Article

Modeling and Optimizing an Emergency Medical Centers Location Problem using Meta-heuristic algorithms

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**Abstract:** Quick access to emergency treatment (trauma) centers is one of the main and necessary issues in any society, especially in high-accident communities, because the rapid transfer of the injured to medical centers would minimize morbidity and mortality from accidents. In this regard, the optimal location of trauma centers and how to transfer the injured to these centers affect the efficacy of the relief process significantly. This study aimed to provide an integrated model to determine the optimal location for trauma centers and helicopter stations. The proposed model also determines how to assign the injured to trauma centers and helicopter stations, along with the number of helicopters required for every station. The model proposed in this study is a mixed linear programming model, in which the duration of the transfer of the injured to medical centers and helicopter stations is considered in a probabilistic way to make the problem more realistic. A new efficient meta-heuristic algorithm called cloud theory-based simulated annealing is introduced for the proposed model optimization while also comparing the proposed algorithm efficiency with the simulated annealing and genetic algorithms. Based on the obtained computational results, the cloud theory-based simulated annealing algorithms outperform the two genetic and simulated annealing in both response quality criteria and computational time.

**Keywords:** Cloud Theory-based Simulated Annealing; Emergency Treatment (Trauma) Centers; Location

1. Introduction

The healthcare system can be regarded as a considerably large industry within the service sector in many industrialized countries (Weber, 1929). The demand for health services is increasing with the aging process in societies. At the same time, providing high-quality health care services with limited resources and high demand is the most important challenge in these systems. In recent years, spending on health care has grown in countries like the United States and many large European countries to 17% and 10% of GDP, respectively, according to available research. In these conditions, decisions on the location of medical centers contribute significantly to the performance of such systems. Beyond cost and service cost standards, wrong decisions about the location of the facilities in the health sector have a serious impact on society. For instance, difficult access to health facilities is potentially related to higher morbidity and mortality rates. Hence, modeling the location of the facilities for health care has much more importance compared to similar modeling in other fields. Also given the growing trend in declining birth rates in the world, longer life expectancy, and the growth of elderly-related facilities, along with the increase in environmental concerns (such as noise and air pollution), health care and location of its facilities become more important and serious issues. These factors make the problem of modeling the Healthcare Facility (HCF) location an attractive one in operations research (OR). The present study has focused on the location-integrated allocation of helicopter stations to patients and planning emergency care centers. Accordingly, this problem seeks to find optimal places to establish helicopter and exchange stations while examining how to allocate patients to helicopter stations. For this purpose, all the considerations in the problem are expressed in the form of a mathematical model.

The remaining parts of this article are organized in the following way: Section 2 provides a literature review in this area. Section 3 describes the problem and provides hypotheses, signs, and mathematical models. The next section proposes the solution method, which is then evaluated by using random samples. Finally, the last section is related to the conclusion and future perspective.

2. Literature Review

Gould and Lienbach (1996) first studied the allocation of HCF location to locate the hospital and determine its capacity as a P-Median problem, which was solved using a transport algorithm. Since 2000, the HCF location problem has been investigated from different perspectives. For instance, Rahman and Smith [2] used location-allocation models to plan the development of health services in developing countries. They considered four categories for the articles in their research, including (1) discovering a set of optimal areas, (2) determining optimal locations in new areas, (3) assessing the efficiency of the previous location decisions, and (4) enhancing current facility locations. Brotcorne et al. (2003) examined the development of ambulance location models during a 30-year period, classifying them into definite and probabilistic types. In addition, they investigated dynamic models in ambulance locations. In another study, Daskin and Dean (2004) categorized location models in the health care literature according to three characteristics: (1) accessibility, (2) adaptability, and (3) availability. According to their research, the three classical facility location models (Set covering, Maximal covering, and P-median) underlie many HCF location models. In their view, the accessibility model is a type of location model mainly aimed at maximizing coverage or minimizing average distance. Adaptability models focus on finding possible solutions in a variety of situations. Availability models, on the other hand, are divided into definitive models, based on queue theory and probability. These models examine the short-term changes due to overcrowding of facilities. Li et al. examined the literature on coverage set models and optimization procedures for the location of emergency centers. Rais and Vianna (2011) studied the role of operations research in health planning (such as demand forecasting, location, and capacity planning), healthcare management and procurement (including resource and staff planning), and many other areas (including the diagnosis and treatment of diseases). Wang (2012) studied the literature on three issues associated with unequal access to health care: 1) measurement, 2) optimization, and 3) impact emphasizing methodological advances and public policy implications. Gutiérrez and Vidal (2013) investigated research on home healthcare using a three-dimensional structure. The first dimension included dividing different levels of health planning into three levels of strategy, tactics, and operations according to the time horizon. The second dimension focused on dividing the procurement decisions into network design, transportation, staff, as well as inventory management. The third dimension provided a definition of the service process as a series of steps taken to provide home health services, including prescription services, patient admissions, appointments, scheduling, and patient examinations. Ingolfsson et al. (2008) investigated the planning and management of emergency medical services (EMS), emphasizing four issues of performance assessment, ambulance station location, ambulance allocation to the station and demand forecast, response time, and workload. In a recent study, Günes and Nickel (2015) reviewed the issues related to the location of health facilities focusing on three core healthcare areas, including the location of public facilities, ambulance planning, and hospital layout.

