Enhancing Emergency Response: A Smart Ambulance System Using Game-Building Theory and Real-Time Optimization

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***Abstract*—Dispatching ambulances early and efficiently is paramount and difficult in the field of emergency medical services. In this regard, the paper designs a smart ambulance system based on game-building theory. The system employs an advanced Negamax algorithm for optimizing the dispatch of ambulances during emergencies. Besides traditional methods, real-time traffic data, patient condition severity, and dynamic resource allocation also improve the system further. With the integration of predictive analytics and real-time data, it allows dynamic adaptation to changing urban conditions, optimal resource allocation as well as minimizing response time. According to our simulations involving extensive scenarios, our Negamax-based system performs significantly better with respect to average response times when compared with traditional methods averagely reducing them by more than 50%, hence, showing double improvement. The study not only improves efficiency in the operation of emergency services but also presents an expandable framework that can be used for future developments in critical response systems thereby leading to their association with smart city infrastructure and AI-based predictive emergency management.**

Keywords—Emergency medical services; ambulance dispatch optimization; advanced game theory; Negamax algorithm; real-time optimization; predictive analytics

I. Introduction

When it comes to saving lives and improving patient outcomes in urban areas, the speed of action taken by emergency medical services (EMS) is very important [1]. Often, traditional ambulance dispatches rely on static positions and heuristic approaches which are simple and fail to take into account the dynamic nature of urban emergencies and traffic conditions [2]. This research is motivated by the need for a more sophisticated adaptive ambulance allocation approach that can respond to real time conditions, predict patterns of emergency, and optimize resource utilization within complex urban settings.

The subject of this study is to develop and implement an advanced system based on game theory for optimizing the dispatch of ambulances in large urban areas with a high population density, complex road networks, and changing traffic conditions. We go beyond mere distance optimization to consider factors such as real-time traffic information, historical emergency patterns, and dynamic health facility capacity changes. The primary objectives of this research work are as follows:

- To customize the Negamax algorithm (from game theory) [3], [4] with multi-factorial decision-making for ambulance dispatch optimization.
- To combine real-time data feeds like hospital capacities, emergency severity levels, and traffic conditions in the process of optimizing ambulance dispatches.
- To design a scalable platform for handling emergency response coordination throughout the city.

Efficient ambulance dispatch is undoubtedly a crucial aspect. In the cases of cardiac arrests, survival odds are lower by 7-10% per minute delay [5]. It shows how rapid response saves lives. There could be improved resource utilization through efficient dispatch systems which can reduce operational costs and improve coverage with existing resources [6]. In addition, the implementation of smart routing systems [7], [8] could reduce traffic congestions associated with emergency vehicle movements and facilitate urban mobility in general. Moreover, this data can help city planning and health care to optimize resource allocation based on facts instead of assumptions for a better public health outcome as well as improved emergency medical services.

The existing approaches are somehow limited on several accounts which reduce their effectiveness in modern urban environments. To be considered here, traditional ambulance dispatches are often based on static decision-making and use rule-based methods that are easy to apply but do not consider the evolving nature of the emergencies and traffic in urban environments [9], [10]. Although 5G and IoT have emerged and recently integrated into ambulances, they are still unable to relieve the demanding nature of emergency services in the urban environment [11], [12]. Various knowledge-based systems have been developed [13], but they are not capable enough to provide proper time-based optimization and predictive analysis. A few recent research works have tried to include real-time data and predictability in the model [14], [15]. However, there are very few studies that have included a holistic approach of adaptive methods. Moreover, though attempts have been made to solve problems like traffic congestion [16], still it is the dire necessity to design an efficient and enhanced adaptive ambulance allocation model considering the current situation, patterning emergency and the best utilization of resource in the context of urban environment. These drawbacks, which are discussed in more detail in Section II, all point to the need for more flexible, real-time, and big data-based solutions for ambulance dispatching.

To this motivation, we hypothesize that applying a customized version of the Negamax algorithm from game-building theory, combined with machine learning techniques for predictive analytics, can significantly improve the efficiency of ambulance services. We consider the Negamax algorithm because of its efficiency in exploring decision trees and adaptability to adversarial scenarios. In the context of emergency response, it represents the competition between different possible dispatch decisions. Moreover, the Negamax algorithm considers the thinking process of both participants while making a move, which consequently increases the win probability. Our customized version incorporates real-time data updates and considers multiple factors simultaneously, enhancing its suitability for the ambulance dispatch problem. Hence, this approach aims to create a dynamic, predictive, and highly responsive ambulance dispatch system. The system would be able to minimize response times, maximize resource utilization, and adapt to the complex and dynamic environment of urban emergencies.

