Journal of Administrative and Economic Sciences • Vol 18, Issue 2 (2025) • p 619-642

A Novel Approach for Dynamic Ambulance Routing: Integrating K-Means++ Clustering with Time-Variant Multi-Objective SPEA2

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Abstract:

This study introduces a novel two-phase approach to tackle the Dynamic Ambu-lance Routing Problem (DARP), a significant issue in emergency services where numerous injured individuals across various areas require immediate medical care. The challenge is intensified by the limited number of ambulances and the fluctuating nature of demand for services. To address this, we propose a hybrid method that combines K-Means++ clustering with a Time-Variant Multi-Objective SPEA2 algorithm. This model classifies patients into two categories: Hard Emergency Injury (HEI) and Soft Emergency Injury (SEI), taking into account the emergence of new demands during ambulance operations.The pro-posed framework frames DARP as a multi-objective optimization issue, focusing on minimizing overall travel distance and patient ride time. In the initial phase, K-Means++ clustering organizes injury locations into spatially coherent groups, enhancing fleet management efficiency. The second phase applies a Time-Variant Multi-Objective SPEA2 algorithm to optimize ambulance routes within these clusters. We evaluate the performance of our approach against leading methods such as NSGA-II, NSGA-III, and traditional SPEA2, using key metrics for Pareto front assessment, including Hypervolume, Spacing, and the R2 Indicator. The findings indicate that our approach effectively balances multiple objectives and significantly enhances ambulance response efficiency.Our proposed K-Means++-TVSPEA2 algorithm demonstrates superior performance in ambulance routing optimization, achieving an average traveled distance reduction of 49.3% compared to K-Means-SA-TS, 8.6% compared to PA-PSO, and 12.2% compared to GA. Additionally, it improves ride time by 9.1% over K-Means-SA-TS and 12.7% over PA-PSO. These results highlight the efficiency of our approach in optimizing emergency response routing.

Keywords: Dynamic Ambulance Routing Problem, Health Care, TVSPEA2, kmeans++, NSGA-III, NSGA-II, SPEA2, Bi-objective Optimization.

1. Introduction

Catastrophic events have surged significantly over the last twenty years [1]. Notable examples include the devastating tsunami in Indonesia on Boxing Day (2004), the earthquake in Haiti (2011), and the earthquake in Nepal (2015). The Sendai Frame-work for Disaster Risk Reduction 2015-2030 outlines four key areas for action: understanding disaster risks, enhancing disaster governance, promoting risk reduction, and improving disaster preparedness. These priorities necessitate improved emergency response systems and policies that bolster the public sector's capacity to respond effectively [2].

Given the frequent lack of sufficient funding and staffing in emergency manage-ment divisions [3], investments needed to support Ambulance Routing Problem (ARP) units are often overlooked. Consequently, while ARP resources are limited, there is an abundance of qualified personnel and a high demand for companies engaged in disas-ter relief services. This situation underscores the urgent need for effective management of existing ARP resources.

Disaster can be defined as a catastrophic event that results in significant property loss, destruction of ecosystems, loss of life, and widespread suffering, necessitating a response from resources beyond the usual framework [4]. This encompasses natural disasters such as earthquakes, hurricanes, tornadoes, fires, floods, blizzards, droughts, and terrorism, all of which can lead to extensive destruction of human life and property. Literature on the response phase indicates that large-scale disasters disproportion-ately impact communities, highlighting that the effectiveness of response efforts can significantly mitigate the occurrence of such tragic events [5].

This paper addresses the Ambulance Routing Problem (ARP), aiming to create an effective routing scheme that minimizes response times, late arrivals, and inefficiencies following disasters. We propose a mathematical model that optimally clusters injuries and determines their routes. Our approach considers different types of ambulances with varying capacities and classifies incoming requests into two categories based on patient severity. The model distinctly identifies the start and end times for each ser-vice within a specific service window to provide the most effective routing solution. To manage task variability and expected delays, we implement soft time windows (STW) and impose penalties for service delays, addressing a static ARP (SARP) as our initial contribution, followed by a focus on Dynamic ARP (DARP) in the second phase. Both problems are analyzed within the framework of multi-objective optimiza-tion, targeting the minimization of both travel distance and time. We utilize the Time-Variant SPEA algorithm for routing and K-Means++ for clustering, facilitating efficient patient grouping for enhanced management.

Highlights

- Two-Phase Approach for DARP: This paper introduces a novel hybrid approach integrating K-Means++ clustering and a Time-Variant Multi-Objective SPEA2 algorithm to address the Dynamic Ambulance Routing Problem (DARP). The first phase groups injuries into geographic clusters using K-Means++, while the second phase optimizes ambulance dispatch using the enhanced evolutionary algorithm.

- Multi-Objective Mathematical Model: The study presents a comprehensive mathematical model for DARP, formulated as a multi-objective optimization prob-lem. The objectives are to minimize the total travel distance of ambulances and the total response time for patients. The model also considers the dynamic nature of demand, distinguishing between Hard Emergency Injury (HEI) and Soft Emergency Injury (SEI) cases.

- Performance Comparison with State-of-the-Art Methods: The proposed K-Means++-SPEA2 approach is benchmarked against prominent multi-objective optimization algorithms, including NSGA-II, NSGA-III, and the traditional SPEA2. Evaluation metrics such as Hypervolume, Spacing, and the R2 Indicator are used to compare the Pareto front solutions.

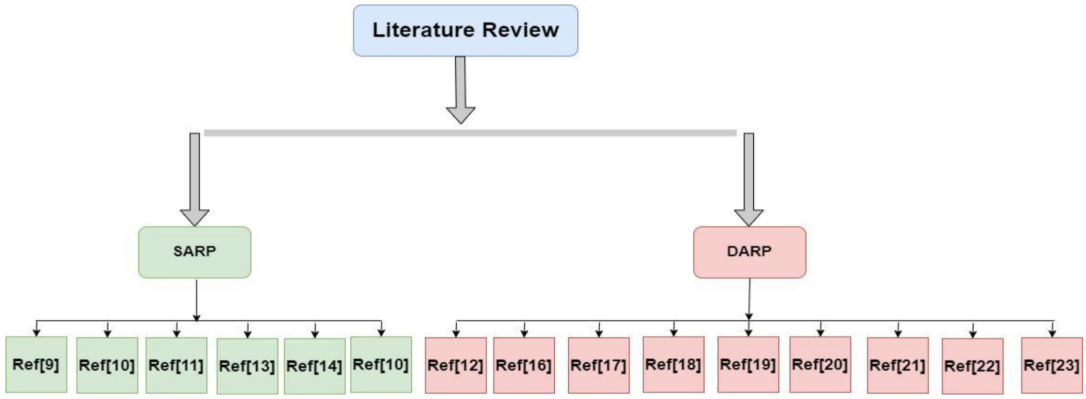
- Extension and Benchmarking: The paper extends the Augerat (1995) bench-mark dataset to model disaster response scenarios specific to DARP. It also explores future research opportunities, including the strategic placement and potential relo-cation of rest points to improve disaster preparedness and mitigate the impact of transportation network disruptions.