Dae ko et al. (2016) introduced a mathematical model to support an emergency medical system by designing the location, capability, and capacity of the emergency medical center. The application of the minimum survival rate was aimed at ensuring the patients’ survival. The development of a hybrid genetic algorithm was considered an alternative solution procedure. The simulation studies were used to derive and validate a deterministic solution.

Chen et al. (2016) improved the post-disaster EMS efficiency effectiveness through the application of integer programming and network-based partitioning to identify short-term locations for on-post facilities required for emergency medical services.

The EMS demands have already been 107 clustered taking into account the Euclidean distance, 108 searching for the potential locations of temporary EMS facilities (Chen et al., 2015b), and need development to take into consideration 109 network distance with MIP or network-based clustering methods. EMS has not completely benefited from the MIP or network-based clustering, given the 110-utility transportation infrastructure costs in response to disasters.

Gao et al. (2017) focused on the final value of the patients’ mortality risk (severity of injuries) due to the primary mortality risk value and travel distance (time) to highlight the location-allocation of the temporary centers for emergency medical services.

In research conducted by Liu et al. (2019), a distributionally robust model was developed to optimize the location, ambulance number, and demand assignment in EMS systems through the reduction of the expected total costs. The model introduced joint chance constraints and characterized the expected total costs by moment uncertainty according to a data-driven procedure to guarantee the greater possibility of meeting the maximum concurrent demand in the entire system compared to a preplanned level of reliability.

In another research Moeini et al. (2017) investigated the dynamic EMS systems while presenting a dynamic location model to locate and relocate a fleet of ambulances. The model introduced by them could control the ambulance movements and locations to propose a better coverage of the demand points.

Researchers have used simulation approaches to deal with the evaluation of the deterministic EMS location models. As shown, the performance evaluated using the simulation-based would differ based on the characteristics of the problem characteristics. Accordingly, the performance of an apparently good deterministic model may not be as good as evaluated by the simulation method (Ünlüyurt & Tunçer,2016).

Degel et al. (2015), introduced an ambulance locating model that was supposed to enhance the demand coverage in the case of dynamic demands and the dependence of the travel time on various times.

Wei et al. (2015) introduced a coverage locating model called “Continuous Space Maximal Coverage Problem (CSMCP)”, with an emphasis on the continuous demand distribution across the entire coverage area and the location of facilities wherever within the area.

Mosayebi et al. (2020) developed an integer mathematical model for the optimum site selection in the construction of medical and emergency centers, taking into account the failure probability of every center. The objective function of the research model minimized the costs of the system concerning the construction, transfer of patients, and failure of these centers. They eventually designed and investigated a numerical example by real-world problems to confirm the accurate performance of their developed model.

Deng et al. (2021) presented location optimization for the facilities of emergency medical services in Chengdu, southwest China, which had a population of over 16.5 million people. Their study focused on the optimization of the EMS systems through the addition (upgrade) of a minimum number of facilities for emergency medical services.

Jánošíková et al.[(2019)](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8097057/#cit0016) used the p-median model to determine the best location for the existing EMS stations in the Slovak Republic and ensure considerable enhancement in EMS accessibility with no further additions to the new stations.

Fritze et al. (2018) focused on restructuring the station location of the Austrian emergency medical services by providing a solution for the maximum coverage location problem. Better coverage with fewer EMS stations was obtained by their solutions compared to the existing situation.

Zhu et al. [(2016)](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8097057/#cit0017) sought to optimize the location of trauma centers in Shenzhen, China, using a modified location set covering model. As shown, the coverage of a large service area was possible, while the optimized solution could also provide a quick response time.

Boonmee et al. (2017) surveyed the facility location problems associated with emergency humanitarian logistics according to both data modeling types and problem types to investigate the pre- and post-disaster situations concerning the location of facilities, including distribution centers, warehouses, shelters, debris removal sites, and medical centers.

Sadeghi Moghadam and Ghasemian Sahebi (2018) determined the EMS location to enhance the demand coverage while reducing the rescue time in a humanitarian supply chain. They introduced a mathematical model for the solution of the EMS location problem, taking into account a number of conditions for the problem and seeking to determine the optimal locations to establish the centers. The authors introduced an innovative algorithm, using two meta-heuristic algorithms to solve the proposed problem. Finally, the model developed by them was used to solve 16 scenarios.

