Multiple Criteria Decision Making for Hospital Location Allocation Based on Improved Genetic Algorithm

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Abstract - *Overcrowding in hospitals is a major problem for every society, and population distribution in these areas is an important issue to consider in urban planning. This paper uses the performance and impact of chromosome combination to improve genetic algorithms. An experiment was conducted to compare Optimal Arrays Optimization (IGA) with GA and Particle Swarm Optimization (PSO) to evaluate the performance of the new algorithm. To narrow down your search area, try the ability to analyze Geospatial Information System (GIS) and Statistical Hierarchy Process (AHP) to select candidate sites. The algorithm described above is then used to determine the best location and share the peer group in the real data. The research results of this article suggest that selecting a combination of chromosomes with high activity and chromosomes with weak activity will lead to improved algorithm development and research. In this way, the algorithm will not participate in local minima, the convergence process of the algorithm will be improved and the algorithm will show more stability in different performances. According to the results of this article, IGA has better performance than other algorithms. The convergence speed of IGA is higher than GA and PSO. All algorithms show different levels of reproducibility. However, IGA is safer than other algorithms. Additionally, IGA's running time is shorter than other algorithms. Note: This is the review article of the work already done by [1] Dr. Mehrdad Kaveh and his team.*

Key Words: Location Allocation, Analytic Hierarchy Process (AHP), Improved Genetic Algorithm, Optimization, Meta Heuristics, Geospatial Information Systems (GIS).

1.INTRODUCTION

Today, with the growth of the economy and the population increasing towards the city, the city has developed and is developing. As a result, urban lifestyles have greatly diminished in terms of health, safety and access to resources. In fact, large cities now face major traffic problems caused by the lack of good facilities and the layout of city services and public facilities. Providing healthcare and developing hospitals are new strategies to achieve health goals and global solutions to improve people's lives. Urban planners have long struggled with the distribution of healthcare and medical facilities. The location of the hospital is important in providing medical services and reducing the cost of settlement. Lack of right location options for the construction of medical facilities will cause many problems that have occurred in developed cities in the last few years.

2. LITERATURE SURVEY

The first paper [2], "Halting decisions for gas pipeline construction projects using AHP: a case study" by Abdelmaguid and Elrashidy, examines the application of the Analytical Hierarchy Process (AHP) in decision-making for gas pipeline construction projects. It effectively enhances decision-making but is limited in scope to pipeline projects.

In a paper by Kaveh, Mesgari, and colleagues [3], "Multiple criteria decision-making for hospital location-allocation based on improved genetic algorithm," they employ an improved genetic algorithm for optimizing hospital location-allocation. While the paper enhances hospital location-allocation, specific drawbacks were not identified in the information available.

Abebe and Megento's work [4], "Urban green space development using GIS-based multi-criteria analysis in Addis Ababa metropolis," focuses on improving urban green space planning through GIS-based multi-criteria analysis. Its limitations lie in its context specificity, potentially restricting broader applications.

In another study [5] by Ahmed, Mahmoud, and Aly, "Site suitability evaluation for sustainable distribution of a hospital using spatial information technologies and AHP," the paper explores sustainable hospital distribution, primarily focusing on upper Egypt, which limits its generalizability.

Khehra and Pharwaha [6] conducted a comparative analysis in their paper, "Comparison of genetic algorithm, particle swarm optimization and biogeography-based optimization for feature selection to classify clusters of microcalcifications." The paper provides valuable insights into feature selection analysis but is constrained by its specificity to a particular classification problem.

Li and Yeh [7] explored the integration of genetic algorithms and GIS for optimal location search in "Integration of genetic algorithms and GIS for optimal location search." The paper offers the integration of GIS and genetic algorithms but is limited by its age, considering its publication in 2005.

3. METHODOLOGY

1. Problem Statement

The purpose of this study is to improve the selection and classification of city hospitals in the city by taking into account various factors. To achieve this goal, various decision-making methods are used by integrating Geospatial Information Systems (GIS), Research Hierarchy Process (AHP) and Improved Genetic Algorithm (IGA).

2. Data Collection

Data collection involves collecting a variety of geographic, demographic, and residential data. These data include population distribution, transportation, land values, crime rates and emergency services. Geographic information is obtained from public archives and relevant organizations.

3. Critical Considerations

Many factors such as cost, accessibility and security are taken into account during the site selection process. Each measure is differentiated according to criteria such as "land value", "construction value", "proximity to densely populated areas" and "transportation infrastructure". Models are divided into two groups: effective and ineffective.

4. Analytic Hierarchy Process (AHP)

AHP is used to determine the importance of criteria and sub-criteria. Pairwise comparisons are made to create a weight vector that reflects the importance of each factor in the decision. AHP provides decision makers with a framework to evaluate patterns and make critical decisions.

5. Decision Matrix

Create a decision matrix where each row represents the candidate hospital location and each row represents variables and processes. The decision matrix is created from the collected data and the parameters obtained with AHP.

6. Improved Genetic Algorithm (IGA)

IGA is used to search for the best combination of candidate sites that meet the design criteria. IGA is a different type of genetic algorithm that has been modified to improve its use and search. It uses perturbations and functions to ensure good convergence and avoid local minima.

7. Genetic Algorithm Operators

IGA includes genetic operators such as selection, crossover and mutation. The selection process favors individuals with better values. While crossover creates new solutions by combining the genetic material of selected individuals, mutation adds diversity to the population.

8. Fitness Function

The fitness function evaluates the quality of candidate solutions according to defined criteria and key criteria. This function assigns each location a value indicating its suitability as a hospital location. İGA's aim is to maximize this benefit.

9. Development and Optimization

IGA has evolved over many generations by continually improving candidate solutions. This algorithm aims to find a group of candidates that maximize the objective function by considering various factors in the hospital domain.

10. Model Evaluation

Further performance of IGA by comparing its results with those obtained using optimization methods such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). Key metrics include turnaround speed, safety, repeatability and operational performance.

4. MODELLING IGA

GA is one of the meta-heuristic methods in optimization problems. It was first introduced by Holland in 1975, and it is, in fact, a virtual simulation of Darwin's Theory of Gradual Evolution (Holland 1992). This algorithm is a population-based method that is operated on a number of chromosomes in each computational repetition and implements random changes on them through implementing merging and mutation operators. At first, parent chromosomes are selected for reproduction, and then children are reproduced by using the combination operator. For the entire searching of the problem's space, the mutation operator is implemented on them. Finally, the performance of different responses was evaluated as a fitness function and the best chromosome according to the consensus of the problem was recorded as the optimal solution to the problem. (Saeidian et al. 2016).

This paper applies IGA to the location allocation problem. Since the present problem is formulated discretly, a better response is achieved by swapping the genes for the combination process in the genetic algorithm between the two selected parents. Therefore, selecting the selection and combination processes of parents plays an important role in the progress of the algorithm. For this reason, the effective and affectability rates of the chromosomes have been used. In fact, each chromosome has an effective rate and affectability rate which is used for selection and combination operations. The higher the activity of each chromosome, the better and smaller the effect. The opposite is true for chromosomes with poor function. The combination (effective and affectability rate) in IGA is a number between 0 and 1. The best response is its effective rate of one and affectability rate of zero. In other words, the ideal chromosome gives its genes to the chromosome with poor function. Additionally, the worst reaction has an efficiency of

0 and an effect of 1. This means that this chromosome must be optimized so that it can combine with the required chromosome. In Eq. (1), the effective rate and, in Eq. (2), the affectability rate have been defined as functions of their fitness function as follows:

$$Effective\_rate = \frac{n_i}{N} \quad .. (1)$$

$$Affectability\_rate = 1 - \frac{n_i}{N} \quad .. (2)$$

in which $\boldsymbol{n_i}$ is the rank of the goodness of a chromosome based on the fitness function and $\boldsymbol{N}$ is the best rank possible for the chromosomes of the current generation.

