

## Article

# Designing Sustainable Healthcare Additive Manufacturing Networks Using a Multi-Objective Spatial Routing Framework

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## Abstract

**Background:** This study evaluates an additive manufacturing (AM) network designed to balance economic performance, lead time, and environmental impact within the healthcare logistics and supply chain. **Methods:** An integrated framework is proposed that identifies optimal AM facility locations using spatial K-means clustering and optimizes delivery routes through a multi-objective vehicle routing problem with time windows (MOVRPTW). This framework was applied to a case study in Phra Nakhon Si Ayutthaya, Thailand, utilizing hospital geocoordinates, demand profiles, and CO<sub>2</sub> emission factors to evaluate centralized versus decentralized network configurations. **Results:** Findings demonstrate that hub structures derived from K-means clustering achieve the highest economic efficiency, reducing the AM part cost per unit to 698.51 Baht. In contrast, a fully centralized network resulted in a significantly higher unit cost of 4759.79 Baht, while clustering based on hospital types yielded a unit cost of 959.34 Baht. Quantitative results indicate that the multi-objective approach provides a superior trade-off, achieving lead time requirements while maintaining operational costs and emissions. **Conclusions:** The results indicate that the proposed framework, particularly through spatial clustering, offers a practical decision-support tool for designing AM networks that achieve a balance between operational efficiency and sustainability objectives in healthcare logistics.

**Keywords:** additive manufacturing; healthcare supply chain; sustainability; K-means clustering; multi objective vehicle routing problem with time windows



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## 1. Introduction

Additive Manufacturing (AM), or Three-Dimensional Printing (3DP), plays an increasingly important role in a wide range of applications, including healthcare and medical fields. Its capability to produce patient-specific parts allows AM to enhance treatment quality, reduce risks, shorten operating times, and support medical education and training [1]. The successful integration of Additive Manufacturing within healthcare (HAM) frameworks is contingent upon the efficient management of logistics systems capable of navigating logistics constraints, while simultaneously ensuring patient safety and economic viability [2]. Crucially, the strategic resilience of a HAM network resides in a holistic paradigm that integrates facility location and vehicle routing [3,4]. By transcending the traditional silos of these logistics problems, this integrated approach ensures that the strategic selection of AM production hubs is inherently synchronized with downstream operations, thereby securing the long-term sustainability of the HAM. Currently, the global HAM market is

experiencing rapid expansion, with a projected Compound Annual Growth Rate (CAGR) of 18.5% to 21.7% between 2024 and 2030, reaching an estimated value of USD 27.3 billion by 2030. While North America currently dominates the market with a 38% revenue share, the Asia-Pacific region is identified as the fastest-growing market, with a CAGR of 19.8%, [5] driven by increasing healthcare expenditures and the rising demand for personalized medical solutions in countries like Thailand.

HAM projects also align with several Sustainable Development Goals (SDGs). For instance, they support SDG 3 (Good Health and Well-being) by enabling the rapid production of patient-specific medical parts and devices, thereby reducing waiting times and improving access to care across all levels of the healthcare system. They further contribute to SDG 9 (Industry, Innovation and Infrastructure) by enhancing healthcare network infrastructure through the adoption of advanced manufacturing technologies. In addition, HAM initiatives advance SDG 13 (Climate Action) by facilitating production and distribution network configurations that reduce total travel distance, fuel consumption, and CO<sub>2</sub> emissions per part [6]. Collectively, HAM promotes greater cost-effectiveness, timeliness, and environmental sustainability in healthcare delivery [7,8]. While healthcare operational requirements are vital, the present study is primarily strategic in nature, focusing on the long-term configuration of AM networks through infrastructure design and capital investment. In contrast to daily operational scheduling, the strategic design of a HAM network necessitates a holistic evaluation of performance measures that underpin the system's long-term viability. From a financial perspective, this involves assessing significant capital expenditures—specifically the strategic acquisition and placement of AM hardware—alongside longitudinal trade-offs between fixed facility costs and variable logistics expenses. By prioritizing these strategic dimensions, the proposed model ensures that capacity utilization and network scale are optimized to fulfill healthcare demands over the planning horizon. This research distinction lies in the integration of operational lead times into the strategic decision-making process. Unlike conventional location–routing studies that focus solely on vehicle-related metrics, this study emphasizes the optimization of both internal and external logistics to ensure the expedited delivery of healthcare products. Consequently, this multi-objective approach provides a more comprehensive solution that satisfies financial and ecological objectives while prioritizing the rapid synchronization required in healthcare supply chains. These considerations are directly linked to decisions regarding the number and geographical distribution of AM hubs, as well as associated transport routing plans within the resulting medical AM network [9].

In response to these challenges, this study develops a network design model for HAM that systematically integrates healthcare facility location planning with transportation routing using an illustrative case-study dataset. Initially, spatial data for hospitals in Phra Nakhon Si Ayutthaya Province, Thailand, are collected to define alternative AM hub configurations. Next, a k-means clustering algorithm is employed to identify candidate AM production hubs and assign hospitals to appropriate service groups. Subsequently, a vehicle routing and scheduling model is formulated within a Multi-Objective Vehicle Routing Problem with Time Windows (MOVRPTW) framework to determine routing and pickup–delivery cycles that incorporate time-window constraints and vehicle availability. Multiple sustainability-oriented objectives, including minimizing total cost, reducing lead time, and lowering carbon emissions, are then investigated for conflicting behavior and trade-offs. The resulting solutions are used to assess economic feasibility and to compare centralized and decentralized network structures, thereby identifying the HAM configuration that provides the most effective balance between operational feasibility and sustainability in the study area. The research contributions are summarized as follows.

- Most existing research on HAM continues to focus on process performance and printer efficiency, while comparatively limited attention has been given to network design and the distribution of printed parts at the hospital-network level.
- Current studies predominantly examine the siting of AM centers, with less emphasis on the design of distribution patterns and routing plans within hospital networks. The present study addresses this gap by proposing an integrated location–routing framework that serves as a decision-support system for HAM network planning.
- A multi-objective optimization model is developed to analyze trade-offs among sustainability-related objectives, including total cost, operational lead times, and carbon emissions, thereby addressing a research gap in which most prior studies have considered only a limited subset of these dimensions.
- Existing studies typically focus on either centralized or decentralized network structures, with little attention to economic feasibility analysis for AM. In this study, part-level economic costs are examined by incorporating both AM operational costs and logistics costs.
- The proposed framework is applied to a regional case study in Phra Nakhon Si Ayutthaya Province, Thailand, to analyze model parameters and evaluate alternative production and distribution network configurations under realistic local conditions.
- The remainder of this manuscript is organized as follows: Section 2 reviews the relevant literature; Section 3 presents the methodology; Section 4 introduces the case study and reports the results; Section 5 discusses managerial and policy implications; and Section 6 concludes the study and outlines directions for future research.

## 2. Literature Review

### 2.1. Additive Manufacturing (AM) Technology

According to the American Society for Testing and Materials (ASTM), additive manufacturing (AM) spans seven technology families, each with distinct characteristics and use cases across diverse applications, including healthcare. The three most widely reported AM technologies are Stereolithography (SLA), Fused Deposition Modeling (FDM), and Selective Laser Sintering (SLS) [10]. SLA utilizes ultraviolet lasers to photopolymerize liquid resin layer by layer, producing high-resolution parts with fine detail governed by laser optics and machine settings. Material extrusion, commonly referred to as FDM, melts and deposits thermoplastic filament through a nozzle to fabricate parts additively. Powder bed fusion methods such as SLS use high-energy lasers to sinter polymer powders, often without the need for support structures. The typical AM workflow begins with a digital model file, followed by slicing to generate layers and define process parameters such as layer thickness, support structures, temperature or laser power, and build orientation. The printing process is then executed on an AM machine. Post-processing steps are required before concluding with quality inspection, which covers dimensional accuracy, surface finish, and porosity. For medical applications, traceability in accordance with ASTM standards and regulatory requirements for material biocompatibility and medical device approval may also be required [11,12]. The selection of AM technology and materials is therefore guided by part specifications, performance requirements, and total cost considerations across the entire manufacturing workflow [13,14].

Several studies have reported the use of AM technologies in healthcare applications. For example, Ferretti et al. [15] present the application of thermoplastic polyurethane in FDM to create organ models for surgical planning and training. This approach enables surgeons to practice procedures in a realistic manner, thereby reducing surgery times and minimizing potential complications. Iqbal et al. [16] review the status of FDM in the pharmaceutical industry, emphasizing its potential for producing personalized solid

dosage forms, such as tablets. The authors suggest that FDM holds significant promise for transforming drug manufacturing; however, further development of polymer materials is required to overcome current production challenges. Msallem et al. [17] evaluate the dimensional accuracy of medical models produced using SLA and SLS technologies. Their findings confirm that both technologies can fabricate models with high dimensional accuracy, while SLS demonstrates superior precision. The authors further suggest that lower-cost SLA printers represent a reliable option for point-of-care AM due to their affordability and broader capability to process essential biocompatible materials for surgical guides. In addition, other AM technologies—such as Material Jetting, Laminated Object Manufacturing, Directed Energy Deposition, and Binder Jetting—have also been reported in the literature, with each presenting distinct benefits and limitations [18].