- The following sections outline the structure of the paper. Section 2 provides a review of recent and relevant literature. Section 3 defines the problem, intro-duces the mathematical formulation, and explains the key notations. Section 4 details the principles of K-Means++ clustering and the Time-Variant Multi-Objective SPEA2 algorithm. Section 5 presents numerical experiments to validate the proposed approach, while Section 6 concludes the paper with a discussion of findings and future research directions.

2. Literature Review

This study aims to achieve two primary objectives: first, to analyze the dynamic characteristics of the Ambulance Routing Problem (ARP), and second, to propose a meta-heuristic framework capable of addressing both static and dynamic variations of the problem. To provide an overview, this section begins by highlighting contemporary methods for solving the static formulation of ARP, followed by a discussion of research related to the dynamic version. Additionally, a concise review of existing multi-objective optimization strategies for problems analogous to ARP is presented.

Although a substantial body of literature exists on routing and scheduling challenges in disaster response operations—such as assessment services, network restoration, search and rescue efforts, evacuations, and medical assistance, as discussed in [6–8]—this study focuses on research directly relevant to the topic at hand. Past studies in disaster management have



explored various aspects, including transportation reliability, survival probabilities, and victim prioritization during disasters. However, the current research systematically categorizes existing studies and identifies specific gaps within this domain. Figure 1 illustrates a classification of the reviewed literature, highlighting studies on the Static Ambulance Routing Problem (SARP) and the Dynamic Ambulance Routing Problem (DARP).

Fig. 1 Literature Review Classification.

2.1 The Static Ambulance Routing Problem: SARP

The study presented in [9] makes a significant contribution to the literature by introducing a hybrid SA-TS algorithm, which combines Simulated Annealing (SA) and Tabu Search (TS) to address the Ambulance Routing Problem (ARP). This research proposes a theoretical framework based on a mathematically formulated Vehicle Routing Problem (VRP), specifically designed to optimize emergency ambulance routes in disaster scenarios and multi-casualty incidents. The methodology involves applying the k-Means algorithm for clustering based on distance metrics, followed by the hybridization of the SA-TS approach for route optimization. Experimental results demonstrate that the proposed method produces solutions of comparable quality to state-of-the-art techniques, including Particle Swarm Optimization (PSO) and Genetic Algorithm (GA).

This work builds upon the research conducted by Tlili et al. [10], which focuses on efficiently scheduling and routing emergency medical service (EMS) ambulances during the COVID-19 pandemic. In that study, the authors propose a Multi-Origin-Destination Team Orienteering Problem (MODTOP) model that incorporates patient triage scores while adhering to duration and capacity constraints. To solve this NP-hard problem, they employ two innovative algorithms: the Hybrid Genetic Algorithm (HGA) and the Memetic Algorithm (MA). Experimental findings indicate that these algorithms are highly effective, with MA outperforming other methods and providing optimal or near-optimal solutions for real-world scenarios, including case studies conducted in Tunis.

The authors of [11] contribute to the ambulance routing (AR) problem by modeling it within the context of disaster relief, emphasizing the importance of equity and fairness in delivering services to a large number of critical patients. They also address the complexities involved in identifying the most efficient routes. To mitigate these challenges, the researchers introduce a modified version of the team orienteering problem that incorporates Brandes' approach along with an additional hierarchical objective function aimed at minimizing inefficiencies. Their proposed methodology integrates a machine learning component with an iterative neighborhood search algorithm for enhanced efficiency. The accuracy of this algorithm is rigorously tested against realistic benchmark instances, with quantitative analyses demonstrating its effectiveness in improving solution times as complexity increases. Additionally, they conduct a comparative analysis between the results of the fair solution and the system optimum solution.

Farnaz et al. [12] make a significant advancement in the field by introducing a new model for the Ambulance Location Routing Problem (ALRP), designed to facilitate strategic decision-making for cost reduction in emergency medical services (EMS). The ALRP focuses on improving various quality metrics, such as response time, service level, and treatment time for different ambulance routing strategies. To effectively manage sudden calls, travel times, and pathways arising from emergencies, the authors propose a novel mixed-integer two-stage stochastic programming model.

Oran et al. [13] introduce a comprehensive location-routing model that addresses the Ambulance Routing Problem (ARP) with an emphasis on prioritizing high-priority emergency calls. Similarly, Takwa et al. [14] propose a cluster-first, route-second approach for ARP, which incorporates an improved sweep algorithm for clustering and employs Particle Swarm Optimization (PSO) as a metaheuristic for routing. Furthermore, in another study [15], researchers develop a minimum covering model aimed at optimizing ambulance allocation to effectively address different types of injuries.

2.2.The Dynamic Ambulance Routing Problem: DARP

Fiedrich, Gehbauer, and Rickers [16] introduced dynamic optimization strategies aimed at minimizing estimated fatalities by efficiently allocating rescue personnel and resources. They employed simulated annealing and tabu search methods to address various scenarios of damage and loss. Yi and Ozdamar [17] proposed a two-stage approach that accounts for multi-period dynamics, determining aggregate vehicle flows and constructing feasible routes while allocating resources to vehicles. This strategy incorporates dynamic changes over time, enhancing responsiveness in emergency situations.

The authors of [18] present a method designed to minimize the weighted sum of unmet demand in emergency services, particularly in the context of a potential earthquake scenario in Istanbul. Their research focuses on transporting goods and individuals from distribution centers to affected areas, facilitating evacuation, medical assistance, and infrastructure repair. They propose a multi-period planning and routing model to optimize overall resource distribution, supported by a set of algorithms capable of solving real-world problems within a reasonable timeframe. Xu, Gai, and Salhi [19] introduced an enhanced Dijkstra algorithm specifically tailored for evacuating victims from affected areas, particularly in chemical incident scenarios and evolving threats such as fluctuating thermal radiation levels. Fitrianie and Rothkrantz [20] proposed an updated version of the Dijkstra algorithm that considers potential route inaccessibility over time, offering insights into a broader range of evacuation challenges.