In IGA, the selection process is conducted in two different affectability ways. At first, a parent with poor fitness function (high affectability rate) and another parent with a good fitness function (high effective rate) were selected for crossover operation. The selection method of the two parents is different as well. For selecting a chromosome through affectability rate, a random number was selected within zero and one, and if this number is smaller than the affectability rate, the chromosome is selected as one chromosome with poor fitness function. Moreover, for selecting a chromosome through effective rate, a roulette wheel is applied that results in a chromosome with good fitness function. The combination in IGA is such that the chromosome with high effective rate sends its genes to chromosomes with high affectability rate, and all the responses will move toward correction that results in improved algorithm's performance and modified optimization process.

The main difference of the developed algorithm for the problem studied and the general genetic algorithm is that in IGA, instead of removing weak chromosomes, they are improved by using chromosomes with high fitness function. The logic is that the main response of the problem is likely found in these weak chromosomes and they are merely in need of a minor change. In GA, both parents are selected by using the same method, but in IGA, each parent is selected according to its fitness function by applying a different method.

In GA, the selection process is such that the chromosomes with poor fitness function have a low chance to be selected, and chromosomes with strong fitness function have a high chance of being selected. However, in IGA, not only weaker chromosomes are given a chance of being selected but also all chromosomes are selected purposefully and based on their amount of merit. This attitude will result in two things; first, the algorithm is less likely to be involved with the local minimum, and second, the convergence velocity of the algorithm will increase without decreasing random searching. Figure 1 shows the general trend of the improved genetic algorithm (IGA). As can be seen, other parts of this algorithm, including the definition of the chromosome, primary population, mutation, and the elitism method, are like those of the GA.

Fig.1 Flow chart of IGA

5. WORKING

The working process in this article is divided into three steps:

Step 1: Involve in data preparation and selection of key sites using GIS analysis and AHP methods.

Step 2: Participate in the design and development of a genetic algorithm using performance and cost implications, design problems in the algorithm, and test and evaluate the algorithm using simulated data.

Step 3: Apply the algorithms to real data and compare and evaluate the results.

The purpose of this study is to find the best location through genetic algorithm development. In this way, we first transform the continuous space of the problem into a discrete space according to appropriate spatial conditions. We even selected some large areas as candidate sites using some GIS and AHP analysis. It is important to use different tests to determine thresholds that are candidates for optimization. The accuracy of the main output of the preparation depends on this stage. Because the algorithm's search space is limited to the output of this analysis. Therefore, this study uses the Analytic Hierarchy Process (AHP) to select initial sites to obtain a higher estimate.

In Summary:

1. We used GIS and AHP analysis to transform the continuous area of the study area (Tehran District 2) into a discrete area. So far, 675 sites have entered the optimization process as sites.

2. Using IGA, 6 centers were selected as the best hospitals.

Formulating the location allocation problem

In this paper, the number of genes of each chromosome indicates the number of centers needed. The number of necessary hospital centers needs to be defined based on analyzing factors such as population, area, budget, and equipment. Here, as many as six new centers were considered without analyzing such factors. Thus, one chromosome is defined as a six-array including the candidate centers without any repetition (Fig. 2).

12	56	6	66	87	45

Fig. 2 The coding of a problem's response within a chromosome

The aim of this optimization is finding a combination of six centers from among 675 candidate sites with the best coverage of the blocks in the studied district. The objective function is considered as the total of distances between the blocks and the closest centers to these blocks. In Eq. (3), the objective function has been provided; the main aim is minimizing this function.

$$Objective\ Funtion = \sum_{j=1}^{m}\sum_{i=1}^{n} D_{ij} \quad ..(3)$$

in which j is the number of centers, i is the allocated block for this center, and Dij is the distance between the centers and their allocated blocks. The roulette wheel has been used for selecting the parents of each generation. According to Eq. (4), a chromosome with a better fitness function has a higher chance of being selected (Saeidian et al. 2016).

$$P_r = \frac{F(X_r)}{\sum_{k=1}^{n} F(X_k)} \quad ..(4)$$

in which $\mathbf{P_r}$ is the likelihood of selecting chromosome **r**, F($\mathbf{X_r}$) is the fitness function of chromosome **r**, and **n** is the total number of the chromosomes.

Parent 1	12	56	6	66	87	45
Parent 2	1	69	54	24	98	12

Child 1	12	56	6	24	98	12
Child 2	1	69	54	66	87	45

Fig. 3 Example of single point crossover

In this problem, a single-point combination was applied. After selecting two parents, first the likelihood of crossover is studied based on the combination rate, and then, the combination process is conducted like Fig. 3. For each chromosome obtained from a crossover, a random number is produced within one and zero, and if this number is smaller than the mutation rate, one of the genes of the chromosome is randomly selected. This gene is then replaced with one of the centers (from among the candidate centers) that is not included in the related chromosome In Fig. 4, an example of the mutation process is shown.

Initial	12	56	6	66	87	45
Mutated	12	56	98	66	87	45

Fig. 4 Example of Mutation operator

Formulation of location-allocation problem in PSO

The definition of a particle and fitness function in the PSO is like the definition of a chromosome in GA. In the following sections, the main steps of designing the PSO are described.

Continuing the previous movement (inertial movement)

Given the definition of a particle in the present problem, the mutation operator of GAwas applied for the modeling of this movement. Continuing the previous movement is the random part of the PSO; there is no certainty over the goodness or badness of the movement. In fact, apart from the position of the particle, this movement is completely random and lacks an absolute logic. For this reason, the mutation operator is applied. The intensity of this movement is proportional to the inertial coefficient.

The movement toward the best personal experience

For implementing this movement, a number of decision parameters from the particle's best experience are randomly placed in the particle. That is, every particle enters part of the decision parameters of the best personal experience into its position in every iteration. In Fig. 5, the movement method toward the best personal experience has been indicated.

Particle	12	56	6	66	87	45
Best Personal	5	23	44	11	100	88
Update	12	23	6	11	87	45

Fig. 5 Movement towards the best personal experience

The movement toward the best global experience

In this movement, the generation's best particle is applied to replacing the decision parameters. However, this movement is such that the effect of the previous movement is not negated. That is, some parameters of the particle are replaced with parameters of the best global particle that do not result from the replacement of the best personal experience. The number of decision particles replaced depend upon the significance of the vectors; the significance rate is determined in the calibration section by the user. An example of this movement is indicated in Fig. 6.

