A Multi-Objective Facility Coverage Location Problem for Emergency Medical Service Decisions in Hajj

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Abstract

This paper proposes a multi-objective facility model of coverage location problem to determine the number, locations, and redeployments of Emergency Medical Services (EMS) system. The EMS runs with two types of ambulances, Basic Life Support (BLS) and Advance Life Support (ALS). The suggested Multi-objective Coverage Location model (MO-CL) considers a bi-objective function, which is minimizing the EMS costs and the fatigue of EMS crew members. This can be managed by reducing the number of redeployments for both types of ambulances while still providing the required coverage levels. The MO-CL model is based on the approximation hypercube model that eliminates the assumptions of autonomous ambulance operation and system-wide busy probability. It can be solved by applying a modified MO-CL search algorithm. The model and solution method have been applied for a case study based on real data collected from the Al Noor Specialist Hospital in Makkah, Saudi Arabia during the period of fifteen days of Hajj pilgrimage. The results showed that, to achieve the 95% coverage threshold of critical and non-critical demand, the MO-CL model needs at least 64 ambulances (29 ALS, 12 for BLS backups, and 23 for BLS) and 19 redeployments for every day (9 for ALS, 2 for BLS backup, and 8 for BLS).

Keywords: Comprehensive search algorithm, Emergency medical services, Facility coverage location problem, Hajj Pilgrim, Incremental search algorithm, Multi-objective model.

Introduction

One of the most important services that communities provide to their residents is the EMS. They must be accessible around-the-clock since their main objective is to react immediately and consistently to provide everyone who needs an emergency medical service with first aid care. In such critical cases, there is a need to reduce the response time by imposing location and relocation restrictions on EMS facilities. However, the goals and limitations of situating or assigning EMS facilities based on the spatial arrangements [1,2]. The Facility Coverage Location Problem (FCLP) developed by Hotellin [3], was one of the methodologies used to solve real-world problems. The majority of the FCLP was designed with a single objective function. However, such models are not always ideal, especially when demand locations are geographically distributed and not weighed equally [4,5]. Consequently, a multi-objective FCLP is established. According to Rabbani [6], a multi-

objective analysis has various benefits over single objective analysis. The multi-objective approach allows for the evaluation of multiple criteria in their natural units of measurement. It is not essential to convert the different objectives to a standardized unit of measurement. In addition, it provides the decision-maker with a collection of non-inferior or non-dominated alternatives. Moreover, the multi-objective model offers a mechanism for analyzing the consequences of strategic policy choices, which usually include reordering priorities. There are many studies that consider the multi-objective FCLP [7,8]. Such studies focused on variety of topics including the EMS, operations connected to security and defense, helicopter search and rescue, relief distribution points and firefighting operations [9,10]. For example, Shahparvari et al., [11] proposed a model that considers a wide variety of strategic considerations in order to locate fire station facilities in Melbourne, Victoria in Australia. The authors have applied location allocation models under the GIS environment to test the optimality of spatial of the existing fire stations. Similar work have been proposed by [12] where authors introduced a goal-programming method. Using a fuzzy bi-objective model, Fukushima and Moriya [13] examined the reasons that ambulance used longer travel time through applying an analysis of emergency vehicle activity sign a GPS system in the City of Saitama in Japan. The study includes the following assumptions: (i) the length of response time was longer because of hug volumes of received calls. (ii) various factors could affect the travel time of ambulances such as, weather conditions, congestion of road traffic, time of day and day of the week from the location to the hospital. Han et al. [14] proposed a simple model of selection of emergency locations based on real traffic state and the simulation approach that is based on random demand in space. The work also considers real data and uses the K-means clustering algorithm to quantitatively simulate and describe fire demand. Thereafter, an optimization technique confirmed that the integration of real speed of road network into the model of site is a set cover. This participates in minimizing the travel time between the fire station to the simulated demand locations with real speed. Other research works were done on using multi-criteria decision making methods (MCDM) to select the best location of health facility location problem. The research [15] applied a MCDM analysis to select the best location of

hospital site where a real case study was considered. Drezner et al [16] proposed a multi-objective model for casualty collection points location problem. The authors introduced a minimax regret multi-objective model based on the concept of minimax regret in decision analysis. A tabu Search (TS) and descent heuristic are used as solution methods. The research [17] developed a multi-objective optimization model to determine the location and allocation of mobile aeromedical staging facilities assets over the phases of a military deployment. Mohammed et al. [18] introduced the TS algorithm with multi-objectives to design multi-product, multi-echelon and multi-objective supply-chain network problem. They applied an improved algorithm that considers different features related to strategic decisions in the supply-chain. Moreover, the proposed model that tested with TS algorithm includes five echelons, which are manufacturing plants, suppliers, warehouses, customers, and distribution centers. Based on the three core objectives of fairness, efficiency, and cost, He and Xie [19] introduced a multi-objective bi-level L-A mathematical model to maximize the social and economic benefit. Also, it is used to determine the service areas and shelter locations. In addition, the proposed model considers several factors comprehensively, for example, the utilization efficiency, the level of decision-making and capacity constraints of shelters. The gravity model is proposed to simulate the behavior of decision-making of evacuees. Zhang et al. [20] studied a two-level medical facility location problem (TLMFL) with multiple patient flows between medical facilities and demand points. The study was carried out to improve the application of a hierarchical diagnosis and treatment system. The model used a direct interpretation of the TLMFL as a multi-objective problem to balance distinct conflicting criterion efficiently. The multi-objective TS and the speedy construction procedure of the Pareto non-dominated solution have been used in their work. They proposed a procedure that produces a set of solutions, which represents the trade-off among the conflicting objectives. Wang et al. [21] suggested a multi-objective location problem with uncertainty of facilities where the multiple coverage of variable radius is used to minimize the impact of disruption of facilities. To solve this problem, an evolutionary algorithm based on dual population has been used to optimize the location and radius together. This was done where the strategy of interaction is adapted to collaborate with

each other. Ghobar et al. [22] provided a model of hub location for fundamental commodities to reduce the pollution of emissions and to meet dynamic demand. Since the introduced model is a bi-objective function with the objectives of minimizing pollution emission and costs, two solution methods of Pareto-based have been used, which are the Non-dominated Ranking Genetic algorithm and Non-dominated Sorting Genetic algorithm (NSGA-II). Yakıcı et al. [23] introduced a model of multi-objective facility location analytics for real case study. The model was used to determine the number of temporary emergency service centers and their locations. The study also is carried out for the regional natural gas distribution company in Turkey. Olivos et al. [24] presented a multi-objective ambulance location problem considering Antofagasta (Chile) as the case study. The model was solved by using the ε-constraint method, obtaining efficient solutions that improve the current state. Also, a multi-objective model under dynamic environment with the objective of optimizing the location and allocation of search and rescue boats has been introduced in [25]. Doolun et al. [26] created a multi-goal approach for finding supply chain facilities. The authors employ a hybrid NSGA-II and DE algorithm to maximize cost, CO2 reduction, and fill rate.

