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Detection of Communities on Social Networks Based on Label Propagation Algorithm and Fuzzy Methods

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Abstract. The proliferation of the web and social networks has made people more connected to their friends and neighbors than ever before. The desire of individuals to relate to similar tastes and choices in a social network leads to the formation of clusters or virtual communities. Such information can be useful for commercial, educational or developmental purposes and therefore a large number of algorithms for detecting communities have been presented. There are many algorithms for detecting communities on social networks. In this paper, using the label propagation algorithm and fuzzy Delphi method, an improved method is presented that can identify communities more accurately and quickly than other similar methods. Accordingly, in the proposed algorithm, instead of randomly selecting from the maximum labels of the neighboring nodes, the label with the highest weight is chosen. By doing this, random selection is eliminated, and stability and certainty in the outcomes of the algorithm are achieved.

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1 Introduction

Today, the Internet and virtual social networks have a fundamental role and impact on human life that cannot be ignored. Social networking is the use of Internet-based sites and applications to connect with friends, family, colleagues or customers. Social networks can have a social purpose, a business purpose, or both [10]. The tendency of individuals with similar tastes, choices, and preferences in relation to a social network leads to the formation of clusters or virtual communities. Detecting these communities can be useful for a variety of applications, such as finding a common research area, finding a set of similar users for the marketing and educational purposes, analyzing social networks, and detecting communication structures.

A social network is a website that allows people with similar interests to come together and share information, photos and videos. People who work on social media may do this as a personal task. Do something. People who engage in personal work on social networking sites interact about their lives and interests using a variety of media. The most popular social networks for this familiar interaction include Facebook, Google+ and Twitter. People who are in a social network are considered nodes of that network. Therefore, nodes can communicate with each other and form communities. The general purpose of detecting communities in social networks is to understand the structure of these complex networks and ultimately to extract useful and practical information. Communities in complex networks include large data samples, which are usually time consuming to study and analyze these data samples with basic and traditional methods. In addition,

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traditional methods can increase the probability of error in the output. For this reason, new methods for detecting communities have been proposed. This topic is widely used in disciplines that can represent societies using graphs, such as detecting societies in sociology, biology, and computer science [7]. A method that can analyze big data in an acceptable time and also be compatible with the dynamic nature of social networks is considered a suitable method because these networks evolve over time and become wider. For these reasons, the analysis of social networks using different algorithms has been considered by many researchers and many methods have been proposed to identify communities. One of the best methods presented in this field is the labeling propagation algorithm or the so-called label propagation algorithm, which is used to identify communities. Features of this method include reducing the complexity of calculations, increasing accuracy and increasing speed.

The main challenge in the label propagation algorithm is the random selection of values for some nodes, which means that in some cases, for example, when the maximum number of neighbor's labels is equal, the node cannot be valued, so random selection algorithm performs that makes the final output unreliable [2]. For this reason, the algorithm may produce different outputs with the same inputs, which is a major weakness in the labeling method. To solve this problem and avoid completely random selection of the algorithm, in this research, an optimal method based on scoring nodes based on the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) criterion is presented, which means that the nodes are scored based on their importance. Then, using the TOPSIS criterion, the most important label is selected and given to the node. This method prevents the algorithm from randomly labeling in certain cases, which makes the output more stable and makes the results more reliable.

In the real world, social networks have interesting patterns and characteristics that can be analyzed for many useful purposes. The process of discovering coherent groups or clusters in the network is known as community detection, which is one of the main tasks of social network analysis. Detecting communities on social media can be useful in many applications where group decisions are made, for example sending a favorite message to a group instead of sending a separate message to each individual offering a set of products to a group Special [1]. Community identification in networks is one of the most popular topics in modern network science. Communities or clusters are groups of heads that are more likely to be related to each other than members of other groups, although this can be expressed in other patterns, there is no universal protocol for a single definition of community [5].

Social networks such as Facebook and Twitter are among the most visited websites on the Internet, and these networks also play a major role in the dissemination of innovation and information. These websites have a lot of information from different people, and there are links between these people. These links represent the relationship of individuals with each other, so the identification of communities shows how the structure of links affects people and their relationships. In some networks, public communities can exchange information because people in the community have the same tastes and desires. These types of associations are used in various applications of network analysis such as customer categorization, link reference, recommendations, and vertex labeling [14]. This algorithm randomly assigns a label to the desired node, and as mentioned, this causes the algorithm not to produce reliable outputs. In the proposed method, a solution is proposed for this issue, which is considered as the winning node using the TOPSIS criterion, and its node is given to other nodes without labeling.

There are many algorithms for detecting communities on social networks, but many of these algorithms have drawbacks and therefore cannot be used in the real world. To solve this challenge, more research and analysis are needed in the field of community identification. There are many methods for detecting communities on social networks, and LPA (Label-Based Algorithms) algorithms have attracted the attention of many researchers because of their simplicity and speed than other methods of detecting communities. For this reason, in order to identify communities, a node-based labeling algorithm based on the Fuzzy Delphi Method has been proposed to achieve optimal responses. In this Section, the organization of the paper is stated. In Section 2, some virtual communities in social networks and label propagation algorithms will be described in detail. In section 3, the proposed method based on the label propagation algorithm and fuzzy Delphi method will be introduced in detail. Finally, in section 4, the results of the simulation of the proposed method in comparison with some other methods in the social networks will be presented.

2 Related Works

There are various algorithms for detecting communities, each of which has its strengths and weaknesses. This section examines previous methods proposed by other researchers in the field of community detection. The algorithms in this paper are categorized from several perspectives. In this section, the method used in each of these perspectives is briefly discussed and evaluated.

2.1 Label Propagation Algorithms

Label propagation algorithms can predict the information of unlabeled nodes by other nodes that have labels. Due to their simplicity and low complexity, these methods are used in a variety of subjects.

Cao et al. in [3], the author proposed a similarity and weight-based label dispensing algorithm. The SWLPA (Similarity and Weighted Based Label Propagation Algorithm) algorithm focuses on the similarity and weight of the neighboring node. This article first calculates the probability of label release based on the similarity between nodes and the weight of neighboring nodes then filters the labels according to the effect of each node and releases the label, and finally the result of dividing the community. Experimental results show that this method effectively improves the accuracy of community division results. SWLPA algorithm must first calculate the similarity between nodes according to the structural similarity of nodes and the similarity of user settings, and then from the similarity between nodes and weight Neighbor nodes use labels to analyze the probability of propagation between nodes and perform replication according to the probability of propagation. In real life, people are more inclined to connect with people who have similar interests because it will be easier to understand and accept each other's views. Based on this feature, this paper creates a node similarity formula to solve this problem that is applied between two nodes. In addition, in the real world, each person has a different effect, and the opinions of influential people are more convincing, so calculating the effect of a neighbor node should be based on the neighbor node weight formula. In iterations, a node selects a learning target from neighboring nodes according to the strength of the priority.

In this paper, the propagation probability model is used to evaluate the priority. However, not all information obtained from neighboring nodes will be retained, just as we will forget trivial and interesting information in real life. Therefore, when all the information is integrated, it is necessary to calculate the screening threshold according to the threshold formula and remove all labels that are less likely to be published below the threshold. In this paper, the community segmentation model is created according to the similarity of the node, the weight of the neighboring node, the probability of propagation of the label and the filtering the label.

