Expert Systems with Applications xxx (2014) xxx–xxx

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Optimizing Municipal Solid Waste collection using Chaotic Particle Swarm Optimization in GIS based environments: A case study at Danang city, Vietnam

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A R T I C L E I N F O

Article history:
Available online xxxx

Keywords:
ArcGIS
Chaotic Particle Swarm Optimization
Vehicle routing model
Heuristic algorithms
Municipal Solid Waste collection

A B S T R A C T

Municipal Solid Waste (MSW) is an increasing concern at any municipality in the world, and is one of the primary factors that contribute greatly to the rising of climate change and global warming. MSW collection and disposal especially in the context of developing countries are indeed the urgent requirements for the sustainable development of environment and landscape, which rule over the quality-of-life and life expectancy of human being. In this paper, we concentrate on MSW collection at Danang city, which is one of four largest municipalities in Vietnam having high quantity of the average waste load per person and is bearing negative impacts of climate change such as severe weather conditions and natural disasters as a result. A novel vehicle routing model for the MSW collection problem at Danang city is presented. A novel hybrid method between Chaotic Particle Swarm Optimization and ArcGIS is proposed to generate optimal solutions from the vehicle routing model of Danang. Experimental results on the real dataset of Danang show that the proposed hybrid method obtains better total collected waste quantity than the relevant ones including the manual MSW collection procedure that is currently applied at this city.

1. Introduction

Municipal Solid Waste (MSW) is an increasing concern at any municipality in the world. Reports from some articles in Consonnia, Giuglianob, and Grosso (2005), Weitza et al. (2002) pointed out that MSW is one of the primary factors that contribute greatly to the rising of climate change and global warming. The bad side effects of MSW are not only limited to environmental pollution and hygiene but also indirectly affected to traffic jam, financial budget and quality-of-life. Nowadays, most of developing countries in the world are currently in the progress of urbanization and industrialization, resulting in the augmentation of various types of wastes that leave a burden to both the municipality's infrastructure and the community. MSW collection and disposal especially in the context of developing countries are indeed the urgent requirements for the sustainable development of environment and landscape, which rule over the quality-of-life and life expectancy of human being. Additionally, optimizing MSW collection in those countries brings much meaning in terms of environmental, landscape developments and economic savings. In the extent of this research, **our focus** is the *MSW collection problem at Danang city*, which is one of largest industrial zones of Vietnam. According to Harmeling (2009), Vietnam is one of 11 countries in the world that suffered greatest damage from climate change and sea-level rise. As a consequence, Danang has to cope with negative impacts of climate change such as severe weather conditions and natural disasters. Optimizing MSW collection at Danang both minimizes the vulnerability caused by climate change and ensures the sustainable ecological environments. Monre (2010) stated that Danang is one of four largest municipalities in Vietnam, having high quantity of the average waste load per person, approximately 0.84–0.96 kg/person/day, which is higher than that of Southeast Asia with the number being 0.85 kg/person/day. A summary from Danang Bureau of Statistics (2011) showed that the quantity of solid waste increases much larger than the number of households in the duration of years from 1995 to 2010. 91% of the solid waste quantity at Danang in that period came from the households whilst 7% and 2% were reserved for markets and hotels & restaurants, respectively. The total waste quantity per day at Danang is around 661.6 tons, and it tends to increase dramatically by years and can attain 550 thousands tons till 2020. Current manual MSW collection scenario at Danang involving the uses of

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http://dx.doi.org/10.1016/j.eswa.2014.07.020
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some semi-automated vehicles such as the tricycles, the forklifts and the hook-lifts could not guarantee the operation if such huge waste quantities are present. Those facts raise the need of an effective optimization method for the MSW collection problem at Danang city. This is **our objective** in this paper. The MSW collection optimization problem can be described by a *vehicle routing* (VR) model including some basic components such as the vehicles, nodes and their relations in order to ensure pre-defined goals. Several VR models for different places and scenarios were presented in the literature. For example, Apaydin and Gonullu (2008) presented a VR model for Trabzon city, Turkey taking into account the exhaust emission of vehicles to minimize the environmental emission. Tavares, Zsigraiova, Semiao, and Carvalho (2009) integrated some factors such as the driving situations, vehicle load and road gradient to the VR models of the city of Praia, the capital of Cape Verde, and Santiago Island. Fan, Zhu, Zhang, He, and Rovetta (2010) proposed a VR model for Pudong city, China considering energy utilization with the supports of incineration in transfer stations. Shoba and Rasappan (2013) integrated the degree of industrialization and climate to waste generation rates for the VR model of Coimbatore town, India. Other examples of designing VR models could be referenced in Apaydin and Gonullu (2011), Arebey, Hannan, Basri, and Begum (2012), Arebey, Hannan, and Basri (2013), Aranda Usón, Ferreira, Zambrana Vásquez, Zabalza Bribián, and Llera Sastresa (2013), Faccio, Persona, and Zanin (2011), Gharaibeh, Haimour, and Akash (2011), Huang et al. (2001), Huang, Pan, and Kao (2011), Kanchanabhan, Mohaideen, Srinivasan, and Sundaram (2011), Nithya, Velumani, and Senthil Kumar (2012), Tai, Zhang, Che, and Feng (2011), Zhang, Huang, and He (2011). Nevertheless, the VR model for Danang city was not available in the literature, and we cannot utilize other models for the case study at Danang since each studied site has own MSW collection scenario. Thus, **our first contribution** in this paper is the design of a novel VR model for the MSW collection problem at Danang city. Once the VR model for Danang is constructed, the next step is to seek out an effective optimization method to find optima solutions of this model. There are several groups of methods proposed in the literature for the MSW collection problem. The first group so-called *Graph–Heuristic* (Kytojoki, 2007; Maniezzo, 2004; Tung & Pinnoi, 2000) represented a map as a graph where each node is an important site, e.g. depot, landfill and gather sites and each arc is a connected line between two neighbored nodes. Using greedy algorithms such as the well-known Solomon's I1 insertion heuristic, an initial solution is quickly found and improved in some next steps by the local search procedures, namely Or-opt and 2-opt*. The disadvantage of this group is the quality of the final solution since it depends on results of the greedy algorithm. Since all variables in a VR model are non-negative integers, the second group namely *Integer Programming* (Huang & et al., 2001; Maqsood & Huang, 2003; Wang, 2001) uses the chance-constrained programming and (fuzzy) linear integer programming such as Cutting Planes, Ellipsoid algorithm and Conic sampling to determine optimal solutions from a VR model. The activities of this group are often complicated and require large computational time when the graph is complex and the number of nodes is very large. The third group so-called *GIS-Functions* employs available routing algorithms such as Dijkstra in GIS softwares for the searching of optimal solutions. Some examples could be listed, to name but a few: Chalkias and Lasaridi (2009), Huong, Tuyet, Nga, and Huong (2012), Karadimas et al. (2007a) used ArcGIS Network Analyst (ESRI, 2009) to identify the best route for the municipal waste collection of large items; Badran and El-Haggar (2006) investigated Municipal Solid Waste management in Port Said, Egypt through MPL software V4.2 (Rosen, 2005); Apaydin and Gonullu (2008) relied on MapInfo (Daniel, Loree, & Whitener, 2002) to find optimized routes in Trabzon city, Turkey. Nevertheless, the quality of solutions achieved by this group is not high since the built-in routing algorithms in GIS softwares are either simple or obsolete. The last group of this topic namely *evolutionary algorithms* (EA) uses some sorts of Ant Colony Optimization (ACO) Ismail & Loh, 2009; Karadimas, Papatzelou, & Loumos, 2007b, Particle Swarm Optimization (PSO), Genetic Algorithm (GA) Fan et al., 2010 and Fuzzy Clustering (Son, 2014a, 2014b; Son, Cuong, Lanzi, & Thong, 2012; Son, Cuong, & Long, 2013; Son, Lanzi, Cuong, & Hung, 2012; Son, Linh, & Long, 2014) to determine approximate solutions in polynomial time instead of exact solutions which would be at intolerably high cost. Mimicking the evolution natural process such as selection, mutation, cross and inheritance, the quality of final solutions and the computational time are somehow better than those of other groups. The only limitation is that the outcomes are not accompanied by a GIS-based interface so that viewers could not validate whether or not the optimal paths are valid according to the structure of streets on a map. For example, an optimal route founded by GA may not be opted since it travels through many construction places or playgrounds that are likely to cause the traffic jam and unsafe situations for drivers. Another example is routes crossing over historical places should not be selected. Besides these four groups, there are still some standalone/hybrid EA algorithms such as the heuristic-based algorithm (Ai & Kachitvichyanukul, 2009), the tabu search-based algorithm (Brandão, 2011), the hybrid discrete PSO (Chen, Yang, & Wu, 2006), the hybrid GA-PSO (Marinakis & Marinaki, 2010), the hybrid PSO and multi-phases neighborhood search (Marinakis, Marinaki, & Dounias, 2010), the hybrid electromagnetism-like algorithm (Yurtkuran & Emel, 2010) and other ones (Banos, Ortega, Gil, Fernandez, & De Toro, 2013; Kuo & Wang, 2012; Tarantilis, Stavropoulou, & Repoussis, 2012; Yu, Yang, & Yao, 2011; Yücenur & Demirel, 2011; Zachariadis & Kiranoudis, 2011; Zarandi, Hemmati, & Davari, 2011). Nevertheless, those algorithms are designed for the general VR models or other applications but not for the MSW collection problem, which requires special components, architectures and operations so that they could not be applied herein. Based upon the advantages of the third and fourth group, **our idea for the new optimization method** is integrating evolutionary algorithms with GIS softwares. In the other words, the built-in routing algorithms in GIS softwares are replaced with an EA algorithm so that the limitations of those groups could be handled. More specifically, a modification of *Chaotic Particle Swarm Optimization* (CPSO) Gholipour et al., 2012 incorporation with the binary gravitational search algorithm (Rashedi, Nezamabadi-Pour, & Saryazdi, 2010) is presented and integrated to the ArcGIS software (ESRI, 2009). The hybrid approach is used to generate optimal solutions from the VR model of Danang. This is our **second contribution** in this paper. The *advantages and the novelty* of the hybrid method between CPSO and ArcGIS (a.k.a. CPSO-ArcGIS) in specific and our whole contributions including the VR model for Danang and the hybrid method in general are expressed as follows. *Firstly*, the hybrid method utilizes the advantages of both an EA algorithm and GIS software presented in the survey above into the activities of the new algorithm. This means that an optimal solution derived by the CPSO algorithm is modified according to the status quo in a map expressed by GIS software; thus giving a better, more optimal and adaptable solution than those of the built-in GIS functions in GIS software of the third group and the single EA algorithm of the fourth group. *Secondly*, the hybrid method employs CPSO incorporation with the binary gravitational search algorithm (Rashedi et al., 2010), which have never been used for the MSW collection problem in the literature, to produce the list of optimal solutions. As being mentioned above, CPSO relying on the basis of Chaos theory (Ott, 2002) is a strong EA tool and is capable to overcome some limitations of current variants of PSO (Gholipour et al., 2012). Therefore, using a modification of CPSO with the binary gravitational search algorithm for the MSW collection problem would achieve better results than other variants of PSO and some EA algorithms. *Thirdly*, the optimal results could be quickly displayed on a map interface using the ArcGIS software. It is convenience for decision makers to choose appropriate planning solutions that make great benefits of socio-economic strategies. *Finally*, the whole work consisting of the VR model and the hybrid algorithm could be an instructional guide of how to handle the MSW collection problem at a given studied site such as the Danang city. Besides the above advantages, the proposed work still contains *some limitations* such as the time complexity and the proprietary GIS software. Since CPSO-ArcGIS requires training and adjusting the solutions until the stopping conditions or certain constraints are met, this may take long processing time in comparison with the standalone EA algorithms of the fourth group and the built-in GIS functions of the third group. Furthermore, the proprietary ArcGIS software could limit the wide usages and the capability to expand the new ArcGIS-based integrated software. Nonetheless, those limitations could be acceptable if considering our goal stated in some first lines of this section. The proposed work will be validated on the real dataset of Danang and compared with the relevant ones including the manual MSW collection procedure that is currently applied at this city. The rests of the paper are organized as follow. Section 2 presents the proposed VR model and the hybrid method CPSO-ArcGIS. Section 3 describes the experiments from the real dataset of Danang city. The last section gives the conclusions and outlines future works of this study.

