Abstract
Facility location selection is one of the most important decisions of companies and industries. At the same time, since a business process begins with the selection of a facility location, it is the first step to consider. Everything starts with the facility location selection. If a location far to suppliers, manufacturers or the market is selected, this will lead to increasing costs in the long run for both the company and other items in the supply network. The distant location also affects the mutual contracts in detail. Besides, the facility location has effects on labor costs and other related costs. Almost all of the costs in the company is closely related with the facility location. Based on this mentioned importance, the facility location selection problem is considered in this study, and the clustering based genetic algorithm method is proposed for the solution of facility location selection problem. In the introductory part of the study, facility location selection problem and the related literature is introduced. After, methods used in the solution are presented as K-means clustering algorithm, genetic algorithm and the proposed algorithm respectively. Detailed numerical results of the study is given in the facility location selection section by using Ruspini75 data set from Operations Research Library. All obtained results are interpreted in the results and discussion section and the study is concluded with the suggestions for future works.

Introduction
Facility location problem, which is one of the most important vital decisions of companies and industries economically, is firstly introduced by Weber and Friedrich (1962). Facility location selection is the determination of geographical location of a facility to start, relocate or expand the operations of a firm in order to optimize at least one objective i.e. cost, profit, distance, service etc. (Singh, 2016). However, facility location selection is not the only important decision to start operations. Firms implement their manufacturing strategies with the following decisions in their production–distribution system (Verter and Dincer, 1992):
- Facility Location

Öz
Tesis yer seçimi, şirketlerin ve endüstrilerin en önemli kararlarından biridir. Aynı zamanda, bir iş süreci tesis yer seçimi ile başladığında, üzerinde durulması gereken ilk adımdır. Eğer tedarikciler, üreticiler veya pazar uzak bir konum seçilirse; bu durum, hem şirketi hem de tedarık ağındaki diğer öğeler açısından uzuına vade eden maliyetler neden olacaktır. Ayrıca uzak konum, karşılıklı yapılan sözleşmeleri de detaylı olarak etkileyecektir. Bununla birlikte tesis yerinin, iş gücü maliyetleri ve diğer maliyetler üzerinde de etkilidir. Şirket tesislerinin maliyetlerini neredeyse tamamen tesisin konumuna ile yakından alakaldır. Bütün bununla birlikte tesis yer seçimi problemi ele alınmakta ve problemi çözümlü için, müşteri hizmeti gümüşü genetik algoritmaları yöntemi önerilmiştir. Çalışmanın, giriş bölümünde, tesis yer seçimi problemi ve ilgili literatür tarihimaktadır. Ardından; çözümlü kullanılan yöntemler, K-ortalamalar kümeleme algoritmaları, genetik algoritmaları ve önerilen algoritmalar açıklanılarak Ruspini75 veri seti kullanarak tesis yer seçimi yöntemi verilmektedir. Tartışma ve sonuçlar bölümünde, elde edilen tüm sonuçlar yorumlanmaktadır ve gelecekteki çalışmalar için öneriler ile çalışma sonuçlandırılmaktadır.
- Capacity Acquisition
- Technology Selection
- Production Mix
- Time-phasing of Investments
- Financial Planning

When the decisions given above are analyzed, all of them integrated with the facility location selection and starts after it. Therefore, the most important step for companies to start the operations is the selection of the best facility location. A worse selected facility location increases the other costs cumulatively related with the facility location. On the contrary, the best selected facility location also decreases the other costs both partially and cumulatively.

In this study, facility location selection using clustering based genetic algorithm is studied and applied to the data set named Ruspini75 from OR–library (Operations Research Library). The outline of the study is as follows. The related literature is introduced in the first section. Then, k-means clustering algorithm, genetic algorithm and the proposed algorithm are presented in the following sections respectively. Detailed numerical results of the study are given in the facility location selection section. In the results and discussion section, all obtained results are interpreted and the study is concluded with the suggestions for future works in the conclusion section.

1. Literature Review

Before introducing the theoretical background and the proposed algorithm, some of the important facility location studies will be presented in this part to clarify the importance of the problem. Even though facility location selection problem is one of the most important problem, there are not enough effective studies in the literature. Almost all of the studies in the literature were done by using multi criteria decision making (MCDM) methods, which are not really effective and enough to meet the needs of today’s companies. Because the companies have too many criteria and data that are also more complex for MCDM solutions in today’s world.