According to the previously mentioned research works, multi-purpose models were utilized in several sectors of life. However, these models have only applied to a few situations of congestion issues of pilgrim [27-29]. There are many research in the literature include hybridization of heuristics and metaheuristics to various optimization problems. Iqbal et al. [30] applied a Particle Swarm Optimizer-based Hyper Heuristic to solve the university course timetable problem.

A hybridization of search heuristics and TS algorithm are applied in this paper. Also, this work presents a multi-objective facility coverage location problem for dynamic settings based on the premise of an EMS system. The EMS operates with ALS and BLS and receives critical and non-critical demand. In this problem, the ALS ambulances handle critical demand while the BLS ambulances supply "backup" coverage for non-critical demand. Also, the BLS ambulances handle non-emergency calls. The model permits redeployment of ambulances throughout a specific time period while reducing EMS crew member fatigue. It is also predicting coverage to critical and non-critical demand based on the ALS and BLS allocations, which boosts the model's realism during Al-Hajj. In addition, a metaheuristic search approach is employed to solve the proposed problem. Moreover, both model and solution method are applied to study case of Al Noor Specialist Hospital in Makkah, Saudia Arabia, during the period of fifteen days of Hajj pilgrimage.

The remainder of this paper is structured as follows. Section 2 introduces the proposed MO-CL model with two types of servers. Section 3 describes the MO-CL search algorithm. The experimental study and analysis are given in Section 4. Finally, the conclusion and future works are presented in Section 5.

Methods

MO-CL Model with Two Types of Servers
In this section, the proposed MO-CL model is formulated to achieve the following two objectives:

- Minimizing the number of BLS and ALS to save the EMS costs.
- Minimizing redeployments of the two types of ambulances to reduce the EMS staff fatigue while fulfilling the goals of coverage.

Non-critical calls for service are deemed "covered" if the ambulances ALS or BLS can be deployed within the time frame and with the required level of reliability α_t, whereas BLS ambulances are considered "covered" when one of BLS can be deployed within the time frame and with the required level of reliability α_t. According to Jarvis [31], the suggested MO-CL model assumes that the servers of ALS and BLS ambulances operate at time period t independently. Then this "error" is corrected by using the correction factors, which is a function of the number of servers (m_t^A, m_t^B), the average busy probability ($\rho_{i,t}^A, \rho_{i,t}^B$) and the preferred server that is providing the service j, $Q^A(m_t^A, \rho_t^A, j), Q^B(m_t^B, \rho_t^B, j)$, respectively. To derive the correction factor, consider the $M/M/m/loss$ queuing system with the average busy probability of ALS and BLS (ρ_t^A, ρ_t^B), the probability that all ambulances of type ALS and BLS are free with the loss system (P_0^A, P_0^B), and probabilities of all ALS and BLS are busy with the loss system (P^A, P^B), respectively [32,33]. The

correction factors of servers ALS and BLS are given by:

$$Q^A(m_t^A, \rho_t^A, j) = \frac{R_1^A}{R_2^A}, \quad j = 0, 1, \cdots, m_t^A - 1 \qquad 1$$

$$Q^B(m_t^B, \rho_t^B, j) = \frac{R_1^B}{R_2^B}, \quad j = 0, 1, \cdots, m_t^B - 1 \qquad 2$$

Where

$R_1^A = \sum_{k=j}^{m_t^A-1} (m_t^A - j - 1)! (m_t^A - k) \left(\rho_t^{A^{k-j}}\right) P_0^A$,

$R_2^A = (k - j)! (1 - P^A)^j (m_t^A)!$,

$R_1^B = \sum_{k=j}^{m_t^B-1} (m_t^B - j - 1)! (m_t^B - k) \left(\rho_t^{B^{k-j}}\right) P_0^B$

and $R_2^B = (k - j)! (1 - P^B)^j (m_t^B)!$.

The values for the correction factors $(Q^A(m_t^A, \rho_t^A, j), Q^B(m_t^B, \rho_t^B, j))$ are utilized as input in the proposed model. The Jarvis' approximation algorithm for the correction factors occupied probability of ALS can be given by the following steps:

Step 1. Initialize $\rho_t^A = \frac{\lambda_i^A \tau_i^A}{m_t^A}$ where ρ_t^A is the average ALS busy probability, m_t^A refers to number of ALS, λ_i^A is critical call arrival rate at interval time t, τ_i^A is ALS service time at node i.

Step 2. Compute the following:

$$Q^A(m_t^A, \rho_t^A, j) = \left[\frac{\left(\sum_{k=j}^{m_t^A} (m_t^A - j - 1)(m_t^A - k) \left(\rho_t^{A^{k-j}}\right)\right) P_0^A}{((k - j)! (1 - P^A)^j (m_t^A)!)}\right]$$

for $j = 0, .. m_t^A - 1$.

Step 3. Use the following formula to calculate the revised estimate for ALS workloads:

$\rho_{j,t}^A(new) = \frac{(V_j^A)}{(1 + V_j^A)}$ where

$$V_j^A = \sum_{k=1}^{m_t^A} \sum_{i:a_{ik}^A = j} \lambda_i^A \tau_i^A Q^A(m_t^A, \rho_t^A, k - 1) \prod_{l=1}^{k-1} \rho_{a_{il}^A}^A$$

Step 4. Stop when the maximum change is smaller than the convergence threshold.

Else calculate $P^A = 1 - \frac{(\sum_{j=1}^{m_t^A} \rho_{j,t}^A)}{m_t^A \rho_t^A}$.

Step 5. Return to step 2.

