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Evaluating the Routing Strategies for the Delivery between Distribution Centers and Retail Outlets

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Abstract: For decades, a great number of VRP solution algorithms have been developed in numerous studies. However, in reality, quite many companies still use some fixed routes to fulfill the delivery with variable demand between distribution centers (DCs) and retail outlets. This study tries to explore the potential of the decision support tools based on optimization models and evaluate the pros and cons of different routing strategies. Through the simulation experiment based on the real data of the case company, it is found that the potential cost saving achieved by the adaptive routing strategy considering demand change is very impressive. In addition, even if the fixed-route policy is preferred, the optimization-based fixed routes generated by the method developed in this study can be better than the fixed route based on the experience of the DC operators.

Keywords: Vehicle Routing Problem; Routing Strategy; Transportation Cost; Spreadsheet Solver

1. INTRODUCTION

Transportation costs occurring in the distribution of goods have always been a big logistics concern. Therefore, minimizing the relevant costs has become the top priority for operators. Meanwhile, from the research point of view, various decision problems have been formulated as optimization models. Eksioglu *et al.* (2009) classified the models related to transportation network into the following eight types: the Shortest Path Problem, the Transportation Problem, the Assignment Problem, the Transshipment Problem, the Vehicle Routing Problem, the Optimal Network Design Problem, the Spanning Tree Problem, and the Network Flow Problem. Among them, the Vehicle Routing Problem (VRP) has received the most attention. In general, as a combinatorial optimization problem, the VRP seeks to find an optimal set of routes for a given fleet of vehicles to serve a number of customers with the objective of minimizing the total cost.

Due to its popularity in the research society, many VRP solution algorithms have been developed, providing great potential to save a huge amount of transportation cost. However, industries still tend to make the routing/scheduling decision of the distribution vehicles based on their experience. For example, a DC manager may assign a specific set of retail outlets to each courier, who then picks up or delivers the shipments they are responsible for. The routes chosen by the manger based on experience may remain unchanged for a period of time. For the case company in this study, the fixed routes are used for 6 months before a new set of routes is planned. One advantage of this practice/strategy is that route planning effort can be significantly saved. Another advantage would be that couriers are very familiar with their designated routes and customers. However, these benefits come with a price, losing the possibility of fully realizing the potential of the VRP algorithms.

In this study, we try to explore the potential of the decision support tools based on the VRP optimization models and algorithms and to evaluate the pros and cons of several possible routing strategies for the distribution between DCs and retails outlets. From the case company, we have collected the real operational data to serves as the basis to simulate the demand in the experiment. In addition, we also have summarized the current route planning of the case company, and this existing practice has been used as the base strategy for performance evaluation. With respect to each realization of the simulated demand, we solve the associated VRPs by making use of the VRP Spreadsheet Solver (Erdogan, G., 2013) to model the strategy with full flexibility to adapt to the demand change every day. Finally, in order to provide the decision support for the companies preferring to maintain a set of fixed routes for a period of time, we have developed an approach to generate an optimization-based fixed routing strategy, which is also included in the simulation experiment for evaluation. The three strategies are later referred to as the Experience-based Fixed Routing (EFR), the Optimal Adoptive Routing (OAR), and the Optimization-based Fixed Routing (OFR) respectively.

The structure of this paper is organized as follows. In the next section, the basics of the VRP and the brief summary of the solver utilized in this study are presented. In the third section, the details of the demand simulation and the features of three routing methods, namely EFR, OAR, and OFR, are provided. The numerical results are analyzed and discussed in the fourth section. Finally, the findings of the study are concluded in the last section.

2. RESEARCH BACKGROUND AND TOOLS

In this section, the classical VRP is first described, including the formulation of its basic version. In the second sub-section, the on-line resource used to solve the VRP in the simulation experiment is introduced.

2.1 Basics of Vehicle Routing Problem

Since first formulated under the title “The Truck Dispatching Problem” by Dantzig and Ramser (1959), the vehicle routing problem (VRP) has been one of the most important research topics for logistics management. Laporte (2009) summarized the fifty-year developments of the VRP. Golden *et al.* (2008) also pointed out the recent development and challenges researchers have been facing.