Particle	**12**	**56**	**6**	**66**	**87**	**45**
Best Global	**2**	**72**	**33**	**8**	**40**	**111**
Update	**12**	**23**	**33**	**11**	**87**	**111**

Fig. 6 Movement towards the best generated experience

Formulation of location-allocation problem in IGA

In IGA, the definitions of a chromosome, objective function, initial population, and mutation are the same as the definitions used in GA. For selecting parents from among the population created, the effective and affectability rates of the chromosomes are used. As it was explained in Section 3.3, a weak parent based on affectability rate and another parent based on the effectiveness rate are selected. After selecting two parents by the selection operator, for conducting the combination operation between parents, a number of random genes (varying from 2 to 4 genes) with the high effective rate were sent to the chromosome with high affectability rate. If more than three genes are replaced, the convergence velocity of the algorithm will increase, but there is an increased risk of falling to a local minimum for the algorithm. Furthermore, if less than three genes are selected, the searching space of the algorithm will broaden, but the convergence velocity will reduce. Figure 7 indicates an example of such a combination, the output of which is two children.

Parent 1	**12**	**56**	**6**	**66**	**87**	**45**
Parent 2	**1**	**69**	**54**	**24**	**98**	**12**

Child 1	**1**	**56**	**6**	**24**	**98**	**45**
Child 2	**12**	**69**	**54**	**66**	**87**	**12**

Fig. 7 Combination based on the effective and affectability rates

Data preparation and determining candidate sites

District 2 of Tehran is one of the urban areas of Tehran located northeast of Azadi Square and continues from the center to the north. This area is bounded on the south by Azadi Street, on the west by Ashrafi Esfahani and Mohammad Ali Jinnah highways, and on the east by Chamran highway. Tehran's District 2 is one of the most populated districts of northern Tehran. Its area is 98.1 KM2. According to 2012 Census of the Iranian Statistical Yearbook, the population density of this district is about 624,244 people in the entire district and 6363 people per each square kilometer (KM2). The population density of this district is relatively high, and most the population of this district are old people. Figure 8 indicates the spatial distribution of the population in this region. This district has ten hospitals at present, and given the high population density of the district, the hospitals do not have an appropriate distribution. Thus, determining the new sites for building new hospitals is essential to meet the welfare and comfort of the people living in this district. The data needed for conducting the present study were collected from the Ministry of Roads and Urban Development, and their spatial scale and accuracy were sufficient and appropriate for conducting the present study. In this paper, the urban blocks (as a spatial unit of population) were allocated to hospitals, and the main aim is minimizing the total distances between urban blocks and hospital centers distances. As it was indicated in the review of related literature, determining the primary sites as candidate centers to enter the optimization section is of significant importance. The main accuracy and output of the suggested program is related to this section; since the searching space of the algorithms is limited to the output of this part of analyses. Thus, in this paper, to achieve an evaluation with higher accuracy and preciseness, multiple criteria decision-making (MCDM) with the AHP method was used for selecting the primary centers. The analytic hierarchy process is one of the most comprehensive methods designed for decision-making with multiple criteria that was first introduced by Saaty (Abdelmaguid and Elrashidy 2019). By organizing and assessing alternatives in regard to a hierarchy of multifaceted attributes, AHP provides an effective tool to deal with complex decision-making and unstructured problems. AHP allows a better, easier, and more efficient framework for identification of selection criteria, calculating their weights and analysis. By applying this method, it will be possible to formulate a problem hierarchically. The output of the analytic hierarchy process is the priority rating of different criteria. One of the advantages of this method is the possibility of studying and analyzing different scenarios by managers (Vahidnia et al. 2009).

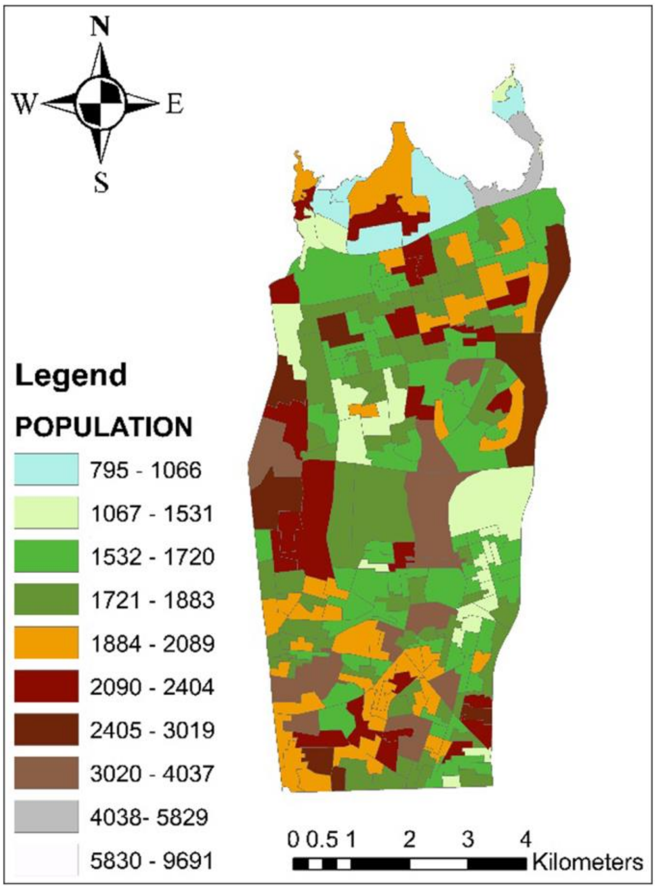

Fig. 8 Population density map of Tehran's District 2

For determining the potential sites for building new hospitals through using the AHP method, seven criteria have been used. These criteria include distance from the existing hospitals (considering the service covering a radius of each center and meeting the standards of the distance existing between hospitals); distance from fire stations (to receive services during a fire); distance from population centers (to cover the demand areas); distance from road and street network (to establish appropriate access between population centers and hospitals); distance from green spaces and parks (to ensure the appropriate weather around the hospital and people's relaxation in terms of health and cheerfulness); distance from strong power lines (to prevent the destructive effects of these lines); and distance from fault (to avoid the destruction of buildings during an earthquakes and aftershocks). Figure 10 shows the criteria maps. The significance rate of these criteria has been specified in comparison to one another (by using the ideas of specialists and (Chamchali et al. n.d.; Vahidnia et al. 2009; Soltani and Marandi 2011; Rahimi et al. 2017; Ahmed et al. 2016; Şahin et al. 2019)), and the weight of each of these criteria was measured by using Expert choice software. The criterion maps were prepared by using GIS functions and analyses in ArcGIS10.4 software. Then, the weights measured in the AHP method were used for overlapping the layers. Figure 9 indicates the output map of the AHP that is classified into six classes. For finding the candidate points to enter the optimization algorithms, three classes were used: most suitable, suitable, and moderate suitable. Then, the candidate sites were extracted by using the "Create Point" analysis in ArcGIS10.4 software. In this way, as many as 675 sites entered the optimization section as candidate sites.

