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Hybrid genetic algorithm for vehicle routing problem with manual unloading consideration

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Abstract: Often, delivery workers are required to manually unload goods at customer locations. These manual tasks induce physiological fatigue in the workers and increase delivery time. This paper discusses a genetic algorithm (GA) approach to the vehicle routing problem with manual materials handling (VRPMMH) that considers physical workload and working time. The nearest neighborhood search technique is employed to help generate an initial population. Heuristic crossover and mutation are developed to generate a set of utilised vehicles and their delivery routes so as to minimise the total operation cost. In addition, each worker must not expend his/her energy beyond the recommended level and all delivery tasks must be completed within one workday. From the computation experiment, the GA-based approach is found to be efficient and can obtain near-optimal VRPMMH solutions.

Keywords: vehicle routing, genetic algorithm, manual unloading, physical workload

INTRODUCTION

The vehicle routing problem (VRP) deals with finding a minimum set of delivery vehicles and/or delivery routes for a given set of vehicles to serve all customers such that the total travel distance (or cost) is minimised. Since Dantzig and Ramser [1] introduced the capacitated VRP, there have been numerous research studies on the VRP and its variants. Examples of these variants of VRP are: the vehicle routing problem with backhauls (VRPB), the vehicle routing problem with time windows (VRPTW), the multiple depot mixed vehicle routing problem with backhauls (MDMVRPB), the vehicle routing problem with backhauls and time windows (VRPBTW), and the vehicle routing problem with simultaneous deliveries and pickups (VRPSDP). The descriptions of these problems can be found in Ropke and Pisinger [2].

The classical VRP and its variants are combinatorial optimisation problems. While mathematical programming models can be developed to represent those problems and solved to obtain exact solutions, they are only applicable for small problems. Researchers have developed heuristic methods to obtain near-optimal solutions for the VRP and its variants. For example, Clarke and Wright [3] developed a distance saving method to schedule vehicles from a central depot to a number of delivery points. Asano et al. [4] developed a new approximation algorithm to yield a solution for the capacitated VRP. Chabrier [5] proposed a heuristic approach using the column generation procedure to develop the shortest paths for delivery vehicles. However, when the VRP becomes complex, so does its heuristic procedure. The meta-heuristic methods such as tabu search, simulated annealing (SA), ant colony optimisation (ACO), particle swarm optimisation (PSO), and genetic algorithm (GA) are practical alternative solution procedures for solving the VRP. For example, Cirovic et al. [6] used an adaptive neural network that was trained by a simulated annealing for the routing of light delivery vehicles. Among the meta-heuristic methods, the GA is perhaps the most common method used by VRP researchers [7-10]. When the GA is applied, researchers could either utilise simple crossover and mutation techniques or develop specialised techniques which are specific for the problem being investigated. In addition, several researchers developed heuristic or meta-heuristic methods to assist the GA in obtaining VRP solutions efficiently [11-15].

There are a number of researchers who studied intra-city logistics [6, 16-18]. However, to our knowledge, very few VRP researchers considered manual materials handling (or manual unloading) in their studies. When goods are delivered from a distribution centre (DC) to retailed stores in the city, they are manually unloaded and moved by delivery workers. At a customer location, the amount of physical work that any worker has to perform depends on the amount of goods to be unloaded. When the vehicle is assigned to serve several stores, the required physical energies are added up to represent the worker's daily total energy expenditure. Failure to consider the daily physical workload when developing the VRP solution could cause the worker to work too exhaustively. Nanthavanij et al. [19] developed a mathematical model for the vehicle routing problem with manual materials handling (VRPMMH). They assumed that delivery workers were pre-assigned to vehicles. Solving the above problem without considering manual delivery tasks, they showed that some workers might be required to work too exhaustively. Kim et al. [20] studied the combined manpower-vehicle routing problem. Their objective was to find an efficient schedule for the manpower-teams to perform multi-stage tasks at customer locations and to minimise the cost of vehicle routing. Boonprasurt and Nanthavanij [21] applied a workforce assignment model to match workers and vehicles based on the physical work capacity (or working energy capacity) and daily total energy expenditure.

