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Unmanned Aerial Vehicle Routing and Facility Location Selection for Healthcare Supply Chain Management: A Case Study in Türkiye

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Abstract

Healthcare supply chain management is of great importance, particularly for hospitals. To manage medical supply chains quickly and effectively requires new and optimized logistics strategies. The use of an unmanned aerial vehicle (UAV) enables the swift delivery of medical supplies, overcoming obstacles like traffic, natural disasters, or infrastructure damage, and saving lives in critical situations. This study focuses on the distribution phase of emergency medical supply chains using electric UAVs, aiming to save lives during crises by establishing an efficient, technological, and sustainable transportation system in healthcare. The strategic locations of the charging stations, which can also serve as medical supply depots, and the optimal routes for the vehicles are integrated. Using Multi-Criteria Decision-Making (MCDM) techniques, specifically the AHP and TOPSIS methods, the optimal charging points for electric unmanned aerial vehicles are determined by considering various criteria. From these identified facilities, a multi-depot vehicle routing model was developed for supplying emergency medical supplies to hospitals, considering vehicle characteristics, hospital demand quantities, and facility capacities. This integrated methodology was applied to the province of Trabzon in Türkiye. Three different routes covering a total distance of 29.59 kilometres were generated to supply medical materials from five identified facilities to ten hospitals.

Keywords Medical supply chain management · Vehicle Routing Problem · AHP · TOPSIS

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Unmanned Aerial Vehicle Routing and Facility Location Selection for Healthcare Supply Chain Management: A Case Study in Türkiye

Efficient supply chain management in healthcare is crucial for ensuring timely medical supply delivery, particularly in critical scenarios where delays can have life-threatening consequences (Chen & Ruan, 2024). Hospitals rely heavily on well-structured medical supply chains that can adapt to both routine operations and emergency situations. However, traditional supply chain systems often face significant challenges during crises or disasters, including traffic congestion, damaged infrastructure, and natural obstacles (Patil et al., 2021). These challenges underscore the need for innovative and resilient logistics solutions to ensure that medical supplies reach their destinations swiftly and reliably.

Healthcare, in an era of accelerating technological advancements, is focused on delivering fast, reliable, and effective healthcare services. In this context, the urgent and secure delivery of medical supplies to hospitals is a critical component of healthcare services. Healthcare products include blood, medical equipment, pharmaceutical products, vaccines, and more (Dixit et al., 2019). Medical supply transportation using unmanned aerial vehicles (UAVs) holds significant potential as a solution (Eichleay et al., 2017; Khan et al., 2021; Ozkan, 2023). UAVs stand out for their rapid delivery capacity, low carbon emissions, and environmentally friendly attributes. The effective use of electric unmanned aerial vehicle (e-UAV) technology in healthcare aligns with strategies to ensure the swiftest possible deliveries during crises and emergencies.

Furthermore, by focusing on the integration and applicability of this technology in daily hospital operations, the suitability of e-UAVs for medical supply delivery can be demonstrated. This approach not only ensures the timely provision of essential supplies but also addresses an important environmental issue by reducing the waste associated with perishable medical materials through optimized supply quantities.

Recent advancements in e-UAVs present a promising solution for overcoming logistical challenges. Their ability to bypass ground-level obstructions makes them ideal for delivering critical medical supplies in time-sensitive situations, such as natural disasters, pandemics, or large-scale accidents. To maximize the efficiency of e-UAVs in medical supply distribution, strategic planning of charging station locations and optimal routing is essential. Integrating these elements into a cohesive distribution model can enhance the responsiveness and reliability of the medical supply chain. Multi-Criteria Decision-Making (MCDM) methods such as the Analytic Hierarchy Process (AHP) (Saaty, 1980) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) Hwang & Yoon (1981) provide a systematic approach for determining the best locations for charging stations based on various operational, environmental, and logistical criteria. AHP and TOPSIS are often preferred in decision-making because they provide a structured approach to both qualitative and quantitative criteria, enabling a clear ranking of alternatives (Sindhu et al., 2017; Tyagi et al., 2014). AHP's ability to handle complex, hierarchical structures and TOPSIS's capability to identify the most ideal solution based on closeness to the ideal alternative make them highly effective in addressing multi-criteria decision-making problems.

Since facility location and vehicle routing are inherently interconnected, addressing these problems separately may lead to suboptimal outcomes and increased risk. Consequently, integrating both decisions into a unified framework can be described as a Location-Routing Problem (LRP), enabling a more comprehensive and efficient solution (Fathollahi et al., 2022; J. Wang et al., 2021; C. Zhang et al., 2020).

Considering the aforementioned issues, this study focuses on developing a methodology that addresses the location-routing problem by simultaneously planning both facility location selection and vehicle routing. In the proposed methodology, the facility placement of depots for UAVs is evaluated according to several criteria. In this phase, AHP is applied to determine criterion weights and TOPSIS is used for alternative location evaluation. The other pillar of the proposed study focuses on determining the most appropriate route for UAVs. The mixed integer linear programming model is developed for UAV routing. The methodology is applied to the province of Trabzon, where specific facilities and hospitals are considered for emergency medical supply distribution. By addressing the challenges of medical logistics through the use of e-UAVs, this study aims to improve healthcare system resilience, ensuring that life-saving supplies are delivered efficiently during crises or emergencies.

