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Application of Hybrid GA-SA Heuristic for Green Location Routing Problem with Simultaneous Pickup and Delivery

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Abstract: Satisfaction of customer, either in product quality point of view, or in delivery lead time point of view, is considered as a pivotal challenge among producers and distributers in supply chain. This leads to both augmentation of service level and declining the total costs of the supply chain. In this paper, we regarded a variant of the Location-Routing Problem (LRP) with consideration of green aspects, namely the green LRP with simultaneous pickup and delivery (GLRPSPD). This problem seeks to minimize total cost by simultaneously locating the distribution centers and designing the vehicle routes that satisfy pickup and delivery demand of each customer at the same time, in a way that ecological aspects are observed. The formulated problem was a mixed integer programming (MIP) model and it used, GAMS optimization software for solving that. Finally, to solve the real-size problem in an acceptable time, we considered a hybrid heuristic Genetic Algorithm-Simulated Annealing (GA-SA). The compared solutions of GAMS and those obtained from the hybrid GA-SA depicts that the hybrid heuristic GA-SA is proficient in terms of both computational time and the quality of the solutions obtained.

Keywords: Location-routing Problem, Green Routing, Simultaneous Pickup and Delivery, Hybrid Heuristic Genetic Algorithm-Simulated Annealing

1. Introduction

Network Design determines the physical configuration and infrastructure of the supply chain. Key decisions are made on the number, locations, and size of manufacturing plants and warehouses, the assignment of retail outlets to warehouses, etc. At this stage, major sourcisng decisions are also made. The typical planning horizon is a few years. Classical facility location models assume that each customer (i.e. customer, market, etc.) is served on a straight-and-back basis on a given route while computing distribution cost. The location-routing problem (LRP) deals with determining the location of facilities and the routes of the vehicles for serving the customers under some constraints such as facility and vehicle capacities, route length, etc. to satisfy demands of all customers and to minimize the total cost including routing costs, vehicle fixed costs, facility fixed costs and facility operating costs. In its general form, the LRP assumes that customers have only delivery demand and it is interested in how to distribute the goods to customers with a fleet of vehicles, which are stationed in the opened depots. However, in practice, customers can have pickup and delivery demands and they often request that both demands should be met at the same time. By taking into consideration this kind of demand structure of customers, a variant of the LRP called the LRP with simultaneous pickup and delivery (LRPSPD) is applied in 2012 which was introduced by Karaoglan et al [7].

As mentioned above, before 2012 there was no previous study on LRPSPD in literature. In this paper, we considered a variant of the Location-Routing Problem (LRP) with consideration of green aspects, namely the green LRP with simultaneous pickup and delivery (GLRPSPD). This specific problem seeks to minimize total cost by simultaneously locating the distribution centers and designing the vehicle routes that satisfy pickup and delivery demand of each customer at the same time, in a way that ecological aspects are observed. Since the problem was explained for the first time in our previus research, we refer the interested readers to that. The problem is unknown in literature. So we must explain the literature of FLP, Green Routing and VRPSPD [23]. The review of the problem wa previously explained in Abedinzadeh et al [23] but due to the necessity of the problem, it will be described here again. Generally, this paper is the complement of the our previuos research which used a MIP model and was solved by exact method of GAMS optimization software in small-size problem. For solving the problem in real-size, we considered a hybrid heuristic Genetic Algorithm-Simulated Annealing (GA-SA) in order to compare the solutions of these two methods.

First of all, to better comprehension of the basic and classic FLP, it is really necessary to read the review papers of Melo et al and Smith et al [12, 16].

Secondly, we must review the literature of Green Routing. In 2006, Christie et al focused on the estimation of emission reduction benefits and the potential energy. The objective of the problem was to quantify the benefits and potential efficiency gains in terms of emission reduction with computerized VRS optimization (CVRSO) implementation by making a comparative analysis between different CVRSO methods and existing manual VRS methods [1]. Three years later, Yong et al considered the designing the optimal set of routes for fleet of vehicles in order to serve a given set of customers. They also considered a vehicle routing schedules in order to minimize fuel consumption and the travel distance. The comparison of these two problems were delineated that a different vehicle routing schedule is probable found if the optimization objective was to minimize fuel consumption other than to minimize travel distance [21]. In the same year, approximations to the average length of vehicle routing problems (VRP) with time window, route duration, and capacity constraints was developed by Figliozzi et al. This purpose of this paper was to introduce the concept of the average probability of successfully sequencing a customer with time windows. The approximation proposed was tested in instances with different customer spatial distributions, depot locations and number of customers. Regression results indicated that the proposed approximation was not only intuitive but also predicts the average length of VRP problems with a high level of accuracy [2]. In 2010, an evolutionary Multi-Objective Algorithm (MOA) investigate the trade-off between CO2 savings, distance and number of vehicles used in a typical vehicle routing problem with consideration of Time Windows (VRPTW) was developed by Urquhart et al used. The Results show that it was possible to save up to 10% CO_2, depending on the problem instance and ranking criterion used [19]. A comprehensive review of the development of research in Environmentally Conscious Manufacturing and Product Recovery (ECMPRO) was presented by Ilgin et al in 2010 [5]. Since, decreasing carbon emissions was considered as a controversial issue, in 2011, Kuo et al started to realize the importance of environmental protection and the problem of global warming and green transportation was one of the policies that is relevant to these efforts. This research optimized the routing plan with minimizing fuel consumption. To solve this problem, a simple Tabu Search was used to optimize the routing plan and an experimental evaluation of the proposed method was performed [9]. In 2012, the the classical capacitated vehicle routing problem (CVRP) was extended with the consideration of the Fuel Consumption Rate (FCR) in order to reduce the fuel consumption. For this specific issue, Xiao et al presented a mathematical optimization model to formally characterize the FCR considered CVRP (FCVRP) as well as a string based version for calculation. A simulated annealing (SA) algorithm with a hybrid exchange rule was developed to solve FCVRP and shows good performance on both the traditional CVRP and the FCVRP in substantial computation experiments [20].

