

A Practical Case Study of a Heterogeneous Fleet Vehicle Routing Problem with Various Constraints

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Abstract—In this research, the problem addressed involves sets of practical case studies relating to a third-party logistics firm that mainly provides services to a big industrial estate in Thailand. This study considers constraints consisting of time windows, multiple trips, multi-product deliveries, a limited number of drivers and mixed fleets with limited and unlimited numbers of available vehicles. An adapted genetic algorithm hybridizes three inter-route search operators, i.e. relocation, exchange and elimination are developed and used to determine the best solution to a heterogeneous fleet vehicle routing problem with various constraints as mentioned previously. The benchmark problem sets do not exactly fit the addressed unique problem; therefore, the performance of the proposed method is evaluated against a branch-and-bound algorithm as a built-in solver. Due to the limitations of the solver for solving large-scale problems, percentage deviations of the solutions with respect to the best results and computation times are measured to confirm the quality of the presented method.

Keywords— *Genetic Algorithm; Heterogeneous fleet; Various constraints; Multi-product delivery; Multiple trips; Driver constraints; Time windows; Split deliveries; Real-world case.*

I. INTRODUCTION

Many companies have recently been focusing on their core business strengths. Third-party logistics providers may be chosen to fulfil the needs of warehouses and logistics management. Route optimization is one of a number of key performance-based logistics agreements and goals that logistics organizations utilise. Many articles published in recent years have presented alternative methodologies for solving benchmark problem sets, but few researchers have addressed these through analysis in real life. In previous research [1], heterogeneous vehicle routing problems have been surveyed. Special attention has been given to variants of heterogeneous fleet vehicle routing problems. In classic problems, a truck is allowed to perform only one trip. But in practical situations, trucks are probable assigned to complete more than one trip as long as working-hour and time-window restrictions are not violated. A truck that arrives at a customer's location before or after a time window interval is not permitted to perform any activities. Furthermore, in practice, product types can be extended from single- to multiple-product deliveries. On industrial estates, most companies have continuous process factories where products are mass-produced. This characteristic of operations leads to demands for goods transportation greater than a truck's capacity; therefore, split deliveries are allowed. Even if third-party logistics providers have their own fleet of vehicles, customer demands may be higher than the

available number of available trucks. Then, additional fleets from other external courier companies are required to offer the required capacity and satisfy customer needs.

In most published scientific research papers, real-life case studies are very limited in number. A literature review on real application studies proceeds as follows. A multi-depot multi-period heterogeneous fleet-vehicle routing problem is introduced in [2]. Trucks are assigned by applying an adaptive large neighbourhood search method. These trucks begin their service from several depots and operate over a weekly planning-time horizon. A multi-depot heterogeneous vehicle routing problem with time windows, as presented in [3], applies a modified variable neighbourhood search consisting of insert and exchange operators. Furthermore, a variable neighbourhood search algorithm is another technique that is used to determine an optimal solution to a multi-depot heterogeneous vehicle routing problem that appears in [4]. Three-dimensional loading constraints, i.e. stacking, load-balancing and capacity limitation, are considered in [5]. This research discusses a heterogeneous fleet vehicle routing problem involving distributing fibre boards in Australia. An optimal solution is found by using a simulated annealing algorithm. A method based on dynamic programming is introduced in [6] for solving various real-life constraints, including time-dependent travel times, driving-hours regulations, a rolling-time horizon, multiple compartments and customer combinations. Various permutations of these variants can be combined in a dynamic programming framework. A study of split product deliveries with time windows using a heterogeneous fleet is found by the research [7]. A scatter-search approach is designed to solve the problem. This scheme is implemented in the real-life case of a major Brazilian retail group. A genetic algorithm is proposed in [8] to find the minimum transportation cost of frozen-food deliveries. A particular restriction is to maintain the temperature of the cargo to ensure keeping multiple kinds of food fresh. There are no benchmark problem sets that match the constraints considered, hence an experimental computation run is performed based on real examples. Another real-life case study involving a site-dependent heterogeneous vehicle routing problem can be found in [9]. A greedy search procedure is developed and applied to solve a problem which has restrictions on time windows and limitations on vehicle types that can access each customer area.

According to the above discussion, the characteristics of practical cases in different business operations are unique. Purely theoretical problem models cannot cover all the various restrictions found in real situations. Hence models are designed based on different business scenarios. The complexity is increased when many constraints are involved; then, a heuristic algorithm is the best choice to apply and develop and thus solve these specific problems. Due to differences in the details, experiments cannot be performed on a benchmark problem set. Test cases based on real situations are examined to evaluate the performance of the proposed methodologies. There is a more detailed discussion in the following sections. The problem description and model are described in Section II. An adapted genetic algorithm that hybridizes search operators is presented in Section III. The computation results are presented and discussed and a conclusion drawn in the last two sections.

II. PROBLEM DESCRIPTION

A. Problem Statement

A classic problem of route planning is to assign a single type of vehicle to carry a single product type from a central depot to various destinations. A truck can only provide services on one trip; in other words, the truck can visit more than one customer but it has to return to the depot and its work is terminated after it has delivered the last load on a single route. In this paper, a truck can be assigned more than once as long as the working hours regulations for drivers are not violated. Battarra *et al.* [10] define this task as a minimum multiple-trip vehicle routing problem. The objective is to minimize the overall number of multiple trips, the best solution to minimizing the routing cost is obtained when the total number of vehicles used is minimized.

