A NOVEL VEHICLE ROUTING ALGORITHM FOR ROUTE OPTIMIZATION USING BEST-WORST METHOD AND RANKING ALTERNATIVES FOR SIMILARITY TO IDEAL SOLUTION

Mouhamed Bayane Bouraima[1] – Ibrahim Badi[2] – Željko Stević[3] – Clement Kiprotich Kiptum[4] – Dragan Pamucar[5*] – Dragan Marinkovic[6]

[1]Department of Civil Engineering, Sichuan College of Architectural Technology, Deyang, China
[2]Mechanical Engineering Department, Libyan Academy, Misrata, Libya
[3]Faculty of Transport and Traffic Engineering, University of East Sarajevo, Doboj, Bosnia and Herzegovina
School of Industrial Management Engineering, Korea University, Seoul, Korea
[4] Department of Civil and Structural Engineering, University of Eldoret, Kenya
[5] Department of Operations Research and Statistics, Faculty of Organizational Sciences, University of Belgrade, Belgrade, Serbia
[6] Faculty of Mechanical and Transport Systems, Technische Universität Berlin, Germany

ARTICLE INFO

***Article history*:**
Received:
Received in revised form:
Accepted:

Keywords:
Vehicle Routing Problem
Supply Chain Optimzation
Multi-Criteria Decision Making
Best-Worst Method
Ranking Alternatives For Similarity to Ideal Solution

DOI: 10.30765/er.2597

Abstract:

The Vehicle Routing Problem (VRP) is important in supply chain management as it optimizes goods and services delivery to customers, resulting in improved organizational productivity. This study introduces an innovative hybrid methodology integrating the Multi-Criteria Decision Making (MCDM) approach with Clarke and Wright's savings algorithm to tackle the capacitated vehicle routing problem. In addition to the conventional aim of optimizing truck routes, this strategy considers customer satisfaction. The initial step involves clustering all customers through the utilization of Clarke and Wright's savings algorithm, which efficiently organizes customers into groups based on their geographical closeness. Following this, the hybrid Best-Worst Method (BWM) and Ranking Alternatives For Similarity to Ideal Solution (RAFSI) method are utilized to allocate the best routes and establish customer prioritization. The major objective of this study is to reduce overall transportation expenses while ensuring compliance with vehicle capacity limitations, aiming to improve customer satisfaction. The proposed approach seeks to balance cost-efficiency and customer-centricity in vehicle routing by including customer prioritizing and Clarke and Wright's savings algorithm. The effectiveness and practical application of the proposed methodology are demonstrated through a case in the food industry. The obtained results using the proposed methodology give a more precise platform for decision-making and highlight its relevance for enhancing supply chain performance and addressing the intricate challenges associated with the capacitated vehicle routing problem. The hybrid technique presented in this study provides a comprehensive framework for effectively tackling the intricate challenges associated with the capacitated vehicle routing problem.

* Corresponding author
E-mail address: dpamucar@gmail.com

1 Introduction

The Vehicle Routing Problem (VRP) stands as a significant and pressing challenge for logistics companies in the present era. Extensive research has been dedicated to the optimization of vehicle routes and the efficient scheduling of deliveries [1]-[3]. Dating back to 1959, scholars have delved into the intricacies of distributing goods from a central depot to customers dispersed across different geographical locations. This particular problem, often referred to as the paradigmatic case of the VRP, has garnered substantial attention from the logistics community [4], [5].

The implications of solving the VRP extend far beyond individual logistics companies, impacting the entire supply chain. Efficient vehicle routing is crucial in supply chain analytics since it improves the overall effectiveness and responsiveness of supply networks [6]. Effective VRP solutions can lead to significant cost savings, enhanced delivery times, and increased flexibility, all of which are essential for keeping a competitive advantage in the market [7]. Furthermore, optimizing vehicle routes helps in better resource allocation, resulting in a reduction of environmental impact by minimizing fuel consumption and emissions. By integrating VRP solutions into supply chain management, companies may ensure more efficient operations, from inventory management to last-mile delivery, thereby improving the end-to-end supply chain performance [8].

Over the past few decades, a number of factors that have had an impact on the VRP have been introduced. These factors include the variability in the capacities of vehicles, time-related constraints such as time windows specified by customers, and the presence of multiple depots involved in the distribution process [5], [9]. These characteristics and requirements can be converted into either constraints that shape the problem or variables that define the problem. The aforementioned challenge presents a multifaceted issue that necessitates the simultaneous consideration of various criteria and constraints, including the specific demands of each individual customer. The variables and constraints that arise from real-life scenarios encountered by logistics companies are converted by researchers into variants of the VRP [10]. Hence, the subsequent analysis pertains to VRP variants that are associated with real-world scenarios. The primary goal, in both practical and theoretical contexts, typically remains consistent: to minimize overall distribution costs while maintaining a high level of distribution services [4].

A plenty of methods and approaches have been proposed and developed to tackle the VRP over the years [11], [12]. These methods aim to optimize the allocation of vehicles and the sequencing of deliveries in order to minimize costs, improve efficiency, and enhance customer satisfaction. One widely employed technique is the heuristic algorithm, which involves using intuitive rules and strategies to construct feasible solutions. Heuristics such as the Nearest Neighbor and Clarke-Wright algorithms have been widely adopted due to their simplicity and ability to generate reasonably good solutions [13], [14]. Another prominent category of approaches is metaheuristic algorithms, which encompass a range of optimization techniques inspired by natural phenomena or problem-solving paradigms. The existing literature on the VRP has extensively explored several methodologies, including genetic algorithms, ant colony optimization, and simulated annealing [2], [15], [16]. In addition, mathematical models, such as integer programming, have also been employed. [17], [18]. Additionally, recent advancements in technology and data availability have led to the emergence of data-driven and machine learning-based approaches for VRP [19]. These methods leverage historical data, real-time information, and advanced algorithms to make accurate predictions, generate efficient routes, and dynamically adapt to changing conditions [20]. Neural networks, reinforcement learning, and deep learning are examples of approaches used [21]-[23]. Method selection relies on several factors such as problem size, desired solution quality, and data availability [24]. While methods such as heuristic algorithms, metaheuristic approaches, mathematical models, and data-driven techniques have been employed to solve the Vehicle Routing Problem (VRP), they often fail to incorporate multiple criteria into the models or prioritize customer satisfaction, leaving notable research gaps [25], [26]. Therefore, it is crucial to develop hybrid techniques that combine various approaches to effectively address the complexities of VRP and deliver more efficient, customer-focused solutions.

In VRP models, the primary objective is often to minimize the distance, and the optimal route is determined based on this criterion. It is possible for certain distributors to possess multiple criteria. However, the primary challenge that persists is the existence of a substantial number of customers within a single route. Resolving such issues with some MCDM techniques is intricate [27]. The use of VRP models into multi-criteria decision-making methods is a potential avenue for considering additional criteria [28]. To ensure that the considered

VRP system aligns with the specific requirements of the problem at hand, we employed a rigorous selection process for the criteria used in the optimization process. These criteria were carefully chosen by domain experts based on their expertise.

1.1 Main objectives

The objective of this research is to address the limitations of traditional VRP solutions by integrating Multi-Criteria Decision Making (MCDM) approaches and customer prioritization into the vehicle routing process [29], [30]. To achieve that, a hybrid methodology that combines the Clarke-Wright algorithm with the Best-Worst Method (BWM) and Ranking Alternatives For Similarity to Ideal Solution (RAFSI) method. It is worth noting that other modern ranking methodologies have also been developed in recent years [31]-[33]. These methodologies represent alternative approaches that could be explored for prioritization alternatives, further enriching the field of ranking methods in MCDM frameworks.

1.2 Motivation

The VRP is a significant challenge for logistics companies, and optimizing vehicle routes and delivery scheduling has received a lot of research attention. VRP involves distributing goods from a central warehouse to customers located in different geographical areas. Over the years, various factors, such as vehicle capacity, time windows, and multiple depots, have been introduced, giving rise to different forms of VRP. There are various characteristics that are crucial to take into consideration. For example, the importance of the customer, and the level of service necessary. Most research assumes that these criteria are equally important, and some of them are difficult to measure.