2. The proposed methodology

In this section, we will present a novel VR model for Danang (Section 2.1) and a novel hybrid method between CPSO and ArcGIS to solve that model (Section 2.2).

2.1. VR model for MSW collection at Danang

We begin this section by a short introduction about the current scenario of MSW collection at (Danang Bureau of Statistics, 2011). Current model of Danang includes a depot, a landfill, many gather sites and many transfer stations. Solid waste at Danang is contained at three primary sources: streets, markets and hotels & restaurants. These sources are called the gather sites. There are three types of vehicles serving for MSW collection namely tricycles, forklifts and hook-lifts. The two first vehicles are responsible for collecting waste at gather sites. The last one has to transport waste in containers from transfer stations to the landfill. The tricycle can carry up to a 6601 bin of waste (~170 kg) or two 2401 bins (~140 kg/bin). The forklift and the hook-lift have the maximal capacity around 9 tons of waste. After loading waste at some gather sites, a tricycle will unload it at a transfer station and start a new route. Waste at a transfer station is sprayed by chemical and compressed into containers. When the hook-lift is full of containers, it starts traveling the landfill to unload them. The works of forklifts are similar to those of tricycles except that the destination of forklifts is the landfill. In the current scenario of Danang, tricycles are allowed to work from 8 am to 6 pm (the day shift) whilst forklifts are from 8 to 12 pm (the night shift). The restricted working times of all vehicles are from 6.30 to 8 am and from 5 to 6 pm. From this scenario, some highlights below are taken into account in order to generate the VR model for Danang.

(a) Since the working time of tricycles and forklifts are independent, total collected waste quantity, the traveling time and distances of vehicles may not be optimal. Our idea is putting those vehicles in the same shift in order to get better results.
(b) The scenario at Danang consists of inhomogeneous vehicles so that different operations should be applied to various types of vehicles.
(c) The main objective of MSW collection at Danang city is to maximize the collected waste quantities.

Based on those highlights and motivated by the ideas of Huong et al. (2012) and Tung and Pinnoi (2000) we will present a novel VR model for Danang with the following assumptions.

(a) Distances between nodes and waste quantities at a gather site are determined.
(b) The numbers of bins as well as their locations on the map are fixed.
(c) Since the day and night shifts are equivalent, we consider the day shift in the model only.
(d) Departure time of vehicles from the depot is equal. Velocities of vehicles are equal to a constant.
(e) Load and unload time of a vehicle are equal. Partial loads are allowed.
(f) The number of gather sites is larger than the number of tricycles/forklifts. However, the number of transfer stations is smaller than or equal to the number of hook-lifts.
(g) Tricycles and forklifts are allowed to wait at a gather site.
(h) Capacities of each type of vehicles are equal.
(i) Each type of vehicle has a maximal number of working times.

These assumptions are given according to the MSW collection scenario at Danang city and for the sake of the simplicity of the proposed model. Specifically, assumptions (a) and (b) are stated for a given subject map that is the input of the VR system. Assumptions (c), (f), (h) and (i) are taken from the scenario of MSW collection at Danang Bureau of Statistics (2011) which consists of waste sources from 247 hotels and 948 restaurants (1195 gather sites in total), 1 depot, 1 landfill and 10 transfer stations (2 inoperative), and 327 vehicles including 190 tricycles, 95 forklifts and 42 hook-lifts. Assumptions (d), (e) and (g) are made for the simplicity of the proposed model. In fact, it could be different departure time of vehicles from the depot, for instance, in the assumption (d). Yet this makes the model more complex and huge processing time since additional variables must be provided. For the efficiency of both the processing time and quality of results of the model, deduction has been made and expressed in these assumptions. In what follows, we give the definitions and denotation of variables and terms that have been used throughout the paper (Table 1).

