İSTANBUL UNIVERSITY PRESS

Journal of Transportation and Logistics
JTL 2023, 8 (1), 1–12
DOI: 10.26650/JTL.2023.1101161

RESEARCH ARTICLE

Fleet Size and Mix Vehicle Routing Problem (FSMVRP), Adapted Large Neighbourhood Search Heuristic Optimization Proposal With a Plant-capacity and Multi-day Planning Algorithm: A Livestock Feed Industry Case Study

Alperen Ekrem Çelikdin[1]

[1](Dr.), Aksaray, Turkiye

ABSTRACT
The vehicle routing problem (VRP) is of great importance for feed factories that do not work with the dealership system. This is especially important in the Central Anatolian region, where customers' number of animals is low. Data used in the study came from the order data of a feed mill which operates in Turkey. Before selecting the most suitable VRP software vendor, the logistics manager of the plant was urged to analyse the results with the scope of percent fleet capacity used, service level (on-time deliveries), and total transportation cost incurred. As a requirement of the enterprise strategy, a multi-day planning algorithm was developed to level the daily production capacity of the factory while maintaining minimum transportation costs and maximum service level. It has been determined that better results are achieved with the developed multi-day planning algorithm for both methods of Simulated Annealing (SA), Genetic Algorithm (GA), and our Adapted Large Neighbourhood Search (ALNS) heuristic. The data set of the real-life problem that was used was applied to those three methods, and 0.45%, 0.81%, and 1.39% improvements were achieved using the methods, respectively.

Keywords: Vehicle routing problem, fleet size mix with time windows, multi-day planning, feed distribution, adapted large neighbourhood search

1. Introduction

Customer satisfaction is a result of multidimensional and hierarchical efforts, which companies have to satisfy simultaneously (C.-M. Liu, 2005). In the feed industry, where this case study is conducted, companies have to produce feed within the quality requirements (Citation, 2001) and deliver the final product on time with the desired vehicle at a competitive shipment cost (Hoff, Andersson, Christiansen, Hasle, & Løkketangen, 2010). On-time and minimum cost delivery stipulates time dependency (Zhang, Lam, & Chen, 2016), a cleverly balanced fleet mix (Sungur, Ordóñez, & Dessouky, 2008),(Hoff et al., 2010) and tight utilization of the capacity of the fleet. Managing all of these requirements requires robust planning of the supply chain. At the end of a planning day, one has to adapt the time frame for customer orders, fill the trucks up to the utmost capacity and respond to order revisions and minimise the total distance travelled. Because of the nature of the problem, it is a daunting task to code in-house software, even if the company has a strong IT department. This study aims to provide suggestions to practitioners for cost reduction and on-time delivery in multi-point feed distribution with a heterogeneous fleet. In order to make these suggestions and use them in real-life problems, the software has been designed to be used by the feed mill. SA, GA, and our ALNS algorithms were compared. Analysis was carried out during the design process of the software.

1.1. Objectives

In the literature search, to the best of my knowledge, there is no study that attempts to design a multi-day plan considering the daily shipping capacity in the feed industry. The main contribution of this study is that it creates a tool that enables multi-day planning taking into account the factory capacity while minimizing the total transportation cost with an acceptable deviation from

Corresponding Author: Alperen Ekrem ÇELİKDİN **E-mail:** a.celikdin@gmail.com
Submitted: 10.04.2022 • **Accepted:** 30.01.2023

the time windows. Based on the request of the enterprise where the case study was conducted, the above-mentioned algorithm has been developed.

1.2. Literature review

The study is organized as follows: a brief summary of the vehicle routing problem (VRP) literature and related variants of the VRP is given. In the second section, the problem definition for the feed industry is given. In the third section, the optimization model framework related to the SA, GA, and ALNS heuristics is explained as applied by the algorithm. Section 2.2 defines the multi-day planning algorithm in detail. The output of the VRP solutions and earnings gained from the method for the real data of the feed mill (multi-day order file, fleet mix, time dependencies) is compared for SA, GA, and ALNS algorithms in the results section. In the conclusion, inferences and future research directions are given according to the results and algorithm proposed.