In our study, a new hybrid methodology for vehicle route optimization is presented. In the hybrid model, customers are clustered using Clarke and Wright's savings algorithm. The weights of the criteria are calculated using the BWM method. Next, the RAFSI approach is used to rank the customers. To weight the criteria, various methods depending on the decision makers evaluations involve their subjective opinions [34]. These approaches, represented by the Level Based Weight Assessment (LBWA), the FUll Consistency Method (FUCOM), and the BWM techniques utilize experts' individual perspectives. The LBWA method diminishes the necessity for extensive pairwise comparisons (PCs) among criteria via a logical mathematical algorithm [34], [35]. Unlike other approaches, LBWA remains manageable even with numerous criteria, simplifying weight calculations [36]. It provides decision-makers with the flexibility to express preferences and resolve inconsistencies logically, without relying on preset scales [37]. The FUCOM method was developed as an approach for determining criteria weights, offering a structured process for multi-criteria decision-making [38]. This method effectively reduces redundancy in PCs, a common issue in subjective models for weight determination [39]. FUCOM requires fewer pairwise comparisons than BWM for the same number of criteria. However, FUCOM lacks validation studies confirming its effectiveness, a notable limitation highlighted in the literature review. BWM, employing a comparison-based approach, demands less data and demonstrates improved consistency in pairwise comparisons, making it a more efficient option [40]. Despite BWM's extensive applications, there's a research gap in applying it to prioritize VRP criteria post-Clarke-Wright algorithm. This gap is unfortunate as it could enhance BWM's practicality. This study uses BWM to evaluate criteria for optimal vehicle routes.

To rank the alternatives, various approaches have been applied over the past years. The Multi-Attributive Border Approximation Area Comparison (MABAC) method was introduced as a widely applicable approach for addressing real-world problems [41]. It ensures consistent outcomes despite measurement changes and offers a simple algorithm for large-scale problems [42]. However, its reliance on the max-min formula may introduce bias, indicating potential for improvement. The Measurement of Alternatives and Ranking according to the COmpromise Solution (MARCOS) technique ranks options as a compromise solution and remains robust with changes in attribute scales [43]. It provides reliable results in dynamic settings but relies solely on linear normalization, limiting its handling of fuzzy or ambiguous information. The Multi Attributive Ideal-Real Comparative Analysis (MAIRCA), using linear normalization, provides a stable solution with a simple framework [44]. It excels in accuracy compared to other methods. Despite its identified advantages, the method's reliance on exact values may overlook the nuances of human opinions and lacks the ability to handle inherent ambiguity [45]. The Ranking of Alternatives through Functional mapping of criterion sub-intervals into a Single Interval (RAFSI) method boasts three primary benefits: a simple algorithm for tackling complex problems, an innovative data normalization technique, and resilience against rank reversal issues [46]. Despite

its extensive application across diverse domains, there remains a dearth of research investigating its integration with BWM and the Clarke-Wright algorithm to determine the optimal vehicle route based on multiple criteria. This gap presents an opportunity to develop a novel integrated vehicle routing algorithm for route optimization.

1.3 Contribution

This research contributes to the advancement of the VRP field by offering a hybrid solution that combines heuristic algorithm, multi-criteria considerations, and decision-making models. By integrating the Clarke-Wright algorithm with the BWM-RAFSI model, the proposed approach enables logistics companies to construct more efficient and customer-centric routes. The research provides a comprehensive framework for solving complex logistics routing problems and offers insights into the integration of multiple methods for optimizing the VRP. A vehicle cluster using the Clarke-Wright algorithm has been built in the first phase. The BWM-RAFSI model is used in the second phase of the model to assess and evaluate the VRP's many criteria and rank customers by importance. The BWM technique enables the methodical evaluation and prioritization of criteria according to their relative significance. It considers both the most favorable and unfavorable aspects, offering a more thorough evaluation. Through the utilization of the BWM approach, we successfully allocated suitable weights to the criteria, thereby accurately representing their importance in the decision-making process. The utilization of the RAFSI method enables the assessment of several alternative solutions by considering multiple criteria. By integrating the Clarke-Wright algorithm with the BWM-RAFSI model, the algorithm aims to overcome the limitations of traditional VRP solutions that focus solely on distance optimization. Our approach enables logistics companies to consider diverse factors when constructing routes, resulting in more efficient and customer-centric solutions.

2 Literature review

The VRP is a frequently studied topic in the transportation area and has garnered significant attention from scholars. While the primary emphasis has been on identifying strategies to decrease vehicle mileage, additional criteria have been introduced, including customer demands and service time benchmarks, so exacerbating the complexity of the problem [47].

Vehicle routing algorithms have been increasingly important in supply chain analytics in recent years. Studies have shown that improved VRP solutions have a positive impact on supply chain efficiency by decreasing operational expenses and enhancing service levels. Researchers have investigated the use of VRP in different supply chain contexts, such as goods transportation, e-commerce logistics, and reverse logistics [48], [49]. For instance, dynamic routing models that account for real-time data and evolving conditions have been proposed to enhance flexibility and adaptability in logistics operations [50]. Furthermore, the application of MCDM methods in VRP models has shown potential in tackling the complex and dynamic nature of supply chains, where multiple conflicting objectives must be considered [51]. Additionally, integrated decision-support frameworks utilizing MCDM techniques are gaining traction, as they enable the simultaneous optimization of cost, time, and environmental considerations [52].

Numerous studies have been undertaken to solve multi-objective VRP, as evidenced by past research. Nevertheless, there is a limited number of studies that have employed MCDM techniques to address this issue [53]. MCDM approaches are automated techniques used to choose a preferred solution from a range of available options, even when there are conflicting criteria. MCDM approaches also enable the allocation of alternative solutions to predetermined classes and their subsequent ranking in descending order [54].

Addressing the complexities of VRPs often requires integrating diverse objectives, such as cost efficiency, service quality, and environmental sustainability. To this end, various approaches have been developed that combine traditional optimization techniques with advanced frameworks for prioritizing multiple criteria. These methods have been applied in areas such as waste collection, transportation logistics, and facility planning, where real-world constraints like dynamic demands, capacity limitations, and accessibility are key considerations [55],[56]. Recent innovations include hybrid models that integrate optimization algorithms with decision-making frameworks, enhancing adaptability to real-time changes and multi-depot challenges [57], [58]. By incorporating factors such as demand variability, environmental impact, and service levels, these approaches provide decision-makers with robust tools to balance competing objectives and optimize logistical performance [51], [59], [60].

MCDM is a powerful analytical framework widely employed in various fields, including transportation and logistics [60]-[62], and supply chain management [63], [64]. MCDM allows decision-makers to evaluate and prioritize alternatives based on multiple criteria or objectives [65]-[67]. By considering various factors simultaneously, MCDM facilitates informed decision-making processes and enables organizations to make optimal choices [68].

The utilization of the MCDM approach has the potential to enhance the quality of VRP solutions [4]. Few studies have combined MCDM and VRP algorithms.

3 Methodology

This research aims to leverage the strengths of both approaches to enhance decision-making in the context of VRP. The methodology presented comprises three primary steps: customer clustering through the utilization of the Clarke-Wright algorithm, the assignment of weights to the chosen criteria using the BWM technique, and the ranking of customers inside each route (cluster) employing the RAFSI approach. The utilization of this integrated methodology facilitates enhanced decision-making within the domain of VRP. Figure 1. shows the suggested methodology framework.