From Table 1, we recognize that the MSW collection at Danang city is modeled by the system $\langle \tilde{N}, R, V, Q \rangle$ where $\tilde{N}$ is taken from a specific map of ArcGIS software that means each node in $\tilde{N}$ has a specific location on the map and the distance between two given nodes is calculated by the shortest path function in ArcGIS (see the function in ESRI (2009)). This is quite different from previous works of EA algorithms in the third group that ignore the integration of GIS software to the determination of $\tilde{N}$ in the design so that optimal solutions derived by those methods could somehow not be applied to reality since the paths are invalid. The components R and Q change dynamically by time. In the first time stamp, the waste quantities of other nodes except those of gather sites are set to zero. But when vehicles in V move to gather sites to take waste and dump them at transfer stations or the landfill, the waste quantities of those nodes increase. Waste quantities that a vehicle takes from a node are added to the component Q of that vehicle. When dumping waste, Q is reduced by the dumped waste quantity. Partial loads are allowed that means a vehicle can take a part of the total waste quantity in a node so that it does not exceed the capacity of the vehicle. The changes of waste quantities of

Table 1
Some terms of the proposed model.

Term	Definition & explanation
num_ts	The number of transfer stations
num_gs	The number of gather sites
$\widetilde{N} = \{1, 2, 3, \ldots, a, a+1, \ldots, b\}$ $(a, b \in N, b > a)$	An ordered list of nodes representing for the MSW collection system including, • Element '1': ID of the depot; • Element '2': ID of the landfill; • Elements '3' to 'a': IDs of the transfer stations with $num\_ts = a - 2$; • Elements '$a + 1$' to 'b': IDs of the gather sites with $num\_gs = b - a$;
$R = \{R_1, R_2, R_3, \ldots, R_a, R_{a+1}, \ldots, R_b\} (R_i \geqslant 0, \forall i = \overline{1,b})$	Waste quantities at all nodes. Notice that in the first time stamp, $R_i = 0$ $(\forall i = \overline{1,a})$. After vehicles start working, they take waste from gather sites to other nodes
num_tri	The number of tricycles
num_fork	The number of forklifts
num_hook	The number of hook-lifts
$V = \{1, \ldots, d, \ldots, e, \ldots, f\} (d, e, f \in N, f > e > d)$	An ordered list of vehicles including, • Elements '1' to 'd': IDs of tricycles with $num\_tri = d$; • Elements '$d + 1$' to 'e': IDs of forklifts with $num\_fork = e - d$; • Elements '$e + 1$' to 'f': IDs of hook-lifts with $num\_hook = f - e$;
$C = \{C_1, \ldots, C_d, \ldots, C_e, \ldots, C_f\} (C_i \geqslant 0, \forall i = \overline{1,f})$	The capacity of vehicles where, • $C_1 = \cdots = C_d$; • $C_{d+1} = \cdots = C_e$; • $C_{e+1} = \cdots = C_f$. (Assumption h) The capacity of each type could be a constant
$Q^j = \{Q^j_1, \ldots, Q^j_d, \ldots, Q^j_e, \ldots, Q^j_f\} (Q^j_i \geqslant 0, \forall i = \overline{1,f}, \forall j = \overline{1,b})$	Current waste quantities of vehicles after leaving a node. Notice that in the first time stamp, $Q^j_i = 0$ $(\forall i = \overline{1,f}, \forall j = \overline{1,b})$
max_*times*	The maximal number of working times of all vehicles (assumption *i*)
$X^i_j(k)$ $(\forall i, j = \overline{1,b};\ i \neq j;\ \forall k = \overline{1,f})$	An arc's weight that measures the capability of vehicle k to travel from node i to node j. The domain is: • 3: if a hook-lift is able to travel this arc; • 2: if a forklift travels this arc; • 1: if a tricycle travels this arc; • 0: Otherwise
$Y_i(k) (\forall i = \overline{1,b}; \forall k = \overline{1,f})$	A node's weight that measures the capability of vehicle k to stay at node i. The domain is: • 3: if a hook-lift stays at this node; • 2: if a forklift stays at this node; • 1: if a tricycle stays at this node; • 0: Otherwise

nodes are under the MSW collection scenario. The number R_2 measures the waste quantity at the landfill and is increased by time. Since each vehicle has max_*times* number of working times, e.g. a forklift is allowed to visit the landfill no more than 3 times per day, the final value of R_2 could be smaller than the sum of waste quantities of gather sites. Thus, the objective of the MSW collection problem is to maximize the total collected waste quantity. The VR model for MSW collection at Danang is described in Table 2.

Example 1. Suppose that we have a system $\langle \widetilde{N}, R, V, Q \rangle$ as in Fig. 1. In this case, we have a depot (ID: 1), a landfill (ID: 2), a transfer station (ID: 3) and 5 gather sites (IDs from 4 to 8). The connections between nodes are represented by their lines. Waste quantities of all nodes in the first time stamp are shown in Table 3.

In the system, there are 5 vehicles including 2 tricycles (IDs: 1 & 2), 2 forklifts (IDs: 3 & 4) and 1 hook-lift (ID: 5). The capacities of vehicles are expressed in Table 4.

Table 2
The optimization problem.

No.	Objective function	Explanation
A_0	$J = R_2 \rightarrow \max$	Maximize the collected waste quantities at the landfill
Constraints:		
A_1	$R_i \geqslant \sum Q^l_j, (\forall i = \overline{3,a}, \forall j = \overline{1,d}, \forall l = \overline{a+1,b}, X^l_i(j) = 1)$	Current waste capacity at a transfer station at a certain time must be greater than or equal to the total waste quantities of tricycles visiting that station in the same time
A_2	$\sum Q^i_j \geqslant R_i, (\forall i = \overline{3,a}, \forall j = \overline{e+1,f})$	Total waste quantity carried by hook-lifts from a transfer station to the landfill must be greater than remain at station
A_3	$Q^i_k \leqslant C_k, (\forall k = \overline{1,f}, \forall i = \overline{1,b})$	Current waste quantity of a vehicle must be smaller than its capacity
A_4	$R_i \geqslant \sum Q^i_k - \sum Q^j_k, (\forall k = \overline{1,e}, \forall i = \overline{a+1,b}, \forall j = \overline{1,b}, X^i_j(k) > 0)$	Waste quantity at a gather site is larger than or equal to the total waste quantities that vehicles will bring out from that site
A_5	$\sum_{k=\overline{1,f}} \sum_{i=\overline{1,b}} X^i_j(k) = \sum_{k=\overline{1,f}} Y_j(k), \forall j = \overline{1,b}$	A node can serve many incoming vehicles
A_6	$\sum_{k=\overline{1,f}} \sum_{j=\overline{1,b}} X^i_j(k) = \sum_{k=\overline{1,f}} Y_i(k), \forall i = \overline{1,b}$	A node can serve many outgoing vehicles
A_7	$\|Y_i(k) - Y_j(k)\| \leqslant \begin{cases} 1 - X^i_j(k) & k = \overline{1,d} \\ 2 - X^i_j(k) & k = \overline{d+1,e} \\ 3 - X^i_j(k) & k = \overline{e+1,f} \end{cases}$	Two connected nodes will be visited by the same vehicle
A_8	$R_i \times \sum Y_i(k) \geqslant R_i (\forall i = \overline{a+1,b}, \forall k = \overline{1,e})$	Any gather site will be visited by at least a vehicle
A_9	$\sum Y_i(k) \leqslant R_i$ $(\forall i = \overline{a+1,b}, \forall k = \overline{1,e})$	Gather sites that do not have waste are not visited

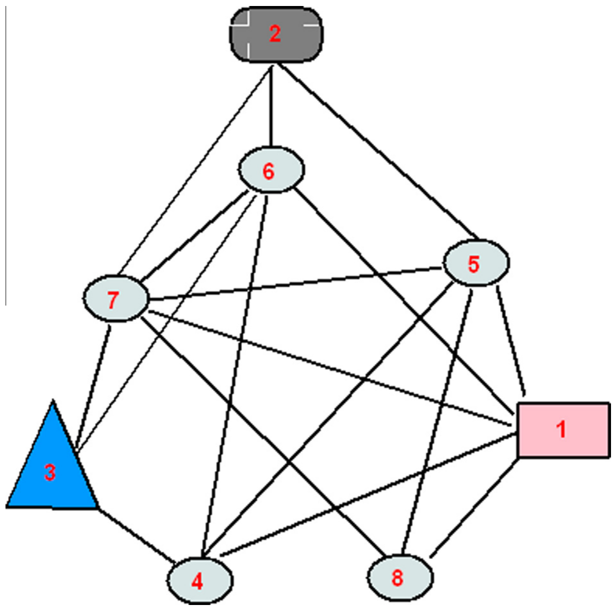

Fig. 1. A MSW collection system.