The same can be applied to adjust factors $Q^B(m_t^B, \rho_t^B, j)$, occupied probabilities to BLS (P^B) with the average BLS occupied probability $\rho_t^B = \frac{(\lambda_i^A + \lambda_i^B)(\tau_i^A + \tau_i^B)}{m_t^B}$ where m_t^B refers to the number of BLS in existence at time t; λ_i^B non-critical calls arriving at time t; τ_i^B BLS service time.

MO-CL model assumes the following:

- The workday is divided into time periods $t = 1, \ldots, T$.
- J_t^A assigned to the node that contains an ALS ambulance at time period t.
- J_t^B assigned to the node that contains an BLS ambulance at time period t.
- α_t^A be available for ALS coverage at time t.
- α_t^B be ALS available coverage for time t.
- c_t^A represent the minimum predicted coverage level of ALS at period t.
- c_t^B be the minimum expected coverage of BLS at t.
- At time period t, let m_t^A and m_t^B are the number of ALS and BLS, $h_{i,t}^A$ and $h_{i,t}^B$ are the fractions of total demand at node i at time t, and $\rho_{i,t}^A$ and $\rho_{i,t}^B$ be the busy probability of ALS and BLS at node i, respectively.
- Let ρ_t^A and ρ_t^B be the average busy probability of ALS and BLS, P_0^A and are the probability that all ambulances of type ALS and BLS are free with the loss system, respectively.
- Assume that P^A and P^B are probabilities of all ALS, BLS are busy with the loss system, $Q^A(m_t^A, \rho_t^A, j)$ and $Q^B(m_t^B, \rho_t^B, j)$ be the correction factors for Jarvis algorithm that adjusts a probability of ALS, BLS that work dependently, respectively.
- Assume that D_i^A, D_i^B the set of the nodes within the maximum relocation (F, H) for ALS and BLS at node i. $(\xi_{i,t}^+)^A$, $(\xi_{i,t}^+)^B$ the number of redeployments for the ALS and BLS that are redeployed out of the location node i.

Then we can define the following decision variables

$x_{i,j,t}^A = \begin{cases} 1, & \text{if the ALS } j \text{ is in the node } i \text{ at time } t \\ 0, & \text{otherwis} \end{cases}$

$x_{i,j,t}^B = \begin{cases} 1, & \text{if the BLS } j \text{ is in the node } i \text{ at time } t \\ 0, & \text{ohterwise} \end{cases}$

$y_{i,t}^A = \begin{cases} 1, & \text{if at least one ALS or BLS covered} \\ & \text{node } i \text{ with } \alpha_t^A \text{ at time } t \\ 0, & \text{otherwis} \end{cases}$

$y_{i,t}^B = \begin{cases} 1, & \text{if at least one BLS covered node } i \\ & \text{with } \alpha_t^B \text{ at time } t \\ 0, & \text{otherwis} \end{cases}$

$$a_{i,j}^A = \begin{cases} 1, & \text{if the node } i \text{ within } S \text{ threshold of} \\ & \text{ALS or BLS at node } j \\ 0, & \text{otherwis} \end{cases}$$

$$a_{i,j}^B = \begin{cases} 1, & \text{if the node } i \text{ within } T \text{ threshold of} \\ & \text{BLS at node } j \\ 0, & \text{otherwis} \end{cases}$$

The objective function is given as follows:

$$Minimize \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{j \in J_t^A} x_{i,j,t}^A + \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{j \in J_t^B} x_{i,j,t}^B$$

$$Minimize \ \sum_{t=2}^{T}\sum_{i=1}^{n}\left(\left(\xi_{i,t}^{+}\right)^A + \left(\xi_{i,t}^{+}\right)^A\right) \qquad 3$$

Subject to:

$$[\{(1-C1)+(1-C2)\}-\alpha_t^A]y_{i,t}^A \geq \alpha_t^A \ , \forall \ i,t \qquad 4$$

$$[(1-C3)-\alpha_t^B] \ y_{i,t}^B \geq \alpha_t^B \ ; \forall \ i,t \qquad 5$$

$$\sum_{i \in I} h_{i,t}^A y_{i,t}^A \geq c_t^A \quad ; \forall t \qquad 6$$

$$\sum_{i \in I} h_{i,t}^B y_{i,t}^B \geq c_t^B \quad ; \forall t \qquad 7$$

$$x_{ij,t}^A - x_{ij,t+1}^A = \left(\xi_{i,t}^{+}\right)^A + \left(\xi_{i,t}^{-}\right)^A \ ; \ \forall \ i,j \in J_t^A, t \qquad 8$$

$$x_{ij,t}^B - x_{ij,t+1}^B = \left(\xi_{i,t}^{+}\right)^B + \left(\xi_{i,t}^{-}\right)^B; \ \forall \ i,j \in J_t^B, t \qquad 9$$

$$x_{ij,t}^A = \sum_{i \in D_i^A} x_{ij,t+1}^A \ ; \ \forall \ i,j \in J_t^A, \forall \ t \qquad 10$$

$$x_{ij,t}^B = \sum_{i \in D_i^B} x_{ij,t+1}^B \ ; \ \forall \ i,j \in J_t^B, \forall \ t \qquad 11$$

$$\sum_{i=1}^{n}\sum_{j \in J_t} x_{ij,t}^A \leq m_t^A, \sum_{i=1}^{n}\sum_{j \in J_t} x_{ij,t}^B \leq m_t^B; \forall t \qquad 12$$

$$x_{ij,t}^A, x_{ij,t}^B, y_{i,t}^A, y_{i,t}^B = \{0,1\} \quad ; \forall \ i,j,t \qquad 13$$

$$\left(\xi_{i,t}^{+}\right)^A, \left(\xi_{i,t}^{+}\right)^A, \left(\xi_{i,t}^{+}\right)^B, \left(\xi_{i,t}^{+}\right)^B \geq 0 \qquad 14$$