In 2013, Pradenas et al applied a scatter Search (SS) in order to decline the emission of greenhouse gases using the vehicle routing problem with backhauls and time windows with consideration of the energy required for each route and estimating the load and distance between customers. The results indicated that the distance traveled and the transportation costs increase as the required energy decreases, but the amount of fuel consumed also decreases; therefore, the emission of greenhouse gases also decreases [14, 23].

Finally, these are the literature related to VRPSPD; In 1989, Min et al first recognized the possibility of simultaneous deliveries and pickups at the same node. The pripincipal goal of the paper was to make a model and a solution procedure efficient enough to handle real-world variants. A case study dealing with a public library distribution system in Franklin County, Ohio, was then conducted [13]. In 1997, Salhi et al developped a multi-echelon composite heuristic in order to simultaneously allocating customers to depots, finding the delivery routes and determining the vehicle fleet composition. [15]. The Capacitated Vehicle Routing Problem with two-dimensional loading constraints (2L-CVRP) is a generalisation of the Capacitated Vehicle Routing Problem, in which customer demand is formed by a set of two-dimensional, rectangular, weighted items. For solving this problem, in 2009 Zachariadis et al proposed a meta-heuristic algorithm which incorporates the rationale of Tabu Search and Guided Local Search [22].

One year later and in ordet to solve the Vehicle Routing Problem with Simultaneous Pickup and Delivery (VRPSPD), Subramanian et al presented a parallel approach with a multi-start heuristic which was consisted of a variable neighborhood descent procedure, with a random neighborhood ordering (RVND), integrated in an iterated local search (ILS) framework. [17]. In 2012, a VRPSPD which considers simultaneous distribution and collection of goods to/from customers, was modeled and Tasan et al proposed a genetic algorithm based approach to solve this problem. [18].

The rest of the paper is as follows. Section 2 explains the characteristics of the problem; the mathematical model and the proposed hybrid heuristic GA-SA algorithm to solve the model, are developed in section 3 and 4, respectively. the computational results and a discussion are included in section 5. Finally, the conclusions and proposals for future research are presented in section 6.

2. Problem Definition

In this section, the definition of the problem definition will be explained. A two-echelon (distribution and customer) single-product supply chain was considered as a main structure of problem and the main problem is LRPSPD which is based on Karaoglan et al [7]. LRPSPD can be defined as follows: let $G = (\mathrm{N}, \mathrm{A})$ be a complete directed network where $\mathrm{N} = \mathrm{N}_0 \cup \mathrm{N}_C$ is a set of nodes in which N_O and N_C represent the potential depot nodes and customers, respectively, and $\mathrm{A} = \{(\mathrm{i}, \mathrm{j}) : \mathrm{i}, \mathrm{j} \in \mathrm{N}\}$ is the set of arcs. Each arc $(\mathrm{i}, \mathrm{j}) \in \mathrm{N}$ has a nonnegative cost (distance), C_{ij}, and triangular inequality holds $(\mathrm{i.e.}, \mathrm{C}_{\mathrm{ij}} + \mathrm{C}_{\mathrm{jk}} \geq \mathrm{C}_{\mathrm{ik}})$. A capacity CD_k and a fixed cost FD_k are associated with each potential depot $\mathrm{k} \in \mathrm{N}_O$. An unlimited fleet of homogeneous vehicles with capacity CV and fixed operating cost FV including the cost of acquiring the vehicles used in the routing is available to serve the customers. It should be noted that we consider the assumption of an unlimited number of homogeneous vehicles with known capacities in order to dimension the fleet from a strategic point of view. Each customer $i \in N_C$ has pickup (p_i) and delivery (d_i) demands, with $0 \prec d_i, p_i \leq CV$. The main goal of this problem is to determine the locations of depots, the assignment of customers to the opened depots and the corresponding vehicle routes with a minimum total cost under the following constraints:

