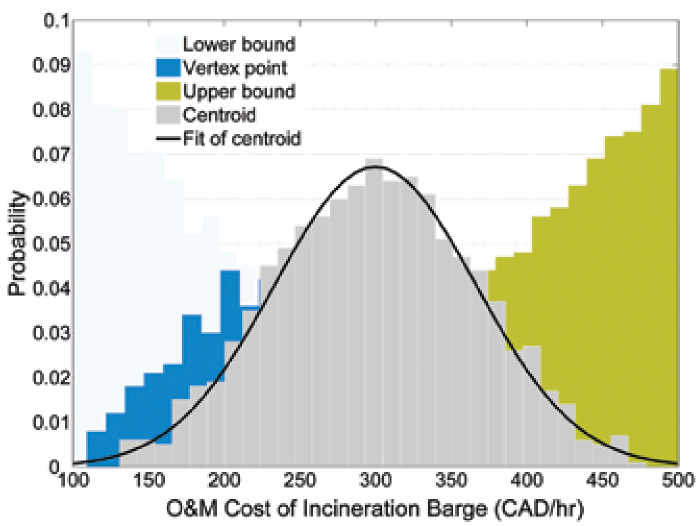


Figure 5: Probability distributions of the lower bound, vertex point, upper bound, and defuzzified centroid of the O&M cost of incineration barge.

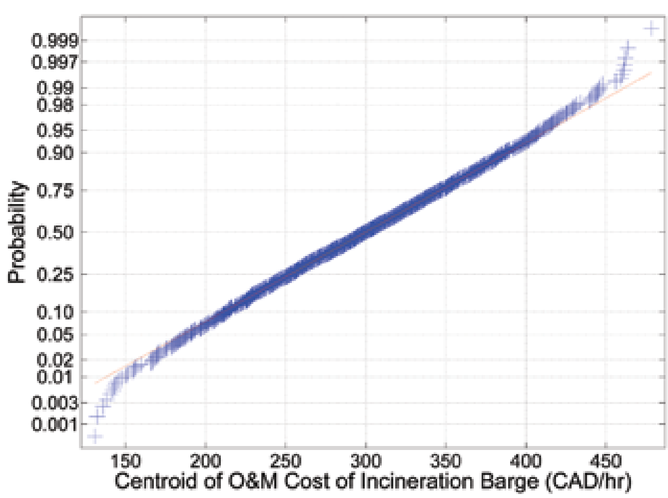


Figure 6: Normal probability plot of the centroid of the O&M cost of incineration barge.

