LogForum

> Scientific Journal of Logistics <

2024, 20 (1), 23-37

http://doi.org/10.17270/J.LOG.001008

http://www.logforum.net p-ISSN 1895-2038 e-ISSN 1734-459X

ORIGINAL PAPER

OPTIMIZING FRESH-CUT FLOWER DISTRIBUTION USING THE VEHICLE ROUTING PROBLEM FOR PERISHABLE GOODS

Sara Rodrigo[1,2], Dilina Kosgoda[1,2], W. Madushan Fernando[1,2], Peter Nielsen[3], Amila Thibbotuwawa[1,2]

1) Center of Supply Chain, Operations, and Logistics Optimization, University of Moratuwa, **Sri Lanka**
2) Department of Transport Management and Logistics Engineering, University of Moratuwa, **Sri Lanka**
3) Department of Materials and Production, Aalborg University, **Denmark**

ABSTRACT. Background: Achieving optimization in complex distribution operations necessitates significant attention to the distinctive operating procedures and features of various distribution systems. One particularly challenging distribution operation is the transportation of fresh-cut flowers. This process demands that a required quality be maintained at every stage, spanning from the flower growers, wholesalers, and retailers to the end customer. Failure to uphold the required level of freshness can lead to adverse outcomes such as decreased profits, customer attrition, and a tarnished reputation. To investigate this complex distribution process, fresh flower distribution was studied using data from a reputed floral company in Sri Lanka with the aim of finding the optimal set of routes for the distribution of fresh-cut flowers.

Methods: Vehicle Routing Problem (VRP) variants were employed and the 'Capacitated Vehicle Routing Problem with Time Windows for Perishable Goods with Single Depot' (CVRPTWfPGSD) was introduced. A hybrid method combining both heuristics and metaheuristics was selected as the methodology by considering several factors such as complexity, solution type, and execution time. The initial solution construction phase adopted the Path Cheapest Arc (PCA) heuristic. To further improve solution quality, the Guided Local Search (GLS) metaheuristic was applied.

Results: This CVRPTWfPGSD model is validated for real-world scenarios, as it does not violate the maximum allowable perishability time provided for each vehicle. Three experiments were conducted by varying the vehicle fleet to measure the applicability of the model under different circumstances to decide on a better vehicle combination while minimizing total distribution time. Based on this analysis, it can be concluded that the composition of the vehicle fleet has a substantial influence on freshness levels and distribution times.

Conclusions: Optimizing the distribution of fresh-cut flowers using VRP assists in reducing spoilage and waste by ensuring that flowers are transported under the best possible conditions. The application of this model holds immense value for floral companies as it offers assistance when planning their distribution network. Specifically, it can assist in identifying optimal routes that maximize freshness with minimum distribution time and an optimal set of vehicles.

Keywords: fresh flower distribution; perishable vehicle routing problem; hybrid algorithms; perishability constraint, capacitated vehicle routing problem.

INTRODUCTION

The quality of perishable products is susceptible to adverse effects caused by external factors such as improper climate and moisture levels when they are being transported and stored (Ruiz-Garcia & Lunadei, 2010). Temperature fluctuations during various processes, including warehousing, quality inspections, and transportation, pose challenges to the preservation of product quality. Moreover, due to the perishable nature of cut flowers, supply chains that deal with fresh flower distribution have to grapple with the precise handling of temperature and timing constraints associated with the floral market (Ruiz-Garcia & Lunadei, 2010). These temperature-sensitive items require a fast decision-making process so products can be shipped within hours. To ensure optimal quality and preservation of perishable products, the industry has prioritized the monitoring of

Citation: Rodrigo S., Kosgoda D., Fernando W. M., Nielsen P., Thibbotuwawa A., 2024. Optimizing fresh-cut flower distribution using vehicle routing problem for perishable goods. LogForum 20 (1), 23-37, http://doi.org/10.17270/J.LOG.001008

Received: 01.01.2024, Accepted: 29.01.2024, on-line: 14.03.2024

temperature gradients inside trucks, containers, and refrigerated rooms (Ruiz-Garcia & Lunadei, 2010). Cold supply chain management has been addressed by Sirisaranlak (2017), as the primary floral supply chain of farmers, wholesalers, and retailers is part of the modern, dynamic, and globally oriented cut flower business. According to Van Rijswick (2015), Colombia, Malaysia, Kenya, Ecuador, and Ethiopia have boosted their market shares globally in the trading of cut flowers as a result of improved logistics, particularly shipping container transit. With the growing global floral supply chain, there is an increasing need to optimize flower delivery routes to reduce costs and maximize freshness (Sirisaranlak, 2017).

Transportation challenges in fresh-cut flower distribution revolve around the maintenance of the appropriate temperature, the prevention of physical damage, and timely delivery. According to Shaabani (2022), there are four types of perishability: “(1) strictly fixed lifetime, (2) non-strict fixed lifetime, (3) random shelf life, and (4) gradual deterioration over time”. Fresh-cut flowers fall under the non-strict fixed lifetime category. The quality of cut flowers is highly dependent on external factors such as stock keeping method, environmental temperature, seasonality, moisture in the air, water levels, heat, and exposure to sunlight. Cold chain management, protective packaging, efficient logistics planning, and advanced technologies are among the strategies employed to overcome these challenges.