The rest of the paper is structured as follows: the literature review is presented in Section 2. The definition of the problem is explained in Section 3, and the proposed methodology is described in section 4. A case study is presented in Section 5, and the results and conclusions are given in Sections 6 and 7, respectively.

Literature Review

The Multi-Depot Vehicle Routing Problem we address for UAVs aims to meet the emergency demands of hospitals in the shortest time and with the highest number of deliveries possible. In line with this objective, a summary of the literature review conducted is provided in Table 1. This table presents recent studies that have developed vehicle routing models for medical supply management. From all these studies, it is evident that the urgency factor is highly significant in the supply chain management of medical materials. Therefore, the use of UAVs in this field will provide substantial benefits. It can be observed that UAVs have been frequently addressed in the vehicle routing problem in recent years (Gao & Zhen, 2024; Gupta et al., 2022; Kouretas & Kepaptsoglou, 2023; Kuo et al., 2023; Stodola & Kutěj, 2024; Young Jeong & Lee, 2023). Although some projects have been implemented in real-world scenarios in certain regions, the number of academic studies focusing on the use of UAVs in healthcare remains limited (Al-Rabiaah et al., 2022; Amirsahami et al., 2023; Escribano Macias et al., 2020; Khan et al., 2021). In the context of blood supply, UAV routing has been conducted by some authors (Al-Rabiaah et al., 2022; Amirsahami et al., 2023; Ozkan, 2023). During the COVID-19 pandemic, Ozkan & Atli (2021) applied UAV routing for testing specimens. For medical supplies, vehicle routing has been addressed by some studies (Zabinsky et al., 2020; Zheng et al., 2023); however, UAVs have not been considered in these studies.

Table 1

Studies in Healthcare Supply Chain Management

Author(s)	Optimization problem	Healthcare Products	Including UAV	Objective	Country
(Zabinsky et al., 2020)	Vehicle Routing and Scheduling	Medical specimens	No	Minimizing the completion time	USA- Washington
(Zheng et al., 2023)	Open dual-objective optimization of vehicle routing	Medical supplies distribution for the urgency of the demand	No	Minimizing the total demand satisfaction rate gap and total delivery time	Unspecified location
(Ozkan, 2023)	Routing	Blood products	Yes	Minimizing the number of UAVs used and their total travel distances	Turkey- Istanbul
(Al-Rabiaah et al., 2022)	Capacitated Vehicle Routing Problem	Blood products	Yes	Optimizing Battery Consumption and Routing Distance	Public dataset (Christofides and Eilon, Set E)

Author(s)	Optimization problem	Healthcare Products	Including UAV	Objective	Country
(Wen et al., 2016)	Scheduling and capacitated vehicle routing	Blood and appendage	Yes	Minimizing the total mileage and number of UAVs	Unspecified location
(Ozkan & Atli, 2021)	Capacitated UAV routing	COVID-19 testing specimens	Yes	Minimizing the quantity of the UAVs and the total transportation distance	Turkey- Istanbul
(Khan et al., 2021)	Capacitated Vehicle Routing Problem	First aid and medical supplies	Yes	Minimizing the total distance	•
(Escribano Macias et al., 2020)	Optimal hub selection	Medical deliveries	Yes	Minimizing battery consumption and the number of hubs and time	Taiwan
(Amirsahami et al., 2023)	Routing, scheduling, fleet sizing, and fleet allocation	Blood	Yes	Maximizing the covered demand and minimizing the costs and operation time	Iran

In this study, since the vehicle routing problem and facility location selection for UAVs are addressed in an integrated manner, one aspect of the literature review focuses on location selection. Studies with similar objectives in the literature have been examined to determine suitable locations for facilities that can serve as landing and take-off sites and storage areas for UAVs. Studies focusing on facilities where aircrafts can perform take-off and landing sites (vertiports) have generally been conducted for urban transport systems (Brunelli et al., 2023; Fadhil, 2018; Jeong et al., 2021; Venkatesh et al., 2020; Y. Wang et al., 2024). To determine the location of the vertiports, it is first essential to identify the key factors influencing the selection process. Recent studies on this issue have considered factors such as commuting demand, transfer convenience, available space, obstacles, and noise and privacy (Y. Wang et al., 2024). In addition, research has also focused on UAV facility location planning in areas such as firefighting (Kim et al., 2022), hangar location for emergency services (Braßel et al., 2023), and landing safety (Mitroudas et al., 2023; Shah Alam & Oluoch, 2021).

Considering the existing literature, the contributions of this study can be summarized as follows:

- A new mathematical model has been developed along with a theoretical framework for the distribution of medical supplies, which is an underexplored topic in the field of medical supply logistics.
- The distribution process has been approached using UAVs, offering an innovative strategy for medical supply logistics.
- While real-world applications exist, the use of UAVs for medical supply distribution has not been studied extensively in academic research.
- This research, applied to Trabzon, Turkey, uses real-world data, ensuring that the study is valid and reliable.