The basic version of the VRP features the combination of two classical problems: the Traveling Salesman and the Bin Packing. Each customer must be assigned to one of the routes. The demand at each customer node is deterministic and may not be split. The vehicles, based at a single depot, are identical, and the only operational constraint applied is the vehicle capacity constraint. The objective is to minimize the sum of all route costs. The following is one of the various VRP formulations (Bodin *et al.*, 1983).

$$Min \quad \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{M} C_{ij}x_{ij}^{k} \tag{1}$$

subject to

$$\sum_{i=0}^{N}\sum_{k=1}^{M} x_{ij}^{k} = 1 \quad j = 1, \cdots, N \tag{2}$$

$$\sum_{j=0}^{N}\sum_{k=1}^{M} x_{ij}^{k} = 1 \quad i = 1, \cdots, N \tag{3}$$

$$\sum_{i=0}^{N} x_{ih}^{k} - \sum_{j=0}^{N} x_{hj}^{k} = 0 \quad h = 1, \cdots, N; \quad k = 1, \cdots, M \tag{4}$$

$$\sum_{i=1}^{N} d_i (\sum_{j=1}^{N} x_{ij}^{k}) \leq W \quad k = 1, \cdots, M \tag{5}$$

$$\sum_{j=1}^{N} x_{0j}^{k} \leq 1 \quad k = 1, \cdots, M \tag{6}$$

$$\sum_{i=1}^{N} x_{i0}^{k} \leq 1 \quad k = 1, \cdots, M \tag{7}$$

$$\sum_{i \in S}\sum_{j \in S} x_{ij}^{k} \leq |S| - 1 \quad \forall \; subset \; S \; with \; |S| \geq 2, \forall k = 1, \cdots, M \tag{8}$$

$$x_{ij}^{k} = binary \quad i = 0, \cdots, N \quad j = 0, \cdots, N \quad k = 1, \cdots, M \tag{9}$$

- i, j, h: index for customers (0 represents the depot, and N is the number of customers.)
- k: index for vehicles (M is the number of available vehicles.)
- C_{ij}: cost from customer i to customer j
- x_{ij}^{k}: binary decision variable indicating vehicle k travels from customer i to customer j
- d_i: demand of customer i
- W: vehicle capacity
- S: subset of customers ($|S|$ is the number of customers in S.)

Given the definition of the binary decision variables, the objective function (1) is to minimize the total costs by combining the costs of the selected links. Constraint (2) and Constraint (3) ensures that each customer is served by one of the vehicles. Constraint (4) is the flow conservation for each specific vehicle at each node (customer). Constraint (5) enforces the capacity limitation of the vehicles. Constraint (6) and Constraint (7) regulate that the number of deployed vehicles does not exceed the number of the vehicles available. Constraint (8) represents one of the ways to eliminate sub-tours. Finally, in Constraint (9), the decision variables x_{ij}^{k} are required to be binary.

The studies that develop the solution algorithms for the VRP are numerous. As an early effort to summarize the types of the solution approaches, Bodin & Golden (1981) provide the following classification for the relatively common VRP algorithms.

(1) Exact Procedure
(2) Interactive Optimization
(3) Cluster-First, Route-Second
(4) Route-First, Cluster-Second
(5) Saving or Insertion
(6) Improvement or Exchanges
(7) Mathematical Programming

As a more recent survey of the classic VRP heuristics, Gendreau *et al.* (2000) also emphasized on the most successful meta-heuristic VRP algorithms based on the technique of Tabu Search. Finally, the two seminal summary works cited earlier, Laporte (2009) and Golden et al. (2008), also serve as an excellent reference for the development of the VRP algorithms. Given these references, the review of individual VRP studies is skipped in this paper as the focus here is on a higher-level issue about routing strategies, not on solving the vehicle routing problem itself.

2.2 Vehicle Routing Problem Solver

For solving the VRP in this study, we utilized a convenient on-line resource, the VRP Spreadsheet Solver, developed by Erdogan (2013) associated with VeRoLog (Euro Working Group on Vehicle Routing and Logistics Optimization). As the snapshot of the interface shown in Figure 1, the solver is an MS Excel-based tool, which is very easy for users to input the information of the parameters, such as locations and demands, etc. After a few simple steps, the solver generates the routes based on its built-in optimization algorithm.

