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Using the Hybrid Fuzzy Goal Programming Model and Hybrid Genetic Algorithm to Solve a Multi-Objective Location Routing Problem for Infectious Waste Disposal

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Abstract:

Purpose: Disposal of infectious waste remains one of the most serious problems in the social and environmental domains of almost every nation. Selection of new suitable locations and finding the optimal set of transport routes to transport infectious waste, namely location routing problem for infectious waste disposal, is one of the major problems in hazardous waste management.

Design/methodology/approach: Case study, which involves forty hospitals and three candidate municipalities in sub-Northeastern Thailand, is divided into two phases. The first phase is to choose suitable municipalities using hybrid fuzzy goal programming model which hybridizes the fuzzy analytic hierarchy process and fuzzy goal programming. The second phase is to find the optimal routes for each selected municipality using hybrid genetic algorithm which hybridizes the genetic algorithm and local searches including 2-Opt-move, Insertion-move and λ-interchange-move.

Findings: The results indicate that the hybrid fuzzy goal programming model can guide the selection of new suitable municipalities, and the hybrid genetic algorithm can provide the optimal routes for a fleet of vehicles effectively.

Originality/value: The novelty of the proposed methodologies, hybrid fuzzy goal programming model, is the simultaneous combination of criteria in order to choose new suitable locations, and the hybrid genetic algorithm can be used to determine the optimal routes which provide a minimum number of vehicles and minimum transportation cost under the actual situation, efficiently.

Keywords: multi-objective facility location problem, fuzzy analytic hierarchy process; fuzzy goal programming model, hybrid genetic algorithm, infectious waste disposal, multi-criteria decision making, location routing problem

1. Introduction

Health-care waste management, including collection, transportation, treatment and disposal, is a very important issue as far as the hospital environment and public is concerned. Improper waste management will cause environmental pollution, unpleasant smells and growth and multiplication of insects, rodents and worms, and may lead to transmission of diseases like typhoid, cholera, and hepatitis through injuries from sharps contaminated with human blood (Abdulla, Abu Qdais & Rabi, 2008). Infectious waste material is one of the hazardous wastes generated at health-care facilities. The collection, transportation, treatment and disposal of infectious waste can cause substantial harm to human health and safety or to the environment when improperly handled (Hansakul, Pitaksanurat, Srisatit & Surit, 2010; Miyazaki & Une, 2005). Selecting locations for the construction of disposal facilities and finding the optimal set of routes for infectious waste disposal are the important steps for pollution control, minimizing environmental hazards and minimizing costs. Infectious waste management remains one of the major problems in the hazardous waste management in Thailand. The government is aware of this problem, and has set policies to manage this waste more effectively. Infectious waste management problems are often found, such as illegal dumping, delayed collection and delayed disposal because the existing incinerators are insufficient to meet demands. Although, in the past, many public hospitals had their own incinerators to dispose of their infectious waste, because of environmental concerns and protests by local residents and hospital staff members, these incinerators inside the hospitals have been shut down. Hence, these hospitals eventually require services from outside agencies. However, there are three serious problems which are often found from using the services of outside agencies. First, the existing outside agencies cannot dispose of all existing infectious waste. Second, waste collection by outside agencies can be delayed, which does not meet the requirements of hospitals. Finally, transporting infectious waste from public hospitals does not meet the regulatory requirements for safety, such as the illegal dumping and illegal disposal in inappropriate places. Hence the Thai government has set up a policy to encourage the construction of new disposal facilities at areas of potential municipalities, in order to address the abovementioned problems and increase the efficiency of infectious waste disposal. These disposal facilities must be able to serve nearby hospitals and at the same time must reduce economic, environmental, health, and social factors. In order to achieve maximum benefit, new disposal facilities need to be planned along with suitable transport routes which provide the lowest transportation cost in accordance with the due date time. Therefore, building new, suitable, disposal facilities and finding the transport routes for infectious waste disposal more effectively is becoming an issue that is particularly important to consider.

Community hospitals, with forty hospitals in sub-Northeastern Thailand, are one type of public hospital that has often found the abovementioned problems, because they are far from the existing disposal facilities of outside agencies. To address such problems, the government has set policies to locate the new sites for infectious waste disposal at areas of potential municipalities. Selecting new suitable sites in this case is a complex problem which is difficult to address using any existing techniques alone, because there are relevant factors which must be considered, including infrastructure, geological, environmental, social and cost factors. Certainly, all factors must be considered simultaneously in designing an optimal transportation network. Finally, in order to achieve maximum benefit, we need to find suitable transport routes which provide minimum transportation cost for each selected municipality.

From the literature reviewed and due to the complexity of this issue, the solution approach for the location routing problem (LRP) for infectious waste disposal consists of the following stages: (i) suitable municipalities are first selected by combining the fuzzy analytic hierarchy process (FAHP) and the fuzzy goal programming model (FGP model), namely the hybrid fuzzy goal programming model (HFGP), and (ii) the vehicle routing problem (VRP) based on the selected municipalities sequentially. Firstly, selecting new, suitable municipalities for infectious waste disposal is an issue with many relevant factors (both tangible and intangible) that need to be considered simultaneously. The facility location problem (FLP) in this case is one of the multi-criteria decision making problems (MCDM problems), namely the multi-criteria/objective facility location problem (MCFLP/MOFLP). This problem is a complex problem which is difficult to solve and interpret. Using only one tool may not be sufficient to solve this problem. From the literature reviewed, FAHP is a powerful tool to solve multi-attribute decision making (MADM) problems which are difficult to interpret, and the FGP model is a suitable tool to solve multi-fuzzy objective problems. Hence, combining FAHP and FGP models should make a suitable model to solve location selection in this case, in order to maximize total priority weight and total cost. Finally, after obtaining the new suitable municipalities from the HFGP model, finding the vehicle trips for each selected municipality is one of the vehicle routing problems (VRPs). The VRPs belong to an NP-Hard problem in combinatorial optimization which is hard to solve by exact solution techniques. Hence, the

Genetic algorithm (GA) is one of various meta-heuristic algorithms which are often used to solve the VRPs in the literature because it is a simple, flexible and powerful algorithm to solve NP-hard problems. However, in order to increase the efficiency of this algorithm, a new hybrid genetic algorithm (hybrid GA) is developed to solve the VRP in this case study, instead of the traditional GA. The major difference between the traditional GA and the hybrid GA in this case is that three local searches (2-Opt-move, Insertion-move and λ-interchange-move) are added to increase the efficiency of the algorithm. This is the major reason why hybrid GA is chosen as a suitable algorithm for solving the VRP in this paper.

The rest of the paper is organized as follows. Sections 2, 3 and 4 are Literature review, Methodology and Application of the proposed methodology respectively, and finally, Section 5 is the Conclusion.