In 2003, Kahraman et al. (2003) presented four different fuzzy multi-attribute group decision-making approaches to select facility locations. The authors also applied all approaches with a numeric example for the comparative analysis. Arogundade et al. (2005) introduced two different methods including branch and bound techniques. They applied the proposed algorithms for the fire and emergency service facility location selection in Nigeria. A fuzzy outranking method for facility location selection was proposed by Kaya and Çinar (2006) in 2006. To deal with uncertainty in decision making problems, the fuzzy set theory was included in this proposed model. The model was also supported by a numerical example. Erteğrul and Karakaşoğlu (2008) applied fuzzy analytical hierarchy process (AHP) and fuzzy technique for order preference by similarity to ideal solution (TOPSIS) methods for the facility location selection. They preferred fuzzy version of the MCDM methods to deal with uncertainty of linguistic assessment. Same year, a fuzzy simple additive weighting system with group decision making was introduced by Chou et al. (2008). The authors used different fuzzy and additive models to select the facility location. Another fuzzy approach with group decision making process was also presented by Shen and Yu (2009). The proposed approach included a risk judgement process to select the best location.

Another MCDM method, preference ranking organization method for enrichment evaluation II (PROMETHEE II), was used to select the real time facility location by Athawale and Chakraborty (2010). Safari et al. (2012) preferred to use fuzzy TOPSIS for the facility location selection. The authors selected three alternatives among five criteria. Wang and Watada (2012) presented a hybrid modified particle swarm optimization for the location selection of facilities with capacities. The authors supported their solution with the numerical experiments. An integrated Delphi and fuzzy AHP method was proposed by Kabir and Sumi (2013) and introduced with a numerical example for facility location selection problem. Fuzzy C-Means and Gustafson-Kessel algorithms were applied to clustering analysis of facility location selection by Büyüksaatç et al. (2014). Then, selection of the best facility location was done by minimizing CO₂ emission levels. Temur et al. (2014) presented a type-2 fuzzy TOPSIS to select the best facility location in reverse logistics. Another fuzzy
TOPSIS method using interval type-2 fuzzy sets was introduced by Çebi and Otay (2015). The authors applied the method to a site selection problem of a cement factory as a real life problem. Ray et al. (2015) applied ELECTRE I (ELimination Et Choix Traduisant la REalite) with various MCDM methods for the facility location selection problems. Basti and Sevklı (2015) used an artificial bee colony algorithm to select the best facility location in the p-median facility location problem. Galvão benchmark problems from OR library was applied in the study and the results were compared with the similar studies. Combinative Distance-based Assessment (CODAS) method integrated with interval-valued intuitionistic fuzzy sets was introduced for facility location selection problems by Bolturk and Kahraman (2018). A wave energy facility location selection problem was solved with this introduced method. Rahman et al. (2018) used AHP method to select the best facility location for a company in Bangladesh. In 2019, Kheybari et al. (2019) applied the best and the worst method for the facility location selection problem of energy production in Iran. Hakli and Ortaçay (2019) studied on uncapacitated facility location problems and improved the scatter search algorithm. The proposed method was also applied with twenty other different methods in the literature to compare the results. Obtained comparative results show that the method improved the performance of the basic algorithm. A new hierarchical group compromise ranking methodology using hesitant fuzzy sets was introduced by Mousavi et al. (2019). The proposed method was applied to a facility location selection and the best alternative was selected by using the new ranking index, which was also introduced by the authors. Seker and Aydın (2020) proposed an interval valued Pythagorean fuzzy TOPSIS method to handle with the uncertain data. Hydrogen production facility location selection problem as a real life problem was solved by using this proposed method. An integrated fuzzy AHP and fuzzy TOPSIS method was presented by Kaul et al. (2020) for facility location evaluation. The application of the presented method was conducted on an Indian company.

As a brief review of the literature, it can be easily seen that almost all of the studies in the literature are related with MCDM methods. In addition, most of the presented MCDM methods are also different fuzzy extensions of existing MCDM methods. There are few examples using or presenting different methods. Therefore, in this study, clustering based genetic algorithm method is proposed for the solution of facility location selection problem, apart from multi-criteria decision making methods.

2. Theoretical Background
This section is allocated to explain the basis of the proposed algorithm, which is introduced in the following section. K-means clustering algorithm is explained step by step in detail in the first sub-section. Then, genetic algorithm is presented with its basic techniques in the second sub-section.

