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An integrated vehicle routing model to optimize agricultural products distribution in retail chains

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ABSTRACT

The Vehicle Routing Problem (VRP) represents a thoroughly investigated domain within operations research, yielding substantial cost savings in global transportation. The fundamental objective of the VRP is to determine the optimal route plan that minimizes the overall distance traveled. This study employs VRP to address the challenge of distributing fresh agricultural products within retail chains. It introduces an integrated bi-objective VRP model that concurrently optimizes resource allocation, order scheduling, and route planning. The proposed model incorporates two objective functions with the goals of minimizing total distribution costs and ensuring timely product deliveries to retail outlets. Real-world characteristics are integrated to enhance practical applicability. All solution algorithms and the developed VRP model undergo testing using data from one of Sri Lanka's largest retail chains. Numerical experiments showcase the efficiency of the proposed algorithm in solving real-world VRP problems. Moreover, the proposed VRP model achieves a 19% reduction in daily distribution costs, including a 24% saving in fuel costs. This not only provides financial benefits but also contributes to the reduction of the carbon footprint of retail chains. The model ensures on-time deliveries to 95% of retail outlets, which is crucial for maintaining the quality of fresh food. The findings of this study underscore the significant cost savings, enhanced sustainability, and improved quality associated with the efficient distribution of fresh agricultural products within retail chains.

1. Introduction

The Vehicle Routing Problem (VRP) is a particularly important problem due to its many practical applications in transportation, logistics, and supply chain management (Braekers et al., 2016). The VRP is a complex problem introduced by Dantzig and Ramser (1959) as a "truck dispatching problem" in 1959 and has since evolved to become one of the most widely studied applications (Braekers et al., 2016; Perera & Perera, 2022; Thibbotuwawa et al., 2020; Sitek et al., 2021). The initial VRP model developed by Dantzig and Ramser (1959) attempted to find optimal routes for a homogeneous fleet of trucks from the central depot to gas stations. Optimization packages based on solving the VRP have achieved substantial cost savings in global transportation (Utama et al., 2020).

Different VRP extensions have been applied to solve interesting applications such as unmanned aerial vehicle routing (Thibbotuwawa et al., 2020; Thibbotuwawa et al., 2019), electric vehicle routing (Çalık et al., 2021), and green vehicle routing with the emission factor (Moghdani et al., 2021), expanding the scope of optimization in diverse domains. This paper intends to focus on the extended VRP for perishable goods distribution (VRPFPG). Perishable products, including fresh agricultural products, dairy, meat, and pharmaceutical products, have a short shelf life and should be delivered before their quality degrades. Therefore, the VRPFPG deviates from the traditional VRP, and it's crucial to tackle the additional operational complexities together with optimizing routes, giving due attention to time sensitivity, handling constraints, and quality assurance and compliance (Utama et al., 2020).

On the other hand, food security is cited as one of the most serious threats to achieving the United Nations Sustainable Development Goals (SDGs) (Krishnan et al., 2020; Pannila et al., 2022). Nevertheless, a significant 33 % of the world's agricultural produce goes to waste as Post-Harvest Waste (PHW) (Surucu-Balci & Tuna, 2021; Jayalath &

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Perera, 2021). Especially, fresh agricultural products must be delivered before they degrade (Zulvia et al., 2020). The complexity is exacerbated by the fact that retail shops cannot keep extra stock for fresh agricultural products due to their perishability, and they thus need to be delivered frequently (Zulvia et al., 2020). This implies the need to optimize transport and distribution processes in agricultural supply chains. Furthermore, reducing distribution costs in agricultural supply chains can lead to lower fuel consumption, helping to reduce the carbon footprint of agricultural distribution networks. The overall environmental impact can be reduced by optimizing transport and distribution processes while ensuring efficient and sustainable delivery of fresh agricultural products.

In this research, the VRP was formulated in terms of optimizing the distribution of fresh vegetables in retail chains. There has been a considerable increase in the demand for commodities as the world's population grows (He & Haasis, 2019). Within retail chains, there has been a significant rise in urban freight volumes (He & Haasis, 2019; Mancini & Gansterer, 2022). Estimates project a 36 % increase in the number of delivery vehicles over the next decade (Gutierrez-Franco et al., 2021). These trends pose numerous problems to urban traffic management, threatening the effectiveness of urban distribution systems (Gutierrez-Franco et al., 2021).

This paper emphasizes the importance of practically oriented VRP models by addressing real-world challenges and providing practical solutions to optimize operations and improve performance. The goal is to bridge the existing gap by combining numerous real-world features connected with fresh agricultural product distribution in retail chains. The following is how the paper is structured: Section 2 examines existing VRPFPG models and their approaches to solution in detail. Section 3 describes the proposed model's mathematical formulation. Section 4 summarizes the details of the applied solution algorithms, while in section 5, you will find information about the case study. Section 6 then presents the outcomes of numerical experiments, including a comparison of different solution approaches and the performance of the suggested model. Finally, Section 7 provides concluding observations and suggests prospective future study avenues.

2. Literature review

Mathematically, the VRP is represented as a directed graph G (V, A), where V = {0,1,2, n} is a set of predefined vertices, and A = {(i, j): i,j ∈ N} represents a set of arcs connecting any two vertices (Clarke & Wright, 1964; Huang & Lin, 2015). The depot is represented by vertex i = 0, while the other vertices represent customer locations. VRP models are primarily formulated to minimize travel distance or time. This literature review discusses scientific works related to VRPFPG models, with the aim of identifying gaps between theoretical models and real-world applications. The rationale for extensively reviewing VRPFPG models lies in recognizing agricultural products as a distinct sub-category within the perishable goods domain. By leveraging insights from existing VRP studies on perishable goods, this study aims to extract valuable methodologies and strategies applicable to the unique challenges posed by the distribution of fresh agricultural products, ensuring a comprehensive foundation for the proposed model. Identifying and addressing the gap between theoretical models and real-world applications of vehicle routing is crucial for ensuring the robustness of logistics systems. Bridging this divide allows for more accurate representation and adaptation of models to the complexities of practical logistics operations, enhancing their effectiveness and contributing to the overall resilience and efficiency of logistics systems (Ezaki et al., 2022; Nanayakkara et al., 2022; Thibbotuwawa et al., 2023).

2.1. Problem characteristics

The majority of the reviewed research primarily concentrates on single-depot close-VRP models, with only a minority delving into intermediate depots (Nadhori and Ahsan, 2019; Tirkolaee et al., 2020). Moreover, the majority of these studies operate under the assumption of uniform vehicle capacities (Sitek & Wikarek, 2014), and only a handful consider fleets of vehicles with different capacities (Nadhori and Ahsan, 2019; Tirkolaee et al., 2020). This means that there are only a limited number of papers that investigate the use of multi-compartment vehicles and the handling of multiple products (Chen & Shi, 2019).

Interestingly, time windows are incorporated in the majority of the reviewed VRPFPG papers. Three types of time window structures are included: hard (Nadhori & Ahsan, 2019), soft (Zulvia et al., 2020), and mixed (Rashidi Komijan & Delavari, 2017). Service providers must meet the hard time windows and if the service provider fails to meet this requirement, they must drop that customer to keep the solutions feasible (Patidar et al., 2019). Amorim and Almada-Lobo, (2014) compare two distribution scenarios with narrow and wide hard time structures. It is highlighted that distribution costs are high for the narrow hard time window structure. In a soft time window structure, it is feasible to violate the time window constraint with a penalty cost (Zulvia et al., 2020). Mixed time windows are a combination of soft and hard time windows. In all the reviewed papers, the time windows had been imposed by the customers. None of the papers reviewed in the study consider the time windows imposed by the distribution center due to the limitations of the loading bays. Moreover, all the studies that incorporate time windows tend to use onsite service time (loading/unloading time) as an input in their models.

Most of the VRPFPG studies develop optimization models as deterministic models. Only a few researchers focus on developing stochastic models, including stochastic travel times and service demands (Zulvia et al., 2020; Rong & Sha, 2014). Moreover, no reviewed article in the study uses real-time data. Usually, travel times are varied based on the time of day due to congestion (Zulvia et al., 2020). Hence, considering time-dependent travel times guarantees the real-world applicability of the VRP models (Zulvia et al., 2020). Time-dependent travel time can be obtained using the average speeds of a considered road network based on varying congestion levels (Zulvia et al., 2020; Sung & Nielsen, 2020). Problem characteristics such as pick-up delivery and multiple product delivery are rarely explored in the existing literature (Abraham et al., 2012; Galarcio Noguera et al., 2018). Moreover, the findings highlight that most reviewed papers use synthetic data to test the models and rarely focus on using real-world case studies.

Most existing VRPFPG models include real-life characteristics either individually or in combination with a limited set of other factors. The literature review highlights those certain real-world aspects, such as multiple distribution centers, diverse vehicle fleets, multiple product deliveries, and actual driving distances, have rarely been integrated into the current VRPFPG literature. Additionally, there is a notable lack of emphasis on the development of integrated VRP models. This study aims to address this gap by concurrently incorporating various real-life complexities, aligning with the prevailing trend in this research area, and supported by advancements in computational power (Utama et al., 2020).

2.2. Objective functions driving VRPFPG models

As shown in Fig. 1, the most common objective function used in single-objective VRPFPG models is to minimize the cost of distribution (Utama et al., 2020). Depending on the focus of the studies, various cost components were taken into consideration. Most studies include transportation costs as a component of distribution costs (Tirkolaee et al., 2020; Yao et al., 2019), and these typically comprise the fuel and fixed costs associated with the vehicles (Meneghetti et al., 2019). Additionally, a few studies incorporated various penalty costs, including those related to time window violations and freshness conditions (Taylor et al., 2013; Agustina et al., 2014).

Temperature-controlled vehicles transport perishable goods such as pharmaceuticals, meat, and dairy products. As a consequence,

Fig. 1. Objective functions of single-objective VRPFPG models.

refrigeration costs were included as part of the distribution expenses (Meneghetti et al., 2019). Additionally, some researchers include production and order scheduling costs as a component of distribution costs since the VRP models integrate production or order scheduling submodels (Seyedhosseini & Ghoreyshi, 2014; Lacomme et al., 2018). Very few considered different objectives other than minimizing the total cost of distribution among single-objective models reviewed in this study (Tirkolaee et al., 2020; Meneghetti et al., 2019).