The choice of AM technology directly dictates network design decisions, necessitating a strategic trade-off between economies of scale and responsiveness [19]. High-cost, complex technologies such as SLS typically require a centralized configuration to amortize substantial fixed costs and maximize capacity utilization. Conversely, the smaller footprint and greater affordability of professional-grade SLA or FDM systems enable effective decentralized networks or point-of-care manufacturing. This distributed approach minimizes last-mile delivery times, thereby ensuring adherence to strict clinical treatment windows. Nevertheless, the successful implementation of such networks relies heavily on integrated information systems to maintain uniform quality control standards across all nodes, thus ensuring patient safety regardless of the production site [20]. Additionally, AM technology for healthcare applications continues to present multiple complexities and challenges across operational, tactical, and strategic planning horizons [3]. A critical gap remains in the operational and tactical planning of HAM, particularly in the integrated design of HAM supply chains. With respect to strategic planning for HAM supply chains, the current literature offers limited methodological frameworks for investigating centralized and decentralized network configurations that incorporate economic feasibility analysis. Furthermore, the synchronization of production throughput with last-mile distribution is often overlooked. Finally, there is a clear need for sustainability-based performance measures in HAM network design to enable policy comparison across different network configurations.

## 2.2. Decision and Planning for Healthcare AM

Decision-making and planning in HAM span interconnected operational, tactical, and strategic levels that together form a complete digital chain under diverse and often conflicting objectives [21]. At the operational level, key tasks include determining part orientation, designing support structures, specifying layer thickness, tuning energy and temperature parameters, and arranging multiple parts on the build platform [22]. The primary outcomes at this planning level are to meet specification requirements, reduce lead time, and minimize scrap, while maintaining full traceability of production data [23–25]. For example, Arefin et al. [23] review polymer AM in healthcare applications, emphasizing the critical importance of integrating key decisions related to materials, processes, and design to achieve high-quality fabricated parts across diverse AM technologies, including FDM, SLA, SLS, and PolyJet. The authors suggest that the complex relationships between process parameters and material properties directly influence part quality and overall mechanical performance in healthcare products. This study illustrates that a comprehensive understanding of HAM is essential for the future development of polymer AM technologies in healthcare. In addition, Schneider et al. [24] investigate the importance of careful material selection for HAM applications. The authors point out that generic materials may present limitations compared to medical-grade materials when patient contact is required, and they emphasize the role of post-processing procedures in ensuring biosafety during AM

planning. Furthermore, they provide insights into print orientation design for controlling surface quality, noting that printing parallel to the build plane generally yields smoother surfaces than printing perpendicular to it.

At the tactical level, the focus is on several planning challenges, such as selecting AM printers and materials that meet healthcare part specifications and service requirements. This planning level also encompasses capacity planning, including determining the number of AM printers, managing spare parts and materials, and designing facility layouts. For example, Alakas et al. [26] address the complexity of selecting the most suitable AM technology for prosthesis production by applying a multi-criteria decision analysis (MCDA) method. The authors develop a hybrid model to determine the relative importance of various evaluation criteria—such as cost, precision, supported materials, and production speed—and to rank the suitability of major AM technologies. Their results indicate that FDM is the most suitable printing technology for prosthesis production under the established criteria, owing to its advantages in low cost and material versatility, which best address the need for prosthesis accessibility in the studied context. Similarly, Anussornnitisarn et al. [27] propose an integrated fuzzy decision analysis framework for sustainable AM technology selection in healthcare applications, comparing injection molding with FDM-based AM technologies. Their healthcare case study reveals that industrial AM experts place greater emphasis on economic performance and environmental aspects, whereas healthcare professionals prioritize social and quality impacts, leading to different preferred technology choices.

At the strategic level, HAM focuses on addressing the evolving needs of diverse stakeholders across the supply chain, including patients, healthcare providers, AM specialists, and the integrated AM–healthcare ecosystem [28]. Strategic planning involves the design of networks that strengthen operational efficiency and facilitate the effective adoption of AM technologies to enhance patient outcomes. It also emphasizes policies that promote collaboration, ensure regulatory compliance, and improve accessibility across all service lines within the healthcare supply chain [29]. Integrating HAM network design into the planning process—while ensuring consistent sourcing, optimized logistics systems, and responsive performance—is expected to further support consistent, cost-effective, and patient-centered care.

### *2.3. Network Design and Planning for Healthcare AM*

AM network design involves determining the locations of AM printing hubs, installing production capacity, assigning customers or healthcare facilities to each hub, and managing the flows of digital data, materials, and printed parts, together with associated distribution and logistics plans [30]. A central challenge lies in evaluating trade-offs among conflicting objectives, such as efficiency gains from centralization, responsiveness to demand, and transport-related emissions under different network configurations [31–33]. A centralized network model, for example, refers to a system in which decision-making authority and control are concentrated within a single entity that manages information and material flows. Although this structure can facilitate rapid coordination and enable efficient resource allocation, it often comes at the expense of flexibility and may limit sensitivity to local conditions [34]. In contrast, a decentralized network model distributes decision-making authority across multiple units within the AM network, enabling faster responses to local events and region-specific needs while reducing the burden on a central authority [35]. Accordingly, there is a critical need to understand both centralized and decentralized policy approaches and their implications for HAM network planning, as each model influences resource allocation, system responsiveness, and overall performance in distinct ways.

The AM supply chain encompasses all stages from raw material procurement and digital design to production, quality control, and distribution for the on-demand printing of parts [36]. AM has also been recognized as an important element in global supply chain structures due to its potential to reshape production and distribution in response to market demand. A key feature of AM supply chain networks is their ability to eliminate or shorten certain stages of the production process—such as reducing reliance on large centralized factories and cross-border transportation—thereby lowering logistics costs and the overall carbon footprint [37]. Moreover, integrating AM with digital platforms enhances data management capabilities and supports real-time decision-making, which is particularly advantageous for industries requiring highly customized products, such as patient-specific components in the healthcare sector [38–40]. Consequently, systematic planning and structuring of the AM supply chain are essential to ensure that HAM products and services are delivered efficiently and effectively.

Recent research has increasingly emphasized supply chain optimization as a means of fully capturing the advantages of AM. For example, Peron et al. [41] quantitatively assess the impact of adopting AM as an emergency solution to enhance supply chain resilience. They note that quantitative studies examining the overall impact and potential of AM in the healthcare sector remain limited and suggest that employing AM as an emergency alternative can significantly improve both revenue and service levels. Oluwole et al. [42] propose a transformative approach to pharmaceutical supply chain management to address complexities and disruptions that traditional operating models fail to handle. Their study introduces value-based healthcare economics frameworks to link logistics decisions with clinical outcomes and cost-effectiveness, emphasizing that an integrated approach is essential for modernizing logistics systems, improving patient outcomes, and reducing per capita costs. Furthermore, studies by [40,43] indicate that persistent barriers—such as high material costs and the need for interoperable producer–supplier networks—remain, underscoring the importance of balanced sustainability evaluation when designing viable AM supply chain configurations. Table 1 presents a summary of existing studies on integrated production and outbound distribution planning in AM supply chains.

**Table 1.** Literature related to AM network supply chain.

| Studies                     | Objective Type |    |       | Methodology                          |       |           | Application        |
|-----------------------------|----------------|----|-------|--------------------------------------|-------|-----------|--------------------|
|                             | Single         | Bi | Multi | Detail                               | Exact | Heuristic |                    |
| Chung et al. [44]           | x              |    |       | Total cost                           | x     |           | Smart Factories    |
| Khajavi et al. [45]         | x              |    |       | Total cost                           | x     |           | Aerospace          |
| Chowdhury et al. [46]       |                | x  |       | Total cost, Carbon emission          | x     |           | Production         |
| de Brito et al. [47]        | x              |    |       | Total cost                           | x     |           | Automotive         |
| Rinaldi et al. [38]         | x              |    |       | Total cost                           | x     |           | Automotive         |
| Carvalho de Sá et al. [48]  | x              |    |       | Total cost                           | x     |           | Healthcare         |
| Ahmed et al. [33]           | x              |    |       | Total cost                           | x     |           | Metal              |
| Rooskhosh et al. [49]       |                |    | x     | Total cost, Service level, Risk      |       | x         | Green Supply Chain |
| Olivarez-Areyan et al. [50] |                | x  |       | Total cost, Emission rate            | x     |           |                    |
| Wang et al. [51]            |                | x  |       | Electrocaloric, Energy use           |       | x         | Metal              |
| This study                  |                |    | x     | Total cost, Lead time, Emission rate | x     |           | Healthcare         |

### 3. Research Methodology

#### 3.1. Problem Statement

The healthcare supply chain encompasses the strategic planning of information, material, and service flows across the entire system, extending from raw material and medical device manufacturers through logistics providers and distribution centers to hospitals, clinics, and laboratories [52]. Ensuring the reliability of such a digitally enabled and responsive system requires sophisticated coordination across the healthcare supply chain to maintain system performance and patient safety [53]. In the physical domain of HAM, the design of an optimal healthcare service network incorporating AM technologies is therefore essential to satisfy stringent service-level requirements while accommodating the needs of diverse stakeholders. Accordingly, key strategic decisions—including the number and locations of AM production hubs, the assignment of hospitals to these hubs, fleet selection, and the optimization of delivery routes—must be integrated to achieve efficient and reliable operations. Furthermore, physical distribution in healthcare supply chains is governed by restricted time windows that represent critical delivery constraints. The comprehensive research methodology developed to address these integrated decisions is illustrated in Figure 1.