Location ID	Name	Address	Latitude (y)	Longitude (x)	TW start	TW end	Must be visited?	Service time	Demand
0	Depot		25.0381298	121.4245377	0:00	23:59	Starting location	0:00	0
1	228	No.115, Z	24.9406796	121.3379364	0:00	23:59	Must be visited	0:00	122
2	114	No.108, Z	25.0447600	121.4449000	0:00	23:5	Must be visited	0:00	329
3	30	No.55, Zh	25.0605106	121.4981613	0:00	23:5	May be visited Don't visit	0:00	139
4	113	No.35, Se	24.9861603	121.4190369	0:00	23:59	Must be visited	0:00	268
5	117	No.21, Siv	25.0359306	121.5481567	0:00	23:59	Must be visited	0:00	234
6	93	No.13, Se	25.0270405	121.5214920	0:00	23:59	Must be visited	0:00	286
7	543	No.102, S	25.0441303	121.5323792	0:00	23:59	Must be visited	0:00	178
8	107	No.1, Ln.	25.1176891	121.5165405	0:00	23:59	Must be visited	0:00	221
9	215	No.89, Da	25.1779900	121.4467000	0:00	23:59	Must be visited	0:00	283
10	235	No.74, Se	25.0697498	121.6117096	0:00	23:59	Must be visited	0:00	188
11	534	No.115, Z	25.0956707	121.5285568	0:00	23:59	Must be visited	0:00	412
12	116	No.30, Ti	25.1200695	121.5263824	0:00	23:59	Must be visited	0:00	96
13	121	No.535, S	25.0921707	121.4623184	0:00	23:59	Must be visited	0:00	227
14	307	No.66, Go	25.0846004	121.4389420	0:00	23:59	Must be visited	0:00	114
15	508	No.4-6, G	25.0462704	121.5148697	0:00	23:59	Must be visited	0:00	203
16	538	No.331, S	25.0629700	121.5731000	0:00	23:59	Must be visited	0:00	378
17	68	No.18, Yi	25.1319695	121.7452927	0:00	23:59	Must be visited	0:00	425

Figure 1. Snapshot of the interface of the VRP Spreadsheet Solver

For a test problem in the simulation experiment presented in the fourth section, the results of the route planning by the solver are illustrated in Figure 2. The details of the solution algorithms are not provided in the on-line manual, but the solver appears to be able to provide a near-optimal solution within a reasonable time. The capability of the solver in terms of computation is good enough for dealing with the test problems of the case company in this study. In particular, it is also assumed the solution provided by the VRP Spreadsheet Solver is (near) optimal, and no further effort is invested to improve its solution.

Apart from its convenience, the VRP Spreadsheet Solver is compatible with some online map servers, such as Google Maps. Thus, although the route planning result is presented as the pure straight lines between nodes, what the decision logic of the solver uses is technically the actual length of the road between a pair of nodes. As a matter of fact, the solver can even take the real-time traffic situation into consideration while planning the routes. However, this study does not leverage this interesting feature.

