Proposing a Novel Method for Optimal Location Finding Based on Machine Learning Algorithms and Gray Wolf Optimization

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ABSTRACT:
With the expansion of human activities, the volume of waste and hazardous waste produced has increased dramatically. Increasing the volume of waste has created challenges such as transportation hazards, cleanup, disposal, energy consumption, and most important environmental problems. The difficulty of unsafe waste control is one of the critical studies topics. Finding the optimal location of hazardous waste disposal is one of the issues that, if done properly, can significantly reduce the aforementioned challenges. The increasing volume of information, the complexity of multivariate decision criteria, have led to the lack of conventional methods for finding the optimal location. Machine learning methods have proven to be effective and superior in many areas. In this paper, a new method based on machine learning for finding the optimal location of hazardous waste disposal is presented. In the proposed method, after applying clustering in the separation of the desired areas, the gray wolf algorithm optimization is used to find the optimal location of waste disposal. In order to apply the gray wolf optimization algorithm, a multivariate target function is defined. Cluster centers as were chosen as location of waste disposal. Proposed method is performed on collected data from the study area in Iran, Tehran province. Proposed clustering method is evaluated and compared with some metaheuristics algorithm. The simulation results of the proposed method show cost reduction in finding the desired locations compared to similar researches. Also, Xi and Separation index was used for evaluation of the proposed clustering method to select the best location. The number of best locations using Xi and Separation index claim the superiority of the proposed method.

KEYWORDS: Waste Disposal, Machine Learning, Clustering, Gray Wolf Optimization Algorithm, Objective Function.

1. INTRODUCTION

Activities increasing causes the volume of hazardous wastes has extended more and more. The manufacturing of hazardous waste has created demanding situations in diverse sectors. Dangers of transportation, easy up, disposal, energy consumption, and most significant environmental problems have led to greater interest being paid to the assignment of waste, in particular dangerous waste [1], [2]. Overcoming these difficulties and challenges calls for the control of health care waste, together with manufacturing, garage, and collection, transportation, processing, and disposal. Prevention of waste generation and care after disposal and preliminary remedy are many of the capabilities of health care waste control that have been taken into consideration due to the hazardous nature of those materials [3].

Harmful emissions of chemical techniques produced in hospitals are referred to as dangerous waste. Flammability or explosion, corrosion, reactivity, and toxicity are among the traits of hazardous waste substances [4].

1.1. Optimal location finding

Proper location finding and choosing for an unsafe and dangerous waste disposal facility is a complex manner. This preference is multivariate selection-making trouble that includes numerous standards which include natural, social sciences, and engineering [5].

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Today, with the improvement of risky waste management technologies, we try to decrease the production of waste, healing, and recycling, power production, disposal, and so on. In the priority and the option of the landfill within the next priorities, regardless of the efforts, a large amount of waste is still generated that has to be managed [6].

Multitudinous new approaches had been deliberated for the disposal of waste. Though, the disposal of this hazardous waste is still used inside the traditional way and through "landfill". Landfilling of hospital waste, in addition to environmental pollution and groundwater, includes the threat of spreading in many circumstances. At present, in most international locations of the world, hospital waste is disposed of through decontamination and sterilization. This technique has changed hospital waste disposal via plasma and incinerators. Disposal of health facility waste inside the cutting-edge method in addition to using incinerated waste is taken into consideration as a severe crisis due to the pollutants it causes. At gift, the infectious waste of medical centers, places of work, and laboratories for medical diagnosis and treatment centers, including hospitals, is disposed of with municipal waste, which influences the properly-being of humans and the ecosystem. For this purpose, finding an appropriate place that has the least challenge is very critical. Figuring out the proper vicinity for the construction of hospitals' infectious waste disposal facilities is a complex and tough method. To optimize the vicinity, environmental and social factors, elements associated with the price of allocating the crucial sources for the development of disposal centers, legal guidelines related to the actual situations of the case observe of health facility waste should be taken into consideration [7], [8].

The optimal location of hospital waste is typically a multi-standard selection difficulty. The problem of opting for the right region will come more apparent whilst a number of the standards for locating are inside the war with every exclusive. These criteria are labeled into two classes of environmental standards and human criteria [9]. The first class refers to natural elements such as land instability, distance from springs, rivers, and lakes, traveler importance, and so on. The second one elegance is due to regulations that must be located due to human activities, collectively with areas under environmental safety, the region of hydraulic structures, groundwater, transmission traces, oil pipelines, telecommunications, etc [10]. In every different check, the standards that ought to be taken into consideration in locating the landfill have been classified into three lessons: very last rate criteria, requirements associated with infrastructure, and requirements related to the geography of the environment [11]. Eight criteria are distance from the disposal center to the collection point, the propinquity of disposal centers to the population, vacuity of suitable land, cost of transporting waste to disposal centers, environmental perceptivity to groundwater, rainfall conditions and faults, the volume of waste Infection, road and road conditions, an area designated for sanitarium waste disposal centers. These discrepancies occur when determining locations and routes and selection criteria, which include: total relocation cost, relocation risk, route reliability, fixed cost of constructing a new proposed site, the risk associated with the population at risk, and so on [12].