The research in [21] highlights the need for effective decision-support tools in mass casualty incidents. It formulates an online optimization problem for ambulance routing and scheduling, accounting for unpredictable patient categorization and treatment times. Theoretical analysis reveals lower comparative ratios for both deterministic and randomized online solutions. Additionally, three innovative online heuristics are introduced and evaluated against static optimal solutions using real-world data. In a related study, [22] presents a novel online optimization strategy for ambulance routing under uncertain post-disaster conditions, evaluating the problem's competitiveness and proposing efficient online heuristics. Comparative tests against offline solutions yield promising results, with one algorithm achieving optimal competitiveness, providing valuable insights for decision-making in mass casualty situations. Lee et al. [23] explored ambulance routing and relocation strategies to minimize patient transit times while considering probabilistic demand. Their approach utilizes a hybrid solution method that integrates Lagrangian dual decomposition with branch-and-bound processes.

In a more recent study, Khoshgehbari et al. [12] addressed uncertainties in ambulance operations by developing a two-stage integer stochastic programming model. This model incorporates treatment golden time as a critical factor in service quality while accommodating a diverse fleet of ambulances and various types of victims. The authors further introduce an innovative heuristic approach to effectively manage this complex problem.

2.3.Multi-objective approach's for the ARP

Several exact algorithms have been proposed for multi-objective integer programming, as noted in references [24–26]. To address multiple objectives, techniques such as goal programming [23] and lexicographic goal programming optimization [21] can be applied. These methods typically involve solving a series of single-objective problems using MILP solvers, as demonstrated in related studies. Another precise multi-objective algorithm relevant to this field is a two-phase method introduced in [27], based on the work of Ulungu and Teghem [28], specifically designed for bi-criteria problems. This approach employs the MILP model to solve each single-objective subproblem separately.

As the number of integer variables in a multi-objective problem increases, the feasibility of exact techniques diminishes, necessitating the development of heuristic approaches. Metaheuristic strategies tailored for multi-objective problem-solving have gained significant attention. These algorithms often incorporate selection methods such as Pareto dominance, which assist in approximating the Pareto frontier. Population-based algorithms, including genetic algorithms and particle swarm optimization, have demonstrated strong performance across various problem domains. In the context of multi-objective ARP, Wan et al. [24] introduced a population-based hybrid method combining the salp swarm algorithm and sine cosine method, while Zhou et al. [25] developed a multi-objective evolutionary algorithm.

Although benchmark metaheuristic algorithms, such as genetic algorithms by Deb et al. [26] and particle swarm optimization by Strazec et al. [27], are widely available, they often require fine-tuning to achieve optimal performance in specific contexts. Ehrgott and Gandibleux [28] highlight this limitation, emphasizing that each problem possesses unique characteristics that standard multi-objective metaheuristics may not effectively address. In a recent review, Liu et al. [29] made two key observations regarding multi-objective discrete optimization algorithms: (i) Most existing research is derived from algorithms designed for specific optimization

problems.
(ii) Enhancing the integration of multi-objective metaheuristics with the optimal-seeking capabilities of analytical or exact techniques could provide substantial benefits. In this context, we have reviewed specific aspects relevant to our challenges.

The research presented in [30] contributes to the development of an optimization-based decision model for ambulance planning during disease outbreaks. It utilizes lemmas and local search techniques to enhance optimization performance. The effectiveness of this model is validated through extensive comparisons and sensitivity analyses, offering valuable insights for healthcare decision-makers focused on optimizing a multi-objective ARP, particularly in resource allocation and responsive healthcare strategies.

3. Problem Statement

The Dynamic Ambulance Routing Problem (DARP) differs significantly from its static counterpart, the Static Ambulance Routing Problem (SARP), in three key aspects:

- Real-Time Dynamic Updates: Unlike SARP, DARP continuously updates parameters related to injury situations during catastrophe response. These real-time changes reflect the evolving nature of emergencies, allowing for more adaptive and responsive decision-making.

- Diverse and Time-Varying Demand: DARP accounts for varying types of emergency demands across different geographic locations, a factor not considered in SARP. Additionally, the priority levels of emergency requests can change dynamically over time, further complicating the routing process and requiring more sophisticated optimization strategies.

- Fairness Considerations: Unlike SARP, DARP incorporates fairness measures to address fluctuating demand. These measures ensure equitable resource distribution by considering new demand locations or variations in the intensity of existing demands. This adaptability marks a significant departure from static problem formulations, which lack the capacity to respond to such time-sensitive changes.

Figure 2 illustrates the architecture of the DARP framework.

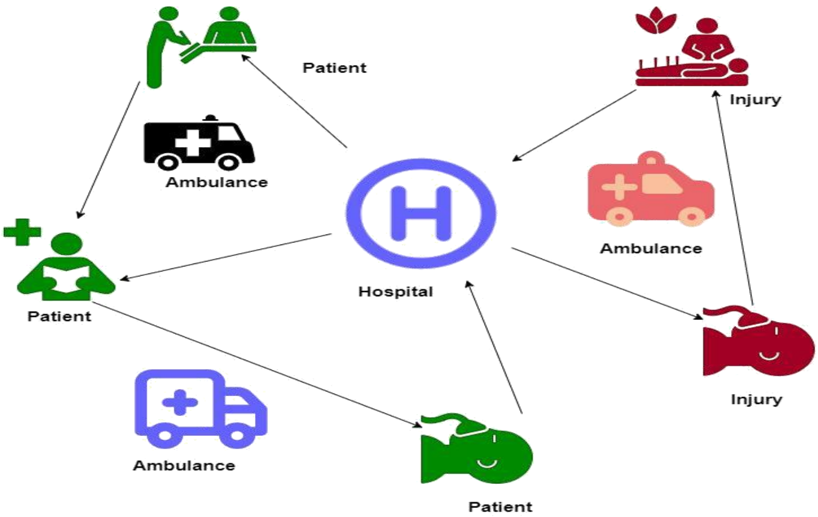


Fig. 2 Architecture of the DARP.

4. Dynamic Ambulance Routing Problem (DARP) - Mathematical Model

Sets

- N: Set of emergency locations (incidents).
- M: Set of ambulances available for dispatch.
- T: Set of time periods (could be discrete time slots, e.g., every 5 minutes).