Mohammadi and Yaghoubi (2017) tried to locate transfer points and distribution centers using a two-objective mathematical model. Their proposed model could address the failure probability of routes and the disruption of distribution centers for medical supplies based on the disaster.

A pre- and post-crisis relief network was developed by Tofighi et al. (2016) for Tehran, the capital of Iran, with central warehouses and local distribution centers. The authors focused on the development of a new two-stage scenario-based possibilistic-stochastic programming. Given the considerable number of torn-out hospitals not equipped with helipad hospital grounds, it is possible to use alternative sites to construct helipads.

Sabouhi et al. (2019) proposed a multi-objective mathematical model with uncertainties to locate shelters and transfer points. The objective function focused on minimizing the maximum transportation time to ensure fairness. They addressed both the transfer of injured people to the hospital and the evacuation of the affected areas to shelters.

Maleki Rastaghi. (2018) presented a hierarchical mathematical model for allocating location to a real-world health service design network. This two-tier hierarchical model considered services by providing services, uncertainty regarding demand, services and geographical access, prioritization of the patients according to their urgency, and adoption of various service approach to serving the patients and the quality of services.

Karatas and Yakici (2019) examined the impact of support facilities in medical emergency centers, proposing different demand allocation strategies and using discrete simulation and combined optimization to determine the best support location according to different levels of service.

As can be concluded from the reviewed papers, research in the literature has addressed one or two aspects of the HCF location. For instance, some studies have considered the uncertainty concerning patient admission while considering the patient service process to be definite or failing to consider all the costs imposed on the system. Also, many researchers have focused on one aspect of the service and, for instance, investigated only the process of transferring the injured to a medical center or the treatment process in a center. Therefore, the lack of integrated models can be considered the main weakness of research in this field. Hence, the current research presents an integrated model for location-allocation of helicopter stations and planning of emergency care centers to solve this problem. The proposed model is a development of the model presented by Bozorgi Amiri et al. (2013), which addresses the optimal location of ambulance stations and rescue helicopters and seeks rapid transfer of patients to medical centers. In the model presented by Bozorgi Amiri, all processes are considered definite, and their possible features are overlooked. On the other hand, this model only focuses on the necessary measures to take the patient to medical centers and does not address the treatment process. Accordingly, the model proposed in this research tries to make the problem more realistic while minimizing the transfer time from the demand point to the treatment center and the service time in the treatment center, considering the real-world settings. The research also offers a combined simulation approach, artificial neural network, and optimization that can efficiently optimize the proposed problem.

3. Problem statement and the mathematical model

The present research has introduced an integrated model for location-allocation of helicopter stations to patients and planning of emergency medical centers. The developed model is a development of the model presented by Bozorgi-Amiri et al. (2013), which seeks the optimal location of ambulance stations and rescue helicopters and studies the rapid transfer of patients to medical centers. In the model presented by Bozorgi-Amiri et al., all processes are considered definite, overlooking their possible features. On the other hand, the model focuses only on the necessary measures to take the patient to medical centers, and the treatment process has not been considered. The model proposed in this research tries to make the problem more realistic by taking into account these cases. The proposed model can be divided into two main sub-sections. The first part examines how to transfer patients to medical centers, while the second part optimizes the service process within medical centers. Under the first part of the model, three modes of transmission are assumed, including 1) direct transport by ambulances, 2) transport to the helicopter station using an ambulance and to the hospital using a helicopter, and 3) transport to a preset point (exchange point) using an ambulance and to the hospital by a helicopter.

The model focused on minimizing the transfer time from the demand points to the hospital according to various modes. To achieve this goal, the proposed model must specify the optimal values ​​of the following decision variables:

1. Locations of establishing helicopter station
2. Number of helicopters for every station
3. How to assign patients to trauma centers and helicopter stations

3.1. Mathematical model

The current section defines the proposed mathematical model. Accordingly, all the problem indices and parameters are explained first. The decision variables are mentioned and the objective function is presented, along with all the constraints in the following.

|  |  |
| --- | --- |
| Demand points index |  |
| Helicopter station index |  |
| Trauma Center Index |  |

|  |  |
| --- | --- |
| The patient transfer time from the demand point to the Trauma center in the scenario π |  |
| Duration of patient transfer from helicopter station k to the demand point and from there to the Trauma center u in scenario π |  |
| Average demand rate at point  |  |
| Helicopter efficiency at station k |  |
| The helicopter station establishment cost at the point k |  |
| The Trauma center establishment cost at the point k |  |
| Average waiting time at the helicopter station k |  |
| Number of available helicopters H |  |

To optimize the problem, the optimal values ​​of the following five groups of variables must be determined.

|  |  |
| --- | --- |
| The direct assignment of the demand point to the trauma center u X |  |
| The assignment of the demand point to the trauma center u by helicopter station K |  |
| The establishment of a helicopter station at point K |  |
| The establishment of a trauma center at point u W |  |
| Number of helicopters assigned to the helicopter station k |  |

The objective function of this model focuses on minimizing the time of patient transfer to trauma centers. The first part of the objective function calculates the patient transport time to the trauma center by ambulance. The second part calculates the patient transfer time to the trauma center by a helicopter. Finally, the third part calculates the average waiting time at the helicopter station.