1) Each vehicle is used at most one route
2) Each customer is served by exactly one vehicle
3) Each route begins and ends at the same depot
4) The total vehicle load at any point of the route does not exceed the vehicle capacity
5) The total pickup and total delivery load of the customers assigned to an opened depot do not exceed the capacity of the depot

By consideration of a variant of the Location-Routing Problem with consideration of green aspectsand the simultaneous pickup and delivery, we will minimize the total cost by simultaneously locating the distribution centers and designing the vehicle routes that satisfy pickup and delivery demand of each customer at the same time, in a way that ecological aspects are observed. There are miscellaneous green criterion in literature. Our effort was to consideration of minimizing the weight of vehicle as a green criterion in order to minimize the effect of greenhouse gases. Besides, vehicles are heterogeneous in this paper. This assumption is exactly opposite of the research of Karaoglan et al (vehicles were homogeneous) [7].

3. Mathematical Model

The following notations are used for mathematical formulation of proposed model:

Sets and indices:

d	Index of distribution center $d = 1,.........., D$
$c, \hat{c}$	Index of customer $c = 1,..........., C$
v	Index of vehicle $v = 1,........., V$

Parameters:

cap_d^{dist}	Capacity of distribution center d
cap_v^{veh}	Capacity of vehicle v
$dis_{\hat{c}c}^{cus}$	Distance between customer c and customer $\hat{c}$
$tm_{v\hat{c}c}^{cus}$	Time interval between customer c and customer $\hat{c}$ passed by vehicle v
dis_{dc}	Distance between distribution center d and customer c
tm_{vdc}	Time interval between customer c and distribution center d passed by vehicle v
$\cos t_d^{dist}$	Construction cost of distribution center d
$\cos t_v^{veh}$	Supply cost of vehicle v
del_c	Delivery demand of customer c
pic_c	Pickup demand of customer c
f_v	Amount of usage of fuel in return for distance unit of vehicle v
$\hat{f}_v$	Amount of usage of fuel in return for transported load unit of vehicle v
c^{fuel}	Cost of usage of fuel
M	A big number

Variables:

x_d^{dist}	Binary variable which is equal to 1 if distribution center d is constructed
x_v^{veh}	Binary variable which is equal to 1 if vehicle v is supplied
$\lambda_{v\hat{c}c}$	Binary variable which is equal to 1 if vehicle v firstly goes to customer $\hat{c}$ then goes to customer c
β_{vd}	Binary variable which is equal to 1 if vehicle v is assigned to distribution center d
at_{vc}	Entering time of vehicle v to the location of customer c
U_{vc}	Available amount of delivery load of vehicle v before serving to customer c
W_{vc}	Available amount of pickup load of vehicle v after serving to customer c
$mass_{vc}$	Available amount of load of vehicle v before entering to the location of customer c

The mathematical formulation of proposed model is as follows:

$$Min\ z^{\cos t} = c^{fuel} \times \sum_{v,d,c>1} (f_v + \hat{f}_v \times del_c) \times dis_{dc} \times \lambda_{v1c} \times \beta_{vd}$$
$$+ c^{fuel} \times \sum_{v,\hat{c}>1,c>1} (f_v + \hat{f}_v \times mass_{vc}) \times dis_{\hat{c}c}^{cus} \times \lambda_{v\hat{c}c}$$
$$+ c^{fuel} \times \sum_{v,d,c>1} (f_v + \hat{f}_v \times pic_c) \times dis_{dc} \times \lambda_{vc1} \times \beta_{vd}$$
$$+ \sum_v x_v^{veh} \times \cos t_v^{veh} + \sum_d x_d^{dist} \times \cos t_d^{dist}$$

s.t:

$$\sum_c pic_c \le cap_d^{dist} \times x_d^{dist} \qquad \forall d \qquad (1)$$

$$\sum_c del_c \le cap_d^{dist} \times x_d^{dist} \qquad \forall d \qquad (2)$$

$$mass_{vc} \le cap_v^{veh} \times x_v^{veh} \qquad \forall v,c \qquad (3)$$

$$\sum_c mass_{vc} \le M \times \sum_d \beta_{vd} \qquad \forall v,d \qquad (4)$$

$$\sum_d \beta_{vd} \le 1 \qquad \forall v \qquad (5)$$

$$\sum_v \beta_{vd} \le M \times x_d^{dist} \qquad \forall d \qquad (6)$$

$$\sum_{\hat{c}} \lambda_{v\hat{c}c} \le 1 \qquad \forall v,c \qquad (7)$$

$$\sum_{\hat{c}} y_{v\hat{c}c} = \sum_{\hat{c}} y_{vc\hat{c}} \qquad \forall v,c \qquad (8)$$

$$at_{vc} \ge \sum_{\hat{c}} (at_{v\hat{c}} + tm_{v\hat{c}c}^{cus}) \times \lambda_{v\hat{c}c} \qquad \forall v,c>1 \qquad (9)$$

