Quality Clustering for Reducing the Search Space for Mobile Stroke Unit Allocation

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Abstract: Mobile stroke units (MSUs), which are specialized ambulances equipped with a brain imaging device and staffed with trained healthcare personnel, have the potential to provide rapid on-site diagnosis and treatment for stroke patients. To maximize the efficiency of utilizing MSUs, it is crucial to strategically allocate these units. When solving the MSU allocation problem, the current methods search the whole search space when looking for the optimal solutions, which causes slow convergence. In the current paper, we propose the Quality Clustering for Reducing the Search Space (QCRSS) framework to reduce the search space by filtering out ambulance locations without negatively affecting the quality of the solution too much when solving the MSU allocation problem. By narrowing down the set of possible locations, the problem becomes more manageable, leading to faster convergence when solving the MSU problem. Extensive experiments under the multiple MSU settings show that the QCRSS is largely faster in convergence toward the optimal solution by reducing the search space by 5x, 11x, 26x, and 67x for two, three, four, and five MSUs, respectively. We illustrate the performance of the QCRSS through both qualitative and quantitative analyses.

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1 INTRODUCTION

A stroke is a severe neurological condition caused by disrupted blood flow inside the brain, caused by either a blockage (ischemic stroke) or a ruptured blood vessel (hemorrhagic stroke) (Patil et al., 2022). Without prompt medical intervention, a stroke can lead to permanent brain damage, disability, and death. The global burden of stroke is staggering; it is estimated that one in six people will experience a stroke during their lifetime, with an annual incidence of 15 million cases and 5.8 million deaths (World Stroke Organization, 2023). In Sweden alone, over $21,000$ individuals suffer strokes every year, with approximately $3,900$ cases occurring within the Southern Healthcare Region (SHR) (The Swedish Stroke Register, 2023), which is the focus area of the current study. The SHR encompasses both densely populated and rural areas, presenting a significant challenge for prehospital care.

Beyond the immediate medical impact, stroke also poses a significant long-term challenge, as it can lead to disability and financial strain not only for patients and their families but also for society (Luengo-Fernandez et al., 2020) (Majersik and Woo, 2020). Therefore, the timely treatment of stroke is crucial, as patients who receive treatment earlier have a significantly better chance of recovery compared to those who receive delayed care (Ashraf et al., 2023). However, providing immediate and effective stroke treatment remains a challenge due to logistical hurdles and difficulties in accurately diagnosing stroke in the field (Blacker and Hankey, 2014). Ischemic strokes, the most common type, require clot-dissolving medications (thrombolysis) or clot removal (thrombectomy) to restore the blood flow. Conversely, hemorrhagic strokes, caused by bleeding blood vessels, necessitate immediate blood pressure reduction to prevent further bleeding. Unfortunately, the initial symptoms of both stroke types are typically similar, making a quick and precise diagnosis essential to avoid administering the wrong treatment, which could be life-threatening.

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Mobile stroke units (MSUs) have emerged as a promising solution to expedite stroke treatment (Bowry and Grotta, 2017) (Navi et al., 2022). These specialized ambulances are equipped with CT scanners, allowing the ambulance personnel on site, together with stroke experts connected by telemedicine, to diagnose stroke type and initiate treatments like thrombolysis directly in the ambulance (Harris, 2021). In many cases, this enables to reduces the time to treatment, at least corresponding to the time needed to transport the patient to an acute hospital with stroke diagnosis facilities. While MSUs offer significant advantages, their high operational costs limit the number of units a region can typically deploy (Southerland and Brandler, 2017). Therefore, strategically positioning MSUs is crucial for maximizing the patient benefit within a specific geographic area (Amouzad Mahdiraji et al., 2021)(Nour et al., 2022). This leads to the MSU allocation problem, which is the optimization problem that aims to identify the optimal locations for a fixed number of MSUs at existing ambulance station locations within a geographic area covering the efficiency perspective. Efficiency refers to covering as many patients as possible to receive treatment in a shorter window of time.

To efficiently allocate the MSUs in a region, Amouzad Mahdiraji et al. (Mahdiraji et al., 2021) apply the exhaustive search. In another study, Amouzad Mahdiraji et al. (Amouzad Mahdiraji et al., 2023) propose a mathematical optimization model (Amouzad Mahdiraji et al., 2023) using mixed integer linear programming (MILP). However, both of these approaches face significant computational challenges for large geographic areas (Abid et al., 2023). In recent studies (Abid et al., 2023) (Abid et al., 2024), Abid et al. use genetic algorithms to solve the MSU allocation problem. Typically, the above-mentioned approaches use the whole search space when searching for the optimal solution. As a result, the convergence can be slow. We hypothesize that if we could reduce the search space by filtering out ambulance locations without significantly compromising the quality of the solution, we can speed up the optimization process by focusing on the smaller search space, thus obtaining faster convergence. Therefore, the question naturally arises: How can we reduce the search space effectively when solving the MSU allocation problem?

