International Journal of u- and e- Service, Science and Technology
Vol.9, No. 5 (2016), pp.77-88
http://dx.doi.org/10.14257/ijunesst.2016.9.5.07

Fuzzy Multi-objective Expected Value Optimization Models for Locating an Automotive Service Enterprise

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Abstract

Automotive service enterprise location is an interesting and important issue in the logistic field. In practice, some factors of its facility location allocation (FLA) problem, i.e., customer demands, allocations, even locations of customers and facilities, are usually changing, and thus FLA problem features with uncertainty. To account for this uncertainty, some researchers have addressed the fuzzy time and cost issues for locating an automotive service enterprise. However, a decision-maker hopes to minimize the transportation time of customers meanwhile minimizing their transportation cost when locating a facility. Also, they prefer to arrive at the destination within the specific time and cost. To handle this issue via a more practical manner, by taking the vehicle inspection station as a typical automotive service enterprise example, this work presents a fuzzy multi-objective expected value optimization approach to address it. Moreover, some region constraints can greatly influence FLA and travel velocity is also an uncertain variable due to the influence of some unpredictable factors in the location process. To do so, this work builds two practical fuzzy multi-objectives programming models of its location with regional constraints, fuzzy inspection demand, and varying velocity. A hybrid algorithm integrating fuzzy simulation, neural networks (NN), and Genetic Algorithms (GA), namely a random weight based multi-objective NN-GA, is proposed to solve the proposed models. A numerical example is given to illustrate the proposed models and the effectiveness of the proposed algorithm.

Keywords: *Uncertainty, Facility location, Optimization, Modeling and simulation, Fuzzy simulation*

1. Introduction

Since facility location allocation (FLA) problems were initialized by Cooper [1] in 1963, there have been many advances in their solution methods, variants and applications *e.g.*, emergency service systems, telecommunication networks, public services, and transportation facilities. The early work mainly focused on FLA location problems, many different models have been formed [1-4], *i.e.*, median models [5-6], center models [7-10], covering models [11-12], hub location modes [13], and hierarchical location models [14-16]. Meanwhile, a large number of solution approaches for different models have been proposed, *e.g.*, simulated annealing, Genetic Algorithm, and Tabu Search [17-25]

In practice, many parameters of FLA, such as demands of clients, cost of operating facilities, may be uncertainty. In order to address these issues, some uncertain FLA problems are presented. For example, Logendran and Terrell solve an uncapacitated FLA problem with price-sensitive stochastic demands [26]. Zhou and Liu establish stochastic models for capacitated FLA problems to minimize the transportation distance [27]. Taaffe *et al.*, present the supply capacity acquisition and allocation with uncertain customer demands. Their goal is to determine stock levels and customer assignments for each facility in order to minimize expected

ISSN: 2005-4246 IJUNESST

procurement, holding, and shortage costs across all facilities [28]. Louveaux and Peeters present a two-stage stochastic programming problem with uncertainty in demand, selling prices, as well as in production and transportation costs [29]. Laporte *et al.*, present capacitated FLA problems in which customer demands are stochastic. The problem is formulated as a stochastic integer linear program, with first stage binary variables and second stage continuous variables [30]. Eppen *et al.*, present a two-stage formulation for capacity expansion [31]. A multi-stage capacity expansion problem under uncertain demand is presented by Ahmed *et al.*, [32]. Amin et al. present a multi-objective facility location model for closed-loop supply chain network under uncertain demand and return in order to minimize the total cost [33].

Probability theory can be regarded as a tool for the description of objective uncertainty. However, in order to obtain the probability distribution of an uncertain factor, we need a lot of samples to apply the statistics inference approach. In fact, a decision-maker lacks data of related factors. Instead, expert opinion is used to provide estimations. In this case, credibility theory, as a branch of fuzzy set theory, can better deal with this ambiguous information. It is a fuzzy measure with self-duality which has many application perspectives, *e.g.*, industrial process planning [34]. In addition, some scholars have addressed the fuzzy location problems. Wen and Iwamura discuss the fuzzy FLA problem with fuzzy demands under the Hurwicz criterion to minimize the transportation cost [35]. Wang et al. analyze the two-stage fuzzy facility location problems to minimize the transportation cost [36]. Zhou and Liu establish fuzzy models for capacitated FLA problems with fuzzy demands to minimize the transportation distance/cost [37]. Wang and Watada address the VaR-based facility location problem with variable capacity in fuzzy random uncertainty [38]. Also, they discuss the recourse-based facility location problems in a hybrid uncertain environment to minimize the transportation cost [39].