 (1)

The following constraints ensure lower costs for establishing trauma centers and helicopter stations compared to the available budget.

The following constraint ensures that each of the demand points is served.

Constraint 4 controls that patients are assigned to pre-established trauma centers. Constraint 5 controls the assignment of the patients to the pre-established helicopter and trauma centers.

|  |  |  |
| --- | --- | --- |
|  |  | (4) |
|  |  | (5) |

Constraints 6-11 calculate the average waiting time at helicopter stations using queuing system theory.

|  |  |
| --- | --- |
|  | (6) |
|  | (7) |
|  | (8) |
|  | (9) |
|  | (10) |
|  |  | (11) |

The following constraint controls the maximum number of helicopters available.

|  |  |
| --- | --- |
|  | (12) |

The values ​​related to the decision variables are controlled by constraints 13 and 14.

|  |  |  |
| --- | --- | --- |
|  |  | (13) |
|  |  | (14) |

4. Solution method

4.1. Simulated Annealing algorithm

The Simulated Annealing algorithm as a probabilistic, sequential, and optimization search technique starts with an initial response and then moves to a neighboring solution in an iterative loop. If the neighbor's solution is superior to the current one, the algorithm sets (moves to) it as the current solution If the above condition is not held, the solution is accepted as the current solution with probability . As the temperature gradually decreases, the likelihood of accepting the worse solutions in the final steps would decrease, converging the algorithm towards better (or of the same quality) solutions. On the other hand, the algorithm easily accepts a weak solution with high temperature, failing to converge rapidly. Escape from the trap, however, is at least a low-temperature, hard-to-find place with low search accuracy. Hence, finding a new implementation technique for the Annealing mechanism, which performs a better measurement of the physical law while providing higher search power and better convergence.

4.2. Cloud theory

This innovative theory is an expansion of the membership function in fuzzy theory, achieved by the transformation of uncertainty between quantity and quality according to the concept of time value. Physical Annealing reflects the random movement of molecules large to small scale as the landing temperature. It is easy to provide a theoretical definition of cloud theory, while its simulation on a computer would be more challenging. Yet, the cloud theory is used to guide implementation given its ability to characterize the transition between a qualitative concept and its numerical representation. Cloud theory generates a continuous Annealing temperature. This theory also represents a random characteristic and is apt to stability. Although the Annealing temperature changes randomly, its fragmentation decreases the variability in search.

Professor Li Di (1995) proposed the cloud model based on traditional fuzzy theory and probability statistics. Supposing L as the linguistic value of the domain V and in the path: , the model represents a normal cloud in the case of a normal distribution . The proposed path leads a set of randomly oriented numbers with the mathematical hope of , the entropy , and the entropy upper bound as three quantitative parameters showing the concept

 and show the cloud center and range, respectively. Figure 1 indicates about 99.74% of the total cloud droplets scattered between 3,-3. The entropy upper bound shows the higher degree of the cloud droplet scattering. the higher shows the higher scattering. As shown below, a drop of cloud is generated by a Normal distribution of Y Condition Cloud Generator (NYCCG) using the values ​​of ، ، and :

 would produce a random number with a normal distribution, a hope of , and a standard deviation of .



**Figure 1.** Three numerical features of a normal cloud.

4.3. Simulated Annealing based on Cloud theory

The continuous annealing temperature is generated using the cloud and normal cloud theory Y. Flexibility can be considered as a critical characteristic allowing the dynamic reduction of the annealing temperature to prevent problems such as falling into the trap local minimum. Figure 2 represents the annealing temperature with each mode in the CSA, indicating the ability of CSA to maintain the characteristics of the gradual slope of the annealing temperature decrease and the convergence of the simulated annealing algorithm. Meanwhile, the variable temperature of annealing from CSA has a considerably broader range than the simulated annealing algorithm, overcoming the disadvantage of simulated annealing algorithm, the temperature of which is discrete and simple in the annealing phase. Therefore, the CSA Annealing process shows higher compatibility with the process of physical annealing.