In the current paper, we propose the Quality Clustering for Reducing the Search Space (QCRSS) method to solve the MSU allocation problem. It is a preprocessing framework for search algorithms that explicitly exploits the spatial distribution of ambulance locations to narrow down the search space. The ultimate aim is to enable the search algorithm to traverse a smaller search space instead of the whole search space. In the QCRSS framework, we first perform a preprocessing step using clustering to group the ambulance locations (or stations). Thereafter, we select only one representative from each cluster. The problem is then solved using the selected set of representatives. The core idea behind the clustering is that geographically close ambulance stations are likely to have similar response times to emergency calls.

The paper's key contributions are summarized as follows:

1. An optimization framework, the Quality Clustering for Reducing the Search Space (QCRSS), which consists of a preprocessing step and a problem-solving step to solve the MSU allocation problem. The primary contribution of the proposed method lies in the preprocessing step.
2. An application to a real-world case study of the Southern Healthcare Region (SHR), Sweden. This region is a combination of densely populated and more rural areas, which is the biggest challenge of pre-hospital care.
3. An illustration through visualization of how the QCRSS framework can significantly improve the convergence speed across different MSUs scenarios. We further validate the effectiveness of our model through a comprehensive quantitative and qualitative analysis.

The rest of this paper is structured as follows: Section 2 presents an overview of related work. Section 3 provides the formal definition of the MSU optimization problem. Section 4 describes the proposed methodology, and Section 5 encompasses the computational study. Finally, Sections 6 and 7 conclude the paper by summarizing the conclusions and proposing future areas for research.

2 RELATED WORK

In the field of emergency medical services, researchers have explored various models for optimal MSUs allocation. Recently, Amouzad Mahdiraji et al. (Mahdiraji et al., 2021) use exhaustive search (ES) to solve the MSU allocation problem for one to three MSUs across 39 potential locations to minimize the travel time to treatment, covering both the efficiency and equity perspectives for prehospital stroke care in the SHR. The ES systematically explores all potential combinations of MSU locations to determine whether each combination meets the problem's criteria and assesses its quality using an objective function.

However, as the number of possible combinations of MSU locations increases, with an increasing number of MSUs, the ES method results in an exponentially increasing search space. Consequently, the computational time required for ES often becomes impractically high.

Another study (Amouzad Mahdiraji et al., 2023) propose a mathematical optimization model for the MSU allocation problem, aiming to determine the optimal placement of MSUs within a given geographic region. The model was applied to the SHR in Sweden. The optimization model is a mixed integer linear programming model. Despite the model's potential, it became apparent when using the Gurobi solver (Gurobi Optimization, LLC, 2024) that the model's complexity limited its application to just two counties in the SHR. In a related study (Abid et al., 2023), Abid et al. propose a time-efficient genetic algorithm to solve the MSU allocation problem. This model demonstrates high efficiency and increased scalability, covering a broader range of regions. However, the random initial population selection causes the traditional GA to converge slowly, necessitating a significantly higher amount of generations to evolve the randomly selected starting solutions into improved ones. The random selection might choose ambulance locations that are close to each other, leading to poor coverage and a lack of diversity in the solution space. Hence, the traditional GA may struggle to explore other, potentially better regions. To overcome this limitation, Abid et al. (Abid et al., 2024) introduce a cluster-based GA model to improve performance. This method uses clustering to strategically select the initial population by including MSUs in geographically distant areas to provide a broader spread and better coverage from the beginning.

The aforementioned methods consider the whole search space (every possible ambulance location) when solving the MSU allocation problem. The search space may contain many ambulance location solutions with similar performance. This can slow down the algorithm's ability to converge to the best solution, as it might spend time exploring these redundant options or suboptimal solutions. This limitation can hinder the overall performance, leading to the inefficient use of computational resources. Therefore, an efficient method is required to solve the MSU allocation problem — one that addresses the limitation of the current methods by ensuring a focus on only the most promising regions of the search space. By narrowing down the search space to the most relevant ambulance station locations, we can reduce the search space by filtering out ambulance station locations without having a significantly negative effect on the quality of the solution when solving the MSU allocation problem, thereby improving the convergence speed.