1.2.1. Basics of Vehicle Routing Problem

VRP is one of the most frequently encountered topics in the supply chain management literature. The method was introduced first by Dantzig and Ramser (Dantzig, G. B., and Ramser, 1959). “The Truck Dispatching Problem” is defined as the generalization of the Travelling Salesman Problem (TSP) with more than one identical truck capacity. In the more than fifty years since the first study, the method has been improved to satisfy the real-world problem requirements with more than 100 constraints (Laporte, 1992). Some additional features are time windows (time intervals suitable for customer deliveries), and heterogeneous VRP, which deals with the capacitated VRP (CVRP) for mixed-type vehicles. One type of the CVRP is the fleet size and mix vehicle routing problem (FSMVRP), where the planner has to choose how many vehicles of each type to use given a mix of vehicle types with varying loading capacity and unit costs. FSMVRP was first introduced by Golden et al. (Golden, Assad, Levy, & Gheysens, 1984). In this type of problem, the fleet is heterogeneous, but the available number of vehicles in the fleet for each type remains unrestricted. This problem is similar to the CVRP, but the difference is that FSMVRP has different types of vehicles to choose from, while CVRP has only one type of vehicle. One has to decide on both the fleet mix and the vehicle routing to be optimised. There are two cost aspects of FSMVRP to manage the total cost. The first cost type is related with the vehicle types having a uniform variable cost (varies by the total route distance) and different fixed costs, which vary by the vehicle types. Golden et al. (1984) presented the first mathematical model for this FSMVRP. The second cost type was offered by Salhi (Salhi, Sari, Saidi, & Touati, 1992). This type ignores the fixed cost and builds the model only with variable cost. This vehicle fleet mix heuristic has the advantage of being flexible enough to generate more than one single solution. This additional information is invaluable to planning managers when faced with conflicting objectives and many external constraints. While VRP proved to be an NP-Hard problem in the 1980s, solution time grows exponentially with the increase of distribution points. It was impossible to find the optimal solution in the cases with an excess of 50 nodes (Cordeau, Gendreau, & Laporte, 1997). In the current setting, modern exact algorithms can solve VRP instances with roughly a hundred nodes (Irnich & Villeneuve, 2006, Danna & Pape, 1998). Researchers implemented some heuristics to find a near-optimal solution. The scope of the study includes three of those algorithms. The first one is the Genetic Algorithm. Genetic algorithm was first proposed by John Holland (Holland, 1975) for the sake of finding solutions to problems that were otherwise computationally intractable. Some FSMVRP-related genetic algorithm heuristics applications can be found in the literature in the following papers: F. H. Liu & Shen (1999), Chen, Gu, & Gao (2020), Nazif & Lee (2010), Mohammed, Ahmad, & Mostafa (2012), Baker & Ayechew (2003), Prins (2004), ant colony systems algorithms can be found in papers Reimann et al and particle swarm optimization algorithms in Ai and Kachitvichyanukul (Ai & Kachitvichyanukul, 2009). The second algorithm is the Large Neighbourhood Search. A large neighbourhood search was first proposed by (Shaw, 1998). The potential of the heuristic for large-sized problems was revealed by Pisinger and Ropke (2007). Some FSMVRP-related heuristics applications are those developed by Erdoğan (2017), Demir, Bektaş, & Laporte (2012), and Tellez et al. (2017). The third algorithm is the simulated annealing algorithm. The simulated annealing is a random search algorithm proposed by Kirkpatrick et al. (Kirkpatrick, Gelatt, & Vecchi, 1983). It was developed based on the similarity between the metallurgical annealing process and the research of the minimum value in a more general system. Some FSMVRP-related simulated annealing applications include Osman (1993) and Kuo (2010). The multi-workday planning approach has been studied by Rattanamanee, Nanthavanij, & Dumrongsiri (2020) within the vehicle routing problem. The method was concentrated in terms of balancing the workload of the employees. In this study, the issue of balancing the workload of the employees was evaluated in terms of the factory loading capacity constraints.

2. MATERIAL AND METHODS

The feed mill manages customer orders on a weekly basis. Delivery of orders is promised within up to 7 days, taking into account the urgency of the order. Feed factories and dairy factories of the same company are integrated. Feed is delivered to milk suppliers. Due to the seasonality effect on milk production, milk supply decreases in the winter period and increases in the spring and summer periods. Since milk and feed are integrated and half a unit of feed consumption is required for one unit of milk production, the feed mill is also affected by these fluctuations. The enterprise manages its production capacity within flexible production capacity principles. The company works with three different vehicle types for the shipment of products in line with the geographical location of the customers, dairy sizes, and needs. Since the company finds it expensive to set up its vehicle fleet compared to the rental method, it chooses to rent the necessary vehicles according to the status of the orders. Contrary to the general acceptance of VRP, the business ignores the costs of returning to the factory, as it rents vehicles from the factory to the final delivery point. Fixed costs vary according to vehicle types, and variable costs are formed according to the length of the route. The company analysed its expectations from the VRP software as follows:

Requirement Analysis

- In order to reduce the fixed costs, vehicle occupancy should be maximized according to vehicle types.
- Depending on the geographical location of the dairies and the conditions of the facilities, the vehicle types chosen by the customers should be complied with.
- The final point is the destination; factory return should be ignored.
- The earliest and latest delivery times determined by the customers must be complied with.
- The planned routes should be displayed on the geographical graphic interface, and revisions should be made manually by planning staff if necessary.
- After taking the load from the factory, the total mileage of the vehicles, the routes they followed, and the delivery hours should be seen on the mobile application.

2.1. Research methodology

After the analysis and software suppliers were investigated, demo studies were conducted with candidate suppliers. According to the analysis performed, the mathematical model of VRP was created. The notation is as follows: vertex set F_D means factory (one factory for the demo), F_C means customers where F = $F_D \cup F_C$.

Let graph G = (F,A) be a fully connected (when a direct line exists between all nodes) network. F=0,. . . ,n is the node set and A is the line set defined between these nodes. In the node cluster, the '0' node represents the factory, and the 1,. . . n nodes represent the customers. p_i is the amount loaded on the vehicle from the factory and r_i is the amount delivered to the customer, where $i \in F_C$. The unloading time at the customer depot is q_i. The early and late delivery time interval at the customer depot is $[s_i, e_i]$. The set of vehicles ready to be leased by the company is denoted by V and each vehicle v $\in$ V. The starting point for all vehicles as $z^v \in F_D$, the work start time of the vehicle as β^v, the fixed cost (can be thought as opportunity cost of leasing the vehicle) of the vehicle v as γ^v, the capacity of the vehicle v as ^{v}, driving distance limit as L^v, working time limit as E^v. For each arc (i, j) $\in$ A, the distance between i and j is d_ij and the duration for this arc is τ_ij. Also, there is a variable travel cost for all arcs (i, j) is $c_i j$. The service time required by the customer as S_i.