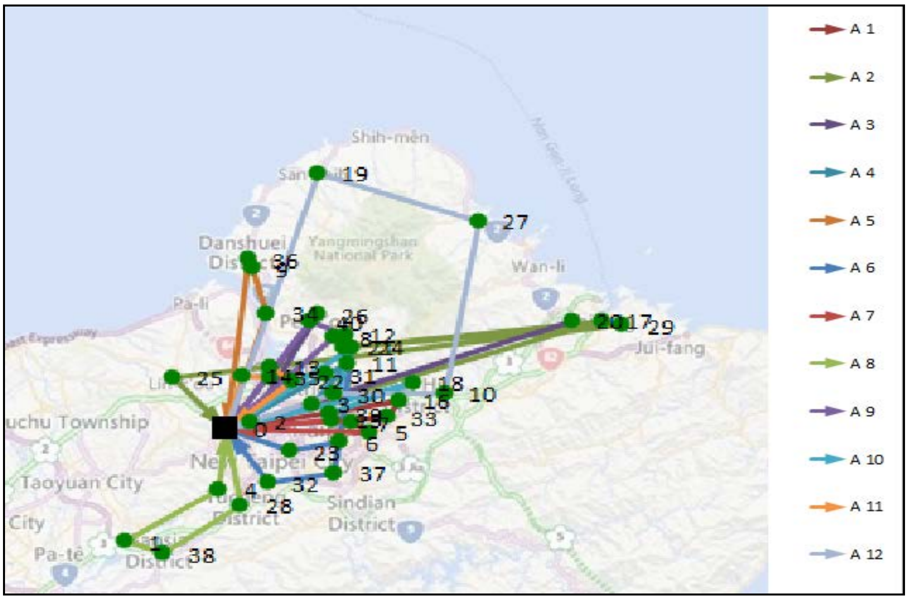

Figure 2. Snapshot of the typical routing result of the VRP the Spreadsheet Solver

3. RESEARCH FRAMEWORK AND ANALYTICAL METHODS

The framework of this study is presented as Figure 3. In order to address the issue of demand uncertainty, the demands at the retail outlets are generated with two levels of variations. For each level of demand variation, the routing decisions are made according to the three strategies to be evaluated, namely the Experience-based Fixed Routing (EFR), the Optimal Adoptive Routing (OAR), and the Optimization-based Fixed Routing (OFR). The results are analyzed by comparing the three strategies with respect to different demand scenarios. The procedure to generate the random demand and the details of the strategies are presented in the following sub-sections.

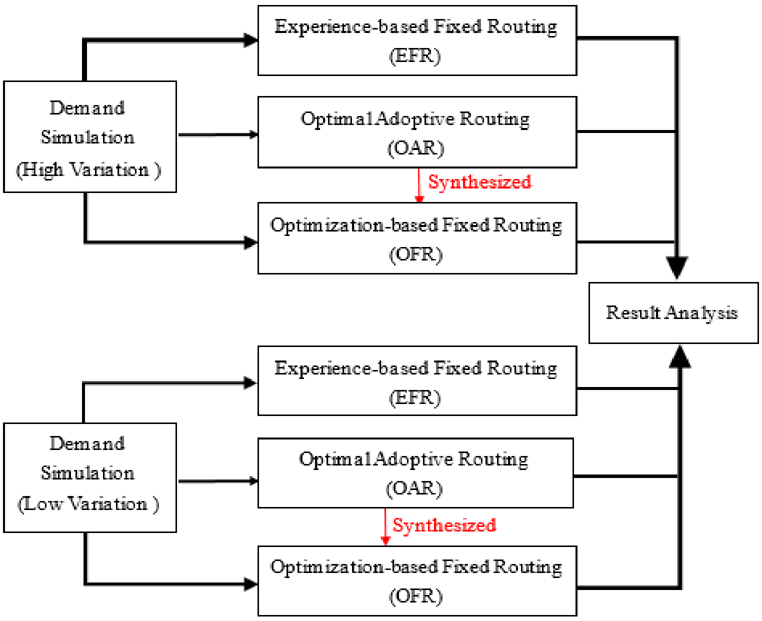

Figure 3. Illustration of the research framework

3.1 Demands Simulation

The case company operates a big retailing chain in Taiwan. One month of historical demand data for the 40 retail outlets served by one single DC in northern Taiwan was provided for analysis. The mean and standard deviation of the demand for each outlet (in terms of logistics box equivalents) is computed. In general, the average demand of an outlet is found to be about 180 boxes. However, the demands were not found to follow any specific well-known distribution. We chose to use a simple way to generate the demand with different levels of variations, which is believed to be an important factor when evaluating the performance of the routing strategies.

For the low-variation scenario, the demands for 30 days at each node are randomly generated based on the uniform distribution specified by the mean value ± 0.5 standard deviation. On the other hand, for the high-variation one, the distribution is changed to the mean value ± 1.0 standard deviation. For example, suppose the mean and the standard deviation of Store X are 180 and 30 boxes respectively. The demands for 30 days of the two scenarios are generated according to the uniform distributions of [165, 195] and [150, 210] respectively. Finally, it should also be noted that the demands at different retail outlets are assumed to be independent during the demand simulation process even though some degree of correlation is expected.