Table 3
The initial waste quantities of nodes (kilograms).

$\tilde{N}$	1	2	3	4	5	6	7	8
R	0	0	1000[a]	230	350	652	434	378

[a] The capacity of a node.

Table 4
The capacities of vehicles (kilograms).

V	1	2	3	4	5
C	60	60	500	500	800

The results of the first move to nodes of vehicles are presented in Table 5 and the waste quantities of nodes after the first move are shown in Table 6. Those results satisfy constraint (A_3, A_4, A_5 & A_8). For example, checking constraint (A_4) for the case of Vehicle 3 moving to node 5 will get the results that $R_5 = 350$, $Q_3^5 = 350$, $Q_3^1 = 0$ and the constraint hold. $X_5^1(3) = Y_5(3) = 2$ so constraints (A_5 & A_8) hold.

From Table 5, we recognize that Vehicles 1, 2 and 4 are full so that they could move to transfer stations and the landfill to dump waste. According to Fig. 1, there are direct connections from current nodes to the transfer stations and the landfill. Moreover from constraint (A_1), the capacity at the transfer station 3 is 1000 and is greater than the total waste quantities of tricycles visiting that station namely 120 in total. Thus, the visited nodes of tricycles 1 and 2 are the transfer station (ID: 3) and the visited nodes of forklift 4 are the landfill (ID: 2). In this case, constraints (A_6 & A_7) hold. Vehicle 3 still has 150 kg remaining so that it continues moving to other nodes to collect. It cannot move to node 6 since there is no direct connection between the current node 5 and node 6. The other nodes such as node 4, 7 and 8 have direct connections to node 5, and the remaining waste quantities of Vehicle 3 are also smaller than the current waste quantities of those nodes. Thus, Vehicle 3 could move to these nodes for collecting. The results of the second move and the waste quantities of nodes are shown in Tables 7 and 8, respectively.

Table 5
The results of the first move.

V	1	2	3	4	5
Visited node	4	7	5	6	No moving
Q^j	60	60	350	500	0
Status	Full	Full	150	Full	800

Table 6
The waste quantities of nodes after the first move (kilograms).

$\tilde{N}$	1	2	3	4	5	6	7	8
R	0	0	0	170	0	152	374	378

In this case, $R_5 = 0$ so that constraint (A_9) forces no moving to this node for collection. Vehicle 3 is full so it moves to the landfill for dumping. Other vehicles start moving to nodes to collect waste. Since the remaining waste capacity at the transfer station is 880, which is still larger than the collected waste quantity (constraint A_2), the hook-lift cannot start moving and still wait at the transfer station. The results of the third move and the waste quantities of nodes are shown in Tables 9 and 10, respectively. Due to the max_*times* number of working times of vehicles, there exists the case that all vehicles stop moving and return to the depot. The value of R_2 at that time stamp is the final collected waste quantity at the landfill. Thus, maximizing this value would help the MSW collection process become more efficient. When the process stops working, some additional values such as the routes of vehicles, the total traveling distance and the total execution time of vehicles could be easily determined.

2.2. The hybrid CPSO-ArcGIS method

We have clearly understood the optimization problem for the MSW collection at Danang city. From Example 1, we recognize that if an effective optimization method including the routes of vehicles is found then the objective of the optimization model in Table 2 could be achieved. In order to generate the optimal solutions, we should notice that (i) the connections between nodes such as those in Example 1 and the shortest path are taken from a map derived by the ArcGIS software; (ii) A greedy-like search method taking into account the constraints in Table 2 must be used to determine the feasible solutions or the routes of vehicles; (iii) An optimization method should be opted to find the optimal solution from the pool of solutions. In this case we have a bi-level optimization problem. Those ideas orient the activities of the new algorithm named as CPSO-ArcGIS depicted in Fig. 2.

Firstly, CPSO-ArcGIS invokes ArcGIS to calculate the connections between nodes including their distances and locations from spatial data and combine them with attribute data to set up the $\langle \tilde{N}, R, V, Q \rangle$ system. Secondly, the binary gravitational search algorithm (Rashedi et al., 2010) is used to set up a pool of solutions including routes of vehicles with the support of the shortest path function in ArcGIS. Thirdly, Chaotic Particle Swarm Optimization (CPSO) is utilized to determine the optimal solution among all. Finally, the optimal solution is expressed and displayed in a map of ArcGIS using the Python script (ESRI, 2009). Users could find out the total collected waste quantities of vehicles and the equivalent routes by simple queries. If some routes are invalid, they

Table 7
The results of the second move.

V	1	2	3	4	5
Visited node	3	3	7	2	No moving
Q^j	0	0	500	0	0
Status	Empty	Empty	Full	Empty	800

Table 8
The waste quantities of nodes after the second move (kilograms).

$\tilde{N}$	1	2	3	4	5	6	7	8
R	0	500	120 1000[a]	170	0	152	224	378

[a] The capacity of a node.

Table 9
The results of the third move.

V	1	2	3	4	5
Visited node	4	6	2	7	No moving
Q^j	60	60	0	224	0
Status	Full	Full	Empty	276	800

Table 10
The waste quantities of nodes after the third move (kilograms).

$\tilde{N}$	1	2	3	4	5	6	7	8
R	0	1000	120 1000[a]	110	0	92	0	378

[a] The capacity of a node.

can be modified by re-running the CPSO algorithm with other configurations of parameters.

Obviously, CPSO plays a very important role to determine the optimal results. It is an extension of the PSO algorithm (Kennedy & Eberhart, 1995) that incorporated the passive congregation (He & et al., 2004) and chaos theory (Ott, 2002) into the activities of the algorithm. PSO is a population-based stochastic optimization technique, which is inspired by social behaviors of bird flocking or fish schooling. Each single solution in PSO is a "bird" or "particle" in the search space. All particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles. He et al. (2004) stated that the flying orientation of a particle is even affected by social behaviors of the swarm that is called "passive congregation". A random particle is opted as the representative of the swarm, appending in the process of updating new velocity and position of a particle. Using passive congregation helps the algorithm to avoid local optima as well as to increase its performance. Gholipour et al. (2012) improved the work of He et al. by attaching the chaos theory with their algorithm. Chaos theory (Ott, 2002) is the study of complex, nonlinear, dynamic systems, pioneered by Lorenz in the research of the dynamics of turbulent flow in fluids. An important remark of chaos systems is that a small change in the initial condition of will lead to nonlinear changes in future behaviors, so the future states of those systems cannot be predicted since different phases have distinct behaviors. The advantage of chaos theory is its ability to demonstrate how a simple set of deterministic relationships can produce patterned yet unpredictable outcomes. CPSO was proven to converge to the global optimum rather than PSO (Kennedy & Eberhart, 1995) or *PSO with Passive Congregation* (PSOPC) He & et al., 2004. The pseudo-code of CPSO procedure incorporation with the binary gravitational search algorithm (Rashedi et al., 2010) for the MSW collection problem is expressed in Table 11.