A large number of standards, from time to time contradictory to those standards, has made the conventional strategies of handling health facility waste disposal useless. One of the commonplace strategies for finding waste disposal is using a questionnaire. In the questionnaire, specialized questions about the criteria in an optimal location are designed, then the validity and reliability of the questionnaire are evaluated using statistical tests. Ultimately, this questionnaire is provided to users and professionals. The final evaluation will be based on conventional methods and based on the scores given to each parameter. On this evaluation technique, it is best for that specific situation and the results obtained cannot be used for other places and even places with similar situations. The use of data mining and machine learning methods makes it possible to use similar data recorded in similar locations for location. In data mining methods, the behavioral pattern of the recorded data for location, which can be in the form of defining the desired features and assigning numerical points to them, using machine learning methods such as networks neural [13], support vector machine [14] or clustering methods are obtained. This template can be extended to other similar locations. Therefore, in this research, data mining and machine learning methods will be used to locate hazardous hospital waste disposal. Machine learning methods and in particular cases data mining methods are composed of different parts. There are several parts to a data mining process, which are preprocessing, feature extraction, and classification [15].

1.2. Machine learning concepts

A large amount of data is generated day by day. The explosive boom of statistics volumes is the result of the mechanization of societies in addition to the improvement of greater powerful tools for data collection and storage [16], [17]. One of the essential and basic needs is to analyze this large amount of data. In short, data mining has acted as a bridge that gives us new insights into records that can be considered in data mining such as computer science, statistics, artificial intelligence, modeling, machine learning, and visual data representation [18]. It can be said that data mining, by combining database theories, machine learning, and artificial intelligence, as well as the science of statistics, provides a new field of application [19], [20]. In substance, data mining is a set of different ways that enables a person to move beyond ordinary data processing and to explore information in the mass of data [21]. Various methods and algorithms have been introduced for data mining, but the subject is the selection and a brief explanation of some of these algorithms. Crucial procedures to data mining and machine learning are divided into supervised [22], unsupervised [23], semi-supervised [24], and reinforcement learning groups [25]. Table 1 describes these cases.

Table 1. classification of the types of important approaches to data mining and machine learning.

Type of Learning	Description
Supervised Learning	This type of learning, although not common in nature, is the most commonplace type of gaining knowledge inside the educational gadget of human societies. on this form of studying, the presence of an observer, or an expert, or records containing knowledge is necessary [22].
Unsupervised Learning	This method of learning, which is one of the most difficult varieties of mastering is seen in many creatures and in unique parts of human existence and is one of the hardest forms of getting to know problems. on this sort of study, there is no want for a professional or observer [23].
Semi-Supervised Learning	This kind of learning is a combination of studying with the observer and studying without the observer, which in addition to the use of the experiences provided by using the observer, the opportunity of the usage of non-observer methods has additionally been taken into consideration [26].
Reinforcement Learning	In reinforcement learning, implicit measurements for indirect learning are used to decide the rightness or wrongness of studying. In truth, stored know-how is weakened or strengthened by the penalty or praise indicators [25].

The main purpose of this paper is to present an efficient and new method in finding the optimal location for the disposal of hospital waste. For this purpose, cost, risk, environmental effects of carbon dioxide emissions and reliability, energy consumption, determination, and amount of transportation are considered. In the proposed method, first, the desired location is clustered based on the visual data. Then, based on the definition of a multi-objective cost function in the gray wolf algorithm, optimal locations will be found for the disposal of hazardous hospital waste. The main contribution of this article can be announced as follows:

- Introducing a new machine-based approach to identifying optimal locations for hazardous hospital waste disposal
- Defining a multivariate cost function to optimize costs in finding the optimal location
- Reducing computational complexity in multivariate decision making with the help of machine learning

In the continuation of this article, it is divided as follows. Section 2 will provide machine learning as well as clustering and optimization algorithm. Section 3 describes the proposed method. In Section 4, the proposed method will be evaluated. Section 5 concludes the article.

2. LITERATURE REVIEW

Machine learning involves algorithms that discover patterns or models in data under acceptable computational constraints. Another definition is that learning is a type of technique for identifying information or decision-making knowledge from data pieces, so that by extracting them, in the areas of decision-making, forecasting, and estimation can be used. Today, machine learning is the most important tool for the beneficial use of diverse and abundant data sources [27]. One of these tools and algorithms is clustering.

2.1. Localization

Location finding is one of the branches of production management, geography, urban planning and civil engineering, and attention to it reduces the costs and success of industrial and commercial units, as well as added value in related cases. Locating centers, choosing a location for one or more centers with other centers and existing constraints in mind so that a specific goal is optimized. This goal can reduce costs, design a distribution system, and find optimal location of antennas. Mobile in the city or outside the city, the optimal location of drones are other things [28]. Doing location studies requires specializations such as: operations research, decision making methods, engineering economics, computer science, mathematics, marketing, sociology, etc. Location is one of the most widely used spatial decisions that can be influenced by many factors. The purpose of locating is to find a set of suitable location options for a particular application. The problem of location is a multi-criteria decision-making problem, and multi-criteria evaluation methods can be used in different decision-making problems in different ways by simplifying the definition of decision-making strategies and facilitating spatial processing [29]

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2.2. Clustering

Information clustering is one of the first and maximum essential processes in system learning and records mining [30]. Presently, one of the most vital problems is the design of a suitable and strong algorithm for clustering statistics types. Clustering is a process of classifying components or patterns in clusters so that comparable patterns are healthy into a cluster [31]. In general, there are two styles of clustering: tough clustering and soft or fuzzy clustering in difficult clustering. Any point may be placed in the best cluster. Consequently, the result is wavy. But, in lots of actual-global situations, the presence of resolution boundaries, poor comparison, frequency of interference, noise, and non-uniformity of brightness will reduce difficult clustering performance. Fuzzy idea introduces club idea with the aid of a club feature.