3.2 The Features of Experience-based Fixed Routing (EFR)

As its name suggests, EFR is derived from the long-term practical experience of the case company. Table 1, provided by the case company, summarizes the routes based on the long-term experience of the DC manager. Given the truck capacity of 700 boxes, these routes approximately consist of 3 outlets, and the required fleet size is 12 trucks.

Table 1. Routes of Experience-based Fixed Routing (EFR)

Route No.	Origin	1st Store	2nd Store	3rd Store	4th Store	Destination
1	DC	No. 307	No. 228	No. 417	-	DC
2	DC	No. 219	No. 235	No. 121	-	DC
3	DC	No. 116	No. 543	No. 392	-	DC
4	DC	No. 126	No. 316	No. 147	No. 383	DC
5	DC	No. 539	No. 429	No. 442	-	DC
6	DC	No. 113	No. 215	No. 114	No. 466	DC
7	DC	No. 508	No. 117	No. 472	-	DC
8	DC	No. 415	No. 251	-	-	DC
9	DC	No. 534	No. 382	No. 451	-	DC
10	DC	No. 016	No. 093	No. 538	No. 416	DC
11	DC	No. 068	No. 322	No. 176	No. 486	DC
12	DC	No. 384	No. 183	No. 030	No. 107	DC

These routes are fixed no matter how the outlet daily demand volumes change. Thus, it is expected that the operator needs to deal with the overloading problem when the aggregate demand of a route exceeds the truck capacity. Following a simple practice currently used, the outlet(s) at the end of the route is removed. Thus, the original route is cut short to meet the truck capacity limit. All of the outlets that are removed from the existing routes are collectively served by one supporting vehicle (or more if necessary). As there is no backup vehicle, the DC manager normally dispatches the first vehicle coming back to the DC to serve this extra supporting route. The optimal routing of the supporting vehicle can easily be found as the number of outlets removed from the original fixed route(s) is limited.

3.3 The Features of Optimal Adoptive Routing (OAR)

With the compatibility of the spreadsheet applications (such as MS Excel) and the on-line map servers (such as Google Maps and Bing Maps), the VRP Spreadsheet Solver enables users to perform route planning easily. Accordingly, the DC operator can readily adjust the routes every day concerning the daily demand changes at the outlets. Thus, for each realization of the outlet daily demands in the simulation experiment, the solver is re-run to determine a new set of routes. Since the OAR is the only routing method adjustable to reach the optimal condition on a daily basis, the associated cost is expected to be the lowest.

For the simulated demands of 30 days, it is found that the number of trucks dispatched is around 10 to 12 vehicles, suggesting that only part of the feet is utilized. In addition, of course, no overloading situation exists due to the capacity constraint of (5) in the VRP model.

3.4 The Development of Optimization-based Fixed Routing (OFR)

As the EFR method in the Sub-section 3.2 is unable to adjust the routes even when the aggregate demand is beyond the capacity, the solution is then to assign supportive vehicles, which often leads to a cost greater than that of the OAR method in Sub-section 3.3. However, the DC operator may still prefer the former method since couriers can be more efficient given their familiarity over their designated routes. On top of that, less administration cost would occur as the DC operator does not have to re-assign the routes every day.

In order to combine the advantages of both routing methods, we design the approach called as the Optimization-based Fixed Routing (OFR), in which the fixed routes for each demand scenario are synthesized based on the routes from the OAR method. Given all of the OAR routes from the 30 simulated days, the procedure begins with ranking the routes in the *descending* order of frequency. For the scenario of high demand variation, the top 11 routes, including their average load factor, are summarized in Table 2.
Table 2. Results of the OAR method for the scenario of high demand variationエラー! リンクが正しくありません。
The next step is to determine the route for each outlet, according to the sequence based on the average demand in the 30 simulated days. For example, in the demand scenario of high variation, the top 5 outlets are Store 538, Store 68, Store 534, Store 114, and Store 215 respectively. Since Store 538 possesses the highest relative importance, its route is determined first by selecting the one with the highest frequency, *i.e.*, Route 538-117 (with the average load factor of 89%) in Table 2. The next outlet to be dealt with is Store 68, and the route selected is Route 68-486-16. The same procedure is taken repeatedly until 12 routes are all chosen. Of course, during this process, an outlet is skipped if it is already included in a selected route. Thus, more than 12 outlets are likely to be tested in the route selection process.

