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Improving delivery routes using combined heuristic and optimization in a consumer goods distribution company

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Abstract. XYZ is a distributor of various consumer goods products. The company plans its delivery routes daily and in order to obtain route construction in a short amount of time, it simplifies the process by assigning drivers based on geographic regions. This approach results in inefficient use of vehicles leading to imbalance workloads. In this paper, we propose a combined method involving heuristic and optimization to obtain better solutions in acceptable computation time. The heuristic is based on a time-oriented, nearest neighbor (TONN) to form clusters if the number of locations is higher than a certain value. The optimization part uses a mathematical modeling formulation based on vehicle routing problem that considers heterogeneous vehicles, time windows, and fixed costs (HVRPTWF) and is used to solve routing problem in clusters. A case study using data from one month of the company's operations is analyzed, and data from one day of operations are detailed in this paper. The analysis shows that the proposed method results in 24% cost savings on that month, but it can be as high as 54% in a day.

Keywords: nearest-neighbor heuristic; vehicle routing problem; heterogeneous vehicles; time windows; consumer goods distributor.

1. Introduction

Logistics operations are oriented toward the fulfillment of customer needs from the point of origin to the point of consumption. One mode of operation in this field is the vehicle routing problem (VRP) that has received considerable attention from academics and practitioners, mainly due to its relevant applications that are often encountered in real world. Being a popular routing model in logistics studies, a number of variants have been developed, tested, and applied. These variants follow the characteristics of the problem being studied, e.g. VRP with time windows (VRPTW) [1], VRP with pickups and deliveries [2], or more specific variants such as VRPTW with evolutionary algorithm [3], VRP with split deliveries [4], or VRP with multiple objectives [5]. More recent VRP studies include, e.g. VRPTW with probabilistic travel times [6], green VRP [7], or VRP in maritime logistics [8].

VRP literature grew exponentially with an annual rate of 6.09% between 1956 and 2005, and the period between 1985 and 2006 recorded 918 published VRP articles [9]. This trend continued with 277 articles appeared between 2009 and 2015 as cited in the latest survey [10]. Despite the massive amount of literature described above, *heterogeneous* VRP (HVRP) is rarely studied due to its increased complexity compared to the basic capacitated VRP (CVRP). While reduced complexity allows more in-depth study of the problem on hand, it deviates from reality in industrial applications. In contrast to the number of general VRP articles cited in [9], only 22 articles related to HVRP were published between 1984 and 2007 [11]. In this particular area where analytical approach is hardly efficient, metaheuristics spur as sensible substitute in dealing with complex VRP problems. A few successful examples worth mentioning are record-to-record [12], scatter search [13], genetic algorithm [14], variable neighborhood search [11], multi-start adaptive memory programming [15], iterated local search [16], and tabu search [17].

This paper demonstrates the application of HVRP in a consumer-goods distribution company operating in Surabaya, Indonesia. Being a large city, there are hundreds of wholesalers and retailers in Surabaya served by the company. The complexity of the problem arises both from the number of customers and the heterogeneity of vehicles (in terms of capacity and fixed cost) that the company uses. Time windows are also demanded by the customers. Thus, the model is called HVRP with time windows and fixed costs (HVRPTWF). Routing of distribution is planned on a daily basis therefore computation time has a higher priority than optimality of the solution. To address the problem complexity, an approach integrating the classical time-oriented, nearest neighbor (TONN) heuristic [18] and optimization via mathematical programming is proposed. This integration is a necessity since mathematical programming alone will clearly be impractical as it will suffer from long computation time on complex problems. The proposed model will be compared to the method that the company applies in its daily operations.

Given the above background, the objectives of this paper are twofold:

- To develop an integrated model combining heuristic and optimization in solving routing problem that considers heterogeneous vehicles and time windows.
- To compare the solution from the proposed model with the actual routing obtained from the company's operations.