**Figure 2.** The temperature changes in the SA and CSA algorithms.

4.3.1. Solution structure

The structure of the proposed solution in this paper consists of a matrix. The first row of the matrix represents the centers selected for the trauma center and the helicopter station, and the second row indicates the number of helicopters assigned to every helicopter center. For instance, the sample response shown in Figure 3 occurs at points 1, 4, and 5 of the trauma centers and at points 6 and 7 of the helicopter station. Also, the number of helicopters assigned to the station is 6 times 2, and the number of helicopters assigned to the station is 3 times 3. Demands in Areas 1 and 2 are assigned to Trauma Center 5 and Helicopter Station 6, respectively, and so on.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 4 | 1 | 7 | 6 | 5 |
|  |  | 3 | 2 |  |

Fig3: Solution structure in CSA algorithm

4.3.2. Fit function

a fit function must first be devised for any problem solution using meta-heuristic algorithms. For each solution, this function returns a non-negative number that indicates the fit of that solution. In this research, the fit function of each solution is equal to the objective function plus the penalty function. The penalty function is used to prevent unjustified solutions. Penalty functions are one of the most popular methods for dealing with solutions that do not meet the limitations of the problem. Depending on the response pattern, only the constraints of the total budget and the threat of available helicopters may not be met. Penalty functions are one of the primary ways to deal with this problem. As a result, we add the values of deviations from these constraints together while only adding one penalty parameter as the total constraint penalty to the objective function. Finally, the solutions are fined based on the following linear function:

 (15)

Where, Z and b represent the objective function and the sum of the violations of the constraints, respectively. Because the optimization problem is minimization, represents a large positive value.

4.3.3. Neighborhood operator

Neighbors of a state (solution) are new states of the solution created by changing the current state according to a predetermined method. According to the neighborhood structure used in this study, the first one of the cells of the first row of the matrix is ​​selected, and its value is replaced by a random value. Also, when selecting one of the cells in the second row, the value is selected and a new random value is given to it. According to Figure 4, the number of the Center 6 helicopters has been reduced from two to one. Potential location 3 has also been selected for the construction of a trauma center.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 4 | 1 | 7 | 6 | 5 |
|  |  | 3 | 2 |  |

.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 4 | 3 | 7 | 6 | 5 |
|  |  | 3 | 1 |  |

**Figure 4.** Neighborhood operator in CSA algorithm.

4.3.4. Initial temperature

The initial temperature at which the algorithm starts should be high enough to allow movement to the neighboring state. If the initial temperature is too high, the search can move to any neighborhood, and the search turns into a random search until the temperature cools enough. It is difficult to find the right starting temperature, and there is no specific method for different problems. If we know the maximum distance (cost of different functions) between a neighborhood and other neighborhoods, we can use this information to calculate the initial temperature. That is, we can calculate the required energy. Thus, a significant number of random solutions can be primarily generated while also determining their objective function. The initial temperature can be determined by calculating the standard deviation in the results. The algorithm introduced in the study uses 1.5 times the standard deviation of the initial solutions to find the initial solution.

4.3.5. Decreasing the temperature in each step

The current study has used the linear relationship below for the temperature reduction:

|  |
| --- |
|  |
|  |

Where, is the value of the base temperature in a particular equilibrium, and shows the temperature used in the acceptance function. As can be seen in Figure 2, leads to the production of a continuous temperature range, which in turn increases the quality of the algorithm. The optimal value of the α parameter is also determined through the analysis of experiments.

4.3.6. Iteration at each temperature

At each temperature, the number of iterations is considered such that there is no change in the solution in 100 consecutive iterations.

5. Computational results

The current section provides the computational results of the solution introduced, and the effectiveness of the presented algorithm in optimizing the research model is examined after reviewing and describing the proposed structure of the mathematical model and the proposed algorithm. The efficacy of the presented algorithm was measured against two conventional Simulated Annealing algorithms and a genetic algorithm. First, the design method of Taguchi experiments was used and the parameters of the whole algorithm were determined with an emphasis on achieving the highest performance in the algorithms. Then random sample problems were generated and solved by all algorithms. In the following, the proposed algorithms were evaluated using two criteria of response quality and computational time. Minitab 17 software was used to design experiments and determine the optimal levels of input parameters of algorithms, while Matlab software was used to program algorithms. Also, all calculations were performed by a PC, which had a 4-GB RAM and an AMD X2 3.2 GHz processor.

5.1. Parameter setting

The first step in applying meta-heuristic algorithms is to find the values ​​of the initial parameters. First, the domains associated with factors changes and the specific levels to be considered for agents must be selected. It is usually best to keep the number of operating levels under consideration small. Table 1 indicates the search range of the levels of input parameters for the three algorithms. Three levels are considered for each parameter. The selection of the initial levels is based on preliminary tests that give an overview of the algorithm quality at different levels of parameters.

