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Optimizing AED Placement and Human Resource Dispatch for OHCA Emergency Medical Services Considering the Stochastic Behavior of Volunteers

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Abstract

In the event of an out-of-hospital cardiac arrest (OHCA), providing emergency care within the golden rescue time is crucial for maximizing patient survival. However, due to insufficient Emergency Medical Services (EMS) resources, timely defibrillation or CPR is often not possible. To address this challenge, we leverage volunteers registered through the "First on Scene" app to provide immediate care before EMS arrival. This research aims to optimize Automated External Defibrillator (AED) placement and volunteer dispatch to maximize the expected survival rate of OHCA patients. Our approach ensures that the probability of providing emergency care within the golden rescue time meets a specified service level, considering the stochastic behavior of volunteers. We propose a stochastic simulation-optimization method using mixed binary and integer variables, incorporating data-driven models of OHCA occurrences, pedestrian flow volumes, and real road network data to simulate volunteer rescue routes. To identify the most effective AED locations and volunteer assignments, we employ a Rapid Screening algorithm based on OCBA-CO combined with a Nested Partition (NP) algorithm. In collaboration with the National Science and Technology Center for Disaster Reduction (NCDR) in Taiwan, we conduct simulations in the Sanmin District of Kaohsiung City to validate our algorithm's effectiveness and provide valuable management insights for OHCA emergency medical services.

Keywords
AED, OHCA, EMS, simulation optimization, stochastic volunteer behavior.

1. Introduction

Medical emergencies can be broadly classified into two categories: emergency and non-emergency, based on the severity of the patient's condition and the need for immediate medical intervention. Emergency medical events often pose a threat to life or limb, such as Out-of-Hospital Cardiac Arrest (OHCA), respiratory distress, severe trauma, or stroke. In particular, for OHCA patients, every second after cardiac arrest is critical, requiring immediate Cardiopulmonary Resuscitation (CPR) or the use of an Automated External Defibrillator (AED) for initial treatment to significantly increase survival chances.

OHCA represents a major global public health challenge, particularly in Taiwan, where approximately 20,000 people experience OHCA annually due to "cardiac causes." Empirical studies have shown that the survival rate of OHCA patients is closely related to the speed of emergency response. Each minute of delay in performing CPR reduces the chances of successful resuscitation by 7–10%. Moreover, the first six minutes following OHCA, referred to as the "golden rescue time," are crucial. CPR or defibrillation with an AED during this period greatly enhances survival rates and reduces the likelihood of permanent brain damage. However, statistics from Taiwan in 2022 reveal that the national average response time for 119 ambulances is 6.78 minutes, exceeding the golden rescue window. This is particularly problematic in remote areas and during peak traffic hours, where limited Emergency Medical Services (EMS) resources result in missed opportunities for optimal rescue, further underscoring the challenges and urgency of OHCA rescue efforts.

To address the limitations of EMS systems, many countries have explored ways to improve the availability of medical resources during the Pre-EMS stage, before the arrival of emergency services. For example, early SMS-based alert systems in Nordic countries, as well as emergency apps in the United States, the United Kingdom, and Singapore, leverage push notification technology to mobilize volunteers. In Taiwan, the "First Responder" app was launched in 2022, integrating mobile positioning technology and volunteer dispatch functions to notify nearby volunteers to perform CPR or retrieve AEDs during OHCA incidents. Despite the app having over 18,000 registered volunteers, 60% of whom are members of the general public, only 6% of OHCA cases have successfully dispatched volunteers for rescue. Low participation rates and the uncertainty of volunteer behavior—such as whether they accept tasks or abandon them mid-way—significantly impact rescue efficiency, highlighting the need for further optimization of existing strategies.

Current research on the Pre-EMS stage largely focuses on theoretical analyses of equipment deployment, particularly optimizing AED placement. However, these studies often overlook the impact of stochastic volunteer behavior on rescue efficiency. In real-world scenarios, even if AEDs are deployed near OHCA locations, their rescue effectiveness cannot be fully realized without timely utilization by volunteers. Therefore, this study focuses on OHCA events by not only optimizing AED placement but also integrating volunteer dispatch strategies that account for stochastic behaviors, such as task acceptance and mid-task abandonment. By incorporating historical data, this research aims to explore more comprehensive Pre-EMS setups and resource deployment strategies, providing decision support for EMS systems, addressing gaps in the existing literature, and improving emergency rescue efficiency under resource constraints, ultimately contributing to public health.