The logistics firm in this study is a large organization that offers expert services to a specific industry in Thailand. Various products from different customers can be categorized into community types. To serve multi-commodity category demands, the company uses its own vehicle fleet comprising different kinds and capacities. Although the company mainly use its own couriers, sometime customer demands exceed their own fleet's availability. Outsourcing is a call-up service option that may be used to fulfil customer needs. Thus, in this study, fleet availability is considered to be a semi-unlimited type, i.e. a mix of limited and unlimited truck supplies. In addition, each truck can transport a single product to one customer on each trip, but it can be assigned as many trips as are allowed within determined time-interval constraints. Furthermore, this research includes a limitation on the number of drivers and assumes that the total number of absent operators is known and can be planned for. This factor impacts on own-vehicle usage. The company does not permit any subcontractors to drive the company's trucks. If the number of drivers is less than the available trucks, outsourcing services are used to compensate for missing drivers.

It is generally like the traditional problem, and so overweight carrying is not allowed. However, the dimensions of containers impose an additional delivery limitation. The carrying capacity of a vehicle, or payload, is specified for individual products. Most customers in this research have demands that exceed one truck's capacity, therefore these requirements are fulfilled by allowing partial loads. Some customers determine the limitations of operation time intervals and strictly request that trucks provide service within time windows. In real service situations, the travel time is probably uncertain for many reasons, such as traffic, road accidents, vehicle breakdowns etc. A cycle time is supposed to represent the average time or distance travelled from/to the distribution centre to/from each customer node proposed to reduce complicated events due to an uncertain work environment. The objective is to achieve the minimum total transportation cost where the total number of trips is minimized.

B. Problem Formulation

In this research, the objective is to minimize the total transportation cost where only the minimum number of multiple trips is considered. In order to accomplish this cost-minimization goal, the total number of trucks used has to be determined. The published paper [11] presents the objective function of the homogeneous fleet multi-trip vehicle routing problem. The objective is applied to a heterogeneous fleet to serving multiple products as follows:

$$\min \sum_{j \in N \setminus \{0\}} \sum_{p \in P} \sum_{k \in K} c_{0j}^{pk} x_{0j}^{pk} \quad (1)$$

The problem can be formed as a directed graph $G = (N, A)$. N represents the node set, consisting of the customers and a depot: $N = \{0, 1, \dots, n\}$. The depot is denoted by the node $\{0\}$, the remaining set of nodes $\{1, 2, \dots, n\}$ is a given customer set. Arc A is a route set that has to be arranged. The notation c_{0j}^{pk} is the cheapest routing cost where a vehicle type $k \in K$ is selected to serve a commodity type $p \in P$ being transported from the distribution centre to customer j . The capacities and costs of vehicle types are labelled, from the lowest capacity and cost to the greatest capacity and cost as follows: $Q^{11} \leq Q^{12} \leq \dots \leq Q^{21} \leq Q^{22} \leq \dots \leq Q^{pk} \leq \dots \leq Q^{PK}$ and $C^{11} \leq C^{12} \leq \dots \leq C^{21} \leq C^{22} \leq \dots \leq C^{pk} \leq \dots \leq C^{PK}$. After finishing unloading activity, the truck only heads back to the depot, it can perform more than one trip within a determined time window. A resource cannot be assigned to other routes when it is occupied. A feasible route $r \in R$ that belongs to the optimal solution is selected to enhance the lowest cost of transportation. The decision variable x_{0j}^{pk} indicates the number of feasible trips and is greater than or equal to 1. The variable a_{0j}^{pk} is a binary variable that is equal to 1 if and only if customer j is allocated to route $r \in R$ using vehicle k and belongs to the optimal solution. Equation (2) guarantees that every customer is visited at least once and only one customer is assigned to a route.

$$\sum_{r \in R} a_{0j}^{pk} x_{0j}^{pk} \geq 1, \forall j \in N \setminus \{0\} \quad (2)$$

$$x_{0j}^{pk} \in \text{Integer}, a_{0j}^{pk} \in \text{Binary}, r \in R \quad (3)$$

The cost structure comprises two components, i.e. a fixed cost and a variable cost. In this study, the fixed cost is the combination set of 1) depreciation of the vehicle used, 2) vehicle insurance and 3) transportation tax. The variable cost is calculated based on 1) the fuel cost which depends on the distance travelled, 2) the driver cost and 3) the maintenance cost. A set of costs $c \in C$ represents the overall cost which already combines the fixed and variable cost components as mentioned. The cost c depends on the customer visited and the vehicle type used. The following constraints are applied from heterogeneous fleet vehicle routing problem research which is presented in [12] to [16].