2.1. K-Means Clustering Algorithm
K-means clustering provides simple procedures to develop lexicographic classification systems for a large sample of data (MacQueen, 1967). It starts with random centroids of a group of clusters. Then, it computes the centroids and the members of each cluster iteratively by using Euclidean distance measure. It repeats the procedures until the stopping criterion is satisfied.

The basic K-means clustering algorithm used in this study is as follows:

**Step 1:** Determine the number of clusters, \( K \).

**Step 2:** Let \( C_1, C_2, \ldots, C_K \) be the representation of the cluster centroids of \( \{ X_1, X_2, \ldots, X_N \} \) and determine the K-means cluster centroids randomly.

**Step 3:** Assign each element to the closest cluster by using Euclidean distance given in the Eq. (1) for M-dimension space.

\[
d_{ij} = \sqrt{\sum_{k=1}^{M} (X_{ik} - X_{jk})^2}
\]  

(1)

**Step 4:** Re-determine the cluster centroids by using the Eq. (2).

\[
c_i = \frac{1}{n_i} \sum_{X_j \in C_i} X_j
\]

(2)

where \( n_j \) represents the number of elements in the cluster with the centroid \( C_j \).
Step 5: Repeat from Step 3 until the stopping criterion is satisfied.

2.2. Genetic Algorithm

Solutions based on Genetic Algorithm (GA) were firstly introduced by Holland (1975). The method models the problems inspired by genetics. Variables in the problems are defined as genes and chromosomes, and solutions are obtained by using techniques such as crossover, mutation etc. like in the genetics.

In the following paragraphs, the basic genetic operators used in this study and their definitions are given briefly.

**Fitness Function (FF):** FF is calculated by using the objective function, which is derived from Euclidean distance function in this study. The Objective function is also known as penalty function. Generally, in the literature, FF is equal to the objective function in maximization problems. In contrast in this study FF is used for minimizing the objective function given in Eq. (3), to obtain the minimized distance from the cluster centroids.

\[
FF = \frac{1}{\sum d_j}
\]

**Mutation:** Altering the random genes by using a predefined percentage value. Mutation is mostly preferred in GA-based solutions, because it eliminates trapping to the local optimums. In problems defined by binary system, mutation operator alters 0 to 1 or 1 to 0. But, if the problem defined by different systems, the mutation operator is also defined according to the problem or the solution. For example, in a shortest path problem defined by the combination of the routes, if the routes are defined as genes, the mutation operator can alter a route randomly with another one. Examples of the mutation operator are shown in the Figure 1.

![Figure 1. How the Mutation Operator Works?](image)

**Roulette Wheel Selection (RWS):** RWS is used for the selection of parents to form the next generations. Two of the population is selected with the technique, and then a child solution is generated by using crossover the parent solutions. RWS technique increases the selection chance of better solutions, and worse solutions vanished faster from the population. An example of RWS possibility is given in Eq. (4) with the FF, which means that minimum value is better.

\[
p_j = \frac{\frac{1}{\sum d_j}}{\frac{1}{\sum d_j}}
\]

where \(p_j\) is selection chance of the parent solution \(j\) and \(\sum d_j\) is the penalty cost of parent \(j\).

**Crossover:** Crossover techniques are used to generate child solutions from parent solutions. There are three main crossover techniques, which are one-point crossover, two-point crossover and uniform crossover, have been using in the literature. Two-point crossover is used in this study. An example for all three main crossover techniques is given in the Figure 2 respectively.
3. The Proposed Algorithm

The proposed algorithm for the solution of facility location selection problem is given in this section. The proposed algorithm consists of two parts, which are K-means clustering algorithm and genetic algorithm.

The beginning of the algorithm is the determination of the number of clusters, which is also number of facilities in the handled problem. After the determination, k-means clustering algorithm is run and the memberships of each element for the clusters are obtained. Then, GA is executed to improve the best facility location for each cluster. Flowchart of the proposed algorithm is shown in Figure 3 and the pseudocode of the proposed algorithm is given in detail in Figure 4.

