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Application of simulated annealing in logistics vehicle allocation system: A case study from Vietnamese FMCG company

Le Duc Dao* and Dao Quang Chinh

Ho Chi Minh City University of Technology, Vietnam National University, Vietnam

ABSTRACT

Fast-moving consumer goods (FMCG) are products that sell quickly with a reasonable price. The FMCG business segment is characterized by efficient distribution systems to manage a vast array of products with varying shelf lives and consumer demand patterns. For any FMCG and consumer durables company, optimizing the market converge may be a very profitable and productive activity. Sales managers of FMCG products can enhance their overall sales by allocating their field resources such as deliver staff to reach the greatest number of customers. Through the process of analysing related documents and object characteristics in FMCG companies, paper aim to build vehicle routing with time window (CVRTW) model to optimize the delivering process, thus satisfying customer demand. To ensure the quality of the results, the model will be solved using the simulated annealing algorithm (SA-algorithm). The overall results support the decision maker the delivery allocation strategy, ensuring the delivery time and client contentment.

Keywords: capacitated vehicle routing problem with time windows - CVRPTW, delivery, simulated Annealing Algorithm – SA Algorithm, FMCG, mixed integer

1. INTRODUCTION

In the logistics sector, optimizing route planning to minimize travel times is of paramount importance. The primary issue addressed is the Traveling Salesman Problem (TSP) [1], where the goal is to find the shortest route for visiting various locations. An in-depth exploration of TSP solution methods is provided by [2], comparing various exact and heuristic algorithms on benchmark problem instances. A generalization of TSP to multiple vehicles is known as the Vehicle Routing Problem (VRP) which involves not only finding optimal routes but also properly assigning destinations to available fleet to minimize overall distance travelled [3].

The literature reviews of VRP algorithms are presented in [4], covering both exact methods and heuristics. While exact algorithms guarantee optimal solutions, they struggle computationally on large problem sizes. Heuristics such as Tabu Search (TS) can provide near-optimal solutions more efficiently, but simpler constructive heuristics like Clarke and Wright are faster still at the cost of solution quality. More advanced metaheuristics are also proposed including Genetic Algorithms (GA) [5] and Simulated Annealing (SA) [6,7] which balance solution quality and computational time. The reviews find GA and SA to be promising methods for the VRP able to provide good solutions with reasonable efficiency. For this study, articular attention is given to the Simulated Annealing (SA) algorithm. This decision is based on its proven ability to generate a reasonably optimized plan, especially in scenarios involving the Vehicle Routing Problem with Time Windows (VRPTW). The suitability of SA for this application is supported by findings in references [8-11], which emphasize its effectiveness in handling smaller-scale problems, making it a valuable tool in the logistics sector for route optimization.

2. CASE STUDY

The organization currently segments its delivery points solely into specific delivery routes manually.

Corresponding author: Le Duc Dao Email: Iddao@hcmut.edu.vn Indeed, fixed route division table without analysis tools for each vehicle. The allocation of traffic routes is based on a predetermined schedule, resulting in fixed routes that adhere to a set timetable. These issues have negatively affected the efficiency of shipping processes and service levels.



Figure 1. Graph showing the impact on transportation cost versus expectation

Therefore, it is necessary to comprehensively analysing the process and develop a model to improve transportation efficiency by shortening transportation distances.

2.1. Problem formulation

The goal of the problem is to develop a routing solution for delivering goods within each cluster. The model's effectiveness is measured by its practical application and its ability to guide delivery personnel in their daily tasks. The requirements for the solution are as follows:

- Establish delivery routes for each cluster that minimize the total delivery time.
- Operational staff should be able to use the model for daily routine.
- The results should be sufficiently good and fast to ensure the operational time of the warehouse and coordination department is optimized.