2. Methodology

We first described in this section the background of the company in our case study. The company XYZ was founded in 1995 as a distributor of consumer goods products serving mainly the Eastern part of Indonesia. The products varied from toiletries (shampoo etc.) to foods (snacks etc.) and the customers also varied from small retailers to giant hypermarkets. XYZ's fleet of vehicles comprised more than 300 trucks/vans and 100 motorcycles, operating from 85 branch offices and 25 warehouses in Indonesia. Orders were received daily from sales force then processed by the planning department to produce delivery plan for the next day. In our study, we focused on Surabaya office (the company's headquarters) and the foods division.

XYZ's customers were classified in three groups: small, large, and super stores. The small stores were served between 8.00 and 13.00, and in Surabaya they were clustered into six areas where each was visited weekly on different days. The large stores were served between 9.00 and 14.00 and clustered into three areas that could be visited every day based on the orders placed. The super stores, given their large demand, had no regular service hours and clusters, and could be served any time within XYZ's working hours. This clustering was the basis of XYZ in making its daily distribution plan. Since drivers were already assigned areas of operations, it was possible that two vehicles depart to two different stores, adjacent on the map but on different distribution areas, without maximizing the vehicle capacity (not fully loaded). Often it was possible for these stores to actually be served by the same vehicle, but the drivers who were used to work in specific areas found it uncomfortable to go to different ones. In addition, the planning department only provided the list of stores to be visited without route and rely on the drivers' experience to plan their own routes every day. All this led to inefficiency in the operations which was visible from the uneven workload of vehicles where some returned after 12 hours but some did after 18 hours.

To solve this problem, an integration model utilizing a time-oriented, nearest-neighbor heuristic and mathematical programming was proposed. The TONN heuristic was used to cluster the number of drop points if they exceeded a certain number that prevented the mathematical model HVRPTWF to be run in an acceptable time. Figure 1 shows the path of solution in the methodology.

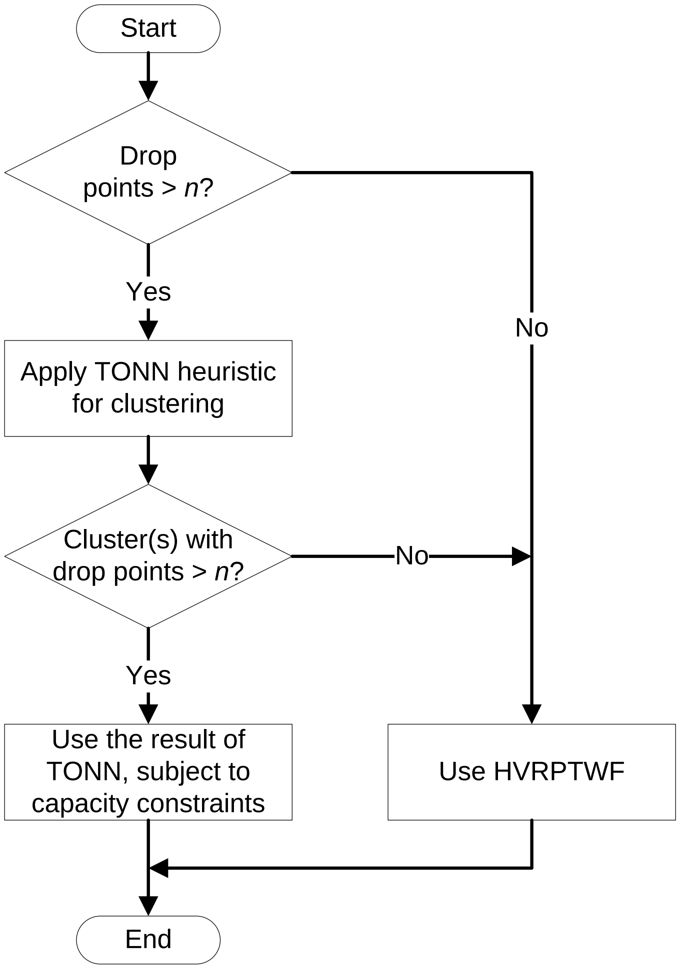

Figure 1. Solution path in proposed methodology.