The paper is organized as follows: Section II covers the literature review. Section III explains the mathematical modeling followed by the proposed system in Section IV. Section V is about experimental evaluation, results, and discussion. The paper is finally concluded in Section VI along with the future research considerations.

II. Literature Review

This section covers the related research works in the domain of smart ambulance system. A smart ambulance system was suggested by Gupta et al. in 2016 using IoT and smartphone technologies [9]. The research was aimed at enhancing the emergency medical response. They proposed a system that has two main modules: (i) Module 1 is about locating nearby ambulances and hospitals using GPS and Google Maps; (ii) Module 2 transmits real-time patient health data from an ambulance to a hospital. They also claimed that there were reduced response times and improved patient care during emergencies.

In 2017, Udawant et al. designed “Green Corridor” smart ambulance system using IoT framework to mitigate traffic congestion issues faced by emergency services [10]. The system reads patients vital signs in an ambulance while transmitting it to hospitals, as well as controls automatically signal lights for clear passage of vehicle when it reaches signals. Authors assessed different MAC protocols for data transmission in the proposed system concluding that CSMA is mostly efficient.

A timely ambulance service was proposed by Marimuthu et al. (2018) that employs the use of an Android application [17]. The proposed service allows for user requests of ambulances and selection of hospitals. Tracking the movement of ambulances in real-time is made possible through GPS and GSM modules while providing an emergency button to assign automatically the nearest ambulance. This application intends to enhance ambulance response durations and provide more effective life-saving services.

In 2021, Zhai et al. proposed a 5G-based smart ambulance structure and evaluated it through simulation experiments [11]. The experiment was conducted on the test platform which consisted of two scenarios namely, remote video consultation with medical data transmission from a moving ambulance and large medical image file transfers under both 4G and 5G networks. The resulting figures indicated impressive enhancements in capacity, speed, and latency for 5G as compared to 4G systems.

Merza and Qudr (2022) presented an ambulance-based healthcare system using Raspberry Pi and Internet connectivity to monitor patients’ vital signs in real-time for data transfer to hospitals [18]. The system incorporates various sensors for ECG, heart rate, respiration, temperature as well as audio/video monitoring thereby improving hospital readiness status and communication between paramedics on board with specialists on call.

In 2022, Sultana et al. defined an IoT-enabled intelligent ambulance routing system using LOADng-IoT routing protocol to reduce emergency response time and enhance patient care [12]. To speed up ambulances to hospitals yet keep transferring the most recent patients’ medical records, this is done by integrating traffic light control, health monitoring sensors and efficient path-finding algorithms. Additionally, authors discuss how the technology can facilitate achieving some of the UN SDGs concerning health, infrastructure and sustainable cities.

In 2023, Chanchai Thaijiam developed a smart ambulance system with knowledge base and decision-making support for improved rescue operations [13]. The design includes wearable biometric sensors, GPS tracking technology. Video conferencing platform was installed in order to have smooth communication between medical personnel in hospital and the emergency team inside ambulances. These systems enhance selection of destination hospitals for patients which is guided by an algorithm that uses decision trees procedure based on certain parameters such as distance or type of injuries.

Siddiqi et al. (2023) developed a smart signalization system for emergency vehicles [14]. The system uses Arduino, GSM modules, and a mobile application and it facilitates the drivers to control traffic signals from afar through SMS. Consequently, it minimizes any delays that may be caused. The system was evaluated by conducting field tests which proved the system's effectiveness for avoiding probable intersections for emergency vehicles. In addition, it maintains minimal waiting time for other traffic on the route.

In 2023, Sutherland and Chakrabortty proposed an optimal ambulance routing model [15]. The model considers multiple ambulances, patient medical severities, dispatching locations, and hospitals. The goal of this model is to enhance response times as well as patient transport efficiency. Simulation results prove the model's resilience under critical situations, therefore, laying a foundation for further studies on ambulance routing optimization.