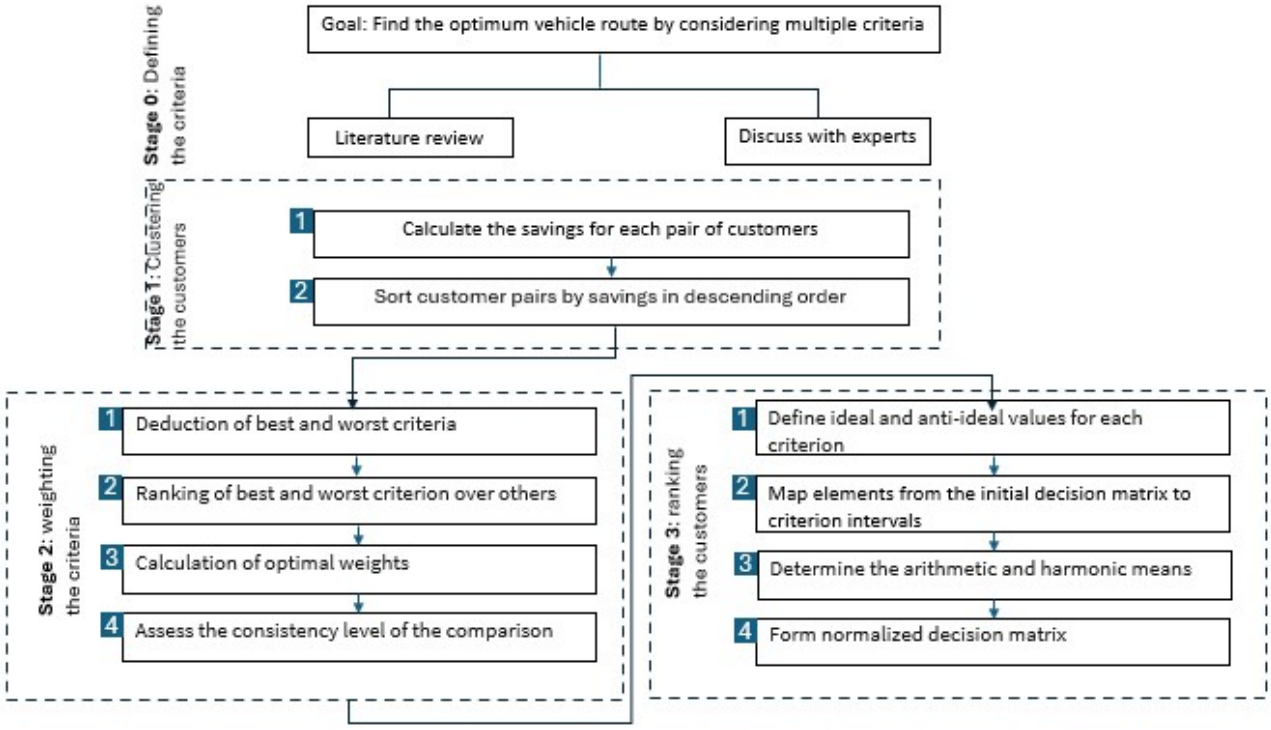

Figure 1. Methodology framework

3.1 Clarke-Wright algorithm

The Clarke and Wright savings method is a well-known VRP heuristic [69]. This approach works for decision variables with an unknown vehicle count. It works for directed and undirected VRP instances. The algorithm merges two possible routes $(0, \dots \dots, i, 0)$ and (0,j,...,0) into a single route (0,...,i,j,...,0), saving distance S(i,j) which can be calculated as follows: $S(i,j) = d(D,i) + d(D,j) - d(i,j)$.

The Clarke and Wright Savings algorithm solves VRPs sequentially. Following are the algorithms' steps:

Step 1: Calculate the savings $S(i,j) = d(D,i) + d(D,j) - d(i,j)$ for all pairs of customers i and j, where d represents the distances between two customers. Note that $S(i,j)$ is the saving in cost that would result if the link (i,j) is made to produce the route $(1,i,j,1)$ instead of supplying i and j on two routes $(1,i,1)$ and $(1,j,1)$.

Step 2: Order the savings in descending order.

Step 3: With the sorted savings list in hand, commence the process of creating larger sub-tours by linking the appropriate nodes i and j, starting from the top of the list and progressing downwards. This iterative step

within the Clarke and Wright Savings algorithm involves identifying pairs of nodes that can be combined to form a single tour. By repeatedly executing this merging process, larger sub tours are gradually formed until a complete tour is established. This sequential procedure ensures that the most beneficial node pairings are selected, optimizing the overall routing solution.

Step 4: Upon considering each link generated during the sub-tour formation process, evaluate its feasibility based on the constraints defined by the VRP. If a link satisfies the constraints and results in a feasible route, it is appended to the solution. Conversely, if a link violates any of the constraints, it is rejected and not included in the solution. This critical step within the Clarke and Wright Savings algorithm ensures that only valid and permissible links are incorporated into the final routing solution, maintaining the integrity of the solution while adhering to the constraints imposed by the VRP.

Step 5: Following the feasibility check and solution update in Step 4, proceed to the next link in the sorted savings list and repeat Step 4. Continuously evaluate each successive link in the list, considering its potential for creating a feasible route according to the constraints of the VRP. Iteratively applying Step 4 allows for the exploration of additional merging possibilities and the potential inclusion of more links in the solution. This process is repeated until no further links can be chosen, indicating that all feasible routes have been identified and included in the final solution.

3.2 Determining weight coefficients using the BWM

The BWM method, has emerged as a novel MCDM technique aimed at addressing the limitations of previous methodologies [70]. The primary distinctions between BWM and most contemporary MCDM techniques lie in the reduced number of pairwise comparisons required by BWM and the higher degree of reliability, consistency, logical coherence, and rationality exhibited by its results. This suggests that the BWM model produces outcomes that are more robust and conclusive. The flow chart of the BWM method is depicted in Figure 2 [38], [71], [72].

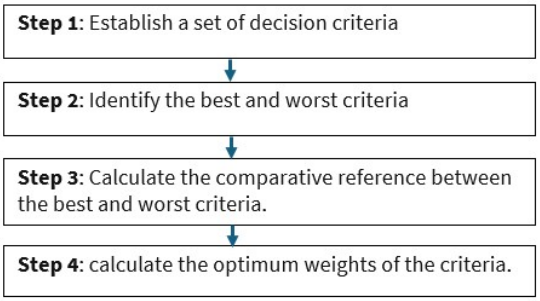

Figure 2. BWM flowchart

3.3 RAFSI method

The RAFSI method was introduced as a novel addition to the repertoire of MCDM techniques, offering innovative approaches to decision-making [46]. The initial decision matrix can be represented as follows for a collection of m alternatives, A1, A2, ..., Am, each with unique weights wj, where j varies from 1 to n [73]:

$$N = \begin{bmatrix} n_{11} & n_{12} & \dots\dots & n_{1n} \\ n_{21} & n_{22} & \dots\dots & n_{2n} \\ & & \ddots & \\ n_{m1} & n_{m2} & \dots\dots & n_{mn} \end{bmatrix}$$

The criteria utilized in the analysis can fall into two categories: maximizing type (max) or minimizing type (min). These categories distinguish between criteria that should be maximized for optimal outcomes and those that should be minimized. The implementation of the model involves the following step-by-step procedure:

Step 1: The initial step involves the establishment of clear definitions for both ideal and anti-ideal values. The decision-maker establishes two values, denoted as a_{I_j} and a_{N_j}, for each criterion. Here, a_{I_j} represents the ideal value of the criterion C_j, while a_{N_j} represents the anti-ideal value of the criterion C_j.

Step 2. The second step involves the mapping of elements from the initial decision matrix into intervals based on the established criteria. Functions $f_{A_i}\left(C_j\right)$ are established based on the predetermined ideal and anti-ideal values. These functions are responsible for mapping the criterion intervals from the aggregated initial decision matrix (N) to the criterion interval $[n_1, n_b]$. Criterion functions are established for each criterion within the given set C_j ($j=1,2,...,n$).

$$\tilde{f}_{A_i}\left(C_j\right)=\frac{n_b-n_1}{n_{I_j}-n_{N_j}}n_{ij}+\frac{n_{I_j}\cdot n_1-n_{N_j}\cdot n_b}{n_{I_j}-n_{N_j}} \tag{1}$$

where n_b and n_1 represent the ratio that shows how much the ideal value is better than the anti-ideal value, while n_{ij} denotes the value of the i-th alternative for the j-th criterion from the initial decision matrix.

It is recommended that the optimal value should be at least six times superior to the anti-ideal value, or $n_1=1$ and $n_b=6$. However, the decision maker (DM) has the option to utilize alternative preferred values, such as $n_1=1$ and $n_b=9$. This results in the creation of a standardized decision matrix $S=\left[s_{ij}\right]_{m\times n}$ ($i=1,2,...,m$, $j=1,2,...,n$) in which all elements of the matrix are transformed to fit within the interval $[n_1,\ n_b]$.

Step 3: This step involves determining the arithmetic and harmonic means for the minimum and maximum sequence of elements, denoted as n1 and n2k, respectively. These means can be calculated using the expressions (2) and (3).

$$A=\frac{n_1+n_{2k}}{2} \tag{2}$$

$$H=\frac{2}{\frac{1}{n_1}+\frac{1}{n_{2k}}} \tag{3}$$

Step 4: Form normalized decision matrix $\hat{S}=\left[\hat{s}_{ij}\right]_{m\times n}$ ($i=1,2,...,m$, $j=1,2,...,n$). Using expressions (4) and (5), elements of matrix S are normalized, and transferred into the interval [0,1]:

a) for the criteria C_j ($j=1,2,...,n$) max type:

$$\hat{s}_{ij}=\frac{s_{ij}}{2A} \tag{4}$$

b) for the criteria C_j ($j=1,2,...,n$) min type:

$$\hat{s}_{ij}=\frac{H}{2s_{ij}} \tag{5}$$

As a result, a new normalized decision matrix is generated, as demonstrated below:

$$\hat{S}=\begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array}\begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} \hat{s}_{11} & \hat{s}_{12} & \cdots & \hat{s}_{1n} \\ \hat{s}_{21} & \hat{s}_{22} & \cdots & \hat{s}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{s}_{m1} & \hat{s}_{m2} & \cdots & \hat{s}_{mn} \end{bmatrix} \end{array} \tag{6}$$

In this context, $\hat{s}_{ij} \in [0,1]$ denotes the normalized elements of matrix $\hat{S}$.