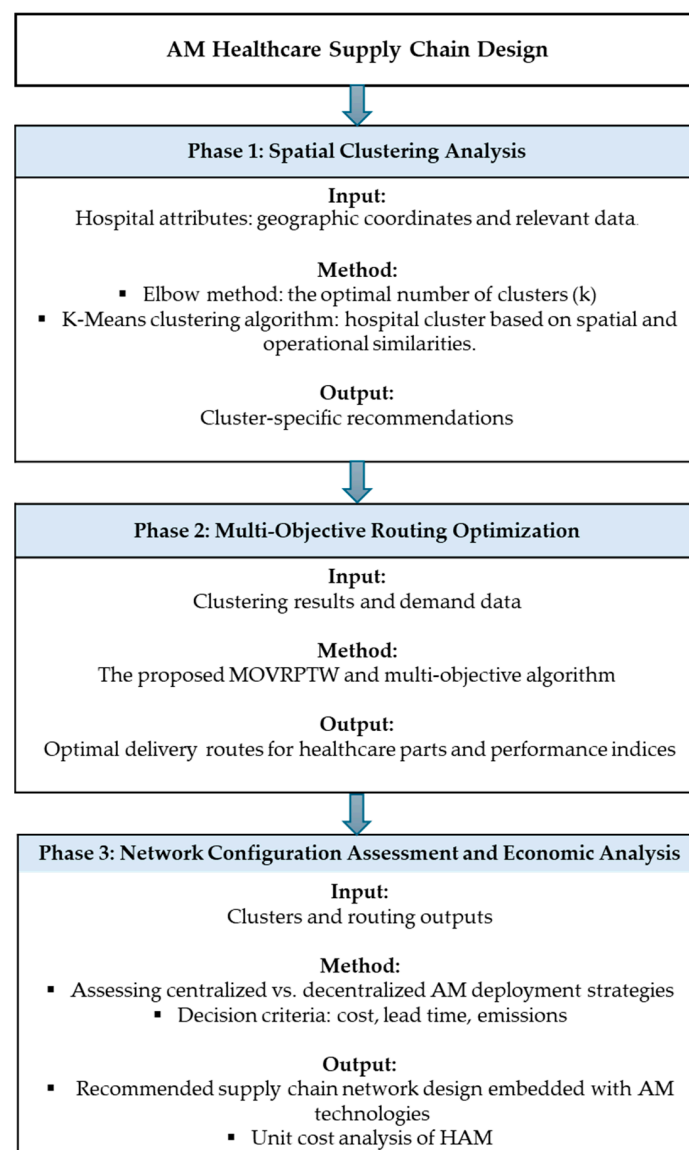


**Figure 1.** Methodology framework for HAM network evaluation.

In particular, this study aims to address the problem of determining the number and locations of AM hubs in the healthcare supply chain, considering multiple objectives related to total cost, lead time, and CO<sub>2</sub> emissions. By using spatial K-means clustering, the study first identifies candidate AM hub locations and preliminary service groupings. These results are then linked to a time-window-constrained vehicle routing model within a multi-objective framework to determine the most appropriate network structure in the second phase of the study. In addition, alternative network configurations are examined using the clustering and routing results to compare centralized and decentralized AM deployment strategies. Finally, an economic feasibility analysis is conducted to evaluate part-level economic costs by incorporating both AM operational costs and logistics costs.

### 3.2. Assumptions

- The analysis considers healthcare parts that have been fully fabricated using AM, including post-processing and quality inspection, and are ready for delivery.
- Demand at each hospital is estimated proportionally to its registered bed capacity, ensuring the model's applicability for strategic regional planning across diverse hospital tiers within the network.
- Internal demand is defined as the immediate AM part requirements of the hospital hosting the AM hub, which incur only internal operational costs. In contrast, external demand encompasses parts delivered to network hospitals, incurring distinct transportation and handling costs.
- Each AM hub is assumed to possess sufficient AM printer capacity to satisfy healthcare demand within the defined planning horizon; therefore, AM printer capacity constraints are not explicitly modeled. Studies that explicitly incorporate AM capacity limitations include [54].
- Deliveries are assumed to occur within the specified time window of each hospital. A known service time per stop is assumed and treated as a constant when calculating route feasibility.
- The problem is formulated as a multi-depot setting with time windows, where the ready-to-ship time from the AM hub is used as an input to schedule routing such that transportation is aligned with the actual availability of printed parts.
- A deterministic framework is assumed for all data parameters to ensure computational tractability in the case study. Sensitivity analyses of key parameters are then conducted to assess the impact of data variability.

### 3.3. K-Means Clustering Method

This study employs a quantitative methodology in the first phase of HAM network design by applying a data-driven K-means clustering algorithm to classify hospitals based on attributes pertinent to network dispersion. The clustering analysis is expected to reveal groupings that inform centralized versus decentralized production and distribution strategies. The K-means clustering technique has been widely used in supply chain design contexts [55,56] and is particularly useful in healthcare supply chains, where spatial and resource-oriented clustering can significantly influence network design and localized decision-making. Initially, data on hospital location coordinates are collected to derive spatial clusters that support network segmentation. The resulting groupings provide a basis for targeted recommendations on localized AM hub placement and for evaluating alternative resource allocation strategies. In this strategic planning stage, geographical coordinates are used as the primary clustering parameters to ensure spatial contiguity and to mitigate biases associated with disproportionate demand weights. By prioritizing spatial proximity, the model maintains long-term structural robustness, allowing the subsequent

location-routing stage to independently optimize varying operational constraints without distorting the underlying logistics framework.

A critical step in the analysis is selecting the optimal number of clusters. Conceptually, the algorithm iteratively identifies a centroid for each cluster and assigns observations to the nearest centroid. The procedure begins by initializing centroids at random, assigning data points to their closest centroid, recomputing centroids based on current cluster memberships, and repeating these steps until the centroid positions stabilize. Equation (1) defines the distance between a data point and a cluster centroid, while Equation (2) represents the K-means objective of minimizing the total Within-Cluster Sum of Squared (WCSS) distances across all data points and their assigned centroids.

$$Distance(x_j, \mu_j) = \sqrt{\sum_{i=1}^n (x_i - \mu_i)^2} \quad (1)$$

where

$x_i$  is the value of data point  $x$  in dimension  $j$   
 $\mu_i$  is the value of centroid  $\mu$  in dimension  $j$

$$J = \sum_{j=1}^k \sum_{x_j \in c_j} \|x_i - \mu_j\|^2 \quad (2)$$

where

$c_i$  is the set of data points in cluster  $i$   
 $\mu_i$  is the centroid of cluster  $i$

Next, to determine the appropriate number of clusters  $k$ , this study employs the Elbow Method [57], a widely used method for selecting  $k$  in unsupervised clustering, including K-means. By plotting WCSS as presented in Equation (3) against  $k$ , the elbow where marginal gains in fit diminish will serve as an indicator of the optimal cluster count. The advantages of the elbow point method include a suggestion for appropriate trade-off between model complexity and explanatory power [57] in which a visualization is useful to avoid underfitting with too few clusters and overfitting with too many clusters.

$$WCSS = \sum_{j=1}^k \sum_{x_j \in C_j} \|x_i - \mu_j\|^2 \quad (3)$$

where

$k$  is the number of clusters  
 $c_i$  is the set of data points in cluster  $i$   
 $\mu_i$  is the centroid of cluster  $i$

$\|x_i - \mu_j\|^2$  is the squared Euclidean distance between a data point and the cluster centroid.

### 3.4. Mathematical Notation for MOVRPTW

#### 3.4.1. Sets

$N$  : Set of all nodes in the healthcare chain, where 0 denotes the planned AM hub  
 $NC$  : Set of investigated hospitals/healthcare facilities  
 $A$  : Set of all arcs of the transportation network  
 $V$  : Set of vehicles

### 3.4.2. Parameters

- $n$  : Total number of nodes for hospitals in the healthcare chain  
 $m$  : Number of available vehicles  
 $c^f$  : Fixed cost per vehicle (Baht)  
 $c^v$  : Variable transport cost per vehicle depending on routing distance (Baht)  
 $f^{trans}$  : Rate of fuel consumption (kilometer per liter)  
 $ef^{CO_2}$  : Carbon dioxide emission factor  
 $d_{ij}$  : Distance to deliver between location  $i$  and  $j$ , where  $(i, j) \in A$  (kilometer)  
 $p_i$  : Amount of AM part to be delivered in each round for each node  $i \in N$  (unit)  
 $pq_k^{cap}$  : Capacity of vehicle (unit)  
 $t^{beg}$  : The start time of planning horizon (min)  
 $t^{end}$  : The end time of planning horizon (min)  
 $t_i^s$  : Service time for the AM parts loading at node  $i \in N$  (min)  
 $t_{ij}^t$  : Travel time of the vehicle between location  $i$  and  $j$ , where  $(i, j) \in A$  (min)  
 $t_i^{ra}$  : Earliest time window for the delivery route at each node  $i \in N$  (min)  
 $t_i^{rb}$  : Latest time window for the delivery route at each node  $i \in N$  (min)  
 $i^{Z1}$  : Auxiliary parameter denoting the ideal value of the first objective function  
 $i^{Z2}$  : Auxiliary parameter denoting the ideal value of the second objective  
 $i^{Z3}$  : Auxiliary parameter denoting the ideal value of the third objective  
 $ai^{Z1}$  : Auxiliary parameter denoting the anti-ideal value of the first objective  
 $ai^{Z2}$  : Auxiliary parameter denoting the anti-ideal value of the second objective  
 $ai^{Z3}$  : Auxiliary parameter denoting the anti-ideal value of the third objective  
 $\alpha_l$  : Relative weight of each objective function  $l$  under consideration

### 3.4.3. Decision Variables

- $X_{i,j,k}$  : Decision variable to assess whether to transport between locations  $i$  and  $j$  using a vehicle  $k$ , binary.  
 $Y_{i,j,k}$  : Decision variable to account for cumulative amount of delivering AM parts from node  $i$ , in an arc  $(i, j) \in A$ , where  $Y_{i,j}$  is within the vehicle capacity.  
 $W_{i,k}$  : Decision variable to denote time to begin an unloading service at node  $i$  by a vehicle  $k$ , where  $W_{i,k}$  is between  $t^{beg}$  and  $t^{end}$   
 $W^{max}$  : Decision variable to denote the worst case to arrive the last node of each vehicle trip (maximum time) with respect to all vehicles under consideration.