2. Literature Review

The facility location problem (FLP) has been studied for over one hundred years. Even though it is old, applications of these models to real world problems are getting more attractive. The FLP is a classic problem, originating from Pierre de Fermat, Evagelistica Torricelli, and Battista Cavallieri (Drezner & Hamacher, 2004). However, it is formally accepted by all scientists that Alfred Weber's book is the most important historic origin of location science (Farahani, SteadieSeifi & Asgari, 2010). Traditional FLP is a single objective/criterion problem, and objectives that are usually considered in location problems can be different. These objectives can be as follows: minimizing the longest distance from the existing facilities, minimizing the total setup cost (Vasko & Wilson, 1986), minimizing the tour total cost (Gendreau, Laporte & Semet, 1997), minimizing the total cost (Nozick, 2001) and minimizing the number of located facilities (Toregas, Swain, ReVelle & Bergman, 1971). Although facility location theory has a long history in single objective/criterion problems, it seems that since the origin of multi-criteria decision making theory (MCDM theory) in management sciences, this theory has been applied in the real word problems of location selection. The MCDM problems are divided into multi-attribute decision making (MADM) and multi-objective decision making (MODM) problems. In the MADM problem there is a limited number of predetermined alternatives and a single goal/objective. MADM aims to select the best from the predetermined alternatives. There are several common tools which are used to tackle the MADM problems, such as simple additive weighting (SAW), hierarchical additive weighting, elimination and choice expressing reality (ELECTRE), technique for order preference by similarity to an ideal solution (TOPSIS), analytical hierarchy process (AHP) and data envelopment analysis (DEA) (Kuo, Yang & Huang, 2008). One tool often suggested for solving MADM problems is AHP (Majumdar, Mangla & Gupta, 2010), because it is a flexible and powerful tool for handling both qualitative and quantitative data (Ünal & Güner, 2009). Since the traditional AHP still cannot reflect the human thinking style, the fuzzy analytic hierarchy process (FAHP) based on the fuzzy set theory of Zadeh (1965a) was developed in order to overcome this weak point for solving fuzzy problems (Kahraman, Cebeci & Ruan, 2004). Nowadays this tool is widely used for solving MADM problems instead of traditional AHP as shown in literature (Shaverdi, Ramezani, Tahmasebi & Rostamy, 2016; Verma & Chaudhri, 2014; Wang, Lestari & Tran, 2017). Since the MADM tools alone cannot handle the multi-existing environmental restrictions of the MODM problems, such as selecting the locations for hazardous waste disposal, choosing the plants for nuclear power and choosing the suitable locations for infectious waste disposal, a group of researchers have taken MADM tools combined with mathematical techniques in order to simultaneously deal with environmental restrictions. Goal programming (GP), proposed by Charnes, Cooper and Ferguson (1955), has been often combined with the MADM tools for solving MODM problems in the literature (Badri, 1999; Blake & Carter, 2002; Fang & Li, 2015; Karsak, Sozer & Alptekin, 2003; Kengpol, Tuammee & Tuominen, 2014). However, in practice, determining exactly the target value of each goal is difficult for decision makers; a decision maker does not have sufficient information related to the different goals. To overcome the weakness, the fuzzy set theory initially introduced by Zadeh (1965b) has been applied to MODM problems with imprecise data. Zimmermann (1976) and Zimmermann (1978) proposed the fuzzy set theory to a linear programming (LP) problem with single and multiple objectives. Narasimhan (1980) first proposed fuzzy set theory to GP, namely the fuzzy goal programming (FGP) model, to specify imprecise aspiration levels of each fuzzy goal. This research first considers a symmetrical FGP model, having equal important weights for each objective. Later, Hannan (1981) simplified the Narasimhan approach by using the interpolated membership functions, and then this model could be solved using the LP. Because various problems in the real world often have different levels of each objective, the solution approach is extended to the case of asymmetrical FGP, having unequal important weights for each goal. Although several asymmetrical FGP models (Lin, 2004; Tiwari, Dharmar & Rao, 1987; Yaghoobi & Tamiz, 2007; Yücel & Güneri, 2011) have been proposed in the literature, the weighted max-min model based on Lin (2004) was developed to solve asymmetrical FGP problems effectively; this model can properly reflect the views of experts, unlike other methods (Amid, Ghodsypour & O'Brien, 2011). Therefore, in this paper, a weighted FGP model based on the max-min FGP model of Lin (2004) has been developed for solving the new MOFLP model for infectious waste disposal in this case study, by taking the priority weights of each candidate municipality into this weighted max-min FGP model. This new fuzzy model enables decision makers not only to consider the imprecision of information but also to take the limitations of available resources into account in calculating new suitable municipalities for infectious waste disposal from each candidate municipality, unlike the traditional FLPs. For this reason, selecting this fuzzy model will enhance the confidence of decision makers for choosing the suitable locations for infectious waste disposal.

The vehicle routing problem (VRP) consists of determining a set of vehicle trips, including customers, a single depot and routes. Each vehicle trip starts and ends at the same depot with known location and capacity, each customer with known location and demands is assigned to exactly one vehicle, and any vehicle cannot carry over its capacity. Each vehicle may also be limited in the total distance (maximum allowed distance). The objective is to determine a set of vehicle routes for each vehicle that will often minimize the total distance/transportation cost. The basic models of VRP were proposed in papers of Dantzig and Ramser (1959) and Clarke and Wright in (1964). Later, the VRP has been very extensively studied in literature because of its wide applicability and its importance to many real world situations for reducing operational costs in transportation networks. The VRP is extended with variants for each problem such as VRP with time windows (Anghinolfi, Paolucci & Tonelli, 2016), VRP with pick-up and delivery (Tasan & Gen, 2012), VRP with backhauls (Brandão, 2006), VRP with multi-depot (Zhang, Zhong, Liu & Wang, 2014) and VRP with multi-objective (Alexiou & Katsavounis, 2015). These VRP models are known to be the NP-hard problems (Meryem & Abdelmadjid, 2015; Narasimha, Kivelevitch, Sharma & Kumar, 2013), and it is difficult to solve large NP-hard problems by exact solution techniques. Hence, when the problems become too large for exact solution techniques, recent meta-heuristic techniques (Montané & Galvão, 2006; Baker & Ayechew, 2003; Goksal, Karaoglan & Altiparmak, 2013; Liu, Xie, Augusto & Rodriguez, 2013; Nagy & Salhi, 2005) are often used for solving various VRP models. However, there are no meta-heuristic techniques to confirm which is best, depending on the variant of each problem and individual preference. The genetic algorithm (GA) is one of the meta-heuristic techniques which is often employed to solve the various VRPs in the literature (Baker & Ayechew, 2003; Potvin, Duhamel & Guertin, 1996) because this algorithm is easy to understand, has great flexibility and is applicable to many kinds of real world problems (Ho, Ho, Ji & Lau, 2008). However, in order to improve the solution efficiency, nowadays the GA technique is often integrated with other tools/techniques for dealing with various VRPs. The various new algorithms of hybrid genetic algorithm (hybrid GA) (Jeon, Leep & Shim, 2007; Shi, Boudouh & Grunder, 2017; Vidal, Crainic, Gendreau, Lahrichi & Rei, 2012) have been continuously developed for solving real world VRPs, depending on the preferences and expertise of each researcher. Hence, combining GA with other tools/techniques, namely hybrid GA, is one of the most popular techniques for solving VRPs in literature, which is appropriate and adequate for solving the VRPs in this case study. This is the major reason why hybrid GA was chosen as an appropriate technique in this paper.

3. Methodology

The solution approach for this case consists of the following stages. (i) The first phase of this research is to select suitable municipalities for infectious waste disposal from candidate municipalities, for which location selection in this case is a complex problem, a multi-objective facility problem. The HFGP model is formed in the first phase by combining FAHP and FGP models in order to achieve the lowest total cost and maximum total priority weight. (ii) After that, the VRP model and hybrid GA are used in the second phase in order to achieve the lowest transportation cost/minimum total distance by using the optimization techniques with LINGO13 and Visual studio 2015 (C++) respectively.

The details of selecting the new suitable municipalities and finding the suitable transport routes for minimizing transportation cost/minimizing total distance are as follows:

- Define the most important criteria for selection of locations for infectious waste disposal,
- Evaluate the global priority weights for each candidate municipality using FAHP,
- Formulate and compute a HFGP model,
- Select the new suitable municipalities for infectious waste disposal.
- Build and compute the VRP model using an optimization technique (LINGO13) and meta-heuristic technique with Visual studio 2015 (hybrid GA with C++), and
- Select the optimal routes for each selected municipality.

The first step is to define the most important criteria for selection of locations for infectious waste disposal, and determining candidate municipalities is considered by using legislation, regulations and expertise. After that, these important criteria and candidate locations are decomposed into a multi-level hierarchical structure. The second step is to evaluate the priority weights of elements in the proposed hierarchical structure using FAHP. The third step is to formulate and compute the HFGP model which takes the weights of candidate municipalities into this model for extension to consider needed criteria for this problem. The fourth step is to choose the suitable municipalities from results of the HFGP model. Another step is to build and compute the VRP model using LINGO13 and hybrid GA, and then the proposed hybrid GA is used to solve the VRP model for a large size problem in this case. The final step is to choose the optimal routes for each selected municipality from results of the proposed hybrid GA.

3.1. FAHP

From the literature reviewed, FAHP is a flexible and powerful tool to solve MADM problems. Hence, using FAHP should make a suitable approach to evaluate the global priority weights of each candidate municipality, in order to take these weights into a HFGP model in Section 3.2. In this paper, we calculated the priorities weights of elements in each level of hierichy via the geometric means method of Buckley (1985) and Buckley, Feuring and Hayashi (2001); see also in similar papers of Cebeci (2009) and Meixner (2009). In this paper, the fuzzy arithmetic operations on triangular fuzzy numbers (TFNs) can be expressed as follows:

$$\text{Addition: } F_1 \oplus F_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (1)$$

$$\text{Multiplication: } F_1 \otimes F_2 = (l_1 \cdot l_2, m_1 \cdot m_2 \cdot m_2, u_1 \cdot u_2) \quad (2)$$

$$\text{Division: } F_1 \,/\, F_2 = (l_1 / u_2, m_1 / m_2, u_1 / l_2) \quad (3)$$

$$\text{Reciprocal: } F_1^{-1} = (1/u_1, 1/m_1, 1/l_1) \quad (4)$$

where l_1 and l_2 are the least possible value; m_1 and m_2 are modal value and u_1 and u_2 are highest possible value respectively. F_1 and F_2 are two TFNs; TFNs will be applied in order to compare a priority scale between criteria/elements as shown in Table 1.

TFNs	Definition
(1,1,1)	Equal importance
(2,3,4)	Moderate importance
(4,5,6)	Strong importance
(6,7,8)	Very strong importance
(8,9,9)	Extreme importance
$\tilde{2},\tilde{4},\tilde{6},\tilde{8}$	Intermediate values between the two adjacent judgments

Table 1. The 9 - point scale of TFNs

The steps of the FAHP are as follows.

3.1.1. Construct the Hierarchy

The relevant decision factors can be defined by asking questions to experts questions about which criterion is more important with regard to the goal. After that, these factors are decomposed into a multi-level hierarchical structure, as shown in Figure 1. At level "0", the goal is to select new suitable municipalities for infectious waste disposal. At level "1", the criteria are C_1, C_2, C_3, at level "2", the sub-criteria are SC_{11}, SC_{12}, ..., C_{34}, and at level "3", the candidate municipalities are L_1, L_2 and L_3.