In 2024, Sakthidevi et al. discussed IoT-enabled smart ambulances and how they can transform emergency response and management of patients [19]. The focus was on real-time monitoring sensors, advanced communication systems, and data processing platforms. The authors contributed to enhance resource allocation, improve response times, and elevate patient outcomes. This paper also focuses on future directions, challenges as well as potential impacts to emergency medical services in the world today.

In 2024, Jeyaseelan et al. put forward an IoT-based smart ambulance system for reducing the time taken in responding to emergencies in cities prone to traffic congestion [16]. The system employs the use of sensors, GPS and wireless communication technology to track ambulances, control traffic signals or even lower speed breakers automatically enabling ambulances to reach hospitals faster as well as safely. Experimental results show high accuracy and availability of the proposed system.

In the present research work, we address several key gaps in the above-reviewed literature. While previous studies have majorly focused on IoT integration, GPS tracking, and basic route optimization; in contrast, our approach leverages advanced game theory, specifically a customized Negamax algorithm, to provide a more adaptive and intelligent solution. The proposed system also incorporates predictive analytics and multi-factorial decision-making, whereas, earlier works primarily considered real-time data transmission and traffic signal control only. Doing this facilitates proactive resource allocation and efficient emergency response. Furthermore, existing research works have confined their scope to either route optimization or patient data transmission. In response, our research integrates these aspects with dynamic resource management across large and complex urban areas. The use of machine learning techniques for emergency prediction and traffic pattern analysis goes beyond the capabilities of systems described in previous literature.

III. Mathematical Modeling

This section describes our mathematical model considered for this research including the customized Negamax algorithm, possible constraints, dynamic updates, and predictive component.

A. Customized Negamax Algorithm

Let $G = (V, E)$ be a graph where V represents nodes (ambulance stations, hospitals, accident locations) and E represents edges (routes between nodes). A time-dependent distance matrix D is considered where $D[i][j][t]$ represents the estimated travel time between node i and node j at time t. Furthermore, a dynamic vector A is also considered where $A[i][t]$ represents the number of available ambulances at node i at time t. Let S be a severity matrix where $S[k]$ represents the severity level of emergency k. Associating all the above notations, the objective function to minimize the total weighted response time T is given in Eq. (1) as follows:

$$T = \sum_{k=1}^{N} min_{i \in V}(D[i][k][t] \cdot I[i][k] \cdot W(S[k])) \quad (1)$$

Where I[i][k] is an indicator function that is 1 if an ambulance from node i is dispatched to emergency location k, and 0 otherwise. W(S[k]) is a weight function based on the severity of the emergency.

For each emergency k, $D[i][k][t] \cdot I[i][k] \cdot W(S[k])$ is calculated for every possible dispatch location i. The minimum of these values is then selected which represents dispatching from the best location. This minimum is then weighted by the emergency's severity. It is done for all emergencies and sum of the results is calculated, giving us the total weighted response time T. The goal of optimization is to find the set of dispatch decisions (represented by $I[i][k]$ values) that minimizes this total weighted response time T, subject to the constraints discussed as follows.

B. Constraints

Following constraints are taken into account while modeling the system:

- Emergency Coverage: It is the first constraint where each emergency must be responded to by at least one ambulance (see Eq. (2)). loc_{emr} represents the emergency locations.

$$\sum_{i \in V} I[i][k] \geq 1, \forall k \in loc_{emr} \quad (2)$$

- Ambulance Availability: This constraint assures that the number of ambulances dispatched from any node cannot exceed the available ambulances at that node (see Eq. (3)).

$$\sum_{k \in loc_{emr}} I[i][k] \leq A[i][t], \forall i \in V \quad (3)$$

- Response Time Limit: In this constraint, it is assumed that the response time for each emergency should not exceed a maximum threshold T_max (see Eq. (4)).

$$D[i][k][t] \cdot I[i][k] \leq T_{max}, \forall i \in V, \forall k \in loc_{emr} \quad (4)$$

C. Dynamic Updates

Three parameters are dynamically updated in the system viz., traffic conditions, ambulance availability, and emergency severity. For traffic condition; historical data $data_{hist}$, real-time traffic $traf_{rt}$, and time t are considered as shown by the function in Eq. (5). Similarly, dispatch events evt_{dp}, return events evt_{ret}, and shift changes chg_{shf} are considered to update ambulance availability (see Eq. (6)). To update the emergency severity, reported condition $cond_{rep}$, historical data $data_{hist}$, and environmental factors $fact_{env}$ are considered (see Eq. (7)).