$$\sum_{k \in K} d_j^{pk} \sum_{k \in K} a_{0j}^{pk} x_{0j}^{pk} - D_j^p \geq 0, \forall p \in P, \forall j \in N \setminus \{0\} \quad (4)$$

$$d_j^{pk} a_{0j}^{pk} \leq q_j^{pk}, \forall k \in K, \forall p \in P, \forall j \in N \setminus \{0\} \quad (5)$$

$$\sum_{j \in N \setminus \{0\}} a_{0j}^{pk} \geq 1, \forall k \in K, \forall p \in P \quad (6)$$

$$\sum_{j \in N \setminus \{0\}} a_{j0}^{pk} \geq 1, \forall k \in K, \forall p \in P \quad (7)$$

$$\sum a_{0h}^{pk} - \sum a_{h0}^{pk} = 0, \forall k \in K, \forall p \in P, \forall h \in N \setminus \{0\} \quad (8)$$

$$e_j \sum_{r \in R} a_{0j}^{pk} x_{0j}^{pk} \leq y_{0j}^{pk} \leq l_j \sum_{r \in R} a_{0j}^{pk} x_{0j}^{pk}, \forall k \in K, \forall p \in P, \forall j \in N \setminus \{0\} \quad (9)$$

$$y_{0j}^{pk} + v_j + 2w_{0j} - y'_{0j}^{pk} \leq (1 - x_{0j}^{pk})B_{0j}, \forall k \in K, \forall j \in N \setminus \{0\} \quad (10)$$

$$(l_j - e_j) - t_{0j}^{pk} u_{0j}^{pk} = 0, \forall k \in K, \forall p \in P, \forall j \in N \setminus \{0\} \quad (11)$$

$$\sum_{r \in R} t_{0j}^{pk} \sum_{r \in R} a_{0j}^{pk} x_{0j}^{pk} \leq (l_j - e_j), \forall k \in K, \forall p \in P, j \in N \setminus \{0\} \quad (12)$$

$$\sum_{k \in K} \sum_{r \in R} t_{0j}^{pk} \sum_{k \in K} \sum_{r \in R} a_{0j}^{pk} x_{0j}^{pk} \leq (l_0 - e_0), \forall p \in P, \forall j \in N \setminus \{0\} \quad (13)$$

$$\sum_{j \in N \setminus \{0\}} (a_{0j}^{pk} x_{0j}^{pk}) / u_{0j}^{pk} \leq m^{pk}, \forall k \in K, \forall p \in P \quad (14)$$

$$\sum m^{pk} \leq M, \exists k \in K, \exists p \in P \quad (15)$$

Customer j has a total demand for commodity type p denoted by D_j^p . The demand can be split into a partial quantity delivery d_j^{pk} , but the final delivered quantity has to be equal to or greater than the total requirement (4). The truck is limited to carrying the product given by the payload q_j^{pk} as specified by the individual customer's product sizing and weighing (5). Whenever a truck is assigned to service customer j , it needs to start from the depot and return to it (6) to (8).

Equation (9) is the time-windows constraints. The earliest and latest arrival times are denoted by interval $[e_j, l_j]$, where $e_j < l_j$. The depot is open for service during $[e_0, l_0]$, the service hours correspond to the working-time regulations for drivers. Every activity has to be performed within a given time, no services are allowed to violate the constraints. The model for the moment at which service begins at customer j can be found by setting $y_{0j}^{pk} = \max \{0, e_j - (y_{0i}^{pk} + v_i + w_{ij})\}$, where v_i and w_{ij} are the service times at customer i and the time taken to travel from customer i to customer j , respectively. A feasible schedule for each vehicle route can be guaranteed by forcing y_i^{pk} to equal zero whenever customer i is not visited by vehicle k [16]. Further work presented in this paper [15] shows the linearization of the formulation by using big B , which may be replaced by $\max \{l_i + v_i + w_{ij} - e_j, 0\}$ (10). Finally, (9) and (10) are a general formulation in case the problem allows having more than one customer node on the same route. In this paper, only one customer can be included in a feasible route, but a customer can have more than one feasible route to allow completion of their requirements. Therefore, the model can be rewritten as $y_{0j}^{pk} = \max \{0, e_j - (y_{0j}^{pk} + v_j + 2w_{0j})\}$. The variable y_{0j}^{pk} represents the moment of the new route when service begins again at customer j . According to the problem statement, the truck travels from the depot to customer j , and then returns directly from customer j to the depot after providing service. Therefore, the total distance or time travelled is calculated based on a round trip.

In practical cases, the travel time is uncertain. The cycle time t_{0j}^{pk} is supposed to represent the average time travelled from/to the distribution centre to/from each customer node. Equations (11) to (13) are proposed to replace (9) and (10) in order to reduce the complexity of this uncertainty and eliminate the variable y_{0j}^{pk} . Then u_j^{pk} denotes the number of trips in which truck k can transport commodity type p to customer j within time restrictions. The number of trips performed by vehicle k is limited by the time-window constraints of both depot and customers (12) and (13). The number of trips in which truck $k \in K$ can provide service within the duration constraint is restricted by the known number of available trucks m^{pk} (14). The numbers of each vehicle type that are capable of carrying commodity type $p \in P$ can be unlimited, none or an integer for some $k \in K$ and some $p \in P$ (16). Although the available vehicle fleet remains, it cannot be used if the number of useable truck types is greater than the known number of drivers M (15).

$$m^{pk} = \begin{cases} +\infty \\ \text{Integer}, \exists k \in K, \exists p \in P \\ 0 \end{cases} \quad (16)$$

III. SOLUTION APPROACH

Due to the difficulties in solving vehicle routing problems and their variants by using exact methods, applied heuristic/meta-heuristic algorithms become the efficient way to obtain the best solutions. In this paper, a two-phase procedure with a genetic algorithm hybridizes three search operators, i.e. relocation, exchange and route elimination are presented to solve the special problem of a heterogeneous fleet vehicle routing problem with time windows for a variety of product deliveries and other additional constraints.