3 MSU ALLOCATION OPTIMIZATION PROBLEM

In the current section, we present a mathematical model for the MSU allocation problem, which aims to identify the optimal locations of a fixed number of MSUs at existing ambulance stations within a geographic area.

Let I represent the set of existing ambulance stations in the considered region and N the total number of MSUs to allocate. Each ambulance station is assumed always to have at least one regular ambulance available. The geographic region R is subdivided into smaller areas r, where all patients located within subregion $r \in R$ is assumed to be located at the centroid of r.

Let t_{ir}^{RA} be the expected time to treatment for a patient in subregion r when served by a regular ambulance located in $i \in I$, and let t_{ir}^{MSU} be the expected time to treatment if the patients are served by an MSU stationed at i. The expected time to treatment for a patient in subregion $r \in R$ when served by a regular ambulance is given by $t_r^{RA} = \min_{i \in I}\{t_{ir}^{RA}\}$. The values of t_r^{RA} ($r \in R$) and t_{ir}^{MSU} ($r \in R$, $i \in I$) can be precomputed and are parameters in the optimization model.

We let Q_r ($r \in R$) denote the share of the stroke cases in R that is expected to take place in subregion r. The decision variables $x_i \in \{0,1\}$ ($i \in I$) are defined as follows:

$$x_i = \begin{cases} 1 & \text{if an MSU is placed at location } i \\ 0 & \text{otherwise.} \end{cases}$$

Using the decision variables x_i, the minimum expected time to treatment for a patient in subregion r when served by an MSU can be calculated as follows:

$$t_r^{MSU} = \min_{i \in I}\{t_{ir}^{MSU} + (1 - x_i) \cdot M\}, \qquad (1)$$

where M is a sufficiently large constant, such as the maximum expected time to treatment for any subregion r from any ambulance station i. This equation ensures that stations without an MSU are assigned such a long time to treatment that they will be excluded from consideration.

The objective function is the weighted average time to treatment across all subregions $r \in R$, which is formulated as follows:

$$\min z = \sum_{r \in R} Q_r \cdot \min\{t_r^{RA}, t_r^{MSU}\}, \qquad (2)$$

where the decision variables ($x_i, i \in I$) are implicitly included in the calculation of t_r^{MSU} (see Eq. 1). The MSU allocation, represented by the x_i values, is constrained by

$$\sum_{i \in I} x_i = N, \tag{3}$$

which ensures that exactly N MSUs are allocated within the region.

4 QUALITY CLUSTERING FOR REDUCING THE SEARCH SPACE

The MSU allocation problem is a complex problem due to the need to search through a large combinatorial space of possible placements. In the current paper, we propose the Quality Clustering for Reducing the Search Space (QCRSS) method for solving the MSU allocation problem. QCRSS is a preprocessing framework for searching algorithms that explicitly exploit the spatial distribution of ambulance locations to narrow down the search space, particularly by incorporating a more global perspective and dynamically adjusting clusters to reflect the true geographical spread of ambulance stations. The ultimate aim is to enable the search algorithm to consider a smaller search space instead of the whole search space. The QCRSS framework includes three key steps: (1) preprocessing using clustering, (2) selecting representatives for each cluster, and (3) solving the MSU allocation problem using the chosen representatives. In this step, any suitable solution-finding method can be applied.

4.1 Preprocessing Using Clustering

In the preprocessing step, we filter out locations that are very close to other locations. The core idea behind the clustering approach is that geographically close ambulance stations are likely to have similar response times to emergency calls within their vicinity. By grouping these stations through clustering, we focus on evaluating a smaller set of representative locations by considering only one representative from each cluster. In the preprocessing step, we explore two clustering mechanisms: (1) K-medoid clustering and (2) Agglomerative hierarchical clustering (AHC).

4.1.1 K-medoid Clustering

We use the K-medoids clustering method on a set of ambulance station locations I, where each location $i \in I$ has specific coordinates (x_i, y_i). The objective of K-medoids clustering is to partition I into K clusters, where each cluster is represented by a central point called a "medoid," selected from actual ambulance station locations. Let M denote the set of these medoids, where $M \subseteq I$. The medoids minimize the total dissimilarity (sum of distances) between the ambulance stations and their respective medoid locations. See below for details about how to select the value of K.