3. Results and discussions

We implemented the CPSO-ArcGIS algorithm in Python embed ArcGIS environment (ESRI, 2009) and tested it on a computer with the configuration: Intel® Core™2 Duo Processor T6400; 2.1–2.0 GHz; FSB 800 Hz; 2M L2 Cache; Graphic card- Gefore 512 MB 102M. In CPSO, the number of particles is set as 200, and the maximal number of iteration steps is 20,000. Experimental results are conducted on the real dataset of Danang city (Danang Bureau of Statistics, 2011), which consists of waste sources from 247 hotels and 948 restaurants (1195 gather sites in total), 1 depot, 1 landfill and 10 transfer stations (2 inoperative), and 327 vehicles including 190 tricycles, 95 forklifts and 42 hook-lifts. Table 12 summarizes the experimental dataset. The experimental results are compared with those of the practical routes (Danang Bureau of Statistics, 2011), PSOPC (He & et al., 2004), ArcGIS (Huong et al., 2012) and PSO (Kennedy & Eberhart, 1995) in terms of the total collected waste, the traveling distances and the operational time. Table 13 describes the comparison of these results in details.

The experimental results in Table 13 have shown that the total collected waste quantity of CPSO-ArcGIS is better than those of the practical route, the standalone ArcGIS using ArcGIS Network Analyst, the standalone PSO algorithm and the PSO with Passive Congregation (PSOPC) algorithm. By combining CPSO, the binary

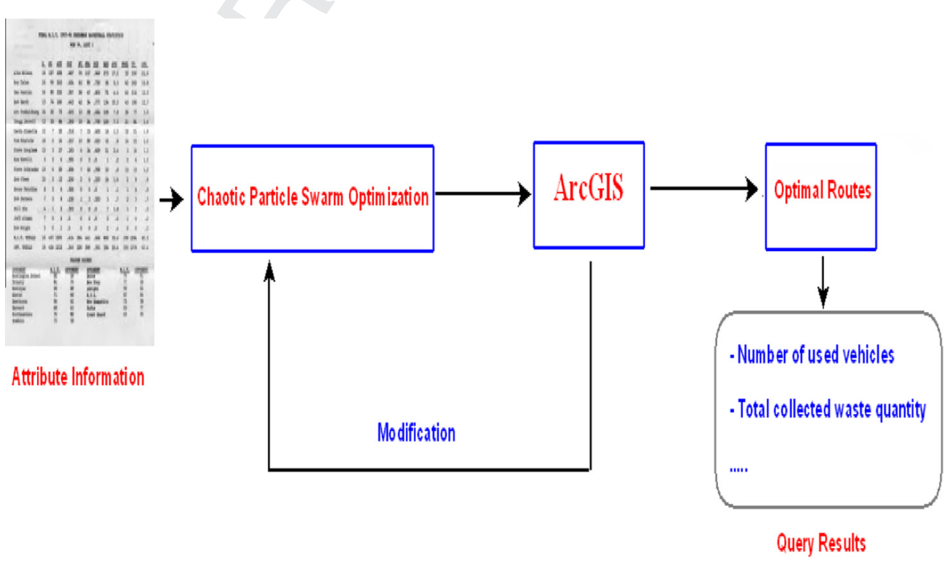

Fig. 2. The mechanism of CPSO-ArcGIS.

Table 11
The pseudo-code of CPSO procedure for the MSW collection problem.

Input
- $\langle \widetilde{N}, R, V, Q \rangle$
- The number of particles in the beginning population (P)
- Maximal number of iteration steps (*MaxStep_PSO*)

Output
- The optimal routes accompanied with the total collected waste quantities

CPSO:

1: Randomly initialize P particles whose velocities are initially set to zeros. Each particle is pair: $X(\widetilde{K}) = (X(1), \ldots, X(f))$ whose components are the routes of vehicles that are initialized according to the type of vehicles such as the tricycles (1), the forklifts (2) and the hook-lifts (3)

$$X(k) = \begin{cases} X_j^1(k)\ (\forall j = \overline{a+1,b})\ \textit{Starting\_Point} \\ \left\{X_j^i(k) \middle| \left(\forall i = \overline{a+1,b} \wedge \left(\forall j = \overline{a+1,b} \vee \forall j = \overline{3,a}\right)\right) \right. \\ \left. \vee \left(\forall i = \overline{3,a} \wedge \forall j = \overline{a+1,b}\right)\right\}, \\ X_1^j(k)\ (\forall j = \overline{3,a})\ \textit{Ending\_Point} \end{cases}, \forall k = \overline{1,d}, \tag{1}$$

$$X(k) = \begin{cases} X_j^1(k)\ (\forall j = \overline{a+1,b})\ \textit{Starting\_Point} \\ \{X_j^i(k), X_2^i(k), X_j^2(k) | (\forall i,j = \overline{a+1,b})\}, \forall k = \overline{d+1,e} \\ X_1^2(k)\ \textit{Ending\_Point} \end{cases} \tag{2}$$

$$X(k) = \begin{cases} X_j^1(k)\ (\forall j = \overline{3,a})\ \textit{Starting\_Point} \\ \{X_2^i(k), X_j^2(k) | \forall i,j = \overline{3,a}\}, \qquad \forall k = \overline{e+1,f} \\ X_1^2(k)\ \textit{Ending\_Point} \end{cases} \tag{3}$$

The starting and ending points are randomly initialized in $\widetilde{N} \setminus \{1,2\}$. The length-varied paths connected those points are constructed using the binary gravitational search algorithm (Rashedi et al., 2010)

2: Repeat

3: For each particle $i = \overline{1,P}$

4: Calculate the collected waste quantities of all vehicles from the paths in Eqs. (1)–(3)

5: Compute the fitness value of particle i by the objective function in (A_0)

6: Update its pBest and gBest by the rules:

If pBest[i] < fitness (i) then pBest[i] = fitness (i), (4)

If gBest < pBest[i] then gBest = pBest[i]. (5)

7: End For

8: For each particle

9: Update new velocities:

$$\Delta V_i = ch_1 \times V_i + ch_2 \times (pBest[i] - V_i) + ch_3 \times (gBest - V_i) + ch_4 \times (V_j - V_i), \tag{6}$$

$$V_i = V_i + \Delta V_i \tag{7}$$

V_j is the velocity of a random particle that reflects the effects of passive congregation. The parameters ch_i ($i = \overline{1,4}$) are the chaotic sequence, generated by Chirikov standard map (Ott, 2002) as follows

$$\theta_{n+1} = \theta_n + p_n + \frac{K}{2\Pi}\cos(2\Pi\theta_n), \tag{8}$$

$$p_{n+1} = \theta_{n+1} - \theta_n, \tag{9}$$

$$\theta_1 = p_1 = 0, K = 1 \tag{10}$$

10: If $\Delta V_i < 0$ then $id = [|\Delta V_i \setminus V_i|^{*} f]$
Else $id = [rand()^{*} f]$

11: Re-initialize vehicle number id in this particle by Eqs. (1)–(3)

12: End For

13: Until *MaxStep_PSO*

Table 12
Summary of the dataset.

ID	ITEM	INFORMATION
1	Depot	–
2	Landfill	
	Quantity	1
	Total capacity	Burry method
3	Transfer Stations	
	Quantity	8
	Total capacity	189,000 kg
4	Gather sites	
	Quantity	1195
	Total capacity	11,389,102 kg/day
5	Vehicles	
	Quantity	327
	Tricycle	- Capacity: 170–280 kg
		- Quantity: 190
	Forklift	- Capacity: 3000–5000 kg
		- Quantity: 95
	Hook-lift	- Capacity: 5000–9000 kg
		- Quantity: 42

gravitational search algorithm and ArcGIS in the activities of CPSO-ArcGIS, the proposed algorithm has collected 10,933,537 kg of waste, which is 7.5% larger than that of the practical routes, 28% larger than that of the standalone ArcGIS, 19% larger than that of the standalone PSO algorithm and 13.7% larger than that of the PSOPC algorithm. The standalone ArcGIS uses the ArcGIS Network Analyst function which relies mainly on the obsolete Dijkstra algorithm to find the optimal routes from the VR model in Table 2 so that it produces the worst result of total collected waste among all. PSO and PSOPC, which are the stochastic heuristic-based optimization methods, produce better results than the ArcGIS. Yet they lacked of the modification of ArcGIS and the greedy algorithm to find feasible solutions such as the binary gravitational search algorithm in CPSO-ArcGIS, the total collected waste quantities of those methods are still smaller than that of CPSO-ArcGIS. The proposed CPSO-ArcGIS not only uses ArcGIS and the binary gravitational search algorithm but also employs a variant of PSO named as CPSO, which was proven to converge to the global optimum rather than PSO and PSOPC. As such, the total collected waste quantity of CPSO-ArcGIS is the largest value among all (Fig. 3).

