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A Two-Stage Approach for Location Selection and Routing of Reverse Vending Machines Using the Entropy-Based QUALIFLEX Method

Hüseyin Başaran [1], Zeynep Yüksel [1] & Süleyman Mete [1]

[1] Gaziantep University, Department of Industrial Engineering, Gaziantep, Türkiye

Abstract Nowadays, the need for recycling is increasing rapidly due to the waste generated because of increasing consumption. Recycling plays an important role in waste minimization. Therefore, the location of Reverse Vending Machines (RVM) is also an important issue in access, reducing transport costs and the efficiency of the process. In this context, the site selection problem for the RVM and the Capacitated Vehicle Routing Problem (CVRP) are considered in this study. A two-stage approach for the location selection and capacitated vehicle routing of the RVM is proposed. In the first stage, a novel integrated approach entropy-based QUALIFLEX method is proposed to determine the best clustering. All clustering models were solved using the GAMS/CPLEX solver. The criteria used in clustering are weighed with the entropy method. Then, different clustering models were ranked with the QUALIFLEX method. In the second stage, using the results of this clustering, the best route was determined in the CVRP. The proposed integrated approach was tested on real case data from the Gaziantep province and a literature dataset. The test results showed that the proposed integrated approach is valid and usable.

Keywords Clustering · Entropy · Location-allocation · Reverse Vending Machine · QUALIFLEX · Vehicle Routing

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Corresponding author: Süleyman Mete smete@gantep.edu.tr

A Two-Stage Approach for Location Selection and Routing of Reverse Vending Machines Using the Entropy-Based QUALIFLEX Method

The increased demand around the globe is contributing to a rise in the amount of waste produced. Integrating this waste into the recycling process is crucial for maintaining sustainability. In order to ensure this sustainability, many countries have started to follow a zero waste policy within the scope of the circular economy. Deposit Return Systems (DRS) serve the purpose of these policies. In this context, DRS plays an important role in increasing recycling levels and minimization of waste (Eren & Taşarsu, 2023). The DRS is a recycling mechanism that enables customers to reclaim the deposit fees paid for beverages by bringing them post-consumption. The most important factor in the high recycling rates in the DRS is that it encourages recycling by enabling people to get back the deposit fee they paid (Görgün et al., 2021).

During the implementation phase of the DRS, the use of the RVM is being extended. In 1920, the first RVM was made in the USA, and nowadays, over 100,000 RVMs are operational worldwide (Amantayeva et al., 2021). Studies are being conducted in this field in Turkey as well as in the world. DRS is expected to be become compulsory in Turkey and these machines will be rolled out nationwide (Eren & Taşarsu, 2023). In this direction, in order to get the expected benefits from these increasingly numerous machines and to reduce costs, it is necessary to make the best use of them. For this reason, the proper location of the machines is essential. Optimal placement of these machines will facilitate access, reduce costs related to transportation, and enhance recycling rates by ensuring system efficiency.

At this point, this paper addresses the location selection problem of the RVM and the CVRP. A two-stage approach integrating Multi-Criteria Decision-Making (MCDM) methods has been proposed for the solution to these problems. Literature contains studies where MCDM has been used in several areas, including choosing suppliers, site selection, performance evaluation, etc. (Aruldoss et al., 2013). In this paper, applying the Entropy-based QUALIFLEX method as an integrated approach in the selection of clustering models increases the originality of the research. In the first stage, P-median, P-center, and K-means clustering models were applied and their criterion values were weighted by the entropy method. Subsequently, the clustering models were ranked using the QUALIFLEX method based on these weight values. In the second stage, the results of the best alternative obtained from the QUALIFLEX method were used in the CVRP. The proposed two-stage approach in the study was validated and deemed applicable based on its implementation with data from the Gaziantep province and existing literature data.

The remaining parts of this paper are as follows. A literature review of the applied methodology is given in the next section. Methodology is presented in Section 3, which includes the clustering models, MCDM methods, CVRP and integrated approach. In section 4, the application results of the proposed approach are analyzed in two different cases. In the last section, the conclusions and recommendations for future studies are discussed.

Literature Review of the Applied Methodology

In this section, the literature review of methodologies is presented in three sub-sections. Studies on clustering algorithms are analyzed in the first part. The second part presents studies on the entropy and QUALIFLEX methods, while the last part addresses studies on CVRP. Table 1 summarizes the relevant literature.

In this subsection, studies about the clustering algorithm literature are given. The performance of the P-median, P-center and maximal coverage models was analyzed by Karatas et al. (2017). They evaluated the performances according to seven criteria that examine the distance between demand and facility points etc. in the Q-coverage framework. Faezy Razi (2019) studied the site selection problem and clustered maintenance stations using the K-means method. The researcher determined the most suitable cluster count with the Silhouette index. Data Envelopment Analysis (DEA) with an input orientation was used for cluster efficiency. Furthermore, the researcher developed a bi-objective 0-1 programming model and identified the Pareto solutions of this model using invasive weed (IW), a population-based algorithm. Meanwhile, NSGA-II for constructing strategies and K-means for strategy clustering are used by Gaur et al. (2021). They used the Davies-Bouldin index to determine the cluster count and utilized VIKOR and TOPSIS for ranking. The K-means and adapted capacitated P-median problem for clustering was implemented on aid distribution by Ilabaca et al. (2022). Kurniawati and Rochman (2023) proposed a mixed-integer linear programming approach built in two stages to address the challenges in halal food delivery. Initially, they used the location-allocation problem in halal clusters, followed by the application of the vehicle routing problem to identify the routes within these clusters. Pekel Özmen and Küçükdeniz (2024) analyzed the school bus routing problem. In the initial phase of their proposed two-stage methodology for solving the problem, the fuzzy C-means and K-means algorithms are used to determine appropriate bus stops, while the next stage utilizes a genetic algorithm to create the bus routes. In the meantime, Yüksel et al. (2024a) employed Latent Dirichlet Allocation (LDA) topic modeling and Fuzzy C-Means clustering techniques to examine the post-disaster applications of unmanned aerial vehicles (UAVs). For more detailed information, see Ezugwu et al. (2022).