An overview of the procedure is presented in Figure 1. In the first phase, an initial solution is obtained by relaxing the number of available vehicle fleets and driver constraints, then other constraints must be satisfied. The constraint relaxations in Phase I are added into Phase II. Moreover, solution improvement is performed in this phase by using an adapted genetic algorithm. Three inter-route search operators are implemented in this study consisting of relocation, exchange and elimination procedures. These search operators are proposed to encourage the crossover and genetic-mutation algorithms to diversify solution candidates. Solution improvement is done in an evolution-operation step, i.e. strong chromosomes with the best fitness functions will survive and be selected as the best solutions.

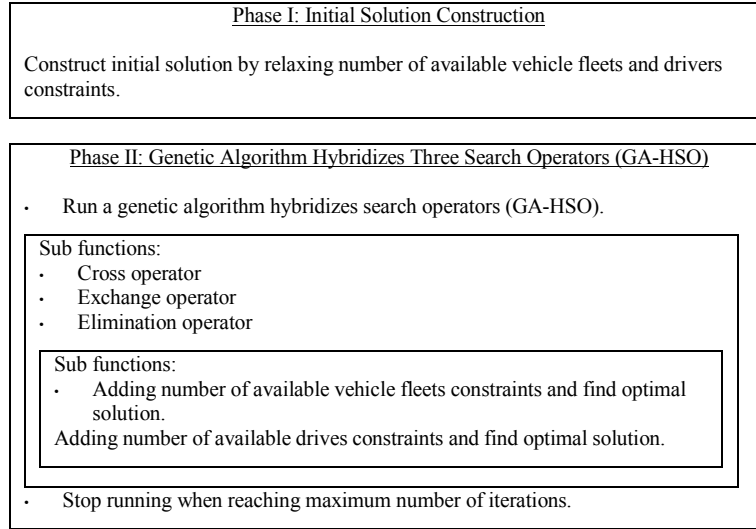


Fig. 1. An Overview Procedure for Solving a Heterogeneous Fleet Vehicle Routing Problem with Various Constraints.

A. Phase I – Initial Solution Construction

In this phase, an initial solution is generated based on an applied lower-bounds formulation, as presented in [14]. The lower-bound objective function minimizes the total cost of transportation where a customer $j \in N \setminus \{0\}$ and a vehicle type $k \in K$ are associated with an optimal solution for pivot j covering $h \in N \setminus \{0\}$. In a general case, more than one customer can be included in a route. In case there is more than one pivot customer in the same route, the pivot of the route (R, k) is called when a customer node has the smallest label. However, in this paper, once a route is selected, a truck can only provide service to one customer. Therefore, the pivot in this research is defined as a customer that belongs to the optimal solution and this customer can be the pivot of more than one route. In addition, the demands of customers can be split. An optimal solution uses the cheapest vehicle type k which can carry the allocated demand, the cheapest vehicle is denoted by q_j^{pk} . In order to obtain a lower-bound solution, the relaxation of constraints as presented in the previous section leads to the following mixed integer programming problem:

$$(LB) \quad \min \sum_{j \in N \setminus \{0\}} \sum_{p \in P} \sum_{k \in K} c_{0j}^{pk} x_{0j}^{pk} \quad (17)$$

$$\text{Subject to (3) to (8) and (11) to (13)} \quad (18)$$

$$\sum_{p \in P} \sum_{k \in K} z_{0j}^{pk} = 1, \forall j \in N \setminus \{0\} \quad (19)$$

$$d_j^{pk} z_{0j}^{pk} \leq q_j^{pk}, \forall k \in K, \forall p \in P, \forall j \in N \setminus \{0\} \quad (20)$$

$$\sum d_j^{pk} z_{0j}^{pk} \geq D_j^p, \forall j \in N \setminus \{0\} \quad (21)$$

$$0 \leq z_{0j}^{pk} \leq 1, \forall j \in N \setminus \{0\}, \forall k \in K, \forall p \in P \quad (22)$$

A lower-bound solution (17) is generated in Phase I. The restrictions of the problem are relaxed so that (19) imposes that a customer can constitute more than one pivot. The smallest truck k with the lowest cost is assigned to service the demand of each customer on every single trip (20). Equation (21) guarantees that all the desires of individual customers are covered. The set of feasible solutions with constraints relaxation is set as the initial solution for Phase II.