In any fresh-cut flower distribution process, temperature control remains pivotal, as high temperatures shorten post-harvest life by speeding up respiration and lowering net carbohydrate stores. Additionally, too little heat harms buds by causing them to freeze (Halevy & Mayak, 2011). The floriculture trade has to manage the problem of extreme perishability due to the limited shelf life of flowers (Sirisaranlak, 2017). A study by Ahumada & Villalobos (2011) restricted the storage time of fruits due to their limited perishability and included parameters that can be utilized as crucial indicators of freshness, like color. To guarantee that every client receives fresh items from distribution facilities, Esmaili & Mousavi (2020) devised a series of restrictions. These included physical limitations involving storing the flowers in a controlled environment with specific temperature and moisture conditions, protecting them from sunlight and heat, and particularly significant constraints on the time within which the flowers could be consumed or used.

In this research domain, VRP for Perishable Goods (VRPfPG) has emerged as a more appropriate VRP model to study perishable products, for which customers judge the quality based on freshness. Transportation issues, temperature, and storage conditions greatly affect the quality of perishable products due to their shorter shelf life. Fresh-cut flowers are another type of perishable product to which VRP for Perishable Goods can be applied. This model could help the flower industry perform more effectively and efficiently. Customer satisfaction is one of the key drivers of revenue generation, and the VRPfPG can play a vital role in enabling accurate and timely decision-making to meet this demand.

In the Vehicle Routing Problem with Time Windows (VRPTW), time windows can be either hard constraints or soft constraints (Calvete et al., 2004). Routes that have hard constraints are deemed infeasible if the service of the customer begins before the earliest time or extends beyond the latest time indicated by their specified time window. Violation of these constraints is strictly prohibited (Toth & Vigo, 2001). This allows for more efficient scheduling, shorter waiting times, and better satisfaction of customer expectations. The Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) also belongs to the category of VRP (Thibbotuwawa et al., 2019; Thibbotuwawa et al., 2020). In soft time windows, vehicles are permitted to arrive at customer locations after the specified time window, but violations of the time windows incur penalties in the objective function (Taillard, Eric; Badeau, P; Gendreau, 1997). By considering time windows, VRP optimizes the routing process, ensuring that fresh-cut flowers are delivered promptly, improving customer satisfaction, and preserving the overall quality of the flowers throughout the distribution process. Galarcio Noguera et al. (2018) advocate for further research into the implementation of specific models that could enhance the freshness and overall quality of perishable products during the distribution phase, thereby ensuring their optimal condition upon delivery.

According to the literature, there is a notable absence of research addressing the optimization of the cut flower distribution network along with the time and temperature variables (Sirisaranlak, 2017, Malindretos, 2018). Specifically, there is a lack of studies with a primary objective of minimizing the total distribution time while simultaneously considering the perishability level of the cut flowers. The perishability of the goods being transported, the form of the vehicle taking the route, and the circumstances under which they are transported can all affect the freshness loss rate (Galarcio Noguera et al., 2018).

Therefore, this study aims to fill an important research gap in the application of VRPs within the context of fresh flower distribution, specifically considering how perishability levels are influenced by temperature conditions. Building on existing literature, this study focuses on the VRPfPG to address the challenges associated with transportation, time constraints, and temperature-sensitive perishable products, with fresh flowers serving as a prime example. The primary objective is to minimize the total distribution time, emphasizing the optimization of routes to ensure the highest level of freshness in flowers throughout the supply chain. Further, this study aims to discuss valuable insights to enhance the efficiency of the floral supply chain, thereby improving customer satisfaction and overall supply chain performance.

MATERIALS AND METHODS

Mathematical Model Formulation

The mathematical formulation of the CVRPTWfPGSD model was adopted for this research. It is based on the optimization model introduced by Fernando et al. (2022). The presented mathematical formulation encompasses the assumptions, notations, objective functions, and constraints of the CVRPTWfPGSD model utilized in the study.

Model Assumptions

a) The deliveries in the CVRPTWfPGSD model start from a central distribution center. This means that all trucks depart from a central location to deliver goods to the designated customer locations. Once the deliveries are completed, the trucks return to the central distribution center.

b) The demand at each customer location is known in advance before transmitting the trucks. This means that the required quantity of perishable products needed by each customer location is predetermined and can be used to optimize the routing plan and ensure that sufficient goods are allocated to each customer.

c) Split deliveries are not allowed. This means that each customer location can only be served by one specific truck. This restriction ensures that the delivery process remains efficient and avoids potential complications that could arise from splitting deliveries between multiple trucks.

d) The trucks have deterministic heterogeneous capacities, meaning that each truck has a specific maximum capacity for carrying perishable products. This heterogeneity in truck capacities allows for more flexibility in optimizing the allocation of goods to customer locations, considering the varying capacity constraints of each truck.

e) All the trucks maintain the same temperature from the beginning to the end of the route.

f) The trucks should focus exclusively on their assigned delivery tasks according to the predetermined schedule. They should not be utilized for any other purposes or additional trips.

g) This problem involves hard time windows, and each customer location has a specific time window during which the delivery must be made. This ensures that the deliveries are made within the specified time constraints.