1.1 Objectives

This study focuses on the Pre-EMS resource allocation for OHCA (Out-of-Hospital Cardiac Arrest) patients by applying simulation optimization methods to determine the optimal AED deployment locations and the most effective volunteer dispatch strategies, aiming to maximize the expected survival probability of OHCA patients. Additionally, the simulation model incorporates stochastic factors related to volunteer dispatch through the First Responder app, making the study more aligned with real-world operations. The objectives of this research are summarized as follows:

1. This study develops a Mixed Binary and Integer Simulation Optimization model with stochastic constraints to solve the Pre-EMS resource allocation problem.
2. This study considers the following stochastic factors during OHCA incidents, including simultaneous volunteer dispatch through the First Responder app and ambulance dispatch:
   (1) The location and time of OHCA occurrences.
   (2) The number of pedestrians near the OHCA location.
   (3) The locations of available volunteers.
   (4) Whether volunteers are available to accept dispatch.
   (5) Whether volunteers abandon the task after accepting dispatch.

(6) The type of tasks assigned to volunteers.
These factors are integrated into the simulation to reflect the stochastic behaviors of volunteers under real-world conditions during OHCA emergencies.

3. This study collaborates with the National Science and Technology Center for Disaster Reduction (NCDR) and utilizes real historical OHCA data, pedestrian flow data, and road network data provided by NCDR. A data-driven approach is adopted to construct the stochastic simulation optimization model.

4. The decision variables of the OCBA-CO-based Mixed Binary and Integer Simulation Optimization model constructed in this study include binary and positive integer variables. To obtain feasible optimal solutions under limited simulation resources, this study proposes a simulation optimization algorithm: OCBA-CO based RSNP. This method comprises three components: OCBA-CO, RS, and NP. Given that the mathematical model includes stochastic constraints to ensure that the probability of OHCA patients receiving initial rescue within the golden rescue time meets a specified level, the OCBA-CO (Optimal Computing Budget Allocation for Constrained Optimization) method simultaneously considers solution feasibility probability and optimality probability for efficient allocation of simulation resources. RS and NP focus on decision-making for binary and positive integer variables, respectively.
5. This study aims to ensure that OHCA patients have a guaranteed probability of receiving initial rescue within the golden rescue time by using simulation optimization methods. The goal is to identify the optimal AED deployment locations and volunteer dispatch strategies to maximize the expected survival probability of each OHCA incident.

2. Literature Review

2.1 AED Deployment Strategies

AED deployment plays a critical role in improving the survival rate of OHCA patients by ensuring timely access to defibrillation. Prior research has proposed various optimization approaches to identify optimal AED locations. Bonnet et al. (2015) demonstrated that AED deployment significantly reduces the time to defibrillation and improves survival outcomes. They introduced an innovative urban planning approach that considers walking paths, device availability, and multi-objective optimization. Their findings in a Hoboken, New Jersey case study showed an 11.44–16.30% improvement in survival rates compared to basic optimization methods.

Chan et al. (2016) applied the Maximum Covering Location Problem (MCLP) to optimize AED placement, incorporating bystander behavior and spatial probability distributions using Kernel Density Estimation. Their results, based on Toronto data, showed a 40% improvement in coverage compared to existing methods. Sun et al. (2016) further extended optimization models to include spatiotemporal accessibility, demonstrating a 25.3% increase in AED coverage over spatial-only approaches.

Recent advancements include Zhang et al. (2023), who proposed an overlayed spatial-temporal optimization (OSTO) model that accounts for dynamic OHCA scenarios with budget constraints. Their application in Washington, D.C., revealed significant improvements in AED coverage and offered a systematic framework for resource-limited municipalities. However, several studies, such as Chan et al. (2018), highlighted limitations, noting that most models assume the constant availability of bystanders, which may overestimate system performance.