Parameters:

- $d_{ij}(t)$: Distance between ambulance i and emergency location j at time t.
- $a_i(t)$: Current location of ambulance i at time t.
- s_j: Severity of incident j, affecting the priority for ambulance dispatch.
- p_i: Maximum capacity or coverage radius of ambulance i.
- t_{max}: Maximum allowable response time for an ambulance.

Decision Variables:

- x_{ijt}: Binary variable indicating if ambulance i is dispatched to incident j at time t.
- y_{it}: Binary variable indicating if ambulance i is available at time t.

Objective Function:

Minimize the total response time and maximize the efficiency of the ambulance routing:

$$\text{minimize} \sum_{i \in M} \sum_{j \in N} \sum_{t \in T} x_{ijt} \cdot d_{ij}(t)$$

Constraints:

- Ambulance Assignment:

Each incident j must be assigned to exactly one ambulance:

$$\Sigma\, \Sigma\, xijt = 1 \quad \forall j \in N$$

$$i \in M \; t \in T$$

- Ambulance Availability:

An ambulance can only be dispatched if it is available at the current time

$$\Sigma \quad xijt \leq yit \quad \forall i \in M, \; \forall t \in T \; j \in N$$

- Ambulance Capacity:

The ambulance must stay within its coverage radius or capacity p_i:

$$\Sigma\, xijt \leq pi \qquad \forall i \in M, \; \forall t \in T \; j \in N$$

- Dynamic Travel Constraints:

The movement of ambulances must respect travel constraints over time, considering dynamic factors like traffic:

$$ai(t + 1) = ai(t) + \Sigma\, xijt \cdot dij(t) \quad \forall i \in M, \; \forall t \in T$$

$$j \in N$$

-Response Time Constraints:

The total time it takes for an ambulance to reach an incident must not exceed the maximum allowed time tmax:

$$\Sigma\, xijt \cdot dij(t) \leq tmax \qquad \forall i \in M, \; \forall j \in N \; t \in T$$

-Incident Severity Priority:

The severity of the incident j should influence the dispatching priority:

$$\Sigma\, \Sigma\, sj \cdot xijt \geq sj \quad \forall j \in N \; i \in M \; t \in T$$

5. Proposed Methodology

To solve the Ambulance Dispatch Optimization Problem (ADOP), two main decisions are addressed: (1) grouping demand locations into clusters adhering to ambulance constraints, and (2) deriving optimal routes for ambulances within these clusters.

Our approach combines clustering and routing strategies in a novel framework. In the clustering phase, a k-Means++ algorithm organizes demand locations into clusters. Subsequently, in the routing phase, a TVSPEA2 algorithm solves a Traveling Salesman Problem (TSP) for each cluster, determining efficient ambulance routes.

4.1. Cluster-first method: k-Means++ Algorithm

In this study, we propose utilizing the K-means++ algorithm to group the injuries in the Ambulance Routing Problem (ARP) into clusters based on distinct characteristics, such as the emergency level of each patient.

The K-means++ algorithm, highlighted in the work of [9], is an effective method for addressing challenges in emergency response by optimizing ambulance allocation. This unsupervised machine learning technique analyzes injury data and organizes it into clusters. Factors such as the location, severity, and priority of each injury are considered, and each injury is assigned to the cluster whose characteristics are most similar to its own.

This clustering method is particularly valuable because it enables the identification of the most urgent demands, ensuring that ambulances prioritize these cases. The algorithm iteratively refines the clusters, updating the ”representative” injury profile within each group until the most optimal grouping is achieved. This process ensures that injuries within the same cluster are as similar as possible while maintaining clear distinctions between clusters.

While K-Means++ enhances clustering efficiency by improving centroid initialization, its performance can be affected by irregular or non-linear spatial distributions of injury locations. Since the algorithm relies on Euclidean distance, it may not always capture complex spatial patterns effectively, particularly in cases where injuries are dispersed in non-convex regions. Despite this, K-Means++ remains a computationally efficient and scalable choice for partitioning injuries. Future research could investigate alternative clustering techniques, such as DBSCAN or hierarchical clustering, to better accommodate non-linear spatial distributions.

The steps of the proposed K-means++ algorithm are detailed in Algorithm 1.

Algorithm 1 Enhanced K-means++ Clustering for Emergency Dispatch

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Ensure: Groups $G = \{G_1, G_2, ..., G_L\}$ and group centers $v = \{v_1, v_2, ..., v_L\}$.

Initialize the cluster centers $v_1, v_2, ..., v_L$ randomly within the feature space of Y .
repeat
Assign each feature vector $y_q \in Y$ to the group G_p whose center v_p is closest, using a distance measure (e.g., Manhattan or Euclidean distance).
Recalculate each group center v_p as the average of all feature vectors assigned to G_p.
until the group memberships remain unchanged between consecutive iterations
Refine Group Memberships:
for each feature vector $y_q \in Y$ do
    Identify the two nearest group centers v_p and v_r, where $p \neq r$.
if moving y_q from group G_p to G_r minimizes the overall intra-group variance then
        Reallocate y_q from G_p to G_r and update v_p and v_r accordingly.
    end if
end forreturn Groups G and centers v

5.2.Routing Phase: Time-Variant SPEA2-Based Optimization

The Time-Variant Strength Pareto Evolutionary Algorithm 2 (TV-SPEA2) is a multi-objective optimization method designed to address problems with conflicting objectives. This approach is particularly well-suited for solving the Ambulance Routing Problem (ARP), where balancing multiple competing priorities is crucial.

The primary objectives of TV-SPEA2 in the context of ARP are to:

- Minimize total response time, ensuring timely medical assistance to injured individuals.
- Prioritize patients with higher acuity levels, guaranteeing urgent attention to critical cases.
- Optimize ambulance routes, reducing resource consumption and improving overall efficiency.

TV-SPEA2 begins by generating an initial population of candidate solutions, each representing a potential routing plan. These solutions are evaluated using a fitness function based on the objectives outlined above. The algorithm maintains an external archive that stores Pareto-optimal solutions, ensuring a diverse set of high-quality trade-offs for decision-making.