In this part, studies on Entropy and QUALIFLEX are mentioned. Liang et al. (2018), in their evaluation of circular economic performance study, used an Entropy-based methodology to calculate the index weights and presented the VIKOR-QUALIFLEX method for ranking purposes. An integrated TOPSIS-QUALIFLEX method for PMVNSs with cross-entropy-based calculations was introduced by Peng et al. (2018). They tested the validity of the proposed method and obtained positive results. Also, Wu et al. (2019) applied a two-stage process for the site selection of wind-PV-SPS facilities and used the results of the Entropy method as part of the TODIM in the second stage. In the meantime, Laha & Biswas (2019) conducted a study using the entropy and CODAS methods to assess bank performance. They used the K-means method to group the banks. Because of the study, they concluded that private sector banks outperformed public sector banks in terms of performance. Song et al. (2019) developed a new rough QUALIFLEX method and applied it to the location selection problem for the shelter. They assessed the developed method against alternative methodologies. A hybrid model with MCDM methods for relocation problems were proposed by Huang et al. (2020). In the proposed model, they used the DANP model and Entropy for criteria weights and differentiated VIKOR for selection. Moreover, Peng et al. (2023) presented an integrated structure with Z-numbers, regret theory and QUALIFLEX for the problem of evaluating new energy vehicles. They showed the usefulness of the framework in a case study. Derse (2024) used Entropy in weighting the criteria and TOPSIS in ranking the provinces in the study of location selection for smart parking in the Marmara region of Türkiye. Çıray et al. (2024) examined the World Bank Logistics Performance Index data for 2023 using an integrated approach that used Entropy and ORESTE. They attempted to distinguish their work from current studies by employing distinct methodologies and criteria weights.

This part presents studies on CVRP and its integration with MCDM and clustering. An approach was proposed using the AHP-TOPSIS integrated method to determine a formulation for the CVRP by Kececi et al. (2017). They have shown that their approach is applicable. Balaji et al. (2018) investigated a solution to the CVRP by using Clarke and Wright in clustering and AHP, one of the MCDM methods, in route assignment. Eligüzel et al. (2021) implemented three scenarios for various vehicle capacities. The applied CVRP-, P-median- and K-means-based clustering approaches were compared. They determined that the P-median and K-means based scenarios save 44%-47% of the distance relative to the first. Febria et al. (2021) considered the CVRP in their study for the distribution of vaccines. They used K-means in clustering and a greedy algorithm in routing and examined the effect of using an initial route on the runtime of the problem. In addition, Sanli & Kartal (2023) developed a two-stage method that combines machine learning methods with classical mathematical methods to solve CVRP. They showed that their proposed approach gives superior results on different test problems. Meanwhile, Takan & Öztürk (2023) used the ANP method, one of the MCDM methods, in the selection of neighborhood structure and its impact on the CVRP was analyzed. They also found the appropriate operator for the problem, such as 2-opt, swap, and insert. Ransikarbum et al. (2024) tried to find the most suitable location for centralized hospitals and used the K-means method for this purpose. They analyzed the delivery plan for medical supplies by combining the CVRP. They applied this approach to a case and showed the results through GIS.

Table 1

A Summary of the Relevant Literature

References	Application	Solution Method
Karatas et al. (2017)	Facility Location	P-median, P-center, Maximal Coverage Comperative Analysis under Q-coverage
Kececi et al. (2017)	CVRP	AHP-TOPSIS-based MILP selection
Liang et al. (2018)	Circular Economic Performance Evaluation	Entropy-based VIKOR-QUALIFLEX and LNN
Peng et al. (2018)	Multi-criteria group decision-making	PMVNS and cross-entropy-based TOPSIS-QUALIFLEX
Balaji et al. (2018)	CVRP	Clarke and Wright, AHP
Faezy Razi (2019)	Multi-criteria Location Selection	K-means, Silhouette, bi-objective, DEA, IW
Wu et al. (2019)	Location Selection	Entropy, TODIM
Laha and Biswas (2019)	Bank Performance Evaluation	Entropy and CODAS, K-means
Song et al. (2019)	Shelter Site Selection	Interval Rough Number QUALIFLEX
Huang et al. (2020)	Supply Chain Relocation	DANP, Entropy and Modified VIKOR
Gaur et al. (2021)	Groundwater Planning	NSGA-II, K-means, Davies-Bouldin, VIKOR, TOPSIS
Febria et al. (2021)	Vaccine Distribution	CVRP, K-means, Greedy Algorithm
Eligüzel et al. (2021)	Employee Shuttle Service Planning	CVRP, P-median and K-means
Ilabaca et al. (2022)	Humanitarian Aid Distribution	K-means, Adapted capacitated P-median
Kurniawati and Rochman (2023)	Halal Food Distribution	Two-stage MILP
Peng et al. (2023)	New Energy Vehicle Evaluation	Z-numbers, Regret Theory and QUALIFLEX
Sanli and Kartal (2023)	Vehicle Routing	Machine Learning, Classical Method
Takan & Öztürk (2023)	Neighborhood Selection	CVRP, ANP
Pekel Özmen and Küçükdeniz (2024)	School Bus Routing	Fuzzy C means, K-means, Genetic Algorithm
Yüksel et al. (2024)	Post-disaster UAV	LDA, Fuzzy C-Means
Derse (2024)	Smart Parking Site Selection	Entropy, TOPSIS, Center of Gravity
Çıray et al. (2024)	Logistic Performance Evaluation	Entropy, ORESTE
Ransikarbum et al. (2024)	Healthcare Chain	CVRP, K-means, GIS
Proposed Integrated Approach (2025)	Location Selection and Routing	P-median, P-center, K-means, entropy-based QUALIFLEX, CVRP

The literature assessment reveals a lack of studies applying MCDM approaches to clustering model selection in site selection, clustering, and routing research, highlighting the potential contribution of this study to the area. While existing studies use clustering methods directly in the routing problem, this study provides decision support for clustering method selection with the proposed approach. Thus, this study, in which Entropy and QUALIFLEX are used as an integrated method in clustering model selection, contributes to the literature in this field.