Figure 1 is explained as follows. First, customers are grouped into drop points because the number of drop points is what affects the routing instead of the number of customers. If there are less than n drop points to be served on a particular day, HVRPTWF is applied. If there are more, TONN heuristic is executed to form the clusters and sequence of visit in each cluster. If, after the heuristic, there are still clusters with more than n drop points, the sequence produced by TONN will be used as the route for vehicles serving that route, subject to capacity constraints. It is possible at this stage to divide a TONN cluster into smaller sub-clusters if vehicle capacity is not sufficient to serve all drop points in that cluster. If the heuristic produces clusters with less than n drop points, HVRPTWF is applied in each of such clusters.

The TONN heuristic is explained with the following example. Suppose $\mathcal{N}$ is the set of all nodes (locations) including node 0 as depot and $\mathcal{C}$ is the set of drop points or $\mathcal{N} \setminus \{0\}$. Given i visited exactly prior to j, s_i and s_j are the arrival times at nodes i and j, respectively, p_i is the service time at node i, and $t_{i,j}$ is the travel time from i to j, then the relationship between s_i and s_j is formulated as $s_i + p_i + t_{i,j} \leq s_j, \forall i, j \in \mathcal{C}$. The lower and upper time windows at node i, L_i and U_i, respectively, bound the arrival time s_i, or $L_i \leq s_i \leq U_i, \forall i \in \mathcal{C}$. Table 1 exhibits distance matrix between all nodes and time windows in each node. The service time p_i is set constant. Note that the distance matrix is symmetrical and also satisfies triangular inequality.

Table 1. Data for Time-Oriented, Nearest-Neighbor heuristic example.

	Distance matrix						Time windows		Service time
	0	1	2	3	4	5	L_i	U_i	p_i
0	-	5	10	13	10	14	-	-	-
1	5	-	7	12	13	17	0	20	2
2	10	7	-	8	14	14	10	30	2
3	13	12	8	-	7	6	10	30	2
4	10	13	14	7	-	5	10	30	2
5	14	17	14	6	5	-	10	30	2

Given the data in Table 1, the first cluster resulting from the heuristic and its sequence from depot is 0→1→2→3→0 and the second cluster and its sequence is 0→4→5→0. The heuristic only solves the clustering problem with respect to time windows and leaves the capacity allocation to the second part in methodology, i.e. mathematical programming with HVRPTWF. In Figure 1, the value of n will be determined after few trial runs of HVRPTWF to see at how many nodes the model becomes impractical with regard to computation time. In the above example, suppose it is found that $n = 2$ (this low figure is only for the sake of this example), then the first cluster will not be optimized with HVRPTWF and the heuristic result will be used with arbitrary vehicle assignment.

For HVRPTWF, the mathematical model follows [19] with more specific elaboration on the lower time window (in [19] the model is applied on maritime logistics case and only the upper time window which reflects due date is used). The sets and equations are explained in the following.

$\mathcal{V}$	Set of vehicles, indexed by v
$\mathcal{A}$	Set of arcs (i, j) denoting a flow from node i to node j
$\mathcal{N}$	Set of all nodes $\mathcal{N} = \{0,1,\dots,N\}$; 0 is depot
$\mathcal{C}$	Set of droppoints$\mathcal{C} = \mathcal{N} \setminus \{0\}$
f^v	Fixed cost of vehicle v
$c_{i,j}^v$	Variable cost of vehicle$v$ if it goes from node i to node j
$t_{i,j}^v$	Travel time of vehicle$v$ if it goes from node i to node j
C^v	Capacity of vehicle$v$
D_i	Total demand at node i
L_i	Lower time window at node i
U_i	Upper time window at node i
p_i	Service time at node i
M	A large constant
$x_{i,j}^v$	Binary variables for vehicle v in arc (i,j); $x_{i,j}^v = 1$ if the vehicle traverses arc (i,j) and $x_{i,j}^v = 0$ otherwise
s_i^v	Time window for vehicle v at node i

