Optimally Allocating Ambulances in Delhi using Mutation based Shuffled Frog Leaping Algorithm

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***Abstract*—This paper presents a reliable and competent evolutionary-based approach for improving the response time of Emergency Medical Service (EMS) by efficiently allocating ambulances at the base stations. As the prime objective of EMS is to save people's lives by providing them with timely assistance, thus increasing the chances of a person's survivability, this paper has undertaken the problem of ambulance allocation. The work has been implemented using the proposed mutation-based Shuffled Frog Leaping Algorithm (mSFLA) to provide an optimal allocation plan. The authors have altered the basic SFLA using the concept of mutation to improve the quality of the solution obtained and avoid being trapped in local optima. Considering a set of assumptions, the new algorithm has been applied for allocating 50 ambulances among 11 base stations in Southern Delhi. The working environment of EMS, which includes stochastic requests, travel time, and dynamic traffic conditions, has been considered to attain accurate results. The work has been implemented in the MATLAB simulation environment to find an optimized allocation plan with a minimum average response time. The authors have reduced the average response time by 12.23% with the proposed algorithm. The paper also compares mSFLA, Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) for the stated problem. The algorithms are compared in terms of objective value (average response time), convergence rate, and constancy repeatability to conclude that mSFLA performs better than the other two algorithms.**

Keywords*—Ambulance allocation; ambulance service; emergency medical service; shuffled frog leaping algorithm; mutation based shuffled frog leaping algorithm

I. INTRODUCTION

Emergency Medical Service (EMS) control centers are vital in modern health systems and act as a pre-hospital component. EMSs provide out-of-hospital medical care and transport activities for the victims of accidents or illnesses. It plays a significant role in the public health system, and its ability to respond to emergency calls can significantly impact a patient's health and recovery [1]. Therefore, EMS control centers need to strategize and work towards handling a significant concern of allocating an appropriate count of ambulances to the base stations in an area [2]. Having a suitable count of ambulances available at the base stations will help the EMS provide a timely response to the persons in need. This motive has attracted many researchers to suggest solutions that prove viable in the working environment of EMS. As per the working procedure, an ambulance is selected and dispatched to the demand site when the EMS control center receives a request call. The rules set by the EMS authority help select and dispatch the ambulance from one of the base stations (with ambulance availability) to serve the request. The rule may select the nearest ambulance to the requested location or the ambulance that will take less time to reach the location [3]–[5]. When the ambulance reaches the requested location, it may provide first aid to the patient or resuscitation. It then takes the patient to the hospital as per the requirement.

Research carried out to date has emphasized many issues related to planning, working, and management activities related to EMS using static models, dynamic models, hypercube models, covering models, etc. To attain optimum service performance, EMS facilities must be positioned strategically in a specific locality. Decisions here are taken from two aspects: selecting appropriate sites at which ambulances should be stationed and the number of ambulances stationed at each site [6]. However, considering densely populated cities and countries, deciding on allotting and constructing new places for base stations is challenging for the government. Therefore, the authors have undertaken the problem of optimizing the performance of EMSs by finding an optimal allocation solution for distributing ambulances among the existing base stations using the details regarding (1) the number of ambulances in the fleet, (2) the location of base stations, (3) frequency of request calls, and (4) tentative demand sites.

The remaining paper is organized as follows: Section II covers the literature review; Section III focuses on the problem background; followed by problem formulation in Section IV. Simulation modeling has been explained in Section V. Section VI covers the details related to simulation, results obtained, and discussions related to the same. Finally, the paper is concluded in Section VII.

II. LITERTAURE REVIEW

Out of all the literature available on this domain, the authors have cited works primarily focusing on optimizing ambulance allocation. Ambulance allocation is the distribution of ambulances to the base stations based on specific criteria [7]. The base station is an area where the ambulances are in standby mode. They are dispatched from the base station when they have to serve any request. However, deciding the locations for positioning the base station is out of the scope of this work. Our work primarily focuses on finding the allocation plan for ambulances at the existing base stations. Many researchers have extensively explored the EMS field to improve the service level provided to society. The research in the field of EMS needs the answer to the following two queries: (1) the optimization criterion that can be used as the

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best proxy for health outcomes, and (2) the model that is apt to be used for designing EMS systems handling a mixed territory comprising urban and rural areas. The work of many authors has covered the answer to the first query. In work put forward by [8]–[10], the authors have tried to determine the attribute that should be measured to assess the performance of EMS.

Many models exist in literature like Location Set Covering Problem (LSCP), Maximal Covering Location Problem (MCLP), Maximum Expected Covering Location Problem (MEXCLP), and Double Standard Model (DSM) for solving the facility location problem that has considered area covered by EMS as a significant attribute for proposing allocation plans. Similarly, some papers in the literature have considered service distance as an attribute for evaluating the performance of EMSs. In addition, the background of many articles has validated response time as a significant factor for gaining better insight into the operational performance of EMS. Some works have demonstrated that the patient's mortality and recovery rates are highly influenced by the response time [11]–[14]. Using the same objective in this paper, the authors have considered response time as the prime attribute for estimating and improving the medical service provided by EMS.

EMS operates in an uncertain environment in terms of demand rate, travel time, and response time. The effect of such an uncertain environment on the working of EMS was studied using a simulation-based evaluation method by Ünlüyurt and Tunçer [15]. Different authors have used various algorithms to attain optimized ambulance allocation plans. A data-driven approach was used to allocate and dynamically relocate the complete fleet of ambulances, using a mixed-integer linear formulation to solve the problem of ambulance allocation [16]. Firooze et al. proposed an optimizing model for allocating the ambulances to the base stations, considering the capacity of every base station, travel time, and service time of ambulances [17]. The authors [10], [18] proposed a new model by integrating survival functions with a motive to capture different categories of patients. The conditions faced by the EMS organization are dynamic in terms of variation in travel time, frequency of requests, speed of ambulances, and coverage of areas while fulfilling the requests. The critical issue of the impact of spatial randomness of demand has been considered in very few studies failing to obtain appropriate solutions. The covering models may not be suitable because the spatial distribution of demands may or may not be covered entirely, violating the assumption of the all-or-nothing binary coverage [19]. In 2018, an adjusted queuing solution for ambulance allocation was proposed by considering a heterogeneous spatial distribution of demands in urban and rural areas [20]. Although this solution helped overcome the overstaffing problem, it ignored the definite spatial distribution of demand in each area. In another solution by Chen et al., the authors used various shapes and sizes of grid systems to overcome the problem of the spatial distribution of demand [21]. However, obtaining a probability density function for request calls in a specific grid is challenging [22]. Moreover, a grid area holds no importance until it is classified as an area with a high frequency of request calls, a hospital, or a community resulting in an unstable demand distribution in the grid.

Considering these factors, Degel et al. proposed a time-dependent ambulance allocation model to improve the quality of emergency services [23]. In another work, the authors used a robust optimization approach to improve the functioning of EMS, considering the spatial demand characteristics and uncertain travel time to the requested site [24]. Geroliminis et al. presented a model and a heuristic solution for the optimal deployment of ambulances. They integrated a location model, Genetic Algorithm (GA), and hypercube model for their work [25]. The work by [26] used GA to propose an optimized solution for ambulance deployment. Later, a simulation model incorporating a Gaussian-process-based search algorithm was proposed to attain an optimal allocation plan for ambulances [27]. The authors in [28] handled the emergency department's overcrowding problem by using game theory-based optimization to propose a new optimized allocation plan for ambulances to reduce patient waiting and treatment time. Similarly, many authors [29]–[31] have used Particle Swarm Optimization (PSO) algorithm to achieve an optimized ambulance allocation plan for ambulances. Work was proposed by the authors [32], where a solution for optimally allocating the ambulances was proposed using Jumping PSO. Ant Colony Optimization (ACO) was also used for deploying and redeploying ambulances by [33], [34]. Another algorithm called Shuffled Frog Leaping Algorithm (SFLA) has been used in some works to explore the field of EMS. The authors [35], [36] used SFLA to optimize the working of EMS. SFLA has also been used in different domains for optimally allocating resources [37], [38]. However, there is a dearth of research papers where SFLA is used in the context of EMS.