Yan et al. in [15], a node-based label propagation algorithm for community detection in networks is presented. The algorithm first calculates the effective value of the node for each node and rates the node in descending order of the effect value of the node. During each label update process, when there is more than one label by the maximum number of nodes, we enter the label impact value into the label update formula to improve stability. After the algorithm converges, nodes with the same label are divided into a community. This algorithm retains the advantages of the original LPA algorithm. In addition, it can achieve sustainable community detection results by preventing the label from being random. Through experimental studies on artificial and real networks, the researcher shows that the proposed algorithm performs better than some of the current representative algorithms.

In [18] the researcher introduces an improved algorithm called LPAc (LPA based on edge clustering coefficient). The experiments were performed on the basis of standard artificial networks with partitions and several networks were performed in the real world. On the one hand, the results of the artificial benchmark network experience show that LPAc results are more accurate than LPAs, when the scale of the community is large and the structure of the actual network community is not very obvious.

In terms of stability, LPAc is still much better than LPA. In this way, errors in the division of the structure of real networks are avoided as much as possible. In addition, the accuracy and stability of the effect become more apparent as the number of samples increases. On the other hand, according to the results of experience in real-world networks, the results of dividing LPAc in terms of quality and structure of society, especially in large-scale real-world network communities containing about 1000 nodes are better than LPA. The edge clustering coefficient presented in this paper preserves the advantages of traditional LPA and improves stability and accuracy in specific cases, especially for large communities. Today, LPA is applied in many applications such as semi-supervised learning, data mining and information processing. In addition, there will be plenty of room for future development. The superiority of the LPA makes it a method of calculating the potential of significant research.

As stated, the main weakness of the LPA algorithm is its uncertainty and instability. In the LPA algorithm if there is no single maximum label at the time of selecting the maximum label of the neighbors of one node, the LPA (in the absence of an appropriate strategy) randomly assigns one of the multiple maximum labels to that node. This random selection results in uncertainty in the output of this algorithm, which means that the algorithm in the same conditions and with the same inputs yields different clusters in its successive runs, which is obviously not desirable. This paper attempts to resolve this problem.

2.2 Graph-based algorithms

In [16] the authors have developed a graph-based label propagation algorithm for community detection. In this paper, a GLPA (Graph-based Label Propagation Algorithm) is proposed to identify communities that use node similarity and connection information during labeling. In the first step, the similarity of the node between adjacent nodes is defined and the label of each node is changed to the most similar neighboring node. Based on the label release process, GLPA creates a label release chart to get candidate communities. Then, GLPA calculates the attached components of the label release diagram. In the next step, each connected component is treated as a candidate community. In the second stage, GLPA A weight diagram is obtained to obtain the final assemblies, in which each of the connected components acts as an extra node and the number of edges that lie between the corresponding components as the weight of the edges. The integration factor of each node is calculated in the weight diagram, and the extra nodes are repeated with a higher integration factor with the most similar node to reach the maximum complement entropy.

Luptakova et al. in [8], the authors use the Euclidean distance of nodes in small dimensions to build a network (for example, proximity or neighborhood diagram) that is used for clustering purposes in community-based diagnosis. The nearest neighbors of the knots are connected by edges. The researcher believes that the proposed method is generally superior to the original clustering methods, which have been tested on popular two-dimensional synthetic criteria and deserve further study. It also has less computational complexity than other comparable approaches.

Sheng et al. in [13], the authors have proposed a new algorithm, CC-GA (Clustering Coefficient-based Genetic Algorithm), to identify them in complex social networks. Researchers have used a number of genetic algorithms to identify communities, but the researcher in this article believes that the proposed algorithm is new in terms of initial population production and mutation method, which has improved its efficiency and accuracy. Experiments on a variety of real-world datasets and comparisons of advanced genetic and non-genetic algorithms show improved results.

2.3 Evolutionary algorithms

Many evolutionary algorithms have been proposed to deal with the problem of community identification in dynamic social networks, some of which are reviewed below.

In [9] propose a new multi-objective Bat algorithm that uses this algorithm to change the average for the production of the initial population, to obtain high quality solutions. In this proposal, the bat algorithm simultaneously optimizes the modularity density and the normalized cross-information of the solutions as target functions. Algorithm operators apply the problem of community Detection in dynamic social networks by providing another sense of speed, frequency, volume, and bat natural pulse rate. This algorithm maintains the principle of the mean change algorithm to generate a new solution and avoid a random process by defining a new mutation operator.

In [12] recommend a new multi-objective optimization algorithm based on the ACO (Ant Colony Algorithm) to solve the problem of community detection in complex networks. In the proposed method, the Pareto archive is intended to store the non-dominant solutions available during the algorithm process. The proposed method for solving the community diagnosis problem maximizes both the community fitness goals and the community score.

In [11], a genetic algorithm for detecting communities on social networks is presented. This method introduces the concept of community privilege and seeks to optimize network segmentation by maximizing community privilege. All the dense communities in the network structure are obtained at the end of the algorithm by selective exploration in the search space, without the need to know the exact number of groups in advance. The concept of community privilege, while simple, is very effective. In fact, experiments on artificial and real-life networks have demonstrated the ability of the genetic approach to accurately identify communities with results comparable to advanced approaches.

3 Proposed method

The label propagation algorithm cannot guarantee convergence after several iterations, which means that if it is repeated several times, we may receive different outputs from the algorithm, which is a very important drawback. This problem is the same as randomly selecting node labels where the maximum number of neighboring nodes is not available. In this part, the algorithm randomly assigns a label to the desired node, and as mentioned, this causes the algorithm not to produce reliable outputs. In the proposed method, a solution is proposed for this issue, which is considered as the winning node using the TOPSIS criterion, and its node is given to other nodes without labeling. In general, this important problem has been improved in the proposed method, which means that the random selection of the node label in the algorithm has been removed and the proposed method has replaced this random selection.

Therefore, first, the basics of the research are compiled by searching scientific databases and libraries and the existing records in the field of community identification in social networks by propagation labels, and through the questionnaire, the final indicators are first identified by the fuzzy Delphi method with the help of experts. In the next step of the research, field data will be collected with a pairwise comparison questionnaire to perform a fuzzy hierarchical analysis method to evaluate and rank the indicators and determine their weight. Fuzzy TOPSIS is then used to prioritize nodes in social networks based on an improved labeling algorithm. In the end, the label is selected with the highest priority and given to the unlabeled node, and then nodes with similar labels are placed in a cluster.

According to Figure 1, with the start of work, the proposed method enters into action and obtains the necessary information. In the next step, the nodes are randomly placed in the network and the work of the algorithm begins. If a node is left unlabeled during the process, and it could not receive the maximum neighbor's label, we must assign the label that has the highest priority and was selected in the previous step, in TOPSIS, to this node, and then the algorithm continues to work. Reach the end stage. If there is no unlabeled node in the path, we reach a stage where all the dense nodes are in one group and the work is completed, with the difference that the proposed method makes the final outputs more reliable, because of the TOPSIS criteria and hierarchical analysis. The output will not be different in repetition. The present study is applied in terms of purpose and survey in terms of descriptive method and is quantitative in terms of data nature.