### 3.4.4. Objective Functions

The multiple objective functions of the proposed MOVRPTW model, with an explicit sustainability focus, are presented next. First, Equation (4) minimizes total cost, comprising the fixed activation costs of utilizing available vehicles and the variable transportation costs incurred across the logistics network. Second, Equation (5) minimizes the maximum trip time (a min–max criterion) among all drivers, defined as the time required to reach the last AM-parts demand node on a route. This nonlinear objective is linearized by introducing an auxiliary variable that upper-bounds each driver's trip time, ensuring that the longest trip does not exceed this bound, as shown in Equation (6). Finally, Equation (7) minimizes total emissions, capturing distance-, vehicle type-, and load-dependent effects. Collectively, the model integrates economic, social, and environmental aspects—the three main pillars of sustainability.

$$\text{Minimize } Z_1 = \sum_{(o,j) \in A; k \in V} c^f X_{i,j,k} + \sum_{(o,j) \in A; k \in V} \left( \frac{c^v d_{i,j}}{f^{trans}} \right) X_{i,j,k} \quad (4)$$

$$\text{Minimize } Z_2 = W^{\max} \quad (5)$$

$$\text{Subject To } W^{\max} \geq W_{i=n+1,k} - W_{0 \in N,k} : \forall k \in V \quad (6)$$

$$\text{Minimize } Z_3 = \sum_{(o,j) \in A; k \in V} ef^{CO_2} \left( \frac{d_{i,j}}{f^{trans}} \right) X_{i,j,k} \quad (7)$$

### 3.4.5. Model Constraint Sets

The model's constraints are presented next in Equations (8)–(21). First, Equation (8) enforces a single-entry-per-trip rule, whereby each vehicle may enter any given node at most once, preventing unnecessary cycles and ensuring route clarity. Next, Equation (9) imposes vehicle-level flow conservation, such that for every node a vehicle enters, the same vehicle must also depart from that node, thereby preserving route continuity. Finally, Equation (10) governs route initiation and continuation from the AM-part collection and processing hub (depot), requiring each vehicle departing the depot to proceed to exactly one subsequent node in order to initiate a feasible route. Collectively, these constraints ensure the operational feasibility of the resulting network design.

$$\sum_{i \in N: i \neq j} \sum_{k \in V} X_{i,j,k} = 1 ; \forall j = 1, \dots, n \quad (8)$$

$$\sum_{i \in N: i \neq j} X_{i,j,k} = \sum_{i \in N: i \neq j} X_{i,j,k} ; \forall j = 1, \dots, n ; k \in V \quad (9)$$

$$\sum_{j \in 1, \dots, n} X_{0,j,k} \leq 1 ; \forall k \in V \quad (10)$$

Next, the combined constraint sets in Equations (11) and (12) compute the cumulative delivery quantity along each route and enforce capacity feasibility. Specifically, these constraints aggregate the load delivered at each visited hospital and ensure that, at any intermediate AM-parts demand hospital, the cumulative amount on board does not exceed the vehicle capacity. This mechanism prevents capacity violations during route progression within the vehicle limit.

$$\sum_{(i,j) \in A} Y_{j,i} - \sum_{(i,j) \in A} Y_{i,j} = p_j ; \forall j = 1, \dots, n \quad (11)$$

$$Y_{i,j} \leq \sum_{k \in V} p q_k^{cap} X_{i,j,k} ; \forall (i,j) \in A \quad (12)$$

The next constraint set establishes the start time of the planning horizon for all vehicles (Equation (13)). Equation (14) then computes the arrival time of each vehicle at each node in the HAM delivery network. Each estimated arrival time is obtained from the sum of the service time (i.e., unloading/handling time of AM parts) and the transportation time. Subsequently, the constraint set in Equations (15) and (16) enforces the time windows established in the healthcare chain, which requires that the service start time of each vehicle at any node must fall within the earliest and latest permissible times by different hospitals. Additionally, the constraint set in Equation (17) computes the bounds on the estimated arrival time of each vehicle at each node.

$$W_{i=0,k \in V} = t^{beg} ; \forall k \in V \quad (13)$$

$$W_{i,k} + t_i^s + t_{i,j}^t - W_{i,k} \leq b \left( 1 - X_{i,j,k} \right) ; \forall (i,j) \in A, k \in V \quad (14)$$

$$W_{i,k} \geq t_i^{ra} \sum_{(i,j) \in A; i \neq j} X_{i,j,k} ; \forall i = 1, \dots, n, k \in V \quad (15)$$

$$W_{i,k} \leq t_i^{rb} + b \left( 1 - \sum_{(i,j) \in A; i \neq j} X_{i,j,k} \right); \forall i = 1, \dots, n, k \in V \quad (16)$$

$$t^{beg} \leq W_{i,k} \leq t^{end}; \forall i = 1, \dots, n, k \in V \quad (17)$$

Finally, the variable-type constraints specifying the domains of the decision variables required by the proposed MOVRPTW formulation are provided in Equations (18)–(21).

$$X_{i,j,k} \in \{0, 1\}; \forall (i, j) \in A, k \in V \quad (18)$$

$$Y_{i,j} \geq 0; \forall (i, j) \in A \quad (19)$$

$$W_{i,j} \geq 0; \forall i = 1, \dots, n, k \in V \quad (20)$$

$$W^{max} \geq 0 \quad (21)$$

### 3.5. Analysis of Multi-Objective Optimization Model

To ensure comparability among conflicting objectives with different units, a linear normalization method is applied as formulated in Equations (22) and (23). This transformation maps the value of each criterion into a dimensionless scale within the interval (0, 1). The process relies on two reference points: the ideal solution and the anti-ideal solution, which correspond to the best and worst achievable performance levels, respectively. Specifically, ideal solution is defined as the maximum value for a profit-type objective and the minimum value for a cost-type objective, whereas anti-ideal solution denotes the minimum for a profit-type objective and the maximum for a cost-type objective. Consequently, this normalization ensures that all transformed values follow a uniform direction where a higher value signifies superior performance.

Next, a non-preemptive weighting scheme is adopted to scalarize the multi-objective model into a single-objective problem via a weighted sum of the objectives under consideration as shown in Equations (24) and (25). In particular, by applying the introduced linear normalization technique, each objective is converted to a profit-type measure on a range between 0 and 1, thereby enabling unitless, inter-criterion comparability.

$$n_j(x) = \frac{f_i(x) - ai_j}{i_j - ai_j}; \text{Profit-type} \quad (22)$$

$$n_j(x) = \frac{ai_j - f_i(x)}{ai_j - i_j}; \text{Cost-type} \quad (23)$$

$$\text{Maximize } Z^{NP} = \alpha_{Z1} \left( \frac{ai^{Z1} - Z_1}{ai^{Z1} - i^{Z1}} \right) + \alpha_{Z2} \left( \frac{ai^{Z2} - Z_2}{ai^{Z2} - i^{Z2}} \right) + \alpha_{Z3} \left( \frac{ai^{Z3} - Z_3}{ai^{Z3} - i^{Z3}} \right) \quad (24)$$

$$\alpha_{Z1} + \alpha_{Z2} + \alpha_{Z3} = 1 \quad (25)$$

## 4. Case Study and Results

### 4.1. Case Study

Currently, Thailand is actively advancing its public health system toward “Smart Health” under the Thailand 4.0 policy [58]. This national strategy emphasizes the integration of digital technologies and advanced logistics to enhance healthcare accessibility and efficiency. In this context, Phra Nakhon Si Ayutthaya Province is selected as a regional case study. The province comprises 16 districts with a registered population of approximately 820,000 [59]. At present, the healthcare system includes only one regional hospital serving as the primary medical center capable of providing specialized care. The provincial health

authority has announced a strategic initiative to upgrade selected community hospitals into secondary medical centers [60]. Given this transitional landscape, the strategic design of the HAM supply chain is essential for managing these structural complexities and supporting future healthcare system development.

To illustrate the application of the proposed framework, a case study of the healthcare network is conducted. Hospitals in Phra Nakhon Si Ayutthaya Province are categorized into four types according to their functional roles within the healthcare system: (A) regional or center hospitals, which act as provincial hub hospitals and are responsible for handling complex cases; (B) general hospitals, which operate at an intermediate level and provide a wide range of secondary care services; (C) public community hospitals, which deliver care at the district level; and (D) private hospitals, which offer healthcare services on a commercial basis. This classification reflects differences in service capacity and patient flow within the network. The geographical locations of the hospitals are summarized in Table 2 and visually illustrated in Figure 2.