2.2 Volunteer Dispatch Strategies

Volunteer dispatch has emerged as a complementary solution to address EMS delays. Cairns et al. (2011) developed a Monte Carlo simulation to evaluate mobile volunteer cardiac first-responder programs, highlighting the potential to reduce defibrillation times and improve survival. Studies from Niki et al. (2019) and van den Berg et al. (2021) proposed models to optimize the number and type of dispatched volunteers (e.g., AED retrieval vs. CPR delivery), considering spatial distributions and response times. These models demonstrated enhanced survival rates compared to rule-based approaches.

Matinrad et al. (2021) addressed uncertainties in volunteer task assignment, such as willingness to accept tasks and abandonment rates. Their proposed optimization model outperformed static methods used in Swedish volunteer programs. Similarly, Lancaster and Herrmann (2021) evaluated novel OHCA response systems, including volunteer dispatch and AED delivery via drones, using geospatial Monte Carlo simulations to predict survival improvements. Recent work by Paz et al. (2022) emphasized the integration of citizen responders with real-time EMS operations, suggesting a locally optimal dispatch procedure to balance immediate response and future resource readiness. Matinrad and Granberg (2023) further refined optimization models to address uncertainties in volunteer availability, though computational challenges remain for large-scale implementation.

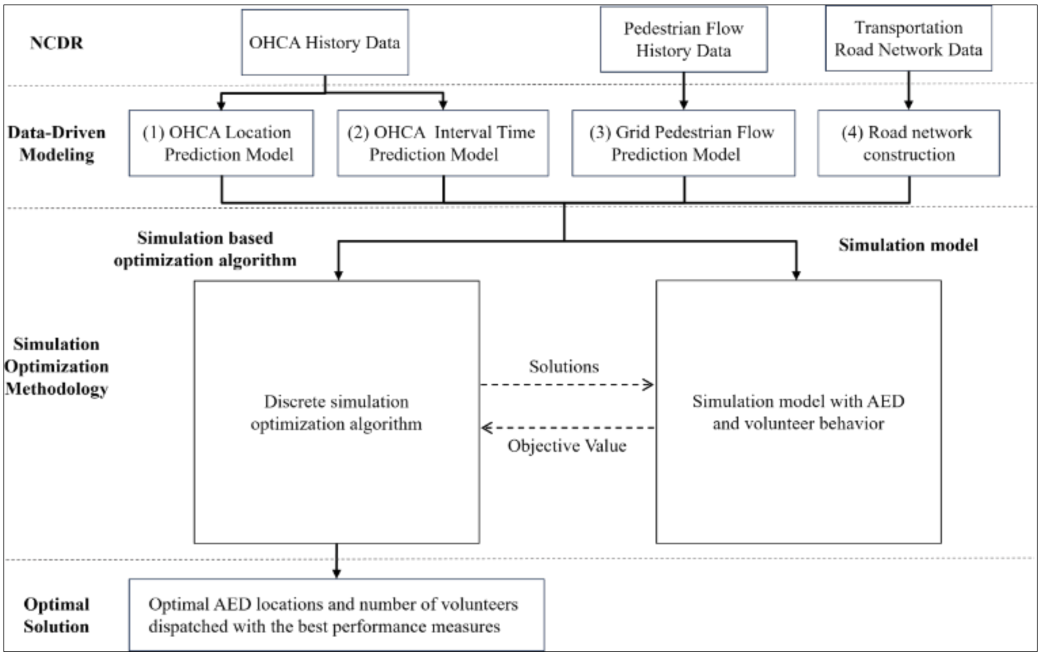

Figure 1. Methodological Framework

3. Data-driven Modeling Framework

To address the gaps in AED coverage for high-risk OHCA zones and improve survival rates, this study aims to redeploy AEDs by considering both spatial and behavioral factors. While AEDs may already be located near OHCA hotspots, their effectiveness depends heavily on the ability of volunteers to retrieve the devices and deliver them to patients in a timely manner. Therefore, this research not only focuses on optimizing AED placement but also takes into account volunteer behavior and dispatch strategies to determine how many volunteers should be sent to each emergency, aiming to maximize the expected survival rate.