The process of this algorithm is this; in the first step, each network node is assigned a unique label, and then, in a repeat process, the algorithm arranges the network nodes in a random order. Next, each node in the ordered list receives the label that is carried by the largest number of its neighboring nodes (if this maximum label is not unique, LPA randomly selects one of them to update the node label). This repeated process continues until we reach the point where the label of all nodes in the network is such that it is labeled with the largest number of neighbors and therefore no change is made to the labels. At the end of the algorithm, all nodes with the same labels are placed in a community or cluster. The pseudo code of this algorithm is presented in Figure 2.

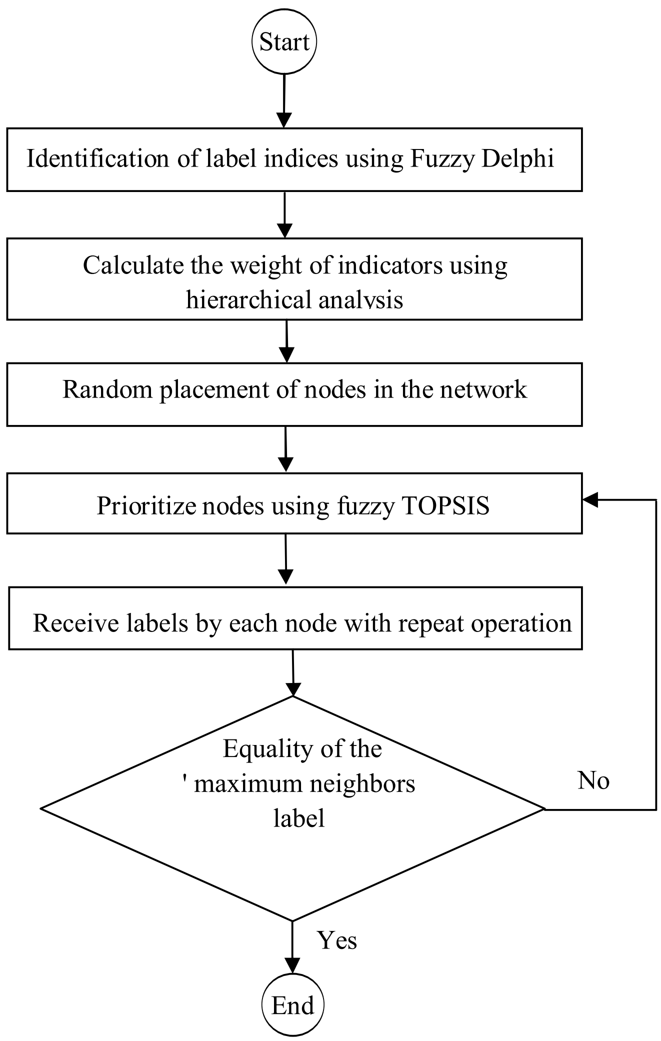

Figure 1: Flowchart of the proposed method

1) Initialize the unique label for each node in the network.
2) Set iteration number t = 1.
3) Arrange the nodes of the network in random order (ordered list X)
4) For each node x ∈ X, iteratively update the node label so that each node takes the label that is carried by the largest number of its adjacent nodes (if this maximum label is not unique, LPA randomly selects one of them to update the node label).
5) If the label of each node is the same as that of most of its neighboring nodes, then the nodes with the same label are placed in the same community, and the algorithm ends; otherwise, set t = t+1 and go to step (3).

Figure 2: Pseudo code of the basic proposed algorithm

3.1 Data Collection Method

To collect another part of the data of the present study, the field method must be used, that is, using the questionnaire, the required data is collected from the specified statistical sample. The data are in this research [17]. According to the two types of evaluation and ranking questionnaires, Table 1 will be used for the fuzzy hierarchy analysis method and Table 2 for the fuzzy TOPSIS method [4]. The questionnaire is designed based on one of the complete spectra in the form of 9. Fuzzy numbers and verbal expressions (linguistic variables) of the importance of numbers 1 to 9 in two-by-two comparisons are presented below.

Table 1: Degree spectrum for use in fuzzy hierarchy analysis

Degree of importance in a pair wise comparison	numerical value
Equal preference	(1, 1, 1)
Low to medium preference	(1, 1.5, 1.5)
Medium preference	(1, 2, 2)
Medium to high preference	(3, 3.5 ,4)
High preference	(3, 4, 4.5)
High preference to very high	(3, 4.5, 5)
Too much preference	(5, 5.5, 6)
Preference is very high to quite high	(5, 6, 7)
Quite a lot of preference	(5, 7, 9)

The method of data analysis in the present study is quantitative. The data of the present study will be analyzed at both descriptive and inferential levels. At the descriptive level, statistical indicators such as frequency, standard deviation and mean, variability, and elongation are used. The results of the literature review are used to identify communities on social media by propagation labels.

3.2 Label Propagation Algorithm

One of the most well-known methods for detecting a community on social media is the LPA (Label Propagation Algorithm) [17]. The LPA algorithm is simple to implement and its time complexity is almost linear, which is why it has attracted so much attention so quickly. Label propagation algorithm is one of the semi-monitoring machine learning algorithms that assigns labels to unlabeled data observations in order to

Table 2: Degree spectrum for use in fuzzy hierarchy analysis

Degree spectrum for use in fuzzy TOPSIS	**numerical value**
Very weak	(0, 0, 0.1)
Weak	(0, 0.1, 0.3)
Weak to medium	(0.1, 0.3, 0.5)
Medium	(0.3, 0.5, 0.7)
Almost good	(0.5, 0.7, 0.9)
Good	(0.7, 0.9, 1)
Very good	(0.9, 0.9, 1)

segment the data observations in the data set. Within a social network, the label propagation algorithm is an algorithm for changing the label of each node based on the social label of the nodes connected to that node. The biggest advantage of the label propagation algorithm is that it has excellent execution time as well as a simple algorithm process. The rules of the label propagation algorithm are as follows [6]:

- Each specific node has its own label.
- The label for each node represents the distinct community to which that node belongs.
- Through replication within the network, each community node updates its membership based on the community of neighboring nodes until all nodes with the same label are assigned to the same community.
- Updated forum each node, community belonging to the maximum number of nodes will be.
- Eventually, the densely connected nodes in a community reach a common label.

The label propagation algorithm starts by giving a unique label to each node, such as an integer and letters, and in each iteration, each node changes its label to another token carried by the largest number of its neighbors. If more than one label is available by the same maximum number of neighbors, one of them is randomly selected. In this iterative process, dense groups of nodes change their different labels to the same label, and nodes with the same label are grouped in the same community. The following equation 1 is the label update formula:

$$c_i = \arg\max \sum_{j \in N^I(i)} l, \tag{1}$$

Where $N^I(i)$ represents the set of neighbors v_i labeled l. For a weight chart G, the edge weight between v_i and u_i is denoted as w_{ij}, and the label update formula changes as follows:

$$c_i = \arg\max \sum_{j \in N^I(i)} w_{ij} \tag{2}$$

However, the label propagation algorithm cannot guarantee convergence after several iterations. In general, this algorithm first assigns a label to each network node and then, in an iteration, the algorithm randomly arranges the network nodes. Next, each node in the sorted list receives a label that is carried by the most neighboring node (if this maximum label is not unique, the LPA randomly selects one of them to update the node label). This iteration process continues until it reaches a point where all network nodes are labeled in such a way that they are labeled with the largest number of neighbors and therefore no change in the labels.