2.2. Mathematical Model Index:

N: number of point (1 - depot, 2, ... n- clients) K: vehicle index (1,2...K) i, j: point index s: time point

Parameters:

 d_{ij} : distance from point i to point j

 t_{ij} : time from point I to point j (calculate by $d_{i,j}$ / speed) q: capacity of each vehicle d_i : demand of customer i $[a_i, b_i]$: time window of each customer I

Decision Variables:

 $X_{ijk} = 1$ if vehicle k drive direct from i to j = 0 otherwise

 f_{ijk} : number of units in a vehicle k go from i to j

Objective function:

$$min\sum_{k=1}^{n}\sum_{i=1}^{n}\sum_{j=1}^{n}d_{ij}x_{ijk}$$

Constraints:

п

$$\sum_{k=1}^{\sum} \sum_{j=1}^{n} x_{ijk} = 1 \quad \forall i = 2, \dots, n$$

$$\tag{1}$$

$$\sum_{i=1}^{n} D_i \sum_{i=1}^{n} x_{ijk} \le q \ \forall k = 1, \dots, n$$
(2)

$$n^{l-1}$$

n

$$\sum_{i=1}^{n} x_{ijk} = 1 \ \forall i = 1, \dots, n; \forall k = 1, \dots, n$$
(3)

$$\sum_{i=1}^{n} x_{ijk} - \sum_{j=1}^{n} x_{ijk} = 0 \quad \forall i = 1, \dots, n;$$

$$\forall j = 1, \dots, n; \forall k = 1, \dots, n$$
(4)

$$\sum_{i=1}^{n} x_{iik} = 1 \ \forall i = 1, \dots, n; \forall k = 1, \dots, n$$
(5)

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$$\sum_{j=1}^{n} f_{jik} - \sum_{j=1}^{n} f_{ijk} = Di \quad \forall i = 1, \dots, n; \qquad (6)$$
$$\forall k = 1, \dots, n$$

$$0 \le f_{ijk} \le q x_{ijk} \forall ij = 1, \dots, n; \forall k = 1, \dots, n$$
(7)

$$\begin{aligned} x_{ijk} \ (s_{ik} + t_{ij} - s_{jk}) &\leq 0 \ \forall i = 1, \dots, n; \\ \forall j = 1, \dots, n; \ \forall k = 1, \dots, n \end{aligned}$$
 (8

$$a_i \le s_{ik} \le b_i \,\forall i = 1, \dots, n; \,\forall k = 1, \dots, n \quad (9)$$

$$a_j \le s_{jk} \le b_j \ \forall i = 1, \dots, n; \ \forall k = 1, \dots, n$$
(10)

$$x_{ijk} \in \{0,1\} \,\forall i = 1, \dots, n; \,\forall j = 1, \dots, n; \quad (11) \\ \forall k = 1, \dots, n$$

The objective function of the research is finding the most shorties routes for a fleet of vehicles that satisfy demand at various points without exceeding vehicle capacity and while respecting time windows. The model ensures that each vehicle's route is continuous, starts and ends at the depot, and services each point within its allowed time frame. (1) Each customer must be visited exactly once by a vehicle. This ensures that no customer is left without service and that no vehicle's time is wasted by visiting a customer more than once. (2) The sum of the demands of all customers assigned to a vehicle cannot exceed the vehicle's capacity. This ensures that the vehicle is not overloaded beyond its ability to carry goods. (3) Each vehicle must leave the starting point (depot) once, ensuring that all vehicles are utilized. (4) For every vehicle and customer, the number of times a vehicle arrives at a customer location must equal the number of times it departs, ensuring a balance and that vehicles do not remain at a customer location. (5) Every vehicle must depart from the depot, ensuring that all vehicles are used and none are left idle. (6) The number of units on each vehicle must be tracked to ensure that deliveries and pickups are accounted for correctly. (7) This constraint measures the load of each vehicle at any point in the routing, ensuring that the load does not exceed the vehicle's capacity. (8) (9) (10) Time Window Constraints: These constraints ensure that all service is performed within specified time windows for each customer, which can include opening and closing times or preferred delivery times. (11) The variables representing the vehicle routes are binary (either 0 or 1), which ensures that the solutions are discrete and that partial routes are not considered.

3. METHODOLOGY

The flowchart demonstrates a Simulated Annealing (SA) algorithm for optimizing vehicle routes in a Vehicle Routing Problem (VRP). Initially, it clusters retailers using the K-medoids method, effectively minimizing dissimilarities between cluster points and their central point, thus enhancing the SA model's initial setup. The focal point of the flowchart is "Apply the SA annealing," where the SA optimization algorithm comes into play. This stage involves inputting an initial solution, then cyclically generating and assessing new solutions. Each solution is subjected to a decision-making process, accepting or rejecting it based on a probabilistic criterion that takes into account the vehicle's capacity and the customer's time-window constraints. The concept of 'temperature,' symbolized as $\beta_0=0.99$, acts as a control parameter in the algorithm, influencing the likelihood of accepting less optimal solutions as the process evolves. This temperature control helps the system gradually stabilize and settle into a low-energy, or optimal, configuration. Throughout, the algorithm continuously evaluates routes against capacity limitations and optimality standards, retaining the best outcomes and concluding once it meets a specified stopping condition. The aim is to identify the most efficient routing solution for the VRP.