Here, a hybrid GA is developed to solve the VRPMMH. Its objective is to select a set of vehicles and to develop their delivery routes such that the total operation (fixed and variable) cost is minimised. The load capacity of the vehicle, physical work capacity of the worker, and daily working duration are considered. The nearest neighborhood search technique is used to help develop an initial population. Specialised techniques for performing the crossover and mutation are also employed to help find the VRPMMH solution efficiently.

MATHEMATICAL MODEL OF VRPMMH – FIXED DELIVERY CREW

The VRPMMH was described in detail by Boonprasurt and Nanthavanij [21]. However, some important issues are re-emphasised here. The number of workers accompanying each vehicle is known and fixed. Workers are pre-assigned to vehicles. Each vehicle performs only one delivery trip and the trip must be completed within one 8-hour workday. All materials handling activities performed at the customer locations are manual. For any worker team, workers share equal physical workload irrespective of their working energy capacities. Based on an ergonomic recommendation, the daily (8-hour workday) energy expenditure of any worker should not exceed 33% of his/her physical work capacity [22]. The amount of energy expenditure when performing the physical work depends on the level of workload. Typically, it varies from about 2.5 kcal/min. (for light work) to at least 7.5 kcal/min. (for heavy work) [23].

The VRPMMH is intended to determine the number of utilised vehicles and their delivery routes such that the total fixed and variable cost is minimised. The fixed cost is the cost of operating the vehicle fleet per day, which includes the vehicle cost, driver cost and total labour cost. The variable cost is the travel cost of the vehicle. Moreover, none of the delivery workers shall perform the physical task (manual unloading) beyond his/her physical work capacity (or working energy capacity).

The notations used in the mathematical model are as follows:

Parameters:

D_{ij} distance (km) between customers i and j
EU average rate of energy expenditure (kcal/min.) of a worker to unload a load unit
FC_k fixed cost (baht) of vehicle k (estimated exchange rate: 30 baht = 1 US dollar)
LQ_k load capacity (units) of vehicle k
$MEPW_{lk}$ working energy capacity (kcal/day) of worker l in vehicle k
N number of customers and central depot
NW_k number of workers assigned to vehicle k
Q_j daily load demand (units) of customer j
S_k average travel speed (km/min.) of vehicle k
T work duration (min.) per workday
TU average unloading time (min.) of a worker team to unload a load unit
U number of utilised vehicles
V number of available vehicles
VC_k variable (fuel) cost (baht/km) of vehicle k

Decision variables:

X_{ijk} 1 if route (i, j) is travelled by vehicle k; 0 otherwise
Y_k 1 if vehicle k from a set of available vehicles is utilised; 0 otherwise

The mathematical model of the VRPMMH is shown below.

Minimise
$$\sum_{k=1}^{V} FC_k Y_k + \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{V} D_{ij} VC_k X_{ijk} \qquad (1)$$

subject to

$$EU \cdot \sum_{i=1}^{N}\sum_{j=1}^{N} \frac{TU}{NW_k} \cdot Q_j \cdot X_{ijk} \le MEPW_{lk} \qquad l = 1,\dots, NW_k;\ k = 1,\dots, V \qquad (2)$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} Q_j X_{ijk} \le LQ_k \qquad k = 1, \dots, V \qquad (3)$$

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$$\sum_{i=1}^{N}\sum_{j=1}^{N}\left(\frac{D_{ij}}{S_k}+\frac{TU}{NW_k}Q_j\right)X_{ijk} \le T \qquad k = 1, \ldots, V \qquad (4)$$

$$\sum_{k=1}^{V}\sum_{i=1}^{N} X_{ijk} = 1 \qquad j = 2, \ldots, N \qquad (5)$$

$$\sum_{i=1}^{N} X_{isk} - \sum_{j=1}^{N} X_{sjk} = 0 \qquad s = 1, \ldots, N;\ k = 1, \ldots, V \qquad (6)$$