Nonetheless, the traveling distance of CPSO-ArcGIS is larger than those of other algorithms. According to Table 13, the traveling distance of CPSO-ArcGIS is 16% larger than that of the practical routes, 35.4% larger than that of the standalone ArcGIS, 6.8% larger than that of the standalone PSO algorithm and 0.23% larger than that of the PSOPC algorithm. The standalone ArcGIS ignores some nodes having low quantities of waste and uses mostly the forklifts

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Table 13
Q4 The comparative results.

Criteria	Practical Routes (Danang Bureau of Statistics, 2011)	ArcGIS Huong et al., 2012	PSO Kennedy & Eberhart, 1995	PSOPC He & et al., 2004	CPSO-ArcGIS
Total collected waste (kg)	10,166,382	8,536,290	9,172,645	9,614,298	**10,933,537**
Travelling distances (km)	2958	2536	3216	3428	**3436**
The operational time (hour)	6.3	5.8	7.0	7.4	**7.5**

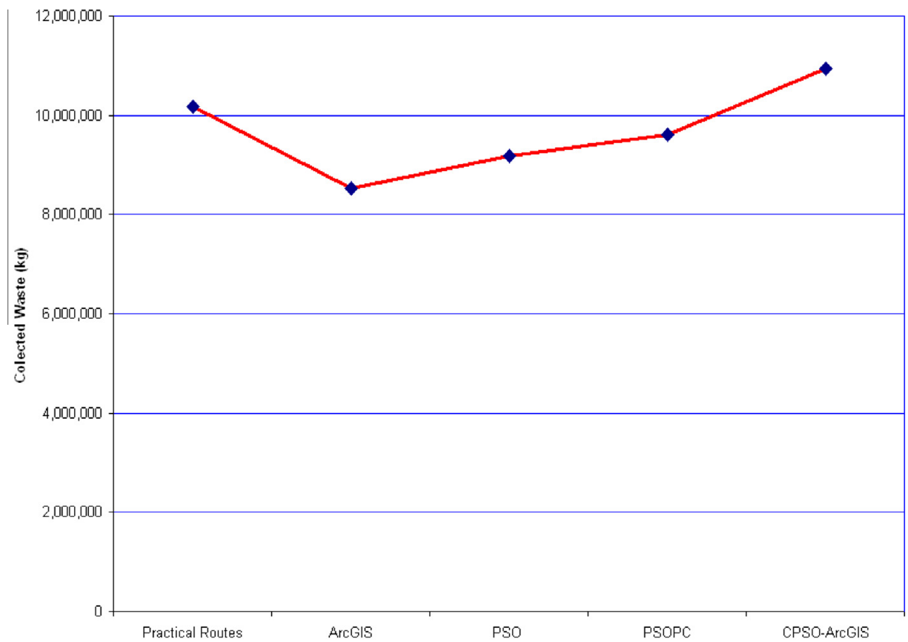

Fig. 3. The total collected waste quantities of algorithms (kg).

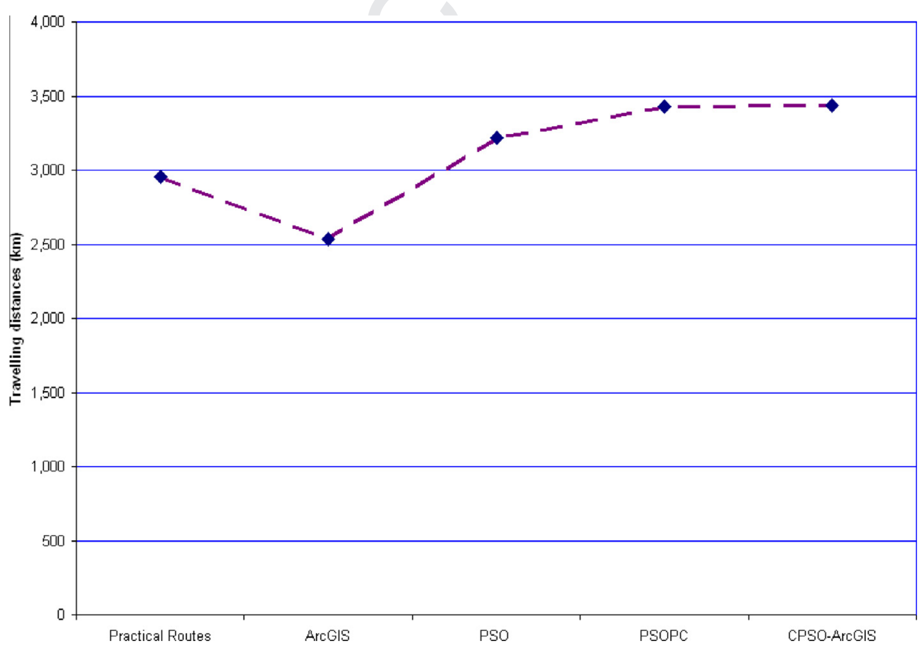

Fig. 4. The total traveling distances of algorithms (km).

to collect waste and dump at the landfill. By this way, the roles of transfer stations and other types of vehicles are ignored. This helps saving the total traveling distances; however the total collected waste is not good as expected. The mechanisms of PSO and PSOPC are similar to that of CPSO-ArcGIS so that the total traveling distances of these methods are nearly equal. However, those optimization methods are still worse than the practical routes in terms of the traveling distances. The reasons for this fact are: (i) the results

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Fig. 5. The operational time of algorithms (hours).

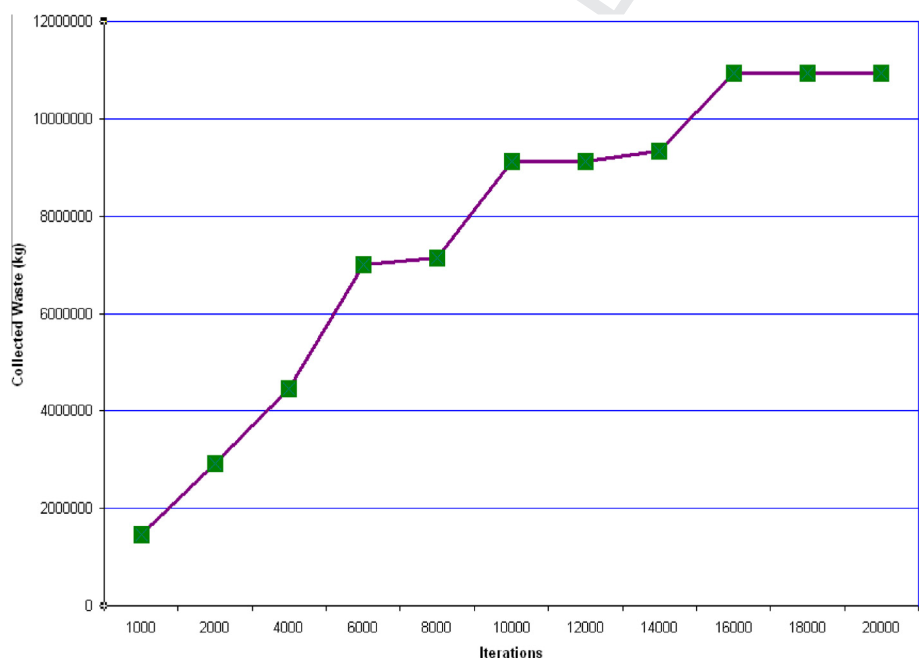

Fig. 6. The collected waste in CPSO-ArcGIS by the number of iterations.

of practical routes are calculated based solely on the works of forklifts. In the other words, the managers did not count the works of both tricycles and hook-lifts in the overall operations due to some special purposes; (ii) many routes of forklifts and hook-lifts are identical in terms of moving to the landfill. For example, a hook-lift and a forklift can meet in a same place and move to the landfill from it; thus doubling the traveling distance. Fig. 4 describes the total traveling distances of methods.