Methodology

This section of the paper is divided into four subsections as follows. Subsection 1 provides details regarding the P-median, P-center and K-means models employed. Entropy and QUALIFLEX, which are the MCDM methods, are included in Subsection 2. The CVRP is introduced in Subsection 3, and the final section provides an integrated approach.

Clustering Models

Clustering is a method that uses the similarities of data when dividing them into clusters (Ercan Cömert et al., 2020). In this paper, clustering was performed using the number of clusters corresponding to the number of source points planned to be opened. For this purpose, the P-median, P-center, and K-means clustering models were used. The notations of the P-median and P-center models are given in Table 2.

Table 2

Notations of P-median and P-center

i, k	Demand and source points
d_{ik}	Distance between points
P	The number of sources points planned to open
x_{ik}	1, if demand point i is assigned to source point k; otherwise, 0
y_k	1, if the source point k is opened; otherwise, 0

P-median Problem

The objective of the P-median problem is to minimize the sum of distances between demand and source points by strategically locating a certain number of facilities (Yüksel et al., 2023). The formulation of the P-median clustering model used is as follows (Özceylan & Özkan, 2019).

The objective function (1) minimizes the total distance between the demand and source points.

$$\min \sum_{i} \sum_{k} d_{ik} * x_{ik} \tag{1}$$

Constraint (2) provides that each demand point is assigned to only one source point.

$$\sum_{k} x_{ik} = 1 \qquad \forall i \tag{2}$$

Constraint (3) ensures that if the source point is opened, the assignment of demand points to the source points.

$$x_{ik} \leq y_k \qquad \forall i, k \tag{3}$$

Constraint (4) determines the number of source points planned to be opened.

$$\sum_{k} y_k = P \tag{4}$$

Constraint (5) is relevant to the decision variables.

$$y_k, x_{ik} \in \{0,1\} \quad \forall i,k \tag{5}$$

This method, which minimizes the total distance between the demand and source points, is preferred as a clustering method for determining the optimum locations of the facilities to be opened in this study.

P-center Problem

$$Min\ Z = Max\ (d_{ik} * x_{ik}) \tag{6}$$

s.t.

Constraints (2) to (5)

The model is linearized through the incorporation of the MaxL decision variable. The objective function (6) is defined as Z=MaxL, with the constraints MaxL≥0 and MaxL≥ $d_{ik}x_{ik}$ included in the model.

The P-center model ensured that assignments were allocated to the facilities to be established while minimizing the maximum distance.

K-means Clustering

K-means is a clustering method that has been widely used in practical applications due to its fast speed and simplicity and has proven to provide effective clustering results. In this method, the data are clustered in such a way that the sum of the error squares is minimized. The formula for the error square is shown below (Gunesen & Kapanoğlu, 2021).

$$E = \sum_{i=1}^{k} \sum_{p \in c_i} |p - m_i|^2 \tag{7}$$

E= sum of the error squares m_i=average of the c_i p=point

The steps of the K-means algorithm are as follows.

Step 1: The starting points indicate the cluster centers that are selected.

Step 2: The data are divided into clusters. This process considers the data's proximity to the starting point.

Step 3: The cluster centers are revised after the data are assigned to the clusters.

Step 4: Steps 2 and 3 are applied until the cluster centers remain constant.

Multi-Criteria Decision Making (MCDM)

In MCDM, criteria are weighted in two different ways: objective and subjective (Atalık & Bakır, 2018). In this paper, the criteria of the clustering models were weighed using the entropy method, which is an objective weighted method. Then, the clustering models were ranked by applying the QUALIFLEX (QUALItative FLEXible) method using these weight values.

Entropy Method

Entropy, one of the MCDM methods, is an objective weighting method that uses the quantitative values of the alternatives. The steps of the method are shown below (Atalık & Bakır, 2018).

The first step in applying the Entropy method is the process of creating the decision matrix (8).

$$X = \begin{bmatrix} X_{11} & \cdots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{m1} & \cdots & X_{mn} \end{bmatrix} \tag{8}$$

In the second step, normalization is performed using equation (9) and decision matrix normalization is provided.

$$r_{ij} = \frac{X_{ij}}{\sum_{i=1}^{j} X_{ij}} \tag{9}$$

i = alternatives j =criteria r_{ij} =normalized values

X_{ij}= the benefit values of the i-th alternative concerning the j-th criterion

In step 3, the entropy values are computed with equation (10).

$$e_j = -k \sum_{j=1}^{n} r_{ij} \ln(r_{ij}) \; (i = 1, 2, ..., m \; and \; j = 1, 2, ..n) \\ k = \{((ln(n))^{-1}))\} \tag{10}$$

$e_j = entropy\ value$ r_{ij} = normalized values

k = entropy coefficient

In step 4, d_j,representing the relationship among the alternative values, is computed using equation (11).

$$d_j = 1 - e_j(\; j = 1, 2, ..n) \tag{11}$$

In the last step, the criteria weight (w_j) are determined by equation (12).

$$w_j = \frac{1 - e_j}{\sum_{i=1}^{n}(1 - e_j)} \tag{12}$$

The sum of the entropy criterion values is 1 (13).

$$w_1 + w_2 + w_j + ... + w_n = 1 \tag{13}$$

The Entropy method was preferred for criteria weighting. This enabled an objective assessment in the study.