$$D[i][j][t] = f(data_{hist}, traf_{rt}, t) \quad (5)$$

$$A[i][t] = g(evt_{dp}, evt_{ret}, chg_{shf}) \quad (6)$$

$$S[k] = h(cond_{rep}, data_{hist}, fact_{env}) \quad (7)$$

D. Predictive Component

Function $P(l, t)$ represents the predictive component as shown in Eq. (8). It gives the probabilistic estimation of an emergency that may occur at location l at time t.

$$P(l,t) = ML\_model(data_{hist}, cond_{rep}, evt_{sch}) \quad (8)$$

It makes the system capable of anticipating where emergencies are likely to occur before they may actually happen. The ML_model is a machine learning algorithm that takes historical data $data_{hist}$, current conditions $cond_{rep}$, and scheduled events evt_{sch} as its input. Historical data consists of past emergency calls, their respective locations, times, and types. It assists the model in identifying different patterns and trends. Similarly, for the current conditions parameter, we consider traffic patterns, weather, ongoing events, and time. For the scheduled events parameter, events that could impact the probability of emergency are considered. They may include sports, concerts or festivals, holidays, and road constructions. Initially, the model is trained on historical data. However, it is continuously updated with new data as it becomes available. The purpose is to make the model rational so that its predictions would improve over time. As the function is probabilistic, it outputs a value between 0 and 1 for each location l at time t. Higher values indicate a higher likelihood of an emergency event. The calculated probability values serve the following purposes:

- To allocate and position the ambulances in high-probability areas proactively.
- Weight adjustment in objective function to prioritize or highlight the areas with higher emergency probabilities.
- To make staffing decisions and shift planning.

Incorporating this predictive component in the system is imperative as it makes the system proactive in making important decisions. In other words, it assists the system in better resource allocation and potentially reducing response times by having ambulances positioned closer to where emergencies are likely to occur.

IV. Proposed System

In this section, we discuss the architecture of our proposed system along with its working.

A. *System Architecture*

The design of the proposed smart ambulance system is made up of several interconnected components/modules that work together to ensure effective resource allocation and ambulance dispatch. The layered architecture of the proposed system is given in Fig. 1. The specific responsibilities for each module are described as follows:

- Data Collection Module: It gathers real-time and historical data from many sources including GPS trackers on ambulances, weather stations, traffic sensors and cameras, hospital information systems, and emergency call centers.
- Data Processing Module: Raw data collected by Data Collection Module is further processed here so that it can be analyzed in depth. This includes activities such as data cleaning, normalization and feature extraction [20], [21].
- Predictive Analytics Engine: The proposed system incorporates a vital component which examines past emergency data against current situations to estimate future emergencies as well as their possible extent. Within this component a suitable machine learning algorithm has been included.
- Traffic Module: It produces and updates time-dependent distance matrix. The matrix shows estimated travel time between different nodes within the network taking into account dynamic traffic conditions.
- Resource Management Module: This module tracks the availability and status of all resources (ambulances) in the system. It is also responsible to update their positions/locations and availability in real-time.
- Dispatch Optimization Engine: This is the core component of our proposed system as the whole research is oriented around this. This engine uses a customized Negamax algorithm (as discussed in Section 3.1) to make optimal dispatch decisions. Each decision takes multiple factors into account for its dispatch [22]. These factors include ambulance availability, predicted emergency severity, and estimated response time.