Decision variables can be defined as follows:

The binary variable $x_i^v j$ is equal to 1 if vehicle v directly travels from i to j, and is 0 otherwise; the binary variable a_i^v is equal to 1 if vehicle v visits and serves vertex i, and is 0 otherwise. The amount of the order delivered by vehicle v on arc (i, j) is given as $d_i^v j$. For the time windows restrictions, variable Ω_i^v is defined as the time that vehicle v arrives at vertex i.

According to the notation given, a desired mathematical model for the FSMVRPTW problem can be given as:

$$\text{Minimise} \sum_{(i,j) \in A v \in V} \sum c_{ij}^v x_{ij}^v \sum_{j \in F_G v \in V} \sum_{Y^v X_{z^v}^v, j} \tag{1}$$

$$\text{Subject to} \sum_{v \in V} \alpha_i^v = 1 \qquad \forall i \in F_M \tag{2}$$

$$\sum_v \in V \alpha_i^v \leq 1 \qquad \forall i \in F_C \ F_M \tag{3}$$

$$\sum_{j \in F \setminus i} x_{ij}^v \leq \sum_{j \in F \setminus i} x_{ji}^v \qquad \forall i \in F_C, v \in V, \tag{4}$$

$$\sum_{p\in S, r\in F\setminus S} x_{pr}^{v} \geq \alpha_i^v \qquad \forall i \in F_C, v \in V, S \subset F : z^v \in S, i \in F \setminus S, \tag{5}$$

$$\sum_{j\in F_G} x_{z^v}^{v}, j \leq 1 \qquad \forall v \in V \tag{6}$$

$$\sum_{j\in F\setminus i} d_{ij}^{v} - \sum_{j\in F\setminus i} d_{ji}^{v} = r_i \alpha_i^v \qquad \forall i \in F_C, v \in V, \tag{7}$$

$$\sum_{i\in F_C} d_{z^v}^{v}, j = \sum_{i\in F_C} r_i \alpha_i^v \qquad \forall v \in V, \tag{8}$$

$$\Omega_i^v + (\tau_{ij+q_i}) x_{ij}^v - E^v (1 - x_{ij}^v) \leq \Omega_j^v \qquad \forall (i,j) \in A : j \in F_C, v \in V, \tag{9}$$

$$s_i \leq \Omega_i^v \leq e_i - q_i \qquad \forall i \in F_C, v \in V, \tag{10}$$

$$\Omega_{z^v}^v = \beta^v \qquad \forall v \in V, \tag{11}$$

$$\rho'^{v}_{ij} + d_{ij}^v \leq C^v x_{ij}^v \qquad \forall (i,j) \in A, v \in V, \tag{12}$$

$$\sum_{(i,j)\in A} \tau_{ij} x_{ij}^v \leq L^v \qquad \forall (i,j) \in A, v \in V, \tag{13}$$

$$\sum_{(i,j)\in\ A} \tau_{ij} x_{ij}^v + \sum_{i\in F_C} q_i \alpha_i^v \leq E^v \qquad \forall (i,j) \in A, v \in V, \tag{14}$$

$$x_{ij}^v \in \{0,1\} \qquad \forall (i,j) \in A, v \in V, \tag{15}$$

$$\alpha_i^v \in \{0,0\} \qquad \forall i \in F_C, v \in V, \tag{16}$$

$$\rho'^{v}_{ij} \geq 0 \qquad \forall (i,j) \in A, v \in V, \tag{17}$$

$$d_{ij}^v \geq 0 \qquad \forall (i,j) \in A, v \in V, \tag{18}$$

The objective function (1) minimises the total cost (fixed hiring cost and variable driving cost). Visiting rules are, by constraint (2), that all of the customers must be visited only once. (3) means by the contribution of the vehicle v all of the customers must be visited by the fleet. (4) is the flow conservation constraint, which means, if there is an inflow there must also be an outflow at the customer site. The connection between the factory of the vehicle v and the visited customer is guaranteed by (5). Vehicles can be used only once, as stated by (6).

Customer order completion constraints are (7) – (8); those are for delivery completion. Constraint (9) is stated for the Miller-Tucker-Zemlin sub-tour elimination constraints (Miller, Zemlin, & Tucker, 1960) and provides the framework for the time windows. (10) designs the upper- and lower-time limits. Vehicle restrictions are given as follows: (11) sets the start time for vehicle v, (12) prohibits the violation of the vehicle capacity C^v, (13) limits the driving time, and (14) limits the total working time for each vehicle v. Integrality and the nonnegativity constrains are stated by (15) – (18).

2.2. Algorithm proposal

Feed factory officials aim to see the extra cost reductions that can be achieved by adding the multi-day planning algorithm to the given model in order to reduce uncertainty, dispatch close customers on the same day and with the same vehicle if possible, and reduce their costs. Thus, while reducing the total cost, it is expected that the fewest concessions will be made in the delivery dates. In order for the specified development to be completed, under the factory loading capacity constraint, the orders with daily delivery dates should be resolved together as if they were to be shipped the same day, and the total deviation from the delivery date should be minimised. Rather than the same vehicle periodically visiting the same customers, as in Rodríguez-Martín, Salazar-González, & Yaman (2019), the proposed algorithm combines the geographically close points of the mixed vehicle fleet with minimal deviation from the late delivery date. In this respect, it differs from periodic VRP.