Fuzzy clustering is taken into consideration as a tender segmentation technique. According to the fuzzy clustering technique, the FCM algorithm is a common method in statistics clustering because it has robust properties for ambiguous factors and can keep greater statistics than tough clustering. The conventional FCM algorithm works nicely on noise-loose and artifact statistics. This method may be very sensitive to noise and pretend pics [32].

The FCM algorithm is the first fuzzy clustering method proposed by Dunn, which became later evolved by way of Cannon et al. (1986). This algorithm is an iterative clustering technique that divides the sum of the weighted squared errors into separate components by minimizing the objective function.

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m} d^2\,(x_i, v_j) \qquad (1)$$

Where $X = \{x_1, x_2, \ldots, x_N\}$ and $X \subseteq R^m$ is the input information, which is a dimension m vector, N is the total number of data in the dataset, c is the number of clusters, u_{ij} is the pixel membership x_i to the cluster is v_j, m is the weight given on each member of the membership matrix, v_j is the center of the cluster number j, $d^2(x_i, v_j)$ is the measure of the distance between the pixels and the centers of the clusters. The steps for clustering are as follows:

1. Value the parameters c, m and ε
2. Initialize the membership matrix
3. First, we set the counter of the performed loops to zero
4. The centers of the clusters are calculated using the membership matrix as Equation 2.

$$v_j^{(b)} = \frac{\sum_{i=1}^{N} (u_{ij}^{(b)})^m\, x_i}{\sum_{i=1}^{N} (u_{ij}^{(b)})^m} \qquad (2)$$

5. The calculation of the membership matrix $U^{(b+1)}$will be done from Equation 3.

$$u_{ji}^{(b+1)} = \frac{1}{\sum_{k=1}^{c} (\frac{d_{ji}}{d_{ki}})^{2/_{m-1}}} \qquad (3)$$

If maxmax$\{U^b - U^{(b+1)}\}$ the calculation process ends, otherwise b = b + 1 and go to step 4.

The FCM algorithm is one of the most effective proposed strategies of observers learning amongst partitional methods. This technique divides n facts items into ok clusters (the variety of that's already given). To begin with, a center is randomly assigned to every cluster. Every data object is assigned to a cluster with the nearest cluster center. After this preliminary allocation, the facilities of the clusters are recalculated and all steps are repeated. At every new release of the set of rules, the facilities of the clusters trade. The set of rules continues until the centers of the clusters no longer change [33]. Even though the finality of the above algorithm is assured, the final answer is not the same and does not always have an optimal answer. In popular, the above simple approach has the subsequent following:

- The final answer depends on the choice of the initial clusters.
- There is no specific procedure for the initial calculation of cluster centers.
- If in the iteration of the algorithm, the number of data belonging to clusters becomes zero, there is no way to change and improve the continuation of the method [34].

2.3. Gray Wolf Optimization Algorithms

advances in computer science during the recent 50 years have caused the formation of various optimization strategies. The cause of optimization is to find the first-rate acceptable answer, given the restrictions and desires of the problem. For a problem, there can be unique solutions, and to compare them and choose the top-rated answer, a function referred to as the goal function is described. The selection of this function relies upon the nature of the problem. Choosing the right objective characteristic is one of the maximum essential optimization steps. Now and again in optimization, numerous dreams are taken into consideration concurrently. Such optimization problems, which contain more than one objective function, are referred to as multi-goal issues. The only manner to address such problems is to shape a brand-new goal function inside the shape of a linear aggregate of the primary objective features, in which the effectiveness of each feature is determined via the burden assigned to it. Optimization techniques and algorithms are divided into preferred classes of deterministic algorithms and probabilistic or approximate algorithms [35]. Definite algorithms can find the optimal solution accurately, but in the case of hard optimization problems, their efficiency is greatly reduced. Approximate algorithms can find near-optimal solutions in the short solution time for difficult optimization problems. Approximate algorithms are divided into two categories: heuristic and meta-heuristic algorithms. The two main problems of heuristic algorithms are local optimization and the inability to apply them to various problems. Heuristic algorithms were proposed to solve the problems of heuristic algorithms. These algorithms are one of the types of probabilistic optimization algorithms that have solutions out of local optimization and are used for a wide range of problems [36].

The main characteristics of meta-heuristic methods can be expressed as follows:

Unlike heuristic methods, the main purpose of these methods is to effectively and efficiently search the answer space instead of just finding the optimal or near-optimal solutions;

• Heuristic methods are the policies and strategies that guide the search process;

• Meta-heuristic methods are approximate and often uncertain (random);

• These methods may use mechanisms to prevent the search process from being trapped in local optimizations;

• Heuristic algorithms, unlike heuristic methods, do not depend on the type of problem; in other words, they can be used to solve a wide range of optimization problems;

More advanced meta-heuristic methods use the experiences and information gained during the search process in the form of memory to guide the search to more promising areas of the response space [37].