These assumptions collectively provide a framework for addressing this model. Based on the assumptions, the routing plan was formulated to ensure efficient delivery operations, considering demand, capacity limitations, and time window constraints.

Table 1 provides a comprehensive overview of the notation used in this study, including sets, parameters, and decision variables. Each symbol is accompanied by a clear description, ensuring a proper understanding of their respective meanings and purposes.

Table 1: Notation used in the Capacitated Vehicle Routing Problem with Time Windows for Perishable Goods.

Sets		
N	-	Set of nodes
V	-	Set of vertices
K	-	Set of vehicles
Parameters		
t_j^k	-	The time the kth vehicle visits node j
t_i^k	-	The time the kth vehicle visits node i
t_{ij}	-	The travel time between vertices i & j
q_j	-	The total quantity delivered to node j
Q^k	-	The capacity of vehicle k
U_j^k	-	The cumulative quantity delivered by the kth vehicle at node j
U_i^k	-	The cumulative quantity delivered by the kth vehicle at node i
ST_i	-	The average service time at node i
T_k	-	The maximum allowed perishability time for a vehicle
e_i	-	The earliest time window
l_i	-	The latest time window
M	-	A large number
Decision Variables		
x_{ij}^k	-	A binary variable that takes a value of 1 if a vehicle k travels from vertex i to vertex j, and 0 otherwise
t_{ij}^k	-	The distribution time from vertex i to vertex j for the kth vehicle

Objective Function and Constraints

The objective function (1) of the fresh-cut flower distribution network problem is intended to minimize the total distribution time by optimizing vehicle routing and scheduling. This is supposed to ensure efficient and timely deliveries, maintain flower freshness, reduce costs, and enhance operational efficiency in the industry. The vehicle flow conservation constraint (2) guarantees that the flow of vehicles leaving the node is equal to the flow of vehicles entering the node for each vehicle and node. The total supply quantity constraint (3) ensures that the cumulative quantity supplied up to the j^{th} customer is the sum of the quantity supplied up to the previous customer and the quantity supplied directly to the j^{th} customer. The truck capacity constraint (4) assures that the overall quantity transported by the k^{th} truck does not surpass its specified capacity. Constraints (5) and (6) are sub-tour elimination constraints. The maximum allowed perishability time constraint (7) guarantees that the remaining perishability time at each node in the distribution network does not exceed the maximum allowable limit for vehicle k (T_k). The time window constraints (8) and (9) ensure that the arrival time at each node in the distribution network adheres to the specified time windows. For each node i and vehicle k, the arrival time t_i^k should be greater than or equal to the earliest time window e_i and less than or equal to the latest time window l_i.

The customer visit constraint (10) guarantees that each customer location is serviced by only one truck, preventing split deliveries where multiple trucks deliver the total quantity. The non-negativity constraints (11) and (12) ensure that the variables involved in the model formulation have valid and meaningful values.

Table 2: Objective function and constraints

Min -> $\sum_{i\in V}\sum_{j\in V}\sum_{k\in K} x^{k}_{ij} t^{k}_{ij}$	- All i,j∈N and k∈K	(1)
$\sum_{j\in V} x^{k}_{ij} = \sum_{j\in V} x^{k}_{ij}$	- All j∈N, k∈K	(2)
$U^{k}_{i} + q_{j} = U^{k}_{j}$	- All x^{k}_{ij} =1 and i,j∈N and k∈K	(3)
$U^{k}_{j} <= Q^{k}$	- All j∈N and k∈K	(4)
$t^{k}_{j} = t^{k}_{i} + t^{k}_{ij} + ST_{i}$	- All x^{k}_{ij} =1 and i,j∈N	(5)
$t^{k}_{j} >= t^{k}_{i} - M(1 - x^{k}_{ij})$	- All x^{k}_{ij} =1 and i,j∈N	(6)
$t^{k}_{i} <= T_{k}$	- All i∈V	(7)
$t^{k}_{i} >= e_{i}$	- All i∈V	(8)
$t^{k}_{i} <= l_{i}$	- All i∈V	(9)
$\sum_{k\in K}\sum_{i\in N} x^{k}_{ij} = 1$	- All j∈N	(10)
$t^{k}_{i} >= 0$	- All i∈N and k∈K	(11)
$x^{k}_{ij} \in \{0,1\}$	- All i,j∈V, i≠j and k∈K	(12)

Model Implementation

In this study, annual sales data were gathered from the distribution center (DC) and the customer locations, including information on the time required to reach each customer and their requested time windows. There were 20,000 data points. Additionally, data were collected on the fleet, such as the number of refrigerated trucks available, their capacity, their temperature settings, and their average speed. Specific data related to Chrysanthemum flowers were obtained, including their perishability time at different temperatures and the average number of flowers per crate (SKU). After analyzing 20,000 data points, per day demand was calculated. The unit of measurement was a crate that could contain 100 chrysanthemum flowers. Within the vehicle fleet of the company, three refrigerated trucks were deployed, each possessing a unique carrying capacity. The capacities of these trucks were measured in terms of the number of crates they could accommodate, with load limits of 150, 150, and 100 crates, respectively, and vehicle travel time was 6 hours per day according to the current conditions.