**Table 1.** Controllable factors along with their levels.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Algorithm | Parameter | Parameters | First Level | Second Level | Third Level |
| SA |  | Number of iterations in the inner loop | 10 | 20 | 30 |
|  | Number of iterations in the outer loop | 200 | 400 | 600 |
| algha | temperature decrease rate | 0.97 | 0.98 | 0.99 |
| CSA |  | Number of iterations in the inner loop | 10 | 20 | 30 |
|  | Number of iterations in the outer loop | 200 | 400 | 600 |
| algha | temperature decrease rate | 0.97 | 0.98 | 0.99 |
| GA | Pop\_ size | Population size | 50 | 100 | 150 |
| Pc | percentage of intersection | 0.7 | 0.8 | 0.9 |
| Pm | Mutation percentage | 0.07 | 0.09 | 0.1 |
| Max-it | Number of iterations | 150 | 300 | 450 |

The number of degrees of freedom needs calculation for the appropriate orthogonal array selection. In such conditions, one and two degrees of freedom are required for the total average and for each three-level factor, respectively. Thus, the total degree of freedom will be 9 for GA and 7 for SA and CSA. A reference to standard orthogonal arrays shows clearly that these conditions are met in L16 orthogonal arrays. The designed experiments are performed and the objective function values are considered as the result of each experiment. The values ​​obtained are then converted to the Signal to Noise Ratios (S/N) index through Equation 18, in which and show the response value in the test (observation) () and the number of performances of each of the designed experiments, respectively.

 (18)

Equation (5-1), known as the S / N S ratio (the less the better), is used when a non-negative feature with an ideal value of zero is considered. Figures 5 to 7 show the S/N ratio diagrams for algorithms. Levels where the S/N index has reached its maximum can be selected as optimal.



Fig5: Changes in the value of S/N index at various GA algorithm levels



Fig6: Changes in the value of S/N index at various AA algorithm levels



Fig7: Changes in the value of S/N index at various CSA algorithm levels

5.2. Algorithms Comparison

We randomly generated numerical examples and executed them on a personal computer to examine the performance of each algorithm using statistical tests. The problems produced were in 3 different classes according to the number of demand points and trauma centers. The first to the third categories included problems with 10 demand points and 5 trauma centers, problems with 15 demand points and 8 trauma centers, and problems with 20 demand points and 10 trauma centers, respectively. In each group, 10 random problems were generated and used to test the performance of the algorithms. Tables 2 and Figures 8 and 9 show the efficiency of the algorithms in the quality index and computational time. In terms of quality, the GA and CSA algorithms outperformed SA, achieving better solutions in most cases. However, concerning the time index, the GA algorithm had the weakest performance, performing poorly in terms of the computational time.

Table 2: Computational results of algorithms in solving 30 sample problems

|  |  |  |
| --- | --- | --- |
|  | COST | TIME (sec) |
| Problem No | GA | SA | CSA | GA | SA | CSA |
| 1 | 223183 | 222134 | 224009 | 70 | 67 | 65 |
| 2 | 216598 | 223192 | 212459 | 74 | 71 | 67 |
| 3 | 227352 | 226403 | 228484 | 76 | 71 | 70 |
| 4 | 205849 | 206688 | 199558 | 72 | 72 | 69 |
| 5 | 209885 | 223876 | 204903 | 70 | 68 | 65 |
| 6 | 225600 | 240557 | 216508 | 71 | 66 | 62 |
| 7 | 208883 | 208459 | 207572 | 73 | 69 | 71 |
| 8 | 221067 | 238003 | 222666 | 74 | 70 | 73 |
| 9 | 209079 | 224758 | 210841 | 76 | 74 | 66 |
| 10 | 229469 | 237658 | 223605 | 75 | 69 | 65 |
| 11 | 1352083 | 1393900 | 1214456 | 213 | 196 | 187 |
| 12 | 1290272 | 1355088 | 1110945 | 200 | 186 | 173 |
| 13 | 1331019 | 1485006 | 1138178 | 215 | 199 | 193 |
| 14 | 1329431 | 1366203 | 1279978 | 213 | 204 | 192 |
| 15 | 1271543 | 1308970 | 1204731 | 206 | 191 | 184 |
| 16 | 1345466 | 1462217 | 1290264 | 211 | 193 | 184 |
| 17 | 1383546 | 1408562 | 1262862 | 208 | 192 | 186 |
| 18 | 1252384 | 1271502 | 1075018 | 207 | 193 | 181 |
| 19 | 1308130 | 1390217 | 1240756 | 211 | 197 | 193 |
| 20 | 1358933 | 1524562 | 1223378 | 211 | 198 | 181 |
| 21 | 3176666 | 3282596 | 2805073 | 902 | 741 | 713 |
| 22 | 3036928 | 3159633 | 2817040 | 970 | 807 | 777 |
| 23 | 3099828 | 3535298 | 2896899 | 913 | 754 | 725 |
| 24 | 3197012 | 3439664 | 3005664 | 903 | 758 | 708 |
| 25 | 3173633 | 3381634 | 3003190 | 939 | 831 | 747 |
| 26 | 3092975 | 3496337 | 2796052 | 959 | 839 | 765 |
| 27 | 3130495 | 3273285 | 2961956 | 966 | 842 | 747 |
| 28 | 3086264 | 3198423 | 2781829 | 946 | 812 | 729 |
| 29 | 3102366 | 3522125 | 2791708 | 933 | 778 | 727 |
| 30 | 3182313 | 3326269 | 2810301 | 930 | 825 | 729 |