Many logistics problems are multi-objective since there are various factors to be considered simultaneously (Montoya-torres et al., 2015). Most of the time, those multiple factors conflict with one another (Montoya-torres et al., 2015). Therefore, considering those factors simultaneously is critical for minimizing the difference between theoretical models and complexities present in real-world applications (Montoya-torres et al., 2015). As illustrated in Fig. 2, the majority of multiple-objective models focus on optimizing distribution costs and the freshness of the products (Amorim & Almada-Lobo, 2014; Khalili-Damghani et al., 2015; Wang et al., 2016; Rahbari et al., 2019; Fatemi Ghomi & Asgarian, 2019). Amorim and Almada-Lobo (2014) studied the trade-off between different distribution scenarios and the cost associated with the freshness states.

Several multiple-objective models focus on incorporating environmental costs incurred during the distribution process. The environmental costs include the cost of carbon and greenhouse gas emissions (Govindan et al., 2014; Sahraeian & Esmaeili, 2018). Other factors that have been considered in multiple-objective models are minimizing travel distance (Buelvas et al., 2018), fuel consumption (Navazi et al., 2019), customer waiting time (Esmaili & Sahraeian, 2017), weighted deterioration ratio (Lu & Wang, 2018), and damage cost (Lu & Wang, 2018; Buelvas et al., 2018; Zulvia et al., 2020), as well as maximizing customer satisfaction (Gong & Fu, 2010; Navazi et al., 2019; Zulvia et al., 2020) and balancing the load (Kuo & Nugroho, 2017).

2.3. Solution approaches

Diverse solution methods are employed to address different extensions of the VRP (Braekers et al., 2016). Fig. 3 distinguishes these methods as exact, heuristic, metaheuristic, and hybrid approaches (Braekers et al., 2016). The metaheuristic method is the most widely used solution approach among the reviewed VRPFPG papers. Compared to metaheuristic algorithms, heuristic algorithms are problem-specific, and applicability is therefore limited (Braekers et al., 2016). Exact methods can find optimal solutions for NP-hard (non-deterministic polynomial-time hardness) problems, but only when the problem size is small (Braekers et al., 2016). In addressing real-world applications of a vehicle routing model using exact methods, there exists a trade-off between the precision of the solution and the computational time required (Wang & Li, 2022). Therefore, only a minimal number of VRPFPG research studies apply exact methods to solve the problems (Utama et al., 2020). Using a single VRP solution method may prove inadequate due to factors like local minima, suboptimal outcomes, and excessive computation time (Moghdani et al., 2021). To overcome limitations, researchers combine two solution approaches, creating hybrid techniques that include metaheuristic-exact, metaheuristic-heuristic, and metaheuristic-metaheuristic methods, all aimed at achieving superior results (Moghdani et al., 2021).

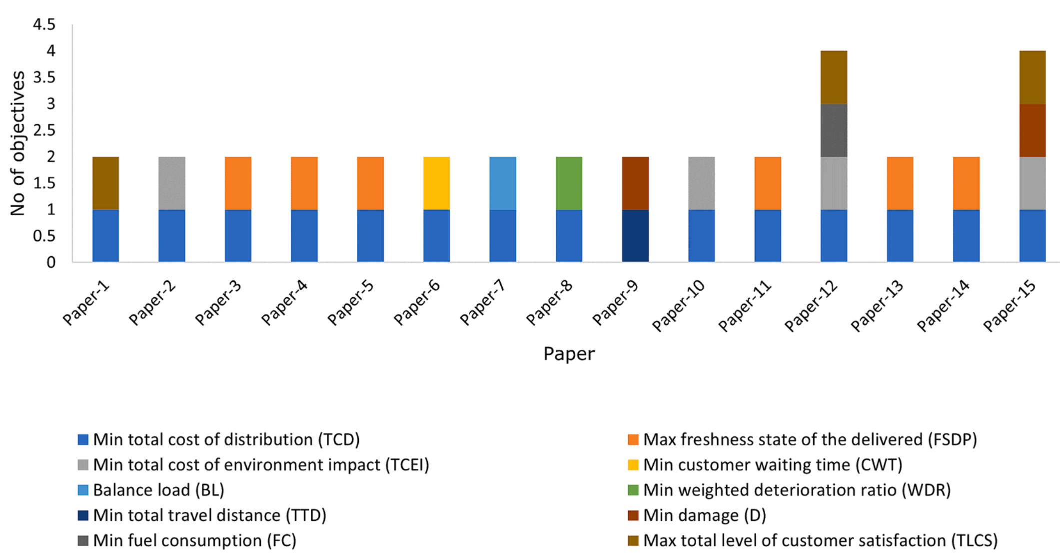

Fig. 2. Objective functions of multiple-objective VRPFPG models.

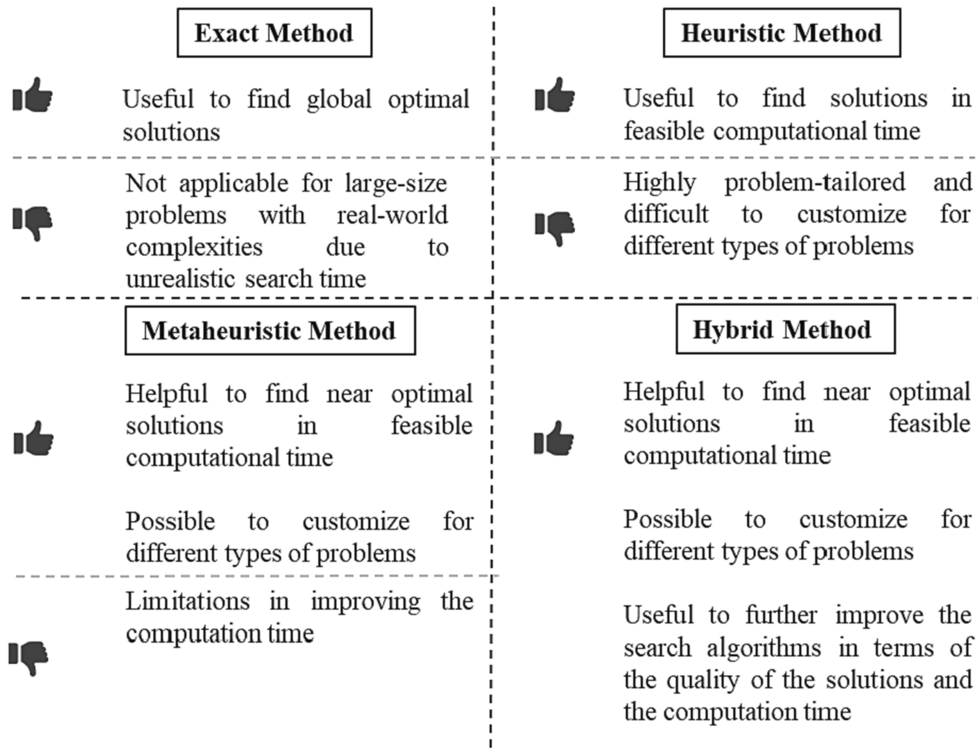

Fig. 3. Comparison of different types of solution methods (Fernando et al., 2022b).

2.4. Gap analysis

Based on the literature review, it appears that there is a scarcity of research devoted to addressing multi-objective VRPFPG models. It is emphasized that many logistics problems are multi-objective by nature and need to consider multiple factors simultaneously. Therefore, further research is required to consider numerous case-sensitive objectives in VRPFPG (Montoya-torres et al., 2015).

RQ1: How can a bi-objective VRPFPG model be formulated with more realistic assumptions and industry-relevant constraints to improve its practical application?

Researchers frequently employ problem-specific solution methods for VRP, which may not readily translate to other problem variations. Additional research is needed to conduct a comprehensive assessment of various metaheuristic methods' performance in solving diverse VRP extensions (Braekers et al., 2016).

RQ 2: *What is the effectiveness of various metaheuristic methods in solving the proposed bi-objective VRPFPG model, and how do they compare in terms of solution quality and computational time?*

Existing VRPFPG models lack comprehensive consideration of real-world complexities such as multiple distribution centers, heterogeneous vehicle fleets, diverse product deliveries, and actual driving distances. Recent trends indicate a growing effort among researchers to address these gaps, leveraging improved computational power. However, integrated VRP models remain an underexplored area in the current literature (Utama et al., 2020).

RQ 3: *How applicable is the proposed bi-objective VRPFPG model to real-world applications, and what are the practical limitations and challenges that need to be considered in its implementation?*

3. Model formulation

The research identified the decision variables, objective functions, and constraints specific to the application of delivering agricultural products in a retail chain. Both the literature review and the unstructured interviews conducted with industry experts were used to define the problem and to get a clear understanding of the goal that needs to be optimized. The proposed model is a combination of CVRP (Capacitated VRP) (Fernando et al., 2022a), VRPSTW (VRP with Soft Time Windows, i.e., soft time windows with upper bounds) (Ma et al., 2017), MDVRP (Multi-depot VRP) (Fernando et al., 2022a), HFVRP (Heterogenous Fleet VRP) (Fernando et al., 2022a; Fernando et al., 2022c), Asymmetric Costs VRP (ACVRP) (Fernando et al., 2022b), and MOVRP (Multi-objective VRP) (Zulvia et al., 2020; Schneider & Nurre, 2019). Fig. 4 depicts a high-level overview of the model. The model's overall goal is to reduce the costs associated with retail chain distribution. Since agricultural products are delivered very frequently in retail chains, it is critical to keep operating costs at a minimum (Zulvia et al., 2020). Furthermore, the model reduces penalty costs caused by late deliveries. The constraints were defined based on real-world assumptions and classified into three categories, namely resource constraints, service constraints, and operational constraints (Yi et al., 2021).

3.1. Assumptions

The assumptions listed below were used to develop the proposed optimization model. When defining the assumptions, emphasis was placed on ensuring the model's real-world applicability, as well as the ability to solve a large-scale problem.

I. Commencing from a central distribution center, each truck initiates the delivery process by transporting goods to designated retail outlets and then returning to its original starting point.
II. The demand for each product at every retail outlet is determined prior to dispatching the trucks.
III. In this distribution system, the policy does not allow split deliveries, meaning that each retail outlet is exclusively serviced by a single truck.
IV. The truck capacities in this system are characterized by deterministic and heterogeneous values, measured in terms of vegetable crates.