In order to prevent too many overloading situations from happening, a criterion is set to adjust the routes during the route selection process. That is, if the average load factor exceeds the threshold of 95%, the outlet on the tail of the route is dropped. For example, for the 12 initial routes shown in Table 3, the average load factor of Route 2, Route 9, and Route 10 all exceed 95%. Therefore, the outlets on the tail, i.e., Store 16, Store 114, and Store 265, are removed. In addition, each outlet should be included in exactly one route. Therefore, duplicate outlets should be eliminated as well, that is, Store 114 in Route 9, Store 117 in Route 11, and Store

508 in Route 12.

Table 3. Initial OFR routes (Scenario of high demand variation)

Route No.	Average Load	Route
1.	89%	538-117
2.	**96%**	68-486-~~**16**~~
3.	95%	316-534-384
4.	55%	114
5.	94%	307-415-215-429
6.	92%	416-93-442-251
7.	95%	107-126-332
8.	93%	472-451-228-113
9.	**96%**	183-121-~~**114**~~
10.	**96%**	383-176-~~**265**~~
11.	94%	508-543-~~**117**~~
12.	92%	~~**508**~~-392-147-539-30

Finally, the remaining outlets, which do not get a chance to be assigned a route or are removed from the initial routes during above adjustment processes, need to be inserted into the 12 selected routes. The assigning rule for these outlets is that the higher the average demand is the higher priority the outlet possesses. The finalized routes for both demand variation scenarios are presented in Table 4.

Table 4. Finalized OFR routes after adjustment

Demand Simulation (High-Variation)			Demand Simulation (Low-Variation)		
Route No.	Average Load	Route	Route No.	Average Load	Route
1.	89%	538-117	1.	81%	383-538
2.	73%	68-486	2.	93%	68-147-486-183
3.	95%	316-534-384	3.	86%	322-114-16
4.	91%	114-382-16	4.	88%	392-534-30
5.	94%	307-415-215-429	5.	91%	415-215-429
6.	92%	416-93-442-251	6.	88%	416-93-539-442-251
7.	79%	107-126	7.	88%	508-543-117
8.	93%	472-451-228-113	8.	89%	472-451-228-113
9.	86%	183-235-121-466	9.	84%	107-116-126
10.	95%	383-116-176	10.	44%	539-219-176
11.	53%	508-543	11.	87%	307-417-121-316
12.	85%	392-147-417-219-539	12.	93%	466-382-235-384

4. RESULTS AND ANALYSIS OF EXPERIMENT

In order to evaluate the performance of different routing strategies, the total route travelling time provided by the VRP Spreadsheet Solver for each routing strategy in the 30-day simulation experiment is recorded. This total traveling time serves as the basis to assess two cost components: fuel expense and courier wage. By assuming the fuel consumption of 8 liters per hour and the fuel price of 0.79 USD per liter, the fuel expense is estimated as 6.32 USD per hour. In addition, the hourly wage of the couriers is assumed to be 3.83 USD. The operating cost per hour is thus 10.15 USD. The total operating costs of the three routing strategies for the entire simulated month are summarized in Table 5. In addition, the percentage cost saving with respect to the base strategy, EFR, is also provided in the table.

Table 5. Estimated month operating costs (USD) of different routing strategies

Demand Scenario	EFR	OAR	OFR

High variation	10,726	6,218 (-42.0%)	8,138 (-24.1%)
Low variation	10,797	6,212 (-42.5%)	8,556 (-20.8%)

As shown by the results in Table 5, the introduction of optimization techniques is helpful. By flexibly changing the route according to daily demand change, a cost saving of more than 40% can be achieved. However, the associated drawback of the OAR is that it might result in higher management costs since the DC operator needs to re-assign the routes every day, and this action may simultaneously cause some ineffectiveness to the couriers due to their unfamiliarity with the frequently changed routes. If fixing the routes is a policy that must be followed, the OFR strategy provides a promising alternative. A significant cost saving of more than 20% still can be achieved when the fixed routs from the OFR method are used every day. The interesting result also indicates that the routing decision based on the experience of the operator may not be very effective, and a better routing decision can be made by combining the techniques of simulation and optimization. Nonetheless, it is noticed that the saving achieved by the OFR for the demand scenario of high variation is lower than that of the demand scenario of low variation. This cost saving reduction implies that the fixed routes derived in the scenario of high variation are less appropriate, and the OFR procedure to generate the routes can probably be further improved.