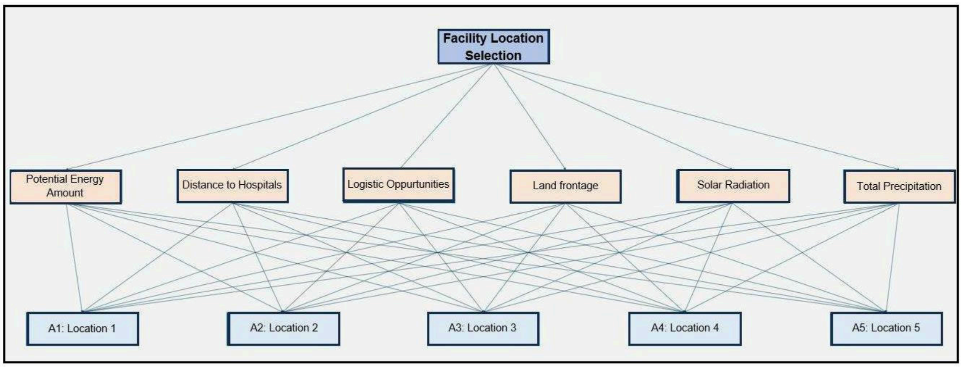
Problem Definition

A location-routing problem is a combinatorial optimization problem involving two interconnected decisions. Determining the optimal locations for facilities such as warehouses, distribution centers, charging stations, or depots and planning the most efficient routes for vehicles to deliver goods or services from the selected facilities to various demand points or customers are interrelated decisions (Fathollahi et al., 2022). In particular, the location-routing problem is essential in medical supply chain management. The complexity of modern healthcare systems and the need for rapid and effective management of emergency medical supply chains have led to the demand for new and optimized logistics strategies. In this context, the problem of meeting hospital demands for medical supplies in the shortest possible time arises during emergencies, crisis situations, or daily operations. Among the solution strategies developed for this problem, the optimization of routes for e-UAVs with the capacity to transport medical supplies between hospitals and depot centers should be addressed. Before route optimization, the selection of locations for facilities where vehicles can charge and serve as depots should be made. Therefore, the problem at hand involves both route optimization and the selection of suitable facility locations. When considering this problem for the Trabzon province, the hospitals, facilities, and criteria for facility location selection are detailed in the following paragraphs.

Facility location selection is conducted based on a set of alternatives and evaluation criteria identified through the application of MCDM. The criterion weights determined by AHP serve as the input for the TOPSIS method, which is used to evaluate the alternative locations. It is assumed that the energy required for the UAVs to charge is available at the facilities. Various criteria, some of which conflict each other, were included in the study to select suitable locations for the facilities. These criteria are given in Figure 1.

Figure 1

Hierarchy of the facility location selection for UAVs



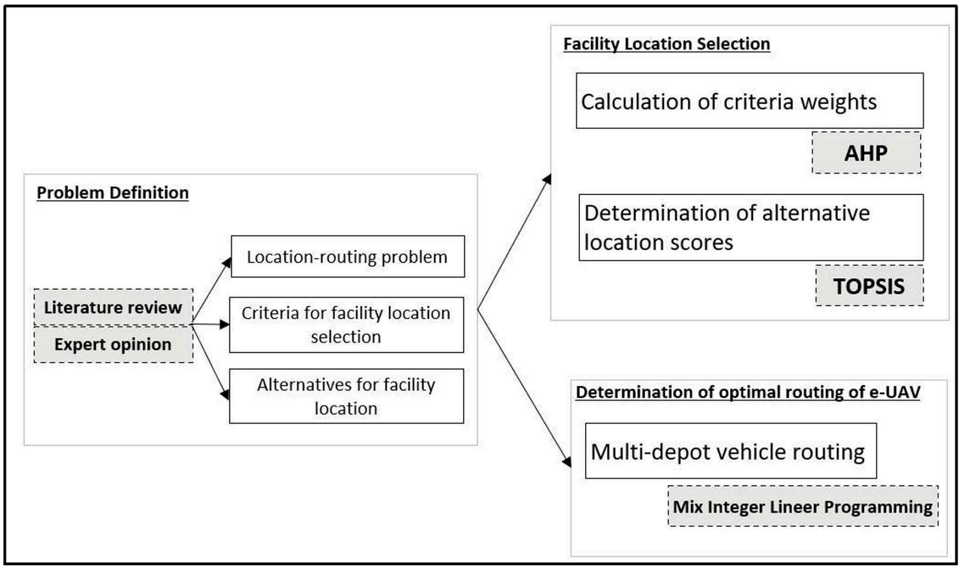
In the routing problem, UAVs depart from multiple facility locations to deliver medical supplies to hospitals and return to the nearest facility for recharging after completing their deliveries. Fully recharged UAVs resume their supply operations. This problem can be formally defined as follows: Given h hospitals and s facilities, each represented as a node in a graph, the edges between nodes are weighted based on the distance between corresponding locations. The objective is to determine a set of routes that ensures all hospitals receive the necessary supplies while minimizing the total travel distance across all UAV routes.