At the end of the algorithm, all nodes with similar labels are placed in an association or cluster [6]. In the present study, in the random node selection stage of network nodes, the fuzzy TOPSIS algorithm is used. This algorithm is required to use the fuzzy Delphi algorithm and fuzzy hierarchical analysis.

3.3 Fuzzy Delphi

The Delphi method is used in cases where incomplete and unreliable knowledge is available or there are limitations in terms of the application of mathematical rules, formulas and models. For this purpose, the opinions and judgments of individuals are collected in a certain area. In other words, the judgment is left to the experts. The Delphi method is mainly used to discover creative and reliable ideas or to provide appropriate information for decision making. This method conducts surveys of individuals in order to examine the attitudes and judgments of individuals and expert groups as well as to establish coordination between views. These surveys are conducted in several stages using a questionnaire and without requiring people to attend a certain place. At the end of summarizing, evaluating and analyzing the set of views and opinions of individuals, the basis for goal setting, program development and decision making is used. This method is a combination of the Delphi method and propagation to fuzzy collections presented by Ishikawa et al. The steps of the fuzzy Delphi method are:

I. Detecting research indicators using a comprehensive review of theoretical foundations of research.

II. Collecting decision-making experts: In this step, after detecting the supply chain criteria, a decision-making group consisting of experts related to the research topic is formed and questionnaires are used to determine the order.

The existence of identified indicators with the main subject of research and screening is sent to them in which the linguistic variables of Table 3 are triangular and Table 4 are trapezoidal, to express the importance of each indicator. In this research, fuzzy triangular numbers have been used.

Table 3: Fuzzy Delphi Triangular Fuzzy Numbers

Very much	**Much**	**Medium**	**Little**	**Very little**
(1, 1, 0.75)	(1, 0.75, 0.5)	(0.75, 0.5, 0.25)	(0.5, 0.25, 0)	(0.25, 0, 0)

Table 4: Trapezoidal fuzzy numbers and variables in trapezoidal fuzzy Delphi

Linguistic variable	**Trapezoidal fuzzy number**
very little importance	(0,0,1,2)
low importance	(1,2,3,4)
medium importance	(3,4,6,6)
high importance	(6,7,7,8,9)
very important	(8,9,10,10)

III. Confirmation and screening of branches: This is done through the value of the acquired value of each index with the threshold value S. The threshold value is determined by the decision maker's mental profile and will directly affect the number of factors being screened. There is no simple and legal way to determine the threshold circuit. In this study, according to the number of factors and news opinions, the value of 0.7 is considered the threshold value. To do this, we must first calculate the triangular fuzzy values of the experts 'opinions and then, to calculate the average of the n respondents' opinions, their fuzzy average must be calculated. The fuzzy number $\tilde{\tau}$ is calculated for each pack of indicators using the following equations.

$$\begin{gathered} \tilde{\tau}_{ij} = (a_{ij}, b_{ij}, c_{ij}) \qquad i = 1, 2, , n \qquad , \qquad j = 1, 2, , m \\ a_j = \sum \frac{a_{ij}}{n}, \qquad b_j = \sum \frac{b_{ij}}{n}, \qquad c_j = \sum \frac{c_{ij}}{n} \end{gathered} \tag{3}$$

In the above relationships, index i refers to the expert and index j refers to the decision index. Also, the de-fuzzy value of the mean fuzzy number is obtained from the following equation 3.

$$Crisp = \frac{a+b+c}{3} \tag{4}$$

IV. Fuzzy Delphi Consensus and Completion Stage: In this stage, if the average difference between two consecutive rounds of fuzzy Delphi is less than 0.1, fuzzy Delphi is completed.

3.4 Fuzzy Hierarchy Analysis

There are different weighting methods in assessing the importance of criteria for decision makers. Methods are based on theoretical principles, accuracy, ease of application and their comprehensibility for decision makers. The most important weighting methods are ranking, relative and hierarchical analysis methods called AHP (Analytic Hierarchy Process). In the AHP method, the pairwise comparison method is used to calculate the weight of the criteria. The input of the AHP method is a pairwise comparison matrix whose values express the relative importance of the criteria. After the formation of the pairwise comparison matrix, the incompatibility rate of the comparison matrix is determined and if the judgments are acceptable, the weight of each criterion is obtained. To calculate the weight, first the comparison matrix is formed and the parameters are compared in pairs and their relative importance is measured. In order to calculate the relative weight of the two criteria relative to each other, their relative importance is expressed in terms such as quite important, very strong importance, etc., and according to experts, each of these expressions is converted into a score between 1 and 9, which is their weight. It is said to be relative. Then, the resulting pairwise comparison numbers are given in the form of a matrix called the comparison matrix. In this matrix, knowledge is the result of comparing the i-th criterion with the j-th criterion. After preparing the comparison matrix and its level of compatibility, the weight of the parameters is calculated by the special vector method. The main criterion for accepting pairwise comparisons is that the comparisons are consistent, for this purpose we must show that:

$$W_{.w} = \begin{bmatrix} 1 & \frac{w_1}{w_2} & \dots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & 1 & \dots & \frac{w_2}{w_n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \dots & 1 \end{bmatrix} * \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} = \lambda.w \tag{5}$$

In this relation, λ a special value, W is an even comparison matrix and w is a special vector corresponding to the specific value λ, which is a matrix N*1. We can define the incompatibility index (II) as follows:

$$II = \frac{\lambda \max - n}{n-1} \tag{6}$$

In this regard, λmax the largest value of the comparison matrix and n is the number of criteria. The incompatibility index values for matrices whose numbers are chosen completely randomly are called the Random Matrix Compatibility Index (IIR). For each matrix obtained by dividing the incompatibility index

(II) by the random matrix incompatibility index (IIR) and later, it is a suitable criterion for judging the incompatibility, which we call the incompatibility rate (IR). The closer the II and consequently the IR to zero, the higher the level of compatibility in the comparison matrix. If the incompatibility rate is less than 0.1, the compatibility of the system is acceptable; otherwise the judgments should be reconsidered.

In the fuzzy AHP method, triangular fuzzy numbers are used to fuzzy the explicit values of the pairwise comparison matrix. For this purpose, the concept of fuzzy development analysis is used, in which the importance of criteria and priority of options is obtained by solving the fuzzy paired comparison matrix. Using the notion concept α, the fuzzy decision matrix is converted to a matrix with a range of uncertainty values, and explicit values are obtained using the optimal index λ.