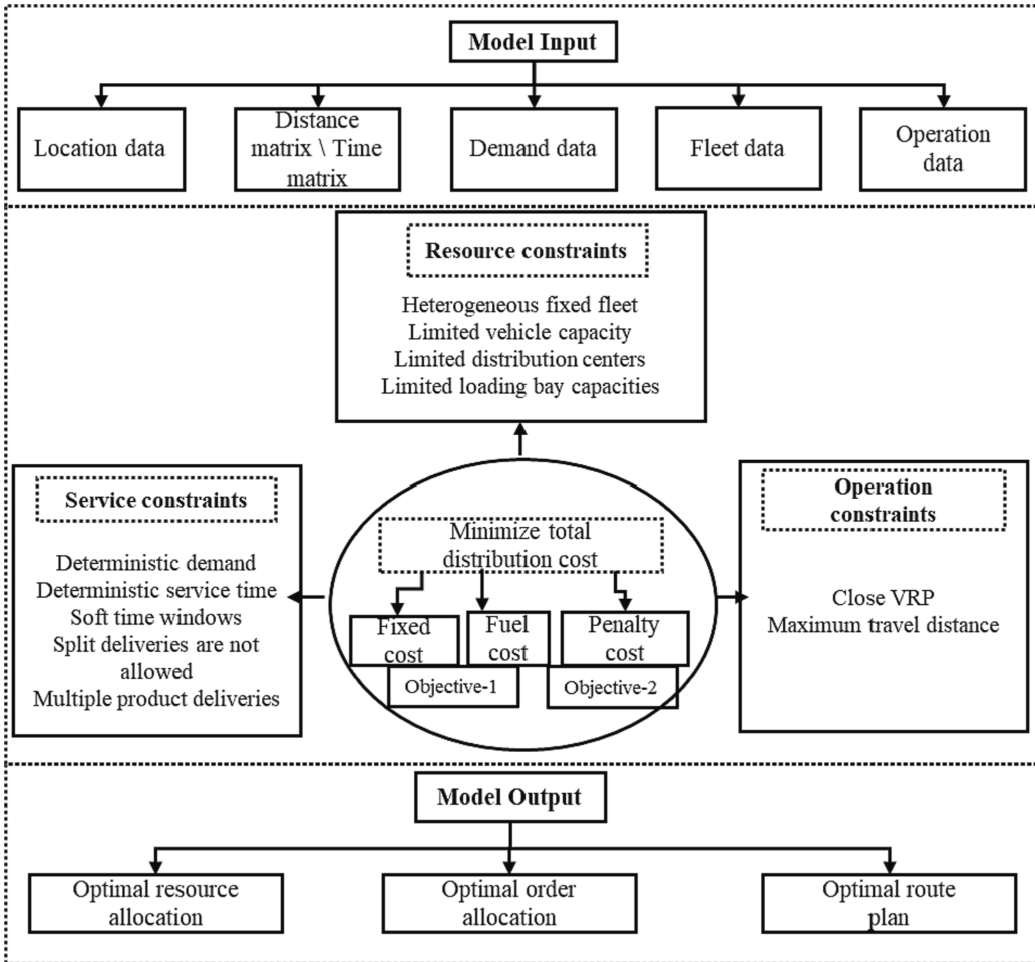

Fig. 4. Model overview.

V. Truck speeds between retail chain network nodes are deterministic and do not vary with the time of day.

3.2. Notations

Table 1 contains the sets, parameters, and decision variables used in the model formulation.

3.3. Objective functions

The model's primary goal is to reduce the overall cost of transporting goods within the retail chain distribution. In pursuit of this goal, the first term of the model's objective function represents the fixed costs associated with truck dispatching, which include expenses such as labor and truck maintenance. Hence, the model aims to minimize the required number of trucks for distribution while optimizing the utilization of each truck's capacity. The objective function's second term is concerned with fuel costs. The proposed model provides guidance for selecting more cost-effective routes by minimizing fuel consumption in the retail chain distribution.

$$Minimize \sum_{k\in k} F^k + \sum_{(i,j)\in A}\sum_{k\in k} c_k x_{ij}^k d_{ij} \tag{1}$$

The second objective of the model minimizes stockout situations that occur due to late deliveries of products. In retail chains, fresh agricultural products are delivered daily. Moreover, limited stocks are kept in retail outlets to avoid wastage due to perishability. It is therefore important to deliver fresh agricultural products to retail outlets during the required time window. This objective has defined a penalty for late deliveries. The model aims to meet the requested time schedules to minimize these penalty costs.

$$Minimize \sum_{j\in R} P_j\left(t_j^k\right) \tag{2}$$

3.4. Constraints

Constraint (1) guarantees that each retail outlet is attended to by a single truck, eliminating the possibility of split deliveries. Split deliveries, involving dividing the goods among multiple trucks, lead to increased transportation expenses. By upholding this constraint, the model promotes efficient and cost-effective distribution by averting unnecessary delivery fragmentation.

$$\sum_{k\in K}\sum_{i\in Nj\neq i} x_{ij}^k = 1 for \forall j \in R \tag{1}$$

Constraint (2) mandates that every truck commences its route from a specified distribution center and also necessitates that all trucks conclude their routes at that very same distribution center following their service at the designated retail outlets.

$$\sum_{k\in K}\sum_{i\in Dj\neq i} x_{ij}^k = \sum_{k\in K}\sum_{i\in Dj\neq i} x_{ji}^k for \forall j \in R \tag{2}$$

Originally, vegetable quantities supplied to each retail outlet were measured in kilograms. However, each product is transported using vegetable crates. Therefore, it is more convenient to use vegetable crates

Table 1
Notations used in the model.

Sets	Descriptions
D	$\{d\|d=1,2,\cdots,n\}$; Set of distribution centers
R	$\{r\|r=1,2,\cdots,n\}$; Set of retail outlets
N	$N\in D\cup R$; Set of nodes
K	$\{k\|k=1,2,\cdots,n\}$; Set of truck fleet
P	$\{p\|p=1,2,\cdots,n\}$; Set of products
A	$\{(i,j):i,j\in N\}$; Set of arcs
Parameters	***Descriptions***
n_d	Number of distribution centers
n_k	Number of trucks
n_c	Number of retail outlets
d_{ij}	Driving distance of arc (i,j) ∈ A
t_{ij}^k	Driving time of k^{th} truck for an arc (i,j)∈ A
v_{ij}	The traffic flow speed of (i,j)∈ A
q_j^p	Quantity delivered to retail outlet j from product p in kilos
r^p	Number of kilos per vegetable crate for product p
$\widetilde{q}_j^p$	Quantity delivered to retail outlet j of product p in crates
q_j	Total quantity delivered to retail outlet j (no of crates)
Q_k	The capacity (no of crates) of truck k
U_j^k	Cumulative quantity delivered by k^{th} truck at retail outlet j
ST_i	Average service time at retail outlet i
t_j^k	Time k^{th} truck visit retail outlet j
t_i^k	Time k^{th} truck visit retail outlet i
e_j	Upper bound of soft time windows
p	Penalty cost
F^k	Fixed cost
c_k	Fuel cost per km
$P_j(t_j^k)$	Penalty cost for violating time windows
d_{max}	Maximum trip length
Y_t^d	Number of trucks can be loaded in distribution center d at a given time t
c^d	Loading-bay capacity in distribution center d
φ	Large number
Decision variables	
$x_{ij}^k=\begin{cases}1, If k^{th} truck is used for arc(i,j)\\ 0, Otherwise\end{cases}$	

as the unit of measurement. Equation 3 ensures this unit conversion. Here, the parameter (r^p) was defined for this purpose.

$$\widetilde{q}_j^p = q_j^p/r^p for \forall p\in P \tag{3}$$

Constraint (4) ensures that the total quantity delivered to each retail outlet aligns with the sum of its specific product quantities.

$$q_j=\sum\nolimits_{p\in P}\widetilde{q}_j^p for\forall j\in R \tag{4}$$

Constraint (5) ensures that the cumulative supply quantity up to the j^{th} outlet equals the sum of the supply quantity up to the previous retail outlet and the quantity supplied to the j^{th} outlet.

$$U_i^k+q_j=U_j^k for\forall x_{ij}^k=1\&i,j\in R\&k\in K \tag{5}$$

Constraint (6) guarantees that the total quantity transported by the k^{th} truck remains within its capacity limit. Given the model's inclusion of a fleet with varying truck capacities, this constraint accounts for each truck's capacity individually.

$$U_j^k\le Q^k\forall j\in R\&k\in K \tag{6}$$

Constraint (7) elaborates how arrival time for the j^{th} retail outlet is calculated. It is calculated by adding the travel time (t_{ij}^k) to the departure time of the i^{th} outlet ($t_i^k+ST_i$).

$$t_j^k=t_i^k+ST_i+t_{ij}^k for\forall x_{ij}^k=1\&i,j\in R \tag{7}$$

Constraint (8) ensures delivery of products to retail outlets before the requested time. The model applies the soft time window with a penalty cost. Here, $P_j\left(t_j^k\right)$ represents the penalty cost if truck k does not meet the time window imposed by the retail outlet j. Specifically, the model needs to minimize stockout situations due to late deliveries. Therefore, the model has applied soft time windows with an upper bound to determine the penalty cost incurred due to late deliveries. The upper bound is represented by e_j, and the products must be delivered before that time to avoid the penalty cost. This constraint is linked to objective (2), and it guides the reduction of late deliveries.

$$P_j(t_j^k)=\begin{cases}0; t_j^k\le e_j\\ p*\left(t_j^k-e_j\right); t_j^k>e_j\end{cases} \tag{8}$$

Constraint (9) is introduced to eliminate sub-tours in the routing plan for the retail distribution chain.

$$t_j^k=t_i^k+ST_i+t_{ij}^k for\forall x_{ij}^k=1\&i,j\in R \tag{9}$$

Constraint (10) imposes a maximum trip length for each truck. Trucks can thus provide services to a limited number of retail outlets while adhering to the maximum trip length (d_{max}). Furthermore, this constraint eliminates impractical trip lengths and manages working shifts of drivers.

$$\sum_{(i,j)\in A}x_{ij}^k d_{ij}\le d_{max} for\forall x_{ij}=1\&k\in K\&d\in D \tag{10}$$

Constraint (11) represents the limited number of loading bays in distribution centers. Accordingly, only a limited number of trucks can be loaded in distribution centers at any given time.

$$Y_t^d=c_d\forall d\in D \tag{11}$$

4. Solution methods

In this research, the primary focus lies on solving a real-world distribution problem rather than developing a completely novel solution approach for addressing a variant of the VRP. By considering the pros and cons of each solution category (Fig. 2), a hybrid solution approach was selected to solve this real-world distribution problem. Researchers typically hybridize heuristic and metaheuristic methods to achieve better results (Moghdani et al., 2021). This research employs a two-phase solution approach using heuristic and metaheuristic methods for each phase respectively. Here, the heuristic approach was used to obtain the initial feasible solutions for the proposed model. Thenceforth, the metaheuristic approach is applied to improve the quality (Fernando et al., 2022b).