QUALIFLEX Method

QUALIFLEX is one of the solution methods of MCDM problems and determines the ranking of alternatives. The steps of the QUALIFLEX method are as follows (Tuş Işık, 2016).

The initial step involves the creation of a decision matrix (14) for the alternatives. This matrix shows the performance of the alternatives.

$$X = \left[X_{ij}\right]_{mxn} = \begin{bmatrix} X_{11} & \cdots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{m1} & \cdots & X_{mn} \end{bmatrix} (i = 1, 2, .., m; j = 1, 2.., n) \tag{14}$$

m: alternative and n: number of criteria

X_{ij}: performance of alternative i under criterion j.

In step 2, the m! number of permutations are written where the rankings of the alternatives are shown. In equation (15), P_I denotes the Ith permutation. In this ranking of alternatives, it is concluded that alternative A_i is superior to alternative $A_{i'}$ or that the two alternatives are at the same level.

$$P_I = (..., A_i, ...A_{i'}, ...) \mathrm{I} = 1, 2, ..., m! \tag{15}$$

In step 3, the concordance/discordance index for the pairs of alternatives belonging to the permutations is found by Equation (16). Equation (17) illustrates the relationship between the ranking of alternatives in the permutation and the ranking derived from the decision matrix.

$$I_j^1 = \sum_{A_i, A_{i'} \in A} I_j^1(\; A_i, A_{i'} \;) \tag{16}$$

$$I_j^1(\,A_i, A_{i'}\,) = \begin{cases} 1\;\, if\; there\; is\; concordance \\ 0\;\, if\; there\; is\; equality \\ -1\; if\; there\; is\; discordance \end{cases} \tag{17}$$

In step 4, the weighted concordance/discordance index is calculated using equation (18).

$$I_j^1 = \sum_{A_i, A_{i'} \in A} I_j^1(\,A_i, A_{i'}\,)\, w_j \tag{18}$$

w_j = weight of the jth criterion

In the last step, the general concordance/discordance index I^1 is determined for P_I using equation (19). The permutation with the highest index value is the optimal permutation.

$$I^1 = \sum_{j=1}^{n} \sum_{A_i, A_{i'} \in A} I_j^1(\,A_i, A_{i'}\,)\, w_j \tag{19}$$

I^1 , general concordance/discordance index

The QUALIFLEX method, which is advantageous when the number of criteria is high and the number of alternatives is low (Mete, 2021), was used as a ranking method.

CVRP

The Vehicle Routing Problem (VRP) constitutes an optimization problem. It is an NP-hard problem that provides the most appropriate route by considering constraints such as the number and capacity of vehicles utilized, the location and demand of the customer, time and cost (Yuksel et al., 2024b). CVRP, one of the VRP types, involves determining the routes that vehicles with limited capacity leaving the depot should follow to meet the demand. The problem's notation and mathematical model are given as follows (Şehitoğlu & Ağayeva, 2022).

The assumptions related to this problem used in the second stage of the approach proposed in the paper are as follows:

- The demand points and quantities are known.
- The location of the depot point is known.
- The number of vehicles is sufficient.
- Vehicles are homogeneous and their capacity is known.
- The process of carrying demands from points within the cluster to the center point is ignored.

Table 3

Notations of the CVRP Mathematical Model

Indices	
i, j	Depot and demand points
k	Vehicle
Parameters	
D_{ij}	Distance between point i and point j
R_j	Quantity of demand at point j
C	Capacity of the vehicle
Positive Variables	
u_i	Arbitrary numbers
Binary Variables	

Indices	
X_{ijk}	1, if vehicle k arrives from point i to point j (i$\neq j$); otherwise, 0

The objective function (20) ensures the minimization of the total distance traveled.

$$\min \sum_{k} \sum_{j} \sum_{i} D_{ij} X_{ijk} \tag{20}$$

Constraint (21) permits only one vehicle to enter a demand point.

$$\sum_{k} \sum_{i} X_{ijk} = 1 \qquad \forall j, j \neq 0, i \neq j \tag{21}$$

Constraint (22) ensures that there is only one exit from the demand point.

$$\sum_{k} \sum_{j} X_{ijk} = 1 \qquad \forall i, i \neq 0, i \neq j \tag{22}$$

Constraint (23) enables each vehicle to depart from the depot only once.

$$\sum_{j} \sum_{i} X_{ijk} \leq 1 \qquad \forall k, i \neq j, i = 0 \tag{23}$$

Constraint (24) provides the cycle of vehicles.

$$\sum_{i} X_{ijk} - \sum_{i} X_{jik} = 0 \qquad \forall j, k \;\; j \neq 0, i \neq j \tag{24}$$

Constraint (25) prevents routes that do not start and end at the depot.

$$u_i - \; u_j \; + C^* \, X_{ijk} \leq C - R_j \qquad \forall i, j, k, i \neq j \; , j \neq 0 \tag{25}$$

Constraint (26) ensures the lower and upper bound of the arbitrary variable, so that the vehicle capacity is not exceeded.

$$R_j \leq \;\; u_j \; \leq C \qquad \forall j \tag{26}$$

Constraint (27) shows the restrictions of the binary variables.