$$X_{iik} = 0 \qquad i = 1, \ldots, N;\ k = 1, \ldots, V \qquad (7)$$

$$\sum_{j=2}^{N} X_{1jk} = Y_k \qquad k = 1, \ldots, V \qquad (8)$$

$$\sum_{i\in S}^{N}\sum_{j\in S}^{N} X_{ijk} \le |S|-1 \qquad \text{for all } S \subseteq \{2, .., N\}, |S| \ge 2 \qquad (9)$$

$$X_{ijk}, Y_k \in \{0, 1\} \qquad \forall\ i, k; j = 2, \ldots, N \qquad (10)$$

HYBRID GA

Chromosome Coding

A VRPMMH solution is encoded as a chromosome. Each chromosome is divided into '*n*' equal sections (for *n* vehicles). Each section consists of '*m*' genes, with the gene value representing a non-repeated customer denoted by C_{ij} where $i = 1, \ldots, m$ and $j = 1, \ldots, n$. Note that *m* is the upper bound of the number of customers that can be visited by each vehicle. Thus, the chromosome length is $n \times m$ genes. Scheme 1 shows (a) the chromosome encoding and (b) an example of a VRPMMH solution. For example, vehicle 1 leaves the central depot, visits customers C1 and C7 (shown as '1' and '7' in Scheme 1(b)), and returns to the central depot. The value 0 in any gene indicates that there is no customer to visit. Also, note that the central depot is not shown in the scheme since it is not included in the chromosome.

C_{11}	C_{21}	…..	C_{m1}	C_{12}	C_{22}	…..	C_{m2}	…………..	C_{1n}	C_{2n}	…..	C_{mn}
Vehicle 1				Vehicle 2					Vehicle *n*			

(a)

1	7	0	0	3	6	0	0	2	4	0	0	5	8	10	9
Vehicle 1				Vehicle 2				Vehicle 3				Vehicle 4			

(b)

Scheme 1. (a) Chromosome encoding; (b) Example of a VRPMMH solution

Initial Population

An initial population is simply a set of chromosomes created to represent feasible VRPMMH solutions. In our hybrid GA these chromosomes are created both randomly and with the help of a heuristic procedure developed by Boonprasurt and Nanthavanij [24]. For those randomly created initial chromosomes, every section in the chromosome must contain at least one non-zero gene.

Customers are randomly inserted into the genes until the chromosome is a representative of a feasible VRPMMH solution.

Using the heuristic procedure, the initial chromosomes are created in two steps. Firstly, the vehicles from the set of available vehicles with their total load capacities and energy capacities sufficient to carry the goods required to serve all customers are selected. Secondly, customers are assigned to the selected vehicles. The nearest neighborhood search technique is utilised to fill customers to the vehicle route without violating its load capacity, energy capacity and daily work duration. If more vehicles are needed, the vehicles previously not selected are added.

Heuristic Crossover

Two parent chromosomes are randomly selected from the current population. For each selected chromosome, a vacant section (vehicle) having a minimum fixed cost and load capacity is chosen as a crossover section. (Note that a vacant section represents a non-utilised vehicle where all genes in the section contain zeros.) If there is a tie, a new pair of chromosomes is chosen. If there is no vacant section, the section having the largest % residual capacity is then selected as a crossover section. (The residual capacity is the difference between the vehicle's load capacity and its carried load.)

The partially matched crossover technique is applied to map all genes in the crossover section. If a zero gene is mapped to a non-zero gene, the zero gene in any non-crossover section which has the smallest % residual capacity and fixed cost is then replaced by that non-zero gene as long as the load capacity, energy capacity and work duration constraints are satisfied.

Heuristic Mutation

From the current population (parent chromosomes and crossover offspring), a chromosome is randomly selected for mutation. Firstly, a vacant section (i.e. a non-utilised vehicle) on the selected chromosome is chosen. If there are several vacant sections, the section (or vehicle) having the lowest fixed cost is chosen. If there is a tie, the vacant section with the largest load capacity is chosen. Next, a non-vacant section (i.e. a utilised vehicle) on the same chromosome is selected that has its fixed cost equal to or higher than that of the vacant section chosen earlier. If there are several non-vacant sections, the section having the largest % residual capacity is chosen. Then all genes between the chosen vacant and non-vacant sections on the selected chromosome are switched.