Research by Elbeltagi et al. [38] indicated that SFLA is a better optimization technique than other evolutionary algorithms such as PSO, ACO, GA, and memetic algorithms. SFLA is a memetic metaheuristic algorithm proposed by Eusuff and Lansey in 2003. This algorithm combines the benefit of the social behavior-based PSO algorithm and genetic-based memetic algorithm. It performs similarly to PSO and surpasses GA in terms of quality of solution, consistency, and processing time. It is considered an efficient and fast algorithm as it can quickly converge to global optima with small population size. However, in some cases, traditional SFLA traps in local optima. To avoid this issue, the authors have proposed mutation-based SFLA (mSFLA) by incorporating the concept of mutation into the working of SFLA.

Considering the previous studies focusing on improvising EMS, most works have used simplified assumptions to come up with a result, while others fail to provide a mutual comparison of models. Computer simulation has proved to be the best way to assess the validation of different processes. Due to the lack of operational data or to avoid ample computation time, many simulation models oversimplify the actual operation. However, the simulation model should consider all the processes, sub-processes, and real-time conditions to find accurate results. The actual operation of the system should be considered while deriving the parameters for the simulation model. Therefore, in this work, the authors have proposed and used a simulation-optimization framework with mSFLA as the optimization component for ambulance allocation. The work considers the spatial distribution of demands and other uncertainty factors associated with the environment of EMS. To verify and validate the suitability of mSFLA, the algorithm is executed in the MATLAB environment to compare the results with PSO and GA.

III. Problem Background

In India, EMS refers to the ambulance service provided for on-the-spot treatment by paramedics or transporting sick or accident victims to the hospital. Despite being an essential component of society, a fully encompassing definition of EMS is impossible as it does not have a strong representation at the federal level owing to numerous local agencies providing EMS to the public. EMS agencies are classified into three categories based on the tasks they perform.

1) EMS that handles scheduled medical transport,

2) EMS that handles emergent inter-facility transport, and

3) EMS agencies that primarily handle 102-based emergency calls with or without transport.

In this study, the authors have focused on the third category that deals mainly with the optimized use of ambulances. In terms of population and vehicle density across any country, extensive growth is visible. With an increase in vehicle density, accidents (fatal and non-fatal) have also increased, thus, raising the concern of providing medical facilities at the location of the accident. Therefore, when an accident occurs at any location, an ambulance or hospital should be within reach in the shortest duration possible. Since setting up hospitals in every area is impossible, ambulances can be strategically deployed so that on-the-spot treatment and transportation can be provided to accident victims at the earliest. Centralized Accident and Trauma Services (CATS) is an autonomous body of government in Delhi, India, that provides EMS to the victims of accidents and trauma with an ART of approximately 13 minutes. CATS has deployed 50 ambulances at 11 base stations covering the southern portion of Delhi. The area of Southern Delhi is approximately 857 square kilometers and comprises four districts South West Delhi, South East Delhi, New Delhi, and South Delhi. The high frequency of request calls from Southern Delhi motivated the authors to select and work upon the data of this region to allocate and dispatch ambulances for handling accidents and reducing the casualty rate.

IV. Problem Formulation

The problem of allocating ambulances involves distributing a specific count of ambulances (*A*) in the fleet among the base stations (*B*) in such a way that the performance of EMS in terms of response time is improved while serving the requests generated from numerous demand points (*D*). The solution for the distribution of ambulances among the base stations is represented by an integer variable a_i, where $i \epsilon B$ specifies the exact count of ambulances placed at different base stations. Thus,

$$A = \{a_1, a_2, a_3 \ldots\ldots, a_B\}$$

Considering the real-world scenario, the authors have assumed that at an instant, only '*p*' ambulances are available out of '*A*' ambulances to handle the requests as the other ambulances are busy handling the patients or are on their way back to the base station. The number of ambulances available at each base station *'i'* is denoted as $a_i(p)$. To indicate the availability or non-availability of an ambulance at the base statio '*i*', a binary variable $x_i(p)$ is used. Values 1 and 0 for $x_i(p)$ indicate availability or non-availability at a particular base station. The mathematical formulation for minimizing *ART* is as follows.

$$\min \mathrm{RT} = \sum_{i \in D} \nu_i * t_{ij} \tag{1}$$

subject to the constraints.

$$\sum_{i \in D} a_i(p) = p \tag{2}$$

$$\sum a_i = A \tag{3}$$

$$x_i(p) \le a_i(p) \tag{4}$$

$$a_i(p) \ge 0 \quad (5) \qquad x_i(p) \ge 0 \tag{6}$$

$$x_i(p) \in (0,1) \tag{7}$$

In the objective function shown in Equation 1, ν_i indicates the arrival rate of request calls per hour and t_{ij} denotes the travel time from location *i* (base station) to location *j* (demand spot). As stated if '*p*' ambulances are available out of *A* ambulances, Constraint (2) checks that the total ambulances available at each base station are equal to the total number of ambulances present in the system at the same instant. Constraint (3) restricts the total count of ambulances to *A*. The fulfillment of requests is constrained by the presence of a certain number of ambulances at the base station by Constraints (4)-(6). Constraint (7) restricts the value of the variable.

V. Simulation Modelling

The essential processes of an EMS system are structured in a simulation model, as shown in Fig. 1. As soon as the EMS center receives a call after an emergency occurs, the dispatcher selects the nearest ambulance available to serve at the accident site. The ambulance commutes from the base station to the requested site to locate the victim and provides on-the-spot treatment. After assessing the victim's situation, an ambulance transports the victim to the hospital if needed. The ambulance crew transfers the victim to the emergency room at the hospital. After completing the call, either at the requested site or the hospital, the ambulance returns to the base station and waits until assigned a new task.

An EMS system's complicated structure and process dynamics can be effectively represented with the help of an operational model. Fig. 2 shows the operational model designed using the workflow of EMS to achieve the objective of the proposed work. The emergency calls exhibit strong randomness in dimensions of time and space as they can occur at any time and place. Therefore, the spatiotemporal randomness of such calls should be described quantitatively for the correct working of the simulation model. Hence, all the data used in the simulation should be defined accurately to attain relevant results. A random two-dimensional variable '*r*' represents the latitude and longitude coordinates of the point from where the request initiates. The EMS system uses these coordinates to know the exact request location to respond to emergency calls. The optimization algorithm used in work determines the state values for base stations and ambulances. These state values act as input for the simulation model. The state values refer to the data on the location (coordinates) of the base station, the id of the base station, and the number of ambulances available at that base station. Whenever a request call arrives, the travel time between the request location '*r*' and each base station 'bs_i' can be calculated using the coordinate data of '*r*', base stations, and Google distance matrix application programming interface. This way, a list of base stations ranked by travel time from the requested location is obtained. Then an ambulance with the status 'available' is selected from the base station with the least travel time to request location and dispatched to serve the patient. The status of the selected ambulance is changed from 'available' to 'busy.'