In brief, it may be stated that meta-heuristic algorithms are advanced and well-known seek solutions. Those algorithms advise steps and standards that are very effective in escaping the trap of local optimization. An essential component in these strategies is the dynamic balance among diversification and empowerment techniques. Diversification refers back to the massive seek inside the answer space, and empowerment method utilizing the stories received within the seek procedure and focusing on the more promising regions of the answer area. Therefore, by using growing dynamic stability among these two strategies, on the one hand, search in the direction of limits of the answer space is pushed wherein higher solutions are discovered, and alternatively, no greater time is wasted in a part of the answer area that has already been tested or includes worse answers. one of the classification criteria of meta-heuristic algorithms is the range of solutions they produce in each generation. Hence, ultra-progressive techniques are divided into businesses: one-factor strategies and demographic methods [38].

In the present study, the gray wolf meta-heuristic algorithm will be used to select the best features of fetal health diagnostic data. Trans-heuristic algorithms are one of the types of probabilistic optimization algorithms that have solutions to exit local optimization and are used for a wide range of problems [39]. An essential component in those strategies is the dynamic stability among diversification and empowerment strategies. Diversification refers to the extensive search inside the response area, and empowerment manner leveraging the studies won within the search procedure and focusing on the extra promising regions of the response space. Therefore, with the aid of growing dynamic stability between these two techniques, on the only hand, the hunt is directed to areas of the solution space in which better solutions are found, and alternatively, it does no longer waste more time in part of the answer space that already is checked or contains worse answers [40].

Gray wolves have a hierarchical life. Gray wolves usually live in protected parks and are at the top of the nature cycle in the food pyramid. Gray wolves usually have 5 to 12 wolves per herd. These wolves have four social classes defined as alpha, beta, gamma and omega. Alpha wolves or alpha wolves are responsible for deciding on prey, where to sleep, when to sleep and when to rest and wake up. These wolves are the leader of the group. Decisions are communicated directly to the lower echelons. However, they may also behave democratically. These wolves are also called the ruling wolf. Alpha wolves are usually not the strongest wolves in the herd, but the behavior of these wolves is decisive. The second group are beta wolves. This group of wolves are in the second social class and usually play the role of alpha wolves. These wolves or wolves may be male or female and are the best replacement for the alpha wolf. Of course, when the alpha wolf grows old, the beta wolf respects the alpha wolf, but gives instructions to lower-class wolves and usually acts as a consultant.

For wolf modeling and GWO design:

• The best alpha solution is α

The second and third, which are the best, are beta β and delta δ

• and the rest of the solutions are considered ω.

The issue is to optimize hunting. α, β and δ guide the problem and ω are the continuation of the solutions.

In the Gray Wolf algorithm, the search process for selecting the best location or cluster center begins with the random generation of the wolf population (candidate solution). In a wolf pack, there are four types of wolves: alpha, beta, delta, and omega. In each iteration, the alpha, beta, and delta wolves estimate the hunting position, which is the best feature to choose from. Each candidate solution updates its hunting distance. The desired parameters in this algorithm will change based on the position of the wolves and update their position, and finally, the algorithm will converge with the defined number of iterations with the defined criterion and the desired feature will be selected [41]. Compared to other heuristic or evolutionary algorithms, this algorithm has a faster convergence rate, and it is also very unlikely that it will be localized to optimize problems [42].

3. METHODOLOGY

The main purpose of this study is to optimally locate hazardous hospital waste. To determine the optimal landfills, a case study of a part of the south of Tehran, which includes areas such as Rey, Baqershahr, Kahrizak, Qayam Dasht has been considered. This area is the densest and busiest area and is located in the center of Tehran. There are 32 hospitals in the area. Fig. 1 shows the study area. Three steps are considered to simulate the proposed method. Each of these steps has several parts. In the first part of the proposed method, a general pre-processing of the data in the relevant database is done. After pre-processing, the main weakness of the FCM clustering method, which is a random start to select the initial centers of the clusters, is improved by the gray wolf optimizer method. After the successful selection of cluster centers, the next steps of FCM clustering are performed and the final clusters are determined. The designated clusters will be used to build the ranking forecasting model and finally offer it to users. Fig. 2 suggests the block diagram of the proposed approach. As show in Fig. 2, the proposed method consists of three main steps. In the first step, preprocessing is done on database, then in the second step FCM clustering and gray wolf optimization are done on the database, finally in last step, cluster centers are chosen for optimal location. These steps are explained as follow.

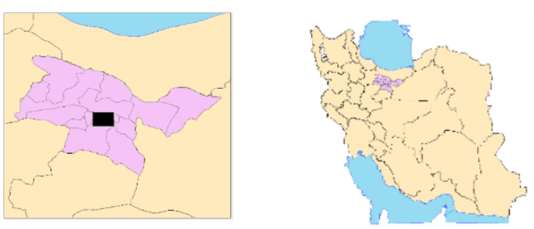


Fig. 1. Location of the study area in Iran and Tehran province.

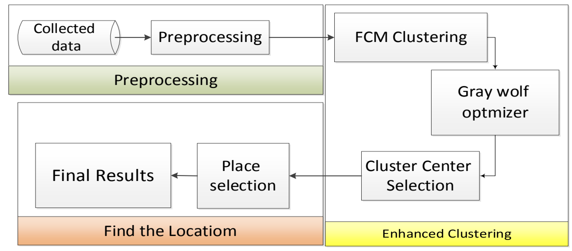


Fig. 2. block diagram of the proposed method.