Step 5: Involves the calculation of the function parameters for the alternatives, denoted as V(Ai). Equation (7) is employed to compute the criteria functions of the alternatives. The calculated value of V(Ai) is subsequently employed to rank the alternatives in a descending order.

$$V(A_i) = w_1\hat{s}_{i1} + w_2\hat{s}_{i2} + ... + w_n\hat{s}_{in} \tag{7}$$

4 Results and discussion

This case study examines the operations of a food industry enterprise involved in the delivery of its products through an in-house fleet. The primary data pertaining to the study was gathered from the company. The provided data includes the geographical locations of customers and the corresponding quantities that are demanded. The vehicles' capacity was also provided. The products are packaged in cartons, with each vehicle capable of accommodating up to 80 cartons. The primary objective of the company is to minimize costs without compromising on customer satisfaction. By delving into the intricacies of their operations, we aim to identify potential areas for improvement and propose strategies that can enhance efficiency, reduce expenses, and ultimately contribute to the enterprise's overall success in the competitive food industry. Table 1 displays the coordinates of each customer in relation to the depot, along with their corresponding demand in cartons. Only 19 customers were included in this study. The customers were selected considering diverse characteristics, including geographical distribution, varying demand levels, and logistical constraints such as accessibility and time windows. Managing a substantial customer base with MCDM models can be somewhat challenging. For instance, when employing the AHP model in case of having 19 customers and 6 criteria, a comparison must be conducted for each customer based on these criteria. Therefore, a total of 6 tables are required to conduct a pairwise comparison between 19 customers on each case. Experts will face challenges when they conduct this task.

Table 1. Coordinates of the customers

Customer ID	X	Y	Demand	Distance Savings
Depot	0	0	-	
1	2.0	3.0	20	7.1
2	2.5	1.0	30	4.6
3	5.2	6.4	16	4.2
4	2.7	2.6	21	3.9
5	2.1	4.7	15	3.9
6	1.9	1.2	20	3.9
7	1.0	4.0	2	3.6
8	5.2	3.3	11	1.2
9	2.3	1.7	12	3.5
10	4.2	4.1	19	3.3
11	3.1	3.2	9	3.2
12	0.5	2.5	23	3.2
13	1.2	4.2	21	3.1
14	5.2	4.1	15	3.1
15	2.7	2.3	3	3.1
16	1.7	3.3	14	3.1
17	1.3	1.3	9	3.0
18	5.7	5.8	28	2.9
19	3.6	1.6	10	4.0

After the group of customers is clustered for the route by a distance-saving algorithm, the routing is created for each group using nearest neighbor algorithm, and the results are displayed in Table 2. In this algorithm, the shortest distances routes are selected.

Table 2. Generated clusters

Route No.	Cluster
R1	19-17-7-14-18-3
R2	15-2-6-12
R3	11-10-5-13-9
R4	8-4-1-16

Table 3 provides a visual representation of the routes to each cluster and delivery quantity, which calculated through the nearest neighbor algorithm.

Table 3. generated routes and delivered quantity.

Route No.	Route	Distance	Delivered Quantity
R1	D-19-17-7-14-18-3-D	24.0	80
R2	D-15-2-6-12-D	10.0	76
R3	D-11-10-5-13-9-D	14.7	76
R4	D-8-4-1-16-D	13.7	66

In typical VRP, the primary consideration is usually the distance. Tables 2 and 3 show the formation of the clusters as well as the determination of the vehicle routes and the distribution order. In this approach, only one objective was considered, which is minimizing the traveling distance. No other criteria were considered. In reality, there is a need to take into account other criteria when carrying out the distribution process.

Within this theoretical framework, distance is identified as a single criterion among the six that have been put forward. The criteria were selected based on expert opinions, considering their practical relevance to vehicle routing decisions. The six criteria that have been proposed are delineated in the following manner.

1. Distance (C1): The distance between the depot and each customer is an obvious factor to consider in the VRP. This can be measured in terms of total distance or travel time.

2. Demand (C2): The amount of goods that each customer requires is another important criterion. Provider would want to prioritize customers with higher demand to maximize the total load delivered.

3. Time window (C3): Many customers may have specific time window constraints within which they can accept deliveries. Adhering to these time windows is crucial to ensure customer satisfaction.

4. Accessibility (C4): The ease of access to each customer's location could also be a factor to consider. Customers located in congested or difficult-to-reach areas may require more time and effort to deliver to, and so may be ranked lower.

5. Service level (C5): The level of service required by each customer could be another criterion. Customers who require a higher level of service (such as faster delivery times or special handling) could be ranked higher.

6. Frequency (C6): The frequency of deliveries to each customer could also be a criterion. Customers who require more frequent deliveries could be ranked higher.

To derive weight coefficients using the BWM method, one must first identify the most significant criterion (B) and the least significant criterion (W).

In addition to the basic data collected regarding customer locations and demanded quantities, a group of experts received two forms. The experts consulted were logistics professionals, including managers and academic researchers with over 10 years of experience in operational decision-making. Consensus among their opinions was achieved using the BWM, ensuring consistency and minimizing bias in the criteria selection process. The first form aims to rank the criteria based on the BWM model. Experts were requested to select the most important criterion and the least significant criterion in this form. Next, participants are instructed to prioritize the most significant criterion in comparison to the other criteria. During the last stage, experts assess

the worst criterion in comparison to the other criteria. Table A1 in the Appendix displays the form that was delivered to the experts. The second form that was delivered aimed to assess customers based on the suggested criteria. Once these forms have been filled, the BO and OW vectors can be calculated and are presented in Table 4.

Table 4. Evaluation vectors

Criteria			
Best: C3	Expert evaluation	Worst: C4	Expert evaluation
C1	1;2;3;2	C1	8;8;8;8
C2	3;2;2;1	C2	7;7;8;6
C4	6;7;6;9	C3	8;8;8;8
C5	3;3;3;3	C5	4;4;3;5
C6	5;4;6;5	C6	2;2;2;2

The BO vector, as shown in Table 2, displays the expert preferences that indicate the superiority of criterion C3 compared to the other criteria within the specified set. In order to assess the relative advantage between criterion C3 and criterion j, $a_{Bj} \in [1,9]$ scale has been employed. A higher value on this scale indicates a greater advantage of criterion C3 over criterion j. The $a_{jW} \in [1,9]$ scale has been utilized to depict the preferences of experts in the WO vector, with a higher value on the scale indicating a greater advantage of criterion j compared to the worst criterion C4.

By employing the arithmetic averaging formula $x_{ij} = \left(\frac{1}{n}\right)\sum_{i=1}^{n} x_i$, the average values of the BP and OW vectors are derived subsequent to the calculation of the average BO and OW vectors. The computation of the optimal weight coefficient values is performed using the criterion vectors of BO and OW. Table 5 shows the final weights of the criteria. The table shows that the time window is the most important criterion. This means that the distribution will not always be available, but rather will be limited to specific time periods. Distance comes in second rank. Accessibility is in the last rank.

Table 5: Optimal criterion values – BWM

Criteria		Weights	Rank
C1	Distance	0.206	2
C2	Demand	0.206	3
C3	Time window	0.332	1
C4	Accessibility	0.036	6
C5	Service level	0.137	4
C6	Frequency	0.083	5

The values of ξ^* are obtained by solving the equation (8) from BMW, which are: $\xi^*_{Criteria} = 0.527$, ..., , $\xi^*_{C_{Policy}} = 0.0282$. The consistency ratio is determined by solving equation in the BMW method, using the provided variables. The determination of consistency index values is not feasible in advance due to its reliance on the collective judgments made by experts. The values of ξ are determined as provided by BMW. Given that all values are CR≤0.25, it can be concluded that the weight coefficients found are optimal.

Upon the determination of criteria weights, the ranking of alternatives was carried out utilizing the RAFSI method. To facilitate this process, an initial decision matrix was prepared, as depicted in Table 6.

Table 6. initial decision matrix

Customer	C1	C2	C3	C4	C5	C6
A1	69	58	57	84	89	91
A2	69	68	59	86	60	93
A3	52	79	76	92	72	87
A4	84	52	94	91	65	59
A5	61	62	62	75	84	89
A6	57	51	56	54	87	70
A7	94	60	95	62	61	94
A8	67	65	57	86	55	65
A9	71	53	57	85	61	93
A10	78	58	85	83	67	69
A11	60	76	61	58	62	89
A12	70	74	67	76	84	65
A13	68	67	59	76	77	70
A14	84	92	55	92	76	76
A15	50	81	92	86	68	71
A16	79	81	52	79	86	88
A17	60	79	63	55	54	58
A18	79	56	58	87	51	63
A19	85	63	95	62	72	78

The implementation of the RAFSI method can be facilitated by following the sequential steps outlined below:

Step 1: The establishment of the ideal and anti-ideal values for the criteria has been determined by the decision-makers (DMs).