B. Phase II – Genetic Algorithm Hybridizes Three Search Operators (GA-HSO)

A genetic algorithm that hybridizes three search operators (GA-HSO) is proposed to improve the solution performance in this stage. Three search operations are performed based on the inter-route moves of relocating, exchanging and eliminating procedures. Two kinds of operations in genetic algorithms are induced: crossover and mutation. An evolution operation is processed based on random permutation selection. The population size is determined and then the population set is constructed by using the initial solution obtained in the previous stage. In order to diversify the population, trip assignments of the initial solution are selected randomly. Three search operators are adapted to generate new genes for each chromosome for some populations. The relocation operator relocates the m trucks used from one route assignment to another one for the same customer. An exchange operation is performed by random selection of the m trucks used. These chosen trucks will be

exchanged between the routes for the same customer. The elimination operator eliminates expensive assigned routes to create new routes are cheaper. After the most suitable trucks have been searched for, the original usage is then equal to none. At the end of each operation, the sub-function of truck utilization is called in order to utilize fully the capacity of each truck, any excess service quantity is balanced with the total customer requirement. The cost-fitness function is calculated based on Formulation (1).

The paradigm of each search operators is displayed in Figure 2. For example, trucks $m^{p,k=1}$ and $m^{p,k=2}$ are assigned to serve the partial demands $d_{j=1}^{p,k=1}$ and $d_{j=1}^{p,k=2}$, respectively. Once the relocation operator is activated, a truck is selected randomly. If truck $k = 1$ is chosen, the partial demand $d_{j=1}^{p,k=1}$ will be transferred to another random route. According to the problem statement that allows servicing only one customer per route, a truck such as $k = 1$ becomes available automatically. However, the algorithm will search for a different truck type to fulfil a transferred partial demand such as $d_{j=1}^{p,k=1}$. In the mode of the exchange operator, the partial demands $d_{j=1}^{p,k=1}$ and $d_{j=1}^{p,k=2}$ will be exchanged. The new number of trucks required will be calculated to cover the exchanged customer desires. When the elimination function is turned on, the most expensive route is picked. The service quantity of such a route is re-matched with another truck type that is cheaper.

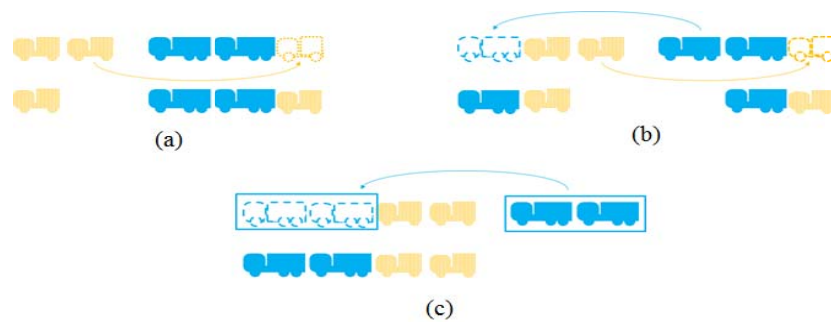


Fig. 2. An example of the conceptual three search operators: (a) Relocation operator (b) Exchange operator and (c) Elimination operator.

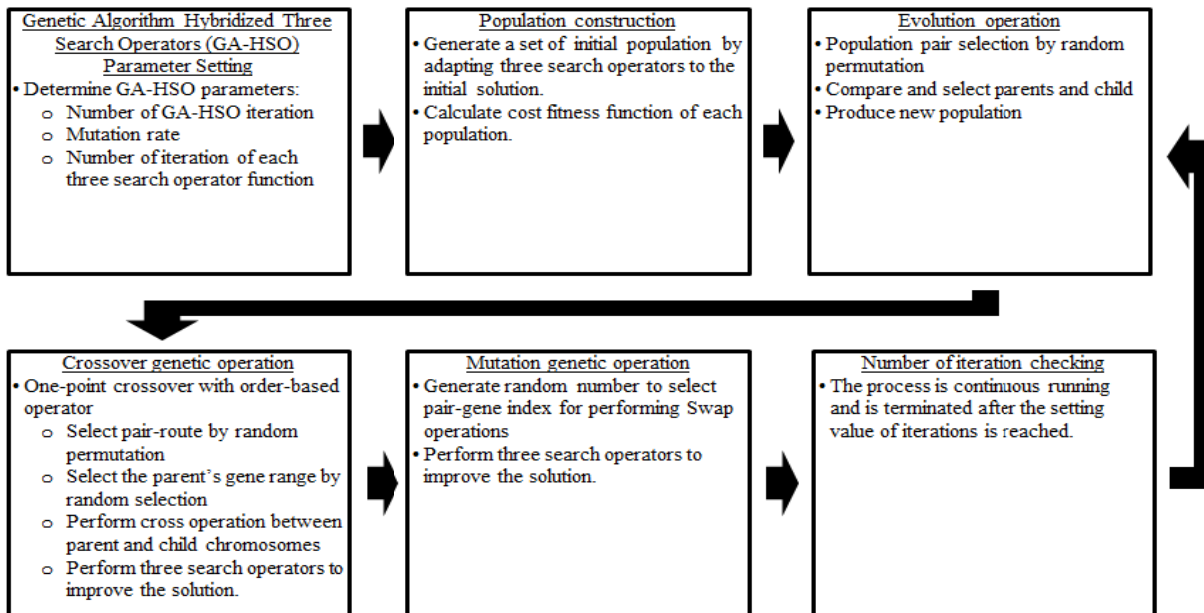


Fig. 3. Genetic Algorithm Hybridizes Three Search Operators (GA-HSO).