The K-medoids clustering approach achieves minimal dissimilarity through two main iterative steps:

1. Assignment Step: Each ambulance location i is assigned to the nearest medoid m_j, effectively minimizing the distance between each location and its assigned medoid:

$$\mathcal{C}_j = \left\{ i \in I \mid j = \arg\min_{m_j \in M} d(i, m_j) \right\}, \tag{4}$$

   where $\mathcal{C}_j$ denotes the set of locations in cluster j, m_j is the medoid of cluster $\mathcal{C}_j$, and $d(i, m_j)$ is the dissimilarity measure (distance) between location i and medoid m_j.

2. Update Step: Each medoid m_j is updated to be the location within $\mathcal{C}_j$ that minimizes the sum of distances to all other locations in the cluster:

$$m_j = \arg\min_{p \in \mathcal{C}_j} \sum_{q \in \mathcal{C}_j} d(p, q), \tag{5}$$

   where p represents a candidate medoid, and q ranges over all locations in cluster $\mathcal{C}_j$. This step ensures that each medoid is the location that reduces intra-cluster dissimilarity.

These two steps are repeated until the cluster assignments and medoid locations stabilize, indicating convergence. At convergence, the minimum total dissimilarity across all clusters can be expressed as:

$$\min \sum_{j=1}^{K} \sum_{i \in \mathcal{C}_j} d(i, m_j), \tag{6}$$

which represents the total sum of distances from each location i to its medoid m_j across all clusters.

Thereafter, we employ a random selection strategy from the clusters formed by the K-medoids. Specifically, for each cluster C_j, we randomly select one location $i \in C_j$ as a representative.

4.1.2 Agglomerative Hierarchical Clustering

Consider the set of ambulance locations $I = \{i_1, i_2, \ldots, i_{|I|}\}$, where each location $i \in I$ has coordinates (x_i, y_i), which represent the geographical coordinates (latitude and longitude) of ambulance station i.

Initially, each ambulance station location is treated as its own cluster, resulting in $k = |I|$ clusters (one for each station). We then compute the Euclidean distance $d(i, j)$ between every pair of ambulance locations,

$$d(i, j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}, \quad (7)$$

to compute the geographical proximity between them.

The next step is to iteratively merge the closest clusters (ambulance stations) using Ward's linkage criterion (Developers, 2024), which minimizes the increase in the sum of squared deviations within clusters (i.e., variance). The centroid of each cluster C_j is defined as:

$$\mu_j = \frac{1}{|C_j|} \sum_{x \in C_j} x, \quad (8)$$

where $|C_j|$ is the size of cluster C_j, and μ_j is its centroid.

The increase in the sum of squared deviations within clusters when merging two clusters C_i and C_j is given by:

$$\Delta E(C_i, C_j) = \frac{|C_i||C_j|}{|C_i| + |C_j|} \cdot d(\mu_i, \mu_j)^2, \quad (9)$$

where $d(\mu_i, \mu_j)$ is the Euclidean distance between the two centroids μ_i and μ_j. Upon merging clusters C_i and C_j, the new centroid μ' of the merged cluster $C' = C_i \cup C_j$ is computed as:

$$\mu' = \frac{|C_i|\mu_i + |C_j|\mu_j}{|C_i| + |C_j|}. \quad (10)$$

The process iterates until the desired number of clusters k is reached, where $k \leq |I|$. This step refers to the *Chosen Representatives* in Step 3 of the proposed method, as discussed in Section 4.3, where the optimal number of clusters is identified. This ideal number is based on the consistency of the solutions in achieving the optimal solutions for different MSU settings.

4.2 Selection of Representative Ambulance Station

Once the clusters are formed, the next step is to select a representative ambulance station from each cluster C_j. Given that the ambulance stations within a cluster are already geographically close to each other, we hypothesize that it is possible to choose any one of them as representative of the cluster. The most logical and efficient way is to pick one randomly to serve as a representative location for the cluster, eliminating the need for further calculations or sorting. Formally, the representative ambulance station m_j is defined as,

$$m_j = x_{j,r} \in C_j, \quad (11)$$

where $x_{j,r}$ is a randomly selected ambulance station from the cluster C_j.

Our proposed method preserves the key spatial properties of the cluster and reduces the search space for the MSU allocation problem, reducing the number of candidate stations from $|I|$ to k as we now focus on the representative ambulance locations $\{m_1, m_2, \ldots, m_k\}$ as candidate locations for MSU placement.