The daily loading capacity of the factory was determined as ∅, if desired by the factory k is to be the factory tolerance limit, and the deviation from the latest delivery date as θ. t, the day the vehicles are loaded, is an integer between the earliest first delivery date of orders (s_i) and the last delivery date (e_i).

The objective function (19) should be revised as follows.

$$\text{Minimise} \quad \sum_{(i,j)\in A v\in V} \sum c_{ij}^{v} x_{ij}^{v} + \sum_{j\in F_C v\in V} \sum \gamma^{v} x_{z^v}^{v}, j + \sum_{i\in F} \vartheta_i \tag{19}$$

In order not to exceed the daily loading capacity of the factory, the following constraint should be added.

$$\sum_{i\in F_C} p_{z^v}^{v}, j \geq \phi_t + k_t \quad \forall i \in F_C, v \in V, z^v \in F_D, \forall t \in (s_i, e_i) \tag{20}$$

In order to allow deviation from the latest delivery date, constraint (21) must be revised as follows:

$$s_i \leq \Omega_i^v \leq e_i - q_i + \vartheta_i \quad \forall i \in F_C, v \in V, \tag{21}$$

Nonnegativity constraints related to the factory capacity (22), tolerance limit for factory capacity flexibility (23), and deviation from the latest delivery date (24) are added as follows:

$$\phi_t \geq 0 \quad \forall t \in (s_i, e_i), \tag{22}$$

$$k_t \geq 0, \quad \forall t \in (s_i, e_i), \tag{23}$$

$$\vartheta_i \geq 0 \quad \forall i \in F_C \tag{24}$$

The solutions to be produced by the developed algorithm will occur depending on the factory capacity $\varnothing_t$ and factory capacity flexibility limit k_t, which are new inputs to be taken from the user.

ALNS Algorithm's Pseudocode

1. **Begin**
2. **Inputs:** factory, distances, customers, vehicles, durations, capacity limit, capacity limit tolerance, CPU time limit
3. Calculate the total order quantity
4. Divide the quantity to factory $\varnothing_t + k_t$
5. Round value to first upper integer n
6. Build the index t ($t_1..t_n$), build the loop index m (1..n)
7. Build the first solution by adding the customers to the initial routes
8. Choose the most cost-decreasing at every phase
9. Advance the candidate solution by using the local search engine with Exchange, one-opt, two-opt, and vehicle-exchange operators.
10. Record the candidate solution as the best-known solution
11. Repeat
12. a. Randomly destroy the candidate solution by removing vertices
    b.Heuristically repair the candidate solution by adding vertices
    c. Advance the candidate solution by using the local search engine
13. If the candidate solution is better than the best-known solution
    Then
    Change the best-known solution value
    Else With probability α first solution is the best-known solution
    Until processing time reaches the CPU time limit
14. End ALNS.

The exchange operator changes pairs of customers and checks whether the objective function value decreases. One-opt changes the order of the customer in the route and checks for minimization. Two-opt removes arc a-b and c-d and crosses the arc as a-c and c-d, and checks for feasibility and improvement in the objective value. Both the operators have a neighbourhood size of $O([F])^2$.

In step 12.b, two of the constructive heuristics are applied. Those are the greedy insertion method and the max regret method. The second heuristic selects the customer, for which the difference between the cost of the cheapest insertion and the second cheapest insertion decision is the largest. At each iteration selection of the heuristics is made with equal probability. Each heuristic searches for several best candidates and selects randomly among them at each step. The probability p of rejecting a candidate solution is set at 15% in the preliminary phase and decreases linearly with time, and reaches 0% at the end of the CPU time limit.

Multi-day Optimization Algorithm’s Pseudocode

1. **Begin**
2. **Assign** $\varnothing_t = 0$
3. For $\boldsymbol{m}$ = 1 to $\boldsymbol{n}$
4. For v = 1 to end of the vehicle set V
5. Compute the average delivery date of the orders in vehicle v.
6. Sort every vehicle v’s average delivery date in an ascending order
7. Assign it to the nearest t value.Assign it to the nearest t value.
8. Calculate θ_t value.
9. For t = 1 to n-1
10. Update best solution date if total deviation $theta_t$ decreases
11. Keep old date if total deviation $theta_t$ tincreases
12. t = t + 1
13. Repeat
14. If $\varnothing_m$ < Capacity assigned by the user
15. $\varnothing_m = \varnothing_m + P^{v}_{z^v},_j$
16. Else m=m+1
17. $\varnothing_m = \varnothing_m + P^{v}_{z^v},_j$
18. Repeat
19. Return best known solution as the solution
20. End ALNS.

The multi-day optimization algorithm takes over the heuristic solution and sorts every vehicle v’s average delivery in an ascending order. Starting from t=1 to n, without changing the routes and order combinations in the vehicles, it checks whether the target function increases or decreases by advancing the current day value one by one for all vehicles. If there is a decrease in the target function, it updates the best solution as the best-known solution. It iterates the planning horizon from the first vehicle to the last by filling the factory capacity with the least deviation from the delivery dates. Iteration of the day exchange operator stops when all vehicles are planned .

To compare the ALNS algorithm, GA and SA algorithms were used. The detailed pseudocodes of the algorithms used can be obtained from Liu (S. Liu, Huang, & Ma, 2009) for the GA heuristic and Kuo (2010) for the SA heuristic.

3. RESULTS AND DISCUSSION

The algorithm was tested with a dataset using the real order data of 2025.95 tons, which was delivered to the feed factory by sales representatives. A summary of the data is given in Table I (details can be seen from the dataset reference).