The location of an automotive service enterprise and transportation facility is one of the important applications of FLA. Some scholars have discussed the related issues under uncertainty. For example, by considering the uncertainty of the number of inspection vehicles, Tian *et al.*, establish a stochastic location model for vehicle inspection station to achieve the minimum transportation cost of vehicle inspection customers [40]. By considering the uncertainty of the number of inspection vehicles and road conditions under different districts of inspection customers, they propose the expected value model for a vehicle inspection station location problem with random inspection demand and different transportation cost [41]. Tian et al. establish a cost-profit tradeoff model for a vehicle inspection station with random inspection demand [42]. Tian et al. establish a cost-profit tradeoff model for a vehicle inspection station with fuzzy inspection demand [43].

Based on the above overview, it should be noted that the current fuzzy location problem for locating an automotive service enterprise research mainly focuses on the analysis of transportation time and cost of oriented-customers. However, in an actual facility location-allocation process, a decision-maker may consider to minimize the total transportation cost of customers, meanwhile minimize their total transportation time. To do so, a fuzzy multi-objective issue for the location needs to be addressed. Moreover, in the actual location process, some regions cannot build the service facility due to the influence of government policy and natural factors, i.e., marshes, lakes, tourist areas, parks, residential areas and some special areas with the policy constraints. These regions should be considered when they are planned. The vehicle travel velocity is also an uncertain variable due to the influence of some unpredictable factors. To do so, by taking vehicle inspection station as a typical automotive service enterprise and an example, this work propose to establish its multi-objective optimization models with fuzzy inspection demand, random varying velocity and regional constraint.

In Section 2, the assumptions and parameters of established models are introduced. In Section 3, multi-objective optimization models of the location for the typical automotive service are established. Section 4 introduces the algorithm to solve these models. In Section 6, some numerical examples are presented to test the effectiveness of the proposed method. Finally, Section 6 concludes our work and describes some future research issues.

2. Problem Statements

In order to conveniently establish our models, the following assumptions and parameters are given in this work.

2.1. Parameters of Establishing Models

The notations are summarized as follows:

(1) i —The index of the demand region of inspection customers, $i = 1,2,\cdots,m$.

(2) j —The index of the vehicle inspection station, $j = 1,2,\cdots,n$.

(3) l_i —The horizontal coordinate of the location of the *i*-th demand region.

(4) u_i —The vertical coordinate of the location of the *i*-th demand region.

(5) c_{ij} —Per kilometer transportation expense from demand region i to inspection station j , with its unit being Yuan.

(6) ξ_{ij} —The number of vehicles from demand region *i* to inspection station *j*, and it is a fuzzy variable.

(7) v_{ij} —The vehicle velocity of from demand region *i* to inspection station *j* , and the unit is m/s. It is subject to the Uniform distribution and its unit is m/s.

Decision variables:

(1) x_j —The horizontal coordinate of the location of the *j*-th vehicle inspection station.

(2) y_j —The vertical coordinate of the location of the *j*-th vehicle inspection station.

2.2. Assumptions

This work makes the following assumptions:

(1) The distribution condition of customers in the demand region is ignored, *i.e.*, the center of the region of customer demand is treated as its coordinate location.

(2) The inspection capability of a vehicle inspection station is ignored, namely inspection capability is designed to be big enough to meet the requirements of users; and

(3) The cost per kilometer C_{ij} from demand region *i* to a vehicle inspection station *j* is constant.

2.3. Evaluation Parameters of Establishing Models

(1) *C*--Total transportation cost of vehicle inspection customers, it is defined as,

$$C = \sum_i \sum_j \xi_{ij} c_{ij} d_{ij} \tag{1}$$

where d_{ij} is the distance between vehicle inspection demand region i and the inspection station j and it is expressed as $d_{ij} = \sqrt{(x_i - l_i)^2 + (y_i - u_j)^2}$.