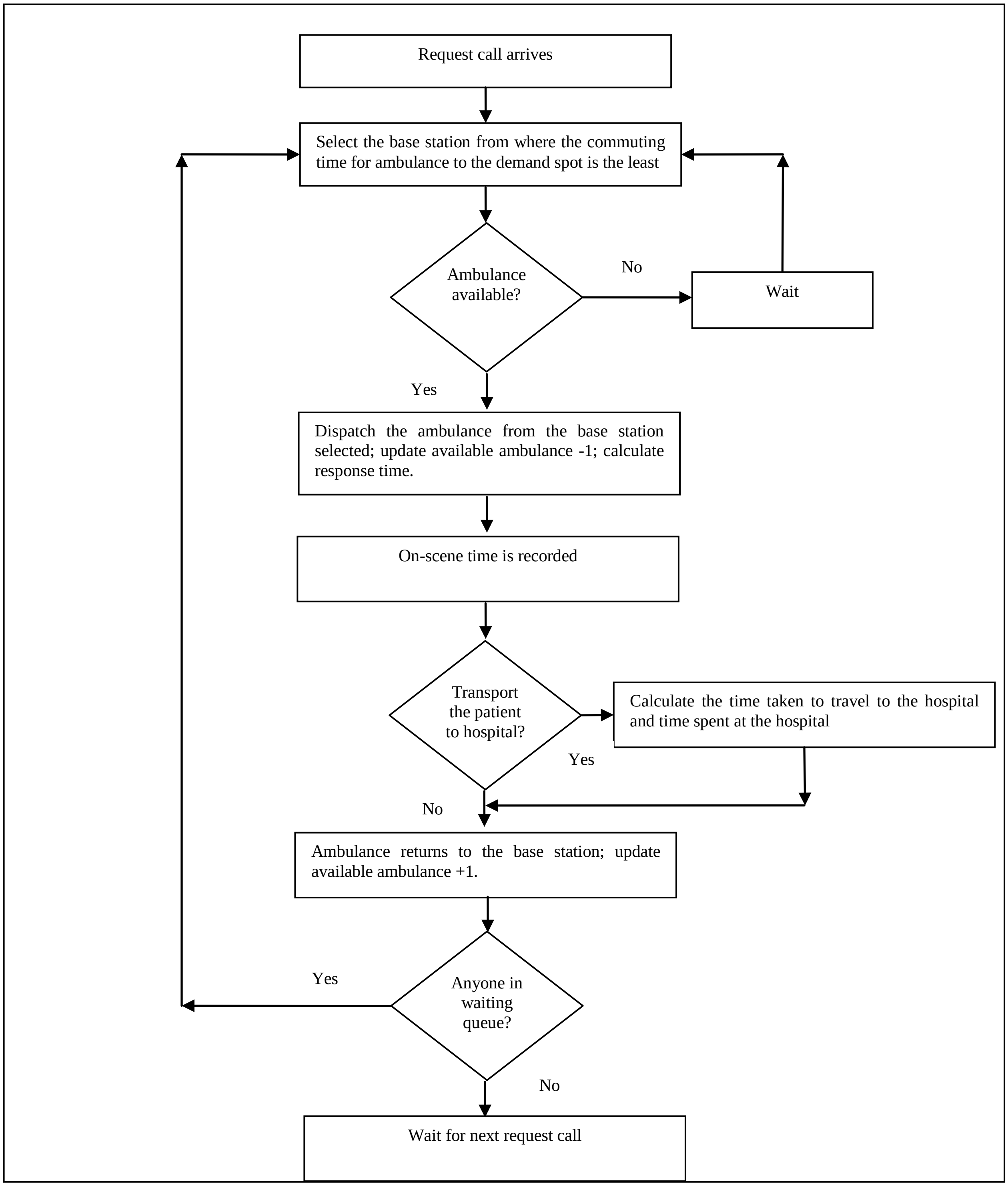


Fig. 1. Simulation Model of EMS System.

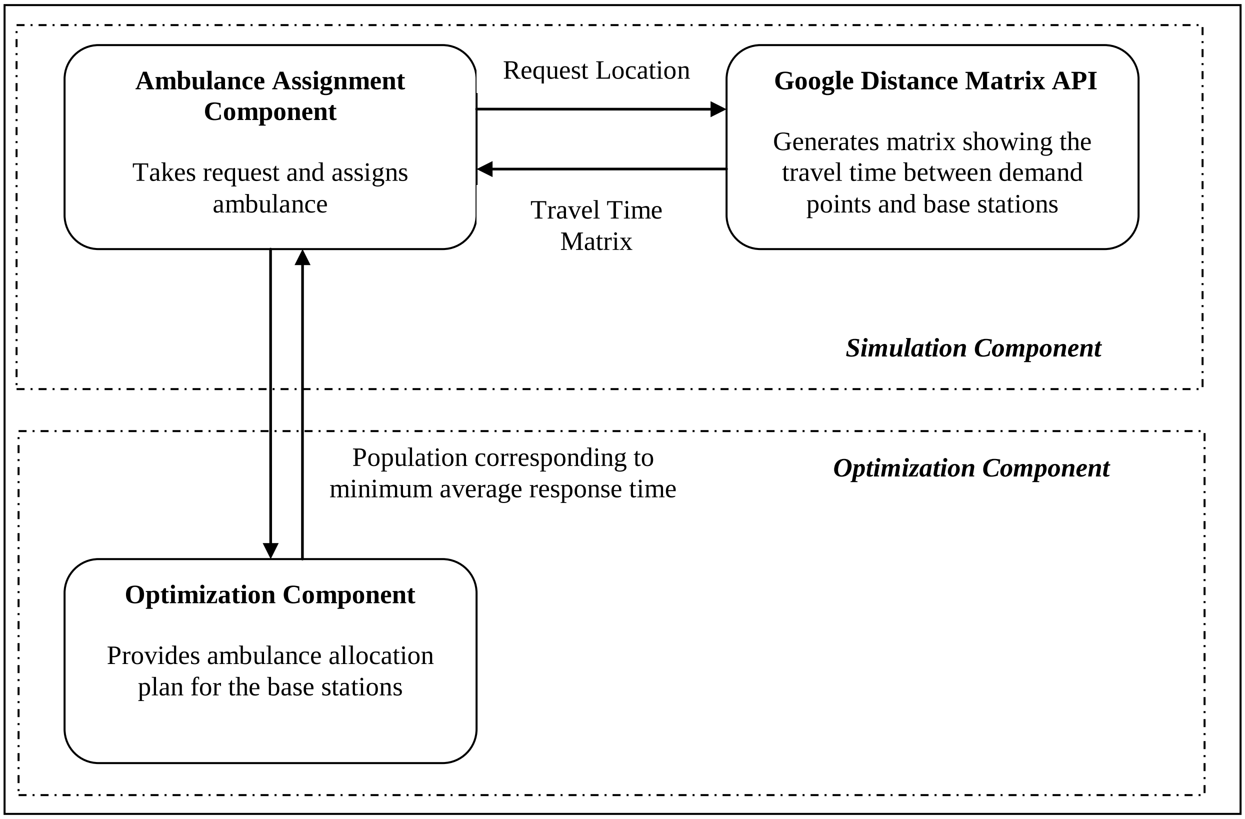


Fig. 2. Operational Model for the Proposed Work.

After the ambulance dispatches, the system calculates response and delay time values. Response time is the time an ambulance takes to reach the patient's location after the request is initiated. As soon as the ambulance arrives at the requested site, the simulation model records the time for on-the-spot treatment. If the patient does not require transportation to a hospital, the ambulance returns to the base station, and its state changes from busy to available. Otherwise, travel and waiting time values are calculated if the patient is transported to a hospital. If no ambulance is available, the patient has to wait in a queue and is served as soon as an ambulance is available. The response time, in this case, is calculated as the sum of travel time and waiting time. After all the requests are served in a day, the total time taken by ambulances to reach the requested locations (response time) is divided by the total number of request calls received at the EMS centre to find the value of ART. The algorithm of mSFLA has been used as an optimizing component and works on the result of the simulation component to find the best allocation plan for ambulances.

A. Shuffled Frog Leaping Algorithm

The shuffled frog leaping algorithm helps in finding an optimal solution. It is a memetic meta-heuristic population-based cooperative search approach that imitates the group behavior (jumping strategy) used by frogs to find a location with the maximum amount of food. The algorithm incorporates techniques for performing local searches and exchanging global information. The frogs are randomly assigned a location in the search space. Several groups are formed by dividing the population of frogs, thus generating memeplexes. The memeplexes then evolve separately in different directions within the search space. Individual frogs can use the information of the population's best frog (global best) or best frog in the memeplex (local best) and change their direction. Each frog experiences memetic evolution because they influence each other and improve their performance to achieve the goal. After a specific number of memetic evolutions, the memeplexes are shuffled to generate new memeplexes, enhancing frogs' ability to attain the best solution in search space. Thus, PSO and Shuffled complex evolution [39] are used for local search and integrating information from parallel local searches in SFLA. The various steps in SFLA are explained below.