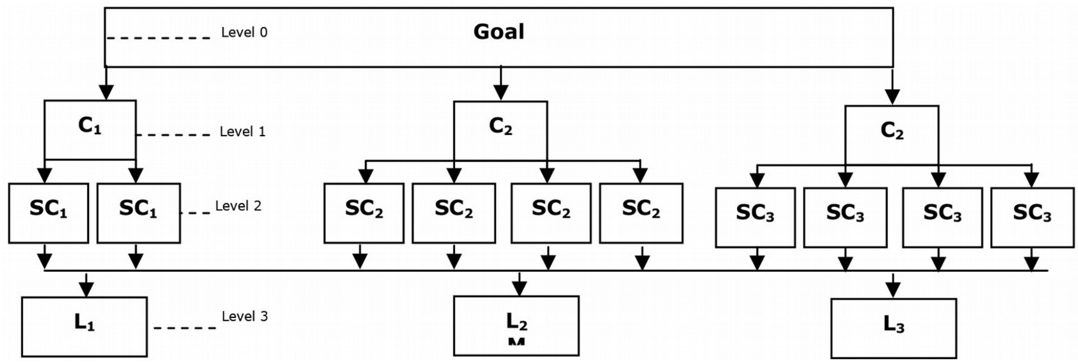

Figure 1. Multi-level hierarchy for selecting locations for infectious waste disposal

3.1.2. Construct the Comparison Matrices of Each Decision Maker

The comparison matrices of each decision maker *k* can be constructed using TFNs in Table 1. After that, integrating the comparison matrices from all experts using the fuzzy geometric mean method (Dong & Cooper, 2016; Meixner, 2009; Wichapa & Khokhajaikiat, 2017) is as shown in Equation (5).

$$\widetilde{A} = (\prod_{i=1}^{K} \widetilde{a}_{ijk})^{1/K} \tag{5}$$

Where $\widetilde{A}$ is a aggregated comparison matrix of *k* decision makers, and $\widetilde{a}_{ijk} = (l_{ijk}, m_{ijk}, u_{ijk})$ is the triangular fuzzy numbers of the k^{th} decision maker.

3.1.3. Estimate Priority Weights of Each Level

The priority weights of each level will be estimate by the geometric means method of Buckley (1985) and Buckley et al. (2001) where:

$$\widetilde{r}_i = (\prod_{j=1}^{n} p_{ij})^{1/n} \tag{6}$$

And

$$\widetilde{w}_i = \widetilde{r}_i \otimes (\sum_{i=1}^{n} \widetilde{r}_i)^{-1} \qquad , i = 1, 2, ..., n \tag{7}$$

The fuzzy priority weights have to be defuzzified, which can be converted to crisp priority weights using Equation (8) (Meixner, 2009; Tsaur, Chang & Yen, 2002).

$$df\widetilde{a}_{ij} = \lfloor (u_{ij} - l_{ij}) + (m_{ij} - l_{ij}) \rfloor / 3 + l_{ij} \quad \forall i, \forall j \tag{8}$$

3.1.4. Check for Consistency Ratio (CR) Values

1. Defuzzify aggregated comparison matrix and then multiply the crisp comparison matrix by the crisp priority weight vector.
2. Divide the weighted sum vector with criterion weight in step 1; average weighted sums ($\overline{w}_i$) will be obtained for each row *i* for the calculation in this step.
3. Compute λ_{max} by Equation (9).

$$\lambda_{\max} = \sum_{i=1}^{n} \overline{w}_i / n \tag{9}$$

4. Compute the consistency index (CI) and CR by Equation (10).

$$CI = (\lambda_{max} - n)/(n - 1) \text{ and } CR = CI/RI \leq 0.10 \tag{10}$$

A *CR* value of 0.10 or less is accepted as a good consistency measure. If the value exceeds 0.10, it is indicative of inconsistent judgment, and it should be revised as shown in related papers of researchers (Cebeci, 2009; Meixner, 2009; Wichapa & Khokhajaikiat, 2017).

3.1.5. Compute the Final Priority Weights for Each Alternative

The priority weight of each alternative is multiplied by the sub-criteria weights and aggregated to get local priority weights with respect to each criterion. The local priority weights are then multiplied by the criteria weights and aggregated to get global priority weights/location weights. The best alternative/location is the maximum value of the global priority weights, and the value of a high location weight means that it is better than a low location weight.

3.2. HFGP Model

The multi-objective facility location problem model (MOFLP model) for infectious waste disposal is formulated to select multi-size incinerators and multiple municipalities. In addition, this model is formulated to respond to two objectives, minimize total cost and maximize total priority weight. Details of the mathematical model of this problem are shown below.

Indices:

i is the index of each municipality, $I = 1,2,..,m$, ($m = 3$).

j is the index of each hospital, $j = 1,2,..,n$, ($n = 40$).

k is the size of each incinerator, $k = 1,..,K$, ($K = 2$).

Parameters:

f_k is the facility cost (baht/week).

o_k is the operating cost (baht/ week).

c_{ij} is the transportation cost between municipality i and hospital j (baht/week)

dt_{ij} is the real distance between municipality i and hospital j (km).

u is the unit transportation cost (baht/km).

s_k is the size of each incinerator i.

d_j is the demand of hospital j (kg/week).

w_i is the global priority weights of municipality i.

DT is the maximum allowable distance.

Decision variables:

X_{ij} is a binary decision variable; $X_{ij} = 1$ if the hospital j is served by the municipality I, $X_{ij} = 0$ otherwise.

Y_i is a non-negative integer decision variable; $Y_i = 1$ if municipality i is opened, $Y_i = 0$ otherwise.

Z_{ik} is a binary decision variable; $Z_{ik} = 1$ if the municipality i is opened by selecting incinerator k, $Z_{ik} = 0$ otherwise.

Objective function:

$$Min.G_1 = \sum_{i=1}^{m}\sum_{k=1}^{K} f_k \cdot Z_{i,k} + \sum_{i=1}^{m}\sum_{k=1}^{K} o_k \cdot Z_{i,k} + \sum_{i=1}^{m}\sum_{j=1}^{n} u \cdot dt_{ij} X_{ij} \tag{11}$$

$$Max.G_2 = \sum_{i=1}^{m} w_i Y_i \tag{12}$$

Subject to:

$$\sum_{i=1}^{m} X_{ij} = 1 \qquad \forall j \quad (j = 1,2,..,n) \tag{13}$$

$$\sum_{j=1}^{n} d_j \cdot X_{ij} \le \sum_{k=1}^{K} s_k \cdot Z_{ik} \qquad \forall i \quad (i = 1....m) \tag{14}$$

$$\sum_{i=1}^{m}\sum_{k=1}^{K} s_k \cdot Z_{i,k} \ge \sum_{j=1}^{n} d_j \tag{15}$$

$$\sum_{k=1}^{K} Z_{ik} = Y_i \qquad \forall i \quad (i = 1....m) \tag{16}$$

$$dt_{ij} \cdot X_{ij} \le DT \quad \forall i \ (i = 1 ....m) \quad \forall j \ (i = 1 ....n) \tag{17}$$

$$X_{ij} \in \{0,1\} \tag{18}$$

$$Y_i \in \{0,1\} \tag{19}$$

$$Z_{i,k} \in \{0,1\} \tag{20}$$

In this paper, the first objective function of the MOFLP model is to minimize total cost as shown in Equation (11), and the second objective function is to maximize total location weight as shown in Equation (12). Equation (13) ensures that the demand of each hospital j is fulfilled. Equation (14) expresses that the service prepared by a site cannot exceed its capacity. Equation (15) expresses that the sum of the service provided by sites cannot exceed the sum of its capacities and Equation (16), the selected municipalities must use only k-size incinerators. Equation (17) expresses that each travel distance from point i to point j cannot exceed the maximum acceptable distance. Equations (18), (19) and (20) are binary.

In this case study, the target value associated with each goal could be fuzzy, and both goal 1 (G_1) and goal 2 (G_2) might not be completed simultaneously under the system constraints. In order to address this problem, based on Zimmermann (1978), he expressed objective functions G_j, $j = 1, 2..q$ by fuzzy sets whose membership functions increase linearly from 0 to 1. In this approach, the membership function of objectives is formulated by separating each objective function into its maximum and minimum values. The linear membership functions for minimization (G_k) and maximization goals (G_l) are given as follows:

$$\mu_{G_k} = \begin{cases} 1 & for\, G_k(x) \le G_k^- \\ f_{\mu_{G_k}} = (G_k^+ - G_k(x))/(G_k^+ - G_k^-) & for\, G_k^- \le G_k(x) \le G_k^+ \\ 0 & for\, G_k(x) \ge G_k^+ \end{cases} \tag{21}$$

$$\mu_{G_l} = \begin{cases} 1 & for\ G_l(x) \ge G_l^+ \\ f_{\mu_{G_l}} = (G_l(x) - G_k^-)/(G_l^+ - G_l^-) & for\ G_l^- \le G_l(x) \le G_l^+ \\ 0 & for\ G_l(x) \le G_l^- \end{cases} \tag{22}$$

G_k^- and G_l^+ are ideal solutions, minimum values of goal G_k and maximum value of goal G_l respectively. G_k^+ and G_l are non-ideal solutions, the maximum value of goal G_k and the minimum value of goal G_l respectively. Linear membership functions $\mu(G_j(x))$ are shown in Figure 2.