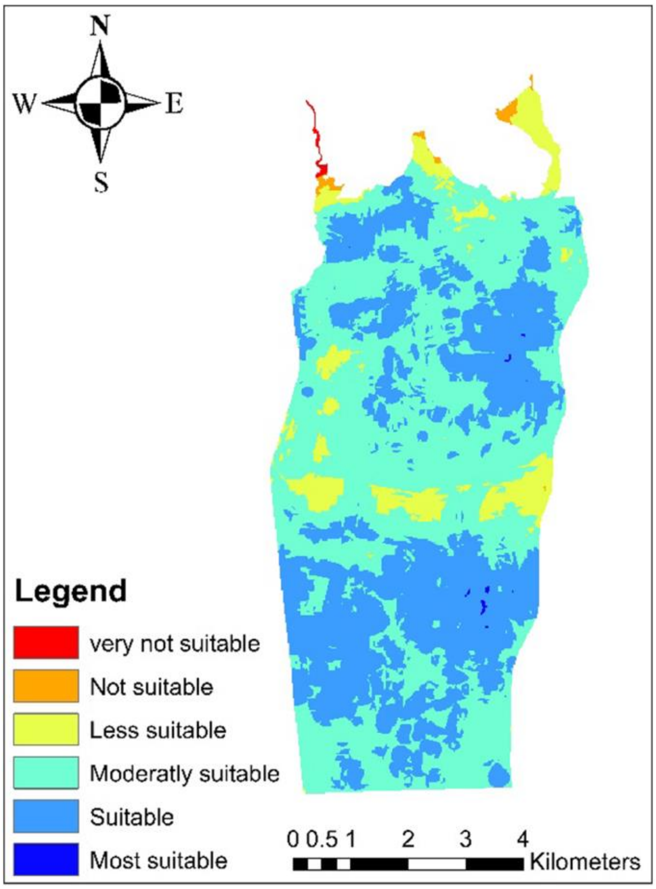

Fig. 9 The output of classified map with AHP method

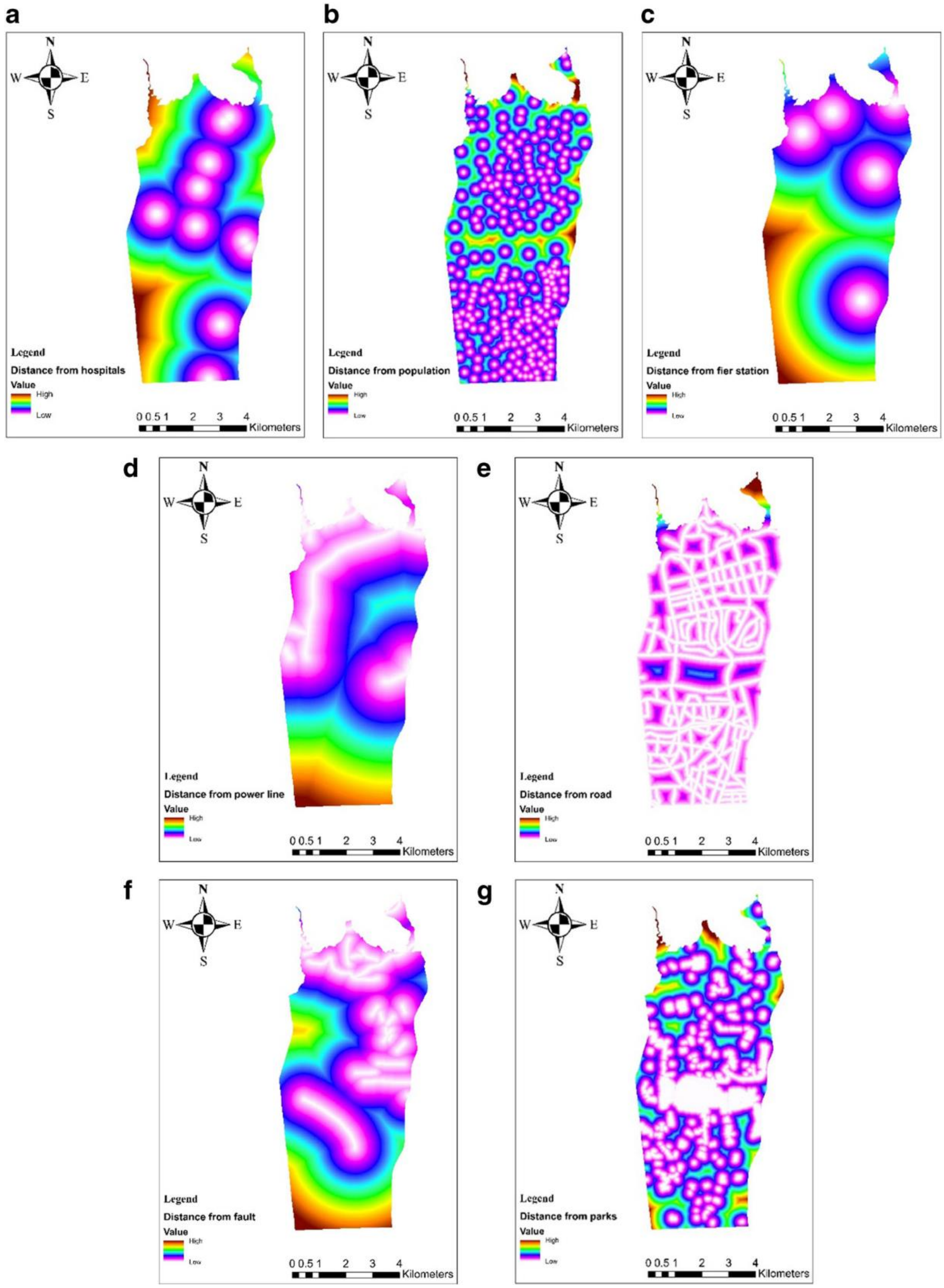

Fig. 10 The criteria maps. (a) Distance from existing hospitals, (b) distance from population centers, (c) distance from fire stations, (d) distance from strong power lines, (e) distance from road network, (f) distance from fault, (g) distance from parks

Table 1 Calibration of IGA variables by trial-and-error method for the simulated data

No.of Runs	No. of Iterations	Initial Population	Elitism percent	Mutation rate	No of genes for crossover	Execution time (second)	Cost function (meter)
1	30	50	10	0.15	3	2.15	2294.351
2	30	50	10	0.55	3	2.60	2319.413
3	30	50	10	0.04	3	3.27	2357.519
4	30	50	3	0.15	3	2.59	2401.085
5	30	50	30	0.15	3	2.44	2313.312
6	30	50	75	0.15	3	2.63	2419.784
7	30	50	10	0.15	2	2.43	2313.231
8	30	50	10	0.15	1	2.70	2418.356
9	30	50	10	0.15	4	3.10	2295.390
10	30	70	10	0.15	3	2.87	2292.563
11	30	100	10	0.15	3	3.44	2290.875
12	30	130	10	0.15	3	4.29	2289.213
13	30	150	10	0.15	3	4.57	2287.563
14	30	100	10	0.15	3	1.06	2375.951
15	30	100	10	0.15	3	3.46	2298.951
16	30	100	10	0.15	3	6.02	2287.563
17	**110**	**100**	**10**	**0.15**	**3**	**7.54**	**2287.1685**
18	**120**	**100**	**10**	**0.15**	**3**	**9.29**	**2287.1685**

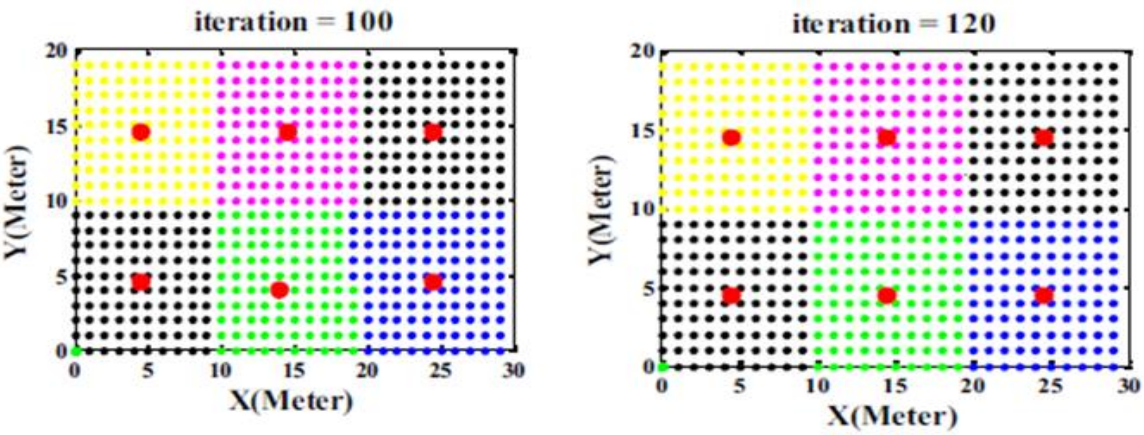

Fig. 11 The findings of IGA Implemented upon simulated data with the values of the variables in table 1.