3.1. Database

The data of this study were collected from hospitals in Tehran, Iran. These database contain information about Slope, Height, Soil type, Distance from the fault Distance from surface water, Groundwater depth, Distance from residential areas, Distance from hospitals and Distance from the road. There are 736 records of information in the collected dataset.

3.1. Preprocessing

Raw data commonly has problems together with noise, bias, drastic adjustments in dynamic range and sampling, and using them in an equal way will weaken subsequent designs. Preprocessing also entails greater complicated conversions which are used to reduce the scale of the data. In short, data processing entails all the conversions which might be made to the uncooked data, making it less difficult and greener for later processing, which includes use in categorization.

3.2. Clustering with FCM Algorithm Improved with GWO

Since the FCM algorithm uses the random center selection method to execute the algorithm, this random selection will increase the execution time and decrease the clustering quality. For that reason, the top-quality case is to use an optimization set of rules to pick the initial centers of the clusters.

The principal idea in the FCM algorithm is to divide the records into clusters iteratively so that the objective characteristic of Equation 1 is minimized.

$$E = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \quad (4)$$

In the above equation, c_j is number of jth clusters, x_i is the data records and its feature, E is the objective characteristic. The FCM algorithm first needs to determine the number of clusters and the data set with n data objects for clustering. In the first step, the k point of n data is selected as the primary centers of the clusters and then the distance of each data from the center of the clusters is calculated repeatedly. Finally, the data are divided based on the shortest distance from the centers of the clusters until the objective function E changes [43].

Since the center of the clusters is randomly selected, the clustering result may not be very solid and the answer acquired might not be "optimally global", so it is very important to select the starting points in such a way that the instability of the algorithm disappear.

As stated, the FCM algorithm requires the dedication of the number of clusters, which throughout professional interviews and diverse operations in the preliminary tiers of statistics studies and guidance, were expertized and reached the very last conclusion. The parameter selection of the number of clusters is very complex and touchy, because how to distribute the information objects is not known earlier. Given the information that exists in the field of research work, the white field approach is used to overcome this challenge to a degree. Consistent with the proposed method to improve the overall performance of the FCM algorithm, the subsequent are offered:

1. To pick the number one centers in line with the fact's similarity density, the use of the grey wolf optimization algorithm is suggested.
2. An assessment coefficient is designed to measure the high quality of clustering.
3. Clustering continues exploratory.

Definition 1. The Sim symbol $Sim(x_i, x_j)$is used to represent the degree of clustering similarity. The data set is defined as $x = \{x_1. \dots . x_n\}$,in which the similarity between each data pair x_i and x_j is defined using Equation 5 [43].

$$Sim_{x_i.x_j \in X}(x_i, x_j) = \lambda d_s(x_i, x_j) + (1 - \lambda)\left|\cos(x_i . x_j)\right| \tag{5}$$

Where, $d_s(x_i . x_j)$ is the normalized Euclidean distance between data record x_i and x_j, and λ is weighting factors. which is defined by Equation 6.

$$d_s(x_i . x_j)_{x_i.x_j \in X} = \frac{d(x_i, x_j) - Min\{d(x_i, x_j)\}}{Max\{d(x_i, x_j)\} - Min\{d(x_i, x_j)\}} \tag{6}$$

Definition 2. The symbol $d(x_i, x_j)_{x_i.x_j \in X}$ in Equation 6 is the same Euclidean $\sqrt{\sum_{k=1}^{m}(x_i - x_j)^2}$. The coefficient λ is a weight factor and its value varies between zero and one and takes different values in vectors. But in experiments, we consider it equal to 0.5. The symbol $\cos(x_i . x_j)_{x_i.x_j \in X}$ is the cosine of the angle between two vectors and can be calculated by the formula (7) and its value varies between [-1.1].

$$\cos(x_i . x_j)_{x_i.x_j \in X} = \frac{\sum_{i=1}^{m}(x_i x_j)}{\sqrt{\sum_{i=1}^{m} {x_i}^2}\sqrt{\sum_{j=1}^{m} {x_j}^2}} \tag{7}$$

$$SimNeighbor(x_i . \alpha)_{x_i \in X} = x | \alpha \leq sim(x_i . x)_{x_i.x \in X} \leq 1. \quad 0 \leq \alpha \leq 1. X = \{x_1. \dots . x_n\} \tag{8}$$

In above equation, adaptive factor is α and $0 \leq \alpha \leq 1$. Usually, for clustering analysis, distance criteria or similar criteria are used to measure similarities. The low triangular matrix $SimNeighbor(x_i . \alpha)$ can also be used to calculate the degree of similarity of the vector set x, because, for the degree of similarity of both vectors, Simx_i and Sim x_i are equivalent to each other.

Definition 3. The density criterion of the x_i vector, calculated using Equation 6, is denoted as $Density(x_i)$.

$$Density(x_i) = \frac{\sum_{j=1}^{\left|P_{neighbor(x_i)}\right|} Sim(x_i . P_{neighbor(x_i)}^{j})}{\left|P_{neighbor(x_i)}\right|} . X = \{x_1. \dots . x_n\}. \tag{9}$$

The symbol $P_{neighbor(x_i)}^{j} \in SimNeighbor(x_i . \alpha)$ indicates that these vectors meet the α threshold in the neighborhood of similarity x_i . $\left|P_{neighbor(x_i)}\right|$ indicates the amount of data in the neighborhood of xi data.