Figure 2. Programming algorithm flow chart

4. EXPERIMENT AND RESULT

The company's fleet consists of 6 different vehicles. Using customer data from a given day [Table 6], simulation results are depicted using Excel's Open solver shown in Table 2 and compared with results generated by Simulated Annealing shown in Table 3. From the outcomes of this problem, proposed algorithms will also be used to compared with the company's current methods in terms of costs and the optimization of each vehicle's efficiency to evaluate the effectiveness. First run the model solver using Mixed integer, optimal distribution points for delivery staffs have been allocated. Using a Mixed Integer model solver, optimal distribution points were assigned for delivery staff. For instance, vehicle 1 starts at point [1] and serves customers at points [2, 15, 7], returning to the starting point upon task completion. This pattern was replicated for the other vehicles. Noted that, for excel solver method, the model has been tested and proven to be effective [8], so it can be included in experimental evaluation. However, there is still an opportunity to improve the model by applying the SA algorithm with the number of loops 40-100-200 shown in Table 3. The

outcomes of applying the Simulated Annealing (SA) algorithm for less than 40 iterations tend to be less effective compared to using the Mixed Integer model solver method. However, when the SA algorithm is run for more than 100 iterations, it starts to outperform the Mixed Integer model solver method. After by applying the SA algorithm with the number of loops 100-200. This algorithm reduces the objective function value 21% compared to the current value (from 2000 km to 1572.8 km) within the allotted time. The results also showed a notable improvement in this area. Specifically, it was found that four out of the six vehicles in the company's fleet were able to utilize over 80% of their available cargo load show in table 4. This level of utilization is significant as it indicates a high level of efficiency in terms of cargo space management. Delivery time also be checked in Table 5 to validate the result. Indeed, based on the Table 5, the algorithm's results meet all the necessary criteria and enhance the efficiency of the company's supply chain by ensuring that all vehicles are completed within a 10-hour window, which falls within customer operating hours from 6 am to 4 pm.

	ROUTE										Total quantity of goods	
	1	2	3	4	5	6	7	8	9	10	11	
Vehicle 1	1	2	15	7	1							3.311212
Vehicle 2	1	6	14	10	13	11	21	25	1			4.9421
Vehicle 3	1	20	18	9	1							3.814552
Vehicle 4	1	22	27	30	1							5.465584
Vehicle 5	1	26	4	31	3	12	8	17	5	16	1	5.579808
Vehicle 6	1	28	23	24	19	29	1					5.821832
Total distance		1587.647										

 Table 1. Results of running the model with actual data generated by excel solver

Table 2. Correlation	between c	objective	function	value	and	number	of	loops
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	ROUTE												
	1	2	3	4	5	6	7	8	9	10	11	Total quantity of goods	% Capacity
Vehicle 1	1	2	15	7	1							3.311212	55.18686667
Vehicle 2	1	6	14	10	13	11	21	25	9	1		4.9421	83.55066667
Vehicle 3	1	20	18	1								3.814552	62.39353333
Vehicle 4	1	22	27	30	1							5.465584	91.09306667
Vehicle 5	1	26	4	31	3	12	8	17	5	16	1	5.579808	92.9968
Vehicle 6	1	28	23	24	19	29	1					5.821832	97.03053333
Total distance		1587.647											

First explanation (Mixed integer)	Apply SA	algorithm	Original value (base on report of the company)		
Result (km)	Number of loops	Result (km)			
	50	1587.647	2000		
1587.647	100	1572 01			
	200	1372.01			

Table 3. Results of running the model after apply S	SA algorithm
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Table 4. Total deliver	y time of vehicle	trips after	apply SA algorithm
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	Time	ROUTE											
Time	1	2	3	4	5	6	7	8	9	10	11	Total Time	
	Vehicle 1	0	0.44	2.8	2.11	0.15							5.5228
	Vehicle 2	0	1.78	1.31	3.45	1.20	0.64	0.34	0.2	0.3	0.37		9.6071
	Vehicle 3	0	2.47	0.15	2.38								5.0085
	Vehicle 4	0	3.02	0.05	0.01	3.08							6.1714
	Vehicle 5	0	0.58	0.26	0.27	0.24	0.17	0.16	0.27	0.24	1.01	1.26	4.5085
	Vehicle 6	0	1.53	1.25	0.20	0.14	0.02	3.05					6.22