$$\text{Minimize} \sum_{v\in\mathcal{V}} \sum_{i,j\in\mathcal{A}} x_{i,j}^v . c_{i,j}^v + \sum_{v\in\mathcal{V}} \sum_{j\in\mathcal{A}} f^v . x_{0,j}^v \qquad (1)$$

Subject to:

$$\sum_{v\in\mathcal{V}} \sum_{i,j\in\mathcal{A}} x_{i,j}^v . C^v \geq D_i \qquad \forall\, i \in \mathcal{C} \qquad (2)$$

$$\sum_{i\in\mathcal{C}} D_i \sum_{j\in\mathcal{N}} x_{i,j}^v \leq C^v \qquad \forall\, v \in \mathcal{V} \qquad (3)$$

$$\sum_{i\in\mathcal{N}} x_{i,k}^{v} - \sum_{j\in\mathcal{N}} x_{k,j}^{v} = 0 \qquad \forall\, k \in \mathcal{C};\ v \in \mathcal{V} \tag{4}$$

$$x_{i,i}^{v} = 0 \qquad \forall\, i \in \mathcal{N};\ v \in \mathcal{V} \tag{5}$$

$$\sum_{j\in\mathcal{C}} x_{0,j}^{v} \le 1 \qquad \forall\, v \in \mathcal{V} \tag{6}$$

$$L_i \le s_i^v \le U_i \qquad \forall\, i \in \mathcal{C};\ v \in \mathcal{V} \tag{7}$$

$$s_i^v + t_{i,j}^v + p_i - M(1 - x_{i,j}^v) \le s_j^v \qquad \forall\, i \in \mathcal{N}; j \in \mathcal{C};\ v \in \mathcal{V} \tag{8}$$

$$x_{i,j}^v \in \{0,1\} \qquad \forall\, i,j \in \mathcal{A};\ v \in \mathcal{V} \tag{9}$$

$$s_0^v = 0 \qquad \forall\, v \in \mathcal{V} \tag{10}$$

$$s_i^v \ge 0 \qquad \forall\, i \in \mathcal{N};\ v \in \mathcal{V} \tag{11}$$

In the above model, the objective function (1) minimizes total cost that consist both variable and fixed costs of using vehicles. Demand fulfillment is warranted by constraints (2) and vehicle capacity is observed by constraints (3). Constraints (4) balance the incoming and outgoing flows. Constraints (5) are loop prevention and constraints (6) regulate so that a vehicle can take only one trip. Constraints (7) set the lower and upper time windows for a vehicle at a node, while constraints (8) manage the arrival times s_i similar to the explanation in the heuristic section. Sub-tour breaking constraints are not required due to constraints (8). Lastly, constraints (9)–(11) state the nature of decision variables involved:$x_{i,j}^v$ are binary and s_i^v are continuous, thus the model falls in the category MILP problem.

3. Case study analysis

Our first step in analysis was determining the threshold *n* to limit the number of drop points that HVRPTWF could still solve efficiently. Using a commercial solver and Intel Core i5 processor running at 2.2 GHz with 4GB RAM on Windows 10, we arrived at the results in Table 2. From this table it can be inferred that *n* should be set equal to 10. With more than 10 locations, the solver was still unable to find an optimal solution after more than 16 hours.