4.1. Initial solution method

As previously stated, using a heuristic technique proved helpful in producing Initial Basic Feasible Solutions (IBFS). This heuristic method is important for reducing the requirement for excessive iterations throughout the enhancement process (Amaliah et al., 2020). This study employs the Clarke and Wright (CW) algorithm for vehicle routing scheduling (Fernando et al., 2022b). The CW algorithm comprises two versions: sequential and parallel (Fernando et al., 2022b). In practice, the parallel version of the CW algorithm performs better (Fernando et al., 2022b). Hence, the choice was made to utilize the parallel version of the CW algorithm to obtain the IBFS.

4.2. Iterative improvement of IBFS

Metaheuristics are widely used in VRP research because of their ability to produce better solutions in less time. To improve IBFS attained by CW algorithm, this study employs three metaheuristic approaches: Guided Local Search (GLS), Simulated Annealing (SA), and Tabu Search (TS). These metaheuristics improve IBFS by utilizing iterative neighborhood search techniques, which include a route-based two-opt procedure and three inter-route procedures: relocate, exchange, and cross.

Local search methods, which are noted for their efficiency and simplicity, are effective even in large-scale issues, providing reasonably excellent solutions quickly. Such local search algorithms are especially useful for VRPs that demand practical, near-real-time solutions (Kilby et al., 2002; Arostegui et al., 2006; Glover, 1986).

4.2.1. Guided local search

Guided Local Search (GLS) is a metaheuristic that employs an augmented cost function, as illustrated below, to incorporate memory and direct the local search process.

$$g(x) = f(x) + \lambda \sum_i (I_i(x)^* p_i) \tag{1}$$

The augmented cost function, denoted as *g(x)*, supplements the original objective function *f(x)* in GLS. This technique penalizes aspects related to previously encountered local minima, directing the search toward improved solutions. In the formula, l_i *(x)* represents a binary decision variable, assuming a value of 1 when the current solution resembles past findings, with p_i denoting associated penalties. The method's search process is influenced by a penalty factor *(λ)* dictating diversification or intensification; higher λ values encourage exploration, while lower ones favor focused search. Importantly, the penalty term undergoes iterative adjustments until nearing an optimal solution (Kilby et al., 2002).

4.2.2. Simulated annealing

Simulated Annealing (SA) is a metaheuristic that applies a probabilistic approach to obtain a near-optimal solution in the process of local search. The SA algorithms' basic concept is to determine whether a given neighbor $\boldsymbol{x_{test}}$ (candidate solution) in the neighborhood $\boldsymbol{N_x}$ should be accepted or not. The acceptance probability $\boldsymbol{P}$ evolves and becomes lower and lower so that at the start of the algorithm a large portion of the search space can be reached, and the probability gradually but steadily converges toward zero. Thereby, the algorithm reaches the final neighborhood. Here, the system is said to be moving toward lower energy states (Arostegui et al., 2006).

4.2.3. Tabu search

Tabu Search (TS) is a memory-based metaheuristic that evaluates neighboring solutions until they reach the global optimal. This technique uses memory structures to store recently evaluated candidate solutions. The candidates stored in these structures are not eligible for further candidate generation and are thus considered "Tabu" by the algorithm. By utilizing these memory structures, the technique trades space for time, thereby speeding up the search for the best solution (Glover, 1986).

5. Case study

This case study is based on data acquired from one of Sri Lanka's leading retail chains, which includes a variety of data categories such as location, demand, fleet, and operations. The location data includes retail outlet and distribution center locations, with a total of 247 retail outlets and two distribution sites included in model testing. The proposed model's major input is distance matrix developed from location data and computed using real driving distances between network nodes in the retail chain. The results of (Fernando et al., 2022a) shown that the VRP models fall short in optimizing routes when relying on Euclidean distances, as they do not account for the actual road network geometry. Additionally, assuming symmetric VRP may not align with real-world complexities. Hence, it is recommended to use real driving distances, as suggested in prior research for real-world VRP applications. In this case study, real-world driving distances were incorporated using the OSRM (Open-Source Routing Machine) API, emphasizing the significance of accurate road network data for improving the model's practicality and effectiveness (Fernando et al., 2021).

The proposed model incorporates multiple product deliveries in the retail distribution network. The research collected demand data for 32 types of vegetables. Demand data were collected for all 247 retail outlets and initially measured in kilograms. In this case study, fresh agricultural products are transported using vegetable crates to minimize wastage. Therefore, demands were estimated in terms of crates since it is convenient to apply to the model. In this case parameter (r^p) (number of kilos per vegetable crate for product p) was defined and estimated for all product types using an unstructured expert interview and it is indicated in Fig. 5. This parameter was used to make the required unit changes. In conclusion, this case study and its associated model were methodically built with a primary focus on applying best practices for the delivery of fresh agricultural products. We streamlined the distribution network by gathering demand data for 32 vegetable types from 247 retail outlets and translating it into crate-based measures.

Fleet data includes information about 55 trucks used in the selected retail chain. The carrying capacities of each truck were measured in terms of vegetable crates that each truck could transport. In addition, the costs associated with the truck fleet were obtained through unstructured interviews with experts. Additionally, operational data such as loading bay capacities, the average time taken for loading at distribution centers, requested time windows, and service times at retail outlets were collected.

6. Results and discussion

6.1. Details of the computational experiment

This research carried out two types of computational experiments; they are highlighted in Fig. 6. In the first type, we investigated various solution techniques for solving the proposed VRP model. Under the second type, the proposed VRP model was tested concerning various model outputs. All computational experiments were performed on a computer equipped with a Core i5, 5200U processor running at 2.40–2.42 GHz, and 8 GB RAM in Windows 10 Home 64 bit. OR-Tools version 7.2 (Laurent and Vincent, 2022) and Python version 3.9.6 in Visual Studio Code version 1.60 were used to develop the algorithms. Furthermore, all the metaheuristic methods (GLS, SA, TS) were implemented with the default search parameters set by OR-Tools version 7.2.

We defined ten problem instances for these numerical experiments, as shown in Table 2. Zulvia et al. (2020) defined problem instances with the number of customers served changing for each problem instance. The research defined problem instances based on the problem's size. The number of retail outlets was used to define problem sizes. Further, objective value (cumulative route length) and computation time were selected as KPIs to compare the selected solution techniques.

6.2. Experiment results: Solution methods

Fig. 7 depicts the results of the proposed VRP model's solution using three metaheuristics for one of the problem instances. The goal of this experiment is to see how three metaheuristics are performed when the number of iterations is changed. Further, this experiment was carried out using the largest problem instance of the selected case study (250), as it is the hardest to solve computationally. Up to 250 iterations, all three methods performed nearly equally, according to the results. Furthermore, a significant improvement in IFBS can be observed up to 250 iterations. When the number of iterations exceeds 250, the objective values of the SA method tend to remain constant.

Furthermore, the results show that GLS outperforms SA and TS in solving the proposed VRP model with the default search parameters set by OR-Tools version 7.2. In comparison to the SA and TS, GLS improved solutions by 4 % and 2.3 %, respectively. Further, GLS improved IFBS by 19 % when solving the model for the selected case study. Kilby et al. (2002) also show that GLS outperforms TS in solving Solomon's instances which are not real. Current research shows the performance of

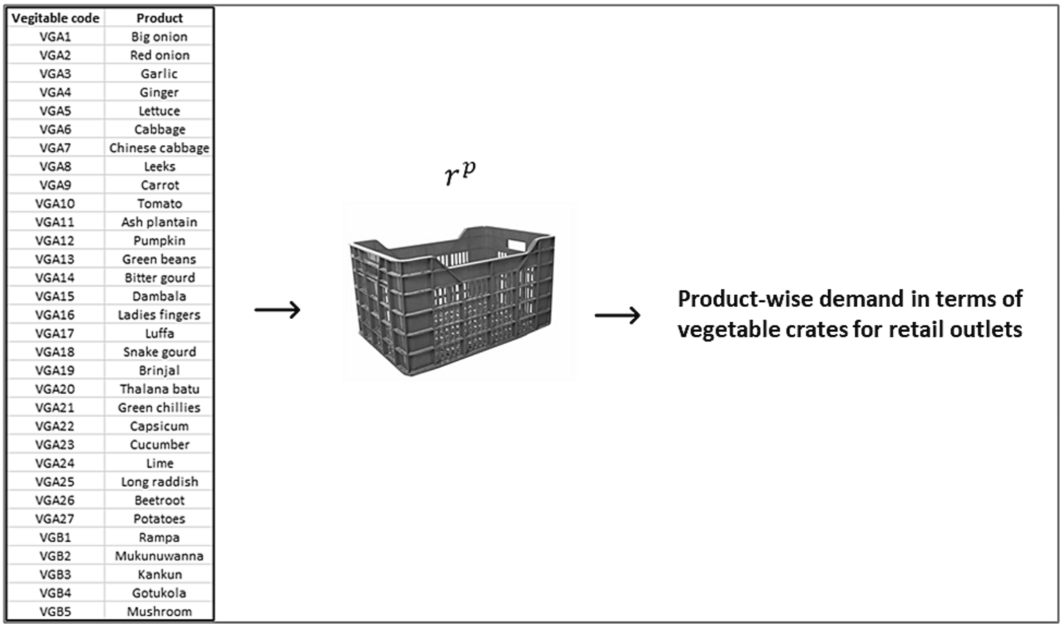

Fig. 5. Estimate product-wise demand in terms of vegetable crates.