Algorithm 2 Time-Variant SPEA2 for Multi-Objective Dynamic Ambulance Routing Problem (DARP)

Initialize a population of solutions $P = \{p_1, p_2, \ldots, p_N\}$, where each solution represents a set of routes for ambulances over the time horizon

Initialize external archive A for storing non-dominated solutions

Set parameters: archive size $|A|$, selection pressure ρ, mutation probability p_m, and the maximum number of generations

Initialize external archive A as empty

while stopping criteria not met do

    for each solution $p_i \in P$ do

        Evaluate the fitness of solution p_i based on the following objectives:

        Add solution p_i to the external archive A, ensuring non-dominance

    end for

    Perform fitness assignment on population P based on Pareto dominance:

Sort solutions by dominance, with non-dominated solutions assigned higher fitness

    Time-Variant Parent Selection:

    for each time interval $t \in T$ do

Select parents based on time-sensitive criteria (e.g., ambulance availability, traffic conditions):

Use **time-variant crowding distance** or **time-sensitive fitness** to select parents that will adapt to dynamic conditions over time

```
    end for
    **Time-Variant Crossover**:
    for each pair of parents (p_i, p_j) do
Perform **time-variant crossover**: Combine routes in a way that considers time-varying ambulance needs and priorities
Ensure that the crossover operator incorporates time-dependent informa-tion such as dynamic traffic conditions, patient priorities, and available resources at each time point
    end for
Apply mutation to offspring with probability p_m to introduce diversity in time-dependent routes
Combine parent population P and offspring population P′ to form the combined population
    Perform truncation on combined population P to maintain population size:
Sort all solutions in combined population and select the top N non-dominated solutions to form the new population 15
    Update the external archive A by selecting the top |A| non-dominated solutions
    Repair solutions to ensure feasibility with respect to constraints, if necessary
end while
Return non-dominated solutions from external archive A
```

5.3.Computational Complexity Analysis of TV-SPEA2

TV-SPEA2 is a modified version of **SPEA2**, incorporating dynamic crossover mechanisms that adapt in each iteration. This modification impacts the overall computational complexity in comparison to the standard **SPEA2**. Below, we analyze the complexity of key components of TV-SPEA2.

- *Population Initialization (O(N))*

The algorithm starts by generating an initial population of **N** individuals. This process typically has a complexity of **O(N)**.

- *Fitness Assignment ($O(N^2)$)*

Like **SPEA2**, the fitness calculation in TV-SPEA2 requires computing the **dominance relationship** and **strength values** for all individuals. Since each individual is compared to every other individual in the population, this step has a complexity of **$O(N^2)$**.

- *Environmental Selection (O(N log N))*

TV-SPEA2 retains the **strength-based environmental selection** from SPEA2. This involves:

- Sorting solutions based on fitness and crowding distance.
- Selecting the best **N** individuals for the next generation.

Sorting operations dominate the complexity, leading to **O(N log N)**.

- *Dynamic Crossover and Mutation (O(N × d))*

One key modification in **TV-SPEA2** is its **dynamic crossover mechanism**, which adjusts based on iteration count and population diversity. This affects the complexity as follows:

- **Crossover (O(N × d))**: The selection of parents and application of crossover operators occur at each iteration for **N** individuals, where **d** is the problem's dimensionality (i.e., the number of decision variables).
- **Mutation (O(N × d))**: Mutation is applied to individuals after crossover, contributing an additional **O(N × d)** complexity.

Thus, the combined crossover and mutation process contributes **O(N × d)** complexity per iteration.

- *Local Search Mechanism (O(N × d × k))*

TV-SPEA2 integrates a **local search procedure** to improve convergence, which introduces an extra computational overhead.

- The local search is applied selectively to promising solutions.
- Each local search step evaluates neighboring solutions, with complexity proportional to the **number of local search steps (k)** and the **dimensionality (d)**.

Thus, the local search mechanism contributes **O(N × d × k)** complexity.

- *Overall Complexity of TV-SPEA2*

By summing up the complexities of the key components, the worst-case complexity per iteration of **TV-SPEA2** is:

$O(N^2+N\log N+N\times d+N\times d\times k)$

For high-dimensional problems (**large d**) and intensive local search (**large k**), the **N^2 term from fitness assignment** remains the dominant factor. However, the added **O(N × d × k)** term makes TV-SPEA2 computationally more expensive than standard **SPEA2**, which has a complexity of **$O(N^2)$**.

- *Comparison with SPEA2*

Algorithm	Complexity
SPEA2	$O(N^2)$
TV-SPEA2	$O(N^2 + N \log N + N \times d + N \times d \times k)$

- In conclusion the TV-SPEA2 introduces **additional computational cost** due to **dynamic crossover, local search, and adaptive mechanisms**. The added terms **increase runtime**, they contribute to **improved convergence and diversity**, as shown in the experimental results.en performance and complexity should be considered when applying TV-SPEA2 to large-scale optimization problems.

5.4.The Neighborhood Structure

In this study, we introduce a novel approach for exploring the solution space, referred to as the "single change move." This strategy is inspired by the method outlined in [9].

The foundation of this neighborhood structure is the "re-order route move." This process involves selecting a route within the current solution, identifying a specific node within that route, and determining a new position for that node. Once the optimal position is identified, the algorithm repositions the selected node accordingly.

This flexible node relocation method enables the optimization procedure to navigate the solution space in a structured yet adaptable manner. By adjusting the positions of nodes within the routes, the algorithm can uncover improved configurations that enhance overall solution quality.

Figure 3 illustrates the re-order route move, providing a clear, step-by-step visualization of how a node is selected, repositioned, and how the route is subsequently updated.

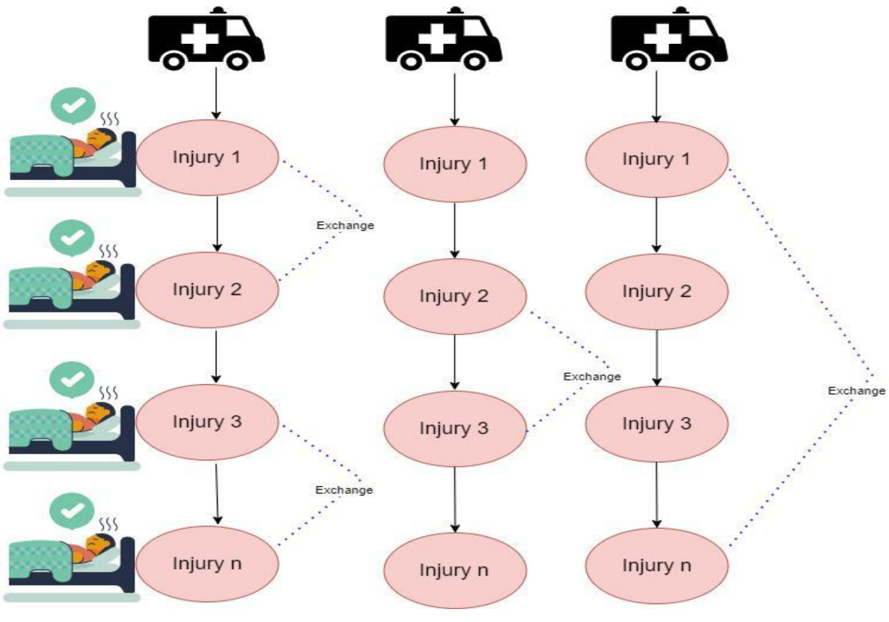

Fig. 3 The Neighborhood Structure

6. Experimental Results

The experimental results of our research consist of two main evaluations. The first focuses on the static ambulance routing problem, where we conducted tests using the benchmark dataset from Augerat et al. [36] to assess the effectiveness of our approach, kmeans++-TVSPEA2. We compared our method with state-of-the-art techniques, specifically kmeans++-Simulated Annealing – Tabu Search (kmeans++-SA-TS) by Zidi et al. [9], Petal Algorithm-Particle