After new chromosomes are generated, the next process is to match random-pair populations. The population of each pair which has the better fitness function is selected to be the parents. A child is produced by the parents, this process is called an evolution operation. The algorithm performs the next steps of crossover and genetic mutation to produce a new population. Crossing over is the random exchange of a pair of parents. A parent's gene range is selected by random selection. The

mutation process produces children via random alternation to individual parents and then swapping the chosen genes. The new population set performs three search operations as described above to form a new generation. The main process flow of the genetic algorithm that hybridizes three search operators (GA-HSO) can be summarized in a diagram, as shown Figure 3.

IV. COMPUTATIONAL RESULTS

In this paper, a problem set is determined by using a real-world business case of a heterogeneous fleet vehicle routing problem with various constraints, i.e. time windows, a variety of product deliveries, limited available drivers and a semi-unlimited available vehicle fleet. A heuristic procedure is developed based on the adaptation of a genetic algorithm in which the methods of three search operators are hybridized. The algorithm has two main phases. An initial solution is found in Phase I and improvement is performed in Phase II. The solution obtained from the first phase is the result for the size of the available vehicle fleet with driver constraint relaxation. These two restrictions are added into the second phase. The proposed algorithm seeks to produce an optimal solution, i.e. a set of route assignments with minimum total transportation cost where all constraints are satisfied.

A problem set contains thirty customers and one depot. Although each customer produces different products, the commodity types can be classified into two groups, i.e. palletized products and bulk products. There are two vehicle kinds with different capacities that can carry palletized commodities, but bulk product can only be fed into one vehicle type. The company has its own fleet consisting of seventeen semi-trailers and seven bulk trucks. The semi-trailers can be categorized into two different kinds based on their capacities, i.e. two-axle and three-axle semi-trailers. In this study, the company's vehicle fleet is supposed to offer prompt service. However, the problem has the restriction of the number of truck drivers, which is assumed to be known before planning. The maximum number of drivers is equal to twenty over each planning-time horizon, but this may vary depending on their vacation plans. If the company's trucks cannot be used, external service providers are called on. Outsource vehicles offer prompt service and are unlimited in number. Furthermore, the difference in truck capacities between two-axle and three-axle trailers is not always valid when another limiting factor is considered, i.e. the size of containers. Payloads are determined and given by the company to define each single truck type's limitations. This parameter is known and depends on agreement with courier conditions between the customer and logistics providers. For example, some customers may allow stacking pallets in multiple layers, while other companies may not. The example mentioned is one of the conditions that may result in two-axle and three-axle trailers being able to carry products having the same weight.

The customers' demands in tonnes are also known before the planning process. Although the time to travel is uncertain in practical cases, this study uses average cycle times to deal with uncertainty. A cycle time is calculated based on historical data records of round trips, including 1) loading service time at the depot, 2) time travelled from the depot to each customer site, 3) unloading service time at the customer, 4) time travelled from the customer to the depot, and 5) lost time due to waiting and other unplanned events such as road accidents. The fleets, either the company's own vehicles or those of outsource service providers, have to start and return to the distribution centre after finishing unloading activity at the customer's warehouse. Only one customer node can be assigned to a route. Since all customers' requirements exceed individual truck capacities, partial deliveries are allowed in this study. However, the total demands of each customer have to be fulfilled within customers' time windows and working-hour regulation constraints.

The total cost structure of each route assignment is made up of fixed and variable costs. The fixed cost is calculated based on depreciation of the vehicle used, road transportation tax and vehicle insurance. The difference in vehicle kinds used vary the fixed costs. The variable cost is calculated based on the length of a round trip between the depot and each customer. The distance travelled determines the variable fuel cost. Moreover, the cost of each driver per round trip is also included in the variable cost. In this research, vehicle costs are given and differ according to the vehicle kind used, the product served and the distance travelled to each customer location.

In this paper, ten sets of problem with different customer demands are used to demonstrate the performance of the proposed algorithm. To the best of our knowledge, no prior published works address this unique problem. Therefore, the solution performance is compared against the solutions obtained from solving using a branch-and-bound algorithm. If the problem size and number of constraints exceed the limitations of the solver, results evaluation is then performed based on problem-size reduction. A solver can find a feasible solution when the problem size is reduced to six nodes with all constraints satisfied. Given the long processing times to find feasible solutions with the solver, three hundred seconds is set as the maximum computational runtime.

Table I displays a comparison of the results from a two dimensional competition comprising total transportation cost (TC) and computation runtime (RT) between a branch-and-bound algorithm (BBA) using a solver and the proposed method of a genetic algorithm that hybridizes three search operators (GA-HSO). The parameters of GA-HSO are set as follows: population size = 16, mutate rate = 0.8, maximum number of iterations = 50. The GA hybridizing three search operators algorithm is set to repeat ten times per problem set, the best solutions over ten runs are reported in Table I.