$$X_{ijk} \in \{0, 1\} \qquad \forall i, j, k \tag{27}$$

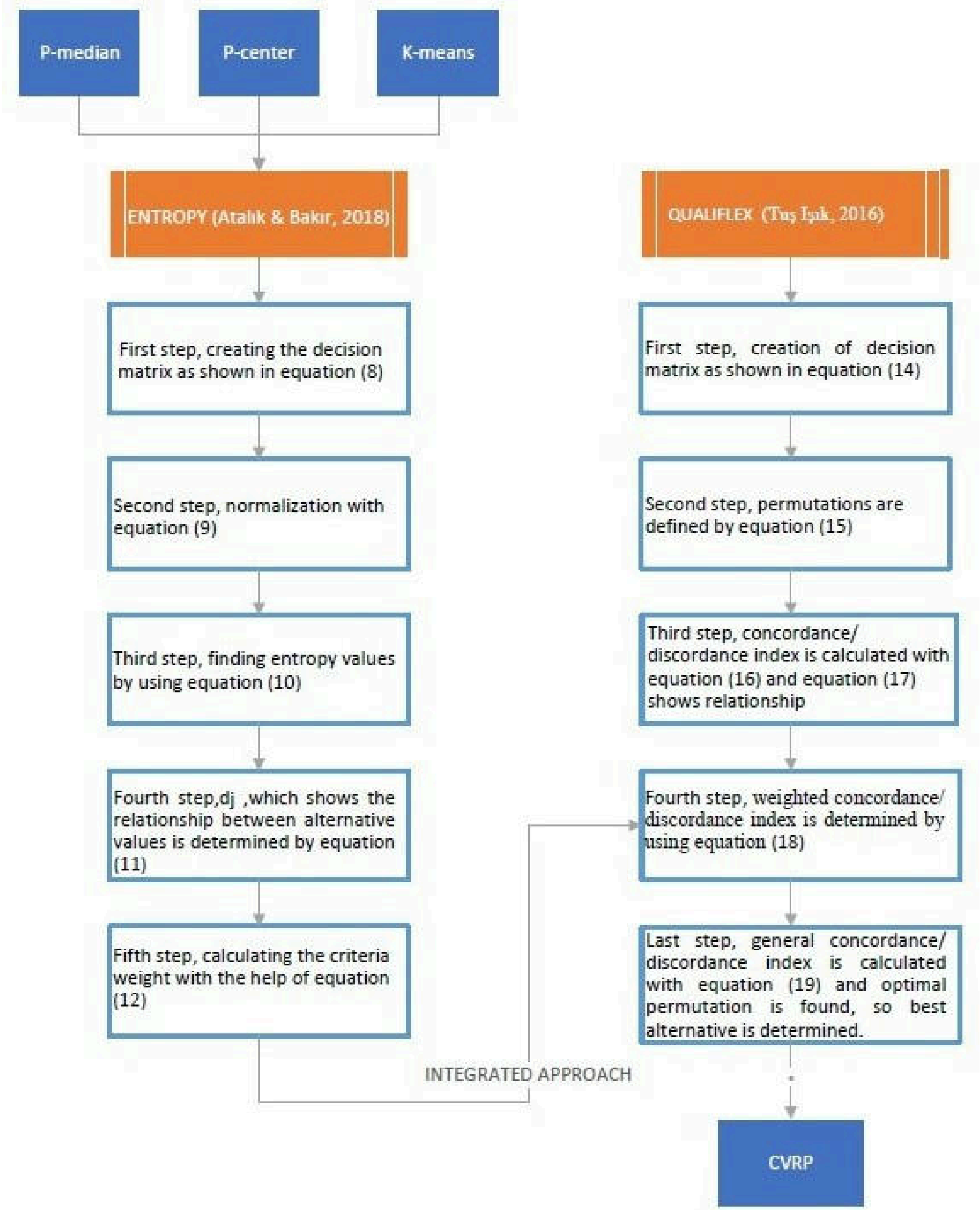
The CVRP implementation enabled distance minimization by determining the best routes for vehicles with capacity constraints.

Integrated Approach

The first step of the two-stage approach proposed in the study consists of solving the clustering models and applying the integrated MCDM to the results. At this stage, the Entropy method was used to weigh the criteria of the clustering models. Then, the clustering models were ranked with QUALIFLEX using these weights. In the second stage, the CVRP was applied according to the best alternative (clustering) obtained. The flowchart of the integrated approach is shown in Figure 1.

Figure 1

Flowchart of the Integrated Approach



Application

This section presents the results for the proposed two-stage approach. The first part indicates the findings for the province of Gaziantep in Case 1, while the second part shows the results for the literature data in Case 2.

Case 1

In this case, 3 different chain markets in 5 large neighborhoods of Şahinbey, which is the most crowded district of Gaziantep province according to the Turkish Statistical Institute 2023 data (Turkish Statistical Institute (TUIK), 2023), are considered as potential demand points and source points for the RVM. The dataset consists of 40 locations and warehouse locations. These were marked on Google Earth, and the latitude and longitude information were acquired. As stated in Durak & Yıldız (2015) study, the smallest of the latitude and longitude values was taken as the origin point and the difference of all points was taken according to this point. The adjusted X and Y points were obtained by multiplying the latitude differences by 111 km and the longitude difference by 85 km. Then, the distances were calculated by applying the Euclidean formula to these points. In this problem, the location selection problem for the RVM planned to be installed at eight locations was solved with the GAMS/CPLEX solver for the P-median, P-center and K-means clustering models. These clustering models form alternatives in the decision matrix. Using these clustering model results, the cluster validity indices described below were found with Python for each model, and these values are shown in Table 4. The cluster validity indices form the criteria in the decision matrix and these indices are as follows.

Table 4

Decision Matrix for the Entropy Method

Clustering Models	Silhouette Index	Dunn Index	Davies Bouldin Index	Degree of Compactness	Degree of Separation
P-Median (A_1)	0,3749	0,2379	0,7715	1,1947	0,2843
P-Center (A_2)	0,2648	0,0925	0,8637	1,3152	0,1217
K-Means (A_3)	0,3568	0,2150	0,6986	1,2832	0,2759

Silhouette is an index that compares the distances between elements in the same cluster and those in the closest cluster. The Dunn Index is expressed as the smallest separation value divided by the biggest compactness value. Davies-Bouldin is an index that assesses the relationship between the cluster and the nearest. While the degree of compactness is an index that analyzes the internal distances between elements in the same cluster, the degree of separation considers the distance between clusters. The values for these indices to indicate good clustering are as follows. Silhouette-higher, Dunn-higher, Davies Bouldin-lower, Degree of Compactness-lower, Degree of Separation-higher (Ben Ncir et al., 2021). These criteria were weighed using the entropy method, and the weight values are shown in Table 5.