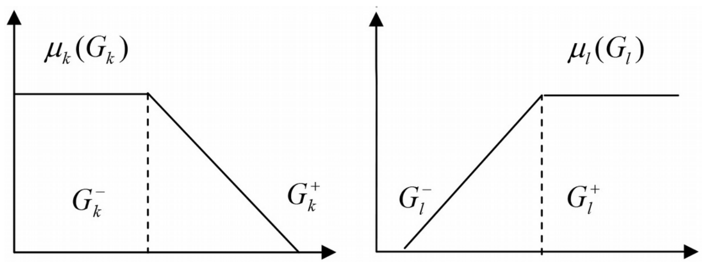

Figure 2. Objective function as fuzzy numbers of min G_k and max G_l

The target of two objectives of the multi-objective facility location problem model for location selection for infectious disposal is fuzzy values, and these objectives can be written for fuzzy goal programming (FGP) as follows:

$$\sum_{i=1}^{m}\sum_{k=1}^{K} f_k \cdot Z_{i,k} + \sum_{i=1}^{m}\sum_{k=1}^{K} o_k \cdot Z_{i,k} + \sum_{i=1}^{m}\sum_{j=1}^{n} u \cdot dt_{ij} X_{ij} \mathrel{\tilde{\leqq}} G_1^0 \tag{23}$$

$$\sum_{i=1}^{m} w_i Y_i \mathrel{\tilde{\geqq}} G_2^0 \tag{24}$$

where $G_1^0(G_1^-)$ and $G_2^0(G_2^+)$ are the aspiration levels of objectives 1 and 2 respectively which DMs want to reach. The symbol $\tilde{\leqq}$ in the constraints set denotes the fuzzified version of $\leq$ and the symbol $\tilde{\geqq}$ in the constraints set denotes the fuzzified version of $\geq$. In order to solve this fuzzy problem, Based on the FGP of Lin (2004), the model is a powerful tool to solve weighted FGP which differs from the other FGP models, the multi-objective facility location problem model in this case can be converted to the HFGP model as follows:

Objective function:

$$Max\ G = \lambda \tag{25}$$

Subject to:

$$w_{G1}\lambda \leq (\max G_1 - G_1)/(\max G_1 - min\ G_1) \tag{26}$$

$$w_{G2}\lambda \leq (G_2 - min\ G_2)/(\max G_2 - min\ G_2) \tag{27}$$

$$a_r x \begin{pmatrix} \leq \\ = \\ \geq \end{pmatrix} b_r \quad r = 1,2,3,\ldots, R \ \ (\text{for system constraint s}) \tag{28}$$

$$\sum_{i=1}^{2} w_{Gi} = 1, w_{Gi} \geq 0 \tag{29}$$

where Equation (25) is an objective function as maximization of the lambda value. Equations (26) and (27) are fuzzy objective constraints. Equation (28) gives system constraints, which refers to Equations (13)-(20) of the MOFLP model. In Equation (29), w_{Gi} are priority weights of each goal according to experts' opinions. The optimal solution of the HFGP model can be solved by LINGO 13.

3.3. VRP Model for Infectious Waste Disposal

After obtaining the suitable municipalities from computing the HFGP model in Section 3.1, the municipalities that have been selected as disposal centers for infectious waste disposal must be assigned the best routes to achieve the lowest total distance. Details of the VRP model are as follows.

Indices:

The VRP model for infectious waste disposal may be defined as the following graph theoretic problem. Let $G = (N, A)$ be a complete graph where $N = \{1, 2, 3, \ldots, n\}$ is a set of hospitals and municipality. A is the arc set, pair of nodes (i, j). N=2, 3, 4, …, n is a set of hospitals, whereas $N = 1$ is a selected municipality/a single depot. K is a set of identical vehicles, which is available at the municipality.

Parameters:

dt_{ij} is actual distance from node i to j (km) that is symmetrical ($dt_{ij} = dt_{ji}$)

K is a set of identical vehicles, $K = \{1, 2, 3, \ldots, k\}$.

N is a set of hospitals and municipalities, $N = \{1, 2, 3, ..., n\}$.

q_k is the capacity of each vehicle k (kg).

d_j is the amount of waste collected from hospital j (kg).

t_{ij} is the travel time from node i to j (min.) that is symmetrical ($t_{ij} = t_{ji}$).

D is the maximum permitted travel time per vehicle (min.). Each vehicle travels from node i to j at a speed of 60 kilometers per hour ($t_{ij} = dt_{ij}$).

Decision variables:

X_{ijk} =1, if vehicle k drives from hospital i to j, $X_{ijk} = 0$, otherwise.

Z_k =1, if vehicle k is used to service hospitals, $Z_k = 0$ otherwise.

Objective function:

$$Min \quad z = \sum_{i \in N} \sum_{j \in N} \sum_{k=1}^{K} dt_{ij} X_{ijk} \tag{30}$$

Constraints:

$$\sum_{i \in N} \sum_{j \in N, i \neq j} X_{ijk} \leq N Z_k \qquad \forall k \in K \tag{31}$$

$$\sum_{j \in N, i \neq j} X_{1jk} \leq 1 \qquad \forall k \in K \tag{32}$$

$$\sum_{i \in N, i \neq j} X_{i1k} \leq 1 \qquad \forall k \in K \tag{33}$$

$$\sum_{i \in N} X_{ipk} - \sum_{j \in N, i \neq j} X_{ipk} = 0 \qquad \forall p, p \in N, \forall k \in K \tag{34}$$

$$\sum_{k \in K} \sum_{i \in N, i \neq j} X_{ijk} = 1 \qquad \forall j \in N \tag{35}$$

$$\sum_{k \in K} \sum_{j \in N, i \neq j} X_{ijk} = 1 \qquad \forall i \in N \tag{36}$$

$$\sum_{i \in N} \sum_{j \in N, i \neq j} d_j X_{ijk} \leq q_k \qquad \forall k \in K \tag{37}$$

$$\sum_{i \in N} \sum_{j \in N, i \neq j} t_{ij} X_{ijk} \leq D \qquad \forall k \in K \tag{38}$$

$$X_{ijk} \in \{0, 1\} \qquad \forall i \in \boldsymbol{N},\ \forall j \in \boldsymbol{N},\ \forall k \in \boldsymbol{K} \tag{39}$$

$$Z_k \in \{0, 1\} \tag{40}$$

$$Y_i - Y_j + N \cdot X_{ijk} \leq N - 1 \quad \forall i = 2, 3, 4, \ldots, n; \forall j \in = 2, 3, 4, \ldots, n; i \neq j;\ \forall k \in K \tag{41}$$

The objective is to minimize the total distance, as shown in Equation (30). Equation (31) guarantees that the number of arcs from node i and node j does not exceed n nodes. Equation (32) and Equation (33) guarantee that a vehicle must start at a selected municipality to hospitals only once. Equation (34) guarantees that if a vehicle visits a hospital j, it also leaves that hospital j. Equations (35) and (36) guarantee that all hospitals are visited only once. Equation (37) guarantees that the amount of infectious waste of each hospital will be fulfilled by vehicles k but does not exceed the capacity of the vehicle itself. Equation (38) ensures that every vehicle k cannot travel more than the tour length restriction. Equation (39) and Equation (40) guarantee the decision variables x_{ijk} and z_k to be binary decision variables. Equation (41) guarantees that there will be no sub tours.

In this case study, hybrid GA will be used to solve the VRP model for infectious waste disposal in this case as shown in the next section.

3.4. Hybrid GA

Genetic algorithms (GA), which were firstly proposed by Holland (1992), are very easy to understand, have great flexibility and are applicable to many kinds of actual problems (Ho et al., 2008). GA is a stochastic and parallel search technique that imitates the principles of evolution and natural selection by using genetic operators (Li, 2011). The process of traditional GA usually starts with a randomly generated population of n chromosomes, called an initial population. According to the nature of VRPs, different positions in each chromosome are often encoded as numbers, and these positions are randomly changed within a range during evolution. The simplest form of GA involves three operators: selection, crossover and mutation. After obtaining population of size p, parents are randomly chosen from the current population for reproduction, on the basis of a value of probability distribution. Any chromosomes with fitter values (higher values of fitness function) are given more opportunities to reproduce by crossover and mutation. After the reproductive process, some parents and some offspring will be chosen to be the new generation in accordance with their fitness values, and by rejecting others to maintain the size of the population constant. After the number of generations is predetermined, the algorithm converges to the best chromosome, which is expected to be the best solution of the problem. GA performance depends on relevant parameters such as probability of crossover, probability of mutation, population size, repetition number, and algorithm.

A hybrid genetic algorithm (Hybrid GA), which integrates GA and three local searches (insertion-move, 2-opt-move and λ-interchange-move), was proposed to solve the VRP in this case. The first objective of the hybrid GA is to minimize the number of vehicles (NV) and the second objective is to minimize the total distance (TD), under the limits of existing resources. The algorithm is shown in Figure 3.