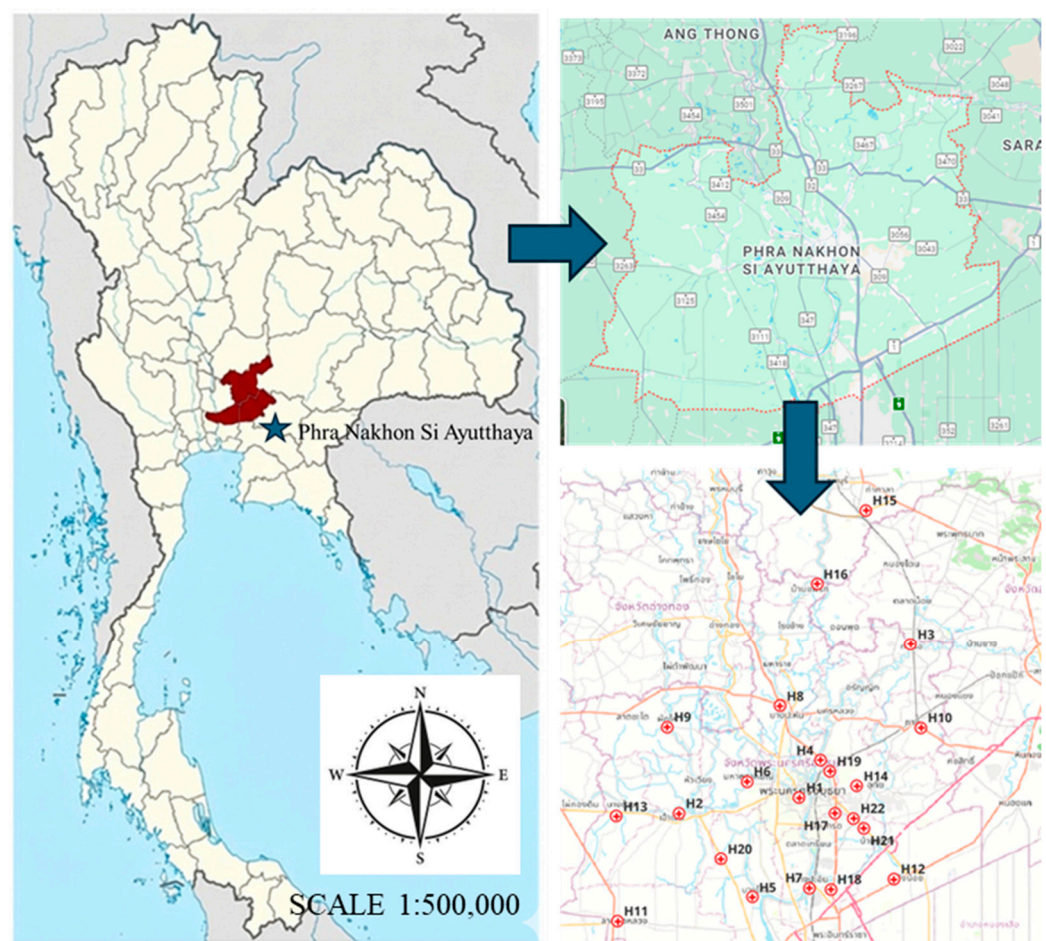


**Figure 2.** The case study for hospital locations in Phra Nakhon Si Ayutthaya province.

#### 4.2. AM Hub Result Using K-Means Algorithm

Based on the collected geographic coordinates (latitude–longitude) of the 23 hospitals in Phra Nakhon Si Ayutthaya Province, the spatial distribution of healthcare facilities across the province can be clearly observed. This distribution enables the identification of proximity-based groupings in a meaningful manner. In addition, the variability in latitude and longitude values indicates a wide geographical spread, which is an important condition for effective clustering, as it allows the K-means algorithm to detect spatial patterns and form clusters that reflect logistics-oriented groupings. These spatial data are subsequently

used to evaluate centralized versus decentralized healthcare network configurations in the subsequent stages of the analysis.

**Table 2.** Location and detail of hospitals in the case study.

| Hospital | Latitude | Longitude | Bed Capacity | Type of Hospital              |
|----------|----------|-----------|--------------|-------------------------------|
| H1       | 14.34391 | 100.55965 | 570          | A: Regional/center hospitals  |
| H2       | 14.32114 | 100.38554 | 208          | B: General hospitals          |
| H3       | 14.56612 | 100.72094 | 34           | C: Public community hospitals |
| H4       | 14.39829 | 100.59041 | 45           | C: Public community hospitals |
| H5       | 14.20061 | 100.49174 | 39           | C: Public community hospitals |
| H6       | 14.36719 | 100.48449 | 26           | C: Public community hospitals |
| H7       | 14.21377 | 100.57425 | 96           | C: Public community hospitals |
| H8       | 14.47647 | 100.53168 | 35           | C: Public community hospitals |
| H9       | 14.44592 | 100.36867 | 31           | C: Public community hospitals |
| H10      | 14.44476 | 100.73576 | 40           | C: Public community hospitals |
| H11      | 14.16569 | 100.29686 | 34           | C: Public community hospitals |
| H12      | 14.22652 | 100.69669 | 77           | C: Public community hospitals |
| H13      | 14.31715 | 100.29504 | 10           | C: Public community hospitals |
| H14      | 14.36113 | 100.64301 | 37           | C: Public community hospitals |
| H15      | 14.76038 | 100.65651 | 22           | C: Public community hospitals |
| H16      | 14.65424 | 100.58554 | 10           | C: Public community hospitals |
| H17      | 14.32149 | 100.61155 | 224          | D: Private hospitals          |
| H18      | 14.21155 | 100.60548 | 105          | D: Private hospitals          |
| H19      | 14.38255 | 100.60441 | 54           | D: Private hospitals          |
| H20      | 14.25591 | 100.44632 | 55           | D: Private hospitals          |
| H21      | 14.30000 | 100.65281 | 100          | D: Private hospitals          |
| H22      | 14.31388 | 100.63843 | 59           | D: Private hospitals          |
| H23      | 14.05651 | 100.25161 | 5            | D: Private hospitals          |

The Elbow method is next employed to determine an appropriate number of clusters for K-means clustering. By plotting the relationship between the number of clusters  $k$  and the WCSS, a suitable balance between model complexity and clustering performance is assessed. The point of curvature change, or ‘elbow point’ is interpreted and suggested as the most appropriate number of clusters for the data set [57]. In this analysis, values of  $k$  ranking from 1 to 10 are evaluated and the corresponding WCSS values are computed to identify the most suitable number of clusters as illustrated in Figure 3. That is, the Elbow curve identifies the point at which the decrease in WCSS begins to level off, which indicates an appropriate number of clusters for partitioning the data. The main aim is to find the point at which the rate of reduction in WCSS balances a reduction against avoiding an unnecessarily large number of clusters. From the figure, the slope and Elbow point begins at three clusters ( $k$ ).

Next, the hospitals in the case study are divided into three clusters, as presented in Table 3 and illustrated in Figure 4. The results indicate that Cluster 1 is centered around a latitude of approximately 14.32149 and a longitude of 100.61155 (H17), Cluster 2 around a latitude of 14.31715 and a longitude of 100.29504 (H13), and Cluster 3 around a latitude of 14.56612 and a longitude of 100.72094 (H3). In this study, the hospital located closest to the calculated centroid of each cluster is designated as the AM hub location and serves the demand from hospitals within its corresponding cluster. This centroid-based selection approach ensures that each hub is geographically well positioned to minimize travel distances and improve accessibility. These findings also support region-specific analysis and provide a practical basis for efficient resource allocation and operational planning within the network.

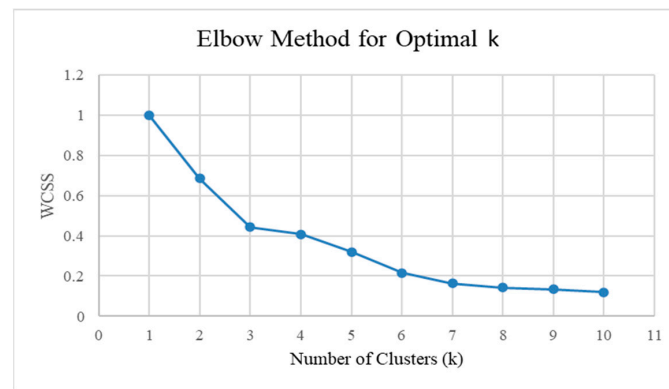


**Figure 3.** Inertia values by number of clusters using the Elbow method.

**Table 3.** Hospital clustering results using K-Means clustering with  $k = 3$ .

| Cluster Number<br>(Nearest Hospital) | Centroid (Latitude, Longitude)  | Hospital Number                                              |
|--------------------------------------|---------------------------------|--------------------------------------------------------------|
| C1 (H17)                             | Centroid1 (14.32149, 100.61155) | H1, H4, H5, H6, H7, H8, H12,<br>H14, H17, H18, H19, H21, H22 |
| C2 (H13)                             | Centroid2 (14.31715, 100.29504) | H2, H9, H11, H13, H20, H23                                   |
| C3 (H3)                              | Centroid3 (14.56612, 100.72094) | H3, H10, H15, H16                                            |