The objective function (3) minimizes the expense of the EMS system by decreasing the ALS and BLS that are available for both demands. It also minimizes the EMS staff fatigue by lowering the number of redeployments for ambulances ALS and BLS, while maintaining preset coverage levels. Constraint (4),

$$C1 = \prod_{j=1}^{m_t^A} \rho_{A,jt}^{\sum_{i \in I} a_{i,j}^A x_{ij,t}^A} Q^A\left(m_t^A, \rho_t^A, \sum_{j=1}^{m_t^A}\sum_{i=1}^{n} a_{i,j}^A x_{ij,t}^A - 1\right)$$

$$C2 = \prod_{j=1}^{m_t^B} \rho_{B,jt}^{\sum_{i \in I} a_{i,j}^A x_{ij,t}^B} Q^B\left(m_t^B, \rho_t^B, \sum_{j=1}^{m_t^B}\sum_{i=1}^{n} a_{i,j}^A x_{ij,t}^B - 1\right)$$

It ensures that a critical demand coming from node i will only be counted if it is reliably serviced by either ALS or BLS within the given α_t^A. In addition, constraint (5),

$$C3 = \prod_{j=1}^{m_t^B} \rho_{B,jt}^{\sum_{i \in I} a_{i,j}^B x_{ij,t}^B} Q^B\left(m_t^B, \rho_t^B, \sum_{j=1}^{m_t^B}\sum_{i=1}^{n} a_{i,j}^B x_{ij,t}^B - 1\right)$$

It assures that nodes serviced by BLS ambulances meet the needed dependability standards α_t^B. Moreover, constraint (6) is to keep the ALS or BLS such that they cannot provide less than the necessary percentage of essential demand coverage c_t^A at time t. Constraint (7) assures that the entire non-critical covering of demand by BLS cannot fall below the required percentage coverage c_t^B at time t. In order to determine the number of ALS ambulance redeployments, the constraint (8) specifies the storing the number of ALS $\left(\xi_{i,t}^{+}\right)^A$ that are redeployed out of node at time period t, and recording the number of ALS $\left(\xi_{i,t}^{-}\right)^A$ that are redeployed into node i at time period t. For BLS ambulances, the restriction (9) specifies the number of redeployments ambulances that will be present in each time period, with the number of deployed BLS and ALS ambulances being stored. Constraint (10) restricts for the time period $t+1$, a new site for the ALS ambulances is guaranteed to be within the maximum standard of relocation (F). Similarly, constraint (11) ensures that new placements for BLS ambulances for the next period $t+1$ meet relocation standards (H). Constraint (12) restricts the number of ALS and BLS. The binary character of the choice variables is given by constraint (13). Finally, Eq. 14 ensures that impose non-negativity criteria.

MO-CL Search Algorithm
Two algorithms are employed to solve the MO-CL model: an incremental search algorithm (ISA) [34] and a comprehensive search algorithm (CSA) [35]. For the proposed MO-CL search algorithm, the most essential objective is to adjust the ISA such that a minimum size of ALS and BLS can be recognized during the first time period t, while providing coverage for incoming critical and non-critical demand. The second objective is to modify the CSA to identify the minimum number of deployments for two ambulance kinds with their locations. The MO-CL search method considers two kinds of ambulances for two kinds of incoming demand. BLS ambulances "back up" ALS ambulances, covering critical and non-critical calls. As a result, the size ambulances for ALS and BLS with their locations at time t are sent as initial data to time period $t+1$. Thus, the MO-CL search algorithm has two phases, which are given in the next subsections.

Locating the Initial Fleet Ambulances Size

At first iteration ($I = 0$) and at time t, the initial ambulances fleet that include ALS and BLS were determined using the following equations: $m_t^A = \frac{\lambda_t^A}{\rho_t^A \mu_t^A}$ and $m_t^B = \frac{\lambda_t^B}{\rho_t^B \mu_t^B}$ where every array ($m_t^A + 1$, $m_t^B + 1$) starts with ALS and BLS coverage and locations at the first period then repeats. ALS allocations at time t were picked at random and also the BLS ambulance sites and fleet size were also chosen at random. Using Jarvis' technique, the busy probability is computed, ALS correction factors and ensuing coverage when the critical emergency call arrives (4) and (6). Similarly, using Jarvis' hypercube approximation approach, the busy probability is estimated, BLS correction factors, as well as evaluated the resultant coverage when a non-critical emergency call comes into the system, using Eqs. 5 and 7. From this model, the search vector consisting of ALS and BLS allocations at time t. Two vectors will be passed as the initial solution in the Reactive TS (RTS) method. The fundamental function of the MO-CL search algorithm is to move one ambulance from i to j (for each ALS and BLS), where node j is regarded as the optimum position in the neighborhood. Whenever the list of tabu is active, all movements (i, j) pairs are retained in the long-term memory. If similar movement repeated in the long-term memory, the tabu list size grows to include it. If a tabu move doesn't recur in $2m_t^A$ ALS iterations or $2m_t^B$ BLS iterations, then it will be eliminated. The RTS implementations stop after 100 iterations. During the 100 iterations, the ideal allocations with the greatest coverage are recorded. In case 100 iterations with a certain number of ambulances are insufficient, additional 100 iterations are then added, this process is repeated until Eq. 4-7 are met. If the initial number of ambulances' coverage exceeds the requirements of tabu, one is cut. The TS is performed 100 times until coverage is inadequate. The minimum fleet sizes are defined by coverage, the minimum of ALS and BLS facilities, as well as their locations. The suggested technique identifies Moore as the ALS and BLS ambulance neighborhoods. Moore Neighborhood consists of the eight neighborhoods around the current neighborhood. Depending on whether the center cell is considered, the Moore neighborhood comprises of 8 or 9 cell arrays.

Establishing the Minimum Number of Redeployments

The MO-CL search algorithm in this phase is based on determining whether the present solutions meet the coverage criteria in the second time period ($t = 2$). In the proposed algorithm, the verification process is dependent on the ambulance type (ALS or BLS) and the type of incoming call (critical or non-critical), with BLS ambulances "back up" ALS ambulances for critical and non-critical demand. A verification procedure can be given as follows:

1. A critical call is made, and the only available ambulance is an ALS ambulance: In this scenario, the MO-CL algorithm determines if the existing ALS ambulance solution exceeds the coverage criteria for important calls at time $t = 2$. If this is the case, a search is conducted to determine which ALS ambulances may be eliminated with a minimum decrease in coverage needs. Once recognized in this scenario, the ALS ambulances are withdrawn until the coverage criteria are satisfied.