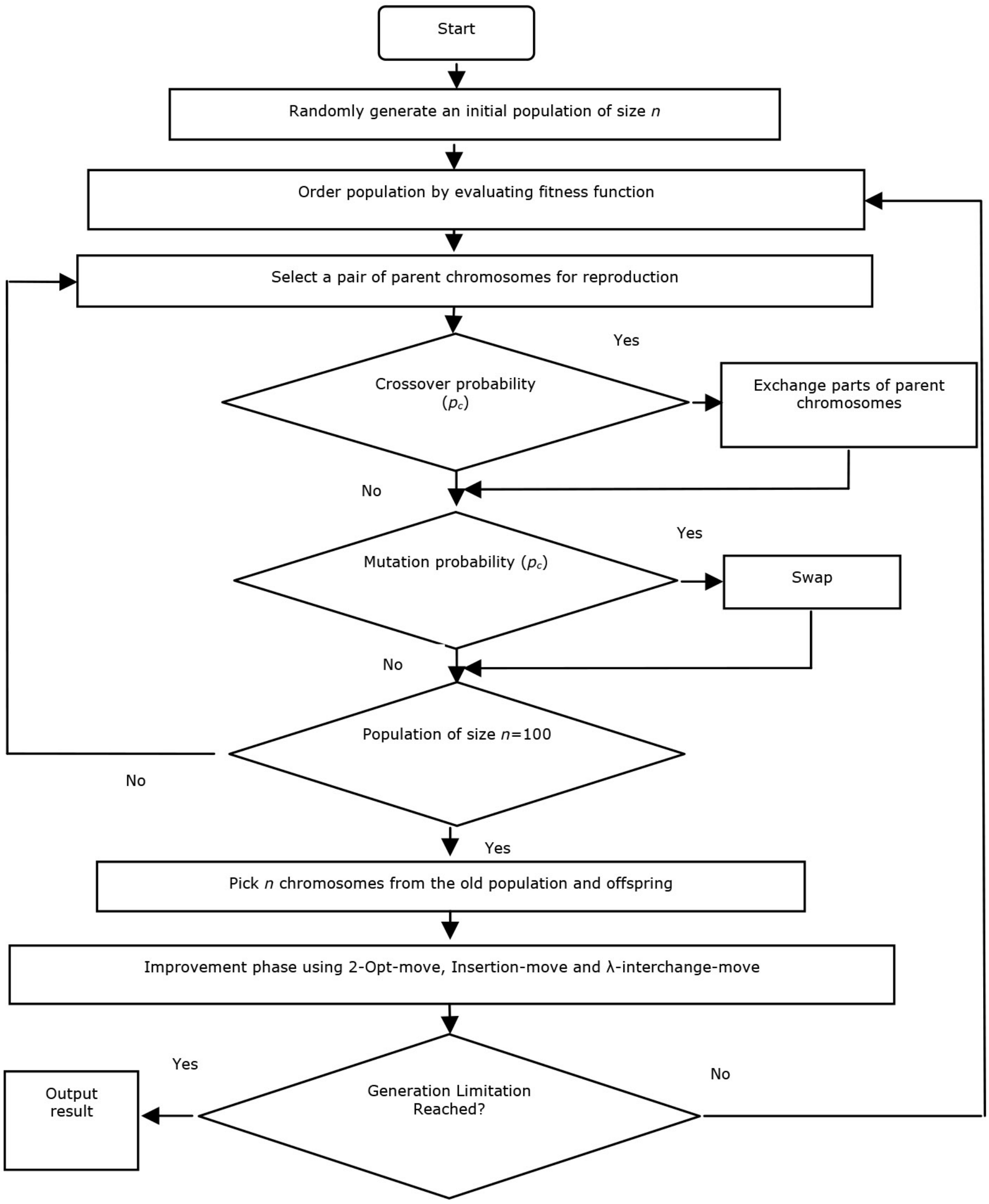

Figure 3. Flow chart of solution of VRP using hybrid GA

Figure 3 can be described as follows. Let *n* be the size of the population at each generation. An initial population will be randomly generated until the size is equal to *n*. After that, the chromosomes in the initial population are sorted by fitness, and then a pair of chromosomes is randomly chosen for mating using the ranking-based selection of Correa et al. (Correa, Steiner, Freitas & Carnieri, 2001), as shown in Equation (42).

$$Select\ (OS) = \left\{ S_p \in OS,\ p = P - \left[\frac{-1 + \sqrt{1 + 4 \bullet rnd\ (P^2 + P)}}{2} \right] \right\} \tag{42}$$

OS is an ordered list of solutions sorted by fitness.

P is the position in the OS to be selected as the chromosome *Sp*.

rnd (M) is a random distribution in the range 0 to *M*-1.

After that, with crossover probability (p_c), exchange parts of a pair of parents and create two offspring as shown in Figure 4.

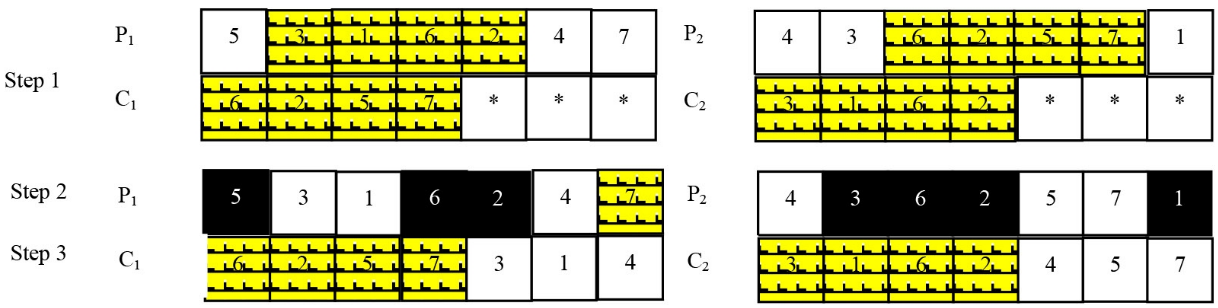

Figure 4. Crossover procedure

- Randomize indices *cut*1 and *cut*2, where *cut*1 < *cut*2
- Step 1: Copy hospitals in parent-1 (P1) from indices *cut*1 to *cut*2 to child-2 (C2) starting at index 0. Also hospitals in parent-2 (P2) from indices *cut*1 to *cut*2 to child-1 (C1) starting at index 0.
- Step 2: mask hospitals in P1 that already are contained in C1 and also mask hospitals in P2 that already are contained in C2.
- Step 3: fill hospitals that unmask in C1 to P1 and C2 to P2.

In the mutation procedure, with the mutation probability p_m, hospitals in the two offspring chromosomes will be randomly swapped as shown in Figure 5A. The mutation procedure is repeated until the size of the new population is equal to 100. After that, offspring and the old population (current population) will be combined and *n* chromosomes picked to be the new population using fitness. If a new chromosome is better than any chromosome in the current population, the new chromosome will be included and the worst one in the current population will be removed. Finally, the chromosomes in the new population will be improved by three local searches, insertion-move, 2-opt and λ-interexchange, as shown in Figure 5B, Figure 5C and Figure 5D respectively.

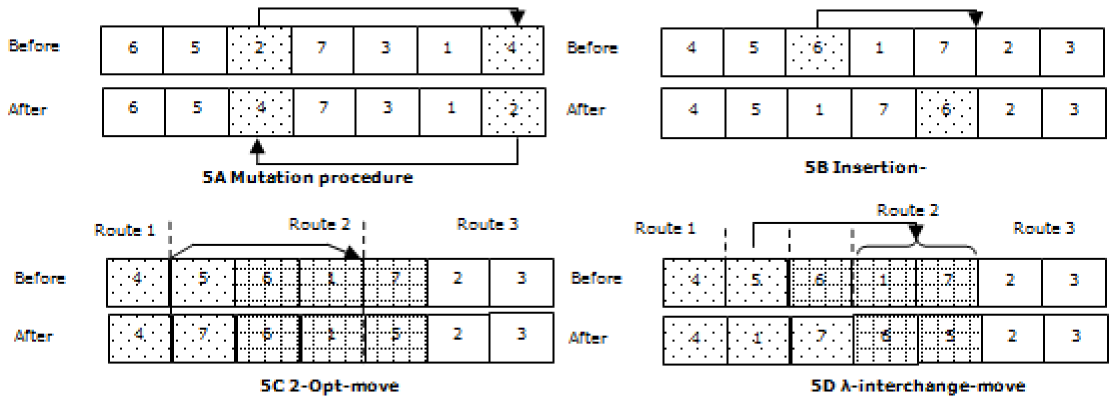

Figure 5. Mutation and three local searches (Insertion, 2-Opt and λ-interchange)

The selection is still a rank-based selection and selects chromosomes *n* times for each local search. This procedure is repeated until the stopping criteria are satisfied. Implementation and computational results of the hybrid GA are reported in the next section.