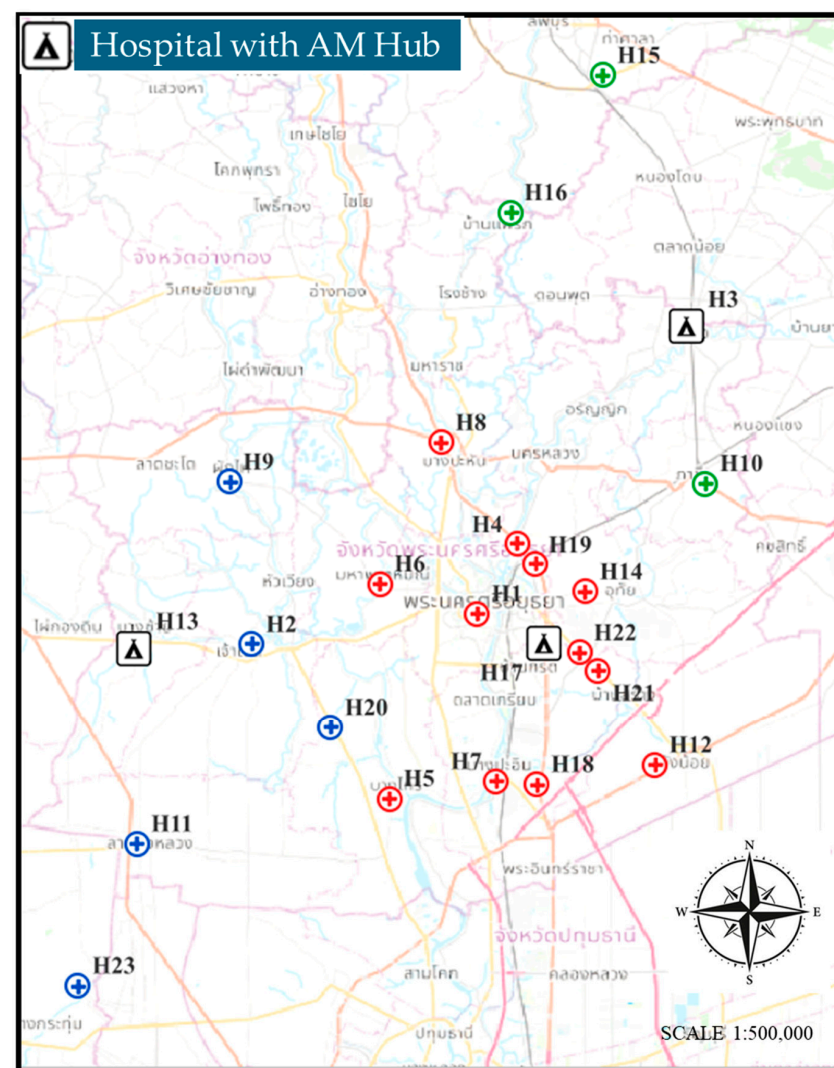


**Figure 4.** Hospital clustering analysis and suggested AM hub.

#### 4.3. Distribution Plan Analysis Using MOVRPTW

In this subsection, the distribution plan is analyzed using the proposed MOVRPTW model, given the clustering results and AM hub locations identified earlier (base scenario). The mathematical model is implemented and solved using AMPL [61] on a computer equipped with an Intel Core i5 processor and 16.0 GB of RAM. The maximum computational runtime for each problem instance is limited to 3600 s. The distribution plan is evaluated for an AM hub configured as a centralized, hospital-based facility equipped with industrial-grade AM technologies, serving hospitals identified through K-means clustering. The resulting distribution plan is then assessed using objective functions that account for total cost, lead time, and emissions, as well as through a multi-objective approach, as presented in Table 4.

**Table 4.** Results of operational routing plan under the Base Scenario (3 K-means Clustering).

| Details<br>(Base Scenario)      | Objective Function Type |          |          |                 |
|---------------------------------|-------------------------|----------|----------|-----------------|
|                                 | Total Cost              | Leadtime | Emission | Multi-Objective |
| Cluster 1 (C1)                  |                         |          |          |                 |
| Total cost (Baht)               | 2749.52                 | 6753.78  | 2749.52  | 2844.35         |
| Num of used vehicles            | 2                       | 5        | 2        | 2               |
| Gasoline (liter)                | 10.94                   | 23.60    | 10.94    | 13.91           |
| Fixed cost (Baht)               | 2400                    | 6000     | 2400     | 2400            |
| Variable cost (Baht)            | 349.52                  | 753.78   | 349.52   | 444.35          |
| Max personal leadtime (minutes) | 480                     | 268      | 328      | 304             |
| Emission (CO <sub>2</sub> )     | 29.33                   | 63.25    | 29.33    | 37.28           |
| Computation time (second)       | 3600                    | 3600     | 3600     | 3600            |
| Cluster 2 (C2)                  |                         |          |          |                 |
| Total cost (Baht)               | 1554.69                 | 6574.92  | 1554.69  | 2776.57         |
| Num of used vehicles            | 1                       | 5        | 1        | 2               |
| Gasoline (liter)                | 11.11                   | 18.00    | 11.11    | 11.79           |
| Fixed cost (Baht)               | 1200                    | 6000     | 1200     | 2400            |
| Variable cost (Baht)            | 354.69                  | 574.92   | 354.69   | 376.57          |
| Max personal leadtime (minutes) | 480                     | 275      | 370      | 275             |
| Emission (CO <sub>2</sub> )     | 29.76                   | 48.24    | 29.76    | 31.59           |
| Computation time (second)       | 3600                    | 3600     | 3600     | 3600            |
| Cluster 3 (C3)                  |                         |          |          |                 |
| Total cost (Baht)               | 1451.37                 | 3943.93  | 1451.37  | 1451.37         |
| Num of used vehicles            | 1                       | 3        | 1        | 1               |
| Gasoline (liter)                | 7.87                    | 10.77    | 7.87     | 7.87            |
| Fixed cost (Baht)               | 1200                    | 3600     | 1200     | 1200            |
| Variable cost (Baht)            | 251.37                  | 343.93   | 251.37   | 251.37          |
| Max personal leadtime (minutes) | 316                     | 250      | 257      | 257             |
| Emission (CO <sub>2</sub> )     | 21.09                   | 28.86    | 21.09    | 21.09           |
| Computation time (second)       | 3600                    | 3600     | 3600     | 3600            |

The obtained results illustrate the trade-offs among the objective functions of total cost, lead time, and emissions. Specifically, strategies that strongly reduce lead time require a larger vehicle fleet (e.g., C1: 5 vehicles; C2: 5 vehicles; C3: 3 vehicles), which leads to higher costs and increased emissions (e.g., C1: cost = 6753.78 Baht; CO<sub>2</sub> = 63.25). Conversely, using fewer vehicles (e.g., C1: 2; C2: 1; C3: 1) reduces both cost and emissions but results in substantially longer lead times, indicating that a sole focus on cost or emissions reduction can adversely affect service punctuality. A multi-objective analysis therefore provides more balanced solutions. For example, in C1, the maximum lead time can be reduced to 304 min with only a modest increase in cost from 2749.52 to 2844.35 Baht while still using two

vehicles. In C2, the maximum lead time can be reduced to 275 min by increasing the fleet from one to two vehicles (cost = 2776.57 Baht; CO<sub>2</sub> = 31.60). In C3, the lead time can be reduced to 257 min using a single vehicle (cost = 1451.37 Baht; CO<sub>2</sub> = 21.09). Overall, these results demonstrate that the multi-objective approach yields operational plans that more effectively balance resource utilization.

In addition, the results of the vehicle distribution evaluation in the base scenario, obtained using the multi-objective approach, are grouped and planned according to the relevant clusters, as shown in Table 5 and illustrated in Figure 5. Specifically, Cluster C1 comprises 12 hospitals served by two vehicles, Cluster C2 comprises seven hospitals served by two vehicles, and Cluster C3 comprises four hospitals served by one vehicle. The operating period is set from 09:00 to 17:00, and all vehicle routes are designed as closed loops that start and end at the AM hub of each cluster. The routes are constructed to satisfy both the hospitals' service time windows and vehicle capacity constraints. Overall, the solution reflects a balanced allocation of fleet size, workload, and total tour duration within each cluster, while maintaining punctual delivery of AM parts across the healthcare network.

**Table 5.** Distribution plan analysis and results (Base scenario).

| Vehicle Number | Distribution Plan                                                                             |
|----------------|-----------------------------------------------------------------------------------------------|
| Cluster 1 (C1) |                                                                                               |
| V1             | H17 (AM hub) → H7 → H18 → H21 → H12 → H22 → H14 → H19 → H17 (AM hub)                          |
| V2             | H17 (AM hub) → H1 → H4 → H8 → H6 → H5 → H17 (AM hub)                                          |
|                | Estimated arriving time                                                                       |
| V1             | H17 (AM hub) 9.00 → 9.40 → 10.11 → 11.00 → 12.05 → 12.50 → 13.13 → 13.31 → 14.04 H17 (AM hub) |
| V2             | H17 (AM hub) 9.00 → 9.30 → 11.56 → 12.23 → 12.53 → 13.26 → 14.04 H17 (AM hub)                 |
|                | Cumulative delivery quantity (units)                                                          |
| V1             | H17 (AM hub) → 27 → 22 → 17 → 12 → 8 → 5 → 3 → H17 (AM hub)                                   |
| V2             | H17 (AM hub) → 34 → 7 → 5 → 3 → 2 → H17 (AM hub)                                              |
| Cluster 2 (C2) |                                                                                               |
| V1             | H13 (AM hub) → H11 → H23 → H13 (AM hub)                                                       |
| V2             | H13 (AM hub) → H9 → H20 → H2 → H13 (AM hub)                                                   |
|                | Estimated arriving time                                                                       |
| V1             | H13 (AM hub) 9.00 → 12.00 → 12.30 → 13.20 H13 (AM hub)                                        |
| V2             | H13 (AM hub) 9.00 → 11.55 → 12.40 → 13.30 → 14.35 H13 (AM hub)                                |
|                | Cumulative delivery quantity                                                                  |
| V1             | H13 (AM hub) → 3 → 1 → H13 (AM hub)                                                           |
| V2             | H13 (AM hub) → 15 → 13 → 10 → H13 (AM hub)                                                    |
| Cluster 3 (C3) |                                                                                               |
| V1             | H3 (AM hub) → H10 → H16 → H15 → H3 (AM hub)                                                   |
|                | Estimated arriving time                                                                       |
| V1             | H3 (AM hub) 9.00 → 11.17 → 12.50 → 13.17 → 13.57 H3 (AM hub)                                  |
|                | Cumulative delivery quantity                                                                  |
| V1             | H3 (AM hub) → 4 → 2 → 1 → H3 (AM hub)                                                         |