Table 1. Order Data Set

Number of Distribution Points	Total Order Quantity	Maximum Distance	Fleet Mix	
		LATITUDE / LONGITUDE	Truck	18
			4 Axle Lorry	2
107	2025,95 tons	234 km / 177 km	3 Axle Lorry	2

Before testing the designed algorithm, the solution to the problem described in §2.2 was provided. In order to test the performance of the proposed Adaptive Large Neighbourhood Search (ALNS) heuristic and the multi-day scheduling algorithm, the data set was compared with the solutions provided by well-known Simulated Annealing (SA) and Genetic algorithms (GA). First of all, a solution was provided without implementing the multi-day planning algorithm. This solution and comparison of ALNS with other methods are given in Table II.

Solution routes can be seen in Figure I.

As can be seen in Table II, the developed ALNS algorithm has been compared with some other heuristic algorithms. With the developed ALNS algorithm, the vehicle occupancy rate increased by up to 5.58% with respect to SA and GA. It reduced the distance travelled by up to 3.41%. By making the vehicle selection more accurate, it reduced fixed costs by up to 4.68%. Likewise, it provided a decrease of up to 3.82% in variable costs. The data sets of the study were created to solve real-life problems which

Table 2. Computational results for the benchmark of Data Set

Best Found Solutions	Capacity (Kg/Type)	Vehicle Type	Quantity Utulized			Amount Carried (Kg)			Occupancy (%)			Distance Traveled (Km)			Fixed Cost (TL)			Variable Cost (TL)			Total Cost Incurred		
			SA	GA	ALNS	SA	GA	ALNS	SA	GA	ALNS	SA	GA	ALNS	SA	GA	ALNS	SA	GA	ALNS	SA	GA	ALNS*
Day 1	27,000	Truck	15	15	15	389,500	393,500	393,500	96.2	97.2	97.2	1,859	1,744	1,744	4,500	4,500	4,500	8,175.6	7,817.9	7,817.9	12,675.6	12,317.9	12,317.9
	21,000	4 Axle Lorry	1			5,500			26.2			25			200			80.5			280.5		
	17,000	3 Axle Lorry	2	2	2	28,250	29,750	29,750	83.1	87.5	87.5	163	163	163	200	200	200	744.6	830.7	830.7	944.6	1,030.7	1,030.7
Sum			**18**	**17**	**17**	**423,250**			**92.0**	**96.4**	**96.4**	**2,048**	**1,907**	**1,907**	**4,900**	**4,700**	**4,700**	**9,000.7**	**8,648.5**	**8,648.5**	**13,900.7**	**13,348.5**	**13,348.5**
Day 2	27,000	Truck	18	18	18	452,350	474,350	474,350	93.1	97.6	97.6	1,690	1,743	1,739	5,400	5,400	5,400	7,792.2	7,811.5	7,792.0	13,192.2	13,211.5	13,192.0
	21,000	4 Axle Lorry	2			32,000			76.2			149			400			620.8			1,020.8		
	17,000	3 Axle Lorry	2	2	2	21,000	31,000	31,000	61.8	91.2	91.2	29	57	57	200	200	200	304.6	289.9	289.9	504.6	489.9	489.9
Sum			**22**	**20**	**20**	**505,350**			**89.9**	**97.2**	**97.2**	**1,868**	**1,800**	**1,795**	**6,000**	**5,600**	**5,600**	**8,717.6**	**8,101.4**	**8,081.9**	**14,717.6**	**13,701.4**	**13,681.9**
Day 3	27,000	Truck	12	12	12	300,250	317,250	317,250	92.7	97.9	97.9	909	944	944	3,600	3,600	3,600	4,506.0	4,230.5	4,230.5	8,106.0	7,830.5	7,830.5
	21,000	4 Axle Lorry	2	2	2	42,000	42,000	42,000	100.0	100.0	100.0	56	58	58	400	400	400	448.4	257.0	257.0	848.4	657.0	657.0
	17,000	3 Axle Lorry	2	1	1	27,500	10,500	10,500	80.9	61.8	61.8	65	29	29	200	100	100	477.6	149.4	149.4	677.6	249.4	249.4
Sum			**16**	**15**	**15**	**369,750**			**92.4**	**96.5**	**96.5**	**1,030**	**1,032**	**1,032**	**4,200**	**4,100**	**4,100**	**5,432.1**	**4,637.0**	**4,637.0**	**9,632.1**	**8,737.0**	**8,737.0**
Day 4	27,000	Truck	7	7	7	186,500	186,500	186,500	98.7	98.7	98.7	853	886	886	2,100	2,100	2,100	3,814.2	3,970.6	3,970.6	5,914.2	6,070.6	6,070.6
	21,000	4 Axle Lorry	1	1	1	20,000	20,000	20,000	95.2	95.2	95.2	126	119	119	200	200	200	439.8	523.7	523.7	639.8	723.7	723.7
	17,000	3 Axle Lorry	1	1	1	10,500	10,500	10,500	61.8	61.8	61.8	39	40	40	100	100	100	180.5	205.8	205.8	280.5	305.8	305.8
Sum			**9**	**9**	**9**	**217,000**			**95.6**	**95.6**	**95.6**	**1,018**	**1,045**	**1,045**	**2,400**	**2,400**	**2,400**	**4,434.5**	**4,700.0**	**4,700.0**	**6,834.5**	**7,100.0**	**7,100.0**
Day 5	27,000	Truck	12	12	12	318,500	318,500	318,500	98.1	97.6	97.7	1,646	1,583	1,583	3,600	3,600	3,600	7,197.1	7,094.5	7,094.5	10,797.1	10,694.5	10,694.5
	21,000	4 Axle Lorry																					
	17,000	3 Axle Lorry	2	2	2	23,000	23,000	23,000	54.4	77.9	76.5	95	91	91	200	200	200	510.9	462.3	462.3	710.9	662.3	662.3
Sum			**14**	**14**	**14**	**341,500**			**95.4**	**95.4**	**95.4**	**1,741**	**1,674**	**1,674**	**3,800**	**3,800**	**3,800**	**7,707.9**	**7,556.8**	**7,556.8**	**11,507.9**	**11,356.8**	**11,356.8**
Day 6	27,000	Truck	6	5	5	139,000	133,000	133,000	85.8	98.5	98.5	703	488	488	1,800	1,500	1,500	2,833.0	2,188.7	2,188.7	4,633.0	3,688.7	3,688.7
	21,000	4 Axle Lorry	1	1	1	16,000	20,100	20,100	76.2	95.7	95.7	34	251	251	200	200	200	80.5	1,105.7	1,105.7	280.5	1,305.7	1,305.7
	17,000	3 Axle Lorry	2	1	1	14,100	16,000	16,000	41.5	94.1	94.1	77	36	36	200	100	100	369.4	182.4	182.4	569.4	282.4	282.4
Sum			**9**	**7**	**7**	**169,100**			**77.9**	**97.7**	**97.7**	**813**	**775**	**775**	**2,200**	**1,800**	**1,800**	**3,283.0**	**3,476.8**	**3,476.8**	**5,483.0**	**5,276.8**	**5,276.8**
Sum	27,000	Truck	70	69	69	1,786,100	1,823,100	1,823,100	94.5	97.9	97.9	7,660	7,388	7,384	21,000	20,700	20,700	34,318.1	33,113.7	33,094.2	55,318.1	53,813.7	53,794.2
	21,000	4 Axle Lorry	7	4	4	115,500	82,100	82,100	78.6	97.7	97.7	391	428	428	1,400	800	800	1,670.0	1,886.4	1,886.4	3,070.0	2,686.4	2,686.4
	17,000	3 Axle Lorry	11	9	9	124,350	120,750	120,750	66.5	78.9	78.9	468	416	416	1,100	900	900	2,587.7	2,120.4	2,120.4	3,687.7	3,020.4	3,020.4
			88	**82**	**82**	**2,025,950**			**91.1**	**96.5**	**96.5**	**8,519**	**8,233**	**8,228**	**23,500**	**22,400**	**22,400**	**38,575.8**	**37,120.5**	**37,101.0**	**62,075.8**	**59,520.5**	**59,501.0**