4. Application of the Proposed Methodology

In Section 3, the proposed methodology was used to identify the suitable locations and transport routes for a case study on the selection of a transportation network for infectious waste disposal in sub-Northeastern Thailand. There are three candidate municipalities, including Nong Bua Lam Phu Town Municipality (NLTM), Nong Khai Town Municipality (NKTM), and Loei Town Municipality (LTM). These candidates were extracted from legislation, regulation and expertise by experts. Therefore, the suitable municipalities were chosen from three candidate municipalities to serve the forty community hospitals, namely H1, H2, ..., H40 (see details in Figure 6), given the resource restrictions and preferences. The steps of the calculation are shown in Sections 4.1, 4.2 and 4.3.

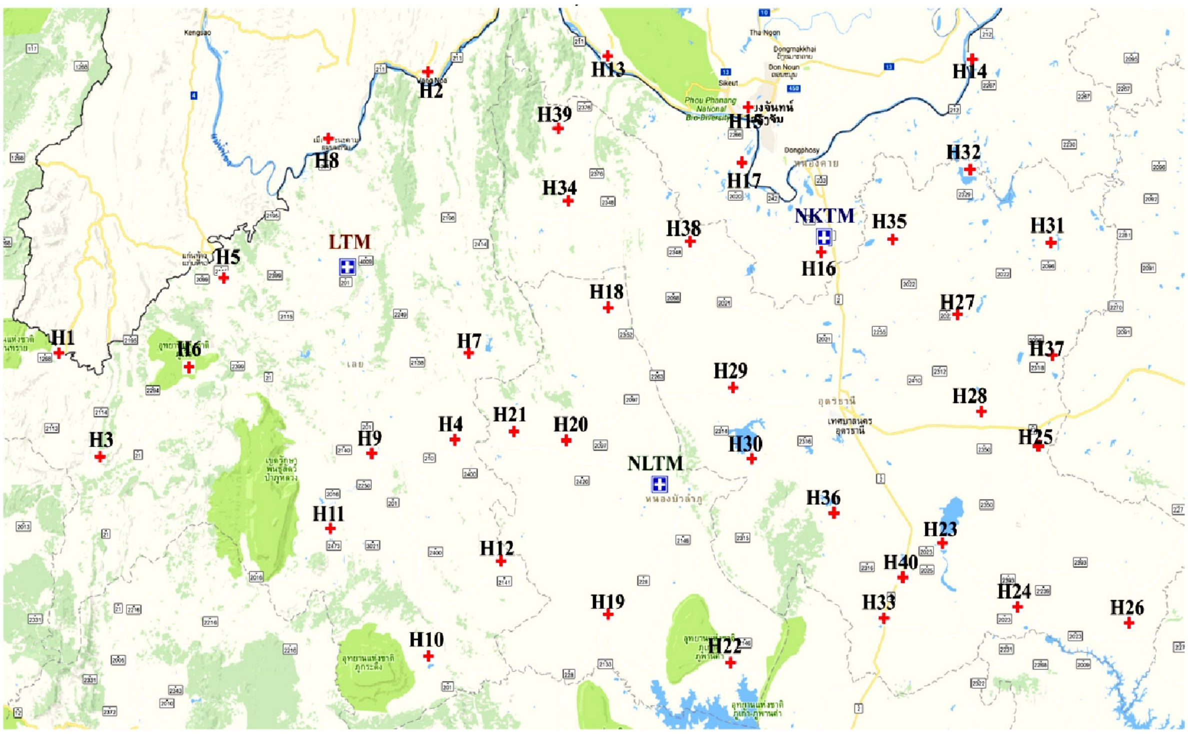

Figure 6. The transportation network of the candidate municipalities and hospitals

4.1. Estimate the Priority Weights of Municipalities Using FAHP

This section presents the steps to determine the priority weights of elements at each level. Firstly, a multi-level hierarchical structure was constructed by consulting six decision makers, who have worked in the field for more than fifteen years, and stakeholders (see Figure 1). In the hierarchy, level 0 was the goal, the new suitable municipalities for infectious waste disposal, and level 1 was three main criteria, infrastructure (C_1), geological (C_2) and environmental & social (C_3). Level 2 was ten sub-criteria, public utilities (SC_{11}), traffic (SC_{12}), area size (SC_{21}), features of area (SC_{22}), flooding in the past (SC_{23}), density of population (SC_{24}), municipal administrators (SC_{31}), ability of municipalities (SC_{32}), distance from communities (SC_{33}) and distance from public water resources (SC_{34}). Level 3 had three candidate municipalities, L_1 = NLTM, L_2 = NKTM and L_3 = LTM. Secondly, fuzzy comparison matrices were constructed from the six decision makers who have worked in the field for more than fifteen years using the 9- scale of FAHP (Table1), as shown in Table 2. Third, the fuzzy comparison matrices of the decision makers were aggregated into a FAHP combined matrix ($\widetilde{A}$) using Equation (5), and the priority weights of level 1 were estimated using Equations (6-10), shown in Table 3. In level 2 and level 3 were estimated in the same way as the first level 1. Finally, the global priority weights were computed, as shown in Table 4.

Goal	C_1	C_2	C_3
C_1	(1.00, 1.00, 1.00), (1.00, 1.00, 1.00), (1.00, 1.00, 1.00), (1.00, 1.00, 1.00) (1.00, 1.00, 1.00), (1.00, 1.00, 1.00)	(0.25, 0.33, 0.50), (0.17, 0.20, 0.25), (1.00, 1.00, 1.00), (2.00, 3.00, 4.00), (0.25, 0.33, 0.50), (1.00, 1.00, 1.00)	(0.11, 0.11, 0.13), (0.11, 0.11, 0.13), (0.13, 0.14, 0.17), (0.13, 0.14, 0.17), (0.11, 0.11, 0.13), (0.17, 0.20, 0.25)
C_2	(2.00, 3.00, 4.00), (4.00, 5.00, 6.00), (1.00, 1.00, 1.00), (0.25, 0.33, 0.50), (2.00, 3.00, 4.00), (1.00, 1.00, 1.00)	(1.00, 1.00, 1.00), (1.00, 1.00, 1.00), (1.00, 1.00, 1.00), (1.00, 1.00, 1.00), (1.00, 1.00, 1.00), (1.00, 1.00, 1.00)	(0.13, 0.14, 0.17), (0.13, 0.14, 0.17), (0.13, 0.14, 0.17), (0.13, 0.14, 0.17), (0.13, 0.14, 0.17), (0.17, 0.20, 0.25)
C_3	(8.00, 9.00, 9.00), (8.00, 9.00, 9.00), (6.00, 7.00, 8.00), (6.00, 7.00, 8.00), (8.00, 9.00, 9.00), (4.00, 5.00, 6.00)	(6.00, 7.00, 8.00), (6.00, 7.00, 8.00), (6.00, 7.00, 8.00), (6.00, 7.00, 8.00), (6.00, 7.00, 8.00), (4.00, 5.00, 6.00)	(1.00, 1.00, 1.00), (1.00, 1.00, 1.00), (1.00, 1.00, 1.00), (1.00, 1.00, 1.00), (1.00, 1.00, 1.00), (1.00, 1.00, 1.00)

Table 2. The comparison matrix of criteria with respect to goal by the six experts

Combined comparison matrix	C_1	C_2	C_3	$\widetilde{w}_i = \widetilde{r}_i \otimes (\sum_{i=1}^{n} \widetilde{r}_i)^{-1}$	w_i	CR
C_1	(1, 1, 1)	(0.52, 0.64, 0.79)	(0.12, 0.13, 0.15)	(0.08, 0.09, 0.12)	0.10	0.03
C_2	(1.26, 1.57, 1.91)	(1, 1, 1)	(0.13, 0.15, 0.18)	(0.11, 0.13, 0.17)	0.13	
C_3	(6.48, 7.50, 8.09)	(5.61, 6.62, 7.63)	(1, 1, 1)	(0.65, 0.79, 0.95)	0.77	

Table 3. The combined comparison matrix of six decision makers

Candidate municipalities	Global priority weights (w_i)
Nongbua Lamphu Town Municipality (NLTM)	0.55
Nong Khai Town Municipality (NKTM)	0.21
Loei Town Municipality (LTM)	0.24

Table 4. Global priority weights of candidate municipalities

4.2. Compute the Suitable Locations Using HFGP Model

The w_i of each candidate municipality are found based on Section 4.1 to be w_1 (global priority weight of NLTM) = 0.55, w_2 (global priority weight of NKTM) = 0.21 and w_3 (global priority weight of LTM) = 0.24. In order to solve the MOFLP in this case, set $w_{G1}>w_{G2}$ according to experts' opinions; the sensitivity analysis of the HFGP was also performed for different levels of objective weights. The actual distance matrix and demands of three candidate municipalities and forty hospitals are shown in Table 5 as d_j, dt_{ij}. The values of u and DT are 4.3 baht/km and 240 km respectively. In Table 6, f_k (k = 1 and k = 2) are 13,248 and 24,395 baht per week, and o_k are 69,090 and 130,508 baht per week respectively. The values of s_k are about 3,000 and 6,000 kg per week. The data set for membership functions of each goal in Equation 26 and Equation 27 need to be evaluated first, the max-min total cost (Z_1) and max-min total weight of opened municipalities (Z_2) are shown in Table 7.