Consider a pairwise comparison matrix such as A whose values range from up $\frac{1}{9}$ to 9. Using triangular fuzzy numbers f = (l, m, u), the initial matrix with explicit values A is converted to fuzzy values. Using fuzzy development analysis on the above matrix, the fuzzy decision matrix is obtained. To obtain the fuzzy decision matrix (x) and fuzzy weight (w) using fuzzy development analysis, the following formula is used:

$$X_i \quad or \quad W_j = \frac{\sum_{j=1}^{k} a_j}{\sum_{i=1}^{k}\sum_{j=1}^{k} a_{ij}} \tag{7}$$

By multiplying the decision matrix and the weight matrix, the weighted decision matrix (P) is obtained as follows.

$$P = X_i * W = \begin{bmatrix} (W_1X11 & W_mX11m & W_mX11n) \\ (W_mX21 & W_mX21m & W_mX21n) \\ .... & .... & .... \\ .... & .... & .... \\ .... & .... & .... \\ (W_mXi1 & W_mXijm & W_mXijn) \end{bmatrix} = \begin{bmatrix} P_{11} & P_{1m} & P_{1u} \\ P_{21} & P_{2m} & P_{2u} \\ ...... & ...... & ...... \\ ...... & ...... & ...... \\ ...... & ...... & ...... \\ P_{i1} & P_{im} & P_{iu} \end{bmatrix} \tag{8}$$

At this stage, we are faced with uncertain limits on values, and therefore decision makers are asked how confident they are in their judgment. The cut α (between 0 and 1) indicates the degree of confidence of the expert in his judgment. If the cut-off value α is close to one, it indicates that the experts were very confident in their judgment. A α cut of zero indicates high uncertainty. After applying the decision makers' confidence in their decision and using the α matrix cutting operation, the following P_α is obtained:

$$P_\alpha = \begin{bmatrix} [P_{1l\alpha}, P_{1r\alpha}] \\ [P_{2l\alpha}, P_{2r\alpha}] \\ .... \\ .... \\ .... \\ [P_{il\alpha}, P_{ir\alpha}] \end{bmatrix} \tag{9}$$

In the above matrix, the parameters r, l represents the left and right values of the interval set, respectively. In the next step, using the optimal index λ, the matrix of explicit values is obtained. The optimal index λ in the set of interval values is applied as follows and leads to the production of a matrix C_λ with explicit values.

$$C_\lambda = \lambda * p_{r\alpha} + (1-\lambda) * p_{l\alpha} \tag{10}$$

The values of the optimal index (λ) are in the range of zero to one variable, which in the most pessimistic case is equal to zero and in the most optimistic view, the λ value is equal to one. Finally, since the values of the comparison matrix do not have the same scales, the explicit values obtained are normalized using the following equation 11. It should be noted that to compare the criteria, it is necessary that they all have the same scale.

$$C_{i\lambda} = \frac{C_{i\lambda}}{\sum C_{i\lambda}} \tag{11}$$

3.5 Fuzzy TOPSIS

The fuzzy TOPSIS method uses triangular fuzzy numbers to convert qualitative measures and weights to quantity. The TOPSIS method is a very technical and robust decision-making method for prioritizing options by simulating the ideal answer. In the TOPSIS method, the selected option must have the shortest distance from the ideal answer and the farthest distance from the most inefficient answer. In this method, the matrix n × m, which has m options and n indices, is evaluated. One of the important advantages of this method is that it is possible to use objective and subjective indicators and criteria at the same time. Its output can specify the order of priority of the options and quantify this priority. The algorithm for performing the fuzzy TOPSIS technique is as follows:

3.5.1 Step 1: Form a decision matrix

First, we design the decision matrix with n criteria and m options based on the desired fuzzy spectrum. When the fuzzy approach with triangular fuzzy numbers is used, the X decision matrix will be displayed as follows. Each decision matrix element is also displayed as x_{ij}:

$$\begin{aligned} \tilde{x} &= [\tilde{x}_{ij}]_{m\times n} \\ \tilde{x}_{ij} &= (l_{ij}, m_{ij}, u_{ij}) \end{aligned} \tag{12}$$

3.5.2 Step 2: De-scale the decision matrix

The fuzzy normal matrix is represented by a symbol and each element of the normal matrix is also displayed as. The following equation 13 is used for normalization:

$$\tilde{N} = [\tilde{n}_{ij}]_{m\times n} \tag{13}$$

If the criterion has a positive charge, we will have:

$$\begin{aligned} \tilde{n}_{ij} &= \left(\frac{l_{ij}}{u_j^*}, \frac{m_{ij}}{u_j^*}, \frac{u_{ij}}{u_j^*}\right) \\ u_j^* &= \max u_{ij} \end{aligned} \tag{14}$$

If the criterion has a negative charge, we will have:

$$\begin{aligned} \tilde{n}_{ij} &= \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right) \\ l_j^- &= \min l_{ij} \end{aligned} \tag{15}$$

3.5.3 Step 3: Fuzzy balanced scale unmatched matrix

In the third step, a fuzzy balanced scale less matrix must be formed. In general, in this step, the scale less matrix (N) should be converted to a weighted scale less matrix (V). This matrix is represented by a V symbol. The weight of each indicator is calculated using FAHP (Fuzzy Analytic Hierarchy Process) technique, entropy, etc. Holding the weights of the indicators that are represented by the vector, we will have:

$$\tilde{V} = [\tilde{v}_{ij}]_{m\times x} \qquad i = 1,2,3,...,m \qquad , \qquad j = 1,2,3,...,n$$
$$\tilde{v}_{ij} = \tilde{n}_{ij}.\tilde{w}_j \qquad , \qquad \tilde{w} = \tilde{w}_1, \tilde{w}_2, \tilde{w}_3, ..., \tilde{w}_n \tag{16}$$

3.5.4 Step 4: Positive and negative ideals

In the next step, the fuzzy positive ideal and the fuzzy negative ideal must be calculated:

$$A^+ = (\tilde{V}_1^*, \tilde{V}_2^*, ..., \tilde{V}_n^*) \tag{17}$$

$$A^- = (\tilde{V}_1^-, \tilde{V}_2^-, ..., \tilde{V}_n^-) \tag{18}$$

According to one view, the best value of criterion i is among all the options.

$$\tilde{V}_j^* = \max\{\tilde{v}_{ij}\}, \qquad \tilde{V}_j^- = \min\{\tilde{v}_{ij}\} \tag{19}$$

Since the normalized triangular fuzzy numbers belong to the range (0 and 1). So proposed positive and negative ideals are as follows:

$$\tilde{V}_j^* = (1,1,1), \qquad \tilde{V}_j^- = (0,0,0) \tag{20}$$

Distance from positive and negative ideals: Then the sum of the options distances from the positive and negative ideals must be calculated. If F1 and F2 are two triangular fuzzy numbers then the distance between these two numbers will be calculated by the following formula:

$$D(F_1, F_2) = \sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]}$$
$$F_1 = (l_1, m_1, u_1), \qquad F_2 = (l_2, m_2, u_2) \tag{21}$$

Here F2 is proposed the same positive and negative ideal. So we will have:

$$\to D(\tilde{V}_{ij} - \tilde{V}_j^*) = \sqrt{\frac{1}{3}[(l_{ij} - 1)^2 + (m_{ij} - 1)^2 + (u_{ij} - 1)^2]} \tag{22}$$

$$\to D(\tilde{V}_{ij} - \tilde{V}_j^-) = \sqrt{\frac{1}{3}[(l_{ij} - 1)^2 + (m_{ij} - 1)^2 + (u_{ij})^2]} \tag{23}$$

The option distance from the positive ideal is displayed and the distance from the negative ideal is displayed. Based on this, the distance of each option from the negative and positive ideal will be calculated as follows:

$$d_i^* = \sum_{j=1}^{n} (\tilde{V}_{ij} - \tilde{V}_j^*), \qquad i = 1,2,3,...,m$$
$$d_i^- = \sum_{j=1}^{n} (\tilde{V}_{ij} - \tilde{V}_j^-), \qquad i = 1,2,3,...,m \tag{24}$$

The final step is to calculate the ideal solution. In this step, the relative proximity of each option to the ideal solution is calculated. To use the following formula:

$$CL_i^* = \frac{d_i^-}{d_i^- - d_i^+} \tag{25}$$

The value of CL is between zero and one. The closer this value is to one, the closer the solution is to the ideal answer and the better the solution.