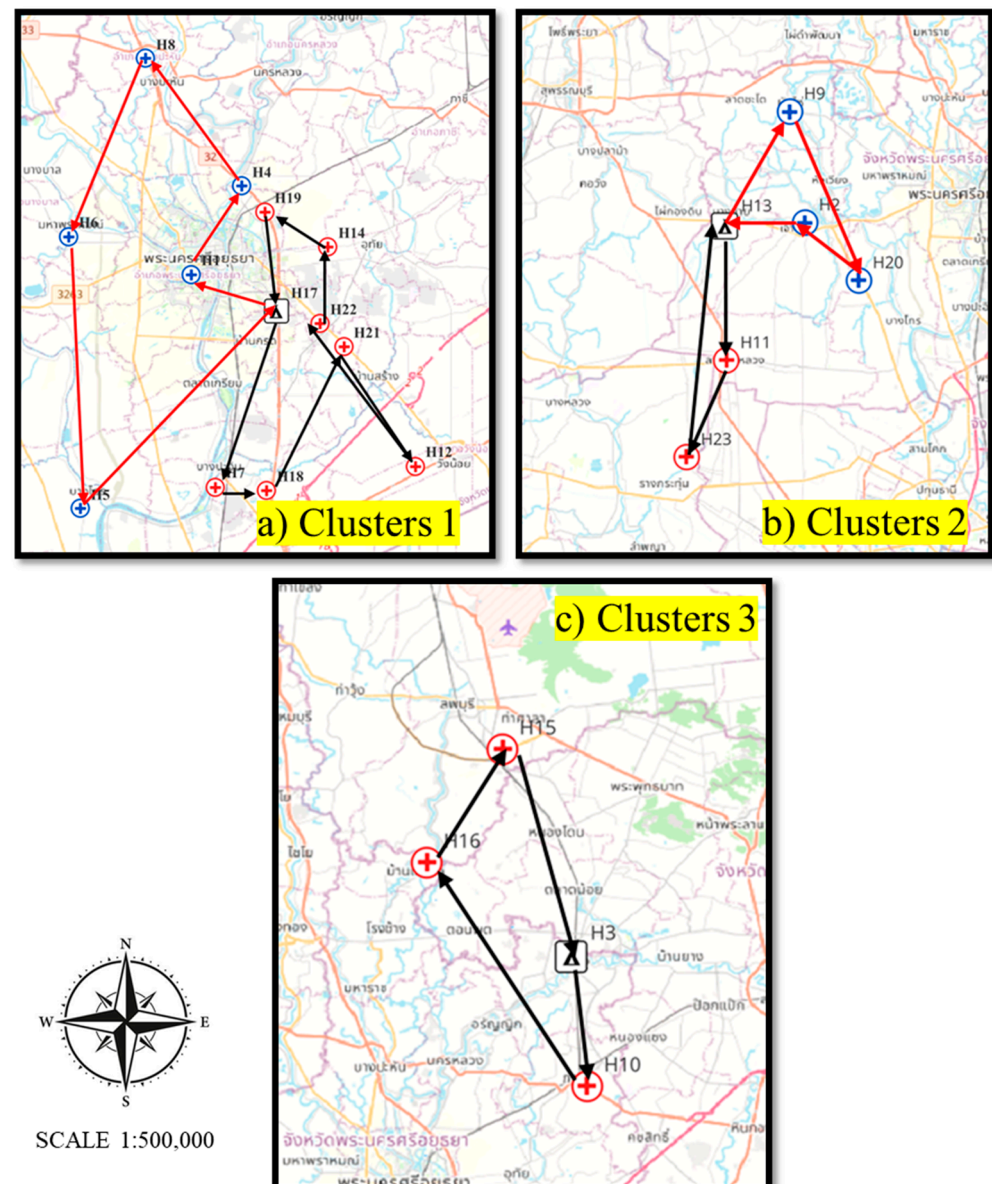


**Figure 5.** Vehicle distribution plan for three clusters (Base scenario).

#### 4.4. Experimental Scenario and Economic Feasibility Analysis

This section discusses experimental scenarios and an economic feasibility analysis based on interviews with healthcare and AM experts, intended to verify and validate the clustering results. Two experimental scenarios for AM hub network design are examined. Experimental Scenario 1 assumes the installation of an AM printer in every hospital, representing a fully decentralized configuration. This setup is expected to significantly reduce lead and waiting times, although it may entail higher total capital and operating expenditures. Experimental Scenario 2 assigns AM hubs according to hospital type. Specifically, hospitals are grouped as follows: (A) regional (center) hospitals, (B) general hospitals, (C) public community hospitals, and (D) private hospitals. The evaluation results for Experimental Scenario 1 indicate that all costs are incurred internally by each hospital (e.g., AM printers and related equipment, materials, and personnel), and no external logistics-related costs arise, since production takes place within the same healthcare facility through fully on-site AM operations, eliminating the need to transport parts between hospitals. In contrast, the analysis of Experimental Scenario 2 shows that hospitals are grouped into four clusters based on hospital type, in which some clusters incur both internal and external

logistics costs, while others do not. Specifically, Clusters 1 and 2 each contain a single hospital and therefore do not require transport routing, as services are provided on-site. Clusters 3 and 4, however, comprise 14 and 7 hospitals, respectively, for which external routing and scheduling are necessary.

Next, an economic feasibility analysis is conducted to investigate the total cost per unit. In this study, total cost is evaluated across three distinct categories tailored to the AM supply chain context: operational expenses, internal logistics expenses, and external logistics expenses, as presented in Table 6. In particular, operational cost refers to the approximate AM production expenses incurred at the AM hub facility, encompassing fixed costs associated with either industrial or desktop AM printers, annual equipment depreciation, and maintenance costs for each type of AM printer. In this study, straight-line depreciation and a 10% annual maintenance fee are applied as approximations. In addition, AM operational expenses include variable costs driven by production volume, namely raw material consumption and the labor required for AM printer operation and post-processing tasks [62]. These operational cost components are aggregated on a daily basis. Internal logistics cost refers to the lump-sum expenses associated with internal transportation, handling, and administration required to move in-house AM-produced parts within the hospital acting as the AM hub. In this study, the internal logistics expense is set at a fixed rate of 200 Baht per unit for workpiece handling [63]. Lastly, external cost consists of logistics expenses derived from a fixed cost component based on the number of vehicles utilized and a variable fuel cost component dependent on travel distance. These costs are calculated based on the distribution planning results for each network cluster obtained using the MOVRPTW model.

**Table 6.** Parameters for AM economic feasibility analysis.

|       | AM Cost Components                                                                                                                       | Approximation        |
|-------|------------------------------------------------------------------------------------------------------------------------------------------|----------------------|
| (1)   | AM operational expense                                                                                                                   |                      |
| (1.1) | AM operational expense (Fixed cost)                                                                                                      |                      |
|       | AM printer cost                                                                                                                          |                      |
|       | <ul style="list-style-type: none"> <li>An industrial AM printer</li> </ul>                                                               | 350,000 Baht         |
|       | <ul style="list-style-type: none"> <li>A desktop AM printer</li> </ul>                                                                   | 100,000 Baht         |
|       | <ul style="list-style-type: none"> <li>Depreciation per year (assume the straight-line method)</li> </ul>                                | 10% residual value   |
|       | <ul style="list-style-type: none"> <li>Maintenance cost per year</li> </ul>                                                              | 10 percent per annum |
|       | <ul style="list-style-type: none"> <li>Total fixed cost per year for industrial AM printer (assume working 260 days per year)</li> </ul> | 98,000 Baht          |
|       | <ul style="list-style-type: none"> <li>Total fixed cost per year for desktop AM printer (assume working 260 days per year)</li> </ul>    | 28,000 Baht          |
| (1.2) | AM operational expense (Variable cost)                                                                                                   |                      |
|       | <ul style="list-style-type: none"> <li>Material cost for industrial AM printer (assume 4 kgs per day)</li> </ul>                         | 4500 Baht per kg.    |
|       | <ul style="list-style-type: none"> <li>Material cost for desktop AM printer (assume 4 kgs per day)</li> </ul>                            | 1000 Baht per kg     |
| (1.3) | Labor cost per month (assume 28 days a month)                                                                                            |                      |
|       | <ul style="list-style-type: none"> <li>Labor cost for industrial AM printer</li> </ul>                                                   | 35,000 Baht          |
|       | <ul style="list-style-type: none"> <li>Labor cost for desktop AM printer</li> </ul>                                                      | 17,500 Baht          |
| (2)   | Internal logistics expense                                                                                                               | 200 Baht per unit    |
| (3)   | External logistics expense (fixed and variable cost)                                                                                     | Based on MOVRPTW     |

Next, a comparative analysis is conducted across all scenarios (i.e., the Base Scenario, Experimental Scenario 1, and Experimental Scenario 2) under an equal total daily workload,

as shown in Table 7. Initially, an industrial AM printer is assumed for all AM hubs to enable a comparative analysis of per-unit part costs across all scenarios. Internal AM part demand refers to AM production that serves the hospital acting as the AM hub, whereas external AM part demand is generated by hospitals within the corresponding cluster. These AM part demands vary across scenarios due to different internal–external production splits. The economic feasibility analysis reveals that the Base Scenario, which employs the K-means clustering approach, demonstrates the highest efficiency. This scenario minimizes operational costs to the lowest level, at 58,880 Baht, by reducing redundancy in fixed costs and improving resource utilization. Although it incurs the highest external logistics expense, totaling 7072 Baht and comprising fixed vehicle usage costs and variable fuel expenses based on travel distance, the AM part cost per unit remains the lowest and most cost-effective at 698.51 Baht. In contrast, Experimental Scenario 1, which assigns operational costs individually to all 23 hospitals, results in a substantial increase in operational expenses to 451,419 Baht. When combined with internal logistics expenses, the cost per unit rises to 4579.79 Baht. For Experimental Scenario 2, which clusters hospitals into four types, the operational cost is moderate at 78,507 Baht; when internal and external logistics expenses are included, the resulting cost per unit is 959.34 Baht.

**Table 7.** Economic feasibility analysis for AM cost per unit.

| Scenario                   |                        | Base Scenario | Experimental Scenario 1 | Experimental Scenario 2 |
|----------------------------|------------------------|---------------|-------------------------|-------------------------|
| AM operational expense     |                        | 58,880        | 451,419                 | 78,507                  |
| Number of workpieces       | Internal demand (unit) | 16            | 99                      | 52                      |
|                            | External demand (unit) | 83            | 0                       | 47                      |
| Internal logistics expense |                        | 3200          | 19,800                  | 10,400                  |
| External logistics expense | Fixed Cost             | 6000          | 0                       | 4800                    |
|                            | Variable Cost          | 1072          | 0                       | 1267                    |
| Total cost                 |                        | 69,153        | 471,219                 | 94,974                  |
| AM part cost per unit      |                        | 698.51        | 4759.79                 | 959.34                  |

Thus, it is evident that the K-means clustering–based configuration (Base Scenario) provides the most favorable balance between operational and logistics costs. These results underscore the economic advantages of economies of scale and shared resource utilization in AM hub-based structures (the Base Scenario and Experimental Scenario 2) compared with the fully decentralized configuration in Experimental Scenario 1. Although the latter reduces lead time and eliminates transportation requirements, it is associated with significantly higher operating costs per part.