6. RESULTS AND DISCUSSIONS

As it was stated in the introduction, the aim is to determining appropriate locations for building new hospitals and allocating urban blocks to these centers. Therefore, the algorithms were implemented in the MATLAB software. Also, for comparing the algorithms and finding the best values for the variables of their calibration, a set of regular simulated data and real data are used.

Implementation of algorithms on simulated data

In this section, the implementation of algorithms on simulated data and the calibration method of variables of all three many as 600 blocks with regular distribution over a network with compatible distance. The aim is finding six centers and allocating all the blocks to the closest centers so that the entire distances between blocks and their related centers will reach the least distance possible. If the district is divided into six parts with equal shape and area, the center of these sections will be the best location for these facilities. If the algorithm works well, one must be able to locate these six centers as the desired responses. Thus, these data can be applied for the evaluation and modeling accuracy of the algorithms. The significant issue in using meta-heuristics is selecting appropriate values for their variables. Since the optimal solution for the simulated data is recognized, one can obtain the best combination of variables and calibrate the variables of algorithms. Table 1 indicates the findings obtained from the implementation of IGA in simulated data by using different variables. For finding the best value for each of the variables, other variables were kept fixed and the algorithm was implemented with different values of variables. The changes in the values of three variables of elitism percentage, mutation rate, and the number of replaced genes for the combination are not affected in the implementation time of the algorithm. Thus, the value of fitness function is considered as the main criterion for the measurement and calibration of the algorithm's variables. The mutation rate of 0.15 resulted in the best findings. Values larger than 0.15 resulted in relatively larger distances (fitness function is got worse). A low level of elitism (such as 3%) will reduce the convergence velocity of the algorithm. In contrast, higher levels of elitism (including 75%) will result in the placement of algorithm in local minimums. The best case of elitism was 10%. Moreover, the number of replaced genes for the crossover operation has resulted in the best findings in three-gene mode. Changing the population number from 100 to 130 and then to 150 is not significantly effective. Thus, the initial population of 100 chromosomes was selected, since this population resulted in a faster implementation. The low number of iterations (such as 10 iterations) did not bring about appropriate findings. The algorithm has improved as the number of iterations increased. Here, as many as 120 iterations were selected. Figure 11 indicates the optimal centers and the blocks allocated to these centers. Given the variables of rows 16 and 18 of Table 1, five centers were found by the algorithm with the iteration of 100. These five centers are located in the desired points, and the sixth center is very close to its best location. At the iteration of 120, the algorithm has found the desired location of all centers, and the blocks were properly allocated to them. Also, like IGA, in Table 2, the best combination of the variables of GA and PSO is presented.

Implementation of algorithms upon real data

Since the complexity of real data is more than that of the simulation data, the run time of the algorithms increases. Thus, for the management of execution time during the implementation of algorithms on real data, two variables of "number of iterations" and "initial population" are studied, and other variables conform to the calibration result of simulation data. Table 3 indicates the findings obtained from IGA implementation on real data by using different variables of "number of iterations" and "initial population." As it is observed, in the first five rows, the number of iterations was fixed, and only the initial population changed. With the initial population of 100 chromosomes, the algorithm did not find proper responses. With the increase of the population to 200 and 250, the algorithm had a significant improvement, but no global optimal was discovered. At the iteration of 500, the algorithm is close to the optimal solution. At the iterations of 800 and 1000, the algorithm has managed to find the global optimal solution. Given the findings provided in Table 3 and the run time of IGA, the iteration of 150 and initial population of 300 were considered; since the algorithm's execution time is shorter, and the algorithm has shown a higher level of stability in different runs. In fact, when the initial population increases, the variety of chromosomes of each generation will increase as well, and as a result, the algorithm's searching space will broaden, and the likelihood of achieving optimal solution will increase. Also, the findings obtained from GA and PSO implementations on real data are classified in Table 4 and Table 5. Given the findings of all three algorithms on real data, it can be said that they are largely dependent on the initial population. In fact, few iterations and large populations have resulted in better results over a shorter time. Moreover, high iterations and small populations have brought about poorer results over longer terms of implementation. This is more evident for the IGA; in comparison to the other two algorithms, IGA has provided better performance in a small population and fewer iterations. Figure 12 indicates the optimal combination of the centers and allocating them to population blocks; this optimal combination is equally found by three algorithms. As can be observed, as many as six centers have been found alongside the other ten previous centers, the total distances of the population points from these centers are at the lowest level. The best fitness function value among the total distances existing between centers and the blocks allocated to them was measured to be 169,337 by all three algorithms. Comparison and evaluation of algorithms on two datasets. The aim of this comparison is to evaluate the performance of the developed algorithm. For comparing and evaluating the three algorithms, different criteria such as convergence trend, repeatability, and the mean of the fitness function at different repetitions and algorithms' execution time have been applied.

Convergence trend

Figure 13 indicates the convergence trend of three algorithmsfor both simulated and real data (based on the parameters of Tables 1, 2, 3, 4, and 5). The convergence trend of IGA is higher than that of the other two algorithms; the reason is likely the selection and crossover methods of parent's chromosomes based on their effective and affectability rates. Since in IGA, the crossover is such that one superior chromosome with high effective rate sends its genes toward a weak chromosome with high affectability rate, the fitness function of all chromosomes will improve. This secures the convergence of IGA. In fact, IGA by using an improved crossover method will search the entire searching space and will achieve better responses.

Table 2 Best combination of the variables of IGA, GA and PSO

IGA	GA	PSO
Population = 100	Population = 100	Population = 100
Iteration = 120	Iteration = 150	Iteration = 100
Elitism percent = 10%	Elitism percent = 10%	The inertial movement rate = 0.20
Mutation rate = 0.15	Mutation rate = 0.15	Number of genes for p-best = 2
Number of genes for crossover = 3	Crossover rate = 0.84	Number of genes for g-best = 2

The mean of the fitness function

In every generation, there is a population called the generation that improves in future repetitions. Figure 14 indicates the mean of the fitness function of all three algorithms in every generation. As it is observed, in IGA, all of the chromosomes tend to have an equal fitness function after a short time, and the average fitness function of the last generations' chromosomes is close to the global optimal solution. The main reason for this issue is applying effective and affectability rates for conducting selection and combination operations. In IGA, all weak chromosomes move toward improvement by using proper responses. Thus, the entire population existing in a generation will change to a chromosome with a high level of the fitness function. However, in GA and PSO, the average fitness functions fluctuate, and they are far from the global optimal solution; the fitness function is highly different in some of the chromosomes, and in every generation, good chromosomes are given the utmost attention. In fact, in these two algorithms, weak responses have little chance of being promoted and improved. However, in the IGA, all the chromosomes are treated purposefully in proportion to their fitness functions, and no chromosome is wasted from the population. The reason is that the main response to a problem is likely to be found in a chromosome with a poor fitness function.