4 Simulation Results

In this section, first, the indicators of the label propagation algorithm are presented by reviewing the literature. Then, by considering the number of nodes and selecting a random label on each of them, by presenting 3 questionnaires in 3 stages among 10 statistical sample people, respectively, to implement fuzzy Delphi methods and fuzzy hierarchical analysis and fuzzy TOPSIS, respectively. MATLAB software examines and verifies that nodes with similar labels are correctly placed in a cluster and the high priority node is identified in the fuzzy TOPSIS stage so that the label of this node can be used in the random selection stages of the label propagation algorithm. 90% of the respondents are men and 10% of the respondents are women. 10% of the statistical populations are single and 90% of them are married. 80% have a master's degree and 20% a doctorate, with the largest number being 80% with a master's degree. 0% is less than 10 years old, 20% are 11-15 years old, 30% are 16-20 years old and 50% are more than 20 years old.

To implement the proposed method, first the indicators related to this research are examined by the fuzzy Delphi method and it is determined that these indicators are important. In the next step, using hierarchical analysis method, these indicators are weighted to determine how to prioritize these indicators. Because in the TOPSIS method, we need the index and the weight of the indicators, so we enter the TOPSIS section using the outputs of the previous steps, and using specific TOPSIS formulas, we prioritize the nodes in the MATLAB software output, and in finally, we review them and select the valuable and high priority node.

4.1 Implementation of fuzzy Delphi method

According to the studied materials and articles, some important indicators regarding the label selection section of nodes in the label propagation algorithm have been selected. These indicators are obtained from various sources and are the result of a comprehensive study of articles in this field. In the fuzzy Delphi method, first, the research indicators are identified using a comprehensive review of the theoretical foundations of the research. The indicators of the present research are: Node distance from the origin, Number of neighboring nodes, Number of similar labels, Node distance from the center.

The decision-making group consists of experts related to the research topic and questionnaires are sent to them in order to determine the order of the identified indicators with the main research topic and screening, and these experts are asked to complete the questionnaires. Indicators are verified and screened by comparing the value of the acquired value of each index with the threshold value. The statistics of the opinions of the experts in the first Delphi period are given in Table 5.

Table 5: Statistics of expert opinions in the first period of fuzzy Delphi

No.	Indicators	Very Low	Low	Average	High	Very High
1	node distance from the origin	0	1	2	3	4
2	number of neighboring nodes	0	2	1	5	2
3	number of similar labels	0	1	2	4	3
4	node distance from the center	1	2	5	1	1

In the next step, converting the experts' language response into fuzzy numbers for the first fuzzy Delphi period, the average of the responses for each index was calculated, the results of which are shown in Table 6. According to the appropriate mean in the first period of the method, the statistics of experts' opinions in the second period of Delphi were calculated, the results of which are shown in Table 7. To ensure the results and reduce the error rate in these cases, the questionnaire can be used several times until the means are quite appropriate. In this research and this section, questionnaires have been given to experts twice, which in the first time the results are appropriate, but in the second time the results of an index is less than the threshold

Table 6: Mean responses for each index in the first fuzzy Delphi period

No.	Indicators	Averages			
1	node distance from the origin	5.7	6.7	7.9	8.5
2	number of neighboring nodes	5.1	6.1	7.2	8
3	number of similar labels	5.5	6.5	7.7	8.4
4	node distance from the center	3.1	4	5.5	6.4

and that index is removed. This can be repeated again but in this study 2 repetitions are considered. In the next step, converting the experts' language response into fuzzy numbers for the second fuzzy Delphi period, the average of the responses for each sub-index was calculated, the results of which are shown in Table 8.

Table 7: Statistics of expert opinions in the second period of fuzzy Delphi

No.	Indicators	Very Low	Low	Average	High	Very High
1	node distance from the origin	0	1	2	3	4
2	number of neighboring nodes	1	2	2	4	1
3	number of similar labels	4	4	1	1	0
4	node distance from the center	2	0	1	4	3

Table 8: Average responses for each index in the second fuzzy Delphi period

No.	Indicators	Averages			
1	node distance from the origin	5.7	6.7	7.9	8.5
2	number of neighboring nodes	4	4.9	6.1	7
3	number of similar labels	1.3	1.9	3	4
4	node distance from the center	5.1	5.9	7	7.7

In this study, according to last researches, the value of 3 is considered as the threshold value and the factors that have a lower arithmetic mean of 3 are eliminated. The results of averaging are shown in Table 9. In this study, after 2 stages of completing the questionnaire, the index of the same number of labels did not acquire the required score and was removed from the indicators.

Table 9: Results of averaging in the second phase of fuzzy Delphi

No.	Indicators	Averages
1	node distance from the origin	7.2
2	number of neighboring nodes	5.5
3	number of similar labels	2.55
4	node distance from the center	6.425

4.2 Implementation of fuzzy hierarchical analysis method

In this section, the selected indicators need to be weighted, so we use the hierarchical analysis method. Finally, each of these indicators has a weight and it is determined which one has a higher priority. The higher the priority, in the main part, ie TOPSIS, these weights have a greater impact on the nodes. First, the general list of indicators of the relevant model is expressed and reviewed. All subsequent steps in completing the evaluation process are commensurate with the levels of decision-making identified. The list of final indicators of the label propagation algorithm is Node distance from the origin, Number of neighboring nodes, Node distance from the center. To make pairwise comparisons between indicators, each expert is asked to determine the importance and priority of each indicator over the other according to the scales provided in the questionnaire. This comparison is designed at the level of the main indicators and at the level of the sub-indicators of each of the main categories in the other two tables, so in each of the questionnaires, there are 3 matrices for them to compare pairs between indicators. In the fuzzy AHP method, triangular fuzzy numbers are used to fuzzy the explicit values of the pairwise comparison matrix. For this purpose, the concept of fuzzy development analysis is used, in which the importance of criteria and priority of options is obtained by solving the fuzzy paired comparison matrix. Using the notion concept, the fuzzy decision matrix is converted to a matrix with a range of uncertainty values, and explicit values are obtained using the optimal index (λ). Consider a pairwise comparison matrix such as A whose values range from up to 9. Using triangular fuzzy numbers f = (l, m, u), the initial matrix with explicit values A is converted to fuzzy values. Experts show.