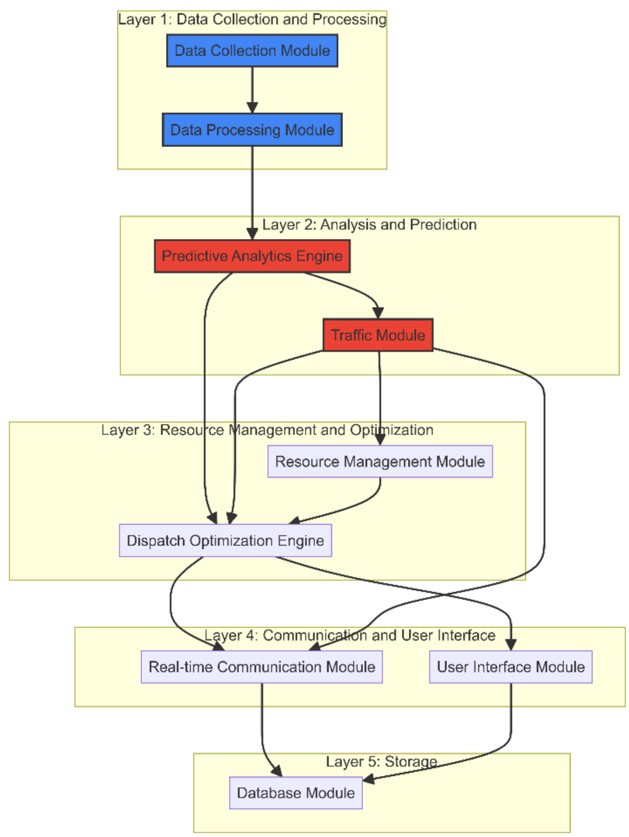

Fig. 1. Layered architecture of the smart ambulance system.

- Real-time Communication Module: As the name suggests, this module facilitates seamless communication between various entities of the system. These entities include a central dispatch system, ambulances, and hospitals. Consequently, this module ensures that all entities have access to the latest information.

- User Interface Module: It is important for the dispatchers to monitor the system, view predictions, and override automated decisions (if necessary). This module provides the graphical user interface for the same.

- Database Module: It is imperative to store historical data, real-time information, and system logs for continuous improvement and auditing. This module provides a centralized database to serve this purpose.

B. System Working

In the proposed system, different modules work together in a coordinated manner to enhance emergency response. Following steps explain the detailed working of smart ambulance system:

- Step 1: The Data Collection Module begins with continuous data ingestion. This module collects real-time information from trackers on ambulances, weather stations, traffic sensors, hospital capacity systems and emergency call centers. The Data Processing Module then cleans and normalizes this raw data, extracting relevant features for analysis. At the same time, this prepared data is processed by the Predictive Analytics Engine along with historical information from the central Database. In this research work, we consider the Random Forest algorithm (in the Predictive Analytics Engine) for its ability to handle complex, non-linear relationships and its robustness against overfitting [23], [24]. The engine produces two major outputs: (a) It predicts probable emergency hotspots as well as their likely severity levels. (b) It estimates current and forecasted travel times between different nodes in the network given prevailing traffic conditions. These predictions continue to be updated in the Traffic Module System that maintains an updated time dependent distance matrix. The dispatch optimization process will depend greatly on this matrix.

- Step 2: Once an emergency call comes in, immediately the system starts its response protocol. The current status and location of all ambulances are evaluated by the Resource Management Module so as to update availability vector. Simultaneously, the Predictive Analytics Engine reviews the reported emergency details against its predictive models to predict its severity and possible complexity. This is then related to current hospital capacities and specializations enabling patients to be directed to relevant healthcare facilities. It is this comprehensive evaluation that provides basis for dispatch decision that will follow.

- Step 3: To determine optimal ambulance dispatch strategies, the Dispatch Optimization Engine uses the customized Negamax algorithm. Several factors are taken into account by this engine at once:

  - The site of occurrence and seriousness of the reported emergency

  - Current and expected traffic situation (from Traffic Module)

  - Presence of ambulances and their locations (from Resource Management Module)

  - Expected future emergencies in different areas (from Predictive Analytics Engine)

  - Hospital capacities and specialties

The goal of the algorithm is to reduce total weighted response time while still achieving comprehensive emergency coverage. It is responsible for choosing both the most appropriate ambulance among those available for an ongoing emergency and accounting for its potential influence on forthcoming emergencies. After a dispatch decision has been made, the system automatically generates an optimized route for the selected ambulance considering real-time traffic conditions. This optimized route is immediately communicated to the crew through the Real-Time Communication Module.

- Step 4: As such, the system continues to monitor and adapt as it responds to emergencies. Real-Time Communication Module allows continual information exchange between an ambulance, a Dispatch Center, and a Receiving Hospital. If there are significant changes in traffic conditions, the Traffic Module will update its matrix and the Dispatch Optimization Engine can make recommendations on route adjustments in real-time. Also, if new emergencies occur then the entire network state should be re-evaluated by this system; hence optimal resources can be reassigned for maximum coverage. Throughout this process, all actions, decisions, and outcomes are logged in the Database Module. This data is then used to continuously refine and improve the system's predictive models and optimization algorithms, creating a feedback loop that enhances performance over time.

This integrated approach allows our smart ambulance system to not only respond efficiently to current emergencies but also to anticipate and prepare for future ones. By leveraging advanced algorithms and real-time data, the system can make complex, multi-factorial decisions that optimize resource utilization and minimize response times across the entire emergency response network.

V. Experimental Discussion

This section gives the experimental evaluation of proposed smart ambulance system and discusses obtained results. Section A introduces the experimental setup and section B analysis the performance of proposed system.

A. Experimental Setup

We conducted extensive simulations to compare the proposed system with a baseline system (discussed in the next sub-section) in order to determine the effectiveness of our proposed smart ambulance system. The experimental design was such that it represented real-life urban emergency response scenarios. Table I as follows shows the considered simulation settings:

TABLE I. SIMULATION SETTINGS

Setting	Number
Number of nodes (hospital/stations)	20
Number of ambulances	50
Simulation time steps	1000
Number of simulations	50

Synthetic data is generated in the simulations that would mimic real-world emergency scenarios. The data consists of the following attributes:

- Emergency locations: In this attribute, emergencies are randomly generated at different locations across 20 nodes.
- Emergency timing: This data attribute is simulated using Poisson distribution [25], [26] with an average of 2 emergencies per time step.
- Emergency severity: It is randomly assigned on a scale of 1-5 with 1 being the least severe and 5 being the most.
- Traffic conditions: It is a two-dimensional parameter, simulated with random fluctuations in travel times between the nodes.
- Ambulance availability: It is updated dynamically based on dispatch and return events.

Three key metrics are considered for the performance evaluation, they are defined as follows:

- Average Response Time: It is defined as the meantime (in minutes) taken by an ambulance after dispatch to arrive at the location of the emergency.
- Coverage Percentage: It is defined as the percentage of emergencies successfully responded to within the simulation period.
- Average Resource Utilization: A percentage measure out here gives the number of ambulances that are engaged in handling emergencies at any given instance.

B. Analysis of Result

The proposed smart ambulance system is evaluated in terms of the metrics defined above. For comparison, we considered a baseline system implemented using the same experimental setup. The baseline system differs with the proposed system in two contexts: (a) It uses a simple dispatch logic based on greedy algorithm (takes first available option). (b) It does not have any predictive and optimization component. The obtained results demonstrate the superiority of proposed system as compared to the baseline counterpart. They are explained in terms of each metric as follows:

Fig. 2 evaluates the proposed system in terms of average response time. It is clearly visible that the smart system shows an average response time of 8.54 minutes which is significantly lower than the one for the baseline system (17.53 minutes). The 51.28% improvement in this respect attributed to our advanced dispatch optimization engine of our system that uses real-time traffic data and predictive analytics for better decision making. The customized Negamax algorithm efficiently reduces response times by considering multiple factors simultaneously such as traffic conditions, ambulance availability, and emergency severity.

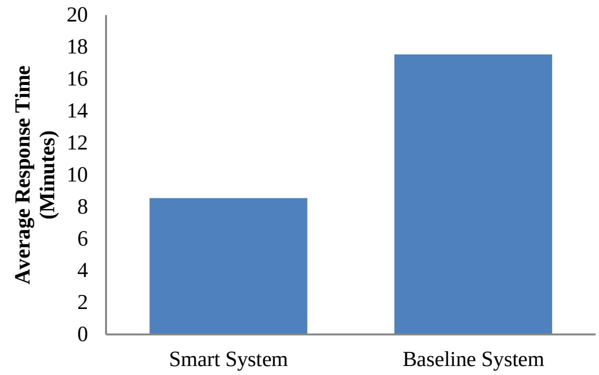

Fig. 2. Comparison of smart system with baseline system in terms of average response time.

Fig. 3 compares the two systems with respect to coverage percentage. It can be seen that both systems perform equally well but on closer examination some subtle yet important differences become apparent. Our smart system always attended emergencies faster thus managing slightly more incidents within a given time span. In reality, though, proposed system covered 98.46% emergencies while baseline covered 96.98%. This slight shift becomes important in a real-world case whereby even one missed emergency would have very dire outcomes.

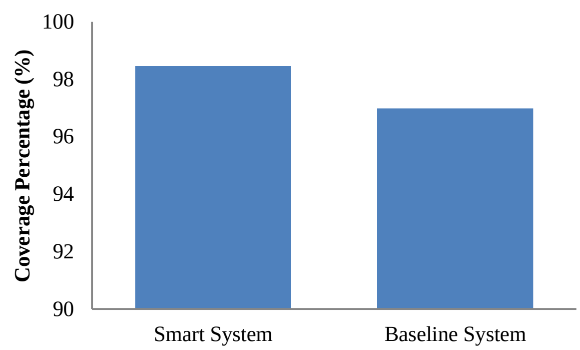

Fig. 3. Comparison of smart system with baseline system in terms of coverage percentage.

From the results in Fig. 4, it is clear that the smart system utilized resources far much better when compared with the baseline system at 41.27%, against baseline’s 33.82%. This means an improvement of about 22% implying that we designed a more efficient method for managing ambulances allocation and usage. The higher utilization rate is achieved without compromising response times, highlighting the effectiveness of our predictive analytics engine in anticipating emergency hotspots and strategically positioning ambulances.

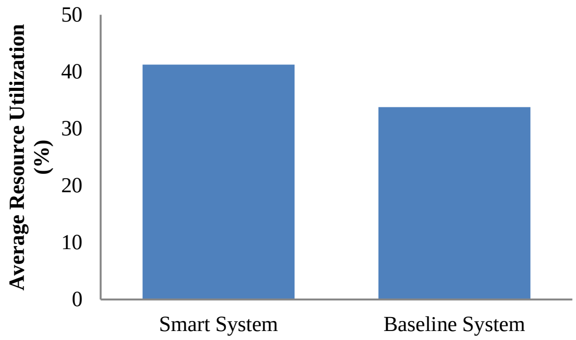

Fig. 4. Comparison of smart system with baseline system in terms of average resource utilization.

The superior performance our proposed smart ambulance system is attributed to five major factors. They are discussed as follows:

- Predictive Analytics: The use of machine learning techniques helps our system to forecast accidents and place ambulances in precarious places beforehand with a view of decreasing response time.
- Real-Time Optimization: Our customized Negamax algorithm can continually adapt to changing conditions and make optimal dispatch decisions based on current traffic, ambulance availability and emergency severity.
- Multi-criteria Decision Making: Unlike the baseline system which mainly focuses on distance, the smart system takes into account several issues while making choices so that resource allocation is more intelligent and better targeted.
- Dynamic Resource Management: The resource utilization in this case improves without affecting performance since it updates ambulance availability in real-time and considers future emergencies when choosing where they should be sent or dispatched.
- Severity-based Prioritization: By using both actual emergency severity level and predicted ones while making a decision, our system ensures that urgent cases receive faster responses hence promoting overall improvement in average response time.
- Despite these promising results, it's important to acknowledge some limitations of our study. The reliance on simulated data, while necessary for initial testing, may not fully capture the complexities of real-world emergency scenarios. Additionally, the computational resources required for real-time optimization could pose challenges in very large urban areas. Future work should address these limitations through real-world pilot studies and further optimization of the algorithm for scalability.

VI. Conclusion and Future Research Scope

This research endeavors to design a smart ambulance system for enhancing emergency response in the urban environments. By customizing the Negamax algorithm from game-building theory alongside real-time optimization and predictive analytics, the proposed system shows considerable improvement as compared to the conventional baseline method. Numerically, more than 50% improvement is observed in the response time besides having a resource utilization of about 22%.

The system acquires a proactive approach to predict emergencies using machine learning. Furthermore, the environment is dynamically updated through real-time optimization. The resource allocation is realized using multi-criteria decision-making. As a result, it provides an efficient way of dispatching ambulances, and in turn, enhances the emergency response. The proposed smart ambulance system can serve as a benchmark for future research advancements in this area. Moreover, it can also be integrated into wider smart city initiatives and AI-driven emergency management platforms.

For the future research perspective, different machine learning algorithms will be considered to model the predictive component. In addition, real-world dataset(s) will be taken into simulation for a better evaluation.

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