Testing and evaluating repeatability

Achieving equal results at different repetitions indicates an algorithm's stability and repeatability. For evaluating the repeatability of the algorithms, the algorithms are executed 40 times on both simulated and real data, and the findings are shown in Fig. 15. In this figure, the distribution pattern of the fitness function of the algorithms is presented at different executions in the space of the studied district. IGA showed a higher level of stability and repeatability for both types of datasets. According to Fig. 15, IGA has resulted in achieving optimal responses in more than 90% of the cases. However, PSO and GA algorithms have achieved the optimum response in less than 60% of the cases.

The execution time

In this section, it is attempted to study the execution time of the algorithms. The termination condition for an algorithm is achieving a specific fitness function at some consecutive executions of the algorithms. Figure 16 shows the execution time of the algorithms at different runs; this figure indicates that the execution time of IGA is shorter than that of GA and PSO. This difference is even larger on real data. As can be seen, the timing diagram of IGA is clearly lower than that of the other algorithms. Moreover, the time spent by PSO is more than that of the other two algorithms. The other significant point of this comparison is the direct relationship existing between the initial population and the execution time of the algorithms on real data. In Table 6, the execution time of the algorithms on real data has been compared for different initial populations. As it can be observed, in smaller populations, the execution time of the three algorithms is not significantly different. However, as the number of the initial population increases, the execution time of PSO will be much more than that of the other two algorithms. When the searching space broadens (a larger initial population), the difference in the execution time of PSO and GA algorithms will be more with that of IGA. In other words, the execution time of the IGA is less sensitive to the increase of the initial population.

Table 3 IGA's calibration of the initial population and the number of iteration on real data

No. of run	No. of iteration	Initial population	Elitism percent	Mutation rate	No of genes for crossover	Run time (s)	Cost function (m)
1	150	100	10	0.15	3	14.03	170,827.01
2	150	200	10	0.15	3	25.27	169,879.65
3	150	250	10	0.15	3	32.23	169,521.32
4	**150**	**300**	**10**	**0.15**	**3**	**40.54**	**169,336.86**
5	**150**	**400**	**10**	**0.15**	**3**	**52.31**	**169,336.86**
6	300	100	10	0.15	3	27.48	169,879.42
7	400	100	10	0.15	3	34.53	169,634.73
8	500	100	10	0.15	3	42.36	169,424.87
9	**800**	**100**	**10**	**0.15**	**3**	**64.19**	**169,336.86**
10	**1000**	**100**	**10**	**0.15**	**3**	**79.68**	**169,336.86**

Discussion

Statistically speaking, the improved genetic algorithm is able to avoid being involved in local minimums, and one can observe its convergence trend in the simulated forms. Since a given combination in IGA is such that a superior chromosome with a high effective rate sends its genes toward a weak chromosome with a high affectability rate, and the fitness function of all chromosomes improves in this way. This secures the convergence of IGA. Moreover, different values of effective and affectability rates will result in various information on the change of chromosomes and improved exploitation. They are also likely to increase the algorithm's exploration ability, and IGA is not involved with the local minimums. The main reason behind the better efficiency of improved genetic algorithm in comparison to the genetic algorithm is the different rates of effective and affectability of each chromosome. In comparison to the genetic algorithm which has a total reproduction rate (merging) for all of the chromosomes of its statistical population, IGA has two rates (effective and affectability) for each chromosome. This will result in different evolutionary behavior identification powers. Moreover, the main reason for the improper results of PSO is the normal nature of this algorithm in a discrete space. PSO does not have an operator for the sudden change of the solution to a problem, and it will be involved in the local minimums. Moreover, PSO is greatly dependent on the initial distribution method of the particles. If a large number of particles are involved in the local minimums, the algorithm gets out of it hardly. In short, it can be concluded that in the location-allocation problem, the exploration and exploitation ability is of significant importance. Thus, solving complex problems by using optimization calls for random and sudden searching steps to avoid being involved in local minimums.

Table 4 GA's calibration of primary population and number of iteration on real data

No. of run	No. of iteration	Initial population	Elitism percent	Mutation rate	Crossover rate	Run time (s)	Cost function (meter)
1	150	100	16	0.20	0.84	15.10	171,643.76
2	150	200	16	0.20	0.84	28.35	170,765.39
3	150	350	16	0.20	0.84	44.23	169,743.87
4	**150**	**500**	**16**	**0.20**	**0.84**	**55.26**	**169,336.86**
5	**150**	**600**	**16**	**0.20**	**0.84**	**69.48**	**169,336.86**
6	400	100	16	0.20	0.84	32.15	170,946.67
7	700	100	16	0.20	0.84	49.29	169,981.52
8	1000	100	16	0.20	0.84	81.62	169,659.19
9	**1200**	**100**	**16**	**0.20**	**0.84**	**92.38**	**169,336.86**
10	**1400**	**100**	**16**	**0.20**	**0.84**	**112.24**	**169,336.86**

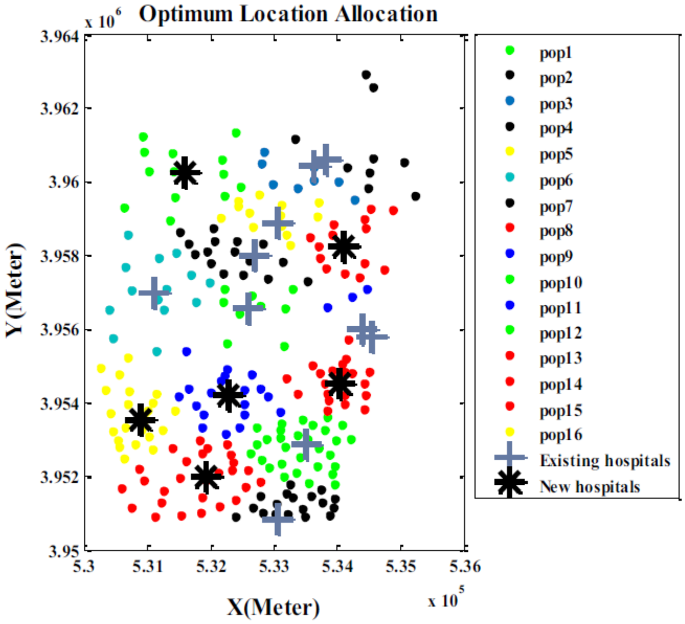

Fig. 12 The optimal hospital centers and the allocation of population blocks to them in real data