Table 5

Criteria Weight Obtained by the Entropy Method

Silhouette Index	Dunn Index	Davies Bouldin Index	Degree of Compactness	Degree of Separation
0,0756	0,4763	0,0260	0,0057	0,4164

These criterion weights were used in the QUALIFLEX method for the ranking of clustering models to calculate the weighted concordance / discordance index. In the first stage of applying the QUALIFLEX method, it was determined which criteria should be maximized or minimized for a good ranking of alternative. In this context, the maximization of the Silhouette Index, Dunn Index and Degree of Separation criteria and the minimization of the Davies Bouldin Index and Degree of Compactness criteria were considered. The decision matrix is as in Table 4, and the lettered form of the criteria and alternatives is shown in Table 6. The ranking of these alternatives is presented in Table 7.

Table 6

Decision Matrix

	A_1	A_2	A_3
C_1	0,3749	0,2648	0,3568
C_2	0,2379	0,0925	0,2150
C_3	0,7715	0,8637	0,6986
C_4	1,1947	1,3152	1,2832
C_5	0,2843	0,1217	0,2759

Table 7

Ranking of the Alternatives

	$\mathbf{A_1}$	$\mathbf{A_2}$	$\mathbf{A_3}$
$\mathbf{C_1}$	1	3	2
$\mathbf{C_2}$	1	3	2
$\mathbf{C_3}$	2	3	1
$\mathbf{C_4}$	1	3	2
$\mathbf{C_5}$	1	3	2

The order of the alternatives is 3! and the permutations are as follows. $P_1 = A_1 > A_2 > A_3$, $P_2 = A_1 > A_3 > A_2$, $P_3 = A_2 > A_1 > A_3$, $P_4 = A_2 > A_3 > A_1$, $P_5 = A_3 > A_1 > A_2$, $P_6 = A_3 > A_2 > A_1$.

In Table 8 and Table 9, the concordance/discordance index and weighted concordance/discordance index values for P_1 are given, and the same procedures were applied for the remaining 5 permutations. Table 10 shows the general concordance/discordance index results for all permutations.

Table 8

Concordance/Discordance Index

$\mathbf{P_1}$	$\mathbf{C_1}$	$\mathbf{C_2}$	$\mathbf{C_3}$	$\mathbf{C_4}$	$\mathbf{C_5}$
$\mathbf{I_j^1}\ (\mathbf{A_1}, \mathbf{A_2})$	1	1	1	1	1
$\mathbf{I_j^1}\ (\mathbf{A_1}, \mathbf{A_3})$	1	1	–1	1	1
$\mathbf{I_j^1}\ (\mathbf{A_2}, \mathbf{A_3})$	–1	–1	–1	–1	–1
	1	**1**	**-1**	**1**	**1**

Table 9

Weighted Concordance/Discordance Index

	$\mathbf{I_1^1}\ (\mathbf{A_i}, \mathbf{A_{i'}})$	$\mathbf{I_2^1}\ (\mathbf{A_i}, \mathbf{A_{i'}})$	$\mathbf{I_3^1}\ (\mathbf{A_i}, \mathbf{A_{i'}})$	$\mathbf{I_4^1}\ (\mathbf{A_i}, \mathbf{A_{i'}})$	$\mathbf{I_5^1}\ (\mathbf{A_i}, \mathbf{A_{i'}})$
$\mathbf{P_1}$	0,0756	0,4763	–0,0260	0,0057	0,4164

Table 10

General Concordance/Discordance Index

	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$\mathbf{P_6}$
$\mathbf{I^1}$	0,9480	2,9480	–1,0520	–2,9480	1,0520	–0,9480

The general concordance/discordance index results show that P_2 is the optimal permutation, so A_1 (P-median) is the best alternative. The results of the best alternative method are given in Figure 2. In the second stage of the proposed approach, CVRP was applied to the results of the best alternative method. In this problem, the truck capacity was assumed to be 800 and the demands were randomized. The routing results of this case are shown in Table 11.