Table 5. Cluster of customers

Cluster	Customer
1	2, 5, 7
2	26, 4, 31, 3, 12, 8, 17, 5, 16
3	20, 18, 22, 27, 30, 28, 23, 24, 19, 29, 6, 14
4	10, 13, 11, 21, 25, 9

Table 6. Demand from customer

STT	Customer	Lat	Long	Demand (tons)
1	KO100001 - TP MT1 WAREHOUSE	10.9302230	106.7282798	0.5680
2	KO100002 - TP MT2 WAREHOUSE	11.0164674	106.6398185	0.5680
3	GOSHOP 247 LTD COMPANY	10.7405850	106.6295185	0.6040
4	KIM VAN PHAT LTD COMPANY	10.7239299	106.7367063	0.1312
5	DUNG THINH HUNG LTD COMPANY	10.8427740	106.6541135	0.0126
6	DANH NHI WAREHOUSE	10.9332510	107.2440939	0.0166
7	LAN ANH PHAT LTD COMPANY	10.9654200	106.7126979	0.0557
8	MILITARY AREA KITCHEN	10.7771224	106.5926855	0.0025
9	XUAN DIEN SAIGON LTD COMPANY	10.8341098	106.7661069	0.0209
10	ANH KHOA AGENCY	11.1809225	108.5785866	0.0063
11	VIET PHAT LTD COMPANY	10.6743544	107.7728856	0.0698
12	BAO THUY - D.TAN PHU LTD COMPANY	10.7879792	106.6180942	0.0736

STT	Customer	Lat	Long	Demand (tons)
13	ANH KHOA LTD COMPANY	10.9300791	108.0823446	0.1214
14	HOAI DUC LTD COMPANY	11.1543016	107.5032480	0.1200
15	THIEN TRANG WAREHOUSE	11.5215536	106.8943761	2.6874
16	BAO THUY - CN TRANG BANG LTD COMPANY	11.0156479	106.4023100	1.4991
17	BAO THUY LTD COMPANY	10.7960857	106.6553282	1.7498
18	TRAN NGOC LTD COMPANY	10.5289220	107.1678116	1.8378
19	TOAN THANG PH LTD COMPANY	10.3668329	107.0781900	0.8053
20	GS25 NGUYEN TAT THANH - BA RIA	10.4935439	107.1792631	1.9058
21	GS 25 HOANG HOA THAM - VUNG TAU	10.3344154	107.0892496	1.5264
22	GS25 THE SONG - VUNG TAU	10.3500246	107.0958627	1.9992
23	GS25 NGUYEN HUU CANH – VUNG TAU	10.3845782	107.1065116	1.0140
24	GS25 PHO DUC CHINH - VUNG TAU	10.3367518	107.0903750	2.8723
25	GS25 THUY VAN 02	10.3334714	107.0893567	3.1315
26	GS25 THUY VAN 01	10.7843710	106.6966602	0.5320
27	GS25 TRAN QUY CAP	10.3386195	107.0903400	0.0164
28	HO CHI MINH CITY COMPANY - CO.OPMART TAN THANH	10.6683854	107.0323042	0.5748
29	SAI GON VUNG TAU LTD COMPANY	10.3670032	107.0857459	0.5554
30	CIRCLE K 04 LE LOI	10.3378931	107.0902219	3.4500
31	CIRCLE K 18 NGUYEN TRUONG TO	10.7685464	106.6868634	0.9750

5. CONCLUSION

This research represented a major advancement in logistics optimization, with profound implications specifically within the Fast-Moving Consumer Goods (FMCG) distribution industry. A key innovative aspect was the strategic clustering algorithm developed for efficiently grouping delivery locations, which were then allocated in an optimized way across six distinct vehicles. This clustering-based routing approach enabled significant streamlining of the overall delivery workflow, while simultaneously maximizing the utilization of load capacity for each vehicle. The research was instrumental in developing a sophisticated and highly accurate model for the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW). The most substantial achievement of this study was the impressive enhancement in operational efficiency. This was quantitatively evidenced by a significant 21% reduction in the objective function's value. These decreases manifested in a remarkable reduction in the total distance travelled, specifically from 2000 km to 1572.8 km. In addition, the model also makes maximum use of the cargo resources of 6 vehicles with more than 4 vehicles utilizing over 83% capacity. This achievement is particularly noteworthy considering the complexities inherent in the routing problem and the time-sensitive demands of Fast-Moving Consumer Goods (FMCG) deliveries. The efficiency gains from this research are not only a testament to its practical applicability but also mark a pioneering advancement in the realm of logistics optimization. By substantially lowering travel distances, the study not only improves operational cost-efficiency but also contributes to more sustainable logistics practices.