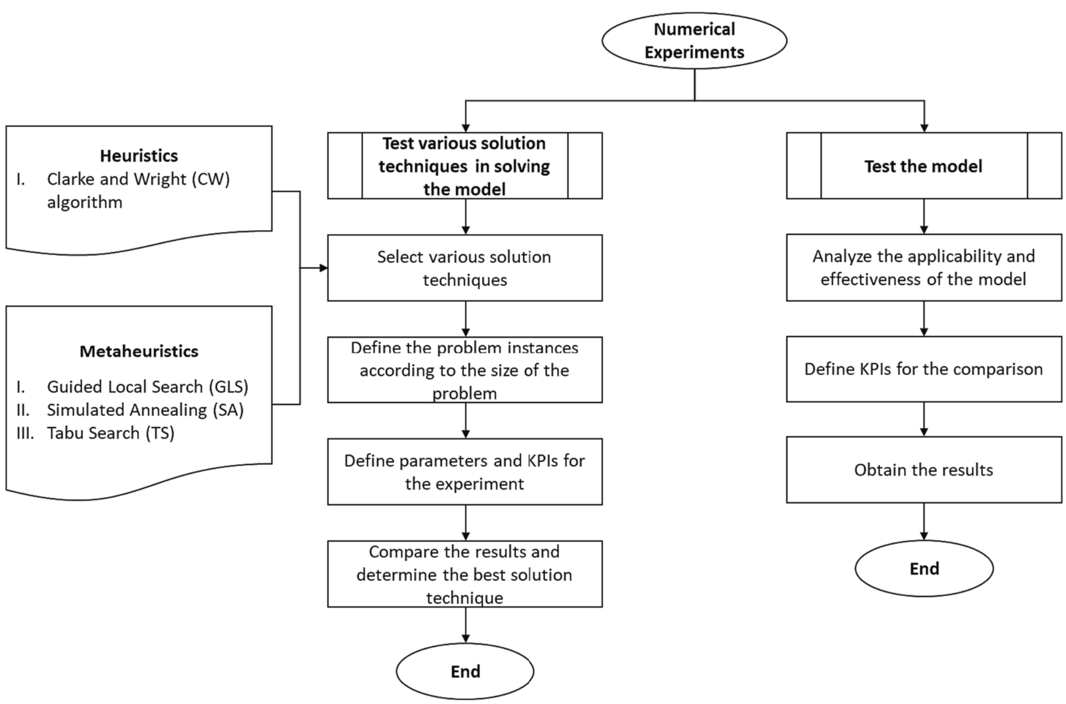

Fig. 6. Conceptual framework for the numerical experiments.

GLS in solving a real-world case study.

Fig. 8 depicts a comparison of the computation time for the three metaheuristic methods. It shows that GLS converges in less computation time than the other two methods. The performance of the TS and SA algorithms do not monotonically increase as a function of iterations for a few occasions due to the stochastic nature of the algorithms. The randomization inherent in TS and SA can lead to variations in the quality of solutions obtained at different iterations, resulting in non-monotonic behavior. GLS saves computation time by 60 % and 73.7 % respectively when solving the proposed model for the selected case study in comparison to SA and TS. According to the results, GLS significantly reduces computation time when compared to the other two metaheuristic methods. This implies that GLS is very effective when solving real-world problems with many nodes.

As presented earlier, current research compared three metaheuristics: GLS, SA, and TS in terms of the objective value and the computation time with the default search parameters set by OR-Tools version 7.2. According to the summary, in terms of the objective value, GLS outperformed the other two metaheuristics by a small margin (2–4 %). Nevertheless, GLS achieved a significant reduction in computation time (60–74 %) when solving the proposed model. The results demonstrate the efficiency of GLS in improving the IFBS as a metaheuristic method concerning the proposed model and the case study.

Table 2
Fuel cost and fixed cost savings realized through the proposed model.

No of outlets	Fixed cost component of daily distribution cost (LKR)			Fuel cost component of daily distribution cost (LKR)		
	Current practice	Proposed model	Cost saving	Current practice	Proposed model	Cost saving
25	36,000	36,000	0 %	249,750	180,400	28 %
50	60,000	60,000	0 %	367,420	202,510	45 %
75	78,000	78,000	0 %	521,390	225,860	57 %
100	114,000	114,000	0 %	605,340	239,090	61 %
125	150,000	150,000	0 %	657,630	285,030	57 %
150	186,000	180,000	3 %	639,450	303,200	53 %
175	222,000	216,000	3 %	761,050	417,290	45 %
200	258,000	246,000	5 %	764,360	483,390	37 %
225	294,000	276,000	6 %	871,840	561,630	36 %
250	330,000	306,000	7 %	923,070	704,290	24 %

6.3. Experiment results: Model

This section is intended to test the proposed VRP model's real-world applicability. To assess the model's performance, all input data were derived from the real-world case study. Moreover, all the model outputs were tested to determine the model's effectiveness.

First, the model output was compared to the current operation practices of the selected retail chain. The current operation practice involves using a Transport Management System (TMS) along with manual adjustments to plan the distribution network. Hence, all the problem instances were solved using the current practice and the proposed model. As highlighted in Fig. 8, total distribution cost was used as the KPI to carry out this comparison. The comparison results obtained through this experiment are illustrated in Fig. 9. As per the results, the proposed model has gained significant cost savings against the current operational practice. For the largest problem instance (250 outlets), this model achieved a 19 % saving in daily distribution costs. Moreover, the size of the search space grows exponentially with the problem size. As the problem size becomes larger, the number of feasible solutions increases exponentially, making it harder to explore the entire space thoroughly. Therefore, the cost saving is relatively low for larger problem instances. The proposed model has resulted in both fuel cost savings and fixed savings, as demonstrated in Table 2. The implementation of the proposed model resulted in substantial cost savings in fuel costs, contributing to a notable reduction in the carbon footprint of the selected retail chain.

The VRP model proposed in this research can assist retail outlets' order allocation with multiple products. This numerical experiment

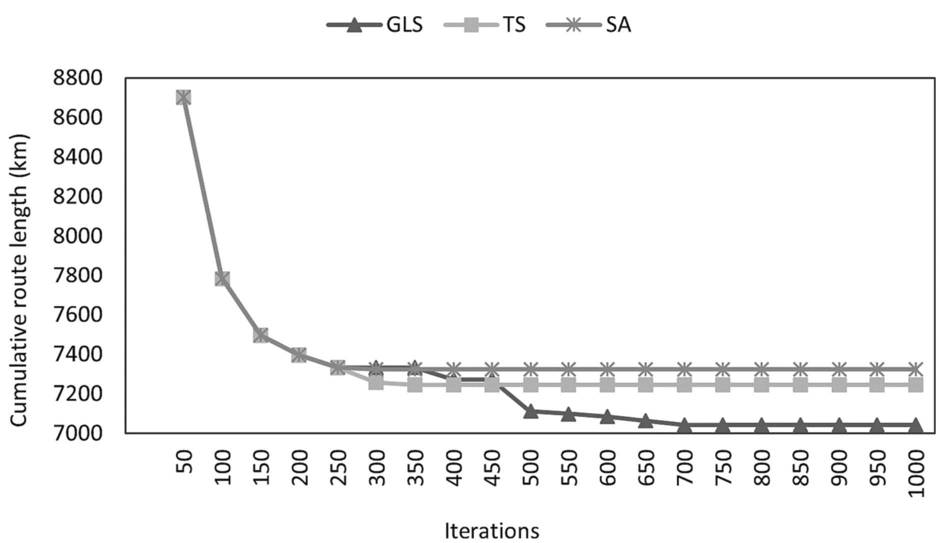

Fig. 7. Comparison of metaheuristic methods in terms of objective value.

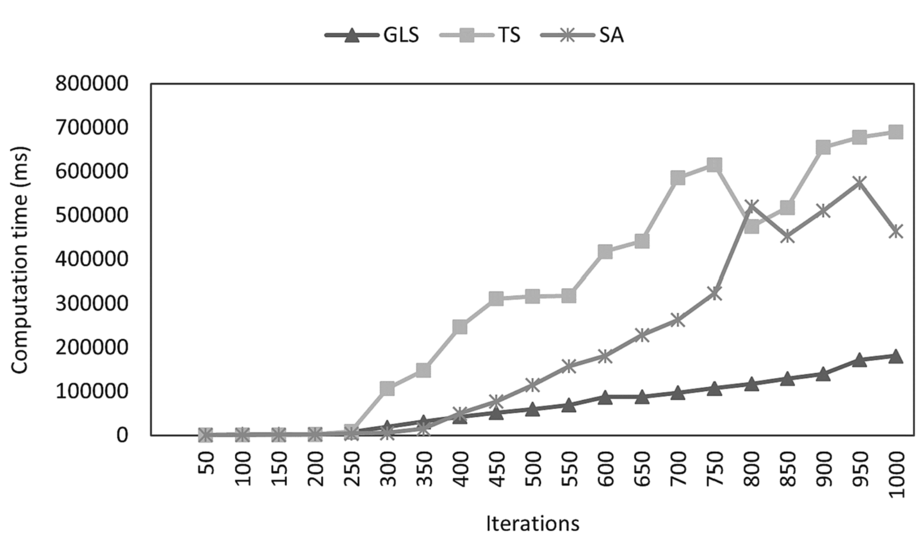

Fig. 8. Comparison of metaheuristic methods in terms of computation time.