Table 11

Routing Results of Case 1

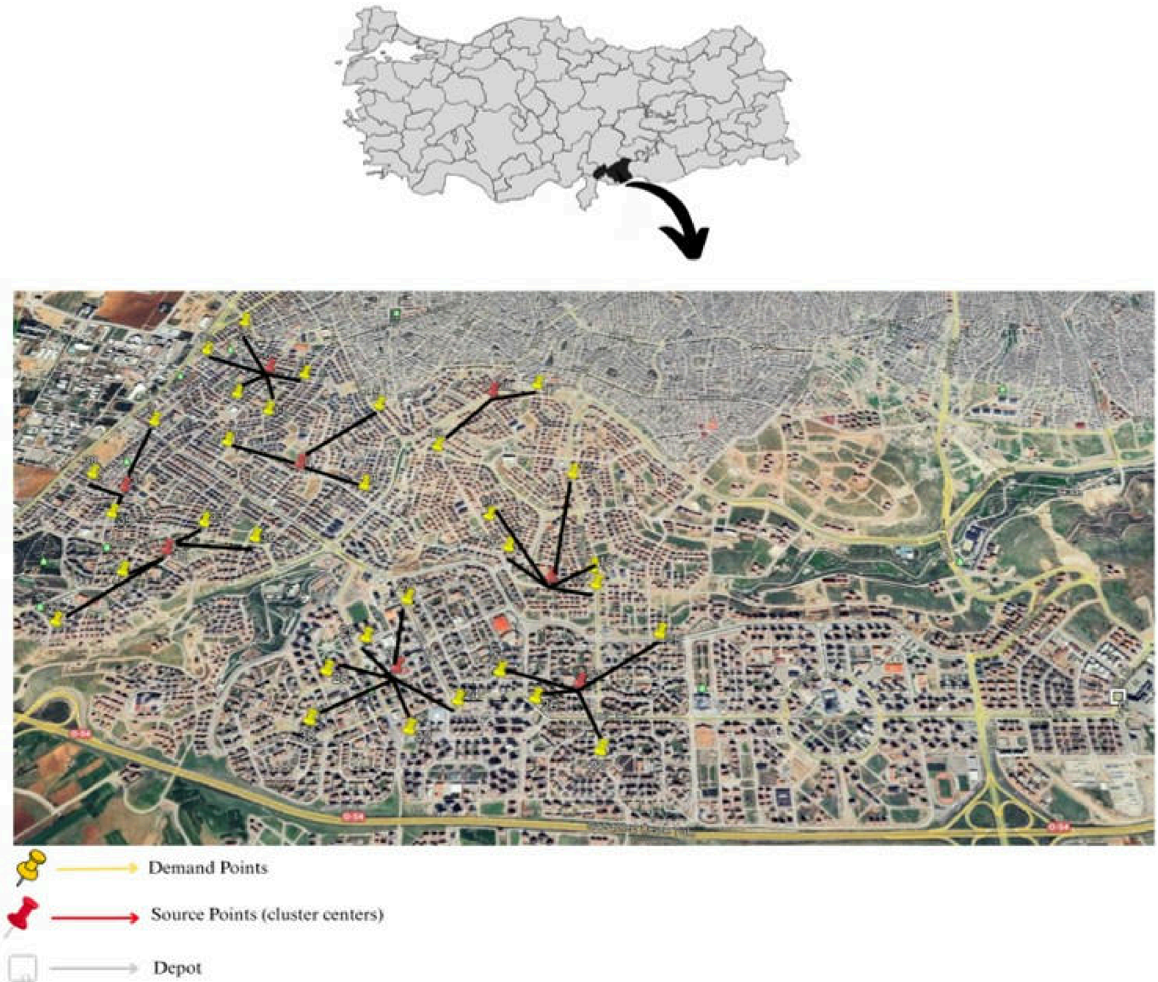
Cluster Points	Cluster Center	Routes	Objective Function
1-4-5-8	4		
2-3-6-9-10-11	6	0-4-40-0	
12-14-15-16-18-19	14	0-6-35-0	40.9808
13-17-20	20	0-14-31-0	
21-22-23-25-26	23	0-23-20-0	

Cluster Points	Cluster Center	Routes	Objective Function
24-27-28-29-30-31-32	31		
7-35-38-39	35		
33-34-36-37-40	40		

Table 11 shows the cluster centers obtained by solving the P-median problem and the points assigned to these centers. In this table, the center points of the clusters indicate the location of the RVMs to be established. The trucks leaving the warehouse collect from these machines installed in the cluster centers and return to the warehouse. In order to solve this CVRP problem, the Gurobi library in Python was used and the optimal solution was found. As indicated in Table 11, the outcomes show that four routes were obtained, and the objective function value is 40.9808. Thus, all the steps of the proposed approach have been implemented successfully, and the results show that it is applicable.

Figure 2

Results of the Best Alternative (P-median) model for Case1



Case 2

The data from the study by Şehitoğlu & İşleyen (2023) were employed in the second case to evaluate the proposed two-stage approach. Bakery (depot), customer locations (30 points), real demand data and vehicle capacity (800) were taken from the study and implemented in accordance with the problem structure in this study. As in Case 1, the adjusted X and Y values were found because of the relevant calculations. After the distances were calculated, clustering models were applied, and 4 clusters were assumed within the scope of the problem. The criteria used in clustering are weighted by the entropy method, and the criteria weights are as indicated in Table 12.

Table 12

Criteria Weight Obtained by the Entropy Method

Silhouette Index	Dunn Index	Davies Bouldin Index	Degree of Compactness	Degree of Separation
0,0255	0,3814	0,0021	0,0285	0,5626

The decision matrix with alternatives and criteria is stated in Table 13, and the ranking of these alternatives is given in Table 14. Out of 6 permutations, the first permutation's concordance/discordance index and weighted concordance/discordance index values are shown in Table 15 and Table 16, respectively.

Table 13

Decision Matrix

	A_1	A_2	A_3
C_1	0,4492	0,3884	0,4151
C_2	0,1761	0,1235	0,1018
C_3	0,7810	0,7772	0,8075
C_4	2,4649	2,1121	2,2989
C_5	0,4342	0,2608	0,2341

Table 14

Ranking of the Alternatives

	A_1	A_2	A_3
C_1	1	3	2
C_2	1	2	3
C_3	2	1	3
C_4	3	1	2
C_5	1	2	3

Table 15

Concordance/Discordance Index

P_1	C_1	C_2	C_3	C_4	C_5
$I_j^1\,(A_1, A_2)$	1	1	–1	–1	1
$I_j^1\,(A_1, A_3)$	1	1	1	–1	1
$I_j^1\,(A_2, A_3)$	–1	1	1	1	1
	1	**3**	**1**	**-1**	**3**

Table 16

Weighted Concordance/Discordance Index

	$I_1^1\,(A_i, A_{i'})$	$I_2^1\,(A_i, A_{i'})$	$I_3^1\,(A_i, A_{i'})$	$I_4^1\,(A_i, A_{i'})$	$I_5^1\,(A_i, A_{i'})$
P_1	0,0255	1,1443	0,0021	−0,0285	1,6877

Table 17

General Concordance/Discordance Index

	P_1	P_2	P_3	P_4	P_5	P_6
I^1	2,8310	0,9328	0,9533	−0,9328	−0,9533	−2,8310

Table 17 presents the general concordance/discordance index values for all permutations. According to the result, in this case P_1 is the optimal permutation so A_1 (P-median) is the best alternative. The clustering and routing results for this alternative are shown in Figure 3.