Definition 4. For the two given clusters C_q and C_q, the clustering heterogeneity criterion indicates the average similarity of the points belonging to the two different clusters. Clustering heterogeneity is calculated using Equation 10.

$$Het(C_p . C_q) = \frac{1}{|C_p||C_q|} \sum_{i=1}^{|C_p|} \sum_{j=1}^{|C_p|} Sim(x_i . x_j)_{x_i.x_j \in X} \tag{10}$$

Definition 5. The purpose of clustering is to optimally segment a data set. In this way, data with defined similarities should be placed in a group as much as possible, and vice versa. The evaluation coefficient of obj or target clustering results is defined as Equation 11.

$$obj = Compactness(C) \times Seperation(C) \tag{11}$$

In Equation 11, the values of Compactness and Separation are calculated using equations 10 and 11, respectively:

$$\mathrm{Compactness(C)} = \sum_{i=1}^{k} \frac{\mathrm{Hom}(C_i)}{k} \tag{12}$$

$$\mathrm{Separation(C)} = 1 - \sum_{i=1}^{k} \sum_{j=1}^{k} \frac{\mathrm{Het}(C_i . C_j)}{k} \tag{13}$$

Comparing the quality of clustering is not a difficult challenge. Clustering nice can be assessed by the use of the density inside each cluster and the amount of difference among clusters. The density variable indicates the similarity of the individuals of a cluster, which is calculated by the usage of Equation 12. The separation criterion, which suggests the degree of dissimilarity of information belonging to distinctive agencies, is calculated the usage of Equation thirteen. Our goal is to maximize the density within a cluster and the minimal similarity among records belonging to different clusters.

Definition 6. As stated earlier, the criterion of similarity in this study is the normalized Euclidean distance between points. The smaller the distance between the two points, the greater the similarity between the two points. Therefore, the smaller the Euclidean distance of the points within the clusters, the higher the density criterion, and the shorter the distance between the points belonging to exceptional clusters, the greater the mean square distance (MSD) with Equation 14. In this example, the MSD criterion may even increase, if you want to indicate a better fine of clustering.

$$MSD = \sum_K \frac{\sum_{i=1}^{m^{(k)}} \left\| d_i - d^{(k)} \right\|^2}{m^{(k)}} \tag{14}$$

In equation (14) m is number of clusters, d_i is the *ith* record of data, and $d^{(k)}$ is the kth cluster center.

3.3. Enhanced Clustering

The main idea of the improved FCM algorithm is to compute the $SimMatrix$ similarity $SimMatrix[n][n]$for the X vector with dimension m. Neighborhood matrices of similarity and density of similarity are also calculated according to the $SimMatrix$. Initially, the ID of the primary center candidates is placed in an array called X'. These are the hunting grounds for gray wolves. In the X array, the point x_i has the highest similarity density in the neighborhood of the determined similarity, and is selected as one of the K centers of the initial cluster, and is recorded in *initC*. In other words, to start the gray wolf algorithm, the starting points are determined based on the maximum similarity density.

Selecting any x_i point removes all points that meet the $SimNeighbor(x_i.\alpha)$ constraint from the X' array. In a similar way, the number K of the original cluster center is specified and registered in $initC$. The selection of K of the primary cluster center using the gray wolf optimization algorithm is shown in Fig. 3 and the block diagram of gray wolf optimization in cluster center selection. All steps of finding the optimal cluster center shown in this figure are explained in following

Algorithm input: Array X contains n data elements with dimension m, Array X' to represent candidate point ID, similar neighborhood threshold α, similarity weighting factors λ, and set of initial clustering centers $C = [0\ \ 2]$, $A = [-2\ \ 2]$, $\vec{a} = [0\ 2]$.

Algorithm output: The number of K clusters that make up the set C, such that the relations $C_i \cap C_j = \emptyset$ and i $\neq$ j. $\neq j.\ 0 \leq i.j \leq K$ is located between the clusters. The method can be done in the following five steps:

Step 1) Using Equation 2, the degree of similarity of each pair of X vector data is calculated and stored in the similarity or $SimMatrix[n][n]$.

Step 2) In the remaining x_i in the set X', the vector x_i is selected for the final attack of the wolves by the condition of the position selection equation of the center of the cluster.

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{x_i}\right| \tag{15}$$
$$\vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{x_i}\right|$$
$$\vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{x_i}\right|$$
$$\overrightarrow{x_{i1}} = \vec{X}_\alpha - \vec{A}_1.\left(\vec{D}_\alpha\right) \tag{16}$$
$$\overrightarrow{x_{i2}} = \vec{X}_\alpha - \vec{A}_2.\left(\vec{D}_\alpha\right)$$
$$\overrightarrow{x_{i3}} = \vec{X}_\alpha - \vec{A}_3.\left(\vec{D}_\alpha\right)$$
$$\vec{X}(t+1) = \frac{\overrightarrow{x_{i1}} + \overrightarrow{x_{i2}} + \overrightarrow{x_{i3}}}{3} \tag{17}$$

$\vec{X}_\alpha$ is position of alpha wolf, $\vec{X}_\beta$ wolfs, $\vec{X}_\delta$ *wolfs.*

Step 3) The x_i vector and all the vectors in $SimNeighbor(x_i.\alpha)$ are removed from the X 'array. The X 'array is updated as $X' \leftarrow X' - \{x_i\} - \{SimNeighbor(x_i.\alpha)$.