(2) T--Total transportation time of vehicle inspection customers, it is defined as,

$$T = \sum_i \sum_j \xi_{ij} d_{ij} / v_{ij} \tag{2}$$

3. Typical Multi-Objective Programming Models of the Location for Vehicle Inspection Station

Based on the presented concepts and assumptions, by taking vehicle inspection station as a typical automotive service enterprise as an example, we build two fuzzy multi-objective programming models for its location, i.e., fuzzy expected value multi-objective programming model for the location of a vehicle inspection station and fuzzy chance constrained multi-objective programming model for the location of a vehicle inspection station, which are presented as follows in detail.

3.1. Fuzzy Expected Value Multi-Objective Programming Model for a Vehicle Inspection Station Location

In the actual location process of a vehicle inspection station, a decision-maker wants to seek the minimum average total transportation cost of vehicle inspection customers meanwhile minimizing their minimum average total transportation time. Moreover, a decision-maker wants to arrive at the destination in the given expected time and cost. Also, in the actual location process, some regions can not build the vehicle inspection station due to the influence of government policy and natural factors, i.e., marshes, lakes, tourist areas, parks, residential areas and some special regions with the policy constraints. These regions should be considered when vehicle inspection station is located. In order to deal with this issue, we establish a fuzzy expected value multi-objective programming model for the location of vehicle inspection station. The objective function of this model is written as:

$$\min\ E(C) \text{ and } \min\ E(T) \tag{3}$$

Subject to:

$$\begin{cases} E(\sum_i \sum_j \xi_{ij} c_{ij} d_{ij}) \le C' \\ E(\sum_i \sum_j \xi_{ij} d_{ij} / v_{ij}) \le T' \\ h(x, y) \le 0 \\ x \in (x_l, x_u) \\ y \in (y_l, y_u) \end{cases} \tag{4}$$

where C' and T' are the given average total transportation cost and time of vehicle inspection customers, respectively. $E(\sum_i \sum_j \xi_{ij} c_{ij} d_{ij}) \le C'$ and

$E(\sum_i \sum_j \xi_{ij} d_{ij} / v_{ij}) \le T$ are average transportation cost and time constraints of vehicle inspection customers, respectively. x_l and x_u are the lower bound and upper bound of the coordinate x, respectively, and while y_l and y_u are lower bound and upper bound of the coordinate y. x_l, x_u, y_l and y_u can be determined by the coordinate of vehicle inspection demand areas. $h(x, y) \le 0$ and $g(x, y) \ge 0$ are regional constraints.

4. Solution Algorithm

Fuzzy simulation is an effective means to assess and calculate stochastic and probabilistic functions. It has effectively solved many fuzzy problems [44-45]. Genetic Algorithm (GA) and neural networks (NN) have successfully solved many complex industrial optimization problems which are hard to solve by analytic methods. In this work, a hybrid intelligent algorithm integrating fuzzy simulation, GA and NN is adopted to solve the proposed two fuzzy multi-objective optimization models [46-49].

4.1. Fuzzy Simulation

Let $\xi = (\xi_1, \xi_2, \cdots, \xi_m)$, where m is the number of customer regions. We denote that μ is the membership function of ξ and μ_i is the membership function of ξ_i, $i = 1,2,\cdots,m$. In order to solve the proposed models, we must handle the following an uncertainty function:

$$U_1 : (x, y) \to E(T(x, y, \xi)) \tag{5}$$

To compute the uncertainty function U_1, the following simulation algorithm is introduced.

Step 1: $E = 0$;

Step 2: Randomly generate real numbers u_i of the ε - level sets of fuzzy variables ξ_i such that $u_j = (u_{ij}), i = 1,2,\cdots,m$ and $j = 1,2,\cdots,N$;

Step 3: Set

$$a = T(x, y, u_1) \wedge T(x, y, u_2) \wedge \cdots \wedge T(x, y, u_N)$$
$$b = T(x, y, u_1) \vee T(x, y, u_2) \vee \cdots \vee T(x, y, u_N);$$

Step 4: Randomly generate r from [a, b];

Step 5: If $r \ge 0$, then $E = E + Cr\{T(x, y, \xi) \ge r\}$;

Step 6: If $r \le 0$, then $E = E + Cr\{T(x, y, \xi) \le r\}$;

Step 7: Repeat the fourth to sixth steps for N times; and

Step 8: $E[C(x, y, \xi)] = a \vee 0 + b \wedge 0 + E \cdot (b - a) / N$.