$a_{I_j} = [30,\ 100,\ 100,\ 100, 100, 100]$

$a_{N_j} = [100,\ 40,\ 30,\ 50,\ 40, 30]$

Step 2: The elements within the matrix S have undergone normalization and transformation processes, resulting in the development of a new matrix as shown in Table 7.

Table 7: Normalized matrix

	C1	C2	C3	C4	C5	C6
A1	0.54	0.73	0.58	0.76	0.73	0.77
A2	0.54	0.97	0.56	0.70	0.38	0.79
A3	0.40	1.24	0.39	0.53	0.52	0.72
A4	0.82	0.58	0.20	0.55	0.44	0.44
A5	0.46	0.83	0.53	1.02	0.67	0.74
A6	0.43	0.56	0.59	1.63	0.70	0.55
A7	1.23	0.78	0.19	1.40	0.39	0.80
A8	0.52	0.90	0.58	0.70	0.32	0.50
A9	0.57	0.61	0.58	0.73	0.39	0.79
A10	0.68	0.73	0.30	0.79	0.46	0.54
A11	0.45	1.17	0.54	1.52	0.40	0.74
A12	0.56	1.12	0.48	0.99	0.67	0.50
A13	0.53	0.95	0.56	0.99	0.58	0.55
A14	0.82	1.56	0.60	0.53	0.57	0.61
A15	0.38	1.29	0.22	0.70	0.48	0.56
A16	0.70	1.29	0.63	0.90	0.69	0.73
A17	0.45	1.24	0.52	1.60	0.31	0.43
A18	0.70	0.68	0.57	0.67	0.27	0.48
A19	0.84	0.85	0.19	1.40	0.52	0.63

Step 3: Table 8 presents the criteria functions V(Ai) of the alternatives, wherein these values are utilized for the purpose of ranking the alternatives.

Table 8. Ranking of the studied customers

Customer	V (A_i)	Rank
A1	1.6552	9
A2	1.6508	10
A3	1.3489	18
A4	1.9870	5
A5	1.4886	16
A6	1.3978	17
A7	2.9184	1
A8	1.5629	13
A9	1.6373	12
A10	1.7872	7
A11	1.5264	14
A12	1.7051	8
A13	1.6401	11
A14	2.3507	2
A15	1.2655	19
A16	2.1055	4
A17	1.4985	15
A18	1.8734	6
A19	2.1546	3

The present step of the procedure involves allocating customers to routes according to their priority ranking. Every customer is assigned a route based on their priority ranking. To illustrate the clustered clients for vehicle V1, we can refer to Table 3. The customer set consists of the numbers 19, 17, 7, 14, 18, and 3. Out of the six customers under consideration, customer A7 has been assigned the highest priority rank of 1, with a weight value of 2.9184. As a result, the assignment of A7 to vehicle V1 is made for the first customer. Following this, A14 is assigned a priority rank of 2, which is the second-highest priority, and it is assigned a weight of 2.3507. Subsequently, A19 is assigned a priority rating of 3, which is the third highest among the options. This ranking is determined by a weight of 2.1546. At the conclusion, A3 exhibits the least significant priority rank of 18, accompanied with a weight of 1.3489. Consequently, vehicle V1 is designated to serve customer A3 as the ultimate assignment. The aforementioned procedure is iterated for each individual customer, thereby guaranteeing their assignment to routes in accordance with their respective priority ranking. The route utilizing the hybrid savings algorithm and MCDM approach is displayed in Table 8.

Table 9. Routes obtained using combined savings MCDM methods

Route No.	Route	Distance	Delivered Quantity
R1	D-7-14-19-18-17-3-D	28.3	80
R2	D-12-2-6-15-D	10.6	76
R3	D-10-13-9-11-5-D	17.4	76
R4	D-16-4-1-8-D	14.8	66

The total distance when utilizing MCDM approach in the VRP increased by 11% compared with the results acquired using traditional models for scheduling vehicle routes. Using just savings approach, on the other hand, just considers the distances. Using the hybrid savings-MCDM approach facilitates using a number of other criteria. Despite having a 0.2 weight, the distance criterion made a significant contribution to the customers' ranking. Figure 3 summarizes the difference between the two approaches.

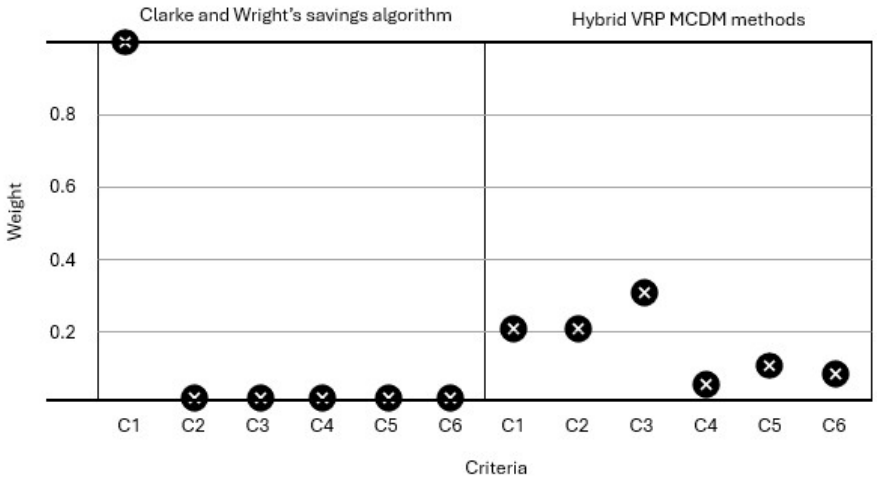

Figure 3. Summary of the two approaches

Compared to both standalone VRP models and hybrid VRP-MCDM approaches, the proposed methodology provides an effective framework for addressing vehicle routing problems with multiple objectives. Standalone VRP approaches, such as those using genetic algorithms [74], particle swarm optimization [75], and savings-based heuristics [76], focus primarily on route optimization while minimizing computational complexity. However, these methods often lack the ability to consider multiple criteria simultaneously, such as customer prioritization or time windows. On the other hand, hybrid VRP-MCDM models, such as those combining VRP with hybrid SWARA-COCOSO methods [77] or BWM-PROMETHEE-II methods to solve routing problems [78], offer more comprehensive decision-making frameworks by integrating additional criteria [79]- [81].

Compared to these approaches, our proposed hybrid model demonstrates a more balanced framework by leveraging the Clarke-Wright algorithm for clustering and integrating BWM and RAFSI for multi-criteria prioritization. This combination enhances the practicality of the methodology in addressing both routing efficiency and customer satisfaction. The results highlight the robustness of our method in scenarios where multiple conflicting objectives must be addressed simultaneously.

5 Policy and Managerial Implications

The findings of this study hold significant implications for both policymakers and logistics managers operating in the transportation and supply chain domains.

From a policy perspective, it is crucial for policymakers to improve a regulatory framework that promotes the implementation of efficient vehicle routing methods. It could be suitable to offer incentives to firms which implement such approaches with the goal of enhancing cost effectiveness and customer satisfaction. These regulations will incentivize corporations to engage in enhancing their mobility planning capabilities, leading to positive outcomes for consumers and communities, such as less environmental impact and improved service quality.

For logistics managers, this study provides a comprehensive framework for tackling the complexities of the VRP. The integration of the Clarke and Wright savings algorithm with the BWM and RAFSI approach offers a powerful decision-support tool. By simultaneously optimizing route planning and customer prioritization, managers can strike a balance between cost-efficiency and customer-centricity, leading to enhanced organizational performance and increased customer satisfaction.

For decision-making in logistics and supply chain management, the research offers a transformative framework by integrating customer prioritization and multi-criteria evaluation into vehicle routing. It enables managers to prioritize high-value or time-sensitive deliveries, ensuring customer satisfaction while optimizing routes for cost, delivery time, and environmental impact. The hybrid methodology could reduce operational costs through minimized travel distances and fuel consumption, while addressing real-world complexities like fluctuating demand and diverse constraints. Its flexibility could support dynamic adjustments and strategic planning, such as identifying demand patterns or aligning operations with sustainability goals. Scalable and adaptable across industries, this approach could empower efficient, customer-focused, and sustainable decision-making, enhancing overall supply chain performance and stakeholder trust.

Furthermore, the flexibility of the proposed hybrid methodology allows for the incorporation of additional criteria, such as delivery time windows, driver preferences, and environmental impact. This adaptability empowers logistics managers to tailor the solution to the unique requirements of their respective organizations and the evolving needs of their customer base.

The limitations of this study, namely the use of a relatively small number of customers per route, present an opportunity for further research and development. Exploring the scalability of the proposed approach to handle larger-scale routing problems would enable its application in more complex, real-world scenarios. Addressing this limitation could yield valuable insights for both academics and industry practitioners, ultimately driving the advancement of vehicle routing optimization in the transportation and logistics sectors.