ID	Hospital name	NLTM (km)	NKTM (km)	LTM (km)	Amount of infectious waste (kg/week)
H1	Nahaeo	190.00	275.00	128.00	80.50
H2	Pakchom	187.00	162.00	71.00	178.50
H3	Dansai	168.00	253.00	106.00	350.00
H4	Erawan	55.70	140.00	61.90	119.00
H5	Tha Li	156.00	240.00	122.00	147.00
H6	Phurua	132.00	216.00	69.30	56.00
H7	Na Duang	65.00	150.00	52.30	91.00
H8	Chiang Khan	148.00	202.00	31.20	105.00
H9	Wang Saphung	78.40	163.00	44.30	210.00
H10	Phu Kradung	94.40	168.00	96.40	108.50
H11	Phu Luang	102.00	187.00	70.00	112.00
H12	Pha Khao	78.60	148.00	98.50	105.00
H13	Sangkhom	142.00	99.00	134.00	112.00
H14	Phon Phisai	154.00	75.40	264.00	217.00
H15	Si Chiang Mai	103.00	60.20	173.00	105.00
H16	Sakhrai	89.60	6.00	200.00	49.00
H17	Tha Bo	102.00	44.00	192.00	217.00
H18	Suwannakhuha	53.00	102.00	145.00	133.00
H19	Si Bun Rueang	40.70	114.00	154.00	185.50
H20	Na Klang	26.80	111.00	90.70	147.00
H21	Na Wang	43.90	125.00	76.40	91.00
H22	Non Sang	55.60	129.00	169.00	105.00
H23	Kumphawapi	95.70	82.00	209.00	80.50
H24	Si That	120.00	106.00	233.00	175.00
H25	Chai Wan	109.00	89.50	222.00	350.00
H26	Wang Sam Mo	147.00	134.00	261.00	189.00
H27	Phibun Rak	94.00	47.50	207.00	217.00
H28	Nong Han	90.20	70.80	204.00	59.50
H29	Kut Chap	52.10	81.80	166.00	91.00
H30	Nong Wua So	27.00	61.70	140.00	108.50
H31	Ban Dung	138.00	71.50	251.00	210.00
H32	Sang Khom	124.00	49.00	237.00	108.50
H33	Non Sa-at	107.00	93.30	220.00	112.00
H34	Nam Som	80.90	95.70	83.90	105.00
H35	Phen	96.10	21.20	209.00	115.50
H36	Nong Saeng	81.60	81.20	195.00	217.00
H37	Thung Fon	121.00	101.00	231.00	105.00
H38	Ban Phue	95.70	82.00	209.00	49.00
H39	Na Yung	120.00	106.00	233.00	217.00
H40	Huai Koeng	109.00	89.50	222.00	42.00
	Total	4,074.00	4,633.30	6,281.90	5,575.5

Table 5. The resource data for the HFGP model

Details of the cost (baht/week)	Size of incinerator (kg/week)	
	3,000	6,000
1. Facility cost		
1.1 Incinerator	1,918	3,836
1.2 Landfill	479.5	959
1.3 Storage	6,902	13,811
1.4 Infectious waste tank	1,725.5	3,451
1.5 Cleaning system	115.5	231
1.6 Emergency generator	2,107	2,107
Total facility cost (baht/day)	**13,248**	**24,395**
2. Operating cost per day		
2.1 Labor cost	51,026.5	102,053
2.2 Maintenance costs (6% of incinerator)	1,151.5	2,303
2.3 Cost of measuring air pollution	7,672	7,672
2.4 Cost of IWD (3.3 Baht/kg)	9,240	18,480
Total operating cost (baht/day)	**69,090**	**130,508**

Table 6. Details of the cost

	$\mu = 0$	$\mu = 1$	$\mu = 0$
Min. total cost, G_1	–	172,421.2	495,848.3
Max. total weight, G_2	0.45	1	–

Table 7. Data set for membership functions

These relevant parameters were taken to place into the HFGP model (Equation 25 to 29). Afterward, the LINGO 13 software was applied, and the optimal solutions for different objective weights were as shown in Table 8.

	$W_{G1} = 0.80$, $W_{G2} = 0.20$	$W_{G1} = 0.70$, $W_{G2} = 0.30$	$W_{G1} = 0.60$, $W_{G2} = 0.40$	$W_{G1} = 0.50$, $W_{G2} = 0.50$
NLTM NKTM LTM	Selected (Size = 3,000) Selected (Size = 3,000) Not selected	Selected (Size = 3,000) Selected (Size = 3,000) Not selected	Selected (Size = 3,000) Not selected Selected (Size = 3,000)	Selected (Size = 3,000) Selected (Size = 3,000) Selected (Size = 3,000)
Total cost (Baht/week)	178,950.30	178,950.30	182,361.0	259,105.2
Total priority weights	0.76	0.76	0.79	1.00

Table 8. Sensitivity analysis for different values of objective's weights

As seen in Table 8, the sensitivity analysis of the HFGP model was performed for different levels of objective weights. The sensitivity analysis is conducted to evaluate the influence of objective weights on the MOFLP. It can be seen that by increasing w_{G1} and decreasing w_{G2} at the same time, the total cost goal has a decreasing trend. On the other hand, it can also be seen that by decreasing w_{G1} and increasing w_{G2} at the same time, the number of locations and total cost have an increasing trend. Finally, the optimal solutions from the sensitivity analysis for different values of objective weights were offered to the four decision makers. The four decision makers made the decision to choose the NLTM and NKTM as suitable municipalities for infectious waste disposal, with the following reasons: "Although total priority weight of selected municipalities is not equal to the maximum predefined value (Target = 1), the total cost is a minimum total cost. If we choose the others, the total cost will be very high, which is not according to experts' opinions ($w_{G1} > w_{G2}$)"

The results show that the suitable candidate municipalities were NLTM and NKTM (selected by $w_{G1} = 0.70$ and $w_{G2} = 0.30$). It can decrease the total cost by selection of NLTM and LTM by about 3,410.7 baht/week. Although the weight of NKTM was slightly lower than the weight of LTM, by about 0.03, the total cost objective was achieved using the new proposed model. Details of optimal solution of HFGP model are shown in Table 9.

Opened location	Size of location (kg/week)	Hospitals
NLTM	3,000	H1, H3, H4, H5, H6, H7, H8, H9, H10, H11, H12, H18,H19, H20, H21, H22, H29, H30, H34, H36
NKTM	3,000	H2, H13, H14, H15, H16, H17, H23, H24, H25, H26, H27, H28, H31, H32, H33, H35, H37, H38, H39, H40
Total cost = 178,950.30 baht/week		**Total priority weight = 0.76**

Table 9. Optimal solution of HFGP model

Therefore, this model can lead to the selection of new suitable locations for infectious waste disposal by considering both tangible factors and intangible factors simultaneously. In addition, the decision makers believed that our work can provide essential support for decision makers in the assessment of infectious waste disposal problems, in this case study and other areas of Thailand and, they also believe that the proposed methodology can be applied to other complex problems.

4.3. Find the Routes for Each Selected Municipality Using Hybrid GA

Based on the actual situation of this case study, the hospitals were determined to be served by each selected municipality (NLTM and NKTM) once a week, and any special vehicle used to pick up the infectious waste should be of a suitable size, appropriate with the design of the transport routes and mobility of the service. Hence, there are three sizes of special vehicles, capacity of 1 ton, capacity of 2 ton and capacity of 3 ton, which are often used and recommended for infectious waste collection in Thailand. The prices of these special vehicles are about 2 million baht, 3 million baht and 4 million baht respectively. Actual distance matrices (dt_{ij}) and d_j of each selected municipality are shown in actual distance matrices of NLTM and NLTM, see details in Appendix A. The experiment was performed on a computer with the following characteristics: An Intel® Core™ i5-4210U processor Dual-core operating at 1.70 GHz with 8 GB of RAM, and Windows 8.1 operating system. The capacity of all vehicles (q_k) is equal to 1, 3 and 6 ton respectively. Each vehicle travels from node i to j at a constant speed of 60 kilometers per hour so the maximum permitted travel time per vehicle (D) is equal to 480 minutes according to the experts' opinions. The input parameters for the experimentation in hybrid GA were made with an initial population of 100 individuals and 10 generations, and hybrid GA was tested to solve the actual problems using Visual Studio 2015 (C++). The probability for genetic operator in hybrid GA were set to be $p_c = 0.8$ and $p_m = 0.3$. The obtained results of each vehicle capacity are compared with computational results using LINGO13 based on the VRP model in Section 4.3, as shown in Table 10.