4.2. Genetic Algorithm (GA)

GA has initialization, fitness function evaluation, selection, crossover and mutation process processes, their detailed description refers to our previous work [36]. To achieve the solution of multi-objective optimization models, the following improvement work of GA is adopted in this paper, namely a random weight based multi-objective GA.

The fitness function is obtained by the random weight method. Specifically, for fuzzy expected value multi-objective programming model for the location of vehicle inspection station, the fitness function f_i of its *i*-th chromosome is written as,

$$f_i = w_1 E(C) + w_2 E(T) \tag{6}$$

For fuzzy chance constrained multi-objective programming model for the location of vehicle inspection station, the fitness function f_i of its *i*-th chromosome is written as,

$$f_i = w_1 \overline{C} + w_2 \overline{T} \tag{7}$$

where w_1 and w_2 are random weights, it is generated as,

$$w_k = \frac{r_k}{\sum_{k=1}^{2} r_k},\ k=1,\ 2 \tag{8}$$

where $r_k \in (0,10)$ in this work.

In addition, the selection probability of *i*-th chromosome is executed based on the following,

$$\rho_i = \frac{f_{\max} - f_i}{\sum_{j=1}^{pop\_size} (f_{\max} - f_j)} \tag{9}$$

where f_{max} is the optimization fineness value in the current generation.

4.3. Neural Networks (NN)

A neural network is treated as a nonlinear mapping system consisting of neurons (processing units), which are linked by weighted connections. It usually consists of three layers: input, hidden, and output layers. There is an activation function in the hidden layer. It is defined as the sigmoid function.

Firstly, the method to determine the number of neurons of the input, hidden, and output layer is presented as follows.

The number of input neurons of NN structure is the number of decision variables, namely, location coordinates, and thus it is set to be 2 in this work.

The number of output neurons is the number of evaluation functions. Namely, the number of output neurons is 2.

In terms of the NN structure, the main problem is to determine the best number of hidden neurons. The number of hidden neurons can be infinite in theory, but finite in practice due to two reasons. Too many hidden neurons increase the training time and response time of the trained NN. On the other hand, too few hidden neurons make the NN lack of generalization ability. Therefore, it can usually be determined by the following formula, namely, $s = \sqrt{u + v} + b$, where u and v are the number of input neurons and output neurons, respectively, and b is a constant from 1 to 10 [46]. Based on the above ideology, s is set to be 7 in this work.

Secondly, back propagation is the most commonly used method to calculate values for the weight and bias terms of the neural network model. In the back propagation method, all weights *w* are adjusted according to the calculated error term using a gradient method. Learning in neural networks, that is the calculation of the weights of the connections, is achieved by minimizing the error between the output of the neural network and the actual output over a number of available training data as given in the following equation. It is set to be 0.04.

Thus the NN algorithm is presented as follows:

Step 1: Initialize the number of neurons of input, hidden, and output layers, and initialize weight vector *w*.

Step 2: Calculate the output of the hidden layer, the output of output layer and adjust the corresponding weights *w*.

Step 3: Calculate the error term, namely training performance goal, if it is larger than the given error term value, go to Step 2, otherwise, go to end.

4.4. Hybrid Algorithm

Based on the above description, a hybrid intelligent procedure is given. Note that NN procedures can refer to our previous work [37].

Step 1: Generate training input-output data for uncertain functions by fuzzy simulation, *e.g.*, U_1 U_2 and U_3.

Step 2: Train a neural network to approximate the uncertain functions based on the generated training input-output data.

Step 3: Initialize pop_size chromosomes whose feasibility may be checked by the trained neural network. Note that the regional constraints should be checked in this Step.