If, however, there are no vacant sections on the selected chromosome, one of the non-vacant sections with the largest % residual capacity is chosen as the first section. Then another non-vacant section with the highest fixed cost is chosen from the remaining sections. If there is a tie, the section with the smallest % residual capacity is chosen. Note that this second section must have its carried load and energy expenditure which do not exceed the load capacity and energy capacity of the first section. Then all genes between the first and second sections on the selected chromosome are switched.

Fitness and Penalty Values

The fitness of chromosome is defined as a total (fixed and variable) cost of the VRPMMH solution. Thus, the lower the total cost of the chromosome is, the fitter it becomes. Each chromosome must be decoded to identify the utilised vehicles and their delivery routes (i.e. a list of served customers and an order of delivery). From the list of served customers and the order of delivery, the delivery route of any utilised vehicle and its travelling distance can be determined. From the given fuel consumption rate of the vehicle, the total variable cost can be determined.

Each chromosome is assigned with a probability. Firstly, the chromosome fitness level (i.e. its total cost) is determined. Next, the ratio of its total cost to the sum of all total costs (from all chromosomes in the current population) is computed. Then its probability is determined by subtracting the ratio from unity and dividing the difference by the number of chromosomes less one. Furthermore, a cumulative probability is computed by adding the chromosome probability to the current cumulative probability.

The penalty function is intended to exclude any illegal chromosome generated from the crossover and mutation. Such illegal chromosome is an unfeasible VRPMMH solution and is not usable. (A VRPMMH solution is unfeasible if the resulting carried load, total energy expenditure or total working time exceeds the load capacity, energy capacity or allowable work duration respectively.) Once an illegal chromosome is found, its cumulative probability is set to be greater than 1.

Selection

From the parent chromosomes and their offspring (from the crossover and mutation), some chromosomes are chosen as survivors and included in the next generation. In our hybrid GA, a fixed percentage (*p* %) of the population size with the highest fitness values are pre-chosen as members of the new population. The remaining members are then chosen using the roulette wheel spinning technique. Note that the population size is always unchanged.

NUMERICAL EXAMPLE AND SOLUTIONS

Consider a logistic network that consists of a central depot and ten customers. The central depot has six vehicles and twelve workers available for the delivery task. For simplicity, it is assumed that the workforce is homogeneous and the average working energy capacity of the worker is 2,493 kcal/day. All deliveries must start from and end at the central depot, and they must be completed within an 8-hour workday (480 minutes). Each vehicle will make only one delivery trip per day. The delivery vehicles have different load capacities, fixed costs, fuel consumption costs, travel speeds, numbers of delivery workers, and energy capacities. Table 1 shows the data of the six vehicles. Additionally, it is assumed that the average unloading time for a worker is 2 min./box. An average energy expenditure rate for unloading a box is assumed to be 6 kcal/min.

Table 1. Data of delivery vehicles

	Delivery vehicle					
	V1	V2	V3	V4	V5	V6
Load capacity (box)	165	165	270	270	350	350
Fixed cost[1] (baht/day)	1,650	1,800	3,500	3,500	5,500	6,000
Fuel cost[1] (baht/km)	5.80	6.00	8.60	9.20	14.00	12.00
Travel speed (km/min.)	0.33	0.33	0.25	0.25	0.17	0.17
Delivery workers (person)	1	1	2	2	3	3
Energy capacity[2] (kcal)	2,493	2,493	4,986	4,986	7,479	7,479

[1] Estimated exchange rate: 30 baht = 1 US dollar
[2] Computed from the product of number of workers and average working energy capacity (2,493 kcal/day)

Each customer location is accessible from the central depot and all other customer locations. It is assumed that between customer locations *i* and *j*, the travel distances from customer locations *i* to *j* and from customer locations *j* to *i* are equal. Table 2 shows the demand requirements of the ten customers, including the distances between the central depot and all customer locations and between all pairs of customer locations.

Firstly, the VRPMMH problem is transformed into an integer linear programming model. It is solved to optimality using an optimisation software program called IBM ILOG CPLEX v12.1.0. The specifications of the computer used are as follows: Windows 7 Professional, 32-bit operating system; Processor: Intel® Core™ i5 CPU M 540 @ 2.53 GHz; RAM 4.00 GB. Table 3 shows the optimal VRPMMH solution. Five out of six vehicles are utilised for delivering goods to the ten customers. The minimum total cost is 17,107 baht. The computation time is 5.25 min.

Table 2. Demands and distances (in km) between central depot and all customer locations

	Demand	Customer location									
	(box)	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Depot	-	15.2	17.7	14.8	11.7	8.4	7.3	7.5	3.9	4.1	11.8
C1	110	-	15.8	19.0	15.7	7.8	8.5	16.7	13.0	19.2	21.8
C2	103		-	7.0	7.0	17.6	13.0	12.2	14.0	20.0	13.6
C3	84			-	3.6	17.9	12.9	7.6	11.5	15.5	7.1
C4	98				-	14.3	9.4	5.3	8.4	13.2	7.5
C5	103					-	5.0	12.6	7.7	12.4	18.0
C6	92						-	8.5	4.5	11.1	13.8
C7	85							-	5.1	8.0	5.4
C8	95								-	7.1	10.5
C9	118									-	14.3
C10	96										-

Table 3. Optimal VRPMMH solution (from optimisation approach)

Vehicle	Delivery route	Load (box)		Energy (kcal)		Time (min.)	
		Capacity	Carried	Capacity	Expenditure[1]	Limit	Total
V1	D[2]→C1→D	165	110	2,493	1,320	480	312
V2	D→C9→D	165	118	2,493	1,416	480	261
V3	D→C4→C2→D	270	201	4,986	2,412	480	347
V4	D→C7→C3→C10→D	270	265	4,986	3,180	480	401
V5	D→C8→C6→C5→D	350	290	7,479	3,480	480	322

[1] Total energy expenditure of vehicle (worker team); [2] D = Central depot

It is seen that the resulting total energy expenditure of all five utilised vehicles does not exceed their energy capacities. This means that each delivery worker does not perform excessive physical work when unloading boxes at the customer locations. The % residual energies of the five vehicles range from 36.22% to 53.47%, with an average of 46.31% and a standard deviation of 6.92%. In addition, the vehicle's load capacity and working time limit (480 min.) are not exceeded.

The same VRPMMH problem is then solved using the hybrid GA algorithm. The algorithm is coded in Visual C Sharp. The GA parameters and condition can be summarised as follows: population size = 10 chromosomes; crossover rate = 40%; mutation rate = 3%; *p* = 10%; termination condition = 5,000 iterations. In the initial population five chromosomes are randomly created while the other five chromosomes are created using the nearest neighbour search technique. The same computer is also used to run the hybrid GA algorithm. The resulting (near-optimal) VRPMMH solution obtained by the hybrid GA is displayed in Table 4.

Table 4. Near-optimal VRPMMH solution (from hybrid GA)

Vehicle	Delivery route	Load (box)		Energy (kcal)		Time (min.)	
		Capacity	Carried	Capacity	Expenditure[1]	Limit	Total
V1	D[2]→C2→D	165	103	2,493	1,236	480	313
V2	D→C1→D	165	110	2,493	1,320	480	312
V3	D→C3→C4→C7→D	270	267	4,986	3,204	480	392
V4	D→C9→C10→D	270	214	4,986	2,568	480	335
V5	D→C8→C6→C5→D	350	290	7,479	3,480	480	322

[1] Total energy expenditure of vehicle (worker team); [2] D = Central depot

It is seen that the hybrid GA also requires five vehicles for performing the delivery. Both ILOG CPLEX and hybrid GA also utilise an identical set of vehicles. However, the lists of customers served by individual vehicles are not the same when compared between the solutions from ILOG CPLEX and hybrid GA. The hybrid GA solution yields a total cost of 17,189 baht, only 0.48% higher than the minimum total cost. Obviously, the total cost difference between the two solutions is due to the differences in the delivery routes of the five vehicles. The delivery routes of the utilised vehicles are shown in Figure 1.

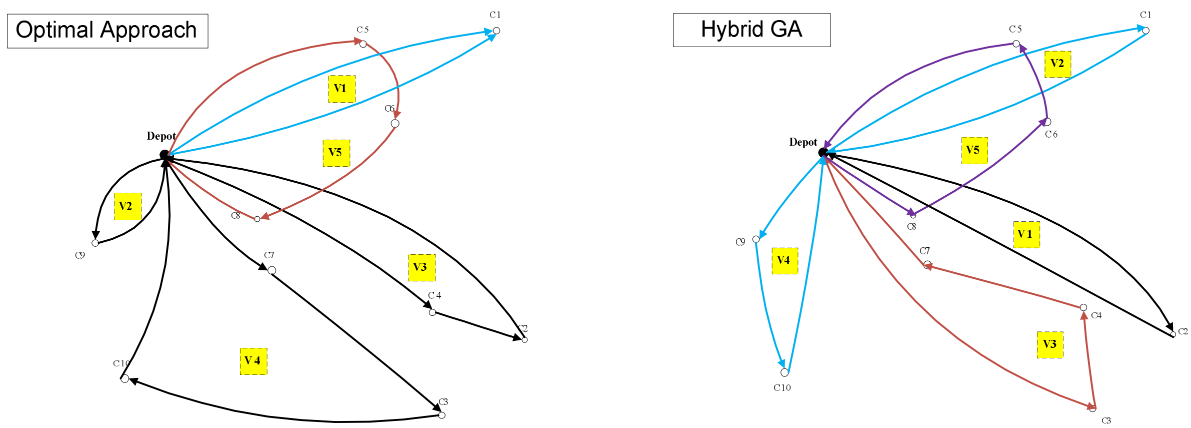

Figure 1. Comparison of delivery routes (optimal approach vs hybrid GA)

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As for the energy expenditure, the delivery workers are not required to spend more than their working energy capacity. Their % residual energies range from 35.74% to 53.47%, with a mean of 47.04% and a standard deviation of 6.76%.

The computation time of the hybrid GA is less than 1 second. In fact, the hybrid GA is able to find the best VRPMMH solution after the 206th iteration.

COMPUTATION EXPERIMENT

A computation experiment was conducted to test the effectiveness and efficiency of the hybrid GA in obtaining the near-optimal VRPMMH solution. Twenty-five VRPMMH problems were randomly created and divided into three groups according to the numbers of customers and delivery vehicles. Group 1 consists of 15 test problems, while Group 2 and Group 3 consist of five test problems each. The ranges of numbers of customers and delivery vehicles in the 15 test problems are shown in Table 5. The load capacities, fixed costs, fuel consumption costs, travel speeds, numbers of delivery workers, and energy capacities of the delivery vehicles are the same as those used in the numerical example. Each test problem was solved using the ILOG CPLEX and the hybrid GA (which was coded in Visual C Sharp) by the same personal computer described earlier.

Table 5. Ranges of numbers of customers and delivery vehicles in test problems

Test problem	Number of	
	Customers	Delivery vehicles
Group 1 (Problems 1.1 – 1.15)	10 – 14	6 – 9
Group 2 (Problems 2.1 – 2.5)	18 – 25	10 – 14
Group 3 (Problems 3.1 – 3.5)	27 – 40	15 – 20

Among the 25 test problems, the ILOG CPLEX could successively solve only 15 test problems in Group 1 (problems 1.1-1.15). The computation times ranged from 5 to 23,573 seconds (6.55 hours). For test problems 2.1-2.5 except 2.3, the ILOG CPLEX was interrupted before obtaining an optimal solution due to an ‘out-of-memory’ error (with its computation time until interruption varying from 14,400 to 26,388 seconds). For test problem 2.3, the ILOG CPLEX was terminated after reaching a pre-set time limit of 36,000 seconds (10 hours). For test problems 3.1-3.5, where the problem sizes are larger than those in Group 2, the ILOG CPLEX was not employed.

The hybrid GA, on the other hand, could solve all 25 test problems very quickly. For test problems 1.1-1.15, the computation time never exceeded four seconds. For large-sized problems (test problems 2.1-2.5 and 3.1-3.5), the longest computation time was only 7 seconds. Table 6 shows a comparison of solutions to problems 1.1-1.15 using the optimisation and the hybrid GA approaches.

The hybrid GA could yield the same numbers of utilised vehicles as those by the ILOG CPLEX in 11 out of 15 test problems (about 73%). Moreover, both the hybrid GA and ILOG CPLEX could yield identical vehicle sets in 6 out of 15 problems (about 40%). When identical vehicle sets are utilised, the total fixed cost will be the same. Any difference in the total cost between the two approaches is due mainly to the total variable cost. It can be seen that for test problems 1.1, 1.2, 1.4, 1.6, 1.8 and 1.9, the differences in total cost fall within a narrow range (0.27-2.51%). Also, their average % residual capacities and average % residual energies by both approaches are the same.

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Table 6. Comparison of VRPMMH solutions by optimisation and hybrid GA approaches (Test problems 1.1-1.15)

Test problem	Approach	No. of vehicles	Total cost (baht)	Average % residual		Working time (min.)	Computation time (second)
				Capacity	Energy		
1.1[1]	Optimisation	5	17,107	19.34	47.37	328	5
	Hybrid GA	5	17,189	19.34	47.37	335	1
	% Difference		(*0.48*)				
1.2[1]	Optimisation	5	15,324	10.98	41.92	350	70
	Hybrid GA	5	15,708	10.98	41.92	382	1
	% Difference		(*2.51*)				
1.3	Optimisation	5	16,571	5.49	38.33	406	343
	Hybrid GA	5	18,608	12.98	44.50	367	1
	% Difference		(*12.29*)				
1.4[1]	Optimisation	5	17,063	13.28	43.41	376	333
	Hybrid GA	5	17,119	13.28	43.41	354	1
	% Difference		(*0.33*)				
1.5	Optimisation	6	20,548	16.60	44.43	354	7,080
	Hybrid GA	6	22,920	19.11	49.06	351	2
	% Difference		(*11.54*)				
1.6[1]	Optimisation	5	16,925	16.15	45.29	307	33
	Hybrid GA	5	16,970	16.15	45.29	316	1
	% Difference		(*0.27*)				
1.7	Optimisation	4	14,062	4.64	39.47	425	151
	Hybrid GA	5	15,728	17.54	46.20	365	1
	% Difference		(*11.85*)				
1.8[1]	Optimisation	5	17,730	17.28	47.24	357	2,090
	Hybrid GA	5	17,951	17.28	47.24	372	2
	% Difference		(*1.25*)				
1.9[1]	Optimisation	5	16,062	11.80	42.45	352	105
	Hybrid GA	5	16,070	11.80	42.45	352	1
	% Difference		(*0.05*)				
1.10	Optimisation	5	16,522	2.79	36.57	408	5,520
	Hybrid GA	5	21,600	16.03	49.98	342	4
	% Difference		(*30.73*)				
1.11	Optimisation	5	16,170	10.16	41.38	381	155
	Hybrid GA	6	18,199	20.87	47.24	335	2
	% Difference		(*12.55*)				
1.12	Optimisation	6	19,023	17.72	46.35	320	2,007
	Hybrid GA	6	19,792	17.72	46.35	340	2
	% Difference		(*4.04*)				
1.13	Optimisation	5	15,003	6.58	35.92	399	134
	Hybrid GA	5	16,716	12.70	43.04	372	2
	% Difference		(*11.42*)				
1.14	Optimisation	5	16,759	6.49	40.36	372	23,573
	Hybrid GA	6	18,696	16.85	45.78	328	2
	% Difference		(*11.56*)				
1.15	Optimisation	5	17,947	4.45	39.06	399	2,685
	Hybrid GA	6	21,561	19.36	49.22	330	2
	% Difference		(*20.14*)				

[1]Both approaches yield identical sets of vehicles.

Note: The number shown in parentheses is a % difference in total cost as compared to the optimal solution.

These results indicate that the two approaches are able to assign identical sets of customers to individual utilised vehicles. The difference found in the total cost is thus attributed to different delivery routes.

In the other five test problems (1.3, 1.5, 1.10, 1.12 and 1.13), where the numbers of vehicles are the same but with different vehicle sets, the differences in total cost range from 4.04% to 30.73%, which are due to differences in fixed and variable costs. In the remaining four test problems (1.7, 1.11, 1.14 and 1.15), where the numbers of utilised vehicles by the hybrid GA are different from those by the ILOG CPLEX, the difference is one vehicle. The differences in total cost range from 11.56% to 20.14%.

With respect to computation time, while the ILOG CPLEX could solve test problem 1.1 in only 5 seconds, it needed 23,573 seconds (or 6.55 hours) to solve test problem 1.14. The hybrid GA could solve all 15 test problems in only 1-4 seconds each.

Table 7 shows the solutions to test problems 2.1-2.5 and 3.1-3.5 obtained from the optimisation approach and the hybrid GA. Note that they are shown only for information, not for comparison, since the ILOG CPLEX was either interrupted or terminated before reaching the optimal solution, or not employed at all. Thus, the optimality of the solutions could not be verified. Nevertheless, the hybrid GA could yield the solutions very quickly, irrespective of the problem size.

Table 7. VRPMMH solutions by optimisation and hybrid GA approaches (test problems 2.1-2.5 and 3.1-3.5)

Test problem	Approach	No. of vehicles	Total cost (baht)	Average % residual		Working time (min.)	Computation time (second)
				Capacity	Energy		
2.1	Optimisation	8	22,869	9.45	38.98	364	24,783[1]
	Hybrid GA	9	26,705	21.15	47.12	332	2
2.2	Optimisation	9	27,911	10.57	40.94	350	20,506[1]
	Hybrid GA	10	30,307	16.82	44.42	356	5
2.3	Optimisation	9	27,725	6.65	38.36	391	36,000[2]
	Hybrid GA	10	31,636	16.02	45.21	349	2
2.4	Optimisation	10	30,854	6.57	38.41	383	26,420[1]
	Hybrid GA	11	35,085	15.02	44.57	353	5
2.5	Optimisation	11	36,484	12.68	43.66	337	14,365[1]
	Hybrid GA	11	39,237	15.09	46.22	329	6
3.1[3]	Optimisation	-	-	-		-	-
	Hybrid GA	13	41,779	19.11	46.76	324	5
3.2[3]	Optimisation	-	-	-		-	-
	Hybrid GA	13	46,871	13.90	44.80	363	7
3.3[3]	Optimisation	-	-	-		-	-
	Hybrid GA	14	51,935	16.96	47.83	331	4
3.4[3]	Optimisation	-	-	-		-	-
	Hybrid GA	16	52,937	15.90	45.14	340	3
3.5[3]	Optimisation	-	-	-		-	-
	Hybrid GA	18	62,874	15.87	45.81	331	7

[1] ILOG CPLEX was terminated due to an 'out-of-memory' error.
[2] ILOG CPLEX was interrupted after exceeding the 10-hour computation time limit.
[3] The test problem was not solved by ILOG CPLEX.

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CONCLUSIONS

The hybrid GA for solving the VRPMMH efficiently has been presented. It uses the nearest neighbour search technique to help develop some chromosomes for its initial population. Special crossover and mutation procedures have been developed to generate offspring that are better (fitter) than the parents. From 15 test problems, the hybrid GA could obtain the VRPMMH solutions which are close to the optimal solutions in both the number of utilised vehicles and total costs.

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