Step 4) The selected x_i point is added to the $initC$ set in the second step. Thus, $initC$ is updated as $itC \leftarrow x_i \cup initC$. If the number of members of the $initC$ set is less than K, the execution of the algorithm continues by jumping to the second step. Finally, the clustering evaluation factor, obj, is calculated.

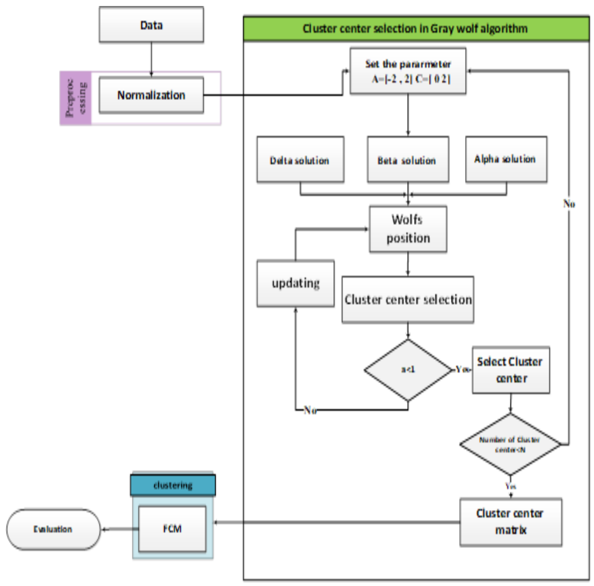


Fig. 3. Cluster center selection in proposed method.

3.4. Objective Function

To optimize the proposed method, a function is defined for the Gray Wolf optimization algorithm. This function is shown in Equation 18.

$$\begin{aligned}\min\ f_1(x) = w1(&\sum_{i\in G}\sum_{j\in T}\sum_{w\in W} c_{i,j}\times x_{w,i,j} + \sum_{i\in T}\sum_{j\in D} cz_{i,j}\times z_{i,j} \\ &+\sum_{i\in H}\sum_{j\in D} cv_{i,j}\times v_{i,j} + \sum_{i\in G}\sum_{j\in H} cr_{i,j}\times l_{i,j} \\ &+\sum_{i\in T}\sum_{j\in H} crr_{i,j}\times k_{i,j} + \sum_{i\in T}\sum_{q\in Q} fc_{q,i}\times f_{q,i} + \sum_{i\in D} fd_i \times dz_i \\ &+\sum_{i\in H} fh_i \times b_i)\end{aligned} \tag{18}$$

In this equation

$x_{w,i,j}$: The quantity of waste of kind w this is transferred among the two centers of waste production and treatment.

$z_{i,j}$: The quantity of waste that moves among the two-waste treatment and disposal centers.

$l_{i,j}$: The quantity of recyclable waste that is transferred from the waste generation center to the waste recycling center.

$k_{i,j}$: The quantity of recyclable waste that is transferred from waste treatment center i to recycling center j.

$v_{i,j}$: The quantity of final waste that is transferred from recycling center i to disposal center j.

$y_{w,q,i}, y_{w,q,j}$: The quantity of waste of type w that will be treated in treatment center i using q technology.

dis_i, dis_j: The quantity of waste misplaced on the landfill i.

hr_i, hr_j: The quantity of waste recycled at Recycling Center i.

$f_{q,i}$: If the treatment technology q is launched in the waste treatment center i.

dz_i: If a waste disposal center is set up in center i.

b_i : If a waste recycling center is set up in center i.

This objective function is made of cost minimization and in the following order:

A: The total cost of waste transfer between the two centers of waste generation and waste treatment.

B: The total cost of waste transfer between the two waste treatment centers and waste disposal.

C: The total cost of waste transfer between the two centers of waste recycling and waste disposal.

D: The total cost of transporting recyclable waste between the two centers of waste generation and recycling.

E: The total cost of transferring the remaining recyclable waste between the two waste treatment centers and their recycling.

F: Overall fixed value of making remedy technologies in remedy facilities.

G: General fixed value of establishing waste disposal centers.

H: Overall fixed fee of setting up waste recycling centers.

4. RESULTS AND DISCUSSION

In this paper, in order to optimally locate hazardous hospital waste landfill, an efficient and new method based on machine learning has been used. To evaluate the proposed method, a map received from google map was used. The written objective function is also compared with ABC bee optimization algorithms, particle swarm optimization PSO, and ant algorithm optimization ACO. The convergence and the speed of reaching the final answer in the proposed method are far better than the algorithms. Fig. 4 shows this comparison. As result shows in Fig. 4, the proposed GWO cluster center selection for FCM caused lower cost compared to ABC, ACO and PSO algorithms. This mainly is because of fast convergence of GWO and also decay from local minimum.

Fig. 4. Comparison of the proposed method in costminimization with other evolutionary algorithms.