Step 4: Update the chromosomes by crossover and mutation operations and the trained neural network may be employed to check the feasibility of off springs.

Step 5: Calculate the objective values for all chromosomes by the trained neural network.

Step 6: Compute the fitness of each chromosome based on the objective values.

Step 7: Select the chromosomes by spinning the roulette wheel.

Step 8: Repeat the fourth to seventh steps to a given number of cycles.

Step 9: Report the best chromosome as the optimal solution.

The above algorithm has been implemented in the visual C++ 6.0 programming language.

5. Case Study

Considering a location problem for the vehicle inspection station of a Fushun city of China, this city is divided into five vehicle inspection regions as shown in Figure 1, *i.e.*, Development, Dongzhou, Wanghua, Xinfu and Shuncheng districts.

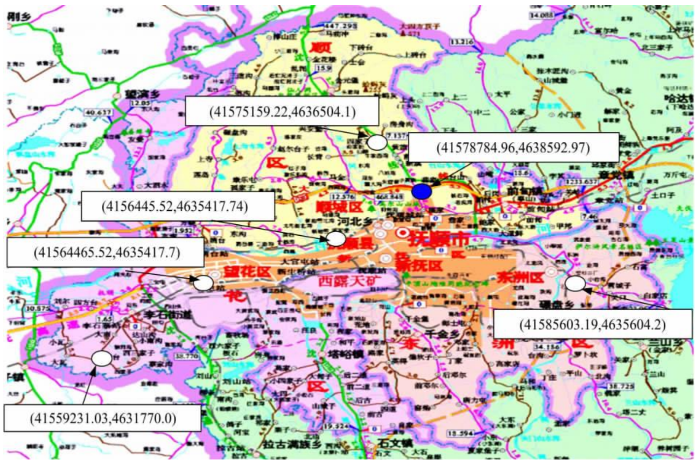

Figure 1. Schematic Diagram of Fushun City

Table 1. Typical Parameters Description of Established Model

Region No.	*Region Name*	l(m)	u(m)	ξ (Thousand)	c (Yuan/ Per kilometer)
1	*Development*	*-19553.93*	*-6822.87*	*(1.5, 2.5, 3.5)*	*2*
2	*Dongzhou*	*6818.23*	*-2988.68*	*(2, 3, 4)*	*2*
3	*Wanghua*	*-14319.44*	*-3175.23*	*(0.5, 1.5,2.5)*	*2*
4	*Xinfu*	*-3625.74*	*-2088.84*	*(2.5, 3.5, 4.5)*	*2*
5	*Shuncheng*	*-1109.74*	*285.12*	*(4, 5, 6)*	*2*

Their center coordinates of districts are listed in Table 1. In addition, the center coordinate of this city is (41578784.96, 4638592.97). In order to conveniently optimize the location problem, taking the center coordinate of this city as relative coordinate origin, the coordinates of these five districts are transformed into the following numerical values, as shown in Table 1. In addition, the number of inspection vehicle and the cost of per kilometer of each demand regions are listed in Table 1. Not that ξ_{ij} is a triangular distribution, *i.e.*, $\xi_{ij} = (a, b, c)$, where *a*, *b* and *c* be pessimistic, possible and optimistic values of fuzzy numbers [40].

The parameters of the hybrid algorithm are set next: the population size pop_size is 30, the probability of crossover pr_c is 0.3, the probability of mutation pr_m is 0.3, the maximum number of generations $g_{\max}$ is 600, and the number of simulation cycles is 3000. The number of input, hidden and output neurons on NN structure is set to be 2, 6 and 2, respectively. The number of training data on NN structure is 200.