Methods

The methodology developed to solve the addressed problem is presented in Figure 2. Because of the experts' opinion in the problem definition section, the alternative facilities were identified as locations where UAVs can take off and land, charge, and be used as medical supply depots. These represent the depots used in the vehicle routing model. The importance levels of the criteria for the charging station locations were determined using the AHP method. The TOPSIS method was used to evaluate the locations of the charging station points, i.e., the facilities. The other pillar of the proposed study focuses on determining the most appropriate route for UAVs. A multi-depot vehicle routing mathematical model was developed to determine the routes of unmanned aerial vehicles between the selected facilities and hospitals. The methods used in this process are detailed under their respective headings.

Figure 2

The proposed methodology for the location-routing problem



Analytic Hierarchy Process

AHP is a multi-criteria decision-making method developed by Thomas L. Saaty. In this study, AHP was employed to determine the importance levels of the criteria, allowing for a systematic evaluation of their relative significance. The AHP methodology consists of the following steps, which include mathematical formulations to ensure a structured and quantitative analysis. For more comprehensive information on AHP, readers are encouraged to refer to (Ayyildiz & Taskin Gumus, 2021; Saaty, 2001).

Step 1: Define the Problem and Establish the Goal: The decision problem is clearly defined, and the main objective (goal) is identified. This step provides the foundation for structuring the hierarchy.

Step 2: Conduct Pairwise Comparisons: Each criterion (or alternative) is compared pairwise with others based on their relative importance. A scale ranging from 1 to 9 is used, where 1 denotes the situation where both factors are of equal importance and 9 denotes the extreme importance of one element over another. The pairwise comparisons are represented in a comparison matrix A:

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \quad (1)$$

The components on the diagonal of the comparison matrix, that is, when *i=j*, take the value 1 and *n* is the number of criteria. Because in this case, the relevant factor is compared with itself. The comparison of the factors is made one-to-one and reciprocal according to their importance values relative to each other.

Step 3: Determine the Percentage Importance Distributions of Factors: The column vectors that make up the comparison matrix are used and a *B* column vector with *n* numbers and *n* components is created.

$$B_i = \begin{bmatrix} b_{11} \\ b_{21} \\ . \\ . \\ . \\ b_{n1} \end{bmatrix} \tag{2}$$

The following Equation (3) is used to calculate *the B* column vectors.

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{3}$$

When *the B* column vectors (the number of columns is *n*) are brought together in a matrix format, the *C* matrix shown below will be created.

$$C = \begin{bmatrix} c_{11} & c_{12} & \dots & c_{1n} \\ c_{21} & c_{22} & \dots & c_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ c_{n1} & c_{n2} & \dots & c_{nn} \end{bmatrix} \tag{4}$$

Using the *C* matrix, percentage importance distributions showing the importance values of the factors relative to each other can be obtained. For this, as shown in Equation (2.15), the arithmetic average of the row components forming the *C* matrix is taken.

$$w_i = \frac{\sum_{j=1}^{n} c_{ij}}{n} \tag{5}$$

The column vector *W*, called the Priority Vector, is obtained.

$$W = \begin{bmatrix} w_1 \\ w_2 \\ . \\ . \\ . \\ w_n \end{bmatrix} \tag{6}$$

Technique for Order Preference by Similarity to the Ideal Solution

TOPSIS is another commonly used multi-criteria decision-making method introduced by Hwang & Yoon (1981). It is proposed to evaluate and rank alternatives based on their distances to the ideal and anti-ideal solutions. The ideal solution represents the best possible values for all criteria, while the anti-ideal solution reflects the worst-case scenario (Karabayir et al., 2020; X. Zhang & Xu, 2014). In this study, TOPSIS was applied to determine the importance levels of alternatives based on specified criteria, facilitating a systematic approach to decision-making. The steps of the TOPSIS method are detailed as follows:

Step 1: Construct the Decision Matrix: The decision matrix D is constructed, where rows represent the alternatives (A_1, A_2, ..., A_m) and columns represent the criteria (C_1, C_2, ..., C_n):

$$D = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{7}$$

where x_{11} represents the performance of alternative A_i according to criterion C_j (*i=1, 2, ..., m* and *j=1, 2, ..., n*).