$$at_{vc} \ge \sum_d tm_{vdc} \times \beta_{vd} \times \lambda_{vc1} \qquad \forall v,c \qquad (10)$$

$$mass_{vc} \le M \times \sum_{\hat{c}} \lambda_{v\hat{c}c} \qquad \forall v,c \qquad (11)$$

$$U_{vc} - U_{v\hat{c}} + cap_v^{veh} \times \lambda_{vc\hat{c}} + (cap_v^{veh} - del_{\hat{c}} - del_c) \times \lambda_{vc\hat{c}} \le cap_v^{veh} - del_{\hat{c}} \qquad \forall v,c,\hat{c} \qquad (12)$$

$$W_{v\hat{c}} - W_{vc} + cap_v^{veh} \times \lambda_{vc\hat{c}} + (cap_v^{veh} - pic_{\hat{c}} - pic_c) \times \lambda_{vc\hat{c}} \le cap_v^{veh} - pic_c \qquad \forall v,c,\hat{c} \qquad (13)$$

$$U_{vc} + W_{vc} - del_c \le cap_{veh}^v \qquad \forall v,c \qquad (14)$$

$$U_{v\hat{c}} \ge del_{\hat{c}} + \sum_c del_c \times \lambda_{v\hat{c}c} \qquad \forall v,\hat{c} \qquad (15)$$

$$W_{vc} \ge pic_c + \sum_{\hat{c}} pic_{\hat{c}} \times \lambda_{v\hat{c}c} \qquad \forall v,c \qquad (16)$$

$$mass_{vc} = \sum_{\hat{c}} (U_{vc} + W_{v\hat{c}}) \times \lambda_{v\hat{c}c} \qquad \forall v,c \qquad (17)$$

$$x_d^{dist}, x_v^{veh}, \lambda_{v\hat{c}c}, \beta_{vd} \in (0,1) \qquad \forall d,v,c,\hat{c}, \qquad (18)$$

$$at_{vc}, U_{vc}, W_{vc}, mass_{vc} \ge 0 \qquad \forall v,c. \qquad (19)$$

Objective function reducesthe cost of transportation (usage of fuel and supply of vehicle) and those of construction of distribution centers. Constraints (1-2) depicts that the total amount of pickup and delivery demand to customers by each distribution center in each period do not exceed the capacity of distribution center. Constraint (3) expresses that the amount of transported products by each vehicle do not exceed the capacity of vehicle. Constraint (4) explains that each vehicle is assigned to one distribution center. Based on constraint (5) each vehicle is at most assigned to one distribution center. Constraint (6) expresses that it is not possible to assign a vehicle to one distribution center, unless that distribution center is constructed. Constraint (7) assures that each vehicle visits each customer at most one in each period but it is possible to visit some vehicle simultaneously. Constraint (8) represents that if a customer enters to a specific location, he must leave there. Sub tour elimination is explained by constraints (9-10). Condition of receiving a product by customer is the visit of customer by vehicle which is expressed by constraint (11). Constraints (12-13) guarantee the satisfaction of delivery and pickup demand. Constraint (14) explaines that total transported load by each vehicle does not exceed the capacity of vehicle. Constraints (15-16) calculate the available amount of pickup and delivery demand of each customer. the availability amount of vehicle load before entering to the location of customer is clear in the constraint (17) Constraint (18-19) represents the range of model variables.

4. Hybrid GA-SA Algorithm

4.1. Simulated Annealing

SA, which was firstly developed by Kirkpatrick et al in 1983 which is considered as a local search algorithm. It is based on the analogy between the process of finding a possible best solution of a combinatorial optimization problem and the annealing process of a solid to its minimum energy state in statistical physics. SA is similar to hill climbing or gradient search with a few modifications but it does not require the optimization function to be smooth and continuous [8]. The SA algorithm is an iterative search procedure based on a neighborhood structure. The quality of the annealing solution is sensitive to the way of selecting the candidate (trial) solutions. Thus, a neighborhood structure, including a generation mechanism and its set size, is crucial for the performance of the SA algorithm. The SA algorithm with a larger neighborhood performs better than that with a smaller one, i.e., a larger neighborhood makes it likely to reach out over a much broader space of the solution set. The neighborhood structure provides global asymptotic convergence for an arbitrary solution. Hence, there exists at least one global optimal solution that can be reached in a finite number of iterative transitions. The process of searching begins with one initial random solution. A neighborhood of this solution is generated using a neighborhood move rule and then the cost between neighborhood solution and current solution can be found, according to Eq. (20).