According to Gupta & Dubey (2018), there are two basic refrigerated storage methods for fresh-cut flowers. The company uses wet storage for chrysanthemums for transportation by refrigerated trucks in the temperature range 10–12°C. Refrigerated chrysanthemum flowers exhibited a vase life of 14 days, whereas non-refrigerated cut flowers lasted for 8 days (FloraLife, 2023). Based on the temperature conditions, the maximum allowed perishability time for a vehicle was set as 6 hours.

As per the descriptive analysis, the means of the lower bound of the time window and the upper bound of the time window were 22 and 180 respectively. The average demand from a customer location was 21.17 SKUs (crates): 2117 chrysanthemum flowers.

After analyzing customer data, 150 clusters were made across the region, and a central point of these clusters was taken separately, generating 150 customer demand points. A random sampling process was adopted to divide these data points into 10 distinct groups considering demand values, as the total capacity of the three refrigerated trucks was 400 SKUs in the initial case. The purpose of this random sampling was to create subsets of the data for further analysis or processing.

It was not possible to employ the Euclidean distances generator as it gives straight-line distances that do not apply to real-world optimal route planning (Fernando et al., 2022). Therefore, real-world driving distances and time durations from the starting node to the ending node were obtained by employing the Open-Source Driving Machine (OSRM) API (Fernando et al., 2021). A hybrid algorithm was utilized that combines heuristics and metaheuristics. The routing model was configured with the chosen initial construction heuristic strategy of PCA, which guided initial solution generation. Additionally, a time limit was set to control the search process, and the GLS metaheuristic was enabled to enhance the solution further. The algorithm was developed using OR-Tools v9. 6. (Perron & Furnon, 2023) and Python version 3.10 in PyCharm Community Edition 2021.3. The input data for the algorithm were latitude, longitude, time matrix, customer demand, service time, maximum allowed perishability time, and vehicle capacities. Then three separate experiments were conducted, varying vehicle capacities in each experiment and keeping other variables at the values in the 10 data sets, each representing a distribution network with a depot and 15 customer locations.

RESULTS

The first experiment was conducted using the actual capacities of the trucks currently owned by the company. Hard time windows according to customer decisions, service times, latitudes, longitudes, and demands for each customer location remained the same, and a further two experiments were conducted for different combinations of vehicles. Table 3 shows all the vehicle capacities that were used. For all 3 experiments, the maximum allowed perishability time was 6 hours per vehicle.

Table 3: Vehicle fleet combinations in 3 experiments.

Vehicle number	Experiment 01	Experiment 02	Experiment 03
Vehicle 01	150	100	150
Vehicle 02	150	100	100
Vehicle 03	100	100	100
Vehicle 04	-	100	100
Allowed Total Capacity	**400**	**400**	**450**

Table 4 shows one of the solutions generated from experiment 1: instance 1. In this solution, the distribution time taken by a vehicle is less than the maximum allowed perishability time, which is 360 minutes for a vehicle. All the solution time windows are inside the constraint time windows, and the load fulfills the vehicle capacity constraints. Therefore, the model provides a 100% service level (in terms of the distribution time) to the customers.

The average distribution timetable obtained from each route is shown in Table 5. The minimum average distribution time per route is shown in the second experiment.

The total distance covered by the set of vehicles assigned in each route network is shown in Table 6. The second and the third experiments covered a larger distance than the first experiment because they utilized a vehicle fleet with 4 vehicles.

Table 4: Example output - Experiment 1- Instance 1

Vehicle and capacity	Node	Constraint time window		Demand	Vehicle	Solution time window		Time (min)	Load
		Lower bound	Upper bound			Lower bound	Upper bound		
01-150 SKU	0	0	0	0	1	0	0	257	142
	1	10	40	20	1	13	15		
	4	30	70	60	1	52	54		
	8	20	100	25	1	69	71		
	13	30	100	25	1	98	100		
	5	40	200	12	1	195	200		
	0	0	0	0	1	257	360		
02-150 SKU	0	0	0	0	2	0	33	211	134
	7	20	100	37	2	21	54		
	2	15	100	34	2	56	89		
	10	10	200	10	2	84	117		
	9	30	200	23	2	118	151		
	6	30	180	10	2	147	180		
	15	10	250	20	2	170	250		
	0	0	0	0	2	211	360		
03-100 SKU	0	0	0	0	3	0	0	126	71
	3	30	70	12	3	30	30		
	14	0	110	14	3	48	48		
	11	15	90	9	3	75	75		
	12	0	300	36	3	96	96		
	0	0	0	0	3	126	126		
	Total			**347**				**594**	**347**

Table 5: Average distribution time per route (min) per instance.