6 Conclusion

This research addresses the limitations of traditional VRP solutions by integrating MCDM approaches and customer prioritization into the vehicle routing process. It identifies six criteria and nineteen alternatives to help policymakers and logistics managers make informed decisions. Employing a hybrid methodology that combines the Clarke-Wright algorithm with the BWM and RAFSI methods, this study moves beyond existing methods such as heuristic algorithms, metaheuristic approaches, mathematical models, and data-driven techniques that often fail to incorporate multiple criteria into the models or prioritize customer satisfaction, leaving notable research gaps. In our hybrid model, customers are clustered using Clarke and Wright's savings algorithm. The weights of the criteria are calculated using the BWM method. Next, the RAFSI approach is used to rank the customers. While minimizing total costs remains a significant factor, long-term success in logistics operations heavily relies on reducing customer discomfort and enhancing customer satisfaction.

This research makes several valuable contributions to the scientific community and society, including:

- The research introduces a hybrid approach combining the Clarke-Wright algorithm with the BWM-RAFSI model to enhance the Vehicle Routing Problem (VRP) solutions.
- The methodology enables logistics companies to construct routes that are both efficient and customer-focused.
- The research provides a comprehensive framework for solving complex logistics routing problems and offers insights into the integration of multiple methods for optimizing the VRP.
- The research evaluates multiple criteria and ranks customers by importance.
- Unlike traditional VRP solutions focused solely on distance optimization, the approach incorporates diverse factors, resulting in balanced and practical routing decisions.

Although significant contributions are made through this research, the use of a limited number of customers per route is noticed as a limitation. The use of large numbers makes it difficult to use some MCDM methods in the solution. In contrast, the use of MCDM methods allows different criteria to be added and taken into account when solving the problem. As a future development for the research, some variables can be added into the VRP model, such as the time window. The solution can be obtained using heuristic algorithms and comparing the results when using a hybrid VRP-MCDM methods.

References

[1] S. M. Raza, M. Sajid, and J. Singh, "Vehicle routing problem using reinforcement learning: Recent advancements," *Advanced Machine Intelligence and Signal Processing*, pp. 269-280: Springer, 2022. https://doi.org/10.1007/978-981-19-0840-8_20

[2] J. Ochelska-Mierzejewska, A. Poniszewska-Marańda, and W. Marańda, "Selected genetic algorithms for vehicle routing problem solving," *Electronics,* vol. 10, no. 24, pp. 3147, 2021. https://doi.org/10.3390/electronics10243147

[3] R. Moghdani, K. Salimifard, E. Demir, and A. Benyettou, "The green vehicle routing problem: A systematic literature review," *Journal of Cleaner Production,* vol. 279, pp. 123691, 2021. https://doi.org/10.1016/j.jclepro.2020.123691

[4] G. D. Konstantakopoulos, S. P. Gayialis, and E. P. Kechagias, "Vehicle routing problem and related algorithms for logistics distribution: A literature review and classification," *Operational research*, pp. 1-30, 2020. https://doi.org/10.1007/s12351-020-00600-7

[5] S.-Y. Tan, and W.-C. Yeh, "The vehicle routing problem: State-of-the-art classification and review," *Applied Sciences,* vol. 11, no. 21, pp. 10295, 2021. https://doi.org/10.3390/app112110295

[6] I. Badi, Bouraima, M. B., Stević, Željko ., Oloketuyi, E. A. , & Makinde, O. O., "Optimizing Vendor-Managed Inventory in Multi-Tier Distribution Systems," *Spectrum of Operational Research,* vol. 1, no. 1, pp. 33-43, 2024. https://doi.org/10.31181/sor1120243

[7] G. D. Konstantakopoulos, S. P. Gayialis, and E. P. Kechagias, "Vehicle routing problem and related algorithms for logistics distribution: A literature review and classification," *Operational research,* vol. 22, no. 3, pp. 2033-2062, 2022. https://doi.org/10.1007/s12351-020-00600-7

[8] D. Prajapati, A. R. Harish, Y. Daultani, H. Singh, and S. Pratap, "A clustering based routing heuristic for last-mile logistics in fresh food E-commerce," *Global Business Review,* vol. 24, no. 1, pp. 7-20, 2023. https://doi.org/10.1177/0972150919889797

[9] L. Gao, M. Chen, Q. Chen, G. Luo, N. Zhu, and Z. Liu, "Learn to design the heuristics for vehicle routing problem," *arXiv preprint arXiv:2002.08539*, 2020.

[10] S. Reong, H.-M. Wee, and Y.-L. Hsiao, "20 Years of Particle Swarm Optimization Strategies for the Vehicle Routing Problem: A Bibliometric Analysis," *Mathematics,* vol. 10, no. 19, pp. 3669, 2022. https://doi.org/10.3390/math10193669

[11] R. Elshaer, and H. Awad, "A taxonomic review of metaheuristic algorithms for solving the vehicle routing problem and its variants," *Computers & Industrial Engineering,* vol. 140, pp. 106242, 2020. https://doi.org/10.1016/j.cie.2019.106242

[12] K. Sar, and P. Ghadimi, "A systematic literature review of the vehicle routing problem in reverse logistics operations," *Computers & Industrial Engineering*, pp. 109011, 2023. https://doi.org/10.1016/j.cie.2023.109011

[13] W. Kosasih, and L. L. Salomon, "Comparison study between nearest neighbor and farthest insert

algorithms for solving VRP model using heuristic method approach.", *2nd TICATE*, p. 012090, 2020. https://doi.org/10.1088/1757-899X/852/1/012090

[14] D. A. Kurniawati, R. P. Kusuma, D. Kristanto, N. M. Yusof, and K. Y. Wong, "Optimizing Distribution Route of Packed Drinking Water with The Clarke and Wright Savings and Nearest Neighbor Methods (Case Study of PT. GSI)," *Journal of Industrial Engineering and Halal Industries,* vol. 2, no. 2, pp. 77-84. https://doi.org/10.14421/jiehis.3422

[15] P. Stodola, "Hybrid ant colony optimization algorithm applied to the multi-depot vehicle routing problem," *Natural Computing,* vol. 19, no. 2, pp. 463-475, 2020. https://doi.org/10.1007/s11047-020-09783-6

[16] İ. İlhan, "An improved simulated annealing algorithm with crossover operator for capacitated vehicle routing problem," *Swarm and Evolutionary Computation,* vol. 64, pp. 100911, 2021. https://doi.org/10.1016/j.swevo.2021.100911

[17] A. Agárdi, L. Kovács, and T. Bányai, "Mathematical Model for the Generalized VRP Model," *Sustainability,* vol. 14, no. 18, pp. 11639, 2022. https://doi.org/10.3390/su141811639

[18] T. Leelertkij, P. Parthanadee, and J. Buddhakulsomsiri, "Vehicle routing problem with transshipment: mathematical model and algorithm," *Journal of Advanced Transportation,* vol. 2021, pp. 1-15, 2021. https://doi.org/10.1155/2021/8886572

[19] R. Bai, X. Chen, Z.-L. Chen, T. Cui, S. Gong, W. He, X. Jiang, H. Jin, J. Jin, and G. Kendall, "Analytics and machine learning in vehicle routing research," *International Journal of Production Research,* vol. 61, no. 1, pp. 4-30, 2023. https://doi.org/10.1080/00207543.2021.2013566

[20] N. Giuffrida, J. Fajardo-Calderin, A. D. Masegosa, F. Werner, M. Steudter, and F. Pilla, "Optimization and machine learning applied to last-mile logistics: A review," *Sustainability,* vol. 14, no. 9, pp. 5329, 2022. https://doi.org/10.3390/su14095329

[21] J. Mandi, R. Canoy, V. Bucarey, and T. Guns, "Data driven vrp: A neural network model to learn hidden preferences for vrp," *arXiv preprint arXiv:2108.04578*, 2021.

[22] A. K. Kalakanti, S. Verma, T. Paul, and T. Yoshida, "RL SolVeR pro: Reinforcement learning for solving vehicle routing problem," *IEEE Xplore*, pp. 94-99, 2019. https://doi.org/10.1109/AiDAS47888.2019.8970890

[23] D. Satyananda, and A. Abdullah, "Deep learning to handle congestion in vehicle routing problem: A review", *Journal of Physics*, p. 012023, 2021. https://doi.org/10.1088/1742-6596/2129/1/012023

[24] K. A. Putri, N. L. Rachmawati, M. Lusiani, and A. Redi, "Genetic algorithm with cluster-first route-second to solve the capacitated vehicle routing problem with time windows: A case study," *Jurnal Teknik Industri,* vol. 23, no. 1, pp. 75-82, 2021. https://doi.org/10.9744/jti.23.1.75-82

[25] N. Al Theeb, M. Abu-Aleqa, and A. J. C. Diabat, "Multi-objective optimization of two-echelon vehicle routing problem: Vaccines distribution as a case study," *Computers & Industrial Engineering*, vol. 187, pp. 109590, 2024. https://doi.org/10.1016/j.cie.2023.109590

[26] S. Koç, C. Erden, Ç. Ateş, and E. Ceviz, "Evaluation of Potential Logistics Village Alternatives Using Bayesian Best-Worst Method," *Optimality*, vol. 1, no. 1, pp. 100-120, 2024.