Fig8: Comparing the performance of the presented algorithms with different sizes in the solution quality criterion (objective function)

Fig9: Comparing the presented algorithms performance in different sizes in the computational time criterion

Tukey simultaneous test was used for analysis of variance and confidence intervals

The statistical analyses were used for more accurate investigations and comparisons. For statistical evaluation of algorithms, the entire results were first normalized according to the Relative percentage division (RPD) criterion, which indicates how far the solutions in each algorithm are from the best solution obtained and is calculated based on the formula below:

|  |  |  |
| --- | --- | --- |
| (19) |  |  |

Where, is the solution obtained from algorithm i for problem j, and , represents the best solution for problem j. Tukey 95% confidence intervals were used for statistical evaluation of algorithms. The results of this evaluation are shown in Figures 10 and 11 for the quality criterion and the computational time criterion, respectively. Based on Figure 10, the CSA algorithm outperforms other two algorithms and has the highest quality in terms of quality criteria. It can also be said that the GA algorithm outperforms the SA. Also, based on Figure 11, the SA and CSA algorithms both have good performance in terms of computational time, while GA algorithm performs much weaker than the other two. The most important reason for the GA weakness in computational time can be the application of crossover and mutation operators in all iterations on all chromosomes.

Fig10: Tukey 95% confidence interval for response quality criteria

Fig11: Tukey 95% confidence interval for the computational time criterion

6. Conclusion

The problem of the medical facilities location is among the most widely used problems in the real world, the optimization of which has always been considered by researchers, taking into account the real-world conditions. This research sought to make the model more practical as much as possible by developing the problem of location of emergency medical centers considering the real-world conditions. The proposed model focused on minimizing the total time of transfer of patients to medical centers. According to the research literature on location problems, this model is in the group of difficult problems, and hence, heuristic and meta-heuristic methods should be used to solve it. A Simulated Annealing algorithm according to cloud theory was utilized for the model optimization. The performance of the proposed algorithm was also evaluated using two Simulated Annealing algorithms and genetics. To achieve more efficient algorithms in this research, their input parameters were set at the best level through the Taguchi method. Finally, the proposed algorithms were implemented on several numerical problems of different sizes, and their efficiency and quality of solutions and the results were evaluated. In general, according to the defined criteria and statistical studies, the proposed algorithm had a better performance in both criteria of computational time and response quality compared to the other two algorithms. Finally, adding new features to the problem, reviewing the research optimization model, and solving the new model can be some suggestions for future research. These features include considering the treatment processes within the treatment centers, taking into account the possibility of damage to ambulances and helicopters.