2. A critical call is received, but an ALS ambulance is unavailable: In this case, the MO-CL algorithm determines if the current solution of ambulances satisfies the coverage criteria for the incoming critical calls at time $t = 2$. If so, a search is conducted to determine whether ambulances may be eliminated with a minimum decrease in coverage requirements. When the ALS and BLS ambulances are recognized, they are withdrawn until the coverage criteria are satisfied.

3. A non-emergency call is received, and a BLS ambulance is nearby: In this situation, the MO-CL algorithm determines if the current BLS ambulance solution exceeds the coverage criteria for incoming non-critical demand at time $t = 2$. The BLS fleet ambulances that fulfill the non-critical incoming call coverage criteria is then evaluated as a new solution for $t = 2$.

4. A non-emergency call is received, but a BLS ambulance is not available: The non-critical call is routed to the other EMS system in this circumstance.

If the initial solutions from the prior time period fulfill the coverage criteria, the ALS or BLS ambulance does not need to be redeployed in all of previous cases.

MO-CL Search Algorithm Contributions

In contrast to the previous search algorithm used to solve FCLP, the proposed MO-CL search algorithm has the following properties:

1. The MO-CL search algorithm is used with the two types of EMS ambulances ALS and BLS that are respond to calls of critical and non-critical types. This is crucial to achieving the MO-CL model's objectives.
2. It is used with the assumption that the BLS ambulances serve as a "backup" for the ALS in providing coverage for important calls, while they also providing coverage for non-critical calls.
3. The proposed algorithm has the following two objectives: decreasing the number of BLS ALS to decrease EMS expenditures and reducing redeployments for two types of ambulances while meeting coverage targets.
4. The algorithm uses a multi-processing technique to minimize the CPU running time while ensuring that the locations of ambulances are optimal.
5. It considers the relationship between time periods in terms of ambulance availability. That is, when the MO-CL search algorithm runs at any moment, it considers ambulances that may still be busy from the preceding time period. Consequently, non-busy ambulances are sent to meet coverage criteria, yielding more realistic coverage statistics.

Empirical Study

A Case Study of Hajj

Hajj is regarded as one of the world's largest yearly mass gathering event [36]. This pilgrimage consists of five days of ceremonies that begin on day 9 and ended on day 13 of the Muslim lunar month of Dull Hijjah [37]. Hajj is a once in a lifetime requirement for physically and financially fit Muslims [38]. A plethora of studies on Hajj have been undertaken from various research perspectives. For example, some studies have concentrated on the quality and safety of pilgrims. Other studies focus on specific Hajj activities include Tawaf and Sayee rites, the Aljamarat Bridge ceremony, pilgrims' travels between Hajj ritual venues (Arafat, Muzdalifah, and Mina city), lodgings at these areas, medical difficulties, and Hajj security [38,39]. Developing Hajj research projects is vital for a variety of reasons, but several were established in reaction to the many pilgrim injuries and deaths that have occurred over

the last two decades because of uncontrolled crowd movement at the Tawaf and Aljamarat regions. As the number of pilgrims grows, current facilities at Hajj locations become even more crowded owing to congestion. Planning EMS during a Hajj is extremely difficult. This is due to several factors, including the unequal and uneven emergency demand at the location, the uncertainty in ambulance response time, and erratic demand, among other things. To test the validity of the proposed approach, a real case study of "Al Noor Hospital" in Makkah for the period of 1st to 15th of Hijrah, 1415 [37]. Al Noor Specialist Hospital is a Saudi governmental hospital, located in the holy city of Makkah, with 500 modern beds. The research was carried out on incoming calls to Al Noor Specialist Hospital's Emergency Department.

Data Collection and Parameter Configuration

The data of on incoming calls have recorded comprises information on the day, time, serial number, file number, gender, nationality, scene, time of occurrence, mode of transportation, blood pressure and scene diagnostic [37]. There are many emergency health issues occur during the hajj pilgrimage. However, trauma is a most emergency cases among patients [40–43]. During the period of 15 days of hajj in 1415, 713 individuals have been recorded in the emergency department for trauma. 465 patients were left the emergency department due to mild trauma (non-critical cases), such as superficial cut wounds, soft tissue contusions, and superficial burns. On the other hand, the remaining 248 patients were admitted to surgery departments and intensive care units (critical cases) due to serious illness. Moreover, 65% of patients were transported to the emergency department by ALS, while only 35% were transported by BLS or other relatives. The peak time for hospital admissions occurred between 8am–4pm, when most pilgrims are outside their accommodations. For this, the proposed model is used to test both critical and non-critical cases. To aggregate the data, a rectangular 2x2 mile square grid ^{2} is used, which resulted in 143 nodes. In addition, this work assumes that ambulances may be found at any node. It also chose three 8-hour time periods for the proposed model, based on the peak and off-peak times. On the other hand, an EMS manager may establish the optimal length for each time period based on statistical analysis [2,35]. The MO-CL search algorithm is employed to meet the average coverage and ALS or

BLS fleet ambulances while also lowering tiredness among EMS crew members. Fig. 1 shows the spatial distribution of demand calls (critical and non-critical) across the demand node problem for the three time periods.
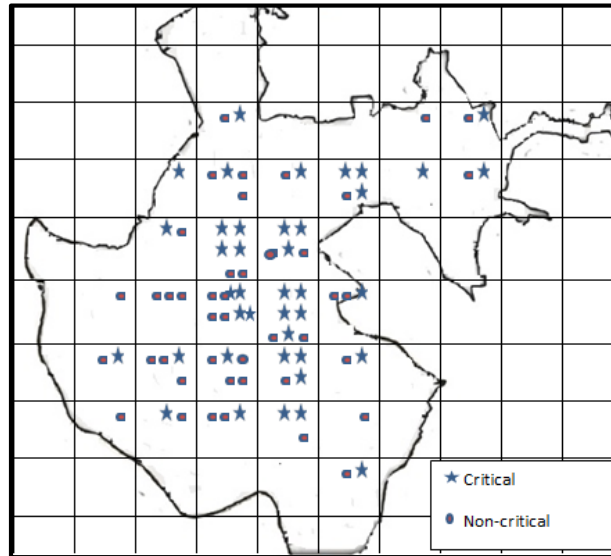
Figure 1. Spatial distribution of demand calls (critical and non-critical)

Results and Discussion

In this work, the C++ language programming was used to implement the proposed solution method, which computes the correction factors and busy probability for ALS and BLS ambulances. The minimum size of ALS and BLS, minimum redeployments, their allocations, and the average percent coverage are given in details in Tables 1 and 2. "Coverage" for critical demand is defined as having a facility, either BLS or ALS who is able to cover the critical demand during eight minutes with a reliability of 90%. On the other hand, "coverage" for non-critical calls is set to have the BLS facility, which can respond to a non-critical demand during ten minutes with 90% of reliability. The ALS ambulances are supposed to be relocated if they can reach the new site within 12 minutes (assuming that the ALS average speed is 60 miles per hour). Similarly, it is assumed that the BLS ambulances can be relocated if they can reach the new site within 15 minutes (assuming that the BLS average speed is 40 miles per hour).