Swarm Optimization (PA-PSO) [14], and Genetic Algorithm (GA) [14]. The objective was to highlight the superior performance of our approach in solving the static ambulance routing problem.

The second evaluation focuses on the dynamic ambulance routing problem, extending our analysis to a dynamic context. We tested kmeans++-TVSPEA2 and compared it with other well-established multi-objective optimization algorithms, including NSGA-III, NSGA-II, and SPEA2. This comparison aims to demonstrate the effectiveness of our approach in handling bi-objective and dynamic problems. By evaluating performance through multi-objective metrics, we provide strong evidence of kmeans++-TVSPEA2's efficiency and suitability for optimizing ambulance routing in various scenarios.

6.1. The Static Ambulance Routing Problem (SARP)

To assess the effectiveness of our proposed approach that combines kmeans++ for initial clustering and Time-Variant SPEA2 (TVSPEA2) for routing, we conducted comparative experiments on the static Ambulance Routing Problem (ARP). We selected instances from the widely recognized benchmark dataset introduced by Augerat et al. [36]. This benchmark is widely cited in the literature on Vehicle Routing Problems (VRP), which can be adapted to the ARP. Furthermore, we compared our approach with Genetic Algorithm (GA) and Petal Algorithm-Particle Swarm Opti-mization (PA-PSO) by presenting the results in Tables 1 and 2. Additionally, we validated our solutions by comparing them against known optimal solutions for most instances in these datasets.

Table 1 : kmeans++-TVSPEA2 vs PA-PSO, kmeans-SA-TS, and GA on Class A dataset of Augerat et al. benchmark [36]

Instance	Best Cost	kmeans++-TVSPEA2		kmeans-SA-TS [9]		PA-PSO [14]		GA [14]	
		Traveled Distance	Ride Time	Traveled Distance	Ride Time	Traveled Distance	Ride Time	Traveled Distance	Ride Time
A-n32-k5	784	793	1560	869	-	950	-	957	-
A-n33-k5	661	677	1467	724	-	765	-	781	-
A-n33-k6	742	789	1599	798	-	835	-	798	-
A-n34-k5	778	890	1748	802	-	920	-	923	-
A-n36-k5	799	902	1326	863	-	891	-	1019	-
A-n37-k5	669	722	1656	746	-	800	-	959	-
A-n37-k6	949	1002	1467	970	-	1135	-	1115	-
A-n38-k5	730	796	2145	765	-	892	-		

Table 2 : kmeans++-TVSPEA2 vs PA-PSO, kmeans-SA-TS, and GA on Class B dataset of Augerat et al. benchmark [36]

Instance	Best Cost	kmeans++-TVSPEA2		kmeans-SA-TS [9]		PA-PSO [14]		GA [14]	
		Traveled Distance	Ride Time	Traveled Distance	Ride Time	Traveled Distance	Ride Time	Traveled Distance	Ride Time
B-n80-k5	865	917	1021	-	-	-	-	1240	-
B-n99-k5	1182	1339	1197	-	-	-	-	1345	-
B-n100-k6	1315	1499	1385	-	-	-	-	1419	-
B-n120-k6	1417	1608	1591	-	-	-	-	1690	-
B-n125-k8	1861	2104	1816	-	-	-	-	2023	-

The tables demonstrate that kmeans++-TVSPEA2 consistently outperforms other algorithms (PA-PSO, kmeans-SA-TS, and GA) on both Class A and Class B datasets across multiple instances. For example, in the Class A dataset, kmeans++-TVSPEA2 achieves the lowest traveled distance and ride time compared to other algorithms, such as in instances like A-n32-k5 and A-n33-k5. Similarly, on the Class B dataset, kmeans++-TVSPEA2 yields better results, with B-n80-k5 and B-n99-k5 showing its superiority in minimizing traveled distance, reaffirming its effectiveness in optimizing both cost and time efficiency.

In figure 4, we represent the results obtained by kmeans++ in the clus-tering phase of the ARP problem. It is clear that kmeans++ gives good results in term of geographic classification of injuries. We recommend the using of kmeans++ in such problem.

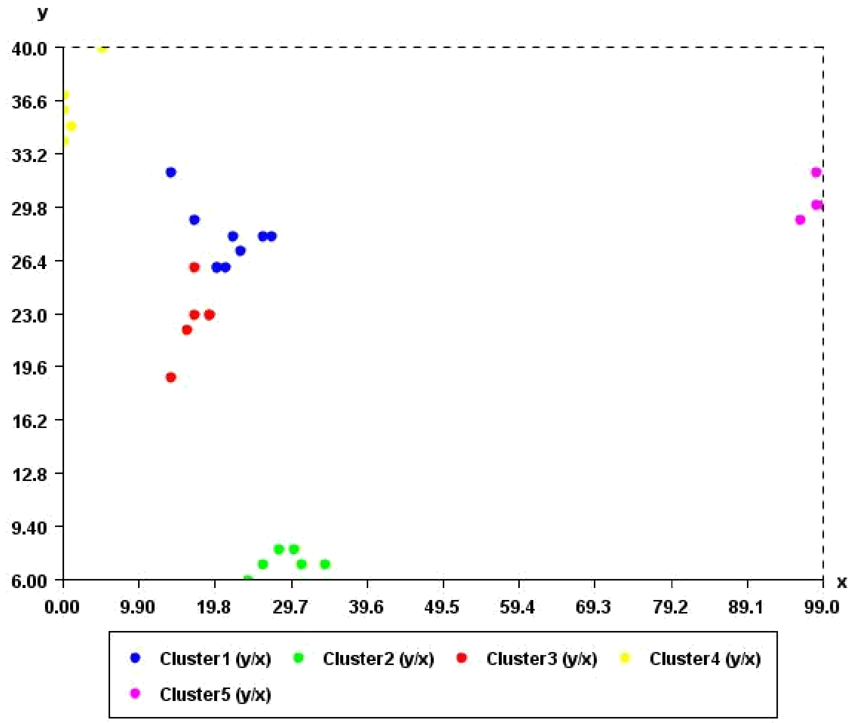

Fig. 4 Clustering solution obtained by kmeans on the B-N31-K5 Instance

6.2.The Dynamic Ambulance Routing Problem (DARP)