Table 2. Computation time of HVRPTWF.

n	Average running time	Status
6	1.5 seconds	Global Opt.
7	7.5 seconds	Global Opt.
8	33.5 seconds	Global Opt.
9	21 minutes 54 seconds	Global Opt.
10	1 hour 5 minutes 4 seconds	Global Opt.
11	16 hours 48 minutes 55 seconds	Feasible

Next, a sample of one-month company's operation in the foods division was studied. In this section, we provided an example of one-day distribution and compared the results between the company's method and our proposed methodology combining TONN heuristic and HVRPTWF mathematical programming. The chosen day consisted of 21 nodes (1 depot and 20 drop points) and the 21× 21 distance matrix (in km) was given in Table 3, including the demands (in m^3), service times and time windows(in minutes) at the nodes. The service times were not correlated to the demands, but to the number of items which were not shown here. Data of vehicles are provided in Table 4.

Table 3. Distance matrix (km), demands (m^3), service time and time windows (mins) of locations.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	D_i	p_i	L_i	U_i
0	-	20.1	13.5	14.7	19.0	20.0	18.4	18.3	18.4	18.5	12.7	24.5	21.4	18.7	17.5	19.8	18.8	18.7	16.7	18.3	13.3	-	-	-	-
1		-	6.6	5.4	11.9	11.5	11.4	11.2	4.5	11.4	7.4	19.5	15.2	10.2	10.3	10.3	11.7	11.6	9.5	9.9	9.4	2.08	8.70	0	300
2			-	1.7	15.5	14.0	15.1	14.9	5.2	15.1	4.2	22.0	17.6	12.7	14.0	12.7	15.4	15.3	13.2	12.4	10.5	0.23	25.00	60	360
3				-	13.8	12.7	13.4	13.2	4.6	13.4	2.5	21.0	16.7	11.3	12.3	11.5	13.7	13.6	11.5	11.1	9.8	0.22	25.67	60	360
4					-	3.4	2.5	2.3	14.4	2.5	13.7	10.5	6.5	3.7	1.6	3.1	2.8	2.7	2.4	3.3	5.7	0.07	7.37	0	300
5						-	3.8	4.2	13.7	3.1	13.0	10.6	6.6	3.0	3.8	2.4	4.2	2.9	3.3	2.7	2.7	0.05	4.37	0	300
6							-	1.5	15.1	1.7	14.4	8.6	4.6	4.4	2.4	3.8	0.4	1.8	2.1	4.1	6.0	0.04	2.37	0	300
7								-	14.5	1.1	13.3	10.1	5.7	4.8	1.6	4.2	1.3	1.3	2.5	4.5	4.0	0.04	2.03	0	300
8									-	13.4	5.7	21.3	16.9	12.0	12.9	12.0	14.7	13.3	13.0	11.6	10.8	0.03	17.67	60	360
9										-	13.7	9.1	5.1	3.9	1.1	3.3	1.3	0.2	2.3	3.5	5.2	0.03	2.37	0	300
10											-	21.2	16.9	11.7	12.6	11.7	14.0	13.6	12.3	11.4	8.8	0.02	17.67	60	360
11												-	4.4	11.3	9.2	10.7	8.8	8.9	10.0	10.9	12.4	0.02	2.70	0	300
12													-	7.4	5.7	6.9	4.9	4.9	6.7	7.1	8.2	0.02	2.03	0	300
13	Symmetrical													-	3.2	1.6	4.3	3.8	4.1	1.9	7.0	0.01	3.37	0	300
14															-	4.2	2.0	1.3	2.9	4.5	4.8	0.01	2.03	0	300
15																-	4.2	3.4	5.3	1.9	8.2	0.01	3.03	0	300
16																	-	1.4	2.5	3.7	5.6	0.01	2.03	0	300
17																		-	2.5	3.4	5.4	0.01	2.37	0	300
18																			-	3.4	4.9	0.01	3.37	0	300
19																				-	6.7	0.01	2.37	0	300
20																					-	0.01	4.37	0	300

Table 4. Data of vehicles.