Step 2 Normalize the Decision Matrix: The decision matrix is normalized to eliminate scale effects using the following formula:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{8}$$

The normalized decision matrix R is constructed as follows:

$$R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix} \tag{9}$$

Step 3 Construct the Weighted Normalized Decision Matrix: Weights w_j has been determined for each criterion based on their importance. The weighted normalized decision matrix V is established as the following equation:

$$v_{ij} = w_j{}^* r_{ij} \tag{10}$$

$$V = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1n} \\ v_{21} & v_{22} & \dots & v_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ v_{m1} & v_{m2} & \dots & v_{mn} \end{bmatrix} \tag{11}$$

Step 4 Determine the positive and negative ideal solutions: The positive ideal solution A^+ and the negative ideal solution A^- are defined as follows:

$$A_j^+ = \left\{ \max\left(v_{ij}\right) \text{ for benefit criteria}, \min\left(v_{ij}\right) \text{ for cost criteria for criterion } j \right\}$$

$$A_j^- = \left\{ \min\left(v_{ij}\right) \text{ for benefit criteria }, \max\left(v_{ij}\right) \text{ for cost criteria for criterion } j \right\}$$

Step 5 Calculate the Separation Measures: The Euclidean distance of each alternative from the positive and negative ideal solutions is calculated as follows:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - A_j^+\right)^2} \tag{12}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - A_j^-\right)^2} \tag{13}$$

Step 6 Compute the Relative Closeness to the Ideal Solution: The relative closeness C_i of each alternative to the ideal solution is calculated as follows:

$$C_i = \frac{S_i^+}{S_i^+ + S_i^-} \tag{14}$$

The value of C_i ranges between 0 and 1, where higher values indicate closer proximity to the ideal solution.

Step 7 Rank the Alternatives: The alternatives are ranked based on their C_i values, with higher values indicating higher preferences.

Proposed vehicle routing model for UAVs

<u>*Sets and indices*</u>

G=(V,A), V constitutes the set of nodes and A constitutes the arcs.

$V_H = \{V_1, V_2, ..., V_D\}$ Hospital nodes

D: The number of hospitals

$V_S = \{V_{D+1}, V_{D+2}, ..., V_{D+T}\}$ Facilities nodes

T: The number of facilities

$V = V_H \cup V_S$

$K_L = \{K_1, K_2, ..., K_U\} e - UAV$

$A = \{(i, j, h) : j \in < V, i \neq j \neq h\}$

i, j : Nodes indices

k : e − UAV indices

<u>*Parameters*</u>

l_i: *Capacity of facility i*

q_k: *Capacity of vehicle k*

d_i: *Demand of hospital i*

c_{ij}: *Distance between nodes i and j*

z_{ik}: *Whether the vehicles can be assigned to the relevant hospitals. If vehicle k can meet the demand of hospital i 1, otherwise 0*

m_{ij}: *Drone charge usage rate*

$$m_{ij} = \frac{\text{distance traveled}}{\text{maximum range}} \tag{15}$$

<u>*Variables*</u>

$x_{ijk} =$ If vehicle k travels from node i to node j 1 , and 0 other wise

$p_{jk} =$ If node j is visited vehicle k 1 , and 0 other wise

y_i : Temporary variable used for sub - round elimination and cap acity restrictions

<u>*Objective function*</u>

$$Min \sum_{i=1}^{D+T} \sum_{j=1}^{D+T} \sum_{k=1}^{U} c_{ij} {}^* x_{ijk} \tag{16}$$

<u>*Subject to*</u>

$$\sum_{i=1}^{D+T} \sum_{k=1}^{U} x_{ijk} = 1, \forall j = 1, 2, ..., D, i \neq j \tag{17}$$

$$\sum_{j=1}^{D+T} \sum_{k=1}^{U} x_{ijk} = 1, \forall i = 1, 2, ..., D, i \neq j \tag{18}$$

$$\sum_{j=1}^{D+T} x_{ijk} = p_{ik}, \forall i = 1, 2, ..., D, \forall k = 1, 2, ..., U, i \neq j \tag{19}$$

$$\sum_{j=1}^{D+T} x_{jik} = p_{ik}, \forall i = 1, 2, ..., D, \forall k = 1, 2, ..., U, i \neq j \tag{20}$$

$$\sum_{i=1}^{D+T} x_{ihk} - \sum_{j=1}^{D+T} x_{hjk} = 0, \forall h = 1, 2, ..., D+T, \forall k = 1, 2, ..., U, z_{\mathrm{hk}} = 1 \tag{21}$$

$$\sum_{i=D+1}^{D+T} \sum_{j=1}^{D} x_{ijk} = 1, \forall k = 1, 2, ..., U, i \neq j \tag{22}$$

$$\sum_{j=D+1}^{D+T} \sum_{i=1}^{D} x_{ijk} \leq 1, \forall k = 1, 2, ..., U, i \neq j \tag{23}$$

$$\sum_{j=1}^{D+T} \sum_{i=1}^{D+T} x_{ijk} \leq (D+1), \forall k = 1, 2, ..., U, i \neq j \tag{24}$$

$$x_{ijk} \leq z_{ik} {}^* z_{jk}, \forall i, j = 1, 2, ..., D, \forall k = 1, 2, ..., U, i \neq j \tag{25}$$

$$y_i - y_j + (D+2) {}^* x_{ijk} \leq (D+1), \forall i, j = 1, 2, ...D, \forall k = 1, 2, ..., U \tag{26}$$

$$\sum_{i=1}^{D+T} \sum_{j=1}^{D+T} d_i {}^* x_{ijk} \leq q_k, \forall k = 1, 2, ..., U \tag{27}$$