Step 1: Population initialization and parameter setting: Various parameters need to be set up for SFLA, such as the size of the population, number of memeplexes and sub memeplexes, and number of memetic evolutions. A random population of 'N' frogs is generated to form the population. For all the frogs in the population, the fitness value is calculated.

Step 2: Grouping: The fitness value obtained above is used to sort the frogs in descending order of their fitness value. These frogs are then divided into 'm' subgroups, with n frogs in each subgroup.

Step 3: Intra-group search: From each subgroup, the frog with the best fitness value 'Xb' and worst fitness value 'Xw' are found. The worst solution in the subgroup is updated by using Equation 8 and 9, and only one solution which is the worst in the subgroup is updated at a sub iteration. For updating the position of the worst frog the following equations are used

$$S_i = rand * (X_b - X_w) \quad (8)$$

$$X'_w = X_w + S_i \quad (9)$$

so that

$$S_{imin} < S_i < S_{imax}$$

where S_i is the variation in the location of frog attained in a single jump. 'rand' is a uniformly distributed random number ranging between 0 and 1. The minimum and maximum step sizes for frogs are represented by S_{imin} and S_{imax}. The new position of the worst frog is represented by X'_w If the value of X'_w is better than X_w then the value of X'_w replaces the value of X_w else the new value for $X'_w$is calculated by Equation 10 and 11.

$$S_i = rand * (X_{bg} - X_w) \quad (10)$$

$$X'_w = X_w + S_i \quad (11)$$

X_{bg} is the best frog in the current population. In case if the value of X'_w is still not better than X_w, then the value of X'_w can be calculated using

$$X'_w = g + rand(1, D) \otimes (h - g) \quad (12)$$

In the above equation *D* represents the dimension of the optimization problem. rand(1, *D*) is a random vector of *D* components with each component between 0 and 1. '*g*' and '*h*' represent the upper and lower boundary vectors of the decisive variables. $\otimes$ means an entry wise multiplication.

The worst frog and best frog is determined from the subgroups attained. Repeated subgroup search is carried out for predefined number of sub iterations. The intra group search stops when the search has been finished by all the subgroups.

Step 4: Exchange of global information: The exchange of global information considers reorganizing all the subgroups into a population of N frogs. Steps 2 and 3 are used again to sort and divide the population into subgroups. Alternate executions of these steps are carried out until either the termination criterion is reached or the best solution is obtained. However, in some cases, a low diversity in the population traps the SFLA into local optima or premature convergence. Therefore, the concept of strong mutation is proposed in this paper to increase the diversity in the population. This concept works upon generating a trial mutated vector using the values of the best solution (Xb) in each memeplex and the value of the globally best solution (Xbg). It is crucial to ensure that the dimension of the mutation vector and the number of memeplexes is the same.

$$X^i_{mut} = X^i_{rand} + ra\left(X^i_b - X^i_{rand}\right) + ra(X^i_{bg} - X^i_{rand}) \quad (13)$$

i = 1,2,3……. number of memeplexes.

Here X^i_{rand} represents a randomly generated vector and ra is random number between 0 and 1. Now, the generation cost of trial vector f(X^i_{mut})and target vector f(X_{bg}) are compared. If the value of the former is better than the latter, then the target vector is replaced by the trail vector in the next generation. Thus using this step, the algorithm can be prevented from being stuck into a local optimum, and convergence of the algorithm to a global value can be assured.

B. Application of mSFLA to the Problem of Ambulance Allocation

The application of mSFLA to ambulance allocation problem is explained in this section. The steps used in the work are as follows:

1) The coordinate data about the base stations, count of ambulances at the base stations, total number of ambulances in the fleet, coordinate data of demand points are defined.

2) Initial population is generated as

$$\text{Population} = \begin{bmatrix} A_1 \\ A_2 \\ A_3 \\ \cdots \\ A_{100} \end{bmatrix}$$

$$A_i = a_{i,1}, a_{i,2}, \ldots\ldots a_{i,N}$$

3) The objective function is defined stating the constraints and values.

4) Compute the fitness value for the objective function.

5) Sort and divide the population into memeplexes on the basis of the value of the fitness function. The local best solution (X_b) and the global best solution (X_{bg}) is defined.

6) The frog with worst solution (X_w) is amended using Equation (8) and (9) or Equation (10) and (11) depending on the situation explained in previous section.

7) The process of mutation is applied and the result obtained is compared with the value of X_{bg}.

8) The values are updated and the amended and steps through 4 to 8 are repeated until the termination criteria is met.

9) The best solution is obtained.

VI. Simulation Results and Discussion

A. Area of Concern

The authors have undertaken the southern portion of Delhi to obtain an optimal allocation plan for a fleet of 50 ambulances at 11 base stations in the area. Fig. 3 and Fig. 4 show the southern portion of Delhi and base stations (BS1-BS11) of that area. The traffic police department of Delhi maintains records and releases a report every year stating the details like count of accidents, locations of accidents, time at which the accident took place, information regarding vehicles involved in accidents, etc. To get an insight into the situation, the authors used the report for the year 2019-2020. The report mentions different locations in Delhi which are accident-prone and must be taken into consideration by EMS organizations while devising and designing any policy or strategy. However, since an accident can occur at any location and at any point of time, the authors invented a robust framework that can handle any request initiated from any point in a short time. Considering each point (latitude and longitude) as a tentative spot for the occurrence of an accident, the authors divided southern Delhi into 230 blocks. Each block covered an area of approximately four kilometers square shown in Fig. 5. In every run of the framework, random requests are generated ensuring at least one request is initiated from each block.

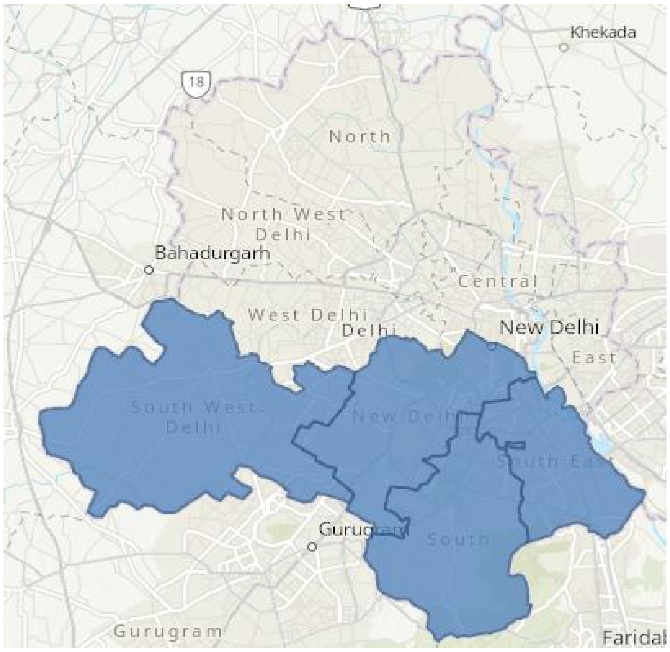


Fig. 3. Southern Portion of Delhi.

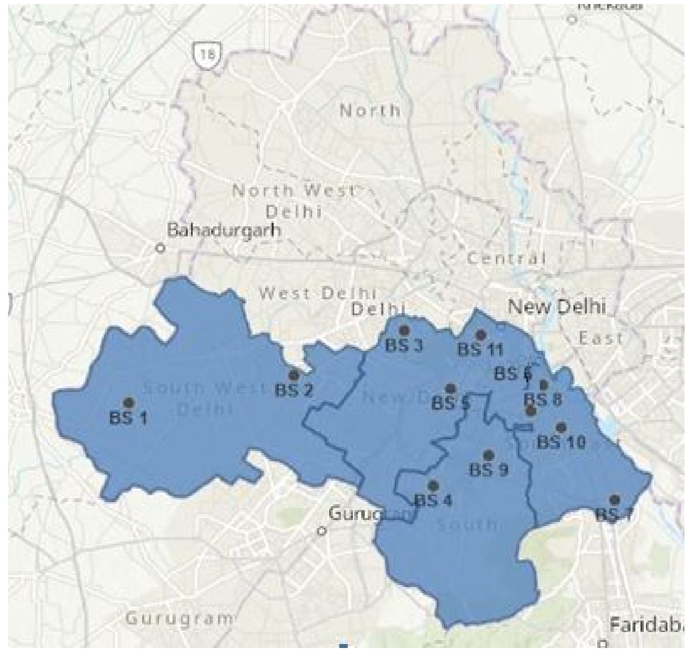


Fig. 4. Base Stations of Southern Delhi.