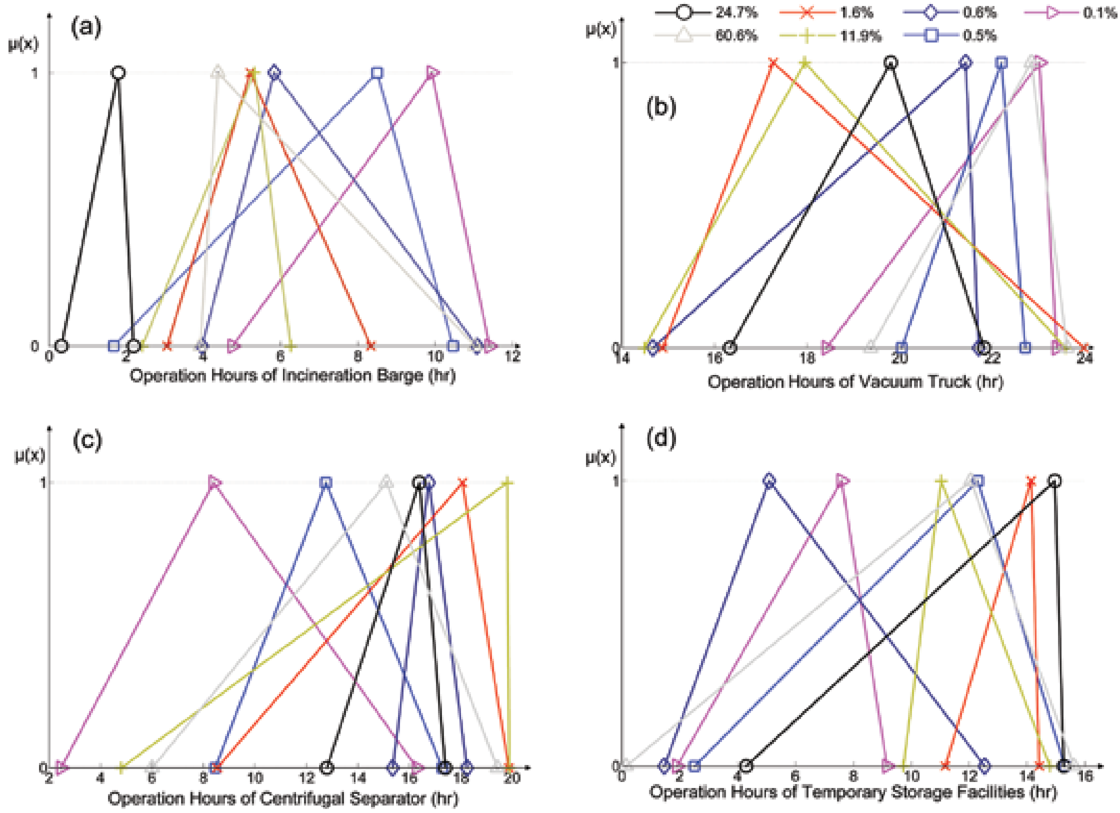


Figure 7: Optimal solutions of operation hours of each treatment facility.

seven different shapes as shown in Figure 7. The percentages listed in the legend illustrate how many times each shape was referred to in 1,000 optimization runs. For example, in Figures 7a-7d, the four triangular fuzzy numbers (TFN) (i.e., operation hours of the incineration barges, vacuum trucks, centrifugal separators, and temporary storage facilities) whose minimum, maximum, and vertex points are marked with triangles, were selected as the optimal variables in 60.6% of the total runs (i.e., 606 out of 1,000). This can be further interpreted as saying that, if the operation hours can be determined within the range of the TFNs marked by the triangles (e.g., (4, 11) in Figure 7a), the probability of achieving maximum treatment capacity would be 60.6% under the condition of uncertain coefficients. Moreover, the fuzzy outputs can help the decision makers choose other compromising points rather than the vertex points (e.g., Figure 7a, TFN (4, 4.2, 11), vertex point 4.2) and provide them with the corresponding possibility of getting the maximum treatment capacity (i.e., possibility of the vertex points is 1 and decreases along both sides as shown in Figure 7). Contrastingly, in Figures 7a-7d, another four TFNs marked by circles denote that in 24.7% of the replications (i.e., 247 out of 1,000), the objective function was maximized by setting decision variables in these shapes. This particular setting might also be considered as viable when the primary choice (settings with 60.6% probability) can not be applied due to safety or technical concerns.

These interesting findings are believed to have important and broader implications relating to oil spill clean-up such that decision makers can wisely allocate limited resources with higher confidence in a short period of time. This is particularly true for harsh environments where available resources are usually in short supply and extreme weather conditions are likely to create more uncertainty in estimating the associated costs and time. In addition, from the ecological prospective, harsh environments tend to have more vulnerable ecosystems and shorter food chains than those in the low-latitude regions. Therefore, making quick and sound decisions will not only help reduce the oil spill clean-up cost but also minimize environmental risks.

CONCLUSIONS

The clean-up of offshore oil spills is often subject to many constraints and the recovered oily water needs additional treatment in order to meet the stringent environmental regulations. Much of the literature indicated that the transportation and treatment of recovered oily water usually requires a large number of personnel and equipment. Good planning can help manage the scheduled tasks within the shortest time period to minimize costs and associated environmental impacts. However, the existence of different types of uncertainties due to imprecise information, subjective judgment, and variable environmental conditions may complicate the planning process. In this study, a stochastic SHIFP approach was developed to tackle uncertainties inherent in the decision-making environment. As with the traditional FLP, fuzzy set theory was used to model uncertainty such that the results would provide the decision makers more flexibility for the choice of the solution. Uniform interval distribution was assumed due to the lack of precise information on both coefficients and variables. A case study related to recovered oily water treatment during offshore oil spill clean-up operations was conducted to test the proposed approach. The results demonstrated that the objective function (maximum daily treatment capacity), if defuzzified by the centroid defuzzification technique, was likely to follow the normal distribution within the range from 3,000 to 3,700 tons. In addition, the shapes of the fuzzy decision variables, corresponding to the maximized objective function, can be categorized into seven groups with different probability such that decision makers can more confidently allocate limited resources. This is particularly true for harsh environments where available resources are usually in short supply and extreme weather conditions are likely to create more uncertainty in estimating the associated costs and time. Emergency planners and administrators are expected to benefit from this study by gaining an insight into how to wisely allocate resources in responding to an offshore oil spill. Future research can be more fruitful if the oil weathering process can be integrated into this framework using dynamic optimization techniques.

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