4.3 Solving the MSU Problem Using the Chosen Representatives

We determine the ideal number of clusters by constructing and evaluating different numbers of clusters and selecting a number that leads to the best solution. We evaluate different numbers of clusters (e.g., 3, 4, 5, etc.) and observe the performance (minimum weighted time to treatment) and consistency in achieving the targeted object values (optimal time to treatment) for different numbers of MSUs. Accordingly, we chose the number of clusters that we consider will yield the best results. To determine suitable ambulance station locations, we focus only on the reduced search space determined by the chosen number of clusters. This reduced search space is then passed to the objective function (i.e., Eq. 2) as outlined in Section 3. From this reduced search space, we choose the solution that gives the minimum weighted time to treatment as the acceptable solution to place the MSUs.

5 COMPUTATIONAL STUDY

5.1 Scenario Description

To assess the efficiency of the QCRSS framework in solving the MSUs allocation problem, we applied the method to the Sweden's Southern Healthcare Region (SHR). The goal was to efficiently find suitable locations to place N MSUs, ranging from two to five, in order to maximize coverage while minimizing the time to treatment. The SHR is a combination of densely populated and more rural areas, which is the biggest challenge of pre-hospital care. The SHR encompasses four counties, comprising 49 municipalities. The region has a population of around 1.9 million and covers an area of $24,000$ square kilometers.

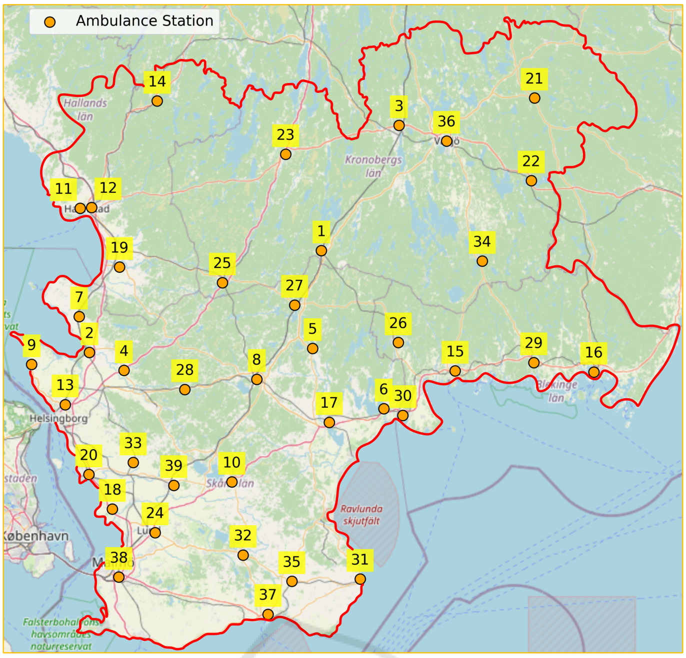


Figure 1: An overview of the SHR, Sweden, where the ambulance locations are indicated by orange dots with a corresponding ambulance location ID.

The SHR has 13 acute hospitals and 39 ambulance sites. An overview of the SHR is provided in Figure 1.

5.2 A Comparison Between the K-medoid and Hierarchical Clustering

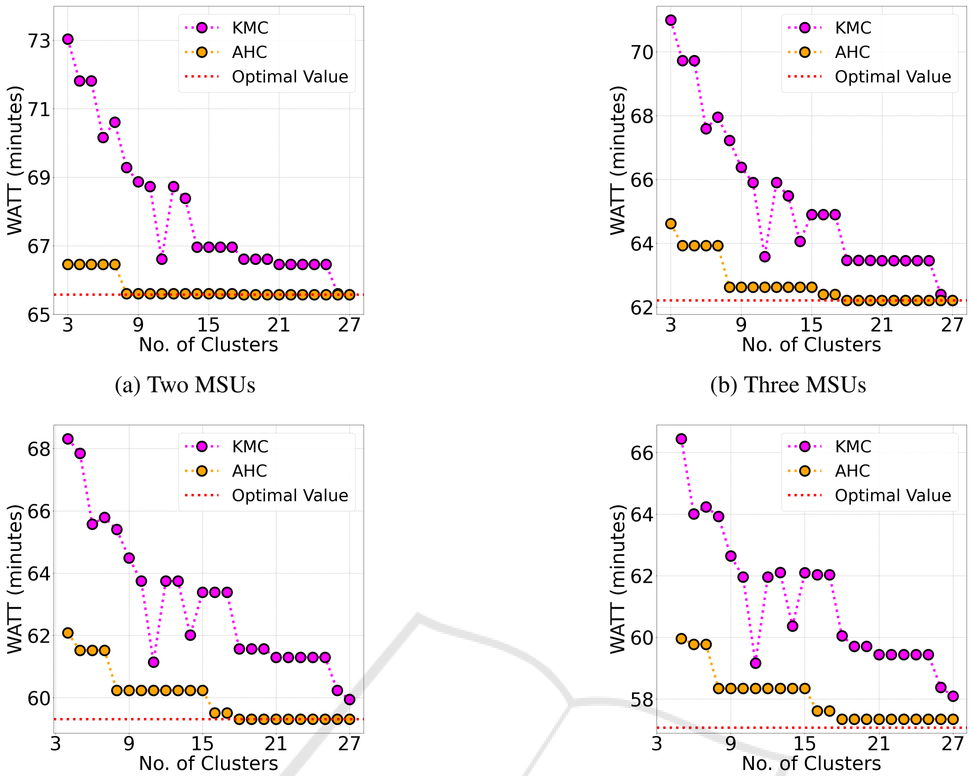
To examine the effectiveness of the two considered clustering methods for MSU placement using the QCRSS framework, we conducted a comparative analysis between the K-medoid clustering (KMC) and the agglomerative hierarchical clustering (AHC) in terms of weighted time to treatment (i.e., WATT). The WATT is calculated using the objective function from Section 3, Eq. 2. We evaluated various numbers of clusters ranging from 3 to 27 for two, three, four, and five MSUs to highlight the impact of solution quality on the performance convergence of the KMC and the AHC. The comparison of cluster quality, number of clusters, and convergence to the optimal solution is depicted in Figure 2.