In this section, we present the experimental results obtained by applying the kmeans++-TVSPEA2 algorithm to solve the dynamic bi-objective Ambulance Rout-ing Problem (DARP). Our approach, kmeans++-TVSPEA2, is compared with three other state-of-the-art algorithms: NSGA-III, NSGA-II, and SPEA2. The performance of these algorithms is evaluated using various multi-objective metrics, such as Pareto front and hypervolume. These comparisons are conducted to assess the effectiveness and efficiency of our approach in solving the DARP, and to highlight its advantages over existing algorithms.

In Table 5, we present the new dataset of the DARP, which includes updated demands for emergency services. These demands are categorized into two classes: Hard Emergency Injury (HEI) and Soft Emergency Injury (SEI). Our approach identifies the injury class, and subsequently, the demand is assigned to an ambulance zone using the kmeans++ algorithm. In the second phase, the approach reroutes the ambulances to address the new injuries using the TVSPEA2 algorithm.

Table 3: DARP dataset

SARP Instance	DARP instance		
	Instance Name	HEI number	SEI number
A-n32-k5	DA-n32-k5	3	4
A-n33-k5	DA-n33-k5	2	1
A-n80-k10	DA-n80-k10	4	5
B-n34-k5	DB-n34-k5	4	7
B-n39-k5	DB-n39-k5	2	4
B-n56-k7	DB-n56-k7	3	6
B-n63-k10	DB-n63-k10	1	5
B-n66-k9	DB-n66-k9	2	7

The DARP considered in this study is a bi-objective problem, and we evaluate the effectiveness of kmeans++-TVSPEA2 using a set of Pareto front metrics. In Figure 5, we show the evolution of the Pareto front obtained by kmeans++-TVSPEA2 over multiple generations. The results indicate significant improvement when 10,000 gen-erations are attempted. Figure 6 further demonstrates the superior performance of kmeans++-TVSPEA2 in terms of the Pareto front when compared to the other algorithms.