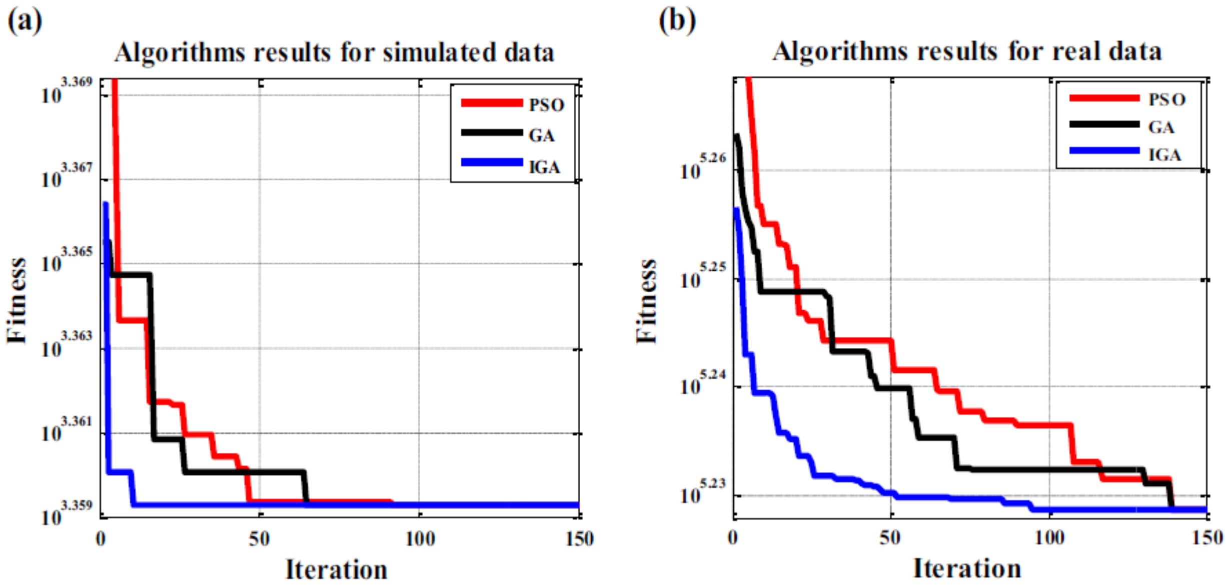

Fig. 13 The convergence trend of algorithms: (**a**) on simulated data; (**b**) on real data

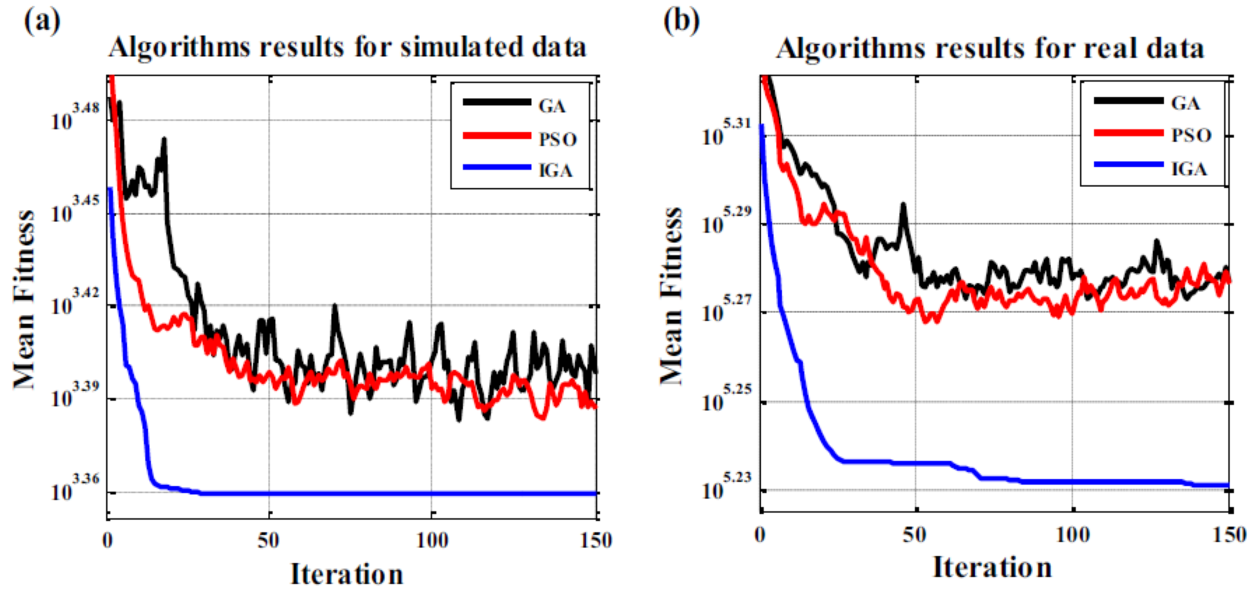

Fig. 14 The mean of the fitness function in every generation: (**a**) on simulated data; (**b**) on real data

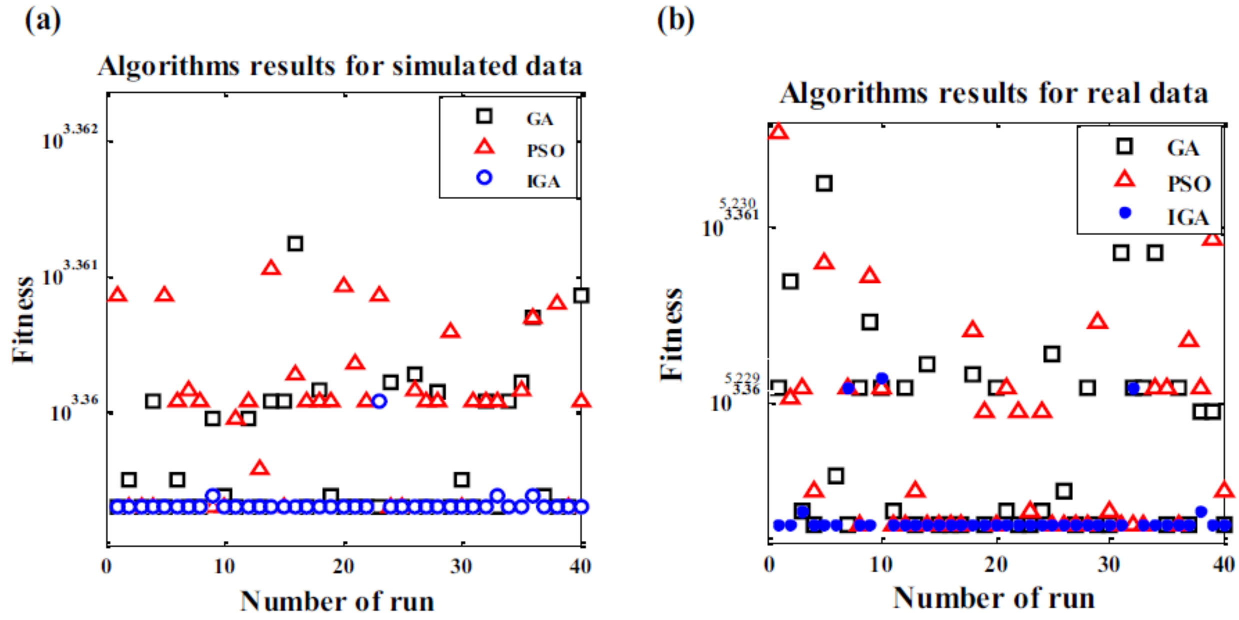

Fig. 15 Repeatability of the algorithms: (**a**) on simulated data; (**b**) on real data