$$\Delta C = C_i - C_{i-1} \tag{20}$$

where ΔC , C_i and C_{i-1} represent change amount between costs of the two solutions, neighborhood solution and current solution, respectively. If the cost declines, the current solution is replaced by the generated neighborhood solution. Otherwise, the current solution is replaced with the new neighborhood solution with some probability, which is generated using Eq. (21) and the same steps are repeated. After the new solution is accepted, inner loop is checked. If the inner loop criterion is met, the value of temperature is decreased using a predefined cooling schedule. Otherwise, a new neighborhood solution is regenerated and the same steps are repeated. The process of searching is repeated until the termination criteria are met or no further improvement can be found in the neighborhood of the current solution. The termination criterion (outer loop) is predetermined:

$$e^{(-\Delta C/T)} \succ R \tag{21}$$

where the temperature (T) is a positive control parameter. R is a uniform random number between 0 and 1. SA operators are described as follows:

4.1.1. Neighborhood Move

First, an initial solution randomly is generated. Then, neighborhood move is used to produces solution close to the current solution in search space. Basically, two neighborhood moves are employed: swapping move and shifting move [10]. In swapping move, two genes are randomly selected and the positions of these genes were swapped. Then, a new neighborhood solution is produced. In shifting move, two genes are randomly selected similarly and the second gene is put in front of other genes. Thus, a new solution is produced.

4.1.2. Cooling Schedule

Each problem requires a unique cooling schedule and it becomes very difficult to pick the most appropriate schedule within a few simulations. These schedules are proportional decrement schedule and Lundy and Mees schedule [11]. In proportional decrement schedule, the relationship between the temperature values in kth and (k+1) th iterations is according to Eq.(22).

$$T_{k+1} = \alpha T_k \qquad \alpha = \sqrt[M]{\frac{T_f}{T_i}} \tag{22}$$

where T_k and T_{k+1} are temperatures in kth and ($k+1$) th iterations, respectively and α is the coefficient between two temperatures that varies between 0 and 1. Besides, M, T_f and T_i are the number of iteration, the final and the initial temperatures, respectively. In Lundy and Mees schedule, the relationship between T_{k+1} and T_k is according to Eq.(23).

$$T_{k+1} = \frac{T_k}{1+\beta T_k} \qquad \beta = \frac{T_i - T_f}{M T_i T_f} \tag{23}$$

$\beta \succ 0$ is the coefficient between two temperatures: T_{k+1} and T_k .

4.1.3. Inner Loop and Outer Loop Criterion

Inner loop criterion determines the number of possible new solutions to produce in each temperature value and outer loop criterion is used to stop the searching process.

4.2. Genetic Algorithms

GA, one of the optimization and global search methods, is based on the simulated natural selection [3]. GA was developed by Holland in the 1970s. It is applied effectively to solve various combinatorial optimization problems and is based on probabilistic rules [4]. Selection, crossover and mutation are the most essential genetic operators. GA searches new and better solutions to a problem by improving current population. The search is guided towards the principle of the survival of the fittest. This is obtained by extracting the most desirable characteristics from a generation and combining them to form the next generation. The population includes a set of chromosomes. Each chromosome in the population is a possible solution. The quality of each possible solution is measured by fitness function. First, GA generates initial population and then calculates the fitness value according to fitness function for each chromosome of the population. Fitness function is specifically generated for each problem. It may be simple or complex according to the problem. Then optimization criterion is checked. If the optimization criterion is met, this solution can be considered as the best solution. Otherwise, new population is regenerated using GA operators (selection, crossover, and mutation). According to their fitness values, chromosomes are selected for crossover operation using a selection operator. Therefore each chromosome will contribute to the next generation in proportion to its fitness. Then crossover and mutation operators are applied to the selected population to create the next population. The process continues through generations until the convergence on optimal or near-optimal solutions. However GA cannot guarantee to find the best optimal solution. GA operators are described as follows:

4.2.1. Population

It is a set of possible solutions to the problem. Since the size of the population varies according to problem, there is no clear mark on how large it should be. Then, fitness value for each chromosome of the population is calculated according to fitness function.

4.2.2. Elitist Selection

Selection operator selects the chromosomes to be mated according to their fitness values. Elitist selection is used here which means that a practical variant of the general process of constructing a new population is to allow the best organism (s) from the current generation to carry over to the next, unaltered. This guarantees that the solution quality obtained by the GA will not decrease from one generation to the next.

4.2.3. Cross Over

Cross over operator is a powerful tool for exchanging information between chromosomes and creating new solutions. It is expected that good parents may produce better solutions.

4.2.4. Mutation

This operator is used to prevent reproduction of similar type chromosomes in population. Mutation operator randomly selects two genes in chromosome and swaps the positions of these genes to produce a new chromosome. This technique is called swap mutation.

4.3. Hybrid Algorithm

Hybridization refers to combining two search algorithms to solve a given problem. This is often a population-based search such as GA with local searches performed by other algorithms like simulated annealing, greedy algorithm, etc. The main drawbacks of SA algorithms are the computation time and limited convergence behavior. For better results the cooling has to be carried out very slowly and this significantly increases the computation time. Various computations in SA operators increase the computation time when the dimension of the problem grows. Optimum iteration should be selected to decrease computation time. With this iteration, hybrid approach is needed to obtain the global optimum solution. It is common to start SA from a random configuration. The performance of SA may be improved if more information is known about the problem in hand.