REFERENCES

[1] Jünger, M., Reinelt, G., & Rinaldi, G. "The traveling salesman problem", *Handbooks in operations research and management science*, 7, 225-330, 1995.

[2] David L. Applegate, Robert E. Bixby, Vasek Chvátal & William J. Cook, "The Traveling Salesman Problem", 2007.

[3] Gilbert Laporte, "The Vehicle Routing Problem: An overview of exact and approximate algorithms", 1991.

[4] Haifei Zhang, Hongwei Ge, Jinlong Yang, "Review of Vehicle Routing Problems: Models, Classifcation and Solving Algorithms", 2021.

[5] Baker, B. M., & Ayechew, M., "A genetic algorithm for the vehicle routing problem", *Computers & Operations Research*, 30(5), 787-800, 2003.

[6] Kaku, I., Xiao, Y., & Xia, G., "The deterministic annealing algorithms for vehicle routing problems", *International Journal of Smart Engineering System Design*, 5(4), 327-339, 2003. [7] Bührmann, J. H., & Bruwer, F., "K-medoid petalshaped clustering for the capacitated vehicle routing problem", *South African Journal of Industrial Engineering*, 32(3), 33-41, 2021.

[8] Aggarwal, D., & Kumar, V., "Mixed integer programming for vehicle routing problem with time windows", *International Journal of Intelligent Systems Technologies and Applications*, 18(1-2), 4-19, 2019.

[9] Granada-Echeverri, M., Toro, E., & Santa, J., "A mixed integer linear programming formulation for the vehicle routing problem with backhauls", *International Journal of Industrial Engineering Computations*, 10(2), 295-308, 2019.

[10] Drexl, M., and Schneider, M., A survey of the standard location-routing problem. Working Paper LPIS-03/2014, Logistics Planning and Information Systems, TU Darmstadt, 2014

[11] Vidal, T., Crainic, T.G., Gendreau, M., and Prins, C., "Implicit depot assignments and rotations in vehicle routing heuristics", *European Journal of Operational Research*, 237, 2014.

Ứng dụng thuật toán mô phỏng luyện kim trong hệ thống phân luồng vận chuyển hàng hóa của một công ty tiêu dùng nhanh Việt Nam

Lê Đức Đạo và Đào Quang Chính

TÓM TẮT

Trong thế giới nhanh chóng và đầy cạnh tranh của ngành Hàng Tiêu Dùng Nhanh (FMCG), việc tối ưu hóa quy trình giao hàng không chỉ là một lợi thế cạnh tranh mà còn là một yếu tố sống còn. Ngành này yêu cầu một hệ thống phân phối linh hoạt và hiệu quả để xử lý đa dạng sản phẩm, từ những mặt hàng có thời hạn sử dụng ngắn đến những sản phẩm có nhu cầu thay đổi thất thường. Qua việc nghiên cứu kỹ lưỡng tài liệu liên quan và tính chất của sản phẩm, bài báo đã chọn mô hình CVRPTW - một kỹ thuật định tuyến tiên tiến và phát triển một mô hình vấn đề rõ ràng. Mô hình này sau đó được kiểm tra và chứng minh hiệu quả thông qua phương pháp số nguyên hỗn hợp trong Excel. Điểm nhấn của nghiên cứu này là việc áp dụng thuật toán mô phỏng luyện kim (SA) vào dữ liệu thực tế, mở ra một kỷ nguyên mới trong việc tối ưu hóa lộ trình giao hàng, giúp các công ty FMCG không chỉ đảm bảo giao hàng đúng hạn mà còn tiết kiệm chi phí một cách đáng kể.

Từ khóa: định tuyến xe có sức chứa có ràng buộc về thời gian - CVRPTW, giao hàng, thuật toán Mô phỏng luyện kim - SA Algorithm, FMCG, phương pháp số nguyên hỗn hợp

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