From the traveling distances, we can determine the total operational time of algorithms. The results in Table 13 and Fig. 5 have shown that the working time of vehicles in CPSO-ArcGIS algorithm is 7.5 h, which is 19% larger than that of the practical routes, 29.3% larger than that of the standalone ArcGIS, 7.1% larger than that of the standalone PSO algorithm and 1.4% larger than that of the PSOPC algorithm. Since the modification of ArcGIS for better and adaptable routes to practical situations, the working time and the traveling distances of CPSO-ArcGIS are larger than those of other algorithms. This guarantees our consideration for the limitations of CPSO-ArcGIS stated in the introduction section. However if we put the priority for the total collected waste quantity then the disadvantages could be compromised.

In what follows, we measure the changes of values of the objective function or the total collected waste quantities in CPSO-ArcGIS following by the number of iteration steps (Fig. 6) and the number of particles (Fig. 7).

From these figures, we clearly recognize that the value of objective function or the total collected waste quantity in CPSO-ArcGIS reaches to the saturated states at the points of 20,000 iteration

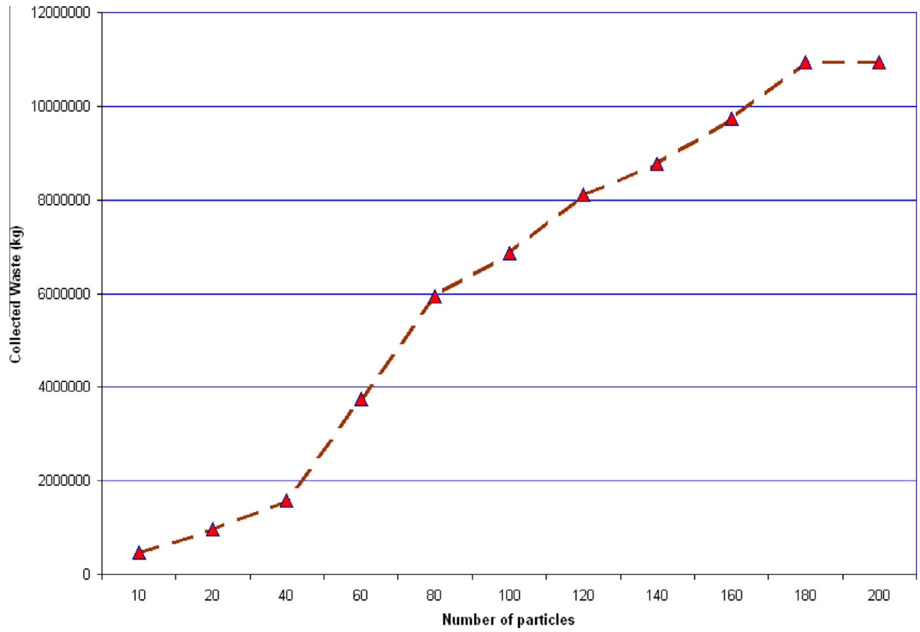

Fig. 7. The collected waste in CPSO-ArcGIS by the number of particles.

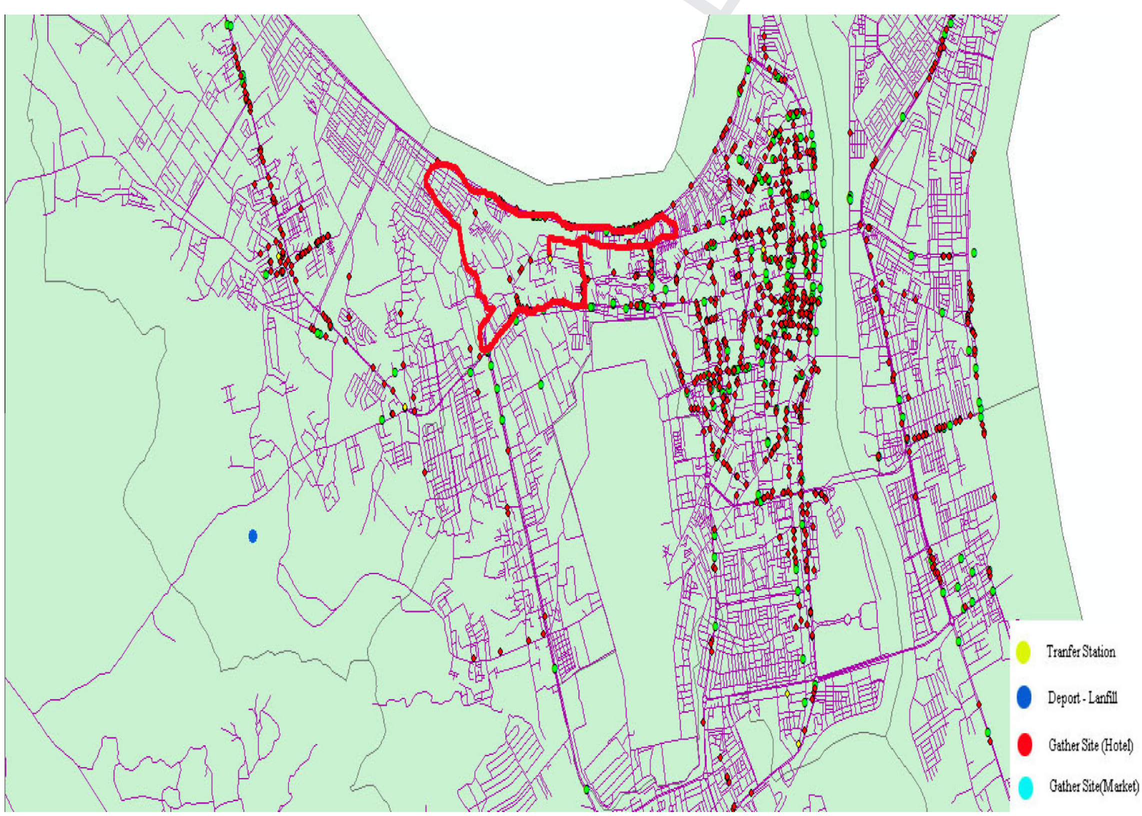

Fig. 8. The optimal route of a tricycle.

steps and 200 particles. Specifically, in Fig. 6, when the number of particles is 1000, the value of objective function is 1,462,954 kg. This value increases dramatically by 6000 iterations, and when the iteration steps between 6000 and 14,000 the value of objective function slightly changes in the interval [6,000,000; 9,000,000] kg. When the iteration steps reach to 16,000 and other next numbers afterward, the value of objective function is stable and approximates to 10,933,537. In Fig. 7, the value of objective function also increases when the number of particles is getting larger. Analogously to Fig. 6, when the number of particles reaches to 180, the value of objective function tends to be stable and approximates to 10,933,537. In most evolutionary algorithms, the numbers of particles and iteration steps contributes greatly to the quality of solutions. Since random solutions are initiated in the first time and improved in each iteration step, large number of iterations would make the results more optimal. However, when the