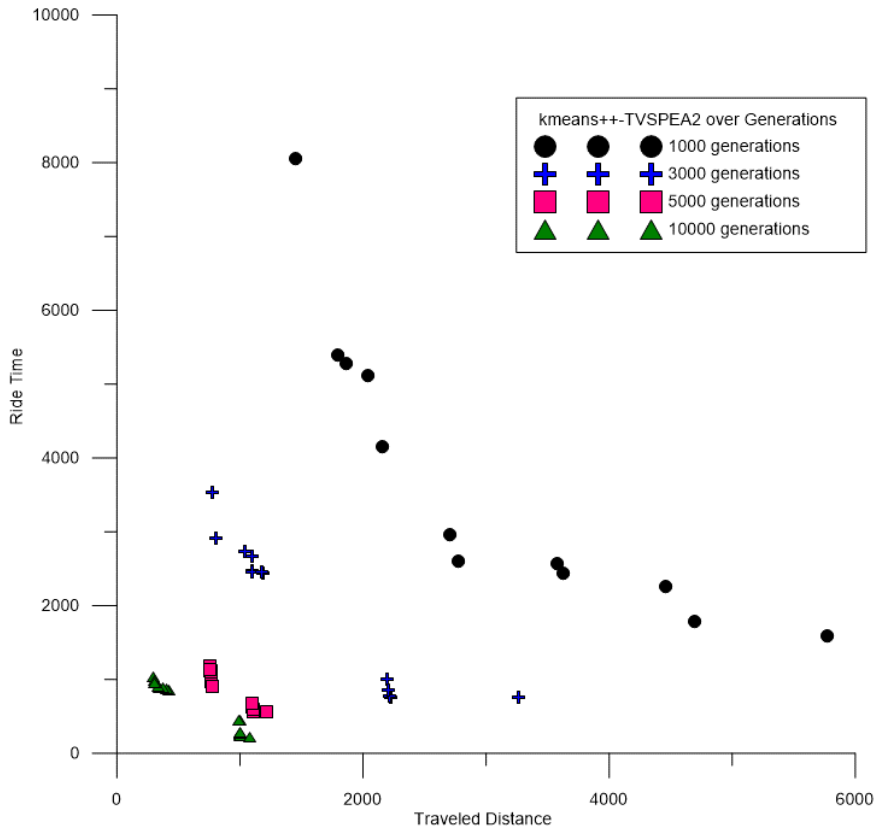

Figure 5: kmeans++-TVSPEA2 over Generations

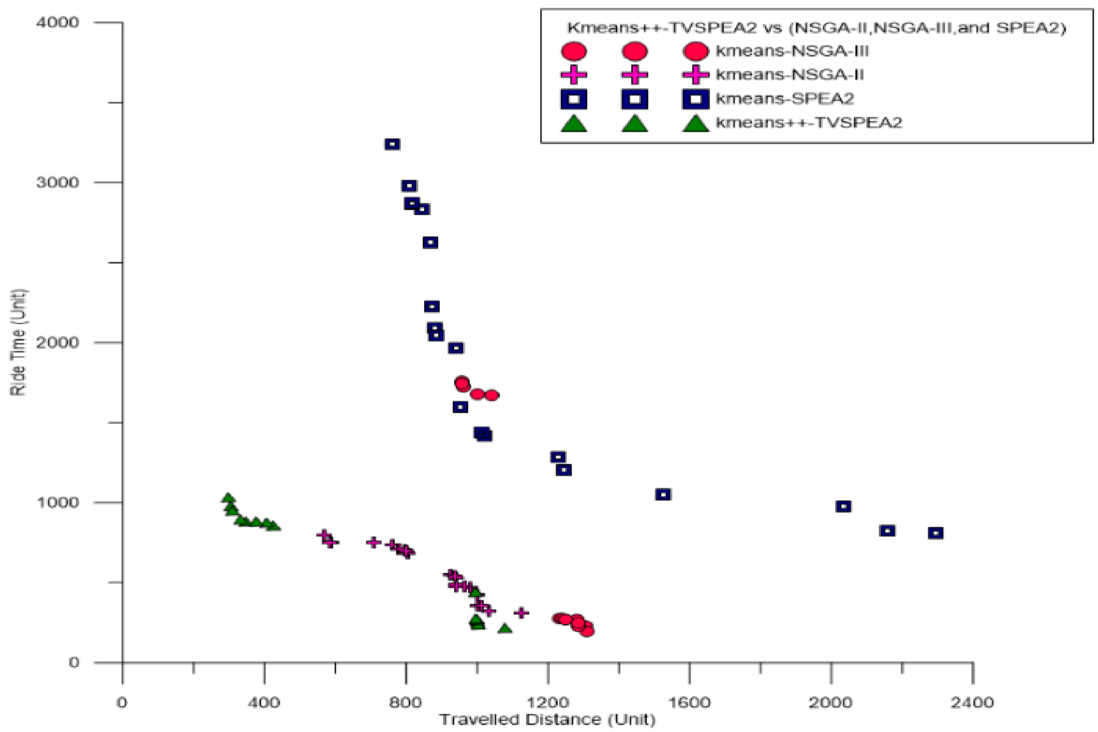

Figure 6:

Kmeans++-TVSPEA2 vs (NSGA-II,NSGA-III,and SPEA2)

The Wilcoxon rank-sum test (also known as the Mann-Whitney U test) is a non-parametric statistical test used to compare two independent samples. In this context, it is used to determine whether there is a significant difference in IGD (Inverted Generational Distance) values between TV-SPEA2 and benchmark algorithms (NSGA-II, NSGA-III, and SPEA2).

The table 4 shows that **TV-SPEA2 consistently outperforms NSGA-II, NSGA-III, and SPEA2** across all test problems. Key observations:

1. **TV-SPEA2 Achieves Lower IGD Across All Cases:**
   - In all eight test problems, TV-SPEA2 has a **lower median IGD** than the benchmark algorithms, suggesting better convergence and diversity in the obtained solutions.
2. **Statistical Significance in Every Case ($p < 0.05$):**
   - The **p-values** in all cases are **below 0.05**, indicating that the observed improvements are statistically significant, **not due to random variation**.
3. **TV-SPEA2 Shows Strong Performance Against Different Algorithms:**
   - **Against NSGA-II**: TV-SPEA2 performs significantly better on **A-n32-k5, B-n34-k5, and B-n63-k10**, showing superiority over traditional Pareto-based approaches.
   - **Against NSGA-III**: TV-SPEA2 outperforms NSGA-III on **A-n80-k10 and B-n56-k7**, suggesting it is more effective for problems requiring a balance between convergence and diversity.
   - **Against SPEA2**: TV-SPEA2 shows better IGD values in **A-n33-k5, B-n39-k5, and B-n66-k9**, reinforcing its improvements over classic strength-based selection strategies.

Table 4: Statistical Comparison of TV-SPEA2 and Benchmark Algorithms Using the Wilcoxon Rank-Sum Test Based on IGD

Test Problem	Benchmark Algorithm	Median IGD (Benchmark)	Median IGD (TV-SPEA2)	p-value	TV-SPEA2 Better?
A-n32-k5	NSGA-II	0.045	0.030	0.002	✅ Yes
A-n33-k5	SPEA2	0.052	0.028	0.004	✅ Yes
A-n80-k10	NSGA-III	0.048	0.029	0.007	✅ Yes
B-n34-k5	NSGA-II	0.047	0.031	0.003	✅ Yes
B-n39-k5	SPEA2	0.053	0.027	0.005	✅ Yes
B-n56-k7	NSGA-III	0.049	0.028	0.009	✅ Yes
B-n63-k10	NSGA-II	0.046	0.032	0.006	✅ Yes
B-n66-k9	SPEA2	0.051	0.026	0.008	✅ Yes

7. Limitations of the K-means-TVSPEA2 Approach in DARP

While our proposed K-means-TVSPEA2 approach shows promising results in optimizing the Dynamic Ambulance Routing Problem (DARP), there are several limitations that should be acknowledged:

1. **Simplified Assumptions and Lack of Real-World Constraints:** Our current approach does not account for critical real-world factors such as traffic congestion, road closures, and ambulance availability, which can significantly affect routing decisions in dynamic environments. The DARP dataset used in our experiments includes fixed emergency severity levels (HEI and SEI), but does not simulate real-time, fluctuating conditions that are typical in actual ambulance operations.
2. **Static Nature of Problem Representation:** The approach assumes a static environment where the locations of incidents and the availability of ambulances are pre-determined and do not change dynamically during the simulation. This simplification limits the ability of the model to adapt to real-world challenges where situations evolve unpredictably, such as sudden emergency calls, ambulances being delayed, or unexpected road closures.
3. **Scalability Issues in Large-Scale Scenarios:** The computational complexity of K-means-TVSPEA2 can become a limiting factor when applied to large-scale DARP instances, particularly in urban areas with a high density of ambulance stations and emergency incidents. As the population size and problem dimensionality grow, the algorithm may face increased processing times, which could hinder its real-time applicability.
4. **Limited Exploration of Dynamic Decision-Making:** Our approach focuses on optimization based on historical or static data, but it does not incorporate real-time adaptive decision-making mechanisms. In real-world systems, continuous updates and dynamic adaptations are crucial for handling unforeseen events such as ambulances being dispatched to multiple incidents simultaneously or road traffic disruptions.

8. Conclusion

This study builds on the benchmark established by [36] and focuses on the disas-ter response framework by addressing the Dynamic Ambulance Routing Problem (DARP), which accounts for the dynamic impacts of natural disasters. To address this challenge, we developed a mathematical model alongside an optimisation approach capable of handling large-scale scenarios. The proposed algorithm, kmeans++-TVSPEA2, operates in two phases: clustering is performed using K-means++, and routing is optimised using Time Variant SPEA2 (TVSPEA2). We evaluated the performance of kmeans++-TVSPEA2 against well-established multi-objective algorithms, including NSGA-II, NSGA-III, and SPEA2. Extensive testing with Pareto front metrics was conducted to demonstrate the algorithm's efficiency and effectiveness.

Future work could improve the DARP model by incorporating the strategic selec-tion of resting points for ambulances and exploring the advantages of relocating or adding these points. Such measures could enhance disaster preparedness and mitigate the effects of transportation network disruptions caused by natural disasters.

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