TABLE I. COMPARISON OF RESULTS BETWEEN BRANCH-AND-BOUND ALGORITHM (BBA) AND GENETIC ALGORITHM HYBRIDIZES THREE SEARCH OPERATORS (GA-HSO)

Problem set	Total cost (TC)			Runtime (RT), seconds		
	BBA	GA-HSO	ΔTC	BBA	GA-HSO	ΔRT
1	104,740	106,397	0.0158	300	1	-0.9967
2	98,657	100,314	0.0168	300	1	-0.9967
3	74,066	75,723	0.0224	83	1	-0.9880
4	72,371	74,028	0.0229	23	1	-0.9565
5	90,227	91,884	0.0184	300	1	-0.9967
6	72,857	74,514	0.0227	4	1	-0.7500
7	90,151	91,753	0.0178	15	1	-0.9333
8	91,429	93,031	0.0175	12	1	-0.9167
9	70,300	71,077	0.0111	14	1	-0.9286
10	55,219	56,022	0.0145	300	1	-0.9967
Average			0.0180			-0.9460

Remark: $\Delta TC = (TC_{BBA} - TC_{GA-HSO}) / TC_{BBA}$; $\Delta RT = (RT_{BBA} - RT_{GA-HSO}) / RT_{BBA}$

The performance of the solutions is evaluated using relative deviation that is a measure of the difference between the results of BBA and GA-HSO against the solution of BBA. The results below, as shown in Table I, indicate that the total costs which are obtained from BBA are better than for GA-HSO, the total cost produced by GA-HSO is about 1.8% higher than that by BBA on average. In contrast, the computational runtime of GA-HSO is significantly faster than BBA.

Although the solver can find solutions with better costs, the variable cells are limited. A heuristic algorithm is an alternative that can find an optimal solution within a reasonable time. An algorithm called GA-HSO has been developed for solving this particular real-business case. The procedure has been coded in MATLAB and run on an Intel(R) Core(TM) i5-3337U CPU@1.80GHz 8.00GB-RAM for a heterogeneous fleet vehicle routing problem with various constraints, i.e. time windows, a variety of product deliveries, limited available drivers and a semi-unlimited available vehicle fleet. Ten test problems with thirty-one nodes including a depot have been tested. Each problem set contains the same customers but different demand sets. Figure 4 shows an analysis of the GA-HSO method. The parameter settings for population size (pop_size = 8, 12, 16) and mutation rate (mutate_rate = 0.6, 0.7, 0.8) vary. The first problem set was used to measure the performance of the various parameters. The y-axis presents the percentage deviation (%dev) of the solutions with respect to the best total cost of 100 runs overall.

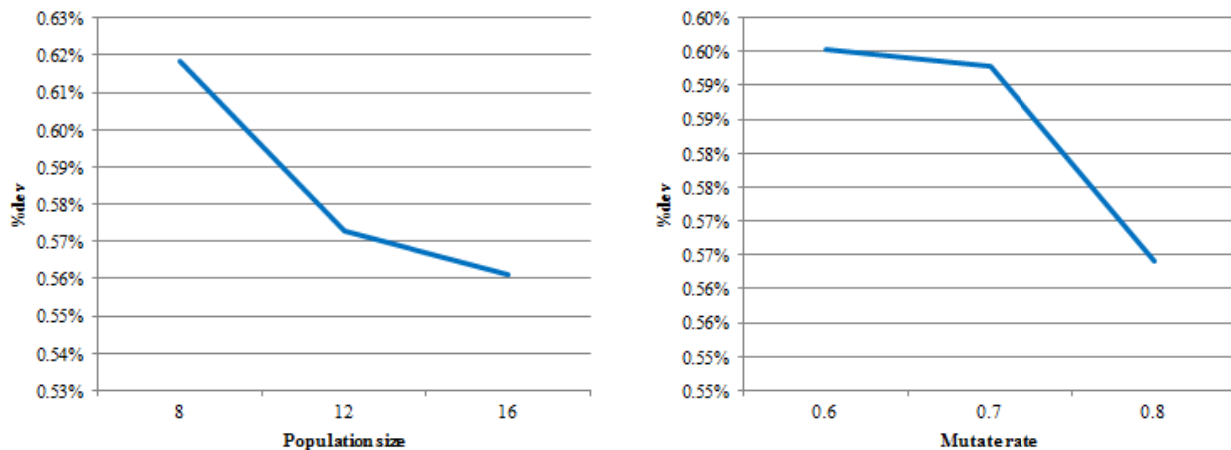


Fig. 4. Analysis results for changes in the parameters of population size and mutate rate.

The parameters which show the best performance, population size = 16 and mutation rate = 0.8, were set up for the GA-HSO to solve 10 problem sets. The results are presented in Table II. Due to the confidential nature of the information, only some data can be shown in this paper. Although the company has 30 customers requiring service, some customers may not have demand over a given planning-time horizon. The number of truck drivers and customer demands are known before planning. Their own vehicle fleet comprises ten 2-axle semi-trailers (A: A01 to A10), seven 3-axle semi-trailers (B: B01 to B07) and ten bulk trailers (C: C01 to C10). The drivers can only drive vehicle types A, B and C. If the drivers or the company fleet cannot cover all demands, the vehicle fleets of outsource service providers (D: D01 to D+∞) are called on to fulfil those. All customers' time windows are assumed to open at the same time, but the closing windows are different. The working hours of all drivers are limited to 12 hours per time period. The total number of trucks used, the total of trips made, the total cost and