[27] F. Kangi, S. H. R. Pasandideh, E. Mehdizadeh, and H. Soleimani, "The optimization of an integrated forward and reverse logistics network based on routing and cross-docking strategy," *Journal of Applied Research on Industrial Engineering,* vol. 11, no. 2, pp. 251-282, 2024.

[28] S. Z. Abidin, N. I. Z. Abidin, and H. J. Daud, "Decision-Making Support in Vehicle Routing Problems: A Review of Recent Literature," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 44, no. 2, pp. 124-134, 2025. https://doi.org/10.37934/araset.44.2.124134

[29] A. Farahbakhsh, and A. Kheirkhah, "A new efficient genetic algorithm-Taguchi-based approach for multi-period inventory routing problem," *International journal of research in industrial engineering,* vol. 12, no. 4, pp. 397-413, 2023.

[30] N. Durmaz, and A. Budak, "An integrated Bi-objective green vehicle routing and partial disassembly line problem for electronic waste: an industrial case study," *International Journal of Computer Integrated Manufacturing,* pp. 1-26, 2024. https://doi.org/10.1080/0951192X.2024.2335984

[31] R. Ali, K. Rahman, and J. Muhammad, "Complex Fermatean fuzzy models and their algebraic aggregation operators in decision-making: A case study on COVID-19 vaccine selection," *J. Oper. Strateg Anal,* vol. 2, no. 2, pp. 119-135, 2024. https://doi.org/10.56578/josa020205

[32] X. Li, Y. Zhang, A. Sorourkhah, and S. J. J. o. t. K. E. Edalatpanah, "Introducing antifragility analysis algorithm for assessing digitalization strategies of the agricultural economy in the small farming section," *Journal of the Knowledge Economy,* pp. 1-25, 2023. https://doi.org/10.1007/s13132-023-01558-5

[33] A. M. Golmohammadi, A. Goli, H. J. I. m. Rasay, and o. strategies, "Employing Efficient Algorithms to Reduce the Distance Traveled in Location-Routing Problems Considering Travel and Service," *Innovation management and operational strategies,* vol. 3, no. 1, pp. 48-61, 2022.

[34] M. Žižović, and D. Pamucar, "New model for determining criteria weights: Level Based Weight Assessment (LBWA) model," *Decision Making: Applications in Management and Engineering,* vol. 2, no. 2, pp. 126-137, 2019. https://doi.org/10.31181/dmame1902102z

[35] S. Korucuk, A. Aytekin, F. Ecer, D. S. S. Pamucar, and Ç. Karamaşa, "Assessment of ideal smart network strategies for logistics companies using an integrated picture fuzzy LBWA–CoCoSo framework," *Management Decision,* vol. 61, no. 5, pp. 1434-1462, 2023. https://doi.org/10.1108/MD-12-2021-1621

[36] S. Biswas, S. Majumder, D. Pamucar, and S. K. Dawn, "An extended LBWA framework in picture fuzzy environment using actual score measures application in social enterprise systems," *International Journal of Enterprise Information Systems (IJEIS),* vol. 17, no. 4, pp. 37-68, 2021. https://doi.org/10.4018/IJEIS.2021100103

[37] F. Ecer, D. Pamucar, A. Mardani, and M. Alrasheedi, "Assessment of renewable energy resources using new interval rough number extension of the level based weight assessment and combinative distance-based assessment," *Renewable Energy,* vol. 170, pp. 1156-1177, 2021. https://doi.org/10.1016/j.renene.2021.02.004

[38] D. Pamučar, Ž. Stević, and S. Sremac, "A new model for determining weight coefficients of criteria in mcdm models: Full consistency method (fucom)," *Symmetry,* vol. 10, no. 9, pp. 393, 2018. https://doi.org/10.3390/sym10090393

[39] N. Zagradjanin, D. Pamucar, and K. Jovanovic, "Cloud-based multi-robot path planning in complex and crowded environment with multi-criteria decision making using full consistency method," *Symmetry,* vol. 11, no. 10, pp. 1241, 2019. https://doi.org/10.3390/sym11101241

[40] J. Rezaei, "Best-worst multi-criteria decision-making method," *Omega,* vol. 53, pp. 49-57, 2015. https://doi.org/10.1016/j.omega.2014.11.009

[41] D. Pamučar, and G. Ćirović, "The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC)," *Expert systems with applications,* vol. 42, no. 6, pp. 3016-3028, 2015. https://doi.org/10.1016/j.eswa.2014.11.057

[42] A. E. Torkayesh, E. B. Tirkolaee, A. Bahrini, D. Pamucar, and A. Khakbaz, "A systematic literature review of MABAC method and applications: An outlook for sustainability and circularity," *Informatica,* vol. 34, no. 2, pp. 415-448, 2023. https://doi.org/10.15388/23-INFOR511

[43] Ž. Stević, D. Pamučar, A. Puška, and P. Chatterjee, "Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS)," *Computers & industrial engineering,* vol. 140, pp. 106231, 2020. https://doi.org/10.1016/j.cie.2019.106231

[44] L. Gigović, D. Pamučar, Z. Bajić, and M. Milićević, "The combination of expert judgment and GIS-MAIRCA analysis for the selection of sites for ammunition depots," *Sustainability,* vol. 8, no. 4, pp. 372, 2016. https://doi.org/10.3390/su8040372

[45] D. Pamučar, M. Mihajlović, R. Obradović, and P. Atanasković, "Novel approach to group multi-criteria decision making based on interval rough numbers: Hybrid DEMATEL-ANP-MAIRCA model," *Expert systems with applications,* vol. 88, pp. 58-80, 2017. https://doi.org/10.1016/j.eswa.2017.06.037

[46] M. Žižović, D. Pamučar, M. Albijanić, P. Chatterjee, and I. Pribićević, "Eliminating rank reversal problem using a new multi-attribute model—the RAFSI method," *Mathematics,* vol. 8, no. 6, pp. 1015, 2020. https://doi.org/10.3390/math8061015

[47] S. Moslem, "A novel parsimonious spherical fuzzy analytic hierarchy process for sustainable urban transport solutions," *Engineering Applications of Artificial Intelligence,* vol. 128, pp. 107447, 2024. https://doi.org/10.1016/j.engappai.2023.107447

[48] M. K. Zuhanda, H. Mawengkang, S. Suwilo, M. Mardiningsih, and O. S. Sitompul, "Logistics distribution supply chain optimization model with VRP in the context of E-commerce," *In AIP Conference Proceedings*, Vol. 2714, No. 1, 2023.

[49] A. Chaabane, J. Montecinos, M. Ouhimmou, and A. Khabou, "Vehicle routing problem for reverse logistics of End-of-Life Vehicles (ELVs)," *Waste Management,* vol. 120, pp. 209-220, 2021. https://doi.org/10.1016/j.wasman.2020.11.008

[50] M. Shafiekhani, A. Rashidi Komijan, and H. J. Javanshir, "Optimizing the routing problem in the vehicle carrying cash considering the route risk (case study of Bank Shahr)," *Journal of applied research on industrial engineering,* vol. 11, no. 1, pp. 143-154, 2024.

[51] M. Rabbani, S. A. Sadati, and H. Farrokhi-Asl, "Incorporating location routing model and decision making techniques in industrial waste management: Application in the automotive industry," *Computers & Industrial Engineering,* vol. 148, pp. 106692, 2020. https://doi.org/10.1016/j.cie.2020.106692

[52] R. Keshavarzfard, and A. Naderi, "A Sustainable HazMat Logistic Network Design Considering Scale of Economy and Route Sensitivity and Solving with Hybrid GA-SA," *International Journal of Research in Industrial Engineering,* vol. 13, no. 3, pp. 257-273, 2024.