Hence it might be better to start from a configuration which is a good local minima, like a configuration obtained by a GA algorithm search. Starting from a good local minimal with initial high temperature will provide an opportunity to escape the poor local minima and attain a better solution, possibly global minima [4, 6]. This paper uses a hybrid scheme to integrate P-D scheduling in SCM using GA and SA. GA can reach the region near an optimum point relatively quickly, but it can take many function evaluations to achieve convergence. A technique used here is to run GA for a small number of generations to get near an optimum point. Then the solution from GA is used as an initial point for SA that is faster and more efficient for local search.

5. Computational Results

This section explains the test problems which aim at showing the applicability of the proposed algorithm. The computational results are reported, evaluated and analyzed with respect to the proposed model. For the small and medium-size problems, the solutions presented by hybrid GA-SA are compared with the results obtained from GAMS optimization software. We previously applied Hybrid Heuristic Genetic Algorithm-Simulated Annealing for solving a scheduling MIP model in large-size problem and the result was really efficient. We refer the interested readers to that [24].

5.1. Designing the Test Problems

Various test problems, with different sizes are considered to assess the performance of the proposed algorithm. We consider three sets of 7 small-size, 7 medium-size and 3 large- size problems to be solved using hybrid GA-SA, i.e., a total of 17 instances were run. In each problem, the values of each group of parameters are generated randomly between their lower and upper bounds, based on Table 1.

5.2. Setting the Hybrid GA-SA Parameters

Parameters of the hybrid GA-SA include *population size*, *cross over rate*, *mutation rate*, *max iteration* and *T*. Primary tests are carried out in order to determine the values of these parameters. A trade-off between the solution time and the quality determined the appropriate value. The values for *population size*, *cross over rate*, *mutation rate*, *max iteration* and *T* are set to 200, 0.5, 0.1 200 and 100, respectively.

5.3. Computational Results

The proposed GLRPSPD model has been solved using CPLEX solver of GAMS for small and medium-size problem. For large-size problem, the hybrid GA-SA is employed. The proposed algorithm is coded in Matlab. All the test problems are solved on an Intel corei5 computer with 4 GB RAM and 2.67 GHz CPU.

A quality criterion, ERROR, is defined to show the deviation of the value of the hybrid GA-SA solutions from the values of GAMS, according to Eq. (24).

$$ERROR = \frac{(\mathrm{GASA.Z} - \mathrm{GAMS.Z})}{GAMS.Z} \tag{24}$$

To investigate the performance of GAMS optimization software and hybrid GA-SA algorithm, two criterions, i.e., objective value and run time have been considered. The results of small and medium-size problem are shown in Table 2 and Table 3, respectively.

Based on the results of Table 2, small-size problem are applicable to the problem in which the run time of GAMS optimization software is less than 700s. On average, hybrid GA-SA achieved 96% of the exact optimal solutions within 16% of the exact run time. In other word, the average deviation from the optimum for small-size problem does not exceed 4% of error. The trivial deviation shows the efficiency of the proposed algorithm. Figure 1 depicts hybrid GA-SA objective value versus GAMS objective value for small-size problem. It is clear that hybrid GA-SA objective value compared to that of GAMS decreases when the problem size increases. Figure 2 delineates hybrid GA-SA run time versus GAMS run time for small-size problem. It is shown that GAMS run time increases exponentially as the size increases. Base on the results of Table 3, in medium-size problem the run time of GAMS optimization software is less than 2000s. As it is obvious, hybrid GA-SA algorithm achieved 89% to 92% of the exact optimal solution, within 5% to 8% exact run time. This result denotes the efficiency of the proposed algorithm. Figure 3 shows, hybrid GA-SA objective value versus GAMS objective value for medium-size problem. The trivial deviation shows the high accuracy of the proposed algorithm to cope with large-size problems. Figure 4 delineates hybrid GA-SA run time versus GAMS run time for medium-size problem. It is observed that the run time and complexity of solving problems by hybrid GA-SA are lower than GAMS optimization software. Besides, the differences between the run time of GAMS optimization software and hybrid GA-SA is increased, as the problem size accelerates. This means that hybrid GA-SA solves the large-size problem in an acceptable time. Objective value and run time for GAMS optimization software and hybrid GA-SA for large-size problem are calculated. As shown in Table 4, out of memory message of GAMS appears regarding test problem 17. This is due to the saturation of RAM and stopping the calculation before achieving an acceptable solution. We also considered 1000s as a limit to stop the algorithm after a specific run time. As it is clear, an error message is appeared in test problem 15 and 16 run by GAMS, which means that the run time exceeded 2000s and GAMS is not able to solve the problem. Furthermore, the proposed hybrid algorithm is not able to converge in considered limit but this algorithm achieved acceptable solution in all 3 test problems. It is observed that, the deviation of hybrid GA-SA from the optimum for test problems 15 and 16 are 8% and 12%, respectively. This denotes the high capability of meta-heuristic algorithms for solving the large-size problem.