Symbols used in the proposed algorithm and the pseudocode of the proposed algorithm are given in the Table 1 with descriptions.

| Symbol | Description |
|--------|-------------|
| \(C_j\) | The centroid of cluster \(j\) |
| \(n\) | Number of clusters |
| \(C'_j\) | New centroid of cluster \(j\) |
| \(p_i\) | Selection possibility of parent \(i\) in RWS |
| \(d_{ij}\) | Distance between element \(i\) and element \(j\) |
| \(X_i\) | Coordinate vector of element \(i\) |
| \(d_j\) | Sum of the distances of elements in cluster \(j\) to the centroid |
| \(X_{ik}\) | Coordinate of the \(k\). dimension of element \(i\) |
| FF | Fitness function |
| \(\sum d_j\) | Penalty cost of parent \(j\) |
| \(N\) | Number of elements in the problem |
| \(\Sigma\) | Summation |

Figure 2. How the Crossover Operator Works?
Figure 3. Flowchart of the Proposed Algorithm.

Figure 4. Pseudocode of the Proposed Algorithm.
4. Facility Location Selection

In this section, computational results of the study are given. Calculations of the proposed algorithm were implemented in Java and executed on a computer with Intel(R) Core(TM) i7-4720HQ 2.60 GHz, 16 GB RAM and windows 10 professional 64 bit operating system.

Computational results of the Ruspini75 (Ruspini, 1970; OR Library, 2019) dataset by using the proposed algorithm are given in Table 2 with the comparison of the best results in the literature. The Ruspini75 data set is a benchmark data set, and the best results are known and exact results for the comparison of the new developed algorithms. The best results known in the literature was taken from the study of Mladenovic et al. (1996).

The first column of the table 2 is the number of the facilities in the solution. The second column shows the solution time of the proposed algorithm. The third column indicates the best results known in the literature. The fourth column presents the results obtained by the proposed clustering based genetic algorithm and the last column of the table (Difference (%)) points the differences between the obtained results and the best results.

| Number of Facilities | Time (Sec.) | Best Known Results | Proposed Algorithm | Diff. (%) |
|----------------------|-------------|--------------------|--------------------|----------|
| 1                    | 1           | 4141.21            | 4141.21            | 0.000    |
| 5                    | 13          | 779.68             | 783.72             | 0.005    |
| 10                   | 29          | 512.21             | 513.82             | 0.003    |
| 20                   | 33          | 314.10             | 316.26             | 0.006    |
| 30                   | 49          | 199.41             | 199.68             | 0.001    |

Obtained results shows that the proposed algorithm works fast and effectively. All results are close to the best known results with difference less than 0.5% and solution for only one facility was obtained exactly same result in one second. At the same time, the solutions were obtained less than a minute, which is really effective as a heuristic and dynamic method. In heuristic methods, reaching the solution faster is at least as important as reaching the best solution. In this way, obtaining the results, which are close to the best known results less than 0.5% difference and solved under a minute, with the proposed algorithm is applicable and realistic.

5. Results and Discussion

As a result of the findings, less number of facility locations can be solved in a less time with the proposed algorithm. However, more time is required for larger number of facilities. If there are more facility locations, less units are connected to the selected facility locations separately. This seems like problem can be solved in less time because of less number of units. But, it also means that more facility locations and more cluster memberships have to be determined. With all of these, all problems are solved less than a minute with the proposed facility location selection algorithm.

Furthermore, Table 2 shows that obtained results for almost all of the number of facilities are so close to the best known results in the literature. All problems are solved with less than 0.01% difference, which is not a significant difference. This means that the best known results can be achieved with minor improvements to the proposed algorithm.

Conclusion

Facility location selection is one of the most important decisions of companies and industries. It is also first step to start a business process. The aim of the problem is determination of facility location in order to optimize the total distance to the facility location. In this study, facility location selection problem has two main parts; clustering of the elements for facilities and determination of the locations of the facilities.

This study focused on the implementation of clustering analysis to genetic algorithm. First part of the proposed algorithm is the determination of initial clusters and their centroids by k-means clustering algorithm. Second part is the improvement of the initial solution by genetic algorithm. It
improves both elements of the clusters and their centroids. The proposed algorithm is applied to Ruspini75 dataset from OR-library. Computational results are compared with the best results in the literature. The comparison shows that the proposed algorithm has a satisfactory performance and the results are competitive with the literature.

For further research, the proposed algorithm can be also implemented to other heuristic techniques or adapted with different operators to improve. The proposed algorithm can be implemented to various location selection problems from different fields with small modifications depending on problem types and constraints.

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