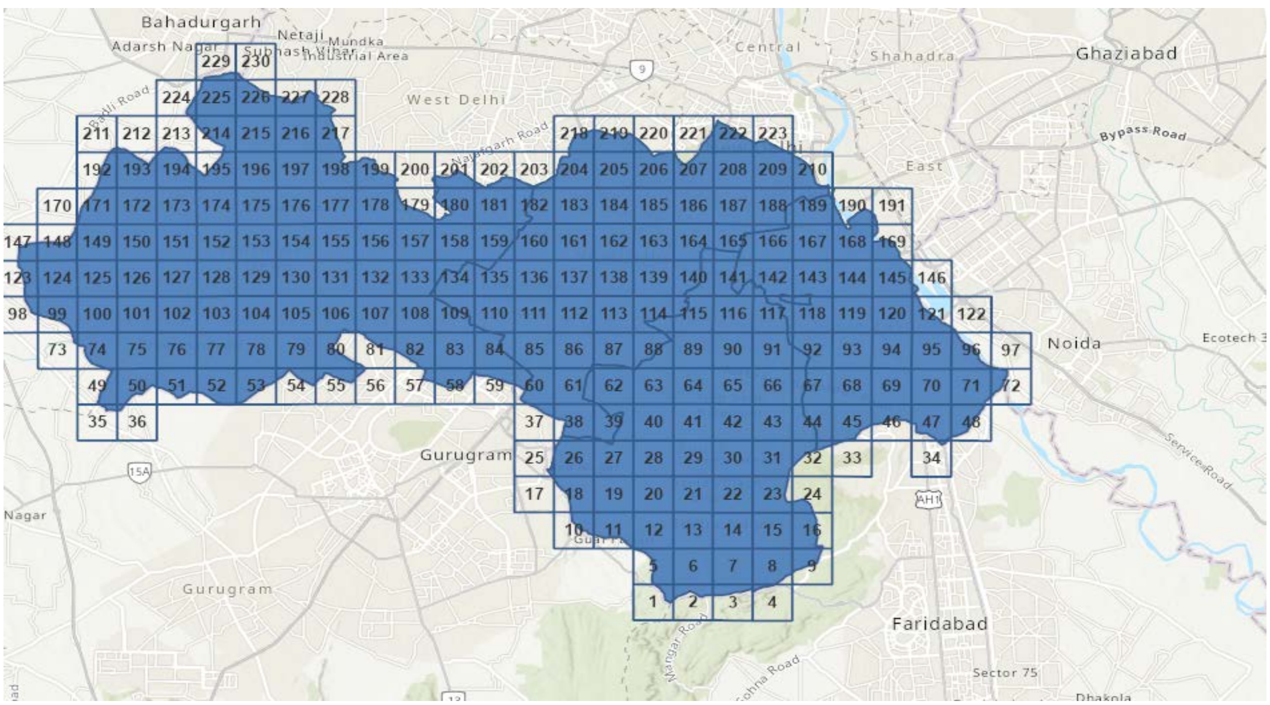


Fig. 5. Tessellations of Southern Delhi.

B. Results and Discussion

MATLAB environment is used to execute the work for 15000 requests and a population size of 100. To exemplify the robustness and efficiency of mSFLA, the algorithm is executed as the optimization component in the operational model of the work. For implementing the mSFLA, the authors conducted many experiments to find appropriate values for various parameters. From the result of the experiments, the authors set values for the parameters: number of memeplexes, number of frogs in each memeplex, iteration count for global exploration, and iteration count for local exploration, as shown in Table I. The parameter values used for GA and PSO are shown in Table II and Table III respectively.

For comparison, similar simulations are performed using PSO and GA as optimization components in the operational model stated in Section V. 20 runs of simulations are performed with each algorithm to compare the performance of the algorithms using the metrics such as the value of the objective function, convergence rate, and constancy repeatability.

TABLE I. PARAMETERS FOR M SFLA OPTIMIZATION

Parameter Name	***Value***
Number of frogs in each memeplex	10
Number of memeplexes	10
Iteration max_1	70
Iteration max_2	100
Iteration of mutation	10

TABLE II. PARAMETERS FOR GA

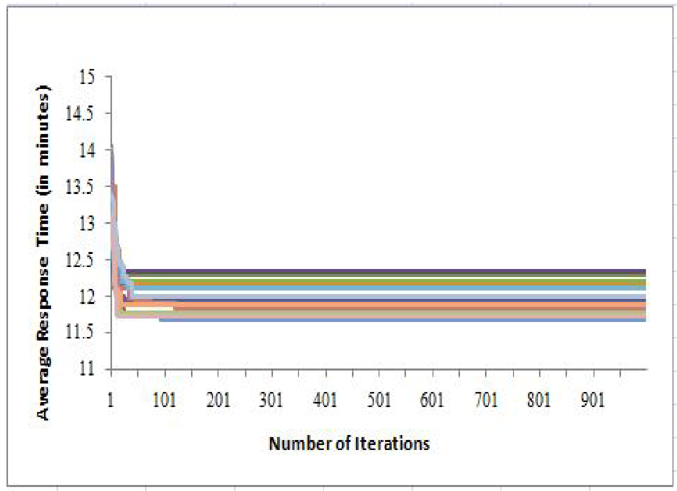
Parameter Name	***Value***
Population size	100
Number of iterations	1000
Crossover fraction	0.1
Mutation fraction	0.8

TABLE III. PARAMETERS FOR PSO

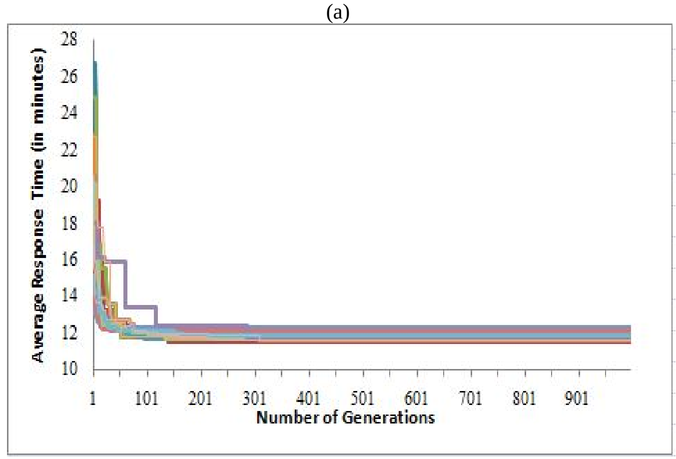
Parameter Name	***Value***
Population size	100
Number of iterations	1000
Cognitive coefficient (c_1)	2
Social coefficient (c_2)	2
Inertia coefficient (*w*)	0.8

1) Convergence rate: The suitability of an algorithm for an optimization problem can be evaluated using convergence rate [36]. The convergence graph can also estimate an algorithm's best, average, worst results, and standard deviation. The convergence graph for PSO, GA, and mSFLA is shown in Fig. 6(a), 6(b), and 6(c). As stated, 20 different runs were carried out for all three algorithms to attain the global fitness value for the objective function. The global fitness value is the best fitness value obtained in each iteration within the defined population size of the algorithm. The graph illustrates that the value of global fitness (in the best iteration/generation of every algorithm) changed from 13.58172 to 11.9733 in the case of PSO, 19.52089 to 11.72735 in the case of GA, and 12.93752 to 11.4127 in the case of mSFLA in 1000 iterations of each. The graph also indicates that the PSO algorithm converged in 94, the GA in 358, and the mSFLA in 41 iterations. The quick convergence of mSFLA indicates that the convergence rate and computational time of mSFLA are better than GA and PSO.