$$\sum_{i=1}^{D+T} \sum_{j=1}^{D+T} m_{ij} {}^* x_{ijk} \leq 1, \forall k = 1, 2, ..., U, i \neq j \tag{28}$$

$$x_{ijk}, p_{jk}, z_{jk} \in \{0, 1\}, y_i > 0, \forall i, j, k \tag{29}$$

Constraint (16) minimizes the total distance between hospitals and facilities. Constraints (17) and (18) pertain to the number of UAVs arriving at and departing from each hospital. Constraint (19) limits the number of vehicles arriving at each hospital. Constraint (20) ensures that every vehicle departing from hospital k must visit a facility. Constraint (21) enforces that a vehicle entering a node must also leave that node. Constraint (22) requires each vehicle to travel from the hospitals to the facilities. Constraint (23) allows vehicles to optionally travel from facilities to hospitals. Constraint (24) limits the number of nodes each vehicle will visit to one more than the number of hospitals. Constraint (25) prevents UAVs from visiting locations other than hospitals where they can provide services. Constraint (26) is developed to eliminate sub-tours. Constraint (27) is related to the load capacity of the UAVs. Constraint (28) handles the range of the UAVs and prevents them from traveling beyond their maximum range.

Case Study

The applicability of the developed methodology was applied in Trabzon, a province on the Eastern Black Sea coast of Turkey. In the first stage of the proposed methodology, the criteria crucial for selecting the locations of facilities where UAVs capable of transporting medical supplies can perform vertical takeoff and landing were identified through a literature review and expert opinions. In the facility location selection problem, whose hierarchical structure is shown in Figure 1, six criteria and five candidate facility locations were determined. The pairwise comparison matrices were created within the scope of AHP and filled by four experts. The matrix *C* is constructed using Equation (3) and given in Table 2. By applying the steps of the AHP method, the weights of each criterion were calculated. The application results indicated that the most significant criterion was the distance to hospitals. This criterion is followed by the amount of energy that can be generated, total precipitation, solar radiation, logistical facilities, and land frontage.

Table 2

C matrix created within the scope of the AHP method

	Energy amount	Distance to the hospital	Logistic opportunities	Land frontage	Solar radiation	Total precipitation	Weight
Energy amount	0.2256	0.1963	0.2149	0.1989	0.2775	0.3697	**0.2472**
Distance to the hospital	0.5365	0.4670	0.3685	0.3345	0.4005	0.4201	**0.4212**
Logistic opportunities	0.0645	0.0778	0.0614	0.0676	0.0219	0.0628	**0.0593**
Land frontage	0.0542	0.0667	0.0434	0.0478	0.0238	0.0223	**0.0430**
Solar radiation	0.0651	0.0934	0.2249	0.1608	0.0801	0.0363	**0.1101**
Total precipitation	0.0542	0.0988	0.0868	0.1904	0.1962	0.0888	**0.1192**

Subsequently, the TOPSIS method was employed to evaluate the alternatives. The weighted normalized decision matrix is given in Table 3. By considering the criteria of distance to hospitals and precipitation levels as cost criteria, while treating the remaining criteria as benefit criteria, the subsequent steps of the TOPSIS were applied. As a result, the relative closeness values of the alternatives were obtained and are presented in the last column of Table 3. According to the TOPSIS results, the highest-ranking alternative location is Facility 3, followed by Facilities 5, 2, 4, and 1.

Table 3

Weighted normalized decision matrix

	Energy amount	Distance to the hospital	Logistic opportunities	Land frontage	Solar radiation	Total precipitation	Relative closeness(C *i*)
Facility-1	0.1366	0.1289	0.0268	0.0286	0.0688	0.0536	**0.1863**
Facility-2	0.1414	0.1032	0.0483	0.0171	0.0712	0.0539	**0.4772**
Facility-3	0.1461	0.0932	0.0483	0.0400	0.0736	0.0543	**0.7941**
Facility-4	0.1508	0.1091	0.0376	0.0171	0.0759	0.0546	**0.4123**
Facility-5	0.1319	0.1091	0.0161	0.0514	0.0664	0.0533	**0.4985**

The other pillar of the proposed study focuses on determining the most appropriate route for UAVs. The capacities of the facilities were assumed to be equal, with each facility set to handle 500 units. The hospitals to be supplied with medical materials by the UAVs and their demand quantities were determined and are presented in Table 4. Three UAVs were considered within the scope of the application, and the capacity of each vehicle was set at 80 units. The distance matrix between hospitals and facilities in kilometres is provided in Table 5. There is an assumption that each UAV can be assigned to each hospital. That is, every z_{ik} value is 1. The range of each UAV was set at 15 kilometers, and accordingly, m_{ij} parameter has been calculated.