After calculating the arithmetic mean of all cells of the pairwise comparison matrix, the results are normalized and by combining the weights of the lower level elements with the weights of the corresponding high level elements in the hierarchy, the weights of the indices are obtained. MATLAB software is used. One of the important points about all matrix comparison matrices is their degree of incompatibility, in order for judgments to be stable, the degree of incompatibility of all matrices must be less than or equal to 0.1. For this reason, it is necessary for the relevant expert to repeat his judgment so that the matrices are stable, then the arithmetic mean of the cells of the comparison matrix is calculated. The calculation of the incompatibility of the indicators with the value of 0.0595 is shown in Table 10. Therefore, weights are obtained and these indicators can be used together with their weights in the TOPSIS calculations (Table 11).

Table 10: Matrix of pairwise comparisons of the final indicators of the label propagation algorithm.

Indicators	**Node distance from origin**			**Number of neighboring nodes**			**Distance from node to center**		
node distance from origin	1	1	1	1.42	1.52	2.78	1.52	2.27	3.07
number of neighboring nodes	0.359	0.657	0.704	1	1	1	0.82	1.65	1.99
node distance from center	0.325	0.440	0.657	0.502	0.606 7	1.219	1	1	1

Table 11: Weight of the final indicators of the label release algorithm

Indicators	**Weight**
node distance from origin	0.493
number of neighboring nodes	0.297
node distance from center	0.21

4.3 Implementation of fuzzy TOPSIS method

One of the methods of MCDM is the fuzzy TOPSIS method which is used as one of the most efficient multi-criteria decision making techniques. The basic logic of this model defines the ideal (positive) solution and the negative ideal solution. An ideal (positive) solution is one that increases the profit criterion and decreases the cost criterion. The optimal index λ is the option that has the shortest distance from the ideal solution and at the same time the farthest distance from the negative ideal solution. In other words, in the ranking of options by the TOPSIS method, the options that have the most similarity with the ideal solution get a higher ranking.

In this section, the options are labeled nodes that are prioritized by fuzzy TOPSIS method based on fuzzy hierarchy analysis weights. The random propagation of nodes and labels are each shown in Fig. 3. Where their number is specified next to each node so that these nodes can be prioritized based on the indicators.

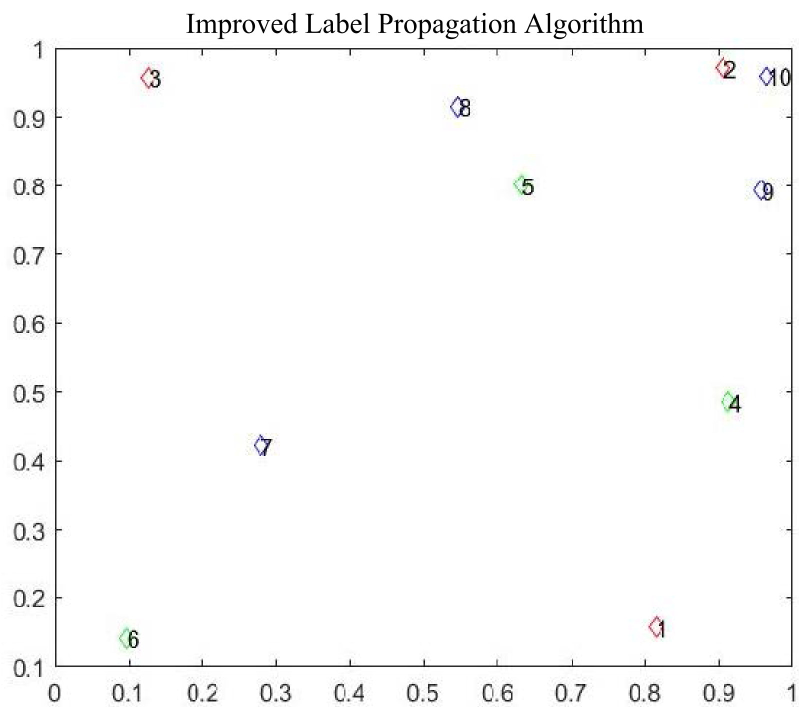

Figure 3: Random placement of nodes in the network

According to the variables identified for fuzzy evaluation and according to the degree of linguistic variable and its fuzzy equivalent as well as the weight vector, the importance of each of the options is evaluated, which are in Tables 12 and 13 is specified. After determining the weight of each criterion, a fuzzy TOPSIS questionnaire was given to 10 people to evaluate the options. The result of the questionnaires was calculated by calculating the arithmetic mean of each and being close to each of the fuzzy language variables and the decision matrix can be seen in Table 14.

Normalized, weighted normalized matrices and positive and negative ideal matrices were calculated. The final ranking of the nodes can be seen in full in Table 15. Due to the prioritization of nodes, the label of nodes has changed according to Fig. 4 and the node with the highest priority has been identified by TOPSIS in the table, which in this study is node 3. In the same way, the red label can be considered the winning label, and if there is a node without a label, the red color is selected as the label of that node and the random selection of the label is ignored. Finally, nodes with similar labels are placed in a cluster.

Table 12: Triangular fuzzy numbers equivalent to a 7-degree spectrum to evaluate options

Fuzzy Equivalent	**Language Variable**
Very Weak	(0, 0, 0.1)
Weak	(0, 0.1, 0.3)
Weak to Medium	(0.1, 0.3, 0.5)
Medium	(0.3, 0.5, 0.7)
Almost good	(0.5, 0.7, 0.9)
Good	(0.7, 0.9, 1)
Very good	(0.9, 0.9, 1)

Table 13: Fuzzy weighting of indicators for fuzzy TOPSIS method

Indicators	**Weight**
	0.9
Node distance from origin	0.9
	1
	0.1
number of neighboring nodes	0.3
	0.5
	0
node distance from center	0
	0.1

Table 14: Node Prioritization Decision Matrix

Nodes	**Node distance from origin**			**Number of neighboring nodes**			**Node distance from center**		
Node 1	3.54	4.54	5.25	3.12	5.24	7.32	1.14	3	5.24
Node 2	3.25	5.58	6.24	2.11	3.22	5.25	1.25	2.36	5.96
Node 3	4.21	7.25	8.32	5.87	6.24	8.54	7.25	8.54	9.25
Node 4	7.21	7.25	8.32	1.14	3	5.24	2.11	3.22	5.01
Node 5	3.54	4.67	5.89	3.12	5.24	7.32	1.14	3	5.24
Node 6	4.21	7.25	8.32	4.12	5.87	6.02	2.58	3.78	4.36
Node 7	7.25	8.54	9.25	1.25	3.22	5.25	1.28	2.57	3.68
Node 8	1.74	2.47	3.14	5.47	6.44	7.53	1.89	2.24	3.87
Node 9	5.65	6.01	8.07	1.24	2.87	3.98	5.15	6.34	7.09
Node10	2.14	3.54	4.25	1.17	2.47	3.14	5.54	6.15	7.46

4.4 Analysis of results

At the end of the proposed method, the ideal coefficient can be seen in the tables, as well as the node that may be unlabeled in the LPA. According to Table 15 in this study, node 3 has obtained the number 0.478, which has a higher priority than other nodes and is considered as the winning node in the TOPSIS method. In this way, the random selection part of the algorithm is solved with this method, and the algorithm uses node 3