5.2.1 Quantitative Results

The results in Figure 2 clearly demonstrate the superiority of the AHC clustering for different numbers of MSU (i.e., two, three, four, and five) in terms of both cluster quality and faster convergence. For instance, as shown in Figure 2a, for two MSUs, the AHC reached the target value with a number of clusters of only 18, making it 1.4x more efficient than K-medoid clustering, which required 26 clusters to achieve the same result.

The results clearly show that for all MSUs settings, when the number of clusters is small, the KMC gives sub-optimal solutions. This trend is evident in Figure 2, where there is a large difference between the obtained WATT and the optimal WATT. This indicates that the KMC is affected by underfitting, which occurs when the method fails to capture the underlying patterns in the data, leading to poor performance. In contrast, the AHC achieves significantly better results for a smaller number of clusters, as demonstrated by the much smaller difference between the obtained WATT and the optimal WATT.

The results indicate that when we increase the number of clusters, the solutions improve relatively in terms of WATT but with noticeable fluctuations for the KMC. This pattern is seen for all of the MSU settings. For example, for two MSUs, the KMC is a relatively better solution for six clusters, but the performance worsens as the number of clusters increases to seven. A similar trend is observed with an improved solution at 11 clusters, followed by a decline as the number of clusters increases to 12, which continues to worsen through the number of clusters from 13 to 17. Interestingly, for 18 clusters, the KMC achieves the same solution as it did for 11 clusters. On the other



(a) Two MSUs

(b) Three MSUs

(c) Four MSUs

(d) Five MSUs

Figure 2: Evaluation of different numbers of clusters for the considered MSUs settings to assess their quality in terms of weighted time to treatment (WATT).

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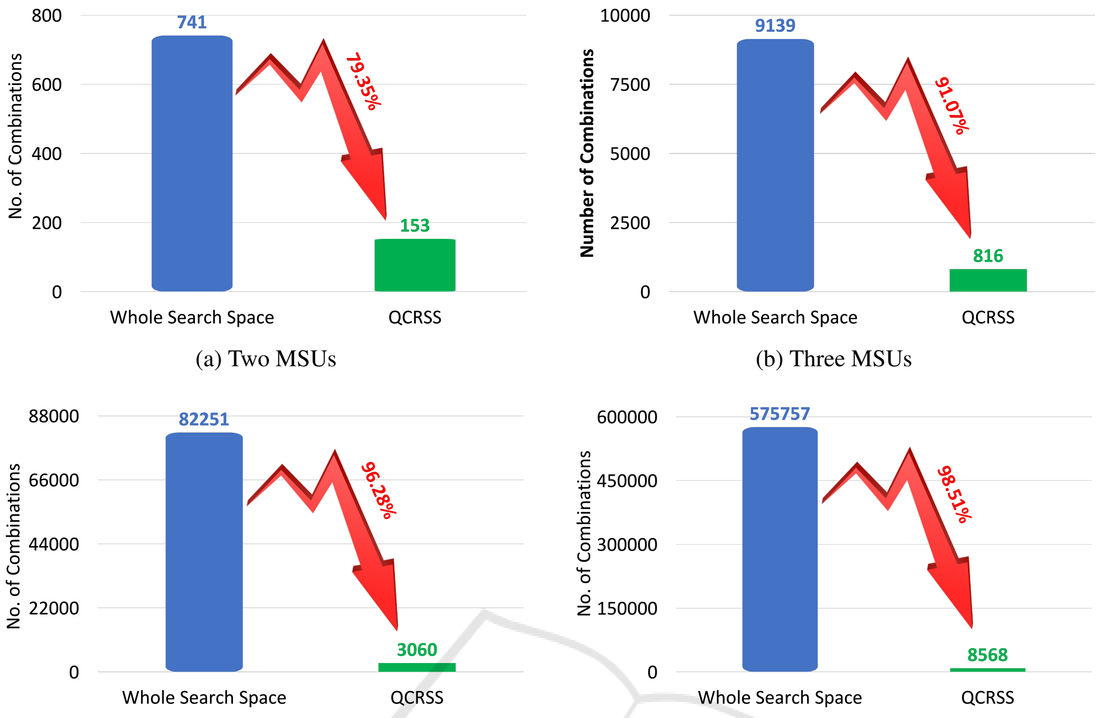
hand, the AHC appears to be more reliable and consistent, with the AHC maintaining stable performance for different numbers of clusters and delivering significantly better solutions.