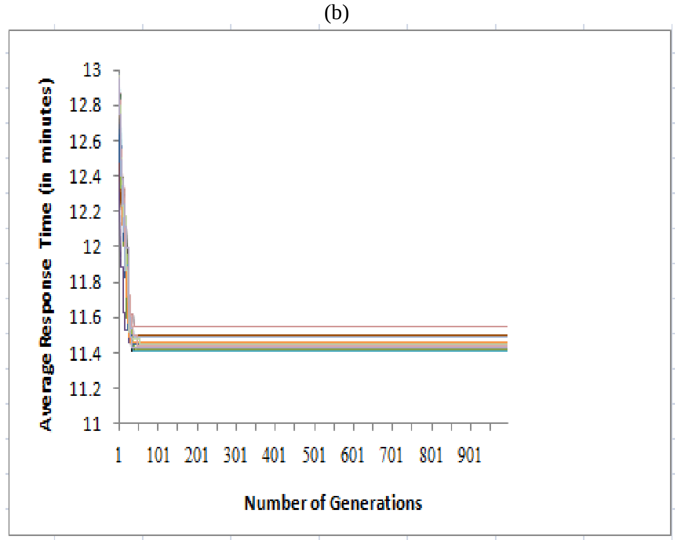
Another comparison result is shown in Fig. 7 and Fig. 8, where the values of standard deviation, best, average, and worst solutions are plotted for each algorithm. The result in Fig. 7 indicates that the even worst solution (maximum ART) provided by mSFLA is better than the other two algorithms' average solutions. In addition, the average result of mSFLA is also better, making it more efficient. The value of Standard Deviation (stdev) for all the algorithms shown in Fig. 8 reveals that the value of stdev i.e. 0.045331 is almost negligible in the case of mSFLA; therefore, it can provide the best solution in each run.



(a)



(b)



(c)

Fig. 6. (a). Convergence Graph of PSO, (b). Convergence Graph of GA, (c). Convergence Graph of mSFLA.

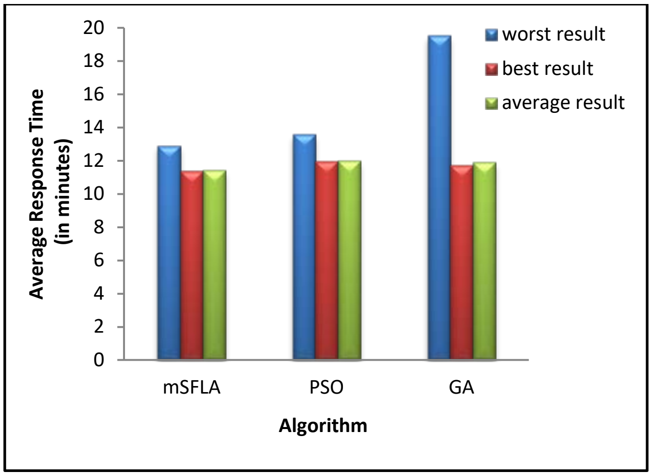


Fig. 7. Comparison of Worst, Best, and Average Result.

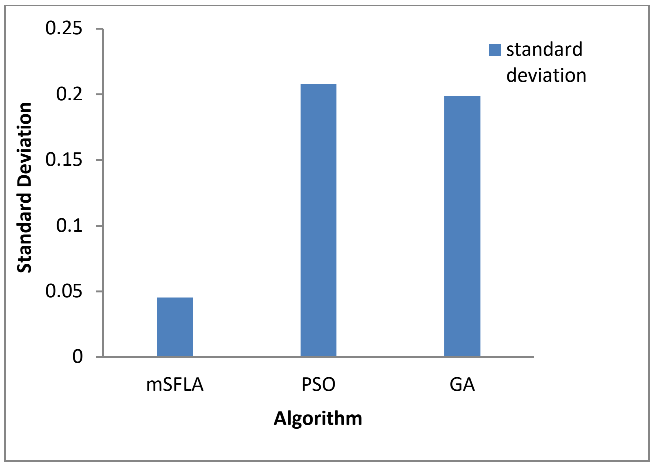


Fig. 8. Comparison of Standard Deviation.

2) Objective function value: In this work, the objective function minimizes the value of ART of EMS to provide a prompt service to the people in need. The evolution graph in Fig. 9 depicts the global fitness values of ART for PSO, GA, and mSFLA are 11.9733 minutes, 11.72735 minutes, and 11.4127 minutes respectively.

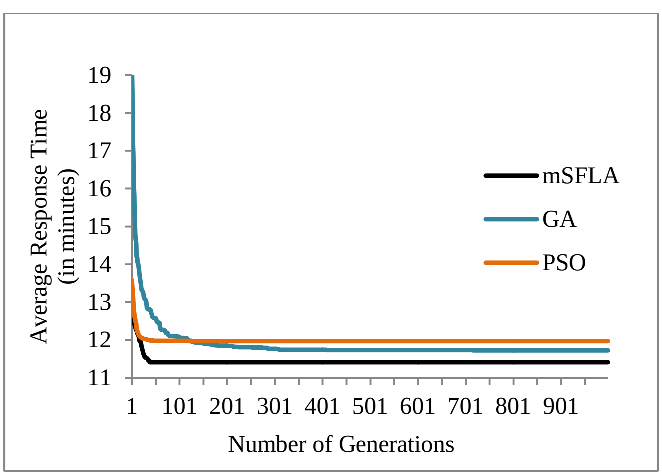


Fig. 9. Evolution Graph of Algorithms.

The convergence of mSFLA to the least value demonstrates that the result and performance of mSFLA is better than PSO and GA for the problem of ambulance allocation.