In order to further understand the impact of different routing strategies, the overloading situations are investigated. A route is said to be overloaded when the aggregate demand of its assigned outlets is beyond the truck capability. Except the OAR, overloading situations occur occasionally for the EFR and OFR. Suppose the proportion of overloading situations is defined as the average number of overloaded routes per day divided by the number of fixed routes (i.e., 12 routes in this experiment). The results about overloading are summarized in Table 6, which suggests that overloading situations occur a bit more often in the EFR than in the OFR. However, the results in Table 6 could be under-estimated as the demands across the outlets are assumed to be independent. Nonetheless, this assumption leads to a more conservative estimation about the cost saving achieved by the OAR method in Table 5.

Table 6. Proportion of overloading situations

Demand Scenario	EFR	OFR
High variation	28.9%	21.7%
Low variation	22.8%	11.1%

As shown in Table 6, it is found, as expected, that higher demand variation leads to more overloading situations for both strategies with fixed routes. As overloading situations must be resolved by sending supportive vehicles, we further investigated the average numbers of supportive vehicles per day as well as the percentage increase of the vehicles dispatched (with respect to the fleet size of 12 vehicles) as summarized in Table 7. In general, the number of supportive vehicles needed depends on the overloading situations. However, as the overloading situations of multiple routes can be resolved by one single supportive vehicle, the percentage values regarding the supportive vehicles in Table 7 are lower when compared to those of the overloading situations in Table 6.

Table 7. Summary of the supportive vehicles dispatched per day

Demand Scenario	EFR		OFR	
	Average	Percentage	Average	Percentage
High variation	2.30	19.2%	1.27	10.6%
Low variation	2.33	19.4%	0.97	8.1%

5. CONCLUSIONS

For decades, a great number of VRP solution algorithms have been developed in numerous studies. However, in reality, quite many companies still use some fixed routes, which are not changed for a relatively long period of time, to fulfill the delivery between distribution centers and retail outlets. The focus of this study is to investigate the impact of this practice and to propose some alternatives to achieve a more efficient way of distribution.

By the simulation based on the real data of the case company, this study evaluates three routing strategies: the Experience-based Fixed Routing (EFR), the Optimal Adoptive Routing (OAR), and the Optimization-based Fixed Routing (OFR). The EFT represents the current routing arrangement, which is based on the experience of the DC operator. The OAR fully leverages the capability of the VRP Spreadsheet Solver to flexibly make the routing decision adaptive to daily demand variation. On the other hand, the OFR is based on a procedure developed in this study with the aim to combine the advantages from the first two types of strategies.

Based on the results in the simulation experiment, a great amount of cost saving can be achieved by both optimization-based methods. For the case company, if the operator is willing to let the routes be dynamically changed from one day to another, the saving in terms operating cost can be as high as 40%. On the other hand, if the operator prefers a set of fixed routes so as to embrace the simplicity for administration and the potential benefit associated with couriers' route familiarity, the OFR proposed in this study should be a promising alternative.

The following are directions for research extensions. First of all, the performance of the OFR method is degraded in the demand scenario of high variation. We believe the procedure to generate the OFR routes can be improved by carefully examining and tuning the associated steps. For example, given the numerous routes derived from the simulation experiment, the way to choose the initial set of routes may consider more factors, in addition to the route frequency and outlet demand size currently used. In addition, how to set the threshold to avoid overloading can be an important question to be answered. Finally, the steps to adjust the duplicate outlets and to re-insert the removed nodes can be re-designed in a more sophisticated fashion. These are all possible ways to further improve the OFR method.

Since this study works on the routing results provided by the VRP Spreadsheet Solver with respect to a specific time, the real-time decision-making feature of the solver is not utilized. However, as the solver can be integrated with some online map platforms, it would be interesting to conduct a study that makes use of the real-time feature of the solver. Thus, a better decision support can be provided to DC operators.

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