Table 1. *Some important inputs for models.*

Number	Parameter		Distribution function
Indices			
1	d	Depot	
2	c	Customer	
3	v	Vehicle	
Parameters			
4	Node position	x	continuous uniform ([0 200], {c})
		y	continuous uniform ([0 200], {c})
5	Node position	$x1$	continuous uniform ([0 200], {d})
6		$y2$	continuous uniform ([0 200], {d})
7	cap_d^{dist}	continuous uniform ([5000 10000])	
8	cap_v^{veh}	continuous uniform ([2000 3000])	
9	$d_{c\hat{c}}^{cus}$	Euclidean distance (x, y)	
10	$t_{vc\hat{c}}^{cus}$	$d_{c\hat{c}}^{cus}$ * continuous uniform ([0.8 1.2])/100	
11	dis_{dc}	Euclidean distance (x1, x), (y1, y)	
12	tm_{vdc}	dis_{dc} *continuous uniform ([0.8 1.2])/100	
13	$\cos t_d^{dist}$	continuous uniform ([2000000 3000000])	
14	$\cos t_v^{veh}$	continuous uniform ([1000000 2000000]){v}	
15	del_c	continuous uniform ([100 300])	
16	pic_c	continuous uniform ([10 30])	
17	f_v	continuous uniform ([10 20])	
18	$\hat{f}_v$	continuous uniform ([0.1 0.3])	
19	c^{fuel}	1000	

Table 2. *Comparison between the performance of GAMS and hybrid GA-SA (optimality and run time) for small- size problem.*

Problem number	Indices			GAMS		GASA		$\left(\frac{\mathrm{GASA}.\boldsymbol{Z}-\boldsymbol{GAMS}.\boldsymbol{Z}}{\boldsymbol{GAMS}.\boldsymbol{Z}}\right)$	GAMS error message	GASA algorithm stop condition
	d	c	v	Objective value	Run time	Objective value	Run time			
1	3	5	3	109195198	21.8	109195198	4.9	0	-	-
2	3	6	3	121659765	32	121659765	6.4	0	-	-
3	4	6	4	123146583	54.2	126272905	12	0.025	-	-
4	4	7	5	143613035	138.8	153481836	24.4	0.069	-	-
5	5	8	5	148069078	274.4	153546597	37.7	0.037	-	-
6	6	8	5	150672113	485.7	158094071	56.5	0.049	-	-
7	6	9	6	161538009	641.5	172950346	58.5	0.071	-	-
Min	3	5	3	109195198	21.8	109195198	4.9	0	-	-
Mean	4.4	7	4.4	136841969	235.4	142171531	28.6	0.035	-	-
Max	6	9	6	161538009	641.4	172950346	58.5	0.071	-	-

Table 3. *Comparison between the performance of GAMS and hybrid GA-SA (optimality and run time) for medium-size problem.*

Problem number	Indices			GAMS		GASA		$(\frac{GASA.Z - GAMS.Z}{GAMS.Z})$	GAMS error message	GASA algorithm stop condition
	d	c	v	Objective value	Run time	Objective value	Run time			
8	7	10	7	181983090	783.7	195448383	68.8	0.074	-	-
9	7	11	8	215230577	894.4	231824854	64.4	0.077	-	-
10	7	12	8	225751229	933.6	246726679	68.4	0.093	-	-
11	8	12	9	235857522	1183.4	258808582	77.3	0.097	-	-
12	8	13	9	235968692	1244.6	253184732	80.2	0.073	-	-
13	9	14	9	244852124	1570.4	264856787	88.8	0.082	-	-
14	9	15	10	249490912	2045.2	276834367	113.1	0.11	-	-
Min	7	10	7	181983090	783.7	195448383	64.4	0.073	-	-
Mean	7.9	12.4	8.6	227019164	1236.5	246812055	80.1	0.087	-	-
Max	9	15	10	249490912	2045.2	276834367	113.1	0.11	-	-

Table 4. *Comparison between the performance of GAMS and hybrid GA-SA (optimality and run time) for large-size problem.*

Problem number	Indices			GAMS		GASA		$(\frac{GASA.Z - GAMS.Z}{GAMS.Z})$	GAMS error message	GASA algorithm stop condition
	d	c	v	Objective value	Run time	Objective value	Run time			
15	10	20	12	1130881553	2000	1037353740	1000	-0.08	Resource limit exceeded	Time limit exceeded
16	15	30	15	1564587999	2000	1366786637	1000	-0.13	Resource limit exceeded	Time limit exceeded
17	20	50	17	-	-	1697631389	1000	-	Out of memory	Time limit exceeded
Min	10	20	12	1130881553	0	1037353740	1000	-0.13	-	-
Mean	15	33,3	14,6	898489850	666,6	1081818460	1000	-0.08	-	-
Max	20	50	17	1564587999	2000	1697631389	1000	0.08	-	-