Table 1. Minimum fleet ambulances, redeployments, allocation and overall coverage for critical demand based on interval.

Interval	Minimum fleet		Allocation		Redeployments		Critical overall coverage
	ALS	BLS	ALS	BLS	ALS	BLS	
12:00am–8:00am	8	3	35, 47, 75, 91, 82, 109, 130, 136	42, 59, 61	0	0	0.988
8:00am–4:00pm	12	5	26, 35, 49, 53, 59, 73, 79, 86, 91, 101, 113, 130	36, 58, 77, 104	5	1	0.960
4:00pm–12:00am	9	4	20, 39, 54, 74, 101, 107, 111, 120, 135	31, 51, 79, 124	4	1	0.986

Table 2. Minimum BLS fleet ambulances, redeployments, allocation and overall coverage for non-critical demand based on interval.

Interval	BLS ambulances	Allocation	Redeployments	Non-critical overall coverage
12:00am–8:00am	6	37, 42, 99, 102, 131	0	0.987
8:00am–4:00pm	10	21, 45, 60, 66, 76, 91, 98, 111, 122, 137	4	0.974
4:00pm–12:00am	7	34, 37, 58, 74, 79, 81, 133	4	0.9859

According to Tables 1 and 2, the 1st time period required fewer ambulances of ALS and BLS to achieve the 95% coverage criteria than the 2nd and 3rd time periods. This is consistent with the time period's data, which indicated less non-critical and critical calls. During the 2nd interval, the amount of demand (critical, non-critical) rises, requiring more ambulances to meet the 95% coverage threshold. During a third interval, the number of non-critical and critical calls rapidly reduced, requiring only 9 ALS, and 4 BLS to achieve the minimum of 95% coverage criteria for critical demand and only 7 BLS ambulances for non- critical demand. On the other hand, Tables 1 and 2, show that the 2nd time period has the largest number of ALS redeployments and the same number of BLS redeployments. Also, this time period has the highest number of received non-critical and critical calls. Table 3 illustrates that at the same time period, there was a need to deploy four BLS from the original sites of 38, 77, 80, and 112 to the new locations of 46, 88, 93, and 113 in order to meet the 95% requirement coverage for non-critical demand. As the volume of both demands gradually decreased in the third time period, it was necessary to redeploy four ALS ambulances from the initial locations of 29, 76, 85, and 104 to the new locations of 38, 89, 74, and 91, and only one BLS ambulance from the initial location of 64 to the new location 44 to achieve at least 95% coverage for critical calls.

Finally, to investigate the effect of various reliability input parameters on the efficiency of the MO-CL model, the proposed model is implemented with varying reliability. Consequently, the solution selected by the decision maker will hinge on the type of reliability that decision maker is prepared to accept. Table 3 displays the minimum number of location/relocations required for ALS, BLS backup and BLS ambulances with the same inputs for other parameters based on the time period for each level of reliability. Table 3 demonstrates that the minimum number of ambulance location/redeployment increases as server reliability increases.

Table 3. Minimum number of location/redeployment for ALS, BLS backup and BLS ambulances and their location under different reliabilities for Makka district

Reliability of server	Time period		NALSCL	NBLSCL	NALSNC
0.80	12:00am–8:00am		0	0	0
		LBR	(14, 79, 110, 130)	(63)	(36, 55, 90)
		LAR	(14, 79, 110, 130)	(63)	(36, 55, 90)
	8:00am–4:00pm		3	1	1
		LBR	(14, 79, 110, 130, 36, 57, 100)	(63, 48)	(36, 55, 90, 77)
		LAR	(14, 79, 110, 130, 37, 65, 99)	(55, 48)	(36, 55, 90, 76)
	4:00pm–12:00am		2	0	1
		LBR	(14, 79, 110, 130, 37, 65, 99)	(55, 48)	(36, 55, 90, 76)
		LAR	(21, 79, 110, 130, 37, 65, 111)	(55, 48)	(36, 63, 90, 76)
0.85	12:00am–8:00am		0	0	0
		LBR	(28, 48, 55, 74, 124)	(92)	(30, 53, 90)