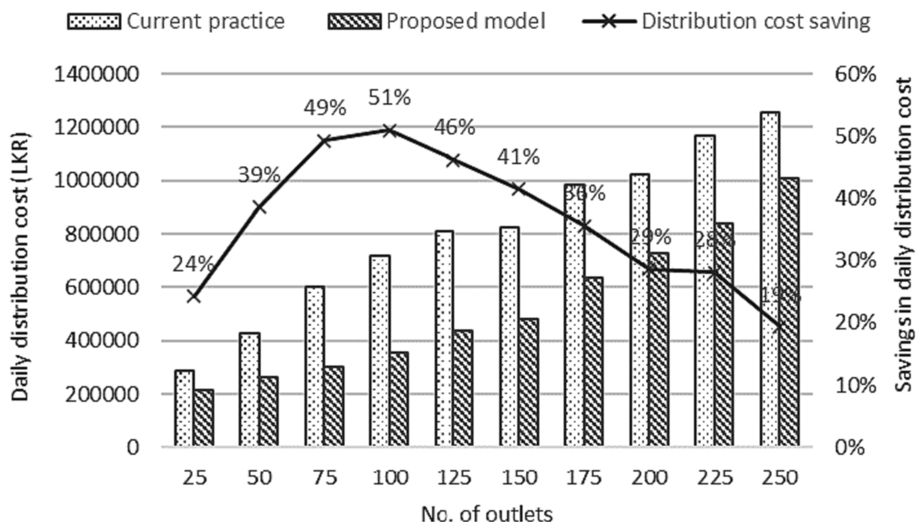

Fig. 9. Benchmark the proposed model against the current practice in the retail chain.

using realistic real-world data aims to investigate the effectiveness of allocating multiple products to heterogeneous truck fleets. As explained previously, the selected case study distributes vegetable products using plastic crates along this retail chain. Table 3 highlights the truck capacity utilization achieved using the proposed model in retail outlet order allocation for all problem instances. As the number of outlets increase, the average truck capacity utilization generally improves, with a relatively low standard deviation, indicating effective allocation of resources and efficient routing. Further, the average truck capacity utilization is 98 % for the largest problem instance, which exceeds the current average truck capacity utilization (83 %) for the selected retail chain. Therefore, the results provide evidence for the effectiveness of retail outlet order allocation of the proposed model while meeting the required standards for transporting fresh agricultural produce.

Table 4 provides details about the optimal route plan generated using the proposed VRP model. It includes details about the allocation of distribution centers and loading bays, route plan (sequence of retail outlets served in each route), the number of outlets supplied by each truck, truckload, the distance of the route, truck dispatching time, and the expected arrival time at the last retail outlet. These results show how the model effectively allocates trucks to limited loading bays (LB) according to their route length. The model dispatched the trucks that served long-distance delivery routes first. Therefore, the model effectively schedules the limited number of loading bays.

The second objective of the proposed model aims to serve retail outlets before the requested service time. As a practice, the selected retail chain targets to supply vegetable products to retail outlets before 4p.m. to meet peak customer demand. Therefore, the model tracks the expected arrival time to the last retail outlet to identify delivery routes with late deliveries. As highlighted in Table 4, there are seven delivery routes with late deliveries (truck numbers 1, 38, 39, 40, 41, 42, 43). The results highlight that 86 % of delivery routes (43 of 50) served their retail outlets before the requested time.

Table 3
Truck capacity utilization realized through the proposed model.

No of outlets	Mean truck capacity utilization	Standard deviation
25	77 %	31 %
50	91 %	13 %
75	85 %	22 %
100	91 %	19 %
125	96 %	10 %
150	94 %	11 %
175	96 %	7 %
200	97 %	5 %
225	96 %	6 %
250	98 %	3 %

Table 5 provides further details about the delivery routes with late deliveries. Only 5 % (13 of 247) of the retail outlets receive their orders after the requested time. Therefore, results show that 95 % of retail outlets receive their order on time. Thereby, the model has successfully achieved the second objective. Delivering fresh agricultural products on time helps ensure freshness (Utama et al., 2020). Moreover, it helps to minimize the stockout costs of retail outlets (Utama et al., 2020). In this study, incorporating time guarantees as an objective function in the model, rather than using them as traditional parameters, has significantly contributed to the successful achievement of on-time deliveries (Fotouhi & Miller-Hooks, 2023).

7. Conclusion

Current VRP research focuses on investigating solution methods and little attention is paid to their practical implications. Practically motivated VRP models are extremely important as they address real-world issues and provide practical solutions that can help optimize operations and improve performance. This study aimed to bridge this gap by integrating multiple real-world attributes related to the distribution of fresh agricultural products within retail chains. Retail chains distribute fresh agricultural produce frequently (daily on most occasions) to maintain freshness. Therefore, planning this daily distribution manually is time-consuming and difficult. The proposed VRP model can be successfully implemented in the real world for integrated planning (i.e., loading bay allocation, order allocation) and route optimization. Numerical experiments show that the proposed model realized significant savings in daily distribution costs while ensuring the timely delivery of fresh agricultural products to retail outlets. Furthermore, the significant savings achieved in fuel costs not only result in financial benefits but also contribute to reducing the carbon footprint. The proposed VRP model is efficient as an operational planning tool since it requires less time to obtain the optimal distribution plan. The research compared three metaheuristic methods (GLS, SA, and TS) for obtaining near-optimal solutions for the proposed optimization model. The numerical experiment showed that GLS outperformed the other two metaheuristic methods in terms of the quality of the solutions and computation time.

This research incorporated a real road network to develop the proposed routing model. The measurement of travel time between nodes was conducted using the actual road network. However, this research did not consider the dynamic travel times which change according to the congestion experienced during the travel time. Therefore, future

Table 4
Model output.

Truck no	Distribution center & loading bay	Route plan	No of retail outlets	Truck load (No of crates)	Distance (Km)	Truck dispatch time	Expected arrival time to last outlet
1	Wattala-LB1	0, 241, 240, 246, 169, 226, 225, 0	6	35	448.2	5:00 AM	5:41 PM
2	Wattala-LB2	0, 185, 223, 224, 221, 222, 0	5	35	359.4	5:00 AM	2:16 PM
3	Wattala-LB1	0, 117, 118, 116, 119, 115, 178, 179, 0	7	35	276	5:20 AM	3:54 PM
4	Wattala-LB2	0, 243, 244, 245, 242, 18, 141, 0	6	35	184.2	5:20 AM	2:17 PM
5	Wattala-LB1	0, 126, 238, 233, 237, 236, 234, 0	6	34	148	5:40 AM	11:58 AM
6	Wattala-LB2	0, 184, 180, 189, 183, 177, 45, 0	6	34	143.8	5:40 AM	12:49 PM
7	Wattala-LB1	0, 19, 29, 175, 174, 20, 159, 0	6	35	106.8	6:00 AM	12:18 PM
8	Wattala-LB2	0, 187, 190, 182, 176, 0	4	28	106	6:00 AM	10:22 AM
9	Wattala-LB1	0, 148, 122, 120, 123, 147, 0	5	30	71.8	6:20 AM	10:14 AM
10	Wattala-LB2	0, 49, 58, 181, 188, 52, 33, 0	6	30	71.8	6:20 AM	11:04 AM
11	Wattala-LB1	0, 34, 42, 23, 153, 0	4	30	71	6:40 AM	9:55 AM
12	Wattala-LB2	0, 27, 55, 25, 24, 26, 76, 0	6	28	63.4	6:40 AM	11:05 AM
13	Wattala-LB1	0, 162, 128, 124, 135, 133, 129, 0	6	35	59.6	7:00 AM	11:38 AM
14	Wattala-LB2	0, 22, 21, 60, 64, 61, 88, 0	6	29	58.4	7:00 AM	11:32 AM
15	Wattala-LB1	0, 62, 54, 56, 53, 80, 0	5	30	57.4	7:20 AM	11:31 AM
16	Wattala-LB2	0, 44, 59, 57, 30, 0	4	30	56.9	7:20 AM	10:35 AM
17	Wattala-LB1	0, 130, 41, 156, 144, 0	4	35	50.5	7:40 AM	10:32 AM
18	Wattala-LB2	0, 28, 72, 63, 71, 0	4	30	48.7	8:00 AM	11:00 AM
19	Wattala-LB1	0, 125, 132, 154, 131, 0	4	35	48.4	8:00 AM	10:56 AM
20	Wattala-LB2	0, 36, 111, 106, 165, 166, 146, 0	6	35	47.7	8:20 AM	12:20 PM
21	Wattala-LB1	0, 151, 142, 152, 149, 155, 0	5	35	46.5	8:20 AM	11:53 AM
22	Wattala-LB2	0, 96, 95, 113, 98, 0	4	30	41.7	8:40 AM	11:26 AM
23	Wattala-LB1	0, 67, 51, 46, 90, 101, 0	5	30	40.2	8:40 AM	12:28 PM
24	Wattala-LB2	0, 83, 84, 82, 99, 39, 32, 43, 97, 0	8	29	36.8	9:00 AM	1:47 PM
25	Wattala-LB1	0, 70, 77, 40, 68, 66, 75, 0	6	30	36.1	9:00 AM	12:41 PM
26	Wattala-LB2	0, 65, 47, 114, 48, 0	4	30	35	9:20 AM	12:02 PM
27	Wattala-LB1	0, 74, 73, 69, 31, 0	4	28	31.7	9:20 AM	11:54 PM
28	Wattala-LB2	0, 108, 35, 107, 38, 79, 0	5	30	31	9:40 AM	12:55 PM
29	Wattala-LB1	0, 186, 91, 100, 87, 92, 105, 0	6	30	30.6	9:40 AM	1:24 PM
30	Wattala-LB2	0, 85, 109, 94, 93, 89, 0	5	30	26.7	10:00 AM	12:30 PM
31	Wattala-LB1	0, 102, 104, 50, 103, 78, 86, 0	6	30	26.6	10:00 AM	1:41 PM
32	Wattala-LB2	0, 37, 112, 110, 0	3	25	25.3	10:20 AM	12:21 PM
33	Wattala-LB1	0, 163, 164, 127, 134, 158, 0	5	32	23.5	10:20 AM	1:26 PM
34	Wattala-LB2	0, 150, 143, 145, 0	3	25	20.7	10:40 AM	12:30 PM
35	Wattala-LB1	0, 138, 137, 139, 0	3	25	17.7	10:40 AM	12:34 PM
36	Wattala-LB2	0, 160, 81, 161, 0	3	19	11.5	11:00 AM	12:43 PM
37	Wattala-LB1	0, 140, 157, 136, 0	3	23	11.3	11:00 AM	12:44 PM
38	Kurunagala-LB1	1, 15, 16, 4, 5, 12, 1	5	35	608.8	5:00 AM	10:44 PM
39	Kurunagala-LB1	1, 207, 173, 172, 171, 248, 9, 7, 1	7	32	630.7	5:20 AM	2:00 AM
40	Kurunagala-LB1	1, 10, 3, 6, 2, 227, 228, 1	6	35	570.9	5:40 AM	9:22 PM
41	Kurunagala-LB1	1, 218, 8, 247, 17, 232, 231, 1	6	29	532	6:00 AM	10:32 PM
42	Kurunagala-LB1	1, 11, 170, 167, 168, 1	4	35	529.8	6:20 AM	6:16 PM
43	Kurunagala-LB1	1, 229, 14, 13, 230, 201, 200, 1	6	33	333.6	6:40 AM	7:12 PM
44	Kurunagala-LB1	1, 239, 212, 1	2	18	178.7	7:00 AM	2:11 PM
45	Kurunagala-LB1	1, 194, 216, 217, 220, 219, 1	5	35	162.5	7:20 AM	1:49 PM
46	Kurunagala-LB1	1, 203, 121, 235, 211, 213, 1	5	30	157.9	7:40 AM	2:40 PM
47	Kurunagala-LB1	1, 197, 195, 193, 199, 204, 1	5	30	123	8:00 AM	1:24 PM
48	Kurunagala-LB1	1, 214, 210, 215, 209, 208, 1	5	28	90.1	8:20 AM	1:42 PM
49	Kurunagala-LB1	1, 198, 191, 192, 196, 1	4	30	80.4	8:40 AM	12:12 PM
50	Kurunagala-LB1	1, 205, 202, 206, 1	3	25	73.6	9:00 AM	1:39 PM

Table 5
Routes with late deliveries.