References

1. Boonmee, C., Arimura, M., Asada, T. (2017). Facility location optimization model for emergency humanitarian logistics. International Journal of Disaster Risk Reduction, 24, 485-498.
2. Bozorgi-Amiri, A., Jabalameli, M. S., Mirzapour Al-e-Hashem, S. M. J. (2013). [*A multi-objective robust stochastic programming model for disaster relief logistics under uncertainty*](https://link.springer.com/article/10.1007/s00291-011-0268-x)*.* OR Spectrum, 35(4), 905-933.
3. Brotcorne, L., Laporte, G., Semet, F. (2003). *Ambulance location and relocation models.* Eur J Oper Res, 147(3), 451–63.
4. Chen, A. Y., & Yu, T. Y. (2016). Network based temporary facility location for the Emergency Medical Services considering the disaster induced demand and the transportation infrastructure in disaster response. Transportation Research Part B: Methodological, 91, 408-423.
5. Chen, A. Y., Yu, T. Y., Lu, T. Y., Chuang, W. L., Lai, J. S., Yeh, C. H., Sun, W. Z. (2015). *Ambulance service area considering disaster-induced disturbance on the transportation infrastructure*. Journal of Testing and Evaluation, 43(2), 1-11.
6. Daskin, M. S., Dean, L. K. (2004). *Location of health care facilities.* In: Brandeau ML, Sainfort F, Pierskalla WP, editors. *Operations Research and Health Care*. New York: Springer; 2004. p. 43–76.
7. Degel, D., Wiesche, L., Rachuba, S., Werners, B. (2015). *Time-dependent ambulance allocation considering data-driven empirically required coverage.* Health care management science, 18(4), 444-458.
8. Deng, Y., Zhang, Y., Pan, J. (2021). Optimization for Locating Emergency Medical Service Facilities: A Case Study for Health Planning from China. Risk Management and Healthcare Policy, 14, 1791.
9. Fritze, R., Graser, A., Sinnl, M. (2018). Combining spatial information and optimization for locating emergency medical service stations: A case study for Lower Austria. International journal of medical informatics, 111, 24-36.
10. Gao, X., Zhou, Y., Amir, M. I. H., Rosyidah, F. A., & Lee, G. M. (2017). *A hybrid genetic algorithm for multi-emergency medical service center location-allocation problem in disaster response*. International Journal of Industrial Engineering, 24(6).
11. Gould, P. R. & Leinbach, T. R. (1966). *An approach to* *the geographic assignment of* *hospital services.* Tijdschrift voor Economische en Sociale Georgia e, 57, 203-206.
12. Günes, E. D. & Nickle, S. (2015). *Location problems in healthcare*. In: Laporte, G., Nickle, S. Saidanha, D. A., Garma, F., editors. Location Science Cham, Springer, 555-579.
13. Gutiérrez, E. V., Vidal, C. J. (2013). Home health care logistics management problems: a critical review of models and methods. Rev Fac Ing, 68, 160–75.
14. Ingolfsson, A., Budge, S., Erkut, E. (2008). *Optimal ambulance location with random delays and travel times.* Health Care Management Science, 11, 262-274.
15. Jánošíková, Ľ., Kvet, M., Jankovič, P., Gábrišová, L. (2019). *An optimization and simulation approach to emergency stations relocation.*Central European Journal of Operations Research, 27(3), 737-758.
16. Karatas, M., & Yakıcı, E. (2019). An analysis of p-median location problem: effects of backup service level and demand assignment policy. European Journal of Operational Research, 272(1), 207-218.
17. Ko, Y. D., Song, B. D., Hwang, H. (2016). Location, capacity and capability design of emergency medical centers with multiple emergency diseases. Computers & Industrial Engineering, 101, 10-20.
18. Li, X., Zhao, Z., Zhu, X., Wyatt, T. (2011). Covering models and optimization techniques for emergency response facility location and planning: a review. Math Methods Oper Res, 74(3), 281–310.
19. Liu, K., Li, Q., Zhang, Z. H. (2019). Distributionally robust optimization of an emergency medical service station location and sizing problem with joint chance constraints. Transportation research part B: methodological, 119, 79-101.
20. Maleki Rastaghi, M., Barzinpour, F., Pishvaee, M. S. (2018). A multi-objective hierarchical location-allocation model for the healthcare network design considering a referral system. International Journal of Engineering, 31(2), 365-373.
21. Moeini, M., Jemai, Z., Sahin, E. (2015). *Location and relocation problems in the context of the emergency medical service systems: a case study.*Central European Journal of Operations Research, 23(3), 641-658.
22. Mohamadi, A., & Yaghoubi, S. (2017). A bi-objective stochastic model for emergency medical services network design with backup services for disasters under disruptions: An earthquake case study. International journal of disaster risk reduction, 23, 204-217.
23. Mosayebi, A., Mojaradi, B., Bonyadi Naeini, A., Khodadad Hosseini, S. H. (2020). *A Mathematical Model for Locating the Medical and Emergency Centers considering the Failure Probability of Centers.* Mathematical Problems in Engineering, 2020.
24. Rahman, S. U, Smith, D. K. (2000). Use of location-allocation models in health service development planning in developing nations. Eur J Oper Res, 123(3), 437–52.
25. Rais, A., Viana, A. (2012). *Operations research in healthcare: a survey*. Int Trans Oper Res, 2011, 18(1), 1–31.
26. Sabouhi, F., Tavakoli, Z. S., Bozorgi-Amiri, A., Sheu, J. B. (2019). *A robust possibilistic programming multi-objective model for locating transfer points and shelters in disaster relief.* Transportmetrica A: transport science, 15(2), 326-353.
27. Sadeghi Moghadam, M., & Ghasemian Sahebi, I. (2018). A Mathematical Model to Improve the Quality of Demand Responding in Emergency Medical Centers in a Humanitarian Supply chain. Modern Research in Decision Making, 3(1), 217-242.
28. Tofighi, S., Torabi, S. A., Mansouri, S. A. (2016). *Humanitarian logistics network design under mixed uncertainty.* European Journal of Operational Research, 250(1), 239-250.
29. Ünlüyurt, T., & Tunçer, Y. (2016). Estimating the performance of emergency medical service location models via discrete event simulation. Computers & Industrial Engineering, 102, 467-475.
30. Wang, F. (2012). Measurement, optimization, and impact of health care accessibility: a methodological review. Ann Assoc Am Geogr, 102(5), 1104–12.
31. Weber, A. (1929). Theory of the location of industries translated by CJ Friedrich from Weber’s 1909 book. Chicago: The University of Chicago Press.
32. Wei, G., Wang, Z., Ke, T., Liu, Y., Deng, W., Chen, X., Xie, L. (2015). *Decadal variability in seawater p H in the West Pacific: Evidence from coral δ11 B records.* Journal of Geophysical Research: Oceans, 120(11), 7166-7181.
33. Zhu, Y., Du, Q., Tian, F., Ren, F., Liang, S., Chen, Y. (2016). *Location optimization using a hierarchical location-allocation model for trauma centers in Shenzhen, China.*ISPRS International Journal of Geo-Information, 5(10), 190.