An important observation can be seen from the results presented in Figure 2 when evaluating the allocation of MSUs for the considered region (SHR, Sweden). The KMC achieved optimal value for two MSUs, with a relatively high number of clusters, that is, 28. The performance of the KMC worsens as we increase the number of MSUs as it fails to achieve optimal or acceptable solutions for three to five MSUs. In other words, it appears that the KMC is not producing quality clusters. However, inconsistency and suboptimal clustering could significantly negatively affect the quality of the solution when solving the MSU allocation problem.

On the other hand, the AHC is showing better performance. It is evident that 18 clusters consistently yield the best solutions for two, three, and four MSUs. Even in the case of five MSUs, 18 clusters lead to a highly acceptable solution. Given this consistent performance across different MSU settings, we can confidently select 18 clusters as the most effective number of clusters, allowing to filter out of ambulance locations while maintaining a satisfactory quality solution for the MSU allocation problem within the SHR geographic region of Sweden.

From this observation, we conclude that utilizing 18 clusters within the QCRSS framework allows for a significant reduction in the search space while maintaining a high level of quality (see Figure 2). By employing 18 clusters, the search space for two MSUs is reduced from 741 to 153 combinations (79.35% of the whole search space), a 5x reduction. Similarly, for three MSUs, the search space is reduced from $9,139$ to 816 combinations (91.07% of the whole search space), an over 11x reduction. For four MSUs, the search space reduces from $82,251$ to $3,060$ combinations (96.28% of the whole search space), representing a more than 26x reduction, and for five MSUs, the search space is reduced from $575,757$ to just $8,568$ combinations (98.51% of the whole search space), a more than 67x reduction. This substantial decrease in the search space becomes increasingly significant as the number of MSUs and potential ambulance station locations grows. In particular, in scenarios involving five MSUs, where the original search space consists



(a) Two MSUs (b) Three MSUs

(c) Four MSUs (d) Five MSUs

Figure 3: Comparison of the complete and reduced search spaces for multiple MSU settings. The impact of search space reduction, achieved by selecting 18 ideal representatives using the QCRSS framework, is illustrated in terms of its effect on the overall search space.

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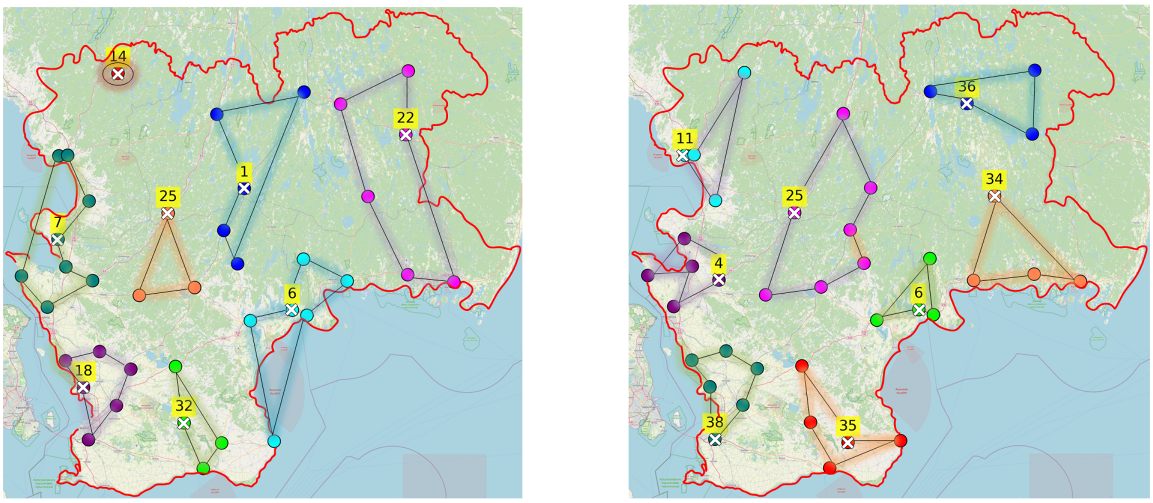
of over half a million possible combinations, the AHC reduces this number to a far more practical subset of $8,568$ combinations.