Table 3. Computational results for the benchmark of Data Set with multi-day planing algorithm applied

Best Found Solutions	Capacity (Kg/Type)	Vehicle Type	Quantity Utulized			Amount Carried (Kg)			Occupancy (%)			Distance Traveled (Km)			Fixed Cost (TL)			Variable Cost (TL)			Total Cost Incurred		
			SA	GA	ALNS	SA	GA	ALNS	SA	GA	ALNS	SA	GA	ALNS	SA	GA	ALNS	SA	GA	ALNS	SA	GA	ALNS*
Day 1	27.000	Truck	18	18	17	453.500	472.600	446.750	93,3	97,2	97,3	2.144	1.934	1.865	5.400	5.400	5.100	9.105,2	8.669,9	8.358,9	14.505,2	14.069,9	13.458,9
	21.000	4 Axle Lorry	2	1	1	15.500	21.000	19.750	36,9	100	94,0	90	27	87	400	200	200	310,9	118,7	383,0	710,9	318,7	583,0
	17.000	3 Axle Lorry	2		2	28.750		33.000	84,6		97,1	102		55	200	-	200	552,8		280,8	752,8	-	480,8
Sum			**22**	**19**	**20**	**497.750**	**493.600**	**499.500**	**88,6**	**97,4**	**97,2**	**2.336**	**1.961**	**2.007**	**6.000**	**5.600**	**5.500**	**9.968,9**	**8.788,6**	**9.022,7**	**15.968,9**	**14.388,6**	**14.522,7**
Day 2	27.000	Truck	17	17	18	448.850	447.500	476.250	97,8	97,5	98,0	1.385	1.628	1.970	5.100	5.100	5.400	6.705,8	7.295,6	8.828,9	11.805,8	12.395,6	14.228,9
	21.000	4 Axle Lorry	1	1	1	21.000	21.000	20.850	100	100	99,3	21	95	90	200	200	200	269,1	419,7	397,8	469,1	619,7	597,8
	17.000	3 Axle Lorry	2	1		29.000	16.250		85,3	95,6		184	54		200	100	-	744,6	274,5		944,6	374,5	-
Sum			**20**	**19**	**19**	**498.850**	**484.750**	**497.100**	**97,1**	**97,5**	**98,0**	**1.589**	**1.777**	**2.060**	**5.500**	**5.400**	**5.600**	**7.719,6**	**7.989,8**	**9.226,7**	**13.219,6**	**13.389,8**	**14.826,7**
Day 3	27.000	Truck	17	17	17	428.750	451.500	451.350	93,4	98,4	98,3	1.891	1.761	1.443	5.100	5.100	5.100	8.605,0	7.893,6	6.469,1	13.705,0	12.993,6	11.569,1
	21.000	4 Axle Lorry	2	2	2	41.000	41.000	41.000	97,6	97,6	97,6	161	139	139	400	400	400	619,1	612,4	612,4	1.019,1	1.012,4	1.012,4
	17.000	3 Axle Lorry	2			13.500			39,7			76			200	-	-	496,5			696,5	-	-
Sum			**21**	**19**	**19**	**483.250**	**492.500**	**492.350**	**90,3**	**98,3**	**98,3**	**2.128**	**1.900**	**1.582**	**5.700**	**5.500**	**5.500**	**9.720,6**	**8.506,0**	**7.081,5**	**15.420,6**	**14.006,0**	**12.581,5**