Table 4

Demand for hospitals

Hospitals		Demand
H1	Farabi	40
H2	Fatih	15

Hospitals		Demand
H3	Kasüstü	15
H4	Kanuni	20
H5	Ahi Evran	23
H6	Yıldızlı	11
H7	Akçaabat	5
H8	Medikal	7
H9	Imperial	4
H10	Yavuz Selim Kemik	12

Table 5

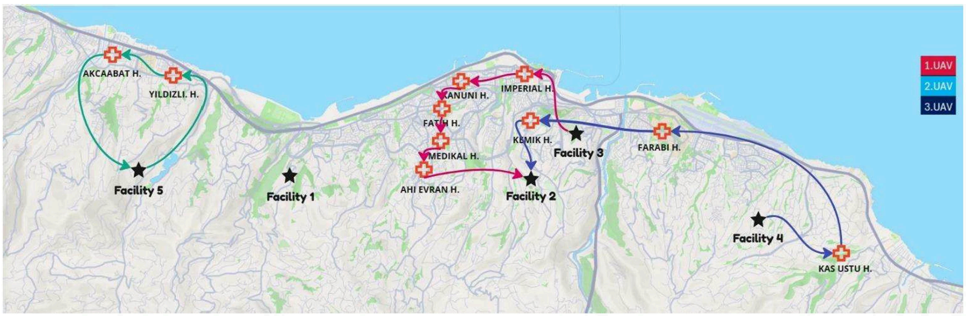
Distances between nodes for the case study

Nodes	Codes	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	F1	F2	F3	F4	F5
Farabi	H1	0	5.88	5.84	5.53	6.13	15.1	12.7	5.85	3.91	3.69	9.58	4.05	2.42	3	13.6
Fatih	H2	5.88	0	11.2	0.635	1.6	9.18	6.81	0.217	2.34	2.15	4.2	2.31	3.37	8.45	7.97
Kasüstü	H3	5.84	11.2	0	11	10.9	20.2	17.8	11.2	9.73	9.09	14.3	9.1	8.1	2.93	18.2
Kanuni	H4	5.53	0.635	11	0	2.15	9.57	7.23	0.843	1.78	1.93	4.8	2.35	3.05	8.19	8.51
Ahi Evran	H5	6.13	1.6	10.9	2.15	0	9.31	6.88	1.39	3.44	2.5	3.4	2.01	3.73	8.32	7.53
Yıldızlı	H6	15.1	9.18	20.2	9.57	9.31	0	2.43	9.13	11.3	11.3	6.2	11.2	12.6	17.6	3.4
Akçaabat	H7	12.7	6.81	17.8	7.23	6.88	2.43	0	6.74	8.97	8.92	3.86	8.79	10.2	15.1	2.54
Medikal	H8	5.85	0.217	11.2	0.843	1.39	9.13	6.74	0	2.5	2.18	4.4	2.25	3.43	8.47	7.85
Imperial	H9	3.91	2.34	9.73	1.78	3.44	11.3	8.97	2.5	0	1.47	6.54	2.39	1.8	6.83	10.3
Yavuz Selim Kemik	H10	3.69	2.15	9.09	1.93	2.5	11.3	8.92	2.18	1.47	0	5.97	0.93	1.27	6.3	9.9
Facility 1	F1	9.58	4.2	14.3	4.8	3.4	6.2	3.86	4.4	6.54	5.97	0	5.55	7.28	11.8	4
Facility 2	F2	4.05	2.31	9.1	2.35	2.01	11.2	8.79	2.25	2.39	0.93	5.55	0	1.84	6.37	9.34
Facility 3	F3	2.42	3.37	8.1	3.05	3.73	12.6	10.2	3.43	1.8	1.27	7.28	1.84	0	5.15	11.2
Facility 4	F4	3	8.45	2.93	8.19	8.32	17.6	15.1	8.47	6.83	6.3	11.8	6.37	5.15	0	15.8
Facility 5	F5	13.6	7.97	18.2	8.51	7.53	3.4	2.54	7.85	10.3	9.9	4	9.34	11.2	15.8	0

Subsequently, the developed mathematical model was solved using the IBM ILOG CPLEX Optimization Studio 22.1.1 solver to determine the optimal routes for the UAVs. UAV 1 was assigned to meet the demands of hospitals 2, 4, 5, 8, and 9; UAV 2 was assigned to hospitals 6 and 7; and UAV 3 was assigned to hospitals 1, 3, and 10. The resulting routes based on this solution are shown in Figure 3.

Figure 3

The optimal routes yielded by the mathematical model



According to the map, UAV-1 takes off from Facility 3, fulfills the demands of the assigned hospitals, and lands at Facility 2. UAV-2 takes off from Facility 5, fulfills the demands of the assigned hospitals (H6 and H7) and lands at the same facility. UAV-3 takes off from Facility 4, meets the hospital demands, and lands at Facility 2.

Results and Discussion

According to the optimal solution, the range and capacity utilization rate of each UAV are presented in Table 6. The developed vehicle routing model demonstrates the effective use of UAVs in emergency medical supply distribution, with three UAVs achieving travel distances of up to 29.59 km and capacity utilization rates ranging from 20% to 84%.