		LAR	(28, 48, 55, 74, 124)	(92)	(30, 53, 90)
			4	1	3
	8:00am–4:00pm	LBR	(28, 48, 55, 74, 124, 89, 100)	(92, 64, 98)	(30, 53, 90, 111)
		LAR	(37, 56, 63, 74, 124, 102, 100)	(92, 64, 86)	(38, 54, 101, 111)
			3	1	2
	4:00pm–12:00am	LBR	(37, 56, 63, 74, 124, 102, 100)	(92, 64, 86)	(38, 54, 101, 111)
		LAR	(45, 56, 63, 74, 112, 102, 75)	(76, 64, 86)	(47, 62, 101, 111)
0.90	12:00am–8:00am		0	0	0
		LBR	(36, 48, 76, 93, 85, 111, 132)	(62, 64)	(38, 43, 112, 100, 102, 130)
		LAR	(36, 48, 76, 93, 85, 111, 132)	(62, 64)	(38, 43, 112, 100, 102, 130)
			5	1	4
	8:00am–4:00pm	LBR	(29, 36, 39, 48, 55, 76, 85, 93, 111, 132)	(62, 64, 79)	(38, 43, 77, 80, 100, 102, 112, 130)
		LAR	(29, 36, 44, 56, 64, 76, 85, 104, 99, 132)	(62, 64, 90)	(46, 43, 88, 93, 100, 102,113, 130)
			3	1	3
	4:00pm–12:00am	LBR	(29, 36, 44, 56, 64, 76, 85, 104, 99, 132)	(62, 64, 90)	(46, 43, 88, 93, 100, 102,113, 130)
		LAR	(38, 36, 44, 56, 64, 89, 74, 91, 99, 132)	(62, 44, 90)	(47, 36, 75, 93, 100, 102, 113, 123)
0.95	12:00am–8:00am		0	0	0
		LBR	(5, 29, 48, 52, 93, 99, 130, 136, 140)	(75, 56, 99, 102)	(7, 22, 48, 52, 98, 99, 130, 140)
		LAR	(5, 29, 48, 52, 93, 99, 130, 136, 140)	(75, 56, 99, 102)	(7, 22, 48, 52, 98, 99, 130, 140)
			5	1	4
	8:00am–4:00pm	LBR	(5, 29, 48, 52, 93, 99, 130, 136, 140)	(75, 56, 99, 102)	(7, 29, 48, 52, 93, 99, 130, 140)
		LAR	(8, 36, 48, 52, 93, 111, 123, 136, 140)	(75, 56, 110, 102)	(8, 36, 48, 52, 93, 111, 123, 140)
			4	1	4
	4:00pm–12:00am	LBR	(8, 36, 48, 52, 93, 111, 123, 136, 140)	(75, 56, 110, 102)	(8, 36, 48, 52, 93, 111, 123, 140)
		LAR	(8, 36,56, 44, 80, 111, 123, 136, 140)	(64, 56, 110, 102)	(8, 36,56, 44, 80, 111, 123, 140)
0.99	12:00am–8:00am		0	0	0
		LBR	(5, 43, 55, 61, 67, 76, 87, 99, 99, 102, 123, 124, 131, 141)	(20, 24, 39, 103, 136)	(8, 14, 21, 23, 44, 56, 63, 77, 80, 88, 93,100, 110, 114, 130, 135, 140)
		LAR	(5, 43, 55, 61, 67, 76, 87, 99, 99, 102, 123, 124, 131, 141)	(20, 24, 39, 103, 136)	(8, 14, 21, 23, 44, 56, 63, 77, 80, 88, 93, 100, 110, 114, 130, 135, 140)
			10	4	9
	8:00am–4:00pm	LBR	(14, 22, 39, 5, 43, 55, 61, 67, 76, 87, 99, 99, 102, 123, 124, 131, 141)	(8, 20, 24, 39, 103, 136)	(8, 14, 21, 23, 44, 56, 63, 77, 80, 88, 93,100, 110, 114, 130, 135, 140)
		LAR	(23, 29, 30, 8, 56, 55, 61, 78, 76, 87, 111, 99, 102, 122, 124, 131, 126)	(8, 20, 24, 47, 91, 130)	(12, 14, 21, 23, 44, 56, 64, 88, 91, 89, 93, 99, 110, 113, 131, 136, 137)
			8	3	7
	4:00pm–12:00am	LBR	(23, 29, 30, 8, 56, 55, 61, 78, 76, 87, 111, 99, 102, 122, 124, 130, 126)	(8, 20, 24, 47, 91, 130)	(12, 14, 21, 23, 44, 56, 64, 88, 91, 89, 93, 99, 110, 113, 131, 136, 137)
		LAR	(23, 38, 30, 12, 56, 65, 62, 90, 76, 87, 110, 99, 78, 129, 124, 136, 126)	(8, 29, 31, 47,102, 130)	(12, 22, 30, 23, 44, 56, 75, 100, 104, 78, 80, 99, 110, 113, 131, 136, 137)
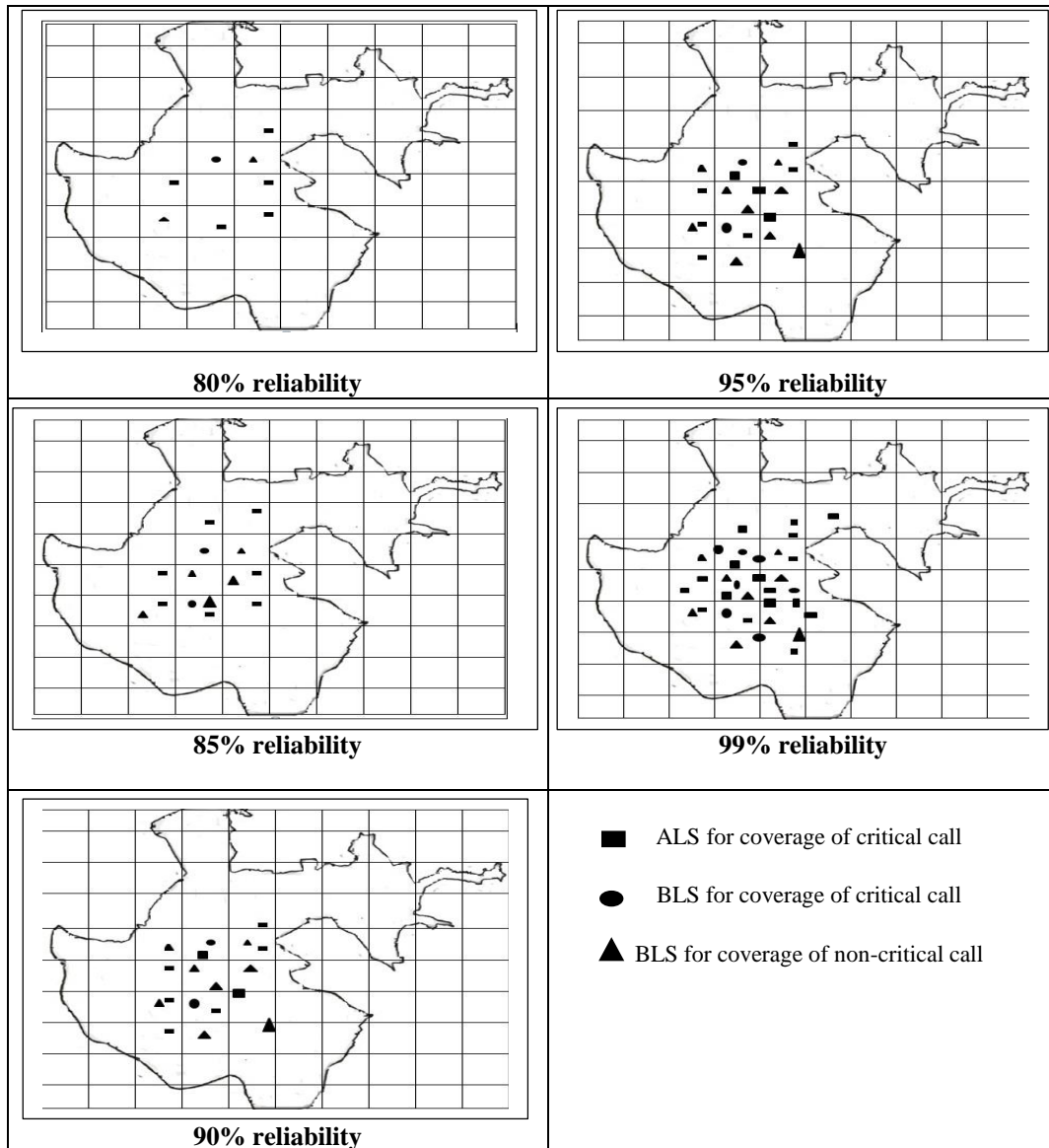
Figure 2. Location of ambulances according to time period under different reliability