Truck number	Distribution center & loading bay (LB)	Route plan	Expected arrival times of late deliver outlets	Penalty cost (LKR)
1	Wattala-LB1	0, 241, 240, 246, 169, **226, 225**, 0	4:10 PM, 5:40 PM	10000
38	Kurunagala-LB1	1, 15, 16, 4, **5, 12**, 1	5:00 PM, 10:44 PM	35000
39	Kurunagala-LB1	1, 207, **173, 172, 171, 248, 9, 7**, 1	4:00 PM, 4:45 PM, 5:30 PM, 10:40PM, 1:55 AM, 2:00 AM	97500
40	Kurunagala-LB1	1, 10, 3, 6, 2, 227, **228**, 1	9:20 PM	15000
41	Kurunagala-LB1	1, 218, 8, 247, 17, **232, 231**, 1	7:10 PM, 10:30 PM	27500
42	Kurunagala-LB1	1, 11, **170, 167, 168**, 1	4:25 PM, 5:55 PM, 6:16 PM	17500
43	Kurunagala-LB1	1, 229, 14, 13, **230, 201, 200**, 1	5:05 PM, 6:40 PM, 7:12 PM	25000

research could extend this model with dynamic travel times, improving its real-world applicability even further. Additionally, upcoming studies ought to focus on promoting the utilization of electric vehicles for transporting agricultural products within urban retail chains, with a particular emphasis on addressing environmental impacts (Helgeson & Peter, 2020; Stamadianos et al., 2023). The proposed VRP model is concerned with distributing fresh agricultural products in retail chains. The second objective function in the optimization model focuses on ensuring the freshness of products by addressing the timely delivery of goods. Further, the research could include the perishability factor of fresh agricultural products. Thereby, the model can further minimize and track the post-harvest wastage that occurs in the distribution process. Despite these limitations, the research has important implications for the fresh produce industry and for future research on VRP. The proposed VRP model can be adapted to other contexts and industries and can serve as a basis for further refinement and innovation in solving more complex problems in the future. Overall, this research offers a practical solution to an important problem and opens up new avenues for research in the field of VRP. Moreover, by incorporating real-world characteristics and comparing different metaheuristic methods, this research contributes to the field of logistics and supply chain management and provides insights into how to solve complex problems in practice.

CRediT authorship contribution statement

W. Madushan Fernando: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Project administration. **Amila Thibbotuwawa:** Conceptualization, Resources, Funding acquisition, Methodology, Project administration, Writing – review & editing, Supervision. **H. Niles Perera:** Funding acquisition, Supervision, Validation, Resources, Project administration, Writing – review & editing. **Peter Nielsen:** Funding acquisition, Supervision, Writing – review & editing. **Deniz Kenan Kilic:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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References

Abraham, A.K., Cherian Jos, B., Mangalathu, G.S., 2012. The pickup and delivery vehicle routing problem for perishable goods in air-cargo industry. Int. J. Emerg. 2 (12), 790–794.
Agustina, D., Lee, C.K.M., Piplani, R., 2014. Vehicle scheduling and routing at a cross docking center for food supply chains. Int. J. Prod. Econ. 152, 29–41. https://doi.org/10.1016/j.ijpe.2014.01.002.
Amaliah, B., Fatichah, C., Suryani, E., 2020. A new heuristic method of finding the initial basic feasible solution to solve the transportation problem. J. King Saud Univ. - Comput. Inf. https://doi.org/10.1016/j.jksuci.2020.07.007.
Amorim, P., Almada-Lobo, B., 2014. The impact of food perishability issues in the vehicle routing problem. Comput Ind Eng. 67 (1), 223–233. https://doi.org/10.1016/j.cie.2013.11.006.
Arostegui, M.A., Kadipasaoglu, S.N., Khumawala, B.M., 2006. An empirical comparison of Tabu Search, Simulated Annealing, and Genetic Algorithms for facilities location problems. Int. J. Prod. Econ. 103, 742–754. https://doi.org/10.1016/j.ijpe.2005.08.010.
Braekers, K., Ramaekers, K., Nieuwenhuyse, I.V., 2016. The vehicle routing problem: State of the art classification and review. Comput Ind Eng. 99, 300–313. https://doi.org/10.1016/j.cie.2015.12.007.
Buelvas, M., Nisperuza, P., López, J., Hernández, H., 2018. Vehicle routing problem for the minimization of perishable food damage considering road conditions. Logist. Res. 11 (2), 1–18.
Çalık, H., Oulamara, A., Prodhon, C., Salhi, S., 2021. The electric location-routing problem with heterogeneous fleet: Formulation and Benders decomposition approach. Comput. Oper. Res. 131 https://doi.org/10.1016/j.cor.2021.105251.
Chen, J., Shi, J., 2019. A multi-compartment vehicle routing problem with time windows for urban distribution – A comparison study on particle swarm optimization algorithms. Comput Ind Eng. 13, 95–106. https://doi.org/10.1016/j.cie.2019.05.008.
Clarke, G., Wright, J.W., 1964. Scheduling of vehicles from a central depot to a number of delivery points. Oper. Res. 12 (4), 568–581. https://doi.org/10.1287/opre.12.4.568.
Dantzig, G.B., Ramser, J.H., 1959. The truck dispatching problem. Manag. Sci. 6 (1).
Esmaili, M., Sahraeian, R., 2017. A new bi-objective model for a two-echelon capacitated vehicle routing problem for perishable products with the environmental factor. Int. J. Eng. Trans. a: Basics. 30 (4), 523–531. https://doi.org/10.5829/idosi.ije.2017.30.04a.10.
Ezaki, T., Imura, N., Nishinari, K., 2022. Towards understanding network topology and robustness of logistics systems. Commun. Transp. Res. 2 https://doi.org/10.1016/j.commtr.2022.100064.
Fatemi Ghomi, S.M.T., Asgarian, B., 2019. Development of metaheuristics to solve a transportation inventory location routing problem considering lost sale for