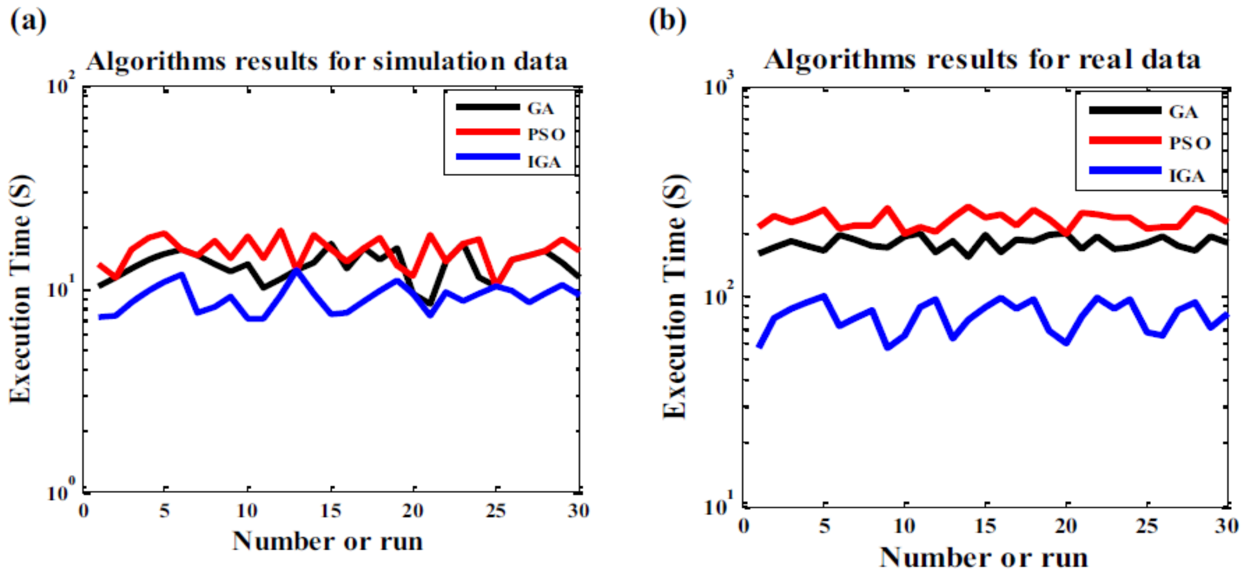

Fig. 16 The execution time of the algorithms: (**a**) on simulated data; (**b**) on real data

Table 6 The execution time of the algorithms with different initial population upon real data (iteration = 150)

Initial population	Algorithm	Execution time (s)
100	GA	15.77
	PSO	18.10
	IGA	14.12
500	GA	56.81
	PSO	80.92
	IGA	50.12
1000	GA	120.41
	PSO	153.09
	IGA	84.72
1500	GA	182.52
	PSO	228.57
	IGA	123.63
2000	GA	275.26
	PSO	350.59
	IGA	177.23

7. CONCLUSIONS

The process of selecting and allocating hospital sites in urban planning is a complex, multifaceted challenge with far-reaching implications for public health and safety. This research project has addressed this challenge by introducing an innovative approach that integrates multi-criteria decision-making techniques, geospatial information systems, and the power of an Improved Genetic Algorithm (IGA). The findings and outcomes of this study reveal the effectiveness and potential of this methodology in optimizing the hospital location-allocation process. The key contributions and insights from this research are as follows:

1. Multi-Criteria Decision-Making (MCDM): The project has successfully employed MCDM to incorporate a wide array of criteria and sub-criteria, ranging from cost considerations to accessibility and safety. The structured use of the Analytic Hierarchy Process (AHP) has enabled the quantification of the relative importance of these criteria, thereby facilitating a more informed decision-making process.

2. Data Integration: The study extensively collected and integrated geospatial and demographic data to form a comprehensive decision matrix. The availability of data on land costs, construction expenses, population distribution, transportation infrastructure, crime rates, and emergency services ratings has provided a strong foundation for the decision-making process.

3. Improved Genetic Algorithm (IGA): The IGA represents a significant innovation in the field of optimization. Its utilization of affectability and effectability rates has demonstrated the algorithm's superior performance in escaping local minima, improving convergence speed, and ensuring stability.

4. Robustness and Efficiency: The IGA has exhibited robustness and efficiency in the optimization of hospital location-allocation. It has consistently generated a set of candidate sites that fulfill the prescribed criteria, ensuring that the selected hospital sites are well-suited to their intended purpose.

5. Comparative Analysis: By comparing the IGA with traditional optimization methods, including Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), the research has underscored the IGA's competitive advantages in terms of convergence speed, stability, repeatability, and runtime efficiency.

In conclusion, this research project's methodology and findings reflect a significant step forward in the field of urban planning and healthcare infrastructure development. The integration of geospatial information systems, multi-criteria decision-making, and the Improved Genetic Algorithm offers a robust framework for addressing complex, real-world challenges. As urban areas continue to grow and evolve, the methods and insights derived from this research provide valuable tools for improving healthcare access and community well-being.

Ultimately, the project's contributions extend beyond the optimization of hospital location-allocation; they emphasize the power of data-driven, community-engaged decision-making in shaping more sustainable and resilient urban environments.

FUTURE ENHANCEMENTS

Integrating IGA Model into a Flutter Application

Taking the work of Dr. Mehrdad Kaveh and his team of developing this IGA algorithm, the next phase of my project focuses on taking the optimized hospital location-allocation model, developed using the Improved Genetic Algorithm (IGA) in Python and MATLAB, and integrating it into a user-friendly and interactive Flutter application. This integration presents several exciting opportunities and potential improvements:

Mobile Accessibility: Developing a Flutter application allows for the deployment of the IGA model on mobile devices, making it accessible to a broader audience, including healthcare professionals, urban planners, and decision-makers.

User Interface Design: The application will feature a user-friendly interface that simplifies the input of location-allocation criteria. Users can easily specify their preferences and constraints for hospital site selection.

GIS Integration: Leveraging GIS capabilities in the Flutter app, users can visualize geographic data, view potential hospital sites on maps, and analyze location suitability based on real-time geographic information.

Data Collection and Real-time Updates: The application can collect real-time data, including population statistics, transportation infrastructure, and emergency service availability, to provide the most up-to-date information for decision-making.

Interactive Decision Support: Users can run the IGA model through the app, which will generate recommendations for optimal hospital site selection. It can rank and present the top candidate sites based on the defined criteria.

Feedback Mechanism: Incorporating a feedback system allows users to evaluate the recommended sites and provide feedback, which can be used to fine-tune the model and enhance its accuracy over time.

Cross-Platform Compatibility: Flutter's cross-platform development capabilities enable the app to run on both Android and iOS devices, ensuring a wide reach.

Community Engagement: The application can foster community engagement by involving local residents and stakeholders in the decision-making process, ensuring that the selected hospital sites align with the needs and preferences of the community.

Scalability: The integration of the IGA model into a Flutter application allows for scalability and adaptation to different urban areas and healthcare infrastructure projects.

Continuous Improvement: Future works include ongoing enhancements and updates to the application based on user feedback and technological advancements.

By integrating the IGA model into a Flutter application, this project takes a significant step toward democratizing the decision-making process for hospital location-allocation, making it more accessible, interactive, and data-driven. The future works outlined above aim to create a tool that not only optimizes hospital site selection but also empowers communities to be actively involved in shaping their healthcare infrastructure.

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