Example 1. A decision-maker hopes to build a vehicle detection station with the minimum average transportation cost and time of vehicle inspection customers, and ask to satisfy regional constraint, *i.e.*, $x_2+y_2 \leq 3.5\times 10^7$ and $x_2+y_2 \geq 1.8\times 10^7$. In addition, expected total transportation cost and time of vehicle detection customers can not exceed 2.8 × 105 Yuan and 1.8×10^7, respectively. The vehicle travel velocity of vehicle inspection customers $v_{ij} \sim U(5,20)$. This problem can be translated to solve the following model:

$$\min\ E(C) \text{ and } \min\ E(T) \tag{16}$$

Subject to:

$$\begin{cases} E(\sum_i \sum_j \xi_{ij} c_{ij} d_{ij}) \le 2.8 \times 10^5 \\ E(\sum_i \sum_j \xi_{ij} d_{ij} / v_{ij}) \le 1.8 \times 10^7 \\ x^2 + y^2 \ge 1.8 \times 10^7 \\ x^2 + y^2 \le 3.5 \times 10^7 \\ x \in (-19553.93, 6818.23) \\ y \in (-6822.87, 285.12) \end{cases} \tag{17}$$

After the algorithm is executed, the following location coordinate and the optimal solution of the model are obtained:

$$(x, y) = (-3695.90, -3057.70);$$
$$f = 225815.17$$

The results denote that the location coordinate of vehicle detection station is (-3695.90,-3057.70), the quasi-optimal solution of this model is 225815.17. The quasi-optimal average transportation cost and time of vehicle inspection customers are 224779.37 Yuan and 14342152.68 s, respectively. In addition, the plane distribution graph for the location of vehicle detection station is obtained and shown in Figure 2.

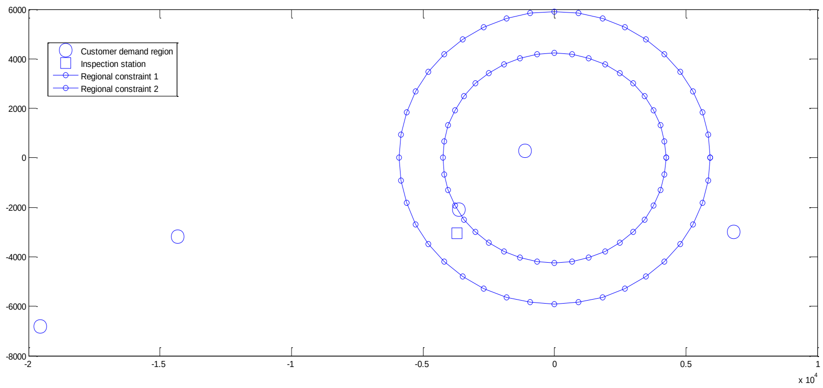

Figure 2. Plane Distribution Graph for the Location of Vehicle Detection Station of Example 1

6. Conclusions

The location of an automotive service enterprise location is important for its sustainable development. However, FLA can encounter some uncertain factors, *i.e.*, customer demands, allocations and facilities. In order to address it, uncertain FLA problems have been discussed widely. However, the current fuzzy FLA problem research mainly merely focuses on fuzzy time/cost of customers. In reality, a decision-maker hopes to minimize the transportation time of customers meanwhile minimizing their transportation cost when locating a facility. Also, they prefer to arrive at the destination within the specific time and cost, also hopes to arrive at the destination with the minimum transportation time and cost. To do so, this work proposes a fuzzy multi-objective optimization issue for locating an automotive service enterprise for the first time. In addition, considering the impact of the region constraints and varying velocity, taking the vehicle inspection station as a typical automotive service enterprise and an example, this work establishes some new fuzzy multi-objective optimization models of its FLA subject to fuzzy inspection demand and varying vehicle velocity, *i.e.*, fuzzy expected value multi-objective programming model for the location of a vehicle inspection station and fuzzy chance constrained multi-objective programming model for the location of a vehicle inspection station. Lastly, a hybrid algorithm integrating fuzzy simulation, NN and GA, namely a random weight based multi-objective NN-GA, is adopted to solve the established models. The results reveal that it is feasible and efficient when used to solve the proposed models. The results can be used to guide decision makers in making better decisions when a FLA problem is analyzed and planned.

There exist some limitations with the proposed method. For example, for the region constraint, this work merely considers the condition of the round shape. However, the region constraint can more likely to be irregular shape in reality and the matter that how to deal with this issue needs to further be discussed.

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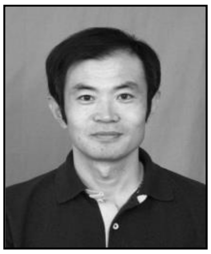

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