This section details the construction of data-driven models using historical data, as shown in Figure 1. Four distinct models form the core of this analysis. Section 3.1 introduces the OHCA Location Prediction Model, Section 3.2 discusses the OHCA Interval Time Prediction Model, Section 3.3 explains the Grid Pedestrian Flow Prediction Model, and Section 3.4 presents the Road Network Construction.

3.1 OHCA Location Prediction Model

Step 1: Obtain OHCA historical data from NCDR, covering the period from 2022/01/01 to 2022/12/31, including the geographic coordinates of each incident.

Step 2: Use publicly available geographic data (TWD97 coordinates) to assign OHCA incidents to specific city districts and select relevant target areas for analysis.

Step 3: Develop a 2D Kernel Density Estimation (KDE) model with Gaussian kernels. Optimize the bandwidth using GridSearchCV combined with Leave-One-Out cross-validation.

Step 4: Apply the KDE model to generate simulated OHCA locations, utilizing the selected optimal bandwidth and Gaussian kernel for further analysis.

3.2 OHCA Interval Time Prediction Model

Step 1: Collect historical OHCA occurrence data provided by NCDR for the period from 2022/01/01 to 2022/12/31. The required data includes the "dispatch time" information.

Step 2: Process the data by using the "dispatch time" column to calculate the time interval between each OHCA incident and the previous one. Store the results in a CSV file.

Step 3: Build the OHCA Interval Time Prediction Model by fitting the "interval time" data to various probability distributions. Perform the Kolmogorov-Smirnov goodness-of-fit test to identify the best-fitting distribution based on the actual data.

Step 4: Use the OHCA Interval Time Prediction Model to generate sample data. Combine the predicted OHCA intervals with the OHCA Location Prediction Model to simulate future OHCA incidents.

3.3 OHCA Location Prediction Model

Step 1: Collect historical pedestrian flow data, including grid codes, dates, time points, and pedestrian flow counts. The grid divides the study area into square cells, and the time points indicate specific intervals for observation.

Step 2: Analyze the pedestrian flow patterns in each grid over a 24-hour period. Create a box plot for each grid to visualize the changes in pedestrian flow throughout the day.

Figure 2: Kaohsiung City Road Network Construction Diagram

Step 3: Use Kernel Density Estimation (KDE) to model the pedestrian flow distribution at each time point (with 10-minute intervals). The KDE is composed of a kernel function and bandwidth to capture the flow distribution for each grid.

Step 4: Sample pedestrian flow counts for each grid and time point using the KDE model, allowing the simulation system to generate pedestrian flow patterns.

3.4 Road Network Construction

The road network data used in this study was provided by NCDR and includes grid codes, road identifiers, road lengths, and widths. This data is used to construct the road network for Kaohsiung City, as shown in figure 2.

4. Simulation Optimization Methodology

4.1 Problem Definition

This study addresses four critical decisions: (1) identifying candidate AED locations, (2) determining the placement of existing AEDs, (3) deciding the number of volunteers dispatched for CPR, and (4) deciding the number of volunteers dispatched to retrieve AEDs.

To ensure both cost efficiency and adequate coverage, there are upper and lower limits on the total number of AED placements. The objective is to choose optimal locations from both candidate and existing AED sets to ensure availability without incurring unnecessary costs or leaving areas underserved. Similarly, upper and lower limits are set for the number of volunteers dispatched to CPR or AED retrieval to avoid resource waste or insufficient emergency response.

The goal is to maximize the expected survival rate of OHCA patients by optimizing AED placement and volunteer dispatch, considering real-world constraints such as volunteer availability, response behavior, and incident locations. The model also aims to ensure that emergency care is provided within the golden rescue time, meeting a specified service level for both AED retrieval and CPR response.