perishable goods. J. Model. Manag. 14 (1), 175–198. https://doi.org/10.1108/JM2-05-2018-0064.
Fernando, W.W.P.M., Dhananjaya, D.D., Munasinghe, J.A., Kumarage, A.S., Sivakumar, T., Perera, A.S., 2021. Post-processing of GPS data for bus link speed determination based on GIS. J. East. Asia Soc. Transp. Studies. 14, 1179–1192.
Fernando, M., Thibbotuwawa, A., Perera, N., 2022. Investigating various solution techniques for real-world vehicle routing problems. Bolgoda Plains 2(1), 51–53. 10.31705/BPRM.v2(1).2022.14.
Fernando, M., Thibbotuwawa, A., Perera, H.N., Ratnayake, R.M.C., 2022a. 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, 10.1109/ICONAT53423.2022.9725977.
Fernando, W.M., Thibbotuwawa, A., Perera, H.N., Chandima Ratnayake, R.M., 2022c. Applying a capacitated heterogeneous fleet vehicle routing problem with multiple depots model to optimize a retail chain distribution network. In: 2022 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), pp. 0588–0592, 10.1109/IEEM55944.2022.9989636.
Fotouhi, H., Miller-Hooks, E., 2023. Same-day delivery time-guarantee problem in online retail. Commun. Transp. Res. 3 https://doi.org/10.1016/j.commtr.2023.100105.
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. Commun. Comput. Inf. Sci. 916, 61–72. https://doi.org/10.1007/978-3-030-00353-1_6.
Glover, F., 1986. Paths for Integer Programming. Comput. Oper. Res. 13 (5), 533–549.
Gong, W., Fu, Z., 2010. ABC-ACO for perishable food vehicle routing problem with time windows. Proceedings - 2010 International Conference on Computational and Information Sciences, ICCIS 2010, 1261–1264. 10.1109/ICCIS.2010.311.
Govindan, K., Jafarian, A., Khodaverdi, R., Devika, K., 2014. Two-echelon multiple-vehicle location-routing problem with time windows for optimization of sustainable supply chain network of perishable food. Int. J. Prod. Econ. 152, 9–28. https://doi.org/10.1016/j.ijpe.2013.12.028.
Gutierrez-Franco, E., Mejia-Argueta, C., Rabelo, L., 2021. Data-driven methodology to support long-lasting logistics and decision making for urban last-mile operations. Sustainability. 13 (11) https://doi.org/10.3390/su13116230.
He, Z., Haasis, H.D., 2019. Integration of urban freight innovations: Sustainable inner-urban intermodal transportation in the retail/postal industry. Sustainability. 11 (6) https://doi.org/10.3390/su11061749.
Helgeson, B., Peter, J., 2020. The role of electricity in decarbonizing European road transport – Development and assessment of an integrated multi-sectoral model. Appl. Energy. 262 https://doi.org/10.1016/j.apenergy.2019.114365.
Huang, S.H., Lin, P.C., 2015. Vehicle routing-scheduling for municipal waste collection system under the "Keep Trash off the Ground" policy. Omega. 55, 24–37. https://doi.org/10.1016/j.omega.2015.02.004.
Jayalath, M.M., Perera, H.N., 2021. Mapping post-harvest waste in perishable supply chains through system dynamics: A Sri Lankan case study. J. Agric. Sci. 16 (3), 526–543. https://doi.org/10.4038/jas.v16i03.9477.
Khalili-Damghani, K., Abtahi, A.R., Ghasemi, A., 2015. A new bi-objective location-routing problem for distribution of perishable products: evolutionary computation approach. J. Math. Modell. Algorithms Operat. Res. 14 (3), 287–312. https://doi.org/10.1007/s10852-015-9274-3.
Kilby, P., Scientific, T. C., Prosser, P., 2002. Guided Local Search for the Vehicle Routing Problem. 10.1007/978-1-4615-5775-3.
Krishnan, R., Agarwal, R., Bajada, C., Arshinder, K., 2020. Redesigning a food supply chain for environmental sustainability – An analysis of resource use and recovery. J. Clean. Prod. 242 https://doi.org/10.1016/j.jclepro.2019.118374.
Kuo, R.J., Nugroho, D.Y., 2017. A fuzzy multi-objective vehicle routing problem for perishable products using gradient evolution algorithm. 2017 4th International Conference on Industrial Engineering and Applications, 10.1109/IEA.2017.7939210.
Lacomme, P., Moukrim, A., Quilliot, A., Vinot, M., 2018. Supply chain optimisation with both production and transportation integration: multiple vehicles for a single perishable product. Int. J. Prod. Res. 56 (12), 4313–4336. https://doi.org/10.1080/00207543.2018.1431416.
Laurent, P., Vincent, F., 2022. OR-Tools (v9.5). Google.
Lu, S., Wang, X., 2018. A fuzzy Bi-objective multi-commodity minimum cost flow-based perishable food transportation problem and its harmony search algorithm. Proceedings of the 2017 IEEE 2nd Information Technology, Networking, Electronic and Automation Control Conference, ITNEC 2017, 10.1109/ITNEC.2017.8284827.
Ma, Z.J., Wu, Y., Dai, Y., 2017. A combined order selection and time-dependent vehicle routing problem with time widows for perishable product delivery. Comput Ind Eng. 114, 101–113. https://doi.org/10.1016/j.cie.2017.10.010.
Mancini, S., Gansterer, M., 2022. Bundle generation for last-mile delivery with occasional drivers. Omega. 108 https://doi.org/10.1016/j.omega.2021.102582.
Meneghetti, A., Ceschia, S., Meneghetti, A., 2019. Energy-efficient frozen food transports : the Refrigerated Routing Problem Energy-efficient frozen food transports : the Refrigerated Routing Problem. Int. J. Prod. Res. 1–18 https://doi.org/10.1080/00207543.2019.1640407.
Moghdani, R., Salimifard, K., Demir, E., Benyettou, A., 2021. The green vehicle routing problem: A systematic literature review. J. Clean. Prod. 279 https://doi.org/10.1016/j.jclepro.2020.123691.
Montoya-torres, J.R., López, J., Nieto, S., Felizzola, H., Herazo-padilla, N., 2015. A literature review on the vehicle routing problem with multiple depots. Comput Ind Eng. 79, 115–129. https://doi.org/10.1016/j.cie.2014.10.029.
Nadhori, I.U., Ahsan, A.S., 2019. Distribution system for perishable farming product. International Electronics Symposium on Knowledge Creation and Intelligent Computing, IES-KCIC 2018 - Proceedings, 10.1109/KCIC.2018.8628606.
Navazi, F., Tavakkoli-Moghaddam, R., Sazvar, Z., Memari, P., 2019. Sustainable design for a bi-level transportation-location-vehicle routing scheduling problem in a perishable product supply chain. In Studies in Computational Intelligence. 803. Springer International Publishing. 10.1007/978-3-030-03003-2_24.
Nanayakkara, P.R., Jayalath, M.M., Thibbotuwawa, A., Perera, H.N., 2022. A circular reverse logistics framework for handling e-commerce returns. Clean. Logist. Supply Chain 5. https://doi.org/10.1016/j.clscn.2022.100080.
Pannila, N., Jayalath, M.M., Thibbotuwawa, A., Nielsen, I., Uthpala, T.G.G., 2022. Challenges in Applying Circular Economy Concepts to Food Supply Chains. Sustainability 14 (24). https://doi.org/10.3390/su142416536.
Patidar, R., Venkatesh, B., Pratap, S., Daultani, Y., 2019. A Sustainable Vehicle Routing Problem for Indian Agri-Food Supply Chain Network Design. 2018 International Conference on Production and Operations Management Society, POMS 2018, 1–5. 10.1109/POMS.2018.8629450.
Perera, H.N., Perera, H.Y.R., 2022. Applications of Pixel Oriented Mobility Modelling in Transport & Logistics. Springer Science and Business Media B.V, pp. 337–348.
Rahbari, A., Nasiri, M.M., Werner, F., Musavi, M.M., Jolai, F., 2019. The vehicle routing and scheduling problem with cross-docking for perishable products under uncertainty: Two robust bi-objective models. Appl. Math. Model. 70, 605–625. https://doi.org/10.1016/j.apm.2019.01.047.
Rashidi Komijan, A., Delavari, D., 2017. Vehicle Routing and Scheduling Problem for a multi-period, multi-perishable product system with time window: A Case study. Int. J. Prod. Manag. Eng. 5 (2), 45. https://doi.org/10.4995/ijpme.2017.5960.
Rong, L.X., Sha, H.B., 2014. Vehicle scheduling model for fresh agriculture products pickup with uncertain demands. Adv. Mat. Res. 974, 282–287. https://doi.org/10.4028/www.scientific.net/AMR.974.282.
Sahraeian, R., Esmaeili, M., 2018. A multi-objective two-echelon capacitated vehicle routing problem for perishable products. Int. J. Ind. Syst. Eng. 11 (2), 62–84.
Schneider, K., Nurre, S.G., 2019. A multi-criteria vehicle routing approach to improve the compliance audit schedule for food banks. Omega. 84, 127–140. https://doi.org/10.1016/j.omega.2018.05.002.
Seyedhosseini, S.M., Ghoreyshi, S.M., 2014. An integrated model for production and distribution planning of perishable products with inventory and routing considerations. Math. Probl. Eng. https://doi.org/10.1155/2014/475606.
Sitek, P., Wikarek, J., 2014. A novel integrated approach to the modelling and solving of the Two-Echelon Capacitated Vehicle Routing Problem. Prod. Manuf. Res. 2 (1), 326–340. https://doi.org/10.1080/21693277.2014.910716.
Sitek, P., Wikarek, J., Rutczyńska-Wdowiak, K., Bocewicz, G., Banaszak, Z., 2021. Optimization of capacitated vehicle routing problem with alternative delivery, pick-up and time windows: A modified hybrid approach. Neurocomputing. 423, 670–678. https://doi.org/10.1016/j.neucom.2020.02.126.
Stamadianos, T., Kyriakakis, N.A., Marinaki, M., Marinakis, Y., 2023. Routing Problems with Electric and Autonomous Vehicles: Review and Potential for Future Research. Oper. Res. Forum. 4 (2) https://doi.org/10.1007/s43069-023-00228-1.
Sung, I., Nielsen, P., 2020. Speed optimization algorithm with routing to minimize fuel consumption under time-dependent travel conditions. Prod. Manuf. Res. 8 (1), 1–19. https://doi.org/10.1080/21693277.2020.1732848.
Surucu-Balci, E., Tuna, O., 2021. Investigating logistics-related food loss drivers: A study on fresh fruit and vegetable supply chain. J. Clean. Prod. 318 https://doi.org/10.1016/j.jclepro.2021.128561.
Taylor, P., Shukla, M., Jharkharia, S., 2013. Artificial Immune System-based algorithm for vehicle routing problem with time window constraint for the delivery of agri-fresh produce. J Decis Syst. 22 (3), 224–247. https://doi.org/10.1080/12460125.2013.810859.
Thibbotuwawa, A., Bocewicz, G., Nielsen, P., Zbigniew, B., 2019. Planning deliveries with UAV routing under weather forecast and energy consumption constraints. IFAC-PapersOnLine 52 (13), 820–825. https://doi.org/10.1016/j.ifacol.2019.11.231.
Thibbotuwawa, A., Bocewicz, G., Radzki, G., Nielsen, P., Banaszak, Z., 2020. UAV mission planning resistant to weather uncertainty. Sensors. 20 (2) https://doi.org/10.3390/s20020515.
Thibbotuwawa, A., Nanayakkara, P.R., Fernando, W.M., Jayalath, M.M., Perera, H.N., Nielsen, P., 2023. A Reverse Logistics Network Model for Handling E-commerce Returns. IFAC-PapersOnLine 56, 138–143. https://doi.org/10.1016/j.ifacol.2023.10.1559.
Tirkolaee, E.B., Hadian, S., Weber, G., Mahdavi, I., 2020. A robust green traffic-based routing problem for perishable products distribution. Comput. Intell. 36, 1–22. https://doi.org/10.1111/coin.12240.
Utama, D.M., Dewi, S.K., Wahid, A., Santoso, I., 2020. The vehicle routing problem for perishable goods: A systematic review. Cogent Eng. 7 (1) https://doi.org/10.1080/23311916.2020.1816148.
Wang, Y., Li, X., 2022. Optimality analysis of train platforming and routing with different interlocking modes. Commun. Transp. Res. 2 https://doi.org/10.1016/j.commtr.2022.100061.
Wang, X., Wang, M., Ruan, J., Zhan, H., 2016. The Multi-objective Optimization for Perishable Food Distribution Route Considering Temporal-spatial Distance. Procedia Comput. Sci. 96, 1211–1220. https://doi.org/10.1016/j.procs.2016.08.165.
Yao, Y., Zhu, X., Dong, H., Wu, S., Wu, H., Carol Tong, L., Zhou, X., 2019. ADMM-based problem decomposition scheme for vehicle routing problem with time windows. Transport Res B-Meth. 129, 156–174. https://doi.org/10.1016/j.trb.2019.09.009.
Yi, W., Wang, H., Jin, Y., Cao, J., 2021. Integrated computer vision algorithms and drone scheduling. Transp. Res. Commun. https://doi.org/10.1016/j.commtr.2021.100002.
Zulvia, F.E., Kuo, R.J., Nugroho, D.Y., 2020. A many-objective gradient evolution algorithm for solving a green vehicle routing problem with time windows and time dependency for perishable products. J. Clean. Prod. 242 https://doi.org/10.1016/j.jclepro.2019.118428.