5.2.2 Qualitative Results

In light of the quantitative results (see Figure 2), we argue that AHC can be more effective than KMC when solving the MSU allocation problem. In this section, we present a qualitative analysis to explain how the AHC and KMC-selected ambulance representative locations can contribute to creating quality clusters. We visually present the geographical locations of SHR in Figure 4, showcasing 39 potential ambulance locations along with their corresponding IDs. Figure 4a and Figure 4b show one of the possible results of the use of clustering in the AHC and KMC, respectively (in this example, the number of clusters is set to eight).

In the KMC output, shown in Figure 4a, the groupings are less intuitive, with some clusters containing ambulances spread across relatively large geographical areas, leading to a suboptimal representative medoid (ambulance station location) selection. For example, the clustered data points in teal color span ambulances across varied coordinates to reduce their cohesiveness. This can lead to higher objective values, as poor medoid choices result in increased travel distances and longer times to treatment. The random initial selection of medoids further exacerbates this issue, as poorly chosen medoids often fail to represent the true central points of clusters adequately. Consequently, the KMC's rigidity in fixing medoids early in the process can lead to suboptimal and relatively less adaptive clusters.

In contrast, the AHC performs better in forming geographically coherent clusters (see Figure 4b), with clusters like clustered data points in purple color and clustered data points in magenta clearly grouping ambulances that are closer together. This creates more balanced and compact clusters, ensuring that the chosen representative locations more accurately reflect the central geography of each group. The AHC's flexibility in progressively merging clusters based on geographical closeness allows it to adaptively represent the spatial distribution of ambulances, making it more effective for minimizing time to treatment. By not including a random initialization step, the AHC provides more stable and interpretable clustering outcomes than the KMC, particularly when the objective is to optimize travel distances in real-world ambulance allocation problems.



(a) KMC Clustering (b) AHC Clustering

Figure 4: An example of creating ten clusters with their corresponding selected ambulance station's representative (yellow label) using the QCRSS framework on the SHR, Sweden map.

6 CONCLUSIONS

In the current paper, we propose the Quality Clustering for Reducing the Search Space (QCRSS) method for solving the MSU allocation problem. QCRSS is a preprocessing framework for searching algorithms that explicitly exploit the spatial distribution of ambulance locations to narrow down the search space. The ultimate aim is to enable the search algorithm to traverse a smaller search space instead of the whole search space. The QCRSS contains three steps: (1) preprocessing using clustering, (2) selecting representatives for each cluster, and (3) solving the problems using the chosen representatives. The proposed QCRSS framework filtered out ambulance locations without negatively affecting the quality of the solution too much, as it appears that the difference is minor for the considered scenario. The proposed framework appears to be both reliable and efficient for solving the MSU allocation problem within the SHR geographic region of Sweden. The proposed QCRSS exhibited significantly faster convergence for all considered MSUs settings. We believe that our method has the potential to contribute to significant improvements in the healthcare domain, particularly by opening new avenues for further research on optimal MSU placement and related healthcare logistics challenges.

7 FUTURE WORK

In this study, we considered the efficiency perspective when solving the MSU allocation problem. Efficiency refers to covering as many patients as possible to receive treatment in a shorter window of time. In the future, we plan to extend our proposed method to consider both efficiency and equity. Equity refers to contributing to equal care for all patients, regardless of where they live. In addition, we plan to consider a trade-off between these two perspectives. Additionally, we plan to investigate our proposed method's performance in wider geographic regions and scopes to obtain more comprehensive insights to improve future stroke care by providing more efficient prehospital treatment.

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