Average distribution time per vehicle (min)			
Instance	**Experiment 1**	**Experiment 2**	**Experiment 3**
1	198	175	158
2	309	205	178
3	228	181	175
4	231	173	171
5	250	188	188
6	225	174	168
7	223	222	217
8	233	197	234
9	267	202	202
10	243	201	241
Average dist. time per route (min) per instance	**241**	**191**	**193**

Table 6: Total distance covered in each instance (km).

Total distance covered by all assigned vehicles (km)			
Instance	**Experiment 1**	**Experiment 2**	**Experiment 3**
1	325	429	362
2	678	585	603
3	394	532	491
4	421	553	552
5	458	530	530
6	427	470	519
7	414	520	525
8	448	496	489
9	487	565	565
10	455	579	559
Average distance per instance	**451**	**526**	**519**

The next stage of this research study involved checking the behavior of the KPIs relevant to this model. The computational experiments were carried out for the average freshness rate and minimum distribution cost for each instance. Galarcio Noguera et al. (2018) give valuable insight into the freshness loss of perishable products. They present a mathematical model aimed at minimizing the degradation of the freshness of perishable products during transportation. The model considers factors such as the time the product is kept inside the vehicle and the frequency with which the storage doors of the vehicle are opened along the route, starting from the departure from the depot and continuing until the final customer has been reached. After considering the mathematical formulations in their study, a freshness factor was introduced to this experiment, as the goods being delivered were fresh-cut flowers. Table 7 shows the equation and the parameters used in the modified equation.

The αk and βk values in the freshness factor equation were decided by industry experts, and the values taken in each scenario are represented in Table 8.

The average freshness rate per vehicle for each experiment is shown in Table 9. The maximum average freshness rate per instance obtained in the second experiment was 0.97.

Table 7: Mathematical equation and notation used to compute freshness rate.

Mathematical equations and variables	**Description**
$1 - \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} \mathrm{xkij}(\mathrm{tkj}\alpha\mathrm{k} + nakj\beta\mathrm{k})$	Freshness rate
Naik	The number of times the storage door of vehicle k is opened during the transportation process from the depot to customer i.
αk	The rate at which the freshness of the product decreases per unit of travel time when transported by vehicle k.
βk	The freshness reduction rate associated with the door openings that occur while the product is transported by vehicle k.

Table 8: Values inserted for alpha k and beta k.

Vehicle Number	**Experiment 01**		**Experiment 02**		**Experiment 03**	
	Alpha k	**Beta k**	**Alpha k**	**Beta k**	**Alpha k**	**Beta k**
V1	0.00018	0.0005	0.00015	0.00045	0.00018	0.0005
V2	0.00018	0.0005	0.00015	0.00045	0.00015	0.00045
V3	0.00015	0.00045	0.00015	0.00045	0.00015	0.00045
V4	-	-	0.00015	0.00045	0.00015	0.00045

Table 9: Average freshness rate

Average total freshness rate per vehicle			
Instance	**Experiment 1**	**Experiment 2**	**Experiment 3**
1	0.963	0.972	0.974
2	0.944	0.968	0.970
3	0.958	0.971	0.970
4	0.958	0.972	0.971
5	0.954	0.970	0.969
6	0.960	0.972	0.971
7	0.960	0.965	0.962
8	0.957	0.969	0.959
9	0.952	0.968	0.967
10	0.956	0.968	0.958
Average total freshness rate per vehicle per instance	**0.956**	**0.970**	**0.967**

The total cost was selected as the next KPI for this analysis. Fernando et al. (2022) conducted a study where the main goal of the objective function was to minimize the overall cost of the distribution process in the retail chain. This overall cost consists of two terms: the fixed cost associated with dispatching trucks (the labor and maintenance cost) and the fuel cost. The objective was to minimize the number of trucks used and maximize their capacity utilization to reduce the fixed cost. Additionally, the model aimed to minimize fuel consumption, resulting in a more cost-effective route plan for the distribution of goods. Table 10 shows the mathematical equation for the cost function and the variable descriptions.

Table 10: Mathematical equation and notation used to compute the cost function.

Mathematical Equation and variables	**Description**
Min -> $\sum_{k\in K}$ Fk + $\sum_{i\in V}\sum_{j\in V}\sum_{k\in K}$ Ck $*$ xkij $*$ dij	Minimize the total distribution cost
F_k	Fixed cost of dispatching the trucks
C_k	Fuel cost of kth truck per km
d_{ij}	Real-world driving distance of arc (i, j)

The same values were used for the fixed cost and variable cost for each vehicle in all three experiments.

The cost values that were obtained in each scenario are presented in Figure 1. The first experiment has the minimum total cost out of the three experiments and when comparing the second and third experiments, the third experiment can be identified as the one with better performance (please refer to Table 11).