Table 6

The obtained range and capacity values of the UAV

	Travel distance	Load use
UAV 1	7.832 km	86.25%
UAV 2	8.37 km	20%
UAV 3	13.39 km	83.75%

When the number of facilities and vehicles is changed, the results of the vehicle routing model are as follows: for 5 facilities and 4 vehicles, the total distance is 29.10 km; for 4 facilities and 4 vehicles, the total distance is 33.22 km; and for 4 facilities and 3 vehicles, the total distance is 33.71 km. The results suggest that increasing the number of facilities can reduce the total distance, but the relationship between the number of facilities, vehicles, and efficiency requires careful analysis to balance operational effectiveness.

UAV-1 and UAV-3 depart from different facilities to fulfill hospital demands and complete their operations at Facility 2. This highlights that Facility 2 holds a strategic position and plays a central role in logistical operations. It is assumed that all facilities have an equal capacity of 500 units. However, the fact that UAV operations predominantly target Facility 2 suggests that its utilization rate may be higher than that of the others. It is crucial to consider this factor in capacity planning. The fact that UAV-2 takes off from the same facility and lands back at the same facility indicates that this route likely has a shorter distance or lower demand intensity. This is a positive aspect in terms of optimizing energy consumption. According to the results of the AHP method, "distance to hospitals" has been identified as the most significant criterion. This indicates that geographical proximity is a critical factor in UAV facility location selection and routing decisions. The fact that Facility 3 ranks first in the TOPSIS ranking may support the transformation of this facility into a central hub for UAV operations in the future. The prominence of the distance to hospitals as a critical criterion indicates that minimizing transportation costs should be a priority in route planning.

According to the MCDM model, Facility 3 has been identified as the most suitable facility, and the vehicle routing model (VRP) results show that the UAV-1 takes off from Facility 3. This indicates that Facility 3 is an operationally significant hub, with both models supporting this importance. The MDCM and VRP results mutually support each other, particularly regarding the operational and strategic significance of Facility 3. Additionally, from the VRP model results, it is notable that Facility 1 was not directly assigned to supply any hospitals, indicating its limited role in the optimized UAV routing network. This outcome further reinforces the MCDM finding that Facility 1 is the least suitable among the alternatives. The combined analysis of the MCDM and VRP results suggests that Facility 1 may not be a strategically optimal location for UAV-based emergency medical supply distribution. Its lower ranking in the MCDM assessment aligns with its lack of use in the VRP model, indicating that other facilities provide better service coverage and routing efficiency.

Consequently, Facility 1 could be reconsidered for alternative uses, such as a backup depot or a secondary charging station, rather than a primary distribution hub.

However, while the VRP model is optimized for short-term operational decisions, the MCDM model serves as a guide for long-term strategic decisions. These inferences are derived from the operational focus of the VRP model in optimizing routes and meeting immediate demand and the strategic focus of the MCDM model in evaluating facility suitability and guiding long-term planning. The combined use of both models can provide decision-makers with a more comprehensive perspective at both the operational and strategic levels.

Conclusion

With an emphasis on the use of e-UAVs for the distribution of emergency medical supplies, this study offers an integrated technique to handle the major issues in medical supply chains. The suggested method ensures the effective, timely, and ecologically friendly distribution of medical supplies, especially in the province of Trabzon, by optimizing vehicle routing and charging station facility placement. Using a mixed-integer mathematical model for routing and combining AHP and TOPSIS for facility location selection, this study shows how e-UAV technology might improve the resilience of the healthcare system in times of crisis and emergency.

The AHP method identified distance to hospitals as the most significant criterion for facility location selection, followed by factors such as energy availability and logistical infrastructure. The TOPSIS method ranked Facility 3, 5, and 2 as the three highest locations, and the UAV routing model, solved using the CPLEX solver, assigned UAVs to specific hospitals to efficiently meet demand using these three location depots. The total routing distance for all UAVs was calculated to be 29,59 kilometers. The results demonstrate that the outcomes of both the MCDM model and the developed vehicle routing mathematical model are consistent with each other.

This study offers healthcare logistics managers useful information on how to incorporate UAV technology into medical supply chains. Decision-makers can ensure the timely and effective delivery of medical supplies by optimizing charging station locations and UAV routing using the location-routing problem methodology described here. Managers can choose the optimum facility locations based on a variety of operational, environmental, and logistical variables by using MCDM approaches like AHP and TOPSIS. Additionally, the use of e-UAVs for medical deliveries offers substantial benefits in terms of cost-efficiency and environmental sustainability, reducing the reliance on traditional ground transportation systems that can be affected by traffic or damaged infrastructure during emergencies. This study highlights the importance of collaboration among healthcare facilities, logistics providers, and policymakers to ensure seamless integration of UAV technology into emergency medical supply chains. Consequently, this study provides a comprehensive approach to optimizing medical logistics using e-UAVs, offering a pathway to enhance supply chain resilience and response times during emergencies.

Several limitations and opportunities for future research have been identified. The model assumes static demand and facility capacities, which may not reflect real-world scenarios. Real-time data integration, including traffic, weather conditions, and hospital demand, would further refine the model's accuracy. Developing time window models that will allow emergency medical supplies to be delivered at certain time intervals would provide valuable insights into the system's adaptability. Additionally, the developed VRP model can be enhanced by incorporating the MCDM criteria, making it applicable for long-term decision-making.

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