Day 4	27.000	Truck	17	16	18	450.100	424.100	477.500	98,1	98,2	98,3	1.920	1.983	2.286	5.100	4.800	5.400	8.577,5	8.887,6	10.247,8	13.677,5	13.687,6	15.647,8
	21.000	4 Axle Lorry		1			19.000			90,5			40			200	-		175,8		-	375,8	-
	17.000	3 Axle Lorry	2	2	1	24.500	32.500	16.500	72,1	95,6	97,1	134	103	41	200	200	100	674,6	524,8	208,8	874,6	724,8	308,8
Sum			**19**	**19**	**19**	**474.600**	**475.600**	**494.000**	**96,3**	**97,7**	**98,2**	**2.054**	**2.126**	**2.327**	**5.300**	**5.200**	**5.500**	**9.252,2**	**9.588,2**	**10.456,6**	**14.552,2**	**14.788,2**	**15.956,6**
Day 5	27.000	Truck	2	3	1	53.000	79.500	27.000	98,1	98,1	100	316	349	45	600	900	300	1.317,8	1.563,4	203,2	1.917,8	2.463,4	503,2
	21.000	4 Axle Lorry														-	-				-	-	-
	17.000	3 Axle Lorry	2		1	18.500		16.000	54,4		94,1	92		36	200	-	100	519,4		182,4	719,4	-	282,4
Sum			**4**	**3**	**2**	**71.500**	**79.500**	**43.000**	**81,3**	**98,1**	**97,7**	**407**	**349**	**81**	**800**	**900**	**400**	**1.837,2**	**1.563,4**	**385,6**	**2.637,2**	**2.463,4**	**785,6**
Total Sum	27.000	Truck	71	71	71	1.834.200	1.875.200	1.878.850	95,7	97,8	98,0	7.656	7.655	7.610	21.300	21.300	21.300	34.311,4	34.310,0	34.107,8	55.611,4	55.610,0	55.407,8
	21.000	4 Axle Lorry	5	5	4	77.500	102.000	81.600	73,8	97,1	97,1	272	301	316	1.000	1.000	800	1.199,1	1.326,7	1.393,2	2.199,1	2.326,7	2.193,2
	17.000	3 Axle Lorry	10	3	4	114.250	48.750	65.500	67,2	95,6	96,3	587	157	132	1.000	300	400	2.987,9	799,3	672,0	3.987,9	1.099,3	1.072,0
			86	**79**	**79**	**2.025.950**			**92,4**	**-**	**-**	**8.514**	**8.113**	**8.058**	**23.300**	**22.600**	**22.500**	**38.498,4**	**36.436,0**	**36.173,0**	**61.798,4**	**59.036,0**	**58.673,0**

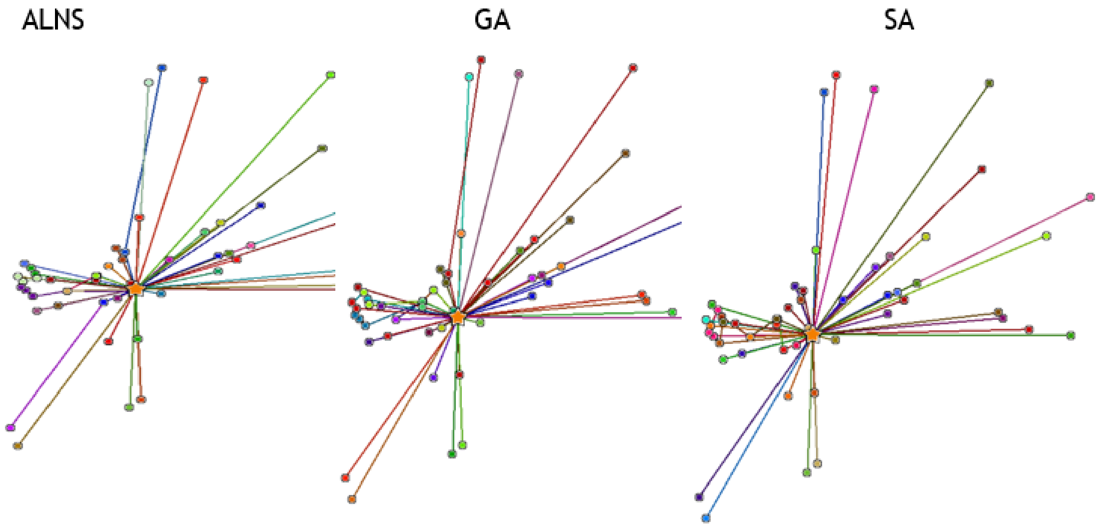

Figure 1. ALNS / GA / SA Heuristics Route Mapping

can be reached from the dataset link. The benchmarked data set was used in the study by creating a distance matrix based on the latitude and longitude information of customers. One can use open street maps (information was obtained from the following world map, whose use is under free and open license: https://www.openstreetmap.org/). For the repeatability of the study, one can check against other heuristic solutions or recode the proposed method.