the percentage deviation (%dev.) of the solutions with respect to the best total cost overall for 100 runs and the computation time in seconds are displayed in Table II. The percentage deviation and runtime are 0.109% and 11 seconds on average. The total cost differs from the best solution by only 0.109% on average. These results indicate that GA-HSO can generate robust solutions. Furthermore, GA-HSO requires very little processing time, only 11 seconds on average for 100 runs per problem set, in order to construct the optimal routes set shown in Table III, for example. The route assignments in Table III are generated from problem set number 1. In this instance, the total demand of 1,857 tons for 30 customers excluding the depot has to be serviced by 20 drivers. The results in the first column (Col-set.1) are customer nodes, for example, the 2-axle semi-trailer number 1 (A01) has to visit 2 customers, i.e. nodes 2 and 7. Truck A01 has to do 4 and 1 round trips in order to fulfil the total requirements of customers 2 and 7 (Col-set.2: total number of round trips made). The last column set (Col-set.3: operation times in hours) is the total operation times, e.g. Truck A01 takes 10 hours to provide service for customer No. 2 and 2 hours for customer No. 7.

TABLE II. TOTAL COST, PERCENTAGE DEVIATION, AND COMPUTATIONAL RUNTIME OF GA-HSO METHOD.

Problem set	Number of available drivers	Total ton-demands	Number of customers having demands during planning time horizon (excl. depot)	Number of total trucks used				Number of total round-trips travelled				Total Cost	% dev.	Run-time, sec
				A	B	C	D	A	B	C	D			
1	20	1,857	30	6.7	7.0	6.2	1.4	31	28	17	3	168,011	0.578	13
2	20	1,835	21	7.4	6.3	6.2	0.3	33	25	17	1	159,210	0.173	12
3	15	992	18	3.5	2.8	5.9	0.0	15	11	16	0	97,125	0.000	10
4	14	1,477	12	2.8	5.3	5.9	1.6	14	21	16	8	129,128	0.000	12
5	18	1,543	21	5.2	6.0	6.2	0.0	24	24	17	0	138,492	0.101	11
6	18	1,579	21	4.8	7.0	6.2	0.0	18	28	17	0	135,750	0.000	10
7	18	1,463	21	4.5	5.6	6.4	0.0	20	22	17	0	126,710	0.085	10
8	19	1,676	23	5.4	6.0	6.7	0.0	25	24	18	0	142,340	0.111	11
9	20	1,429	27	7.8	5.0	4.9	0.0	30	20	13	0	130,747	0.000	11
10	11	745	9	2.8	2.8	3.0	0.0	13	11	8	0	68,779	0.041	12
Avg.												0.109	11	

TABLE III. AN EXAMPLE OF ROUTE ASSIGNMENT (PROBLEM SET NO.1) BY USING GA-HSO.

Vehicle fleet	Col-set.1				Col-set.2				Col-set.3			
A01	2	7	-	-	4	1	-	-	10.0	2.0	-	-
A02	1	8	-	-	5	1	-	-	10.0	2.0	-	-
A03	5	10	-	-	2	1	-	-	8.3	2.0	-	-
A04	11	14	-	-	2	1	-	-	7.5	2.0	-	-
A05	4	13	-	-	2	2	-	-	6.0	5.0	-	-
A06	6	15	-	-	2	2	-	-	5.0	5.0	-	-
A07	2	16	-	-	2	4	-	-	5.0	4.0	-	-
B01	2	17	-	-	3	1	-	-	7.5	3.5	-	-
B02	2	18	-	-	3	1	-	-	7.5	3.5	-	-
B03	2	19	-	-	3	1	-	-	7.5	4.0	-	-
B04	2	21	-	-	3	1	-	-	7.5	4.0	-	-
B05	9	-	-	-	4	-	-	-	8.0	-	-	-
B06	9	-	-	-	4	-	-	-	8.0	-	-	-
B07	9	22	23	-	2	1	1	-	4.0	6.0	2.0	-
C01	24	-	-	-	3	-	-	-	12.0	-	-	-
C02	24	-	-	-	3	-	-	-	12.0	-	-	-
C03	24	-	-	-	3	-	-	-	12.0	-	-	-
C04	24	-	-	-	3	-	-	-	12.0	-	-	-
C05	24	25	26	-	1	1	1	-	4.0	3.0	3.0	-
C06	27	28	29	30	1	1	1	1	2.0	3.0	3.0	3.5
D01	20	-	-	-	1	-	-	-	7.0	-	-	-
D02	3	12	-	-	1	1	-	-	2.8	2.5	-	-

V. DISCUSSION AND CONCLUSION

In this study, a real-world case study is set up. The adaptation of a genetic algorithm is proposed to find an optimal solution, i.e. minimum total transportation cost. Three search operators, i.e. relocation, exchange and elimination, are added to the procedure in order to encourage the genetic algorithm to improve the quality of its solutions. An optimal solution can be generated within a very short period of computational runtime. The proposed technique is able to help the business sector to reduce planning times and can find sets of good quality solutions. In future studies, the authors will include uncertain data characteristics and introduce a more robust approach to find more robust solutions. Furthermore, problems involving broader aspects, such as environmental concerns, society, traffic-safety considerations, transport-related health risks etc., are an

unavoidable and significant global challenge for sustainable development. A multi-objective optimization method is one efficient technique to apply when problems deal with more than one objective function.

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