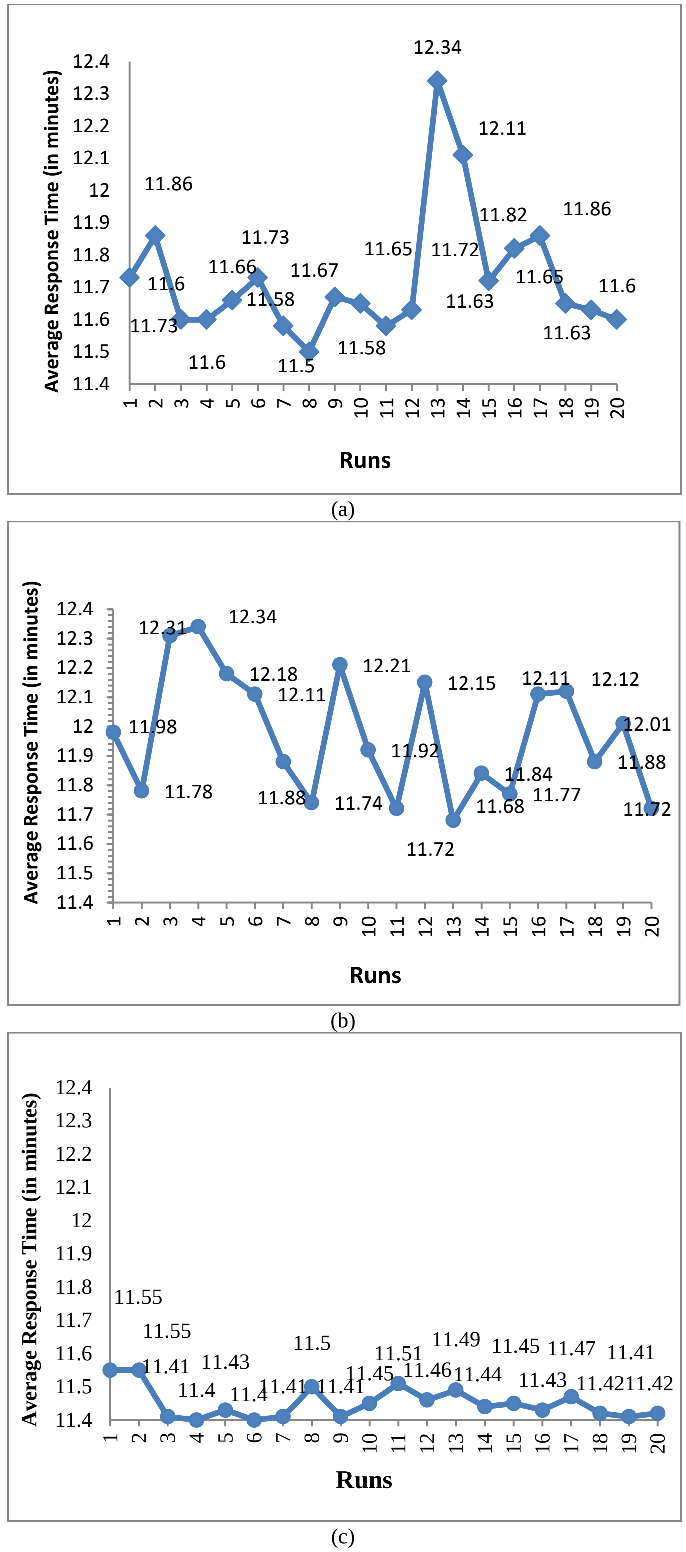


Fig. 10. (a). Constancy Graph of GA, (b). Constancy Graph of PSO, (c). Constancy Graph of mSFLA.

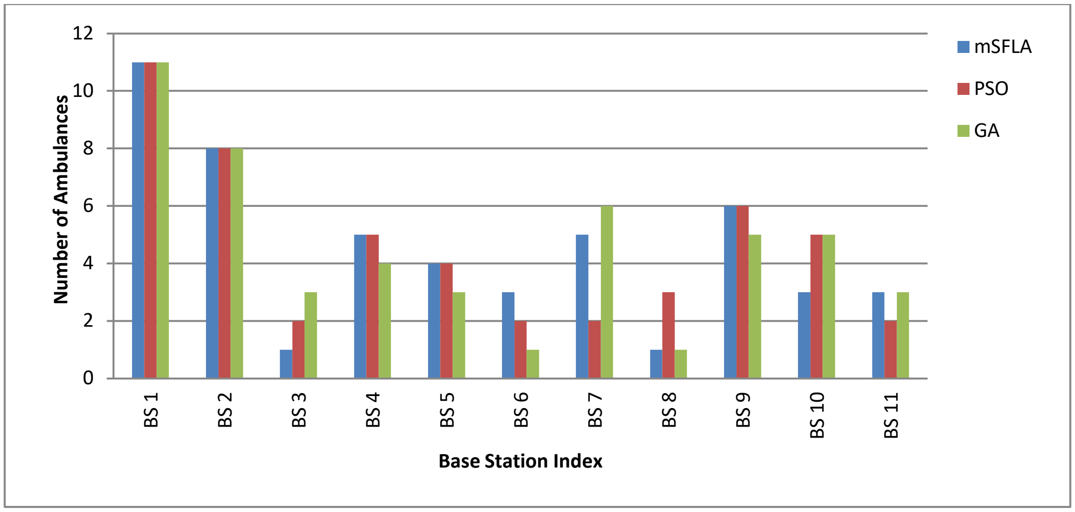


Fig. 11. Ambulance Allocation Plan Attained by Each Algorithm.

3) Constancy repeatability: The performance of any algorithm can also be measured using the concept of constancy repeatability. Constancy repeatability of an algorithm is the similarity rate of the results obtained by the algorithm in different executions with the same input values [40]. To infer the constancy and repeatability of the algorithm, the authors plotted the fitness values obtained by all three algorithms in twenty runs of the operational model. Fig. 10(a), 10(b), and 10(c) show that the changes in the fitness value of GA, PSO, and mSFLA. The changes in the value of GA are from 12.34 to 11.50 minutes, in PSO are from 12.34 to 11.68 minutes, and in mSFLA are from 11.55 to 11.41 minutes. To be more exact, the variance of the results is calculated. The variance values are 0.043178 for PSO, 0.038826 for GA, and 0.00205 for mSFLA. The consistency of any algorithm can be highlighted with the value of variance ranging between 0 and 1. In the proposed work, the variance value is between 0 and 1 for all three algorithms stating that all the algorithms are stable and consistent. However, the global optima results obtained by mSFLA are close to the average value in most runs, so it characterizes mSFLA as the most stable algorithm among the three algorithms. In other words, it can be said that in most cases, mSFLA will converge to global optima or near global optima. The ambulance allocation plan for the area of Southern Delhi provided by each algorithm is shown in Fig. 11.

VII. Conclusion

The performance of EMS significantly affects a country's healthcare system as it is considered responsible for saving people's lives. Response time is considered a key indicator to measure the performance of EMS by evaluating the time an ambulance takes to report at the spot from where the request was generated. To reduce the response time of EMS, the ambulances should be strategically allocated at the base stations so that the commuting time of the ambulance from the base station to the demanded spot is reduced. Considering this motive, the authors undertook the problem of finding an optimal allocation plan for a fleet of 50 ambulances among the 11 base stations in the southern portion of Delhi. The authors used an operational model that showed the flow of data between the simulation component and optimization component. For the optimization component, the authors proposed mSFLA that used the concept of mutation in SFLA to avoid being trapped in local optima. mSFLA was compared with GA and PSO using different metrics. The results shown in Section VI help analyze the performance of mSFLA with PSO and GA. The objective of the work to attain an allocation plan with minimum response time is attained by mSFLA. It is able to reduce the value of ART from 13 minutes to 11.41 minutes, i.e., by 12.23%.

A comparison of standard deviation, best and worst solutions of the proposed algorithm proves that mSFLA is more effective than the other two algorithms. The small value of 0.045331 for standard deviation signifies that mSFLA is consistent and reliable. Quick convergence and short execution time of mSFLA imply that it can be efficiently utilized in optimization problems similar to ambulance allocation problems. Moreover, mSFLA converges to a global optima value of 11.4127 minutes at lower iterations i.e. 41st iteration number taking less execution time than PSO and GA, which converge to a global optima value of 11.9733 and 11.72735 in 94th and 358th iteration number at much higher iterations. Therefore, mSFLA appears superior to the other two algorithms regarding the quality of solution and convergence rapidity. This work also validates the competency of mSFLA to other algorithms in handling problems similar to allocation problems.

As it is impossible to consider all the possible scenarios, the authors would like to extend the work by changing the single objective function to a multiobjective function. In addition, the authors will also focus on proposing an efficient strategy and solution for dynamically allocating and relocating ambulances.

References

[1] V. Bélanger, A. Ruiz, and P. Soriano, “Recent optimization models and trends in location, relocation, and dispatching of emergency medical vehicles,” Eur. J. Oper. Res., vol. 272, no. 1, pp. 1–23, 2019.

[2] H. Andersson, T. A. Granberg, M. Christiansen, E. S. Aartun, and H. Leknes, “Using optimization to provide decision support for strategic

emergency medical service planning – Three case studies," Int. J. Med. Inform., vol. 133, no. July 2019, pp. 103–113, 2020.

[3] T. Andersson and P. Värbrand, "Decision support tools for ambulance dispatch and relocation," J. Oper. Res. Soc., vol. 58, no. 2, pp. 195–201, 2007.

[4] C. J. Jagtenberg, S. Bhulai, and R. D. van der Mei, "Dynamic ambulance dispatching: is the closest-idle policy always optimal?," Health Care Manag. Sci., vol. 20, no. 4, pp. 517–531, 2017.

[5] S. El-Masri and B. Saddik, "An emergency system to improve ambulance dispatching, ambulance diversion and clinical handover communication: a proposed model," J. Med. Syst., vol. 36, no. 6, pp. 3917–3923, 2012.

[6] Y. A. Kochetov and N. B. Shamray, "Optimization of the Ambulance Fleet Location and Relocation," J. Appl. Ind. Math., vol. 15, pp. 234–252, 2021.