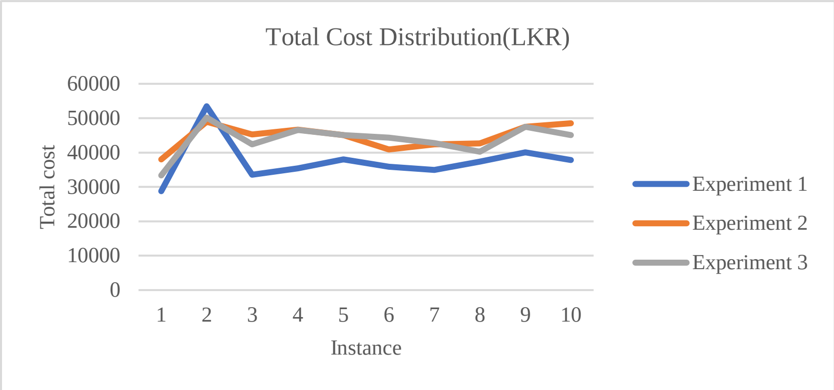

Fig. 1: Total Cost Distribution (LKR).

Table 11: Total distribution cost incurred in each instance in 3 experiments.

Total distribution cost (LKR)			
Instance	**Experiment 1**	**Experiment 2**	**Experiment 3**
1	28764	38005	33349
2	53467	48954	50182
3	33558	45249	42367
4	35437	46684	46614
5	38038	45084	45084
6	35876	40885	44319
7	34987	42404	42771
8	37332	42692	40261
9	40079	47536	47536
10	37835	48502	45106
Average total cost per instance	**37537**	**44600**	**43759**

DISCUSSION

A hybrid algorithm was utilized for the initial solution generation and used PCA heuristics. A GLS metaheuristics algorithm was employed to improve the solution further. 10 input data sets consisting of 15 customer locations and 1 depot were used, and three separate experiments were conducted for each data set to obtain minimum distribution time values, freshness rates, and distribution cost values.

In experiment 1, instance 1 of the study, each vehicle's load was below the maximum capacity of the trucks. Additionally, all customer demands were met within their designated time windows, indicating a satisfactory level of service. Based on the assumptions of the model, a 100% customer service level was achieved in this instance. The analysis of the remaining instances also revealed that all constraints were satisfied, resulting in a 100% service level, as in the first instance. Throughout the investigation, the desired level of customer service was consistently achieved across multiple instances, demonstrating the effectiveness of this approach. Like instance 1, none of the other instances violated the imposed constraints. This model ensures a 100% service level to each customer point, successfully meeting their requirements. Additionally, the perishability time was not exceeded for any of the routes, ensuring the freshness and quality of the delivered goods.

The first experiment involved a vehicle fleet with different capacities maintained by the company, consisting of vehicles capable of accommodating 150, 100, and 100 SKUs respectively. The average minimum distribution time achieved in this experiment was 241 minutes. The freshness rate, which serves as a key performance indicator (KPI), was measured at 0.956. Additionally, the total distribution cost for the company was found to be 37,537 LKR. In the second experiment, a homogeneous vehicle fleet was utilized, consisting of four vehicles with a capacity of 100 SKUs each. The average minimum distribution time in this scenario was 191 minutes. The freshness rate, measured across all four vehicles, reached a value of 0.970. The total distribution cost for the company was found to be 44,600 LKR. In the third experiment, a heterogeneous vehicle fleet consisting of four vehicles with capacities of 150, 100, 100, and 100 SKUs was utilized. In this scenario, the average minimum distribution time was 193 minutes. The freshness rate, serving as a KPI, was found to be 0.967. The total distribution cost for the company in this scenario amounted to 43,759 LKR.

As per the data gathered from the floral company, a vehicle usually takes 6 hours (360 mins) on average to complete one route. This time can be reduced to 241 minutes after setting the maximum allowed perishability time for each vehicle to 360 minutes. In every instance, the maximum allowed perishability time was not exceeded and the time was minimized. This finding implies the critical role of streamlining the distribution within the model. This model ensures prompt fulfillment of customer needs by minimizing the overall time required for distribution. This results in improved customer satisfaction and a higher probability of recurring business engagements, as there are no delays that would incur additional costs (Wang et al., 2018). Furthermore, all customer demands were successfully fulfilled within their assigned time frames, indicating a high level of satisfactory service. This examination of the remaining cases also confirms that all constraints were met, resulting in a 100% service level, similar to the initial instance. The consistent achievement of the desired level of customer service in multiple scenarios showcases the effectiveness of the proposed approach.

Another significant finding of this research is the applicability of the CVRPTWfPGSD model as a tool for comparing the performance of different combinations of vehicle fleets and identifying the best scenario based on vehicle availability. This model provides a valuable means of evaluating and comparing the efficiency and effectiveness of various vehicle fleet configurations in the context of time window constraints, capacity constraints, and perishable goods delivery. By utilizing this model, decision-makers can make informed decisions regarding the selection and allocation of vehicles to optimize the distribution process.

Based on this analysis, the minimum distribution time was identified from the second experiment, which utilizes 4 homogeneous vehicles with 100 SKU capacities. Surprisingly, the third experiment involving 4 heterogeneous vehicles with 150, 100, 100, and 100 SKUs respectively, displayed the maximum average total freshness rate. However, the minimum total cost was achieved in the first experiment, which utilized 3 heterogeneous vehicles with 150, 150, and 100 SKUs respectively. Further, when comparing experiments with an identical number of vehicles (i.e., the second and third experiments), the third experiment produced the minimum total cost. After analyzing these findings, it can be concluded that the composition of the vehicle fleet has a substantial influence on freshness level and distribution time.