Selecting the appropriate number of clusters is obtained by minimizing the function of Equation 17. The number of clusters for which this function has the lowest value is used as the number of clusters suitable for that problem. The form of the above function is a measure of cluster compaction, and the denominator of the fraction is a measure of cluster separation. The more compact the clusters, the smaller the fraction will be, and the larger the denominator of the fraction, the greater the separation of the clusters.

$$V_{XB}(U;V;X)=\frac{\sum_{i=1}^{c}\sum_{k=1}^{n}u_{ik}{}^{m}\,\|x_k-v_i\|2}{n(\min\{v_i-v_j\})} \tag{19}$$

As shown in Fig. 5, the proposed algorithm demonstrates efficient clustering. This will indicate that the centers in the area are properly selected for the disposal of hospital waste.

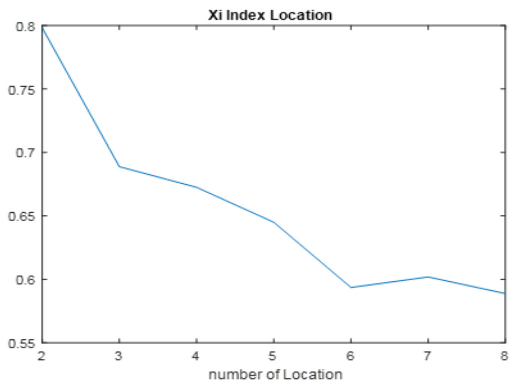
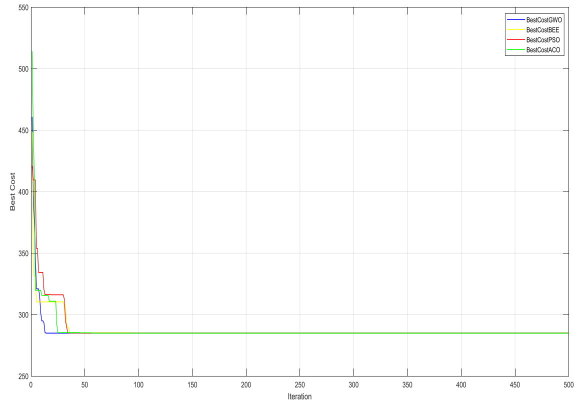


Fig. 5. Xi index.

To evaluate the clustering criteria, the criterion of compaction in clusters and cluster resolution has been used. Fig. 6 shows these two criteria. As shown in Fig. 6, with 8 locations selected in the proposed method, the Separation criterion has reached its maximum value. This is while the compactness criterion has reached its lowest value. This indicates the correct operation of the proposed method in selecting locations. Results in this figure claim the superiority of proposed method.



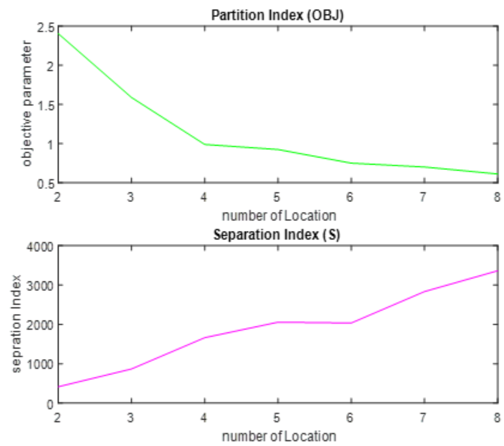


Fig. 6. comparison of separation and objective function as compactness factor.

Based on the characteristics in the area, the best number of clusters, or the number of suitable places for landfilling of 8 points has been obtained. Fig. 7 shows the selected locations on the map.

Fig. 7. Number of selected points on the map for use in hospital waste disposal.

5. CONCLUSION

Currently, landfilling is the main, most acceptable, and most economical method of disposal in many countries, including Iran. The first step in the process of sanitary landfilling of municipal waste is to locate and determine the appropriate location and area for this purpose. In general, a landfill should be located in a place that causes the least damage in various aspects, including environmental, social, and economic. Choosing the right place to dispose of infectious waste centers is one of the major issues in waste management. Determining the location of hospital waste disposal is very complex, because it requires a combination of environmental and social factors. These factors are difficult to interpret, as are the cost factors that require the right allocation of resources. In this paper, a new machine learning method based on the optimal location of hazardous hospital waste disposal is presented. In the proposed method, fuzzy clustering is improved by defining an appropriate objective function in the gray wolf optimization algorithm. In the proposed method, best location for hospital waste disposal is selected based on FCM clustering improved by gray wolf optimizer. Cluster centers were selected as for hospital waste disposal. After finding optimal location, a total of 8 optimal locations were obtained in the study area. The areas obtained by field surveys and other studies are relatively compatible with landfills. These favorable areas are most suitable for burial. Evaluation of the results shows that the selected location is optimal. After determining the objective characteristic of the research, the gray wolf algorithm was used to acquire the desired criteria and layers. Among the located areas, 3 are the most optimal places for landfilling. The first option with an area of 45 hectares, the distance from which is favorable with urban and rural areas south of Tehran. These places are fully compatible with the conditions of choosing the hospital waste landfill. The advantage of these options, which shows their importance over other options, is their optimal distance from the access road and the lack of the need to construct a special route and structure. This reduces energy costs. These locations have been selected as options according to the objective functions used in the article. For more evaluation of the proposed method, cost of simulation and Xi and separation index are used. The number of best locations using Xi and Separation index claim the superiority of the proposed method.

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