Type	Units	Capacity (m^3)	Cost/day (IDR)	Cost/km (IDR)
A	2	2.4	544,687	812.50
B	1	5.6	502,526	812.50
C	1	9.6	603,725	812.50

Using the company's method, three vehicles were used with the following routings:

- Vehicle A1: 0→2→3→8→10→0
- Vehicle A2: 0→20→6→7→9→16→4→14→17→5→13→15→18→19→12→11→0
- Vehicle C: 0→1→0

The above routing demonstrated inefficient use of vehicle C since, despite its large capacity; it was used to serve one particular store simply because that customer had regularly been served by vehicle C and its driver. This one-on-one relationship between customer and driver familiarized the driver with his region of operations. The driver's knowledge on his region helped on some days and was justified when demand size matched vehicle capacity, but more often led to inefficiency as shown above. The routes constructed by the drivers also relied on their judgment and experience, but was proven suboptimal compared to the output of heuristic and mathematical programming as outlined in the next section.

4. Results and discussion

Applying the algorithm in Figure 1 yielded the following results. First, two clusters (instead of three) were formed. The first cluster consisted of 15 locations and the second cluster consisted of 5 locations. For the first cluster, total demand was 0.34 m^3 so it could be served by vehicle A (time windows had already been taken care of by the heuristic). For the second cluster, HVRPTWF was applied, and it produced a different routing from the actual one by the driver. The routings in both clusters were given below:

- Vehicle A1: 0→20→14→9→17→7→16→6→18→4→15→13→19→5→12→11→0
- Vehicle B: 0→2→3→1→8→10→0

It is worth to mention here that since we knew from the data that vehicle A could not be used due to its lower capacity (2.4 m^3) than the second cluster's demand (2.58 m^3), and vehicle B's daily cost was smaller than vehicle C's, then vehicle B was a logical choice for serving the second cluster. Further, since time windows were no longer an issue as a result from the heuristic application, routing problem of the second cluster was actually reduced to a travelling salesman problem (TSP). This advantage, however, was not apparent on other cases in different days, so HVRPTWF formulation was still required. Besides, with less than 6 locations, HVRPTWF required not more than 1.5 seconds to solve.

Next, we compared the total cost of actual operations and that of our proposed methodology. As shown in Table 5, the proposed method combining heuristic and mathematical programming was superior compared to the drivers' assignment-based method from the company. The proposed method reduced the number of vehicles required that led to cost savings in fixed and variable costs. The cost savings in fixed cost, however, were only on paper since fixed cost was calculated based on depreciation, drivers' salaries, etc., i.e. it would be incurred regardless of vehicle utilization. The savings in variable cost, on the other hand, were tangible. For this day only, the savings in variable cost were 53.60%. For the overall month, the company's method yields IDR 2,406,548 whereas the proposed method did IDR 1,849,893 or equivalent to a 23.56% cost reduction.

Table 5. Cost comparison of two methods.

Vehicle	Actual (IDR)		Proposed (IDR)	
	Fixed Cost	Var. Cost	Fixed Cost	Var. Cost
A1	544,687	31,038	544,687	34,125
A2	544,687	65,894	Not used	
B	Not used		502,526	35,344
C	603,725	32,663	Not used	
Total	**1,693,009**	**129,595**	**1,047,213**	**69,469**

5. Conclusions and remarks for future research

In this paper we have demonstrated an application of combined heuristic and optimization to solve practical routing problems in a distribution company. The company planned its delivery routes daily so a methodology that could arrive at good solution in an acceptable time would have a high practical value. Our proposed approach beat the company's method that was based on drivers' regional assignment by 24% on average but on certain days, such as one shown in the example, the savings could be as high as 54%. The only drawback from implementing this method was to reorient the drivers from their comfort zone serving only their regular customers in a particular region.

The comparison in this paper was only made against the actual routings used by the company. It is possible there are still better approaches, be they heuristics or optimization, which should be aimed as future research agenda.

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