An in-depth analysis of the computed freshness rates underscores the pivotal role of vehicle type in ensuring the freshness rate of cut flowers. This is due to the various attributes of the four vehicles, especially delivery time and door openings. The vehicle door openings can directly affect refrigerated trucks, as there is a huge temperature gap between the inside and the outside of the truck. Therefore, it is imperative to minimize the total number of door openings along the route, as Galarcio Noguera et al. (2018) mentioned in their study. Importantly, by using this model, fresh-cut flower distribution can be optimized to satisfy customer requirements while maximizing freshness and minimizing distribution costs.

The utilization of the CVRPTWfPGSD model has the potential to enhance the freshness and longevity of fresh-cut flowers. When delivery time is minimized, the flowers experience less exposure to unfavorable conditions during transit, resulting in improved product quality, extended shelf life, and heightened customer satisfaction. Additionally, this model offers opportunities for efficient resource utilization within the fresh-cut flower industry. It enables companies to optimize their fleet management effectively, utilizing their vehicles efficiently and maximizing productivity by considering factors such as vehicle capacity and time windows. This approach can lead to reduced idle time, improved resource allocation, and overall operational efficiency.

Beyond immediate operational gain, the application of this model can contribute to sustainability endeavors within the industry. Companies can actively reduce carbon emissions and the environmental impact associated with transportation, aligning with the industry's growing emphasis on sustainability and environmental responsibility. This holistic approach not only elevates operational efficacy but also strengthens the industry's commitment to sustainable practices, fostering a more resilient and responsible floral distribution landscape.

This study also shows the significance of prior vehicle and route scheduling in the optimization of distribution systems, especially in the context of perishable goods such as fresh flowers. Efficient vehicle and route scheduling are crucial to ensure timely deliveries, maintain product quality, and minimize operational costs. In the floral industry, where the quality and freshness of products significantly impact customer satisfaction, precise scheduling becomes paramount. By carefully planning and scheduling vehicles and routes in advance, logistics managers can mitigate the adverse effects of external factors like temperature fluctuations, ensuring that perishable products reach their destination swiftly and in optimal condition. This proactive approach not only enhances the overall performance of the supply chain but also contributes to cost-effectiveness and sustainability. Moreover, accurate scheduling allows for better resource utilization, reducing idle time and unnecessary fuel consumption. In essence, the importance of prior vehicle and route scheduling lies in its ability to streamline operations, enhance customer experience, and ultimately contribute to the success and competitiveness of the distribution system.

CONCLUSION

This study aimed to minimize the total distribution time along the designated route while adhering to various constraints, including capacity limitations, time window restrictions, customer visit requirements, perishability time restrictions, and quantity supplied limitations, to ensure the highest level of freshness in flowers throughout the supply chain. It employed a hybrid VRP algorithm consisting of heuristics and metaheuristics. The inputs provided included the latitude and longitude coordinates of customer locations, customer demand, vehicle capacities, time windows, service times, and the maximum allowable perishability time.

The study’s findings highlight the complexity of the distribution process and the need to consider multiple factors when optimizing distribution routes. It is evident that maximizing the freshness factor, minimizing the total distribution cost, or focusing solely on the number of customer visits may not lead to the most efficient distribution routes. In conclusion, this study contributes to the understanding of the relationship between distribution time, distance, and other factors in the context of fresh-cut flower distribution. By considering various constraints and analyzing different variables, the model provides insights into the optimisation of distribution routes and the minimisation of total distribution time.

This research has important implications for academia as well. It opens up exciting avenues for future studies. One area for further exploration is the incorporation of advanced freshness constraints into the model, allowing for a more comprehensive analysis of freshness in the optimization of fresh-cut flower distribution. Furthermore, there is potential to enhance the model by adjusting the objective function to incorporate various other considerations. These may include minimizing expenses, reducing the number of customer visits, maximizing revenue, minimizing overall distance traveled, and minimizing waste. These enhancements would broaden the applicability of the model and enable a more thorough investigation of different optimization goals in the context of fresh-cut flower distribution.

ACKNOWLEDGMENTS

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

Ahumada, O., & Villalobos, J. R. (2011). A tactical model for planning the production and distribution of fresh produce. Annals of Operations Research, 190(1), 339–358. https://doi.org/10.1007/s10479-009-0614-4

Calvete, H. I., Galé, C., Oliveros, M. J., & Sánchez-Valverde, B. (2004). Vehicle routing problems with soft time windows: an optimization based approach. Monografías Del Seminario Matemático García de Galdeano, 31(January 2014), 295–304.