Table 4. Absolute Deviations (Improvement Rates)

Performance Indicator	SA	GA	ALNS
Occupancy (+)	1.46	1.30	1.50
Distance Traveled (-)	0.05	1.45	2.07
Total Cost Incurred (-)	0.45	0.81	1.39

The algorithm proposed in §2.2 (multi-day planning) was coded in C++ and run in an Intel(R) Core (TM) i7-6500U CPU @ 2.50GHz 2.60 GHz with 8 GB RAM. Daily factory capacity is 500 tons/day for the given period. The multi-day planning algorithm was run for all of the ALNS, SA, and GA algorithms where the benchmarks were made, and the results were given comparatively. The obtained solution can be seen in Table III. Regardless of which heuristic method was applied with the proposed algorithm, all results showed significant improvement. This provides an important contribution in terms of being an algorithm that improves each method at the same time rather than comparing the heuristic methods that are dominant in the literature.

Absolute deviations (AD) occur in heuristic solutions with the developed algorithm. These improvement rates can be calculated by (25) as follows.

$$AD = [Abs(WithoutAlgoritm - WithAlgorithm)/WithoutAlgorithm]x100 \tag{25}$$

AD values can be seen in Table IV for benchmark heuristics.

With the proposed algorithm, vehicle occupancy was increased. Total travel distance, fixed, and variable costs are reduced. As a result of these improvements, the total cost was reduced by up to 1.39 percent. Although all methods have provided more successful results with the multi-day planning algorithm, the improvement achieved in the ALNS heuristic is remarkable. When Tables III and IV are compared, it is seen that there are backward and forward changes in the desired delivery dates to level the factory capacity. For benchmark heuristics, the percentage, quantity, and deviation days of the revised orders are given in Figure II, respectively.

As can be seen in the SA heuristic, 93.1% of the orders were planned with a deviation of only up to one day. The weighted average number of deviation days was realized as 0.53 days. In the GA heuristic, 95.4% of the orders were planned with a deviation of only up to one day. The weighted average number of deviation days was realized as 0.46 days. In the ALNS heuristic, 93.0% of

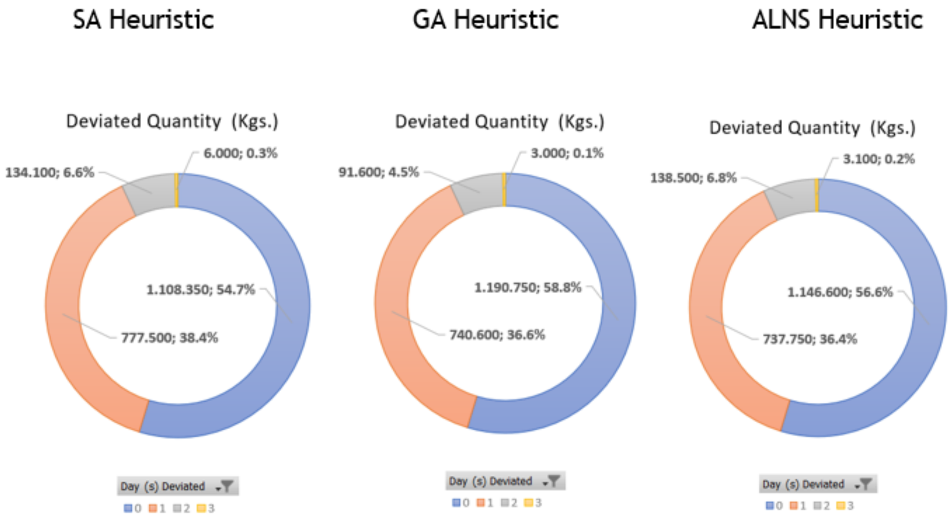

Figure 2. Total Deviation from Desired Shipment Time Windows

the orders were planned with a deviation of only up to one day. The weighted average number of deviation days was realized as 0.51 days.

4. CONCLUSION

As stated by Hoff et al. 3 [3], VRP is seen as a success story of operations research. New extensions and intuitive solutions are needed to make this method more practical in solving real-life problems. The proposed algorithm attempts to gain the ability to organize the planning horizon and reduce uncertainty in the VRP method. The method developed has achieved success in all dimensions, such as fleet occupancy, and reduction of fixed and variable costs, which are parts of the multi-dimensional success factors mentioned at the beginning of the study. Companies mostly invest in VRP software by deciding to develop intuitive solutions according to their needs. The algorithm detailed in the study can be easily adapted to the existing software of businesses that already use VRP software. The use of multi-day planning and uncertainty reduction methods has undeniable improvement opportunities, as can be seen from the results of the study.

5. RECOMMENDATIONS

In future studies, as a suggestion, instead of reaching a solution one at a time with a single heuristic, an algorithm can be developed that uses several heuristic algorithms at the same time and selects the one that provides the most cost reduction with the least delivery day deviation.

Peer Review: Externally peer-reviewed.

Conflict of Interest: Author declared no conflict of interest.

Financial Disclosure: Author declared no financial support.

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Celikdin, A.E. (2023). Fleet size and mix vehicle routing problem (FSMVRP), adapted large neighbourhood search heuristic optimization proposal with a plant-capacity and multi-day planning algorithm: a livestock feed industry case study. Journal of Transportation and Logistics, 8(1), 1-12. https://doi.org/10.26650/JTL.2023.1101161