Table 15: Final ranking of nodes based on fuzzy TOPSIS

Nodes	Negative ideal distance matrix	Positive ideal distance matrix	Amount of coefficient of proximity to the ideal cluster	Ranking	Cluster
Node 1	0.49	0.656	0.428	4	Green
Node 2	0.456	0.74	0.381	8	Blue
Node 3	0.707	0.771	0.478	1	Red
Node 4	0.647	0.957	0.388	7	Blue
Node 5	0.495	0.661	0.431	3	Red
Node 6	0.596	0.802	0.426	5	Green
Node 7	0.696	1.012	0.407	6	Green
Node 8	0.39	0.486	0.445	2	Red
Node 9	0.482	0.873	0.356	9	Blue
Node10	0.279	0.651	0.3	10	Blue

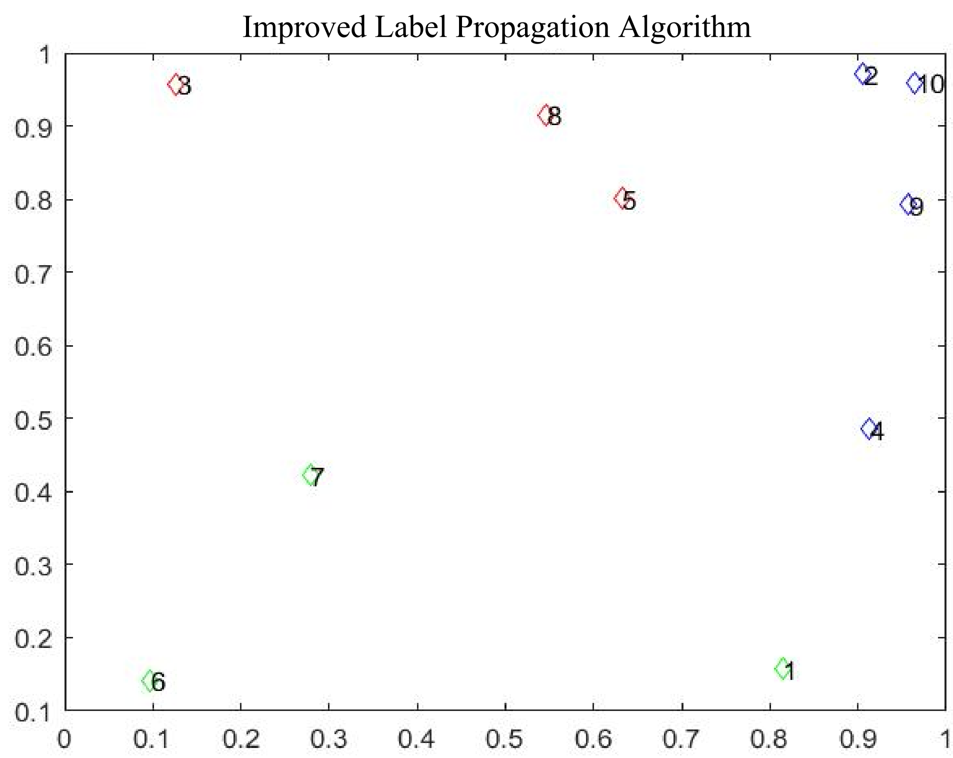

Figure 4: Placement of nodes with similar labels in a cluster

as the maximum label if it reaches and stays in the random selection stage. The results of data analysis were presented using fuzzy Delphi, fuzzy hierarchical analysis and fuzzy TOPSIS methods to identify the index and rank the options based on the indexes. The same numbers of labels were removed using fuzzy Delphi index method. The results of data analysis were evaluated using fuzzy hierarchical analysis method in the form of Fig. 5 for weighting the indicators. The total weight of all the indicators should have been 1 when this happened. The incompatibility of the 6 indicators is also 0.0595 and less than 0.1 is acceptable.

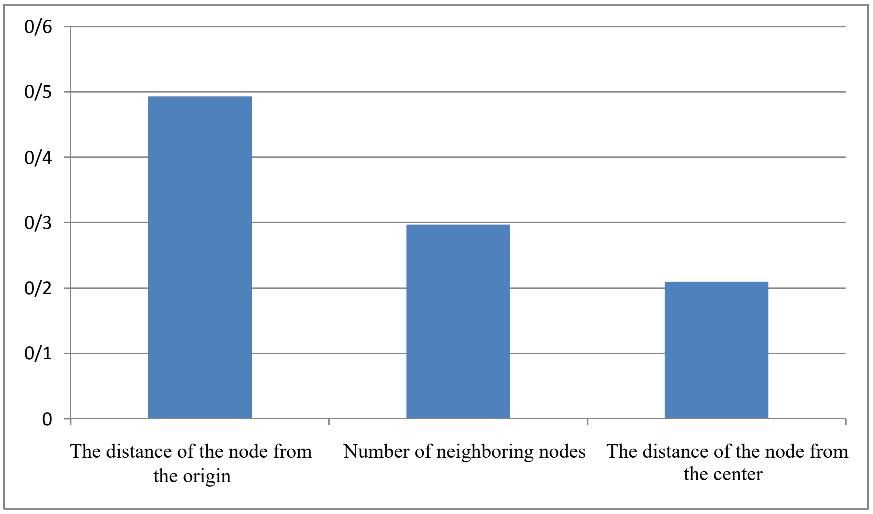

Figure 5: Figure of final evaluation of indicators

As reported in Fig. 5, the coefficient of the node distance index from the origin is 0.493, the coefficient of the number of neighboring nodes is 0.297, and the coefficient of the node distance index from the center is 0.21. According to Fig. 5, the node distance index from the origin can be identified as the most important and the node-center distance index can be identified as the least important indicators. In fuzzy hierarchical analysis method, the indicators showed that the order of importance of each is as follows:

- The distance of the node from the origin.
- Number of neighboring nodes.
- The distance of the node from the center.

According to the fuzzy TOPSIS results, the nodes were also prioritized so that the nodes with similar labels were placed in a cluster. According to the results, with the rapid development of information technology, electronic media are becoming more and more popular for social communication. Discovering communities is a very effective way to understand the properties of complex networks. However, traditional community detection algorithms consider only the structural features of a social organization and waste more information on nodes and edges. At the same time, these algorithms do not consider each node based on its merit. The label propagation algorithm is an almost linear time algorithm that aims to find the community on the network. Due to its high efficiency, it attracts many researchers. In recent years, there are more improved algorithms based on the label propagation algorithm that the present study was able to improve the label propagation algorithm using fuzzy Delphi methods, fuzzy hierarchical analysis and fuzzy TOPSIS.

5 Conclusion

In this study, the indicators and options of the label propagation algorithm were analyzed using the fuzzy Delphi, the fuzzy hierarchical analysis and the fuzzy TOPSIS methods by reviewing the literature of different studies. The results of the fuzzy Delphi method showed that the index of a similar number of labels should be removed. The results of the fuzzy hierarchical analysis showed the node distance index from the source as the most important and the node distance from the center index as the least important indices. According to the fuzzy TOPSIS results, based on the weights obtained from the fuzzy hierarchical analysis, the nodes were also prioritized so that the nodes with similar labels were located in a cluster and also the node with the highest priority was chosen and considered as the winning node. If the algorithm reaches the random selection section, the label of this node should be given as the preferred label to the desired node and random selection should be ignored.

Conflict of Interest: The authors declare no conflict of interest.

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