Esmaili, M. H., & Mousavi, S. M. (2020). An integrated perishable inventory routing problem with consistent driver services and fresh product delivery using possibility and necessity measures. International Journal of Industrial Engineering and Production Research, 31(2), 231–242. https://doi.org/10.22068/ijiepr.31.2.231

Fernando, M., D. D. DHANANJAYA, J.A MUNASINGHE, Amal S. KUMARAGE, T. SIVAKUMAR, & A.S. PERERA. (2021). Post-Processing of GPS Data for Bus Link Speed Determination based on GIS. Journal of the Eastern Asia Society for Transportation Studies, 14(January 2022), 1179–1192.

Fernando, M., Thibbotuwawa, A., Perera, H. N., & Chandima Ratnayake, R. M. (2022). Applying a Capacitated Heterogeneous Fleet Vehicle Routing Problem with Multiple Depots Model to Optimize a Retail Chain Distribution Network. IEEE International Conference on Industrial Engineering and Engineering Management, 2022-Decem, 588–592. https://doi.org/10.1109/IEEM55944.2022.9989636

Fernando, M., Thibbotuwawa, A., Perera, H. N., & Ratnayake, R. M. C. (2022). Close-Open Mixed Vehicle Routing Optimization Model with Multiple Collecting Centers to Collect Farmers' Perishable Produce. 2022 International Conference for Advancement in Technology, ICONAT 2022, 1–8. https://doi.org/10.1109/ICONAT53423.2022.9725977

FloraLife. (2023). Care and Handling Best Practices (p. 0). LivRio Magazine.

Galarcio Noguera, J. D., Hernández Riaño, H. E., & López Pereira, J. M. (2018). Hybrid PSO-TS-CHR Algorithm Applied to the Vehicle Routing Problem for Multiple Perishable Products Delivery. Communications in Computer and Information Science, 916, 61–72. https://doi.org/10.1007/978-3-030-00353-1_6

Gupta, J., & Dubey, R. K. (2018). Factors Affecting Post-Harvest Life of Flower Crops. International Journal of Current Microbiology and Applied Sciences, 7(1), 548–557. https://doi.org/10.20546/ijcmas.2018.701.065

Halevy, A. H., & Mayak, S. (2011). Senescence and Postharvest Physiology of Cut Flowers-Part 2. Horticultural Reviews, 59–143. https://doi.org/10.1002/9781118060766.ch3

Malindretos, G. (2018). Cut-flowers supply chain. September 2016.

Perron, L., & Furnon, V. (2023). OR-Tools.

Ruiz-Garcia, L., & Lunadei, L. (2010). Monitoring Cold Chain Logistics by Means of RFID. In C. Turcu (Ed.), Sustainable Radio Frequency Identification Solutions. IntechOpen. https://doi.org/10.5772/8006

Shaabani, H. (2022). A literature review of the perishable inventory routing problem. Asian Journal of Shipping and Logistics, 38(3), 143–161. https://doi.org/10.1016/j.ajsl.2022.05.002

Sirisaranlak, P. (2017). The Cool Supply Chain Management for Cut Flowers oncordance for Self- English Writing of. 2004.

Taillard, Eric; Badeau, P; Gendreau, M. (1997). A tabu search heuristic for the VRP with soft TW. In Transportation Science (Vol. 31, Issue 2, pp. 170–186).

Toth, P., & Vigo, D. (2001). THE VEHICLE ROUTING PROBLEM. Society for Industrial and Applied Mathematics Philadelphia.

Van Rijswick, C. (2015). World Floriculture Map 2015. Rabobank Industry Note, # 475(January), 1–4.

Wang, X. P., Wang, M., Ruan, J. H., & Li, Y. (2018). Multi-objective optimization for delivering perishable products with mixed time windows. In Advances in Production Engineering And Management (Vol. 13, Issue 3, pp. 321–332). https://doi.org/10.14743/apem2018.3.293

Sara Rodrigo
Center of Supply Chain, Operations, and Logistics Optimization,
University of Moratuwa, **Sri Lanka**
Department of Transport Management and Logistics Engineering,
University of Moratuwa, **Sri Lanka**
e-mail: hasinisararodrigo@gmail.com

Dilina Kosgoda ORCID ID: https://orcid.org/0009-0003-7681-4983
Center of Supply Chain, Operations, and Logistics Optimization,
University of Moratuwa, **Sri Lanka**
Department of Transport Management and Logistics Engineering,
University of Moratuwa, **Sri Lanka**
e-mail: dilinak@uom.lk

W. Madushan Fernando ORCID ID: https://orcid.org/0000-0003-4505-980X
Center of Supply Chain, Operations, and Logistics Optimization,
University of Moratuwa, **Sri Lanka**
Department of Transport Management and Logistics Engineering,
University of Moratuwa, **Sri Lanka**
e-mail: fernandowwpm.22@uom.lk

Peter Nielsen ORCID ID: https://orcid.org/0000-0002-7752-9514
Department of Materials and Production,
Aalborg University, **Denmark**
e-mail: peter@mp.aau.dk

Amila Thibbotuwawa ORCID ID: https://orcid.org/0000-0002-5443-8839
Center of Supply Chain, Operations, and Logistics Optimization,
University of Moratuwa, **Sri Lanka**
Department of Transport Management and Logistics Engineering,
University of Moratuwa, **Sri Lanka**
e-mail: amilat@uom.lk