Table 18

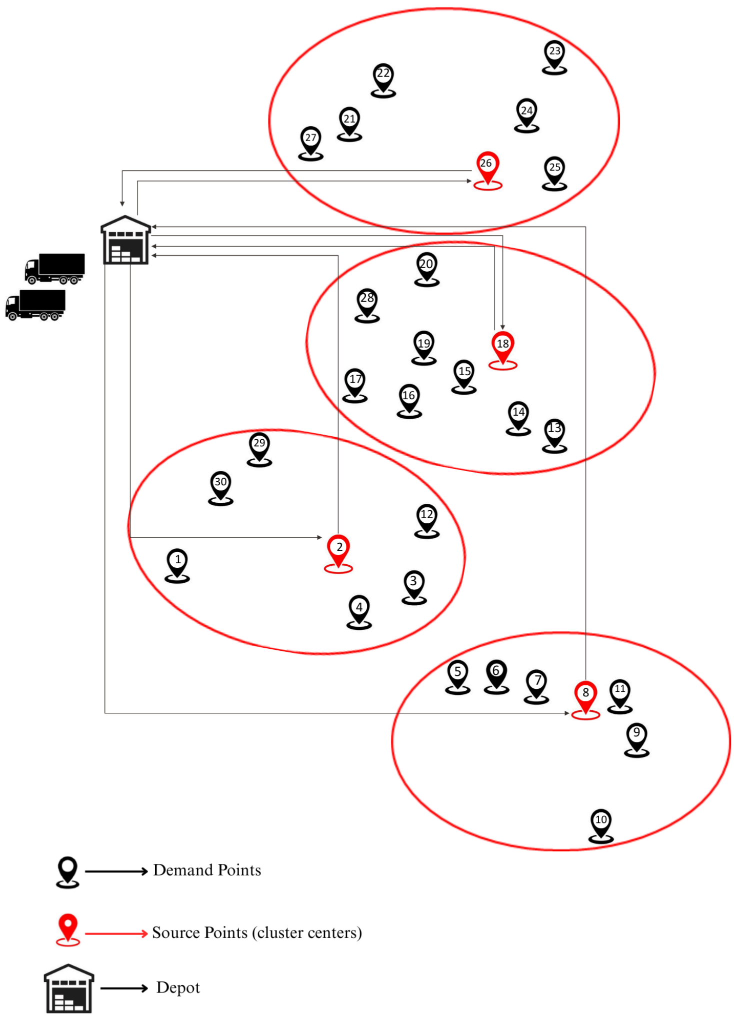
Routing Results for Case 2

Cluster Points	Cluster Center	Routes	Objective Function
1-2-3-4-12-29-30	2	0-2-0	
5-6-7-8-9-10-11	8	0-8-0	
13-14-15-16-17-18-19-20-28	18	0-18-0	17.5135
21-22-23-24-25-26-27	26	0-26-0	

Table 18 shows the results obtained for 4 clusters in this dataset consisting of 30 points. Results obtained according to the best alternative clustering method, and the cluster centers represent the source points in Table 18. These source points serve the demand points in their cluster. The optimal solution was obtained from the CVRP implemented in the second stage. The four route information and the objective function value obtained because of the solution are given in Table 18. As in Case 1, the results obtained from Case 2 also demonstrate the validity of the proposed approach.

Figure 3

Results of the Best Alternative for Case 2



Conclusion

This study focuses on the location selection and CVRP problem of the RVM to effectively utilize RVM for recycling. Accordingly, a two-stage approach integrating the MCDM method is proposed. In the first stage, clustering models were applied and 5 criteria from the cluster validity indices were determined for these models. These criteria were weighed by the Entropy method and the best alternative method was determined by the QUALIFLEX method. Thus, it provides decision support to the decision-maker in selecting the appropriate model according to the cluster quality. In addition, the results of the clustering model provide a solution to the location selection problem by showing the most suitable points for the machines to be installed. Optimal routes for the vehicles are determined by solving the CVRP in the second stage. In this context, the proposed approach is applied to two different datasets. First, the proposed method was applied to the initial dataset of 40 points and depots, revealing that the alternative one was the optimal choice, and routing was subsequently implemented based on the results of this alternative. Consequently, the most suitable locations for RVM were identified, and the optimal routes for collecting waste from these machines were determined. The proposed methodology was similarly implemented for case 2 using data sourced from the literature, and the P-median resulted as the optimal alternative. The optimal routes for the vehicles were obtained using the CVRP applied in the second stage of the problem. All of these results show that the proposed approach is valid and usable. Thus, the study, which uses integrated MCDM methods in clustering model selection, contributes to the literature in this field.

Heuristic solution approaches may be required if the problem dimensions are extensive and complex. Also, when there are more alternatives, the solution for the current ranking method will become longer. For future studies, the proposed approach can be applied to different vehicle routing problems by adding new clustering methods or differentiating the criteria. With the integration of the fuzzy MCDM methods, the scope can be expanded. Other MCDM methods can be applied in different cases.

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Author Details

Hüseyin Başaran
[1] Gaziantep University, Department of Industrial Engineering, Gaziantep, Türkiye
0009-0005-3641-4760

Zeynep Yüksel
[1] Gaziantep University, Department of Industrial Engineering, Gaziantep, Türkiye
0009-0006-8201-372X

Süleyman Mete
[1] Gaziantep University, Department of Industrial Engineering, Gaziantep, Türkiye
0000-0001-7631-5584 smete@gantep.edu.tr

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