#### 4.5. Sensitivity Analysis

Next, a sensitivity analysis is conducted to examine the impact of demand variation on the AM part cost per unit under the Base Scenario, in which industrial AM printers are deployed at each AM hub. Total demand, encompassing both internal and external requirements, is incrementally increased in 25% steps from the baseline up to a doubling of demand (+100%), as summarized in Table 8. The results clearly demonstrate the presence of strong economies of scale within the HAM supply chain. While AM operational expenses remain constant across all scenarios at 58,880 Baht, the total number of workpieces produced increases substantially, allowing fixed operational costs to be distributed over a larger production volume. As a result, the AM part cost per unit decreases markedly from 698.51 Baht in the base case to 356.86 Baht under the +100% demand scenario. Although higher demand levels lead to moderate increases in both internal and external logistics expenses—particularly due to increased transportation volumes and stepwise rises in fixed

external logistics costs—these cost increments are relatively small compared to the savings achieved through fixed-cost amortization. Overall, the findings underscore that demand consolidation is a critical driver of cost efficiency in decentralized AM hub configurations, reinforcing the economic rationale for aggregating production volumes to enhance the viability of HAM-based supply chains.

**Table 8.** Sensitivity analysis for demand data (Base Scenario).

| Scenario                   |                        | Base Scenario |        |        |        |        |
|----------------------------|------------------------|---------------|--------|--------|--------|--------|
|                            |                        | 0%            | +25%   | +50%   | +75%   | +100%  |
| AM operational expense     |                        | 58,880        | 58,880 | 58,880 | 58,880 | 58,880 |
| Number of workpieces       | Internal demand (unit) | 16            | 20     | 24     | 28     | 32     |
|                            | External demand (unit) | 83            | 107    | 130    | 150    | 169    |
| Internal logistics expense |                        | 3200          | 4000   | 4800   | 5600   | 6400   |
| External logistics expense | Fixed Cost             | 6000          | 6000   | 7200   | 7200   | 7200   |
|                            | Variable Cost          | 1072          | 1042   | 1080   | 1080   | 1058   |
| Total cost                 |                        | 69,153        | 69,922 | 71,960 | 72,760 | 73,538 |
| AM part cost per unit      |                        | 698.51        | 550.57 | 467.28 | 408.77 | 356.86 |

In addition, a sensitivity analysis of AM printer costs is conducted for Experimental Scenario 1, which assumes a fully decentralized AM configuration in which an AM printer is installed at every hospital, resulting in a total of 23 AM printers. Given the relatively small production volumes at each hospital, this analysis evaluates whether industrial-scale AM printers are economically justified or whether desktop-sized AM printers represent a more cost-effective alternative. The results presented in Table 9 reveal a pronounced cost disparity between industrial-scale and desktop-scale printers. When industrial AM printers are deployed, the total AM operational expense reaches 451,419 Baht, resulting in an exceptionally high AM part cost per unit of 4759.79 Baht. In contrast, replacing industrial printers with desktop-sized AM printers significantly reduces AM operational expenses to 108,851 Baht and lowers the unit part cost to 1299.51 Baht. This substantial reduction confirms that desktop AM printers may represent a more realistic and economically viable technological choice in low-volume production environments within decentralized AM networks.

**Table 9.** Sensitivity analysis for printer cost data (Experimental Scenario 1).

| Experimental Scenario 1    |                        | AM Printer      |              |
|----------------------------|------------------------|-----------------|--------------|
|                            |                        | Industrial-Size | Desktop Size |
| AM operational expense     |                        | 451,419         | 108,851      |
| Number of workpieces       | Internal demand (unit) | 99              | 99           |
|                            | External demand (unit) | 0               | 0            |
| Internal logistics expense |                        | 19,800          | 19,800       |
| External logistics expense | Fixed Cost             | 0               | 0            |
|                            | Variable Cost          | 0               | 0            |
| Total cost                 |                        | 471,219         | 128,651      |
| AM part cost per unit      |                        | 4759.79         | 1299.51      |

It is noted that, despite the substantial cost savings achieved through the use of desktop AM printers, the fully decentralized configuration remains economically inferior to the Base Scenario, which utilizes three AM hubs serving clustered hospitals and achieves an AM part cost per unit of 698.51 Baht. This cost advantage arises from stronger economies of scale and more efficient utilization of AM assets, even after accounting for additional internal and external logistics costs. Overall, the comparison underscores that while desktop AM printers are preferable to industrial printers in highly decentralized settings, full decentralization still fails to attain cost competitiveness relative to a clustered, hub-based

configuration. These findings reinforce the conclusion that strategic demand aggregation through AM hubs provides a more economically viable balance between decentralization and scale efficiency in HAM supply chains.

## 5. Managerial Insights

The analysis reveals critical decision-making criteria across multiple dimensions—specifically total cost, lead time, and environmental impact—highlighting the necessity of a multi-objective decision-making framework. This study adopts a sequential approach that first determines AM hub locations using spatial K-means clustering, followed by a distribution routing analysis based on the proposed MOVRPTW model within a healthcare network. This integrated framework enables the evaluation of economies of scale and unit cost efficiency through the strategic design of network structures, departure schedules, time windows, and shipment consolidation. The results indicate that an AM hub-based centralized network can significantly reduce operational costs compared to a fully decentralized approach in which production units are located at every hospital. Nevertheless, operational policies must remain aligned with service-specific requirements, such as urgent healthcare cases or the need for temperature-controlled transportation, both of which may favor production points in closer proximity to demand locations [64]. Consequently, policy recommendations depend fundamentally on the trade-offs between centralized and decentralized network designs. In this study, the decision to implement centralized AM hubs is primarily driven by the high capital intensity of AM printers, for which achieving economies of scale through high-volume production is essential for economic viability. The findings demonstrate that employing K-means clustering to establish regional hubs yields a superior network structure. This sub-centralized configuration effectively minimizes total supply chain costs by balancing the high utilization of costly AM assets with reduced transportation distances achieved through spatial optimization, ultimately outperforming both fully centralized and fully decentralized configurations in terms of overall logistics expenditure.

To investigate multi-objective solutions, this study initially assigns equal weights to all objectives using a weighted-average approach. However, in practical healthcare settings, delivery time is often the most critical criterion for patient outcomes [65]. Previous research [66] highlights these conflicting objectives, showing that localized AM healthcare supply chains can reduce delivery times by up to 50% compared with centralized configurations, albeit at a significantly higher cost per part. Consequently, it is essential to examine the trade-offs among these objectives, as optimal policy implementation depends on factors such as technology maturity, demand volume, and network distances. Building on these insights, this study emphasizes that although AM hub-based structures substantially reduce costs, the adoption of a multi-objective optimization framework is crucial for capturing the inherent complexities of the HAM supply chain. In addition, the Pareto-optimal frontier for multiple objectives can be further explored to help policymakers understand the strategic flexibility required to adapt to varying operational priorities and service delivery requirements. Finally, to fully realize the potential of AM technology within the public health system, comprehensive digital transformation is required. This includes the acquisition and integration of enabling technologies such as medical imaging, data transmission platforms, and clinical application systems. Achieving this transformation also necessitates focused workforce development to equip personnel with hybrid competencies in both medicine and digital engineering [67].

## 6. Conclusions and Directions for Future Research

This study proposes an integrated framework that combines spatial K-means clustering with a multi-objective vehicle routing problem with time windows (MOVRPTW) to design a network of HAM hubs in the healthcare supply chain, using Phra Nakhon Si Ayutthaya Province, Thailand, as a case study. The economic feasibility and scenario analyses confirm that AM hub-based configurations are more cost-effective than a fully decentralized structure in which production units are located at every hospital. In particular, the Base Scenario—where hub locations are determined using K-means clustering—yields the lowest total and per-unit costs, while Experimental Scenario 2 (AM hubs grouped by hospital type) emerges as a practical alternative that balances cost efficiency and operational feasibility. By efficiently addressing the multi-objective problem that simultaneously considers total cost, lead time, and emissions, the proposed framework supports the determination of appropriate hub locations, fleet sizes, and distribution plans that comply with time and resource constraints. Overall, the framework provides a structured and systematic basis for designing sustainable, cost-efficient, and responsive HAM networks.

Several avenues for future research can extend this work and further enhance the modeling of HAM supply chains. First, future studies could explicitly differentiate part urgency levels, as healthcare demands range from routine, non-critical items to highly time-sensitive components. Incorporating urgency-based constraints would improve model realism, albeit at the cost of increased complexity. Second, metaheuristic solution approaches could be explored to efficiently solve large-scale problem instances where exact optimization methods become computationally intractable. Third, future research may formulate an integrated location–routing model that simultaneously determines AM hub locations, printer deployment decisions, and distribution routes within a unified framework. Fourth, uncertainty inherent in healthcare supply chains could be addressed through stochastic programming or robust optimization techniques. Fifth, the geographic scope of the model could be expanded beyond intra-regional or provincial settings to investigate inter-provincial or national healthcare networks, enabling the analysis of cross-regional coordination for large-scale HAM deployment. Finally, future studies may explicitly model diverse AM technologies and heterogeneous production requirements. By capturing technology-specific capabilities and limitations, such extensions would allow the model to more accurately reflect real-world decision-making environments.

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