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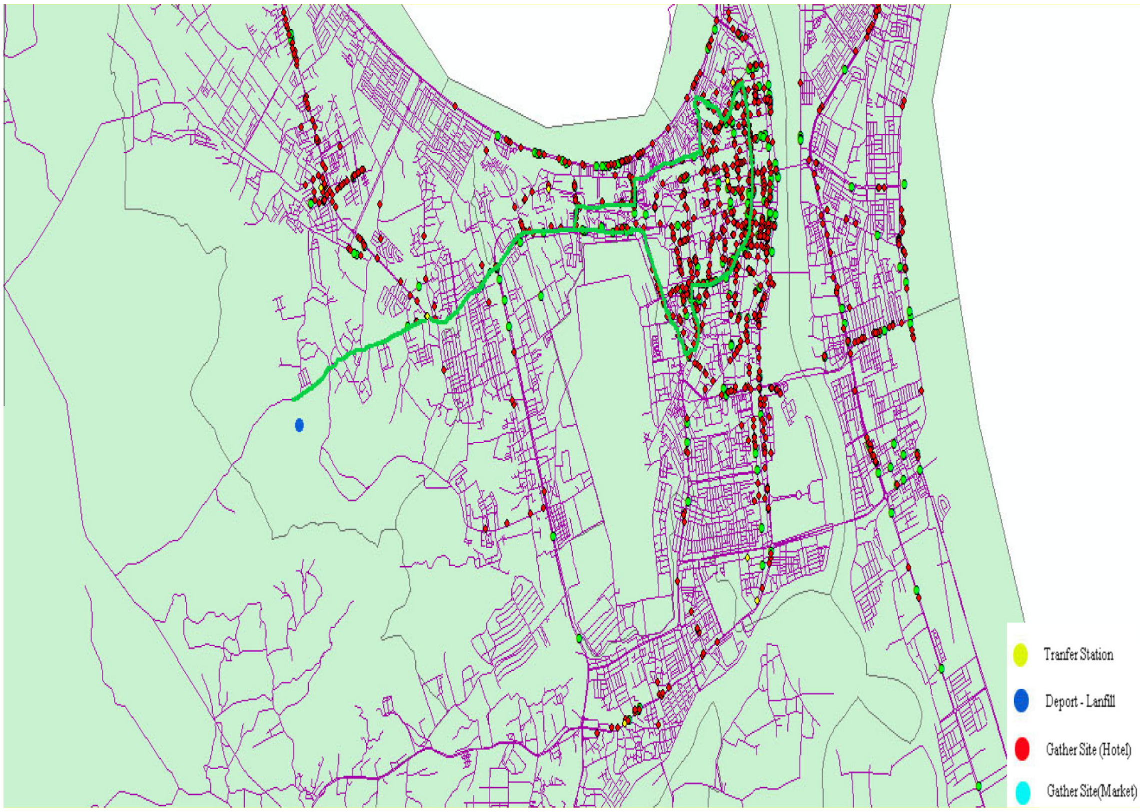

Fig. 9. The optimal route of a forklift.

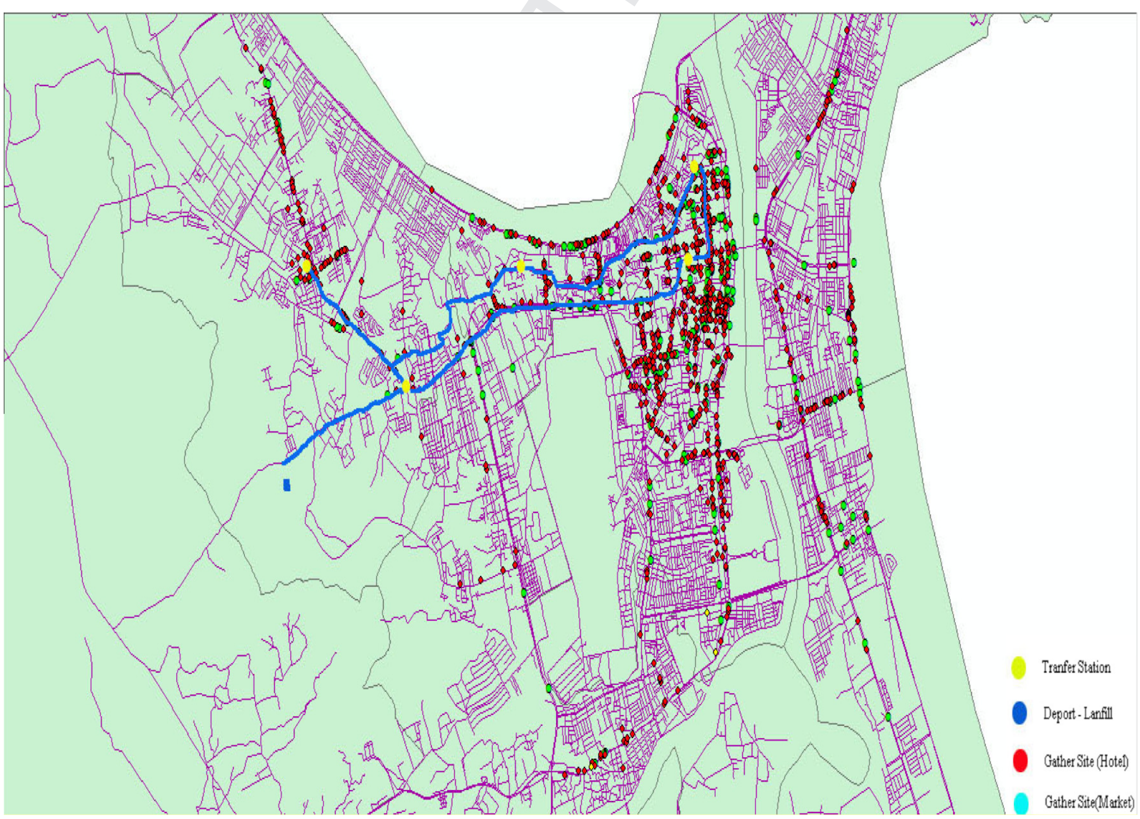

Fig. 10. The optimal route of a hook-lift.

objective function achieves optimal values, it cannot be improved further and the number of iteration steps at that time stamp is the most perfect one among all. This consideration also holds for the number of particles. More particles means more numbers of feasible solutions and more chance of successes. But when the optimal solution belongs to the pool of solutions, more number of particles means nothing to the whole process, yet it even make more time complexity to the algorithm itself. The 'enough' numbers of particles and iteration steps should be opted for the sake of both the quality of solutions and the computational time. In this case and by the observations in Figs. 6 and 7, we should choose these values as 200 particles and 20,000 iterations as a matter of fact. Finally, we illustrate the results of CPSO-ArcGIS in the map of Danang city, Vietnam from Figs. 8–10 below.

4. Conclusions

This paper aimed to present an effective optimization method for the Municipal Solid Waste collection problem at Danang city. A novel vehicle routing model for Danang city aiming to maximize the collected waste quantities of all vehicles was generated. Based upon the model, we proposed the hybrid method between Chaotic Particle Swarm Optimization including the binary gravitational search algorithm to determine a pool of feasible solutions and the ArcGIS software to choose the optimal one expressed on a map interface. The proposed method was implemented in ArcGIS and could return the optimal planning results including the total collected waste quantities of vehicles, the equivalent routes, the traveling distances of vehicles and the total operational time that are retrieved by simple queries. The experimental validation on the real dataset of Danang showed that the proposed method obtains better total collected waste quantities than the relevant methods including the manual MSW collection procedure that is currently applied at this city. Graphical routes of vehicles expressed on the map of Danang were presented to show the applicability of the proposed work.

Further researches of this article could be performed in one of the following directions: (a) extending the VR model and the algorithm in cases of real time traceability data; (b) designing solutions to handle the limitations of CPSO-ArcGIS regarding to the total traveling distances and the operational time; (c) applying the results for other studied sites that require variants of the VR models for Danang and the optimization method; (d) employing the proposed CPSO-ArcGIS in the determination of suitable locations of gather sites in a map; (e) studying some variants of the proposed VR models in cases of the objective functions related to the environmental factors such as the minimum fuel consumption, the minimum greenhouse gas emission, etc.

Acknowledgments

The authors are greatly indebted to the editor-in-chief, Prof. B. Lin and anonymous reviewers for their comments and their valuable suggestions that improved the quality and clarity of paper. Other thanks are sent to Msc. Luong Thu Huong, Mr. Truong Chi Cuong and Mr. Phung Quang Manh for the supports of data and programming especially in the urgent responses of the revised work. This work is sponsored by the NAFOSTED under Contract No. 102.05-2014.01.

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Please cite this article in press as: Son, L. H. Optimizing Municipal Solid Waste collection using Chaotic Particle Swarm Optimization in GIS based environments: A case study at Danang city, Vietnam. *Expert Systems with Applications* (2014), http://dx.doi.org/10.1016/j.eswa.2014.07.020