From Problem 1.1 (N = 5), Problem 1.2 (N = 10), Problem 1.3 (N=15) and Problem 1.4 (N = 20), NLTM has been selected as a disposal center which needs to service 4 hospitals (H1, H3, H4, H5), 9 hospitals (H1, H3, H4, H5, H6, H7, H8, H9, H10), 14 hospitals (H1, H3, H4, H5, H6, H7, H8, H9, H10, H11, H12, H18, H19) and 20 hospitals (H1, H3, H4, H5, H6, H7, H8, H9, H10, H11, H12, H18, H19, H20, H21, H22, H29, H30, H34, H36) respectively. From Problem 2.1 (N = 5), Problem 2.2 (N = 10), Problem 2.3 (N = 15) and Problem 2.4 (N = 20), NKTM has been selected as a disposal center which needs to service 4 hospitals (H2, H13, H14, H15), 9 hospitals (H2, H13, H14, H15, H16, H17, H23, H24, H25), 14 hospitals (H2, H13, H14, H15, H16, H17, H23, H24, H25, H26, H27, H28, H31, H32) and 20 hospitals (H2, H13, H14, H15, H16, H17, H23, H24, H25, H26, H27, H28, H31, H32, H33, H35,H37, H38, H39,H40) respectively.

As seen in Tables 10, the computational results show that the optimal solutions for small size problem (N = 5 and N = 10) were achieved using LINGO13 and hybrid GA for each vehicle capacity. In addition, the computational results of each vehicle capacity using hybrid GA for the problem 1.3 achieved best known solutions at computational times of 48 hrs. using LINGO13. Thus, hybrid GA has enough computational power to be used in this research. Practically, the working days of the government sector in Thailand will run from Monday to Friday, and the number of vehicles will try to use the minimum requirement. Each selected vehicle can only serve one route per day. However, one vehicle can serve a maximum of 5 routes/ 5 days (Monday, Tuesday, Wednesday, Thursday and Friday). If we choose a vehicle size of 1 ton, three routes of each selected municipality will be served by one vehicle. However, for the other sizes, two routes of each selected municipality will be served by one vehicle. In this case study, only one vehicle can be used to be the minimum required number of vehicles (NR $\leq$ 5). The size of the vehicle is considered based on the vehicle and the transport costs. Details of costs for choosing each vehicle are shown in Table 11, and then details of best computational results for the actual problems are shown in Table 12.

Vehicle capacity	Data set	Number of hospitals	LINGO13			Hybrid GA		
			Number of vehicles/routes (NV/NR)	Total distance (TD)	Computational times (hh, mm, ss)	Number of vehicles/routes (NV/NR)	Total distance (TD)	Deviation
1 ton	Prob. 1.1	4 hospitals.	1	405.6	00:00:01	1	405.6	0%
	Prob. 2.1	4 hospitals.	1	427.4	00:00:01	1	427.4	0%
	Prob. 1.2	9 hospitals.	2	703.4	00:16:21	2	703.4	0%
	Prob. 2.2	9 hospitals.	2	672.5	00:01:35	2	672.5	0%
	Prob. 1.3	14 hospitals.	2	832.3	48:00:00	2	832.3	0%
	Prob. 2.3	14 hospitals.	3	842.3	48:00:00	3	842.3	0%
	Prob. 1.4	Actual case for NLTM	3	1,149.5	48:00:00	3	1,149.5	0%
	Prob. 2.4	Actual case for NKTM	3	987.6*	48:00:00	3	987.6	0%
2 tons	Prob. 1.1	4 hospitals.	1	405.6	00:00:01	1	405.6	0%
	Prob. 2.1	4 hospitals.	1	427.4	00:00:01	1	427.4	0%
	Prob. 1.2	9 hospitals.	2	703.4	00:37:27	2	703.4	0%
	Prob. 2.2	9 hospitals.	2	672.5	00:01:41	2	672.5	0%
	Prob. 1.3	14 hospitals.	2	831.7	48:00:00	2	831.7	0%
	Prob. 2.3	14 hospitals.	2	752.9	48:00:00	2	752.9	0%
	Prob. 1.4	Actual case for NLTM	3	1,129.8	48:00:00	3	1,129.8	0%
	Prob. 2.4	Actual case for NKTM	2	880.8	4800:00	2	880.8	0%
3 tons	Prob. 1.1	4 hospitals.	1	405.6	00:00:01	1	405.6	0%
	Prob. 2.1	4 hospitals.	1	427.4	00:00:01	1	427.4	0%
	Prob. 1.2	9 hospitals.	2	703.4	00:37:27	2	703.4	0%
	Prob. 2.2	9 hospitals.	2	672.5	00:01:41	2	672.5	0%
	Prob. 1.3	14 hospitals.	2	831.7	48:00:00	2	831.7	0%
	Prob. 2.3	14 hospitals.	2	752.9	48:00:00	2	752.9	0%
	Prob. 1.4	Actual case for NLTM	3	1,129.8	48:00:00	3	1,129.8	0%
	Prob. 2.4	Actual case for NKTM	2	880.8	4800:00	2	880.8	0%

Table 10. Comparison of solutions using LINGO13 and hybrid GA

Municipality name	Vehicle size	Vehicle cost (Baht/week)	Transportation cost (Baht/week)	Total cost (Baht/week)
NLTM	1 ton	3,835.62 (NV = 1)	1,149.5 × 4.3 = 4,942.85	8,778*
	2 ton	5,753.43 (NV = 1)	1,129.8 × 4.3 = 4,858.14	10,612
	3 ton	7,671.23 (NV = 1)	1,129.8 × 4.3 = 4,858.14	12,529
NKTM	1 ton	3,835.62 (NV = 1)	987.6 × 4.3 = 4,246.68	8,082*
	2 ton	5,753.43 (NV = 1)	880.8 × 4.3 = 3,787.44	9,541
	3 ton	7,671.23 (NV = 1)	880.8 × 4.3 = 3,787.44	11,459

Table 11. Details of costs for choosing each vehicle size

Disposal centers	Transport routes (using vehicle capacity of 1 ton)	Distance (km)	Amount of infectious waste (kg)
NLTM	**Route 1 for Monday:** NLTM, H22, H19, H12, H10, H11, H9, H21, NLTM	331.1	917.0
	Route 2 for Wednesday: NLTM, H7, H8, H5, H1, H3, H6, H4, NLTM	476.4	948.5
	Route 3 for Friday: NLTM, H20, H34, H18, H29, H36, H30, NLTM	342.0	801.5
	Total	**1,149.5**	**2,667.0**
NKTM	**Route 1 for Monday:** NKTM, H35, H27, H28, H26, H24, H23, H40, H33, NKTM	337.6	990.5
	Route 2 for Wednesday: NKTM, H38, H39, H2, H13, H15, H17, H16, NKTM	365.1	927.5
	Route 3 for Friday: NKTM, H25, H37, H31, H32, H14, NKTM	284.9	990.5
	Total	**987.6**	**2,908.5**

Table 12. Details of computational results for the actual problem using hybrid GA

As seen in Tables 11 and 12, in order to minimize the number of vehicles and transportation costs according to the decision makers' opinions, a capacity of 1 ton was selected as a suitable size for NLTM and NKTM because it provides the lowest total cost (vehicles and transportation costs), and then it has been planned to pick up the infectious waste on Monday (Route 1), Wednesday (Route 2) and Friday (Route 3) for each selected municipality. Therefore, the proposed hybrid GA can lead to providing the lowest total cost under this actual case study, according to decision makers' opinions.

5. Conclusion

In this study, the location routing problem, which is a complex problem, is handled within two phases consisting the multi-objective facility location problem to find a suitable new municipality for infectious waste disposal and the vehicle routing problem to analyze transport routes for the newly selected municipality, which aims to minimize transportation cost/total distance.

In the first phase, multi-objective facility location problem is considered with both quantitative and qualitative objectives. HFGP model is proposed to solve this complex problem.

Case study handles forty hospitals and three alternatives, which are candidate facilities in sub-Northeastern Thailand. In first phase, the MOFLP model for infectious waste disposal was formulated to determine the problem statement. Afterwards, the HFGP model was formulated to solve the complex problem. The optimal solution is computed using LINGO13 to choose the best municipalities among alternative municipalities for infectious waste disposal. The results show that NLTM and NKTM are two suitable locations. HFGP model enhances minimum total cost and the highest priority weight. In second phase, hybrid GA model is proposed to solve VRP. Firstly, LINGO13 was used to solve the VRP model in order to compare with hybrid GA.

The results show that the selected municipalities were assigned for infectious waste pickup efficiently using minimum number of vehicles and minimum total cost.

The major advantages of the proposed methodology are that the HFGP model can guide selection of a new suitable municipality by considering subjective and objective criteria simultaneously, and the hybrid GA can find the suitable transport routes, which require the minimum number of vehicles and minimum total cost, efficiently. These approaches are simple but powerful, and are flexible for decision makers to limit costs and environmental impacts. The advantage of this research is that decision makers can select the optimal location network and give significant weights as needed.

For the future research, the authors suggest the other multi-criteria approaches such as ELECTRE III, fuzzy PROMETHEE and fuzzy TOPSIS methods to be used and to be compared in justification of the location routing problem. This research can also be extended by incorporating additional selection criteria such as risk factors and other environmental concerns. Hence, the proposed methodology can be applied to other multi-criteria/multi-objective problems like supplier selection, software selection, project selection and machine selection of companies. Finally, changing problem sizes and criteria may serve another avenue for future research, though it may increase computational difficulties.

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Appendix

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