[7] M. Reuter-Oppermann, P. L. van den Berg, and J. L. Vile, "Logistics for Emergency Medical Service systems," Heal. Syst., vol. 6, no. 3, pp. 187–208, 2017.

[8] L. Yan, P. Wang, J. Yang, Y. Hu, Y. Han, and J. Yao, "Refined Path Planning for Emergency Rescue Vehicles on Congested Urban Arterial Roads via Reinforcement Learning Approach," J. Adv. Transp., vol. 2021, pp. 1–12, 2021.

[9] M. Eusuff, K. Lansey, and F. Pasha, "Shuffled frog-leaping algorithm: a memetic meta-heuristic for discrete optimization," Eng. Optim., vol. 38, no. 2, pp. 129–154, 2006.

[10] V. A. Knight, P. R. Harper, and L. Smith, "Ambulance allocation for maximal survival with heterogeneous outcome measures," Omega, vol. 40, no. 6, pp. 918–926, 2012.

[11] E. Wilde, "Do emergency medical system response times matter for health outcomes?," Health Econ., vol. 22, no. 7, pp. 790–806, 2013.

[12] M. A. Zaffar, H. K. Rajagopalan, C. Saydam, M. Mayorga, and E. Sharer, "Coverage, survivability or response time: A comparative study of performance statistics used in ambulance location models via simulation--optimization," Oper. Res. Heal. Care, vol. 11, pp. 1–12, 2016.

[13] J. J. Boutilier and T. C. Y. Chan, "Ambulance emergency response optimization in developing countries," Oper. Res., vol. 68, no. 5, pp. 1315–1334, 2020.

[14] Ľ. Jánošíková, P. Jankovič, M. Kvet, and F. Zajacová, "Coverage versus response time objectives in ambulance location," Int. J. Health Geogr., vol. 20, no. 1, pp. 1–16, 2021.

[15] T. Ünlüyurt and Y. Tunçer, "Estimating the performance of emergency medical service location models via discrete event simulation," Comput. Ind. Eng., vol. 102, pp. 467–475, 2016.

[16] S. Saisubramanian, P. Varakantham, and H. C. Lau, "Risk based optimization for improving emergency medical systems," in Proceedings of the AAAI Conference on Artificial Intelligence, 2015, pp. 17–22.

[17] S. Firooze, M. Rafiee, and S. M. Zenouzzadeh, "An optimization model for emergency vehicle location and relocation with consideration of unavailability time," Sci. Iran., vol. 25, no. 6, pp. 3685–3699, 2018.

[18] R. Mccormack and G. Coates, "A simulation model to enable the optimization of ambulance fleet allocation and base station location for increased patient survival," Eur. J. Oper. Res., vol. 247, no. 1, pp. 294–309, 2015.

[19] R. Wei, "Coverage location models: alternatives, approximation, and uncertainty," Int. Reg. Sci. Rev., vol. 39, no. 1, pp. 48–76, 2016.

[20] M. van Buuren, R. an der Mei, and S. Bhulai, "Demand-point constrained EMS vehicle allocation problems for regions with both urban and rural areas," Oper. Res. Heal. Care, vol. 18, pp. 65–83, 2018.

[21] A. Y. Chen, T.-Y. Lu, M. H.-M. Ma, and W.-Z. Sun, "Demand Forecast Using Data Analytics for the Preallocation of Ambulances," IEEE J. Biomed. Heal. informatics, vol. 20, no. 4, pp. 1178–1187, 2015.

[22] S. Wajid, N. Nezamuddin, and A. Unnikrishnan, "Optimizing Ambulance Locations for Coverage Enhancement of Accident Sites in South Delhi," Transp. Res. procedia, vol. 48, pp. 280–289, 2020.

[23] D. Degel, L. Wiesche, S. Rachuba, and B. Werners, "Time-dependent ambulance allocation considering data-driven empirically required coverage," Health Care Manag. Sci., vol. 18, no. 4, pp. 444–458, 2015.

[24] J. J. Boutilier and T. C. Chan, "Ambulance emergency response optimization in developing countries," Oper. Res., vol. 68, no. 51, pp. 1315--1334, 2020.

[25] N. Geroliminis, K. Kepaptsoglou, and M. G. Karlaftis, "A hybrid hypercube--genetic algorithm approach for deploying many emergency response mobile units in an urban network," Eur. J. Oper. Res., vol. 210, no. 2, pp. 287–300, 2011.

[26] L. Zhen, K. Wang, H. Hu, and D. Chang, "A simulation optimization framework for ambulance deployment and relocation problems," Comput. Ind. Eng., vol. 72, pp. 12–23, 2014.

[27] W. Yang, Q. Su, S. H. Huang, Q. Wang, Y. Zhu, and M. Zhou, "Simulation modeling and optimization for ambulance allocation considering spatiotemporal stochastic demand," J. Manag. Sci. Eng., vol. 4, no. 4, pp. 252–265, 2019.

[28] A. JA, J. Zayas-Castro, and H. Charkhgard, "Ambulance allocation optimization model for the overcrowding problem in US emergency departments: A case study in Florida," Socio-Economic Plan. Sci., vol. 71, p. 100747, 2020.

[29] AhmadM.Manasrah and H. B. Ali, "Workflow Scheduling Using Hybrid GA-PSO Algorithm in Cloud Computing," Wirel. Commun. Mob. Comput., vol. 7, no. 4, pp. 17–34, 2018.

[30] S. H. R. Hajipour, Vahid and Pasandideh, "Proposing an adaptive particle swarm optimization for a novel bi-objective queuing facility location model," Econ. Comput. Econ. Cybern. Stud. Res., vol. 46, pp. 223–240, 2012.

[31] H. WA, L. CS, A. AF, A. MH, and T. SS., "Solving maximal covering location with particle swarm optimization," Int. J. Eng. Technol., vol. 5, no. 4, pp. 3301–3306, 2013.

[32] Y. Tsai, C. KW, Y. GT, and L. HJ, "Demand forecast and multi-objective ambulance allocation," Int. J. Pattern Recognit. Artif. Intell., vol. 32, no. 7, p. 1859011, 2018.

[33] M. Benabdouallah, C. Bojji, and O. El Yaakoubi, "Deployment and redeployment of ambulances using a heuristic method and an ant colony optimization—case study," in Third International Conference on Systems of Collaboration (SysCo), 2016, pp. 1–4.

[34] Q. Su, Q. Luo, and H. H. Samuel, "Cost-effective analyses for emergency medical services deployment: A case study in Shanghai," Int. J. Prod. Econ., vol. 163, pp. 112–123, 2015.

[35] H. Adarang, A. Bozorgi-Amiri, K. Khalili-Damghani, and R. Tavakkoli-Moghaddam, "A robust bi-objective location-routing model for providing emergency medical services," J. Humanit. Logist. Supply Chain Manag., 2020.

[36] X. Duan, T. Niu, and Q. Huang, "An improved shuffled frog leaping algorithm and its application in dynamic emergency vehicle dispatching," Math. Probl. Eng., pp. 17–28, 2018.

[37] H. P. Hsu and T. L. Chiang, "An improved shuffled frog-leaping algorithm for solving the dynamic and continuous berth allocation problem (DCBAP)," Appl. Sci., vol. 9, no. 21, p. 4682, 2019.

[38] Q. Huang and W. Song, "A land-use spatial optimum allocation model coupling a multi-agent system with the shuffled frog leaping algorithm," Comput. Environ. Urban Syst., vol. 77, p. 101360, 2019.

[39] Q. Y. Duan, V. K. Gupta, and S. Sorooshian, "Shuffled complex evolution approach for effective and efficient global minimization," J. Optim. Theory Appl., vol. 76, no. 3, pp. 501–521, 1993.

[40] B. Saeidian, M. S. Mesgar, B. Pradhan, and M. Ghodousi, "Optimized location-allocation of earthquake relief centers using PSO and ACO, complemented by GIS, clustering, and TOPSIS," Int. J. Geo-Information, vol. 7, no. 8, pp. 292–315, 2018.