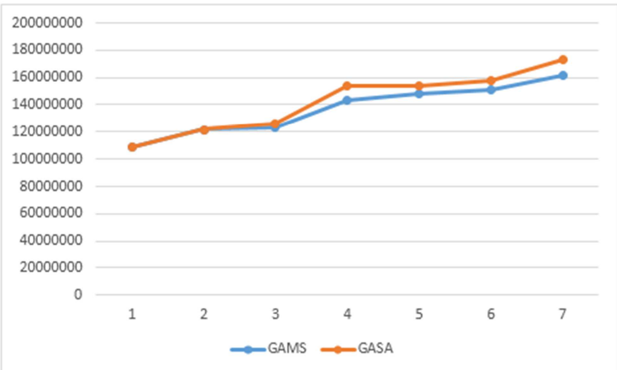

Figure 1. *Hybrid GA-SA objective value versus GAMS objective value for small-size problem.*

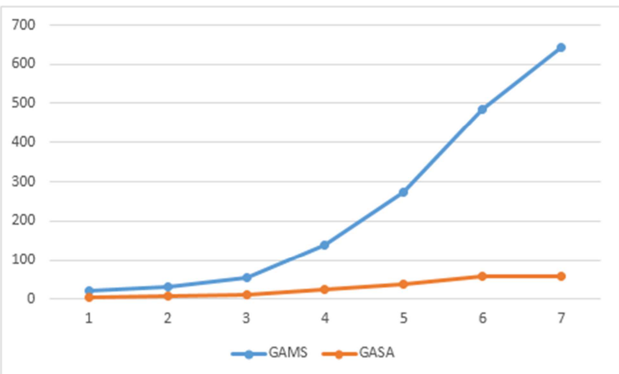

Figure 2. *Hybrid GA-SA run time versus GAMS run time for small-size problem.*

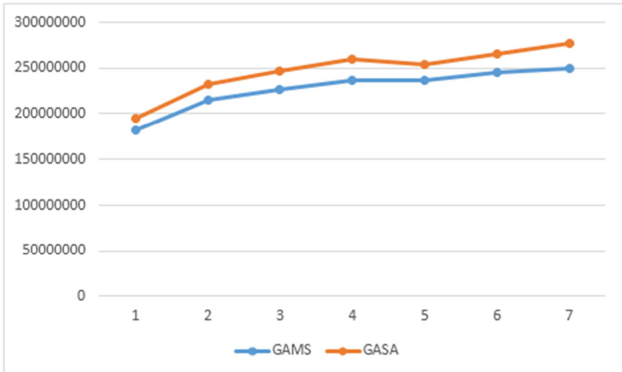

Figure 3. *Hybrid GA-SA objective value versus GAMS objective value for medium-size problem.*

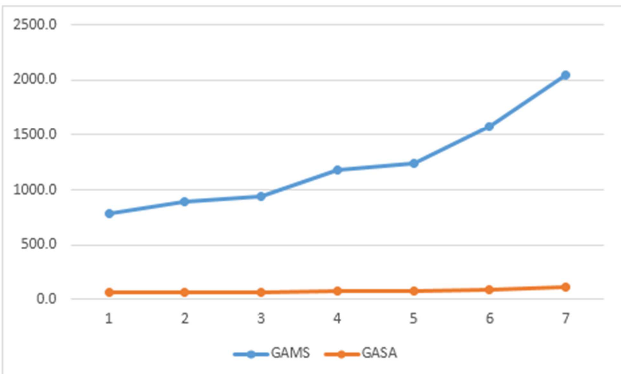

Figure 4. *Hybrid GA-SA run time versus GAMS run time for medium-size.*

6. Conclusions and Future Research Directions

We considered a variant of the Location-Routing Problem (LRP) with consideration of green aspects, namely the green LRP with simultaneous pickup and delivery (GLRPSPD) in this research. The main goal of GLRPSPD is to reduce the total cost by simultaneously locating the distribution centers and designing the vehicle routes that satisfy pickup and delivery demand of each customer at the same time, in a way that ecological aspects are clearely observed. We formulated the mentioned problem with MIP model and solve it with GAMS optimization software. A hybrid heuristic GA-SA was developed to solve the real-size problem in reasonable time period. The solutions obtained by GAMS are compared with those obtained from the hybrid GA-SA and the results show that developed GA-SA is efficient in terms of computational time and the quality of the solutions obtained.

The following approaches are proposed for future work:

1) Cost minimization has been recognized as the most respected performance measure for the evaluation of SC performance. Maximizing the service level and also maximizing the profit can be considered as the objective functions.
2) In this research, we only focused on the integration of distribution and customer. It is also possible to add the supply-side and integrate the whole supply chain.
3) There is still a need to further extend the effectiveness of the existing solution approaches and to test the new arrivals such as Ant Colony Optimization (ACO) and Bee Colony Optimization (BCO) techniques.

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