4.2 Problem Assumptions

1. All deployed AEDs function properly.
2. Volunteers are categorized into two groups: those retrieving AEDs and those performing CPR.
3. All volunteers are pedestrians, and their rescue speed is equivalent to running speed, excluding scenarios involving vehicle use.
4. The number of volunteers registered through the "First On Scene" app follows a given probability distribution.
5. The number of volunteers accepting dispatch assignments follows a given probability.
6. Volunteers dispatched for AED retrieval and CPR follow a given probability distribution.
7. Each OHCA incident will have both an AED retrieval volunteer and a CPR volunteer responding.
8. There is a given probability that volunteers who have accepted the dispatch may abandon the rescue midway.
9. The location of volunteers is distributed proportionally to the road area within each grid.
10. The survival probability is defined by a given two-dimensional function, as proposed by Matinrad et al. (2019), which is determined by the rescue times for receiving AED and CPR assistance in each OHCA event as function (1).

$$f\left(T^{AED^*}, T^{CPR^*}\right) = \frac{1}{1+e^{(-1.3614\,+\,0.3429\,\times\,T^{CPR^*}+\,0.18633\,\times\,T^{AED^*})}} \quad (1)$$

4.3 Mathematical Model

Objective function

$$Maximize\ E[S(\mathbf{X}, \mathbf{Y}, Z^{AED}, Z^{CPR}, \omega)] \qquad (2)$$

Constraints

$$\underline{n} \leq \sum_{i \in I^C} X_i + \sum_{i \in I^E} Y_i \leq \overline{n} \qquad (3)$$

$$\underline{m^{AED}} \leq Z^{AED} \leq \overline{m^{AED}} \qquad (4)$$

$$\underline{m^{CPR}} \leq Z^{CPR} \leq \overline{m^{CPR}} \qquad (5)$$

$$P(\,T^{AED^*} \geq GT^{AED}) \leq (1 - L^{AED}) \qquad (6)$$

$$P(\,T^{CPR^*} \geq GT^{CPR}) \leq (1 - L^{CPR}) \qquad (7)$$

$$X_i \in \{0,\ 1\} \quad \forall_i\ \in I^C \qquad (8)$$

$$Y_i \in \{0,\ 1\} \quad \forall_i\ \in I^E \qquad (9)$$

$$Z^{AED}, Z^{CPR} \in Z^+ \qquad (10)$$

In this study, the objective function (2) is to maximize the expected survival probability for each OHCA patient, where the survival probability formula is as mentioned in assumption 10. In this formula, $\mathbf{X}, \mathbf{Y}, Z^{AED}$ and Z^{CPR} represent the decision variables, and ω represents the stochastic factors.

Constraint (3) limits the total number of candidate and existing AED placements. Constraints (4) and (5) regulate the number of volunteers dispatched for AED retrieval and CPR, respectively. Constraints (6) and (7) are stochastic constraints for volunteers retrieving AEDs and performing CPR, ensuring that the probability of exceeding the golden rescue time is below a certain service level threshold. Constraints (8) and (9) define the candidate and existing AED placements as binary variables. Constraint (10) specifies that the number of volunteers dispatched for CPR and AED retrieval must be positive integers.

4.4 Simulation based Optimization Algorithm

This study proposes the RS-NP algorithm based on OCBA-CO, with its structure illustrated in Figure 3. The decision variables consist of a combination of binary and positive integer variables. The binary variables represent the AED placement decisions, which are handled by the Rapid Screening Algorithm (RS), initially proposed by Tsai (2013). To determine the corresponding number of volunteers to dispatch for each AED placement combination—a two-dimensional positive integer combination—the RS is embedded with the Nested Partitions Algorithm (NP), introduced by Shi and Ólafsson (2000). The combined solution from RS-NP, which includes both AED placements and volunteer dispatch numbers, is then input into a simulation system to obtain the objective value.

Due to the stochastic constraints in the mathematical model, the simulation system incorporates the Optimal Computing Budget Allocation for Constrained Optimization (OCBA-CO) method proposed by Lee et al. (2009). This method allocates simulation resources while considering the feasibility of each solution, significantly reducing the probability of infeasible solutions being returned as the optimal result.

5. Results and Discussion

This study focuses on Kaohsiung City's Sanmin District, aiming to redeploy AEDs and optimize volunteer dispatch to maximize the expected survival rate of OHCA patients. The total number of AEDs is set between 100 and 180, with the original number being 115. The lower limit is chosen to explore whether repositioning existing AEDs can achieve the optimal result, while the upper limit considers the cost of installing new AEDs. During the simulation, 100 to 180 AED locations will be selected from a total of 351 possible sites. The number of volunteers dispatched for AED retrieval and CPR ranges from 3 to 8, with the golden rescue time set at 6 minutes and a service level of 90%.

Table 1: Comparison of Experimental Results and Scenarios

	AED (Exist/Candidate)	Volunteer number (AED , CPR)	Expected survival rate	Expected AED response time		Expected CPR response time			Probability of AED in 6 mins	Probability of CPR in 6 mins	Coverage rate
				Resource proportion (EMS / AED)		Resource proportion (EMS / AED / CPR)					
Only EMS	X	X	0.1193	6 m 21 s		6 m 21 s			X	X	X
Exist AED	115 (115 / 0)	(6 , 8)	0.3349	4 m 56 s		3 m 31 s			0.73	0.94	10.78 %
				49.02 %	50.98 %	24.49 %	3.92 %	70.59 %			
Exist + Candidate AED	351 (115 / 236)	(6 , 8)	0.3946	3 m 58 s		3 m 12 s			0.98	0.98	34.44 %
				18.52 %	81.48 %	11.11 %	31.48 %	57.41 %			
Case 1	101 (19 / 82)	(6 , 8)	0.3726	4 m 16 s		3 m 15 s			0.95	0.98	27.87 %
				30.36 %	69.64 %	16.07 %	14.29 %	69.64 %			
Case 2	168 (37 / 132)	(7 , 5)	0.3773	4 m 17 s		3 m 16 s			0.96	1	33.31 %
				13.04 %	86.96 %	4.35 %	21.74 %	73.91 %			

The rescue time for AEDs is the minimum of the travel times for EMS or AED volunteers, and the CPR rescue time is the minimum of the travel times for EMS, AED volunteers, or CPR volunteers.

EMS travel time follows a normal distribution, with the mean and standard deviation based on 2022 statistics for Sanmin District. Additionally, the dispatch time for both AED and CPR volunteers follows a uniform distribution of 1 to 2 minutes, while AED volunteers' time to deliver a shock after reaching the OHCA site follows a uniform distribution of 15 to 45 seconds. The simulation is limited to 1,000 iterations, and the optimal solution is re-evaluated through a 30-day simulation to ensure accuracy and fairness.

The experimental results are shown in Table 1. In the first scenario, where only EMS is available, the expected survival rate is 0.1193, and the response time exceeds the 6-minute golden rescue time. In the second scenario, with 115 AEDs and 6 AED plus 8 CPR volunteers, the expected survival rate improves significantly, but only 73% of OHCA cases meet the 6-minute AED response time, falling short of the 90% service level target. The third row considers the case of deploying all 351 AEDs, representing the optimal configuration, but this scenario does not meet the study's constraints and is not discussed further.

In Case 1, 101 AEDs are deployed (19 existing, 82 new), with 6 AED and 8 CPR volunteers. The expected survival rate is 0.3726, with all response times under 6 minutes. EMS dependence drops to 30.36% for AEDs and 16.07% for CPR, showing that adjusting AED placements and using volunteers can substantially improve outcomes without increasing the number of AEDs. In Case 2, 168 AEDs are deployed (37 existing, 132 new), with 7 AED and 5 CPR volunteers. The expected survival rate reaches 0.3773, with EMS dependence reduced to 13.04% for AEDs and 4.35% for CPR. Decision-makers can consider whether adding more AEDs to further reduce EMS load is worth the additional cost, or if improving existing placements is sufficient.

6. Conclusion

This study developed a mixed binary and integer variable algorithm that integrates the OCBA-CO simulation resource allocation method, enabling the identification of optimal solutions with high feasibility. The results demonstrate that optimizing the placement of existing AEDs, even under a limited budget, and coordinating with volunteer support can increase the expected survival rate for OHCA patients by 3.12 times. Furthermore, with a sufficient budget for deploying additional AEDs, not only is the expected survival rate further improved, but the reliance on EMS in rescue operations decreases significantly—from 100% to just 13.04%. By accounting for the stochastic behavior of volunteers, this research highlights the critical relationship between the effectiveness of AED deployment and volunteer actions, emphasizing the importance of integrated strategies for enhancing emergency response outcomes.

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