In Table 3, NALSC is the number of ALS redeployment for coverage of critical calls (locations), NBLSC represents the number of BLS redeployment for coverage of critical calls (locations), NBLSNC refers to the number of BLS redeployment for coverage of non-critical calls (locations), LBR is Location before Redeployment and LAR for the Location before Redeployment. Fig. 2 illustrates that the location of the ALS, BLS backup, and BLS ambulances after the redeployment according to time period under different reliability.

Conclusion

Planning the location of EMS facilities by using optimization approaches is a significant strategy to increase the efficiency of first aid, particularly in congested locations. As a result, selecting the location of medical departments and their sizes within the network of the hospital, also, the frequency of relocations that already exist are important in these areas. Consequently, the efficiency of reducing the number of deployed ambulances. This could lead to minimizing the severity of the damage caused by accidents, illnesses, catastrophes and reducing the fatigue of EMS crew. This work considers proposing a multi-objective mathematical model for the problem

under two types of ambulances of BLS and ALS. The BLS handles "back-up" calls and non- critical (non-urgent) calls while the ALS reacts to critical (urgent) calls. The introduced model has been developed by using the approximation model of hypercube, which eliminates the assumptions of ambulances working independently and system wide busy probability. The main objective is to reduce the size of fleet for both type of ambulances ALS and BLS while still satisfying coverage standards. In addition, it minimizes the number of times of redeploying the ALS and BLS and hence decreases overwork among EMS workers. The RTS method is used as the base for the metaheuristic that is used to provide efficient solutions. The proposed multi-objective model and solution method were tested on a case study based on real data from Al Noor Hospital in Makkah, Saudia Arabia. This data covered the period of fifteen days of Hajj pilgrimage from 1st to 15th 1415 Hijrah. The experimental results showed that the MO-CL model demands at least 64 ambulances (29 for ALS, 12 for BLS backups, and 23 for BLS) to achieve the 95%

coverage criterion for both of critical and non-critical calls. Moreover, the results based on the MO-CL model revealed that only 19 redeployments (9 for ALS, 2 for BLS backup, and 8 for BLS) were required every day to reach the coverage of 95% criterion for both non-critical and critical calls.

From this work, it is possible to envisage two lines of future work. For the first line, if the number of servers required to provide the desired service level is fewer than the number needed to cover each demand node, then that node is not considered to be covered. In such circumstances, two additional limitations, goal coverage and basic coverage, may be included. In addition, after completing a call in the suggested models, both ALS and BLS should not be interrupted. For this, another future work could provide the proposed models with more realistic features where ambulances may be intercepted after completing a demand and transferred to another new call before returning to their original location.

Author's Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been

included with the necessary permission for re-publication, which is attached to the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at University of Basrah

Authors' Contributions Statement

This work was carried out in collaboration with all authors. H. N. collected the data and built the mathematical model. M. R. hybridized, applied and implement the proposed algorithms. M. S.

contributed to analysis of results. All authors write, revise the manuscript and approved the final manuscript.

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مشكلة موقع تغطية المرافق متعددة الأغراض لقرارات الخدمات الطبية الطارئة في الحج

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قسم الرياضيات، كلية العلوم، جامعة البصرة، البصرة، العراق.

الخلاصة

يقترح هذا البحث نموذج منشأة متعدد التغطية لمشكلة موقع التغطية لتحديد عدد ومواقع وعمليات إعادة نشر نظام EMS الذي يعمل مع سيارتي إسعاف من النوع: دعم الحياة المتقدم (ALS) ودعم الحياة الأساسي (BLS) . يأخذ نموذج التغطية متعددة الأغراض المقترح (MO-CL) في الحسبان هدفين: 1) خفض تكاليف نظام EMS عن طريق الحد من نوعي سيارات الإسعاف ALS و BLS. 2) تقليل إجهاد أعضاء طاقم EMS عن طريق الحد من عدد إعادة الانتشار لنوعين من سيارات الإسعاف مع الاستمرار في توفير مستويات التغطية المطلوبة. يمكن حل نموذج MO-CL من خلال تطبيق خوارزمية البحث MO-CL. يعتمد النموذج المقترح على نموذج المكعب الفائق التقريبي، والذي يلغي افتراضات تشغيل سيارة الإسعاف المستقلة واحتمال الانشغال على مستوى النظام. تم استخدام النموذج في دراسة حالة بناءً على بيانات حقيقية تم جمعها من مستشفى النور التخصصي في مكة المكرمة خلال فترة الحج التي استمرت 15 يومًا. لتحقيق عتبة تغطية 95 في المائة للطلب الحاسم وغير الحاسم ، يتطلب نموذج MO-CL ما لا يقل عن 64 سيارة إسعاف (29 ALS و 12 BLS احتياطيًا و 23 BLS) و 19 عملية إعادة نشر (9 ALS و 2 للنسخ الاحتياطي BLS ، و 8 BLS) كل يوم.

الكلمات المفتاحية: خوارزمية البحث الشامل، خدمات الطوارئ الطبية، مشكلة موقع تغطية المنشأة، شعيرة الحج، خوارزمية البحث التدريجي، نموذج متعدد الأغراض.