[53] S. Zajac, and S. Huber, "Objectives and methods in multi-objective routing problems: a survey and classification scheme," *European Journal of Operational Research,* vol. 290, no. 1, pp. 1-25, 2021. https://doi.org/10.1016/j.ejor.2020.07.005

[54] S. Moslem, F. K. Gündoğdu, S. Saylam, and F. Pilla, "A hybrid decomposed fuzzy multi-criteria decision-making model for optimizing parcel lockers location in the last-mile delivery landscape," *Applied Soft Computing,* vol. 154, pp. 111321, 2024. https://doi.org/10.1016/j.asoc.2024.111321

[55] J. A. Ferreira, M. Costa, A. Tereso, and J. A. Oliveira, "A multi-criteria decision support system for a routing problem in waste collection," *In Evolutionary Multi-Criterion Optimization: 8th International Conference*, pp. 388-402, 2015. https://doi.org/10.1007/978-3-319-15892-1_26

[56] O. E. Nahum, and Y. Hadas, "A framework for solving real-time multi-objective VRP," *In Advanced Concepts, Methodologies and Technologies for Transportation and Logistics,* pp. 103-120, 2018. https://doi.org/10.1007/978-3-319-57105-8_5

[57] N. Wichapa, and P. Khokhajaikiat, "Solving a multi-objective location routing problem for infectious waste disposal using hybrid goal programming and hybrid genetic algorithm," *International Journal of Industrial Engineering Computations,* vol. 9, no. 1, pp. 75-98, 2018. https://doi.org/10.5267/j.ijiec.2017.4.003

[58] M. Balaji, S. Santhanakrishnan, and S. Dinesh, "An application of analytic hierarchy process in vehicle routing problem," *Periodica Polytechnica Transportation Engineering,* vol. 47, no. 3, pp. 196-205, 2019. https://doi.org/10.3311/PPtr.10701

[59] R. Sarraf, and M. P. McGuire, "Integration and comparison of multi-criteria decision making methods in safe route planner," *Expert Systems with Applications,* vol. 154, pp. 113399, 2020. https://doi.org/10.1016/j.eswa.2020.113399

[60] M. Khodashenas, S. E. Najafi, H. Kazemipoor, and M. Sobhani, "Providing an integrated multi-depot vehicle routing problem model with simultaneous pickup and delivery and package layout under uncertainty with fuzzy-robust box optimization method," *Decision Making: Applications in Management and Engineering,* vol. 6, no. 2, pp. 372-403, 2023. https://doi.org/10.31181/dmame622023640

[61] A. Alosta, O. Elmansuri, and I. Badi, "Resolving a location selection problem by means of an integrated AHP-RAFSI approach," *Reports in Mechanical Engineering,* vol. 2, no. 1, pp. 135-142, 2021. https://doi.org/10.31181/rme200102135a

[62] M. B. Bouraima, E. Ayyıldız, I. Badi, G. Özçelik, F. B. Yeni, and D. Pamucar, "An integrated intelligent decision support framework for the development of photovoltaic solar power," *Engineering Applications of Artificial Intelligence,* vol. 127, pp. 107253, 2024. https://doi.org/10.1016/j.engappai.2023.107253

[63] A. Abdulla, G. Baryannis, and I. Badi, "An integrated machine learning and MARCOS method for supplier evaluation and selection," *Decision Analytics Journal*, pp. 100342, 2023. https://doi.org/10.1016/j.dajour.2023.100342

[64] S. M. S. Moosavi, M. Seifbarghy, and S. M. H. Molana, "Flexible fuzzy-robust optimization method in closed-loop supply chain network problem modeling for the engine oil industry," *Decision Making: Applications in Management and Engineering,* vol. 6, no. 2, pp. 461-502, 2023. https://doi.org/10.31181/dmame622023569

[65] N. Komazec, K. Janković, M. Mladenović, M. Mijatović, and Z. Lapčević, "Ranking of risk using the application of the AHP method in the risk assessment process on the Piraeus-Belgrade-Budapest railway corridor", *J. Decis. Anal. Int. Comp.*, vol. 4, no. 1, pp. 176–186, Dec. 2024. https://doi.org/10.31181/jdaic10002122024k

[66] F. Ullah and S. Waqar Shah, "Optimizing Multi-attributive Decision-making: A Novel Approach through Matrix Theory and Fuzzy Hypersoft Sets", *Spec. Eng. Man. Sci.*, vol. 2, no. 1, pp. 100–109, Jul. 2024, https://doi.org/10.31181/sems2120248r.

[67] D. Tešić and M. Khalilzadeh, "Development of the rough Defining Interrelationships Between Ranked criteria II method and its application in the MCDM model", *J. Decis. Anal. Int. Comp.*, vol. 4, no. 1, pp. 153–164, Oct. 2024.

[68] M. B. Bouraima, A. Saha, Ž. Stević, J. Antucheviciene, Y. Qiu, and P. Marton, "Assessment actions for improving railway sector performance using intuitionistic fuzzy-rough multi-criteria decision-making model," *Applied Soft Computing,* vol. 148, pp. 110900, 2023. https://doi.org/10.1016/j.asoc.2023.110900

[69] A. Pamosoaji, P. Dewa, and J. Krisnanta, "Proposed modified Clarke-Wright saving algorithm for capacitated vehicle routing problem," *International Journal of Industrial Engineering and Engineering Management,* vol. 1, no. 1, pp. 9-16, 2019. https://doi.org/10.24002/ijieem.v1i1.2292

[70] S. Kousar, A. Ansar, N. Kausar, and G. Freen, "Multi-Criteria Decision-Making for Smog Mitigation: A Comprehensive Analysis of Health, Economic, and Ecological Impacts", *Spec. Decis. Mak. Appl.*, vol. 2, no. 1, pp. 53–67, Sep. 2024, https://doi.org/10.31181/sdmap2120258

[71] Z. Stević, A. Bašić, S. Moslem, and K. Zhong, "An Integrated ABC-FUCOM Model for Product Classification", *Spec. Eng. Man. Sci.*, vol. 1, no. 1, pp. 83–91, Dec. 2023, https://doi.org/10.31181/sems1120239k.

[72] S. Biswas, A. Sanyal, and D. Pamucar, "Students' Perceptions About the Webinars: An Intuitionistic Fuzzy Force Field Analysis", Spec. Oper. Res., vol. 2, no. 1, pp. 113–133, Nov. 2024, https://doi.org/10.31181/sor21202513

[73] B. Kizielewicz and W. Sałabun, "SITW Method: A New Approach to Re-identifying Multi-criteria Weights in Complex Decision Analysis", Spec. Mech. Eng. Oper. Res., vol. 1, no. 1, pp. 215–226, Sep. 2024, https://doi.org/10.31181/smeor11202419

[74] M. F. Ibrahim, M. Putri, D. Farista, and D. M. J. J. T. I. Utama, "An improved genetic algorithm for vehicle routing problem pick-up and delivery with time windows," *Jurnal Teknik Industri,* vol. 22, no. 1, pp. 1-17, 2021. https://doi.org/10.22219/JTIUMM.Vol22.No1.1-17

[75] M. A. Islam, Y. Gajpal, and T. ElMekkawy, "Hybrid particle swarm optimization algorithm for solving the clustered vehicle routing problem," *Applied Soft Computing,* vol. 110, pp. 107655, 2021. https://doi.org/10.1016/j.asoc.2021.107655

[76] S. Kunnapapdeelert, C. Thawnern, and M. Sciences, "Capacitated vehicle routing problem for Thailand's steel industry via saving algorithms," *Journal of System and Management Sciences,* vol. 11, no. 2, pp. 171-181, 2021.

[77] N. Pourmohammadreza, and M. Jokar, "A novel two-phase approach for optimization of the last-mile delivery problem with service options," *Sustainability,* vol. 15, no. 10, pp. 8098, 2023. https://doi.org/10.3390/su15108098

[78] M. Rabbani, S. A. Sadati, H. J. C. Farrokhi-Asl, and I. Engineering, "Incorporating location routing model and decision making techniques in industrial waste management: Application in the automotive industry," *Computers & Industrial Engineering,* vol. 148, pp. 106692, 2020. https://doi.org/10.1016/j.cie.2020.106692

[79] N. Ghanbari Ghoushchi, K. Ahmadzadeh, and S. Jafarzadeh Ghoushchi, "A New Extended Approach to Reduce Admission Time in Hospital Operating Rooms Based on the FMEA Method in an Uncertain Environment", *J. Soft. Comput. Decis. Anal.*, vol. 1, no. 1, pp. 80–101, 2023, https://doi.org/10.31181/jscda11202310.

[80] K. Kara, G. C. . Yalçın, E. G. . Kaygısız, and S. . Edinsel, “Assessing the Academic Performance of Turkish Universities in 2023: A MEREC-WEDBA Hybrid Methodology Approach”, J. Oper. Intell., vol. 2, no. 1, pp. 252–272, 2024, https://doi.org/10.31181/jopi21202422

[81] A. Biswas, K. H. Gazi, and S. P. Mondal, “Finding Effective Factor for Circular Economy Using Uncertain MCDM Approach”, Manag. Sci. Adv., vol. 1, no. 1, pp. 31–52, 2024, doi: 10.31181/msa1120245.