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MLP-COMET-based decision model re-identification for continuous decision-making in the complex network environment

Bartłomiej Kizielewicz
0000-0001-5736-4014
Dept. of Artificial Intelligence Methods and Applied Mathematics,
West Pomeranian University of Technology in Szczecin
ul. Żołnierska 49, 71-210 Szczecin, Poland
Email: bartlomiej-kizielewicz@zut.edu.pl

Jakub Więckowski
0000-0002-9324-3241
National Institute of Telecommunications
ul. Szachowa 1, 04-894 Warsaw, Poland
Email: j.wieckowski@il-pib.pl

Jarosław Jankowski
0000-0002-3658-3039
Dept. of Information Systems Engineering,
West Pomeranian University of Technology in Szczecin
ul. Żołnierska 49, 71-210 Szczecin, Poland
Email: jjankowski@zut.edu.pl

***Abstract*—In recent years, complex networks have gained significant attention for their practical potential in data analysis and decision-making. However, assessing node relevance in complex networks poses challenges, including subjectivity and difficulty reproducing criteria relationships. To address these issues, we propose MLP-COMET. This novel approach combines the Multi-Layer Perceptron (MLP) with the Characteristic Objects Method (COMET) in Multi-Criteria Decision Analysis (MCDA). MLP-COMET aims to re-identify decision models using MLP to evaluate characteristic objects. We evaluate the approach to assessing the complex network and demonstrate its effectiveness in evaluating without heavy reliance on domain experts. The MLP-COMET performance is evaluated through ranking comparisons, showing a strong correlation with reference expert rankings. We also analyze the impact of training sample size and number of characteristic objects on ranking similarity, observing high stability and similarity using the r_w metric. MLP-COMET offers an effective and reliable tool for evaluating complex networks and facilitating decision-making processes.**

I. Introduction

COMPLEX networks have been significantly developed in recent years due to their high practical potential [1]. They have been used effectively in the areas of quantum systems [2], information processing [3], decision tree analysis [4], or node relevance assessment problems [5]. The increasing computational capabilities of computer technology allow more complex and efficient solutions to be developed [6]. It has also translated into strengthening the position of techniques included in complex networks in their use for data analysis [7]. By using such approaches in a wide range of practical problems, more efficient and effective solutions can be achieved, and benefits can be derived from the conclusions drawn from the analyzed data.

One highly popular area considering the developed models based on complex networks is connected to blockchain and cryptocurrencies [8]. Since the field related to virtual payments is expanding, there was a need to propose solutions that could be used to make more rational and conscious decisions. Complex networks are applied for analyzing the blockchain structure [9], the performed transactions [10], or for the automation processes [11], among others. Those techniques can be used to extract knowledge that can be used for further analysis and constitute making more effective steps in the area of blockchain and cryptocurrencies.

Complex networks are based on the usage of nodes in the analysis process [12]. It often leads to incompatible nodes assessment taking into account the centrality measures. Since the occurrence of this phenomenon should be limited, various techniques are used to reduce it. For this purpose, Multi-Criteria Decision Analysis (MCDA) methods can be used [13]. The MCDA techniques allow for assessing decision variants regarding multiple criteria that are considered in the evaluation process [14], [15]. Moreover, those methods enable modeling different preferences depending on the outcome and objectives that are expected as the final results [16], [17]. It can be achieved by modifying the criteria weights, representing the relevance of subsequent decision factors [18]. With this approach, the determined models are highly configurable and reusable in different initial conditions.

To model the criteria importance, different approaches can be used [19]. Many decision models rely on professional knowledge and experience that is extracted from the domain expert through the criteria judgment process [20]. The subjective weighting methods can be used for this purpose [21]. They allow for a structured and systematic judgment process, indicating assessment steps that aim to simplify the criteria importance evaluation for the expert. Multiple approaches can be used since various techniques are being developed in this area. One of the most popular methods is the Analytical Hierarchy Process (AHP) [22], which is based on the criteria pairs comparison aiming to establish the relationship between assessed criteria. The other approach that can be applied to extract expert knowledge is the new method of Ranking Comparison (RANCOM) [23], which proved to handle expert judgment inaccuracies significantly better than the mentioned AHP method. The other techniques that can be used for this purpose are Best-Worst Method (BWM) [24], Full Consistency Method (FUCOM) [25], Fixed Point Scoring [18], or Simple Multi-Attribute Rating Technique (SMART) [26], among others.

Despite multiple advantages that can be benefited from engaging the domain expert in the evaluation process, there are also some drawbacks of this approach [27]. The main disadvantages of determining the decision models based on expert knowledge are their unavailability, a certain level of hesitance and inaccuracies of the judgments, or the impossibility of reproducing the previously defined relationships between criteria relevance [28]. It can lead to multiple difficulties in making the determined model reusable in various applications. However, it is worth developing ready-to-use models that guarantee highly effective and reliable results.

In this paper, we propose a multi-criteria decision analysis model for evaluating complex networks, which is an artificial expert in the form of a MultiLayer Perceptron (MLP) combined with a Characteristic Object METhod (COMET). The MLP-COMET approach aims to re-identify the decision model based on the evaluated decision variants. The MLP in the regressor variant is used to represent the domain expert that assesses the Characteristic Objects (COs) in the COMET method. The practical problem of assessing the Bitcoin network is used to verify the model's performance. The main contributions of the study are

- presenting an approach that enables re-identification of decision model
- indicating the methodology that can be used to replace the domain expert in the decision process
- analyzing the Bitcoin network with the determined MLP-COMET technique

The rest of the paper is organized as follows. Section 2 presents the literature review on centrality metrics in complex networks and MCDA and its usage in the practical problems connected to the blockchain field. Section 3 presents the preliminaries of the complex network and MCDA. Section 4 presents the proposed approach for re-identifying the multi-criteria decision model. Section 5 shows the study case of using MLP-COMET to re-identify the decision model based on the evaluated alternatives in the practical problem of analyzing the Bitcoin network. Finally, Section 6 presents the conclusions drawn from the research and the further directions for developing the presented approach.

II. Literature review

A. Selection problems based on centrality metrics

In the area of complex networks, it is possible to distinguish metrics that define the attractiveness of a node concerning the others available in the analyzed network. Their analysis allows more efficient choices to be made regarding selecting nodes that are key to information propagation. Measures of centrality such as degree, closeness, betweenness, and eigenvector are a group of factors that allow efficient analysis of network nodes and their selection [29]. Alexandrescu et al. used the four mentioned centrality measures to identify the sustainability communicators in urban regeneration [30]. The presented measures were applied as the decision criteria in one of the three dimensions that were determined in the assessment, namely, the informal network influence. Karczmarczyk et al. applied the MCDA techniques to select seeds for targeted influence maximization within social networks, where the centrality, betweenness, closeness, and eigenvector centrality measures were also considered in the evaluation of the node [31]. Muruganantham et al. focused on the problem of discovering and ranking the influential users in social media networks by applying the selected MCDA methods, namely Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) II, ELimination Et Choix Traduisant la REalité (ELECTRE), AHP, Statistical Design Institute Matrix method (SDI), Pugh (also known as Decision Matrix Method), and Technique for the Order of Prioritisation by Similarity to Ideal Solution (TOPSIS) [32]. The authors also used the four above-mentioned measures to assess the social influence in the network. Moreover, the centrality metrics can be grouped based on their scope of operation. The closeness, betweenness, eigenvector, coreness, average clustering coefficient, average shortest path length, and PageRank measures belong to global measures, while degree or semi-local centrality are classified as measures with local scope [33]. The global measures are identified based on the necessity of having access to the whole network to determine the global information for the specific factor. On the other hand, local measures can be calculated using the local information of the node.

B. Blockchain and cryptocurrencies in MCDA

MCDA methods are used in many application areas due to the ability to flexibly select decision criteria based on which decision variants are assessed. This configurability and versatility allow decision-making models to be used in the area related to blockchain and cryptocurrencies. Lai and Liao proposed an approach for MCDM based on Double Normalization-based Multiple Aggregation (DNMA) and Criteria Importance Through Inter-criteria Correlation (CRITIC) for blockchain platform evaluation [34]. The authors considered 8 decision criteria, namely performance efficiency, interactivity, scalability, reliability, security, portability, maintainability, and cost. Erol et al. examined blockchain applicability in sustainable supply chains by the MCDM framework determined with Fuzzy Step-wise Weight Assessment Ratio

Analysis (SWARA), Complex Proportional Assessment (COPRAS), Evaluation based on Distance from Average Solution (EDAS) assessment, and COPELAND method [35]. The evaluation considered 6 decision variants and 8 criteria. Öztürk and Yildizbaşi focused on indicating the barriers that keep the implementation of blockchain into supply chain management [36]. Based on the Fuzzy AHP and Fuzzy TOPSIS, the assessment was conducted considering the uncertainties in the problem. The results from the research showed that high investment costs, data security, and utility play the most important role in the evaluation. Çolak et al., on the other hand, directed their research toward an assessment of blockchain technology in supply chain management [37]. Using the Hesitant Fuzzy Sets (HFS) combined with the AHP (HF-AHP) and TOPSIS (HF-TOPSIS), it was possible to examine the decision alternatives and take into account the potential uncertainties. The authors identified 5 main criteria and 17 sub-criteria, which were used to evaluate 5 decision variants. The sensitivity analysis approach was also used to examine if differences in criteria weights could significantly influence the proposed rankings. Based on the obtained results, the authors indicated that the medicine/drug industry seems to be the most suitable sector for introducing blockchain technology. Table I presents the selected approaches used in multi-criteria problems directed to blockchain and cryptocurrency fields.

C. Blockchain and cryptocurrencies in complex networks

The problems connected to blockchain analysis are also addressed by researchers using complex network techniques. Since it is important to identify the most significant nodes in the networks that play a crucial role in the information spread, many approaches have been used for this purpose. Moreover, the centrality measures are eagerly used to investigate the network structures allowing for an in-depth analysis. Tao et al. performed a complex network analysis of the Bitcoin blockchain network, using degree distribution, clustering coefficient, shortest path length, assortativity, and rich-club coefficient [10]. Bielinskyi and Soloviev attempted to identify the complex network precursors of crashes and critical events in the cryptocurrency market [38]. The authors used time series of data considering the days in correction, Bitcoin's high price in \$, Bitcoin's low price in \$, the decline in %, and the decline in \$. As the centrality measures, the authors selected eigenvector values and average path length. Lin et al. focused on understanding Ethereum transaction records with a complex network approach [39]. The authors modeled the transaction records using time and amount features and designed several flexible temporal walk strategies. The degree distribution of the Ethereum transaction network was analyzed with an actual feasible path for money flow. Serena et al. represented cryptocurrency activities ad a complex network to analyze the transaction graphs [40]. Four prominent Distributed Ledger Technologies (DLTs), namely Bitcoin, DogeCoin, Ethereum, and Ripple, were considered. The authors considered three selected centrality measures: degree distribution, average clustering coefficient, and average shortest path length of the main component.

D. Expert knowledge in multi-criteria problems

Multi-Criteria Decision Analysis models can be personalized with the different preferences of criteria importance. This approach can be used to propose an individual and specific set of results compliant with the expert preferences and expectations. To extract experts' knowledge and use it as the input data in MCDA models, subjective criteria weighting methods are used. Since multiple techniques are being developed to assist the expert in identifying the criteria importance, it is important to select methods that are intuitive and reflects the experts' opinion reliably. Various Decision Support Systems (DSSs) were determined to evaluate alternatives using the domain expert knowledge in the specific field. Dweiri et al. proposed a DSS based on the AHP method for supplier selection in the automotive industry, where the AHP method was used to identify the expert preferences regarding the criteria importance [41]. Mahendra used the FUCOM-SAW method to determine the DSS for e-commerce selection in Indonesia [42]. The FUCOM method served as a measure for extracting the expert knowledge based on which the assessment was performed. Sarabi and Darestani applied the Fuzzy Multiple Objective Optimizations on the basis of Ratio Analysis plus full Multiplicative Form (MULTIMOORA) and BWM approach for determining the DSS for logistics service provider selection in mining equipment manufacturing [43]. The BWM method allowed for defining the criteria relevance based on the expert experience in the given field. The RANCOM method was used to identify the decision-maker preferences regarding the laptop selection, and the identified weights were then used in the selected six MCDA methods [23]. Fahlepi proposed a DSS for employee discipline identification, where the SMART method was used for establishing the criteria relevance based on the expert judgment [44]. It can be seen that various approaches are used to define the decision models based on expert knowledge. However, it should be borne in mind that the experts' availability limits these solutions. Moreover, expert knowledge can change over time, translating into assigning different criteria relevance within the same decision problem. The subjectivity of the assessment should also be considered in developing such systems. It should be limited to providing results with high objectivity of the evaluation, increasing the results' reliability. Since it could be challenging to re-identify the experts' preferences over time, it is worth proposing approaches to fill this gap. To this end, the MLP-COMET technique is proposed, which is based on the complex network analysis and aims to identify the decision model which can be applied to assess new decision variants within the same problem.

III. Preliminaries

A. Centrality measures

Complex network centrality metrics are network analysis tools used to identify nodes of high importance or influence

TABLE I
SELECTED APPROACHES FOR SOLVING BLOCKCHAIN AND CRYPTOCURRENCIES PROBLEMS WITH MCDA METHODS

Method	No. of alts.	No. of crit.	Problem	Year	Reference
PROMETHEE II	80	6	Cryptocurrency exchanges evaluation	2021	[45]
AHP, PROMETHEE II	9	7	Cryptocurrency portfolio selection	2021	[46]
Q-Rung Orthopair Fuzzy Hypersoft Sets	4	8	Cryptocurrency market analysis	2022	[47]
MARCOS, Fuzzy MARCOS	6	5	Blockchain software selection	2021	[48]
AHP, TOPSIS	3	16	Cryptocurrency mining strategies	2021	[49]
Fuzzy BWM	3	15	Cryptocurrency trading system	2023	[50]
Fuzzy TOPSIS	3	27	Object selection in blockchain-enabled IoT platforms	2022	[51]
Fuzzy AHP, Fuzzy VIKOR	9	8	Feasibility evaluation of blockchain in logistics operations	2020	[52]

* where: 'No. of alts.' - Number of decision variants, 'No. of crit.' - Number of criteria.

in a network. Over the past few years, the trend of introducing new centrality metrics has continued to grow. The mainly used centrality metrics of complex networks are closeness centrality, degree centrality, eigenvector centrality, or betweenness centrality. In addition, there are also centrality metrics such as Katz centrality, harmonic centrality, or percolation centrality. In assessing the relevance of social network nodes, several centrality metrics are mainly used due to the need for knowledge related to the systematic distinction of these measures of [53]. Therefore, in this article, we will focus on the following measures of social network centrality [54], [55], [56]:

1) **Degree centrality:**
$$D_c(i) = \sum_{j}^{n} x_{ij} \tag{1}$$
where i is the considered node, j is the other nodes present in the network, n is the number of all nodes, and x_{ij} is the connection between node i and node j.
2) **Betweenness centrality:**
$$B_c(i) = \left(\sum_{s \neq i \neq t} \frac{g_{st}(i)}{g_{st}} \right) \frac{n(n-1)}{2} \tag{2}$$
where g_{st} is the count of binary shortest paths from node s to node t, and $g_{st}(i)$ is the count of those paths that pass through node i.
3) **Eigenvector centrality:**
$$E_c(i) = \lambda^{-1} \sum_{j=1}^{n} A_{ij} e_j \tag{3}$$
where e_j is the node score j, A is the adjacency matrix of the network, n is the number of nodes present in the network, and λ is a constant.
4) **Closeness centrality:**
$$C_c(i) = \frac{n-1}{\sum_{j=1}^{n} d_{ij}} \tag{4}$$
where d_{ij} is the distance from node i to node j.
5) **Harmonic centrality:**
$$H_c(i) = \frac{1}{n-1} \sum_{j \neq i} \frac{1}{\text{dist}(x_i, x_j)} \tag{5}$$
where i is the considered node, j is the other nodes present in the network, d_{ij} is the distance from node i to node j.

B. The Multi-Layer Perceptron Regressor

Artificial neural networks are computational models inspired by the structure and operation of the human brain. One type of artificial neural network is the Multi-Layer Perceptron, which is widely used in classification and regression problems. It consists of multiple perceptrons, the structure of which is based on the original approach proposed by Frank Rosenblatt in 1957. A Multi-Layer Perceptron consists of three main layers: an input, hidden, and output layer. The input layer accepts input data, passed on to subsequent layers. Hidden layers are intermediate between input and output and consist of multiple perceptrons. The output layer generates the final results of the network. The connections between perceptrons in the different layers are weighted, meaning each connection is assigned a weight. These weights determine how much the output of one perceptron affects the input of other perceptrons.

A Multi-Layer Perceptron uses supervised learning, which requires a set of learning data consisting of pairs of input and expected output data. The goal is to train the network to learn a function that transforms the input data into the expected output data. The backward error propagation algorithm is most commonly used, which propagates the error from the network's output to the hidden layers and the input layer to adjust the connection weights. The effectiveness of a multilayer perceptron depends on several hyperparameters, such as the number of hