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AN INTRODUCTION OF GENETIC ALGORITHM FOR IMPROVING A VEHICLE ROUTING PROBLEM IN A BAKERY COMPANY

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Abstract

The aim of the study is to apply a Genetic Algorithm (GA) to solve a Vehicle Routing Problem (VRP) for a specific bakery company. This VRP application consists of 1 depot with 32 customers in 6 delivery zones. In the study, the GA is chosen to solve this vehicle routing problem as compared with an existing method currently used by the company, which resembles to the Nearest Neighbor Heuristic (NN). The result of the comparison shows that the proposed GA performs better than the existing heuristic method. In addition, a comparison between different time constraints for vehicles to return to the depot is made to suggest to the company a suitable duration of its delivery time if the company decides to speed up and limit its delivery time in the future.

Keywords: Single depot, vehicle routing problem, genetic algorithm, nearest neighbor heuristic

Introduction

The classical Vehicle Routing Problem (VRP) consists of a predefined number of customers, and 1 depot which has a predefined number of vehicles used to transport products. Each customer in the classical VRP requires a specific number of products which will be delivered from the depot via a vehicle. The capacity of each vehicle is limited and, as a consequence, 1 vehicle can serve only a limited number of customers within a single route. The aim of the classical VRP is to find the route for deliveries that minimizes the total distance and hence the transportation cost. Vehicle Routing Problem with Time Windows (VRPTW) is a variant of Vehicle Routing Problem with adding time windows constraints to the model. In VRPTW, a set of vehicles with limited capacity is to be routed from a central depot to a set of geographically dispersed customers with known demands and predefined time windows in order that fleet size of vehicles and total traveling distance are minimized and capacity and time windows constraints are not violated (Ghoseiri and Ghannadpour, 2010).

This study focuses on a real application of the VRP with and without time constraints for a specific bakery company. This VRP application consists of 1 depot with 32 customers in 6 delivery zones. The main objective of the study is to improve the logistics

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performance of a bakery company with a single depot by introducing the Genetic Algorithm (GA) to optimize the total transportation costs and compare it with an existing system in which operators use their own experience to design the route and which resembles a simple Nearest Neighbor Heuristic (NN). The GA is applied in this study to manage the routes for visiting all the customers in the bakery company's chain. Then, a recommendation can be made for the best possible route as well as the appropriate duration of its delivery service.

The paper is organized in the following way. The next section comprises a literature review related to the 2 algorithms used in the study. The background of the problem is then given in section 3. Section 4 and Section 5 present the mathematical model and numerical example respectively. Section 6 presents the results (both with and without time constraint), and finally the conclusions are made.

Literature Review

The VRP was first introduced by Dantzig and Ramser (1959). It comprises a number of customers and a number of depots, together with a number of vehicles. The process starts with customers ordering the products and vehicles being assigned a specified load of products to be delivered on each trip. Then, the vehicles leave the depot, serve all customers in the network of routes and return to the depot. Most problems in this study are the optimization problems in which customers are to be served by a number of vehicles and the total traveling distance and cost are to be minimized. Many metaheuristics have been applied to this problem, including Tabu Search (Taillard, 1993), Simulated Annealing (de Oliveira *et al.*, 2006), Ant Colony System (Gambardella *et al.*, 1999; Bell and McMullen, 2004) and Genetic Algorithm (Su, 1998; Prins, 2004; Jeon *et al.*, 2007). A comprehensive survey on the capacitated VRP and variants can also be seen from Toth and Vigo (2002) where exact, heuristic methods and meta-heuristics focusing on issues common to VRP were summarized and reviewed.

The process of selecting vehicle routes allows the selection of any combination of customers in determining the delivery route for each vehicle. Therefore, the VRP is a combinatorial optimization problem where the number of feasible solutions for the problem increases exponentially with the number of customers to be serviced. In addition, the vehicle routing problem is closely related to the traveling salesman problem where an out and back tour from a central location is determined for each vehicle. Since there is no known polynomial algorithm that will find the optimal solution in every instance, VRP is considered NP-hard. For such problems, the use of heuristics is considered a reasonable approach in finding solutions and this paper uses Nearest Neighbor Heuristic and Genetic Algorithm to find solutions to the Vehicle Routing Problem.

Nearest Neighbor Heuristic

The NN algorithm is a heuristic algorithm, which was developed as a greedy approach to approximating the Traveling Salesman Problem (TSP). The salesman starts with a number of customers and first visits the customer nearest to the starting city. From there, he visits the nearest customer that has not been visited so far until all customers are visited, and he then returns to the start.

As shown in Figure 1, the step of the NN with a set of N customers and i single depot are given and the problem is to start at node i and find the shortest route to customer j ($j = 1,\ldots, N$) by visiting all customers (with no customer visited twice) and returning to the depot i which was the start.

Chidananda and Krishna (1979) studied a 2-stage iterative algorithm for selecting a subset of a training set of sample for use in the NN algorithm. The proposed method uses the concept of the mutual nearest neighborhood for selecting samples close to the decision line. The efficacy of the algorithm is shown by means of an example.

Zhou and Chen (2006) presented a novel way to optimize the distance measure for the neighborhood-based classifiers. The NN classification assumes locally constant class conditional probabilities, and suffers from bias in high dimensions with a small sample set. They proposed a novel cam weighted distance to ameliorate the curse of dimensionality. Unlike the existing neighborhood-based methods which only analyze a small space emanating from the query sample, the proposed NN classification using the cam weighted distance (CamNN) optimizes the distance measure based on the analysis of inter-prototype relationship.

Jigang *et al.* (2007) proposed the *k*-nearest neighbor rule that is one of the simplest and most attractive pattern classification algorithms. However, it faces serious challenges when patterns of different classes overlap in some regions in the feature space. In the past, many researchers developed various adaptive or discriminate metrics to improve performance. In these tests on several real world datasets, the resulting adaptive *k*-NN rule actually achieves consistently better or comparable performance to the state-of-the-art Support Vector Machines. They demonstrated that an extremely simple adaptive distance measure significantly improves the performance of the *k*-nearest neighbor rule.

Genetic Algorithm

The Genetic Algorithm (GA) was invented by John Holland and his colleagues in the early 1970s (Holland, 1975). Inspired by Darwin's theory, the GA belongs to the group of meta-heuristics. The GA refers to an adaptive search process based on the principles obtained from natural evolution and genetics. The GA is well-known to propose advantageous methods by using simultaneously several search principles and heuristics. The GA can be implemented in various ways to solve any problem.

The GA is a metaheuristic method based on the efficiency of natural selection in biological evolution. It consists of several operators that construct a new generation of solutions from the old one in a manner designed to preserve the genetic material of the better solutions (survival of the fittest). Many GA operators have been proposed; the 3 most common are reproduction, crossover, and mutation. The GA has been receiving great attention and has also been successfully applied in many research fields. Figure 2 shows the procedures of performing Genetic Algorithm (GA).

Literature of VRP with the GA is rich in exact, allowing for the reviews of only those most relevant to the study. Poon and Carter (1995) studied the GA when applied to problems that can be coded naturally as binary strings. The main difficulty is the design of a suitable crossover operator. They compared the performance of several crossover operators, including two new operators and a new faster formulation of a previously published operator. This new formulation performs better than the other operators they had tested while taking no more computation time. In addition, with

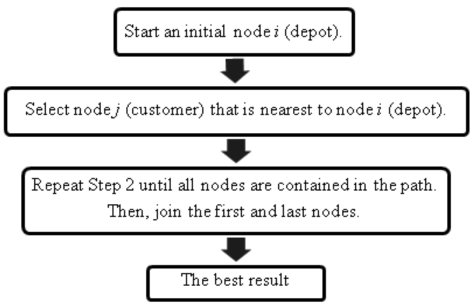


Figure 1. Flowchart of the Nearest Neighbor (NN)'s procedures

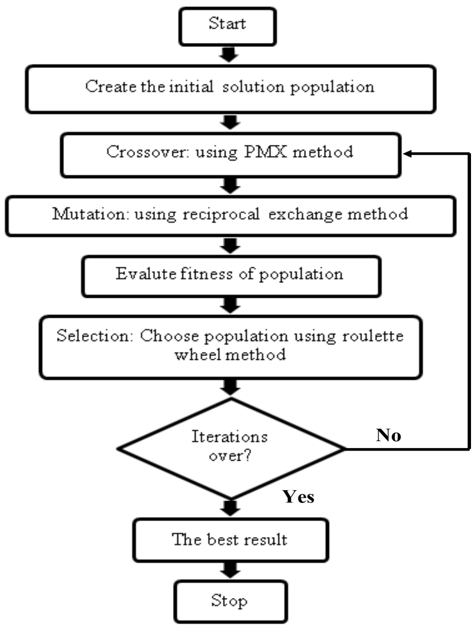


Figure 2. Flowchart of the Genetic Algorithm (GA)'s procedures

practical applications in mind, they showed how the use of problem-specific information can improve the performance of the GA and they described a method for designing a problem-specific crossover incorporating a novel tie-breaking algorithm. The GA can be a useful tool for solving practical ordering problems. Its performance can be improved by exploiting any information that is available additional to the objective function values.

Bräysy and Gendreau (2005) developed GA-based approaches for solving the vehicle routing problem with time windows and compared their performance with the best recent metaheuristic algorithms. The findings indicated that the results obtained with pure GA were not competitive with the best published results, though the differences are not overwhelming.

Baker and Ayechew (2003) considered the application of a GA to the basic VRP, in which customers of known demand are supplied from a single depot. Vehicles are subject to a weight limit and, in some cases, to a limit on the distance traveled. Only 1 vehicle is allowed to supply each customer. The best known results for benchmark VRPs have been obtained using Tabu Search or Simulated Annealing. The results were given for the pure GA which is put forward. Further results were given using a hybrid of this GA with neighborhood search methods, showing that this approach is competitive with Tabu Search and Simulated Annealing in terms of solution time and quality.

In summary, genetic-based methods recently developed for VRP interleaving local improvement procedures through critical steps of the standard genetic algorithm tend to provide good solutions but have not convincingly show to our knowledge, to complete or challenge the best-known methods. It is nonetheless believed that genetic-based methods targeted to the classical capacitated VRP have not yet been fully exploited. Accordingly, we contend that some benefits might be expected in capturing heuristic knowledge on genetic operators explicitly.

Background of the Problem

A bakery company under CP All Public Company Limited in Bangkok, Thailand was used to be our case study. This bakery company is located on Silom Road, Bangrak, Bangkok and was established in 2005. The business has grown successfully over the last 2 years, primarily due to the quality of the products and to the excellent service offered to all the customers of the company. The bakery company handles the production and distribution of bakery products such as Coconut Cookies, Chocolate Chip Cookies and Sugar Puffs. All data of this study were gathered during the internship period (1 semester) during May to October 2009. However, some of the data, especially the financial data, are prohibited from publication due to the confidentiality.

Currently, the company has 1 depot which is located at Soi Chockchairuammit khwaeng Din-daeng Bangkok at the coordinates (13.796146N, 100.567185E) as located by Google Earth. The depot operates both as a managing warehouse and for the distribution of company's products. There are 32 customers located in the Bangkok Metropolitan area. The bakery company's existing transportation policy divides all customers into 6 delivery zones, the delivery plan resembling the NN. The coordinates of each customer and their zones can be presented in Table 1.

Mathematical Model

This study focused on the vehicle routing problem with and without time constraints. The center node is called the depot with a set of customer C to be visited. The customers have 32 nodes and are separated into 6 zones. The homogeneous fleet of vehicles must start from and return to the central depot. There is no limitation on the number of vehicles. The maximum possible capacity of each vehicle is loaded 90 trays. The actual number of vehicles will be found after solving the model that it would be equal to the number of trips. It is assumed that there are $N+1$ customers, $C= \{0, 1, 2, . . .,32\}$, and for simplicity, the depot is denoted as customer 0. The vehicle is starting from the depot, going through a number of customers and ending at the depot. A distance d_{ij} and travel time t_{ij} are associated with all of deliveries in

3 levels of time constraints (3 h, 4 h, and 5 h). The loading and unloading time is permitted at no cost. Since each vehicle has a limited capacity q_k = 90 trays (*for k = {1,...,K}*), and each customer has a varying demand m_i, q_k must then be greater than or equal to the summation of all demands on the route traveled by that vehicle *k*. For each node *(i, j)*, where $i \neq j$, $i, j \neq 0$, and each vehicle *k*, the decision variable x_{ijk} is equal to 1 if vehicle *k* drives from node *i* to node *j* and 0 otherwise. In order to formulate the model, other following notations are defined:

T_m = Maximum delivery time with 3 levels of time constraint (3 h, 4 h and 5 h)
F = Fuel cost per distance (Baht/km)
M = Maintenance cost per distance (Baht/km)
L = Labor wage per day (Baht/day/person)
W = Number of workers (persons)

Objective function

To find the routes of vehicles for serving the customers at the minimal total transportation costs under both with and without time constraints.

Minimize Total Transportation Costs (TTC) =

$$(F+M)\sum_{i=0,j=0}^{N}\sum_{j\neq i}^{N}\sum_{k=1}^{K} d_{ij}\,x_{ijk} + (L \times W) \quad (1)$$

Subject to

$$\sum_{i=1}^{N} m_i \sum_{j=0,j\neq i}^{N} x_{ijk} \leq q_k \text{ for } k = \{1,\ldots,K\} \quad (2)$$

$$\sum_{i=0}^{N}\sum_{j=0,j\neq i}^{N} x_{ijk}\,t_{ijk} \leq T_m \text{ for } k = \{1,\ldots,K\} \quad (3)$$

$$\sum_{j=1,j\neq i}^{N} x_{ijk} = \sum_{j=1,j\neq i}^{N} x_{ijk} \leq 1 \text{ for } i = \{0,\ldots,N\} \text{ and } k = \{1,\ldots,K\} \quad (4)$$

$$\sum_{k=1}^{K}\sum_{j=0,j\neq i}^{N} x_{ijk} = 1 \text{ for } i = \{1,\ldots,N\} \quad (5)$$

$$\sum_{k=1}^{K}\sum_{i=0,i\neq j}^{N} x_{ijk} = 1 \text{ for } j = \{1,\ldots,N\} \quad (6)$$

Table 1. Delivery zones of customers

No. delivery zone	Branch	(Latitude, Longitude)
1	Suppavut Bangna Branch	(13.67311N, 100.60555E)
	Sukhumvit 107 Branch	(13.65853N, 100.60104E)
	Teparuk Branch	(13.61834N, 100.64922E)
	Talad Nikom Branch	(13.561N, 100.67187E)
	Kaha 9 Branch	(13.57378N, 100.79309E)
2	Petburi 39 Branch	(13.75N, 100.5566E)
	Talad Pongeum Branch	(13.61768N, 100.74333E)
	Ladkrabang Branch	(13.72169N, 100.78391E)
	Kingkueng Branch	(13.63455N, 100.71107E)
3	Ramkhamhaeng 34 Branch	(13.76145N,100.63657E)
	Lido Branch	(13.74556N, 100.53254E)
	Tharakorn Branch	(13.79738N, 100.71173E)
	Ramkhamhaeng 65 Branch	(13.76617N, 100.62338E)
	Tepleela Branch	(13.75757N, 100.61528E)
4	Jarunsanitwong Branch	(13.77878N, 100.4867E)
	Petkasem 33 Branch	(13.71329N, 100.43946E)
	Piboonwit Branch	(13.68692N, 100.44407E)
	Salaya Branch	(13.79363N, 100.32026E)
	Saitaimai 2 Branch	(13.79346N, 100.42583E)
	Saitaimai 3 Branch	(13.79346N, 100.42583E)
5	Tait Branch	(13.88064N, 100.45882E)
	Talad Sintong Branch	(13.86516N, 100.48235E)
	Hualampong Branch	(13.73752N, 100.51736E)
	Khao San Branch	(13.75958N, 100.49571E)
	Sriboonrueng Branch	(13.72784N, 100.53335E)
6	Pratanporn Branch	(14.00889N, 100.61493E)
	Thammasat Rangsit Branch	(14.07567N, 100.61741E)
	Nanajaruen Branch	(13.97072N, 100.6449E)
	Major Rangsit Branch	(13.98789N, 100.61602E)
	Wattananan Branch	(13.91315N, 100.59043E)
	Rangsit Pirom Branch	(14.04007N, 100.61607E)
	Jangwattana Branch	(13.88251N, 100.58497E)

$$x_{ijk} \in \{0,1\} \text{ for } i,j = \{1, \ldots, N\} \tag{7}$$

Equation (1) is to minimize the total transportation costs including fuel cost, vehicle maintenance cost and labor cost. Constraint (2) is the vehicle capacity constraint, which is set at 90 trays as the maximum. Constraint (3) is the maximum travel time constraint. Constraint (4) secures every route starts and ends at the central depot. Constraints (5) and (6) define that every customer node is visited once by one vehicle. Equation (7) represents the decision variable.

Numerical Experiment

Both the NN and GA algorithms were coded by Visual Basic Application (VBA) running on Intel Core 2 duo 1.80 GHz CPU with 1 GB of RAM. The experiments can be classified, based on the level of customer demand into 3 categories-low, medium and high. Each customer orders various types of baked products but the products are packed in identical trays before delivery. The company has never experienced any shortages of vehicles (4 wheel pick-ups). As a result, it is assumed that there are a sufficient number of vehicles but each vehicle can load 90 trays as the maximum capacity. In the low customer demand case, the customer demand is randomly between 3 to 9 trays per day. In the medium customer demand case, the customer demand is randomly between 10 to 15 trays per day and in the high customer demand case, the customer demand is randomly between 16 to 22 trays per day. Each category contains 30 instances (days) and each instance is repeated with 10 replications. Based on 10 replications with different seeds, a 95% confidence interval for the traveling distance has a width less than 5% of its mean.

All delivery activities must be carried out during the night (from the mid-night till 5 am for the maximum period of 5 h). This is aimed for not to disturb normal hours of business, avoid the traffic congestion and get the bakery ready for sales in the morning. We did not consider the traffic condition in the model since the delivery is done during the night when there is less traffic. In addition, to comply with the legally defined maximum speed, the vehicle can run at the average speed of 60 km per hour so that it is assumed that 1 km will be travelled in 1 min. The bakery company can load the products into the vehicle at the rate of 10 trays in 5 min or 2 trays per min. When the vehicle arrives at each customer, the products will be unloaded at the rate of 1 tray per minute since it takes longer to leave the products at the customer's shop. Table 2 summarizes all test and cost data for the numerical experiment.

Parameters of Nearest Neighbor Heuristic

The parameter values of the NN are given below:

- Number of nodes = 33, including the depot and the number of customers
- Number of delivery zones = 6, following the existing policy of this bakery company.

Parameters of Genetic Algorithm

The parameter values of the GA can be summarized as below:

- Number of genes = 32
- Number of chromosomes = 32
- Crossover rate = 100%
- Mutation rate = 100%
- Stopping criterion = 10000 generations

Experiments on 4 levels among percentages of crossover and mutation rates were carried out to select the best setting rates. The high demand case is selected to perform in this experiment. The results of 25%, 50%, 75%, and 100% of the crossover and mutation rate can be presented in Table 3.

From Table 3, it can be suggested that the crossover and mutation rate should be set at 100% because better results for traveling distances and total transportation cost have been obtained as compared with the results from other percentages of crossover and mutation rates. This is due to the fact that all chromosomes are added for the solution. With the policy of 100% for the crossover and mutation rate, 100% of the chromosomes or 32 chromosomes, are selected for the crossover and mutation operations. As a result, the population size is 96 (32+32+32 chromosomes), including the number of original chromosomes (32 chromosomes), 32 chromosomes taken from the crossover operations and 32 chromosomes taken from the mutation operations. With only 32 initial chromosomes in the experiment, there is a higher probability for 100% crossover and mutation rates to select a good chromosome during the roulette wheel method as compared with the other percentages' selection. However, this selection has been proven to work well only with this case, and may not be generalized to other cases.

Table 4 also presents an example of a search convergence with 3 interested performance measures (fitness values) including the number of trips, traveling distance and total transportation costs from 1000 to 10000 generations (for the case of low demands with 3 h' time constraint). It was found that all performance measures show to be improved as the number of generations increase. The improvement on these results was quite significant at the beginning but later on the margin of improvement was slimmer. At the 10000 generations (selected stopping generations), it can show sufficient fitness for the best solution as the improved percentage in its results was quite low with little sign for improvement.

It should also be noted that the delivery zone is eliminated under the GA. It was found from the preliminary results that the results without the delivery zone outperformed the ones with the delivery zone. In the case of 32 chromosomes, we found that the results of both the NN and GA without delivery zone can generate the route much better than the ones with the delivery zone. As a result, separating the delivery into 6 zones is proven to be excessive and more expensive for the case of a small number of customers such as in this case. From this finding, the following comparisons will then be made between the actual existing system (which still uses the NN still with 6 delivery zones) and the new proposed system, which uses the GA without a delivery zone.

Results

Minimizing the Total Transportation Cost without Time Constraint

This experiment will be used as a base case for comparison. With no time constraint, there is

Table 2. Test and cost data for the numerical experiment

Item	Details
Number of depots	1
Number of customers	32
Demand of customers	
- Low demand	Random between 3-9 trays/day
- Medium demand	Random between 10-15 trays/day
- High demand	Random between 16-22 trays/day
Vehicle capacity	Each vehicle can load 90 trays as the maximum capacity.
Cost structure	
- Fuel cost per distance	3 Baht/km
- Maintenance cost per distance	2 Baht/km
- Labor wage per day	150 Baht/day
- Number of workers	2 persons/day

Table 3. The experiments on 4 levels of the percentage of crossover and mutation rates

Detail	Percentage of crossover and mutation rate			
	25%	50%	75%	100%
Number of trips (trips)	8	8	8	8
Traveling distances (km)	753	734	725	703
Total transportation costs (Baht)	6165	6070	6025	5915

no limit of time that each vehicle needs to return to the depot. As a result, a fully loaded vehicle can deliver the products until all the loaded trays are unloaded. In order to evaluate the tested approach, the experiment will be carried out to test with all 3 levels of customer demand.

Table 5 summarizes the comparison of the test results between the NN and GA. From the best value for the low demand case, it was found that the GA can reduce the traveling distance by 119 km (or 21.29%) with 4 trips' reduction (or 66.67%) and the total transportation cost reduction is 1795 Baht (or 39.06%). For the medium demand case, it was found that the GA can reduce the traveling distance by 42 km (or 7.51%) with a 1 trip' reduction (or 16.67%) and the total transportation cost reduction is 510 Baht (or 11.10%). For the high demand case, it was found that the GA can reduce the traveling distance by 39 km (or 5.59%) with a 1 trip reduction (or 11.11%) and the total transportation cost reduction is 495 Baht (or 8.82%).

Table 4. Genetic Algorithm's search convergence between the number of generations and interested performance measures (fitness values)

No.	No. generations	No. trips (trip)	Traveling distances (km)	Total transportation cost (Baht)
1	1000	6	638	4990
2	2000	6	633	4965
3	3000	6	626	4930
4	4000	6	612	4860
5	5000	5	602	4510
6	6000	6	594	4770
7	7000	6	591	4755
8	8000	5	584	4420
9	9000	5	579	4395
10	10000	5	576	4390

Table 5. Comparison of test results between the Nearest Neighbor Heuristic and the Genetic Algorithm without time constraint

Demand Level	Performance manner	Best value[1]		Average value[2]		Percentage[3] difference based on the best values	Percentage[3] difference based on the average values
		NN	GA	NN	GA		
Low	Number of trips (trips)	6	2	6	3	66.67%	50.00%
	Traveling distance (km)	559	440	559	515	21.29%	7.84%
	Total transportation costs (Baht)	4595	2800	4595	3475	39.06%	24.37%
Medium	Number of trips (trips)	6	5	7	6	16.67%	14.29%
	Traveling distance (km)	559	517	575	556	7.51%	3.30%
	Total transportation costs (Baht)	4595	4085	4975	4085	11.10%	7.94%
High	Number of trips (trips)	9	8	11	8	11.11%	27.27%
	Traveling distance (km)	655	616	741	679	5.95%	8.37%
	Total transportation costs (Baht)	5975	5480	7005	5795	8.82%	17.27%

Remark: *1. The best value's are taken from the best result among 10 replications.*
2. The average value's results are averaged from the results of all 10 replications.
3. Percentage difference is calculated from $\left(\dfrac{\text{Result of NN - Result of GA}}{\text{Result of NN}}\right) \times 100\%$

From the average value, for the low demand case, it was found that the GA can reduce the traveling distance by 44 km (or 7.87%) with 3 trips' reduction (or 50.00%) and the total transportation cost reduction is 1120 Baht (or 24.37%). For the medium demand case, it was found that the GA can reduce the traveling distance by 19 km (or 3.0%) with a 1 trip reduction (or 14.29%) and the total transportation cost reduction is 395 Baht (or 7.94%). For the high demand case, it was found that the GA can reduce the traveling distance by 62 km (or 8.37%) with 3 trips' reduction (or 27.27%) and the total transportation cost reduction is 1210 Baht (or 17.27%). Table 6 presents the details of the traveled routes as recommended by the NN and GA.

For the low demand case, the NN suggests 6 trips or 1 trip per 1 zone as it is the minimum possible numbers of trips. The first trip starts from the depot to customers no. 4, 1, 16, 17, and 22 and returns to the depot. The second trip starts from the depot to customers no. 7, 21, 13, and 18 and returns to the depot.

Table 6. Details of the traveled route as recommended by the NN and GA

Demand level	Type of algorithm	Zone	Trip	Delivery route (#customer)
Low	NN	1	-	no. 4, 1, 16, 17, 22
		2	-	no. 7, 21, 13, 18
		3	-	no. 25, 32, 5, 11, 10
		4	-	no. 2, 26, 27, 6, 20, 23
		5	-	no. 31, 24, 28, 9, 15
		6	-	no. 30, 19, 12, 14, 3, 29, 8
	GA	-	1	no. 25, 32, 5, 7, 10, 31, 24, 28, 2, 27, 26, 6, 20, 23
		-	2	no. 30, 19, 12, 14, 3, 29, 8, 15, 9, 1, 4, 16, 21, 13 17, 22, 18, 11
Medium	NN	1	-	no. 4, 1, 16, 17, 22
		2	-	no. 7, 21, 13, 18
		3	-	no. 25, 32, 5, 11, 10
		4	-	no. 2, 26, 27, 6, 20, 23
		5	-	no. 31, 24, 28, 9, 15
		6	-	no. 30, 19, 12, 14, 3, 29, 8
	GA	-	1	no. 25, 32, 5, 7, 10, 31, 28
		-	2	no. 2, 24, 20, 6, 27, 26, 23
		-	3	no. 30, 19, 12, 14, 3, 29, 8
		-	4	no. 15, 9, 11, 18, 21, 13, 1
		-	5	no. 4, 16, 17, 22
High	NN	1	-	no. 4, 1, 16, 17, 22
		2	-	no. 7, 21, 13, 18
		3	1	no. 25, 32, 5, 11
			2	no. 10
		4	1	no. 2, 26, 27, 6,
			2	no. 20, 23
		5	-	no. 31, 24, 28, 9, 15
		6	1	no. 30, 19, 12, 14,
			2	no. 3, 29, 8
	GA	-	1	no. 25, 32, 5, 7
		-	2	no. 10, 31, 24, 28
		-	3	no. 2, 27, 26, 23, 20
		-	4	no. 30, 19, 12, 14
		-	5	no. 15, 9, 6, 1
		-	6	no. 11, 18, 21, 13
		-	7	no. 4, 16, 17, 22
		-	8	no. 3, 29, 8

The third trip starts from the depot to customers no. 25, 32, 5, 11, and 10 and returns to the depot. The fourth trip starts from the depot to customer no. 2, 26, 27, 6, 20, and 23 and returns to the depot. The fifth trip starts from the depot to customers no. 31, 24, 28, 9, and 15 and returns to the depot. The last trip starts from the depot to customers no. 30, 19, 12, 14, 3, 29, and 8 and returns to the depot.

While the GA suggested only 2 trips as the zone was eliminated, the first trip starts from the depot to customers no. 25, 32, 5, 7, 10, 31, 24, 28, 2, 27, 26, 6, 20, and 23 and returns to the depot. The second trip starts from the depot to customers no. 30, 19, 12, 14, 3, 29, 8, 15, 9, 1, 4, 16, 21, 13, 17, 22, 18, and 11 and returns to the depot. For the sake of space limitation, all trips' details of other cases will not be reported. Only the summary of the average number of trips, travelling distance and total transportation cost will be presented.

From Figure 3 it was found that the GA can generate the routes better than the NN in all 3 categories of the demand level. When the demand increases, the number of trips, traveling distance and total transportation cost also increase. In the low demand case, we found that the GA has the lowest number of trips, which is 3 trips (or 50% lower than the NN) because the NN has to separate into 6 delivery zones so that there must be at least 6 trips but the GA, which has no delivery zone, can do it with only 3 trips.

In the medium demand case, we found that the NN's results show no significant difference from the results obtained from the GA. This is due to an increase in the demand from customers. So, the number of trips of the GA is quite similar to the minimum required number of trips of the NN which is set at 6 trips as a minimum.

In the high demand case, we found that the GA's results are better than the results from the NN. With the highest demand from customers, more delivery trips are required. As a result, without the zone, the GA can exploit the condition to manage its travel route much better with a lower number of trips. This would lead to a shorter traveling distance and lower transportation cost.

Minimizing the Transportation Cost with Time Constraint

This is to experiment on the limitation of the delivery time (VRPTW) since the company expects to put more control of its delivery in the near future by setting up a regulation which forces

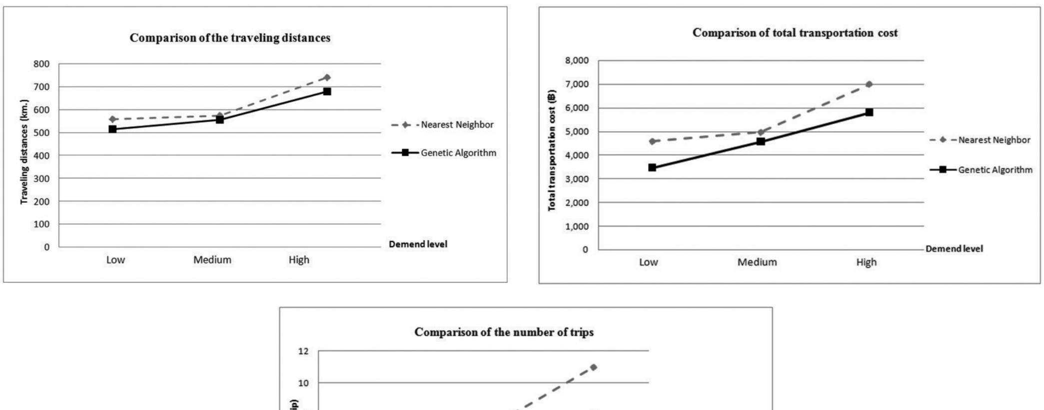


Figure 3. Comparison of the results between Nearest Neighbor Heuristic and Genetic Algorithm under the cases without the time constraint

each vehicle to work faster and come back to the depot sooner. This is done by setting up a time window/constraint. The time window/constraint is related to the total time to deliver the product including the loading and unloading time, delivery time and return time. There are 3 levels of time constraint, which are set within 3, 4, and 5 h. This is corresponding to the maximum period of 5 h between the mid-night and 5 am when the delivery activities must take place. These instances can also be classified, based on the levels of customer demand into 3 categories-low, medium and high.

Time Constraint of 3 Hours

Table 7 summarizes the comparison of test results between the NN and GA for both the best and average values. For the average value in the low demand case, the results of the GA have average values slightly higher than the ones from the Nearest Neighbor Heuristic that is the longer traveling distance by 27 km (or 4.83%) with an equal number of trips and a higher total transportation cost of 135 Baht (or 2.93%). For the medium demand case, it was found that the GA can reduce the traveling distance by 33 km (or 4.53%) with a 1 trip' reduction (or 10.00%) and the total transportation cost reduction is 465 Baht (or 7.00%). For the high demand case, it was found that the GA can reduce the traveling distance by 35 km (or 4.21%) with a 1 trip' reduction (or 7.69%) and the total transportation cost reduction is 475 Baht (or 5.90%).

According to Figure 4, for all demand cases, the NN's results show no significant difference from the results obtained from the GA. This is due to the fact that all vehicles need to return to the depot within 3 h. As a result, the vehicle cannot load the products to full capacity and this forces both systems (especially the GA) to have more trips and longer traveling distances than usual. As a result, no significant improvement with the GA can be presented in this case.

Time Constraint of 4 Hours

Table 8 also summarizes the comparison of test results between the NN and GA. Referring to the average value for the low demand case, it was found that the GA can reduce the traveling distance by 18 km (or 3.22%) with 2 trips' reduction (or 33.33%) and the total transportation cost reduction is 690 Baht (or 15.02%). For the medium case, the GA has the average values higher than the ones from

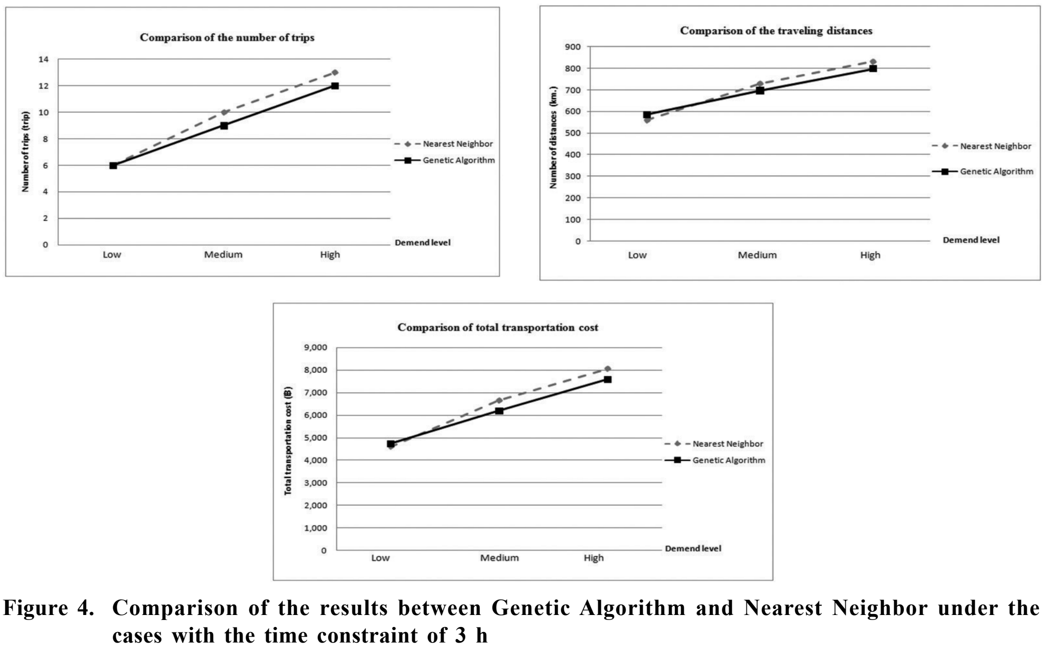


Figure 4. Comparison of the results between Genetic Algorithm and Nearest Neighbor under the cases with the time constraint of 3 h

the NN, which has the longer traveling distance by 22 km (or 3.82%) with equal number of trips and a higher total transportation cost of 110 Baht (or 2.21%). For the high demand case, it was found that the GA can reduce the traveling distance by 62 km (or 8.27%) with 2 trips' reduction (or 18.18%) and the total transportation cost reduction is 910 Baht (or 12.91%).

According to Figure 5, for the low demand case, the NN's results also suggest not much difference from the results obtained from the GA especially with the traveling distance due to there still being the time constraint. However, when comparing between the 3 h and 4 h time constraint, it was found that the GA under the 4 h time constraint has a lower number of trips and traveling distances than the NN's results because a vehicle can serve more products to customers on each trip. As a result, the total transportation cost obtained from the GA has been shown to be lower.

In the medium case, the NN's results suggest no significant difference from the results obtained from the GA. This is due to an increase in the demand from customers. So, the number of trips for the GA is quite similar to the minimum required number of trips of the NN, which is set at 6 trips as a minimum.

In the high demand case, the GA's results are much better than the NN's results. With the highest demand from customers, more delivery trips are required. As a result, without the zone, the GA can exploit this condition to manage the traveling route much better with a lower number of trips. This would lead to a shorter traveling distance and a lower transportation cost.

Time Constraint of 5 Hours

As seen in Table 9, for the average value in the low demand case, it was found that the GA can reduce the traveling distance by 64 km (or 11.45%) with 2 trips' reduction (or 33.33%), and the total transportation cost reduction is 920 Baht (or 20.02%). For the medium demand case, it was found that the GA can reduce the traveling distance by 24 km (or 4.17%) with a 1 trip' reduction or (14.28%) and the total transportation cost reduction is 420 Baht (or 8.44%). For the high demand case, it was found that the GA can reduce the traveling distance by 62 km (or 8.37%) with

Table 7. Comparison of test results between the Nearest Neighbor Heuristic and the Genetic Algorithm under 3 h time constraint

Demand Level	Performance manner	Best value[1]		Average value[2]		Percentage[3] difference based on the best values	Percentage[3] difference based on the average values
		NN	GA	NN	GA		
Low	Number of trips (trips)	6	5	6	6	16.67%	-
	Traveling distance (km)	559	554	559	586	0.89%	(4.83)%
	Total transportation costs (Baht)	4595	4270	4595	4730	7.07%	(2.93)%
Medium	Number of trips (trips)	9	7	10	9	22.22%	10.00%
	Traveling distance (km)	710	623	729	696	12.25%	4.53%
	Total transportation costs (Baht)	6250	5215	6645	6180	16.56%	7.00%
High	Number of trips (trips)	12	10	13	12	16.67%	7.69%
	Traveling distance (km)	776	747	831	796	3.73%	4.21%
	Total transportation costs (Baht)	7480	6735	8005	7580	9.96%	5.90%

Remark: *1. The best value's are taken from the best result among 10 replications.*
2. The average value's results are averaged from the results of all 10 replications.
3. Percentage difference is calculated from $\left(\dfrac{\text{Result of NN - Result of GA}}{\text{Result of NN}}\right) \times 100\%$

3 trips' reduction (or 27.27%) and the total transportation cost reduction is 1210 Baht (or 17.27%).

From Figure 6, we found that the GA can generate the routes better than the NN in all 3 categories of the demand level. No vehicle is required to go back for reloading due to the limitation on the time. This is due to the fact that more delivery time is allowed on each trip. In general, the results obtained from this case are quite similar to the results of the no time constraint case. This indicates that 5 h time constraint would be quite sufficient to accommodate all required trips. In the low demand case with 5 h time constraint, the NN generates 6 trips as a minimum but the GA with no delivery zones can exploit this case to manage the travel route better with a lower number of trips. This would lead to a shorter traveling distance and a lower transportation cost.

In the medium case, the NN's results suggest little difference from the results obtained from the GA, although the results under the GA slightly outperform the results under the NN. This is due to an increase in the demand from customers. So, the number of trips for the GA is quite similar to the minimum required number of trips for the NN, which is set at 6 trips as a minimum.

With the highest demand from customers, more delivery trips are required. As a result, without the zones, the GA can exploit the condition to manage the travel route much better with a lower number of trips. This would lead to a shorter traveling distance and a lower transportation cost.

Comparison of the Results Obtained from Genetic Algorithm

As the results obtained from the GA are generally shown to outperform the company's existing results using the NN, another attempt is made to analyze specific results obtained from the GA under all 3 levels of the customer demand both with and without the time constraint. This is to recommend the best time window if the company would like to limit the delivery time of each vehicle. The comparisons of these results are shown in Table 10 and Figure 7.

In the no time constraint cases, as compared with the results under the time constraints, the results show the lowest number

Table 8. Comparison of test results between the Nearest Neighbor Heuristic and the Genetic Algorithm under 4 h time constraint

Demand Level	Performance manner	Best value[1]		Average value[2]		Percentage[3] difference based on the best values	Percentage[3] difference based on the average values
		NN	GA	NN	GA		
Low	Number of trips (trips)	6	4	6	4	33.33%	33.33%
	Traveling distance (km)	559	516	559	541	7.69%	3.22%
	Total transportation costs (Baht)	4595	3780	4595	3935	17.74%	15.02%
Medium	Number of trips (trips)	6	5	7	7	16.67%	-
	Traveling distance (km)	559	531	575	597	5.01%	(3.82)%
	Total transportation costs (Baht)	4595	4155	4975	5085	9.58%	(2.21)%
High	Number of trips (trips)	10	8	11	9	20.00%	18.18%
	Traveling distance (km)	724	619	750	688	14.50%	8.27%
	Total transportation costs (Baht)	6620	5495	7050	6140	16.56%	12.91%

Remark: *1. The best value's are taken from the best result among 10 replications*
2. The average value's results are averaged from the results of all 10 replications
3. Percentage difference is calculated from $\left(\frac{\text{Result of NN - Result of GA}}{\text{Result of NN}}\right) \times 100\%$

of trips, the traveling distances and total transportation cost due to no limitation on the time. Table 11 summarizes the number of extra trips for the vehicles due to the limitation of the delivery time for both the NN and GA. From our finding, the 5 h time constraint result showed quite a similar result to the case of no time constraint by having no extra trip at all. This suggests that 5 h would be sufficient for product delivery with fully loaded vehicles.

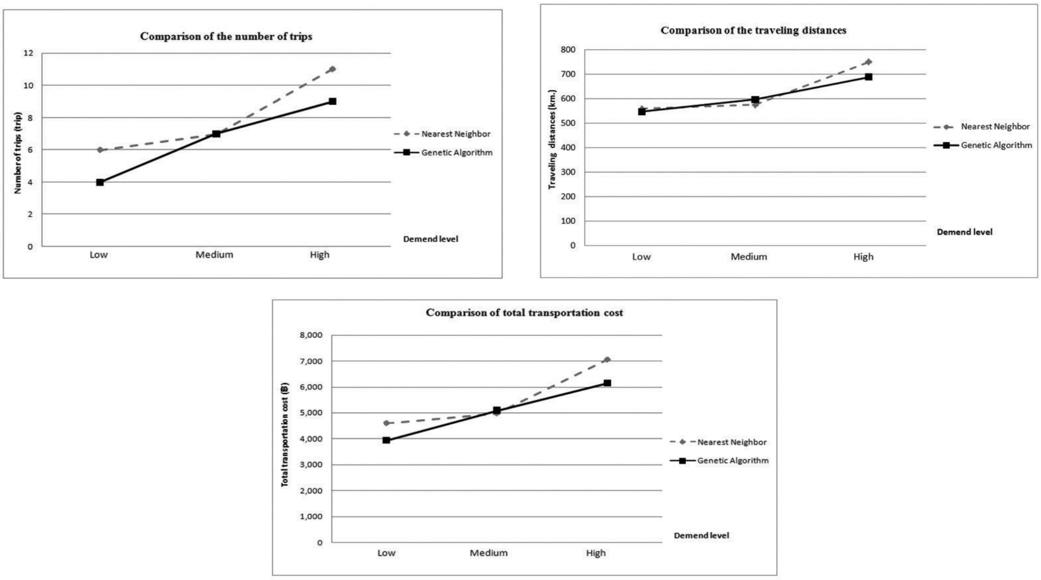


Figure 5. Comparison of the results between Genetic Algorithm and Nearest Neighbor under the cases with the time constraint of 4 h

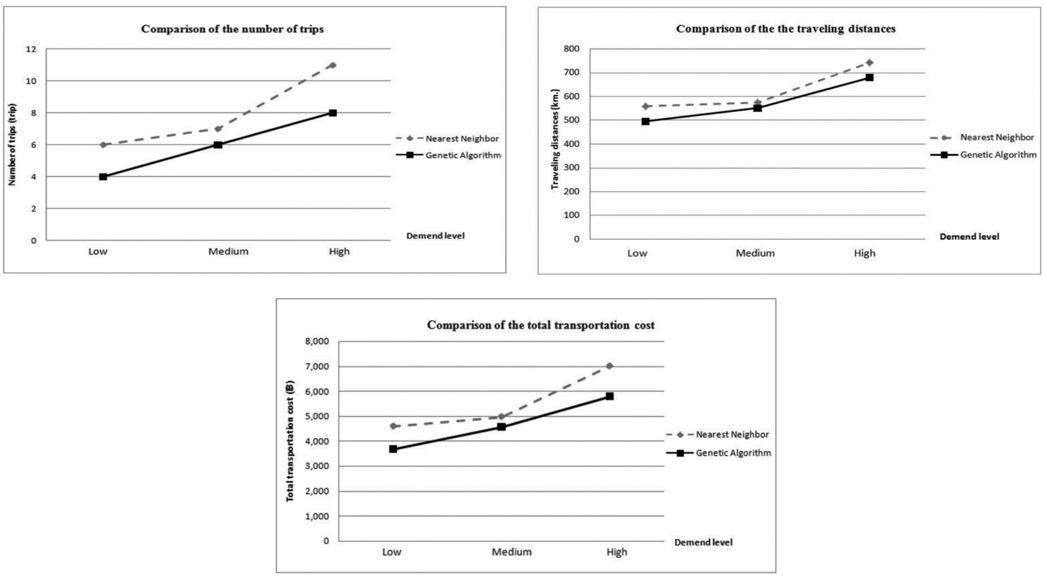
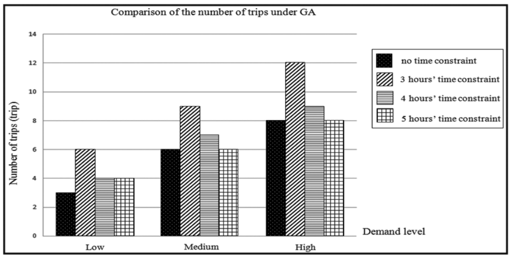
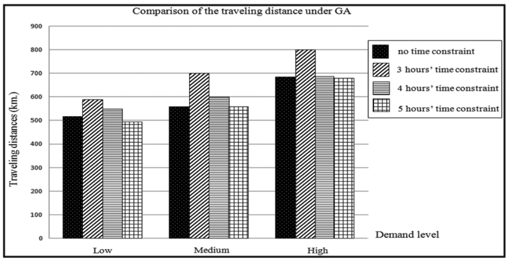


Figure 6. Comparison of the results between Genetic Algorithm and Nearest Neighbor under the cases with the time constraint of 5 h

However, with 3 h time constraint, except only for the low demand case with the NN, the vehicles are forced to go back to the depot in many instances due to the limitation on the time. This leads to a significant increase in the number of trips, traveling distance and total transportation cost. Regarding the 4 h time constraint, only in a few instances with both the NN and GA are vehicles forced to return to the depot due to the limitation on time. As a result, the suitable time for controlling the delivery time should be set around 4 h. Even though the 5 h time constraint cases show a similar or a bit cheaper cost than the 4 h





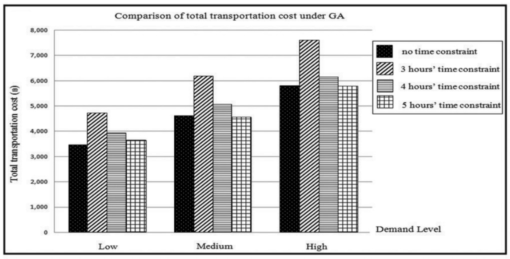


Figure 7. Comparison the results of the total transportation cost under the Genetic Algorithm

Table 9. Comparison of test results between the Nearest Neighbor Heuristic and the Genetic Algorithm under 5 h time constraint

Demand Level	Performance manner	Best value[1]		Average value[2]		Percentage[3] difference based on the best values	Percentage[3] difference based on the average values
		NN	GA	NN	GA		
Low	Number of trips (trips)	6	3	6	4	50%	33.33%
	Traveling distance (km)	559	455	559	495	20.39%	11.45%
	Total transportation costs (Baht)	4595	3175	4595	3675	30.90%	20.02%
Medium	Number of trips (trips)	6	5	7	6	16.67%	14.28%
	Traveling distance (km)	559	516	575	551	7.69%	4.17%
	Total transportation costs (Baht)	4595	4080	4975	4555	11.21%	8.44%
High	Number of trips (trips)	9	8	11	8	11.11%	27.27%
	Traveling distance (km)	655	614	741	679	6.26%	8.37%
	Total transportation costs (Baht)	5975	5470	7005	5795	8.45%	17.27%

Remark: *1. The best value's are taken from the best result among 10 replications.*
2. The average value's results are averaged from the results of all 10 replications.
3. Percentage difference is calculated from $\left(\dfrac{\text{Result of NN - Result of GA}}{\text{Result of NN}}\right) \times 100\%$

time constraint cases, 1 h saved from delivery means 1 h less for customers to receive their products. This could not only increase customer satisfaction but also reduce other relevant costs of the company such as inventory holding, warehouse operation, and manpower costs.

Conclusions

This work studied the classical VRP problem using real data of a bakery company. All information was gathered during the internship period. The company with a single depot has to serve various types of products to its customers. The company currently uses a NN algorithm with 6 delivery zones to generate the routes of delivery. Therefore, the goal is to compare the results between the existing approach based on the NN and the proposed approach based on the GA.

From the finding, we firstly recommended an elimination of delivery zone in our proposed algorithm with the GA because the results without the zone clearly showed a shorter delivery time and lower transportation cost. Currently, with only 32 customers, it appeared that there is no need to divide them into zones. However, when more customers are added in the future, delivery within zone may be more useful since each vehicle can serve its own customers more closely and more rapidly. Another requirement is the time window when the company would like to limit the delivery time of each vehicle in the future. With the time constraint of 3 h, all results have increased since the vehicles are forced to return to the depot within 3 h. As a result, more trips are required. With 4 h time constraint, more time is allowed for delivery so a lower number of trips can be carried out. This leads to a lower traveling distance and total transportation cost. The results of 5 h time constraint appeared to be similar to the ones from the no time constraint case. Since the longest time is allowed for each trip, the vehicles would not be forced by the limitation on the time to go back to the depot during the trip. As a result, the 4 h time constraint was recommended to the company since one hour limited from each trip means

Table 10. Comparison of the average value of number of trips, traveling distances and total transportation costs in 4 c ategories under the GA

Detail	No. trips (trips)			Traveling distances (km)			Total transportation costs (Baht)		
	L	M	H	L	M	H	L	M	H
No time constraint	3	6	8	515	556	679	3475	4580	5795
Time constraint of 3 h	6	9	12	586	696	796	4730	6180	7580
Time constraint of 4 h	4	7	9	541	597	688	3905	5085	6140
Time constraint of 5 h	4	6	8	495	551	679	3675	4555	5795

Remark: L = Low demand case
M = Medium demand case
H = High demand case

Table 11. The number of extra trips forced to return to the depot due to the limitation of the delivery time

Type of algorithm	Demand level	Number of extra trips		
		3 h' time constraints	4 h' time constraints	5 h' time constraints
NN	Low	-	-	-
	Medium	3	-	-
	High	5	1	-
GA	Low	4	2	-
	Medium	6	1	-
	High	6	-	-

1 h less for customers to receive their products. This 1 h saved from each trip could save a lot of costs for the company, which costs are not included in our calculated total transportation costs.

Under the comparison between the existing system operation under the NN and the proposed system operating under the GA, the GA's results generally outperform the NN's results. Only when the demand is medium are the NN's and the GA's results quite close. When the demand is low or high, the system under the GA clearly showed better results with a lower number of trips, traveling distances and total transportation cost. As a result, it may be possible to conclude that the GA could improve the vehicle routing of this bakery company and save the total transportation cost up to 20% as compared with the existing method used by the company. According to the finding, the company can select an appropriate route matching with the suitable demand level. The recommendation has already been passed to the company and it is in their consideration to implement this finding.

This problem is of economic importance to businesses because of time and costs associated with providing a fleet of delivery vehicles to transport products to a set of geographically dispersed customers. It involves finding the minimum cost of the combined routes for a number of vehicles in order to facilitate delivery from a supply location to a number of customer locations. Since cost is closely associated with distance, a company might attempt to find the minimum distance traveled by a number of vehicles in order to satisfy its customer demand. In doing so, the company attempts to minimize costs while increasing or at least maintaining an expected level of customer service. As a result, the accuracy of a company's cost structure plays an important role in obtaining good results. In fact, it is quite difficult for a company to commit to some numbers in its cost structure since they have never been recorded or, in many instances, managers are hesitant to estimate them. Moreover, the cost structure varies from one company (industry) to the other. As poor inputs lead to poor results, without a reliable cost structure, the obtained results could be misleading and could lead to misinterpretation. Sensitivity analysis could also be conducted with respect to some cost parameters to check their influence on the results.

Nevertheless, this approach can also be applied to other types of VRP application such as delivering perishable food or fresh food in which a similar condition applies. Further study can also be extended to other situations such as comparing the results under the GA with other algorithms (such as Tabu Search, Particle Swarm, etc.) aiming to search for a better result. In addition, a greater number of customers can also be added to the current situation. This will make the size of the problem larger and clearly highlight the differences of our proposed algorithm to the existing one. A modification of the transportation cost function could also be done to reflect greater reality. With this case,the transportation cost is merely a direct charge from the delivery distance. As a result, the transportation cost is directly varied with the distance traveled. So, optimizing the transportation cost is always in line with optimizing the delivery distances. Adding other cost factors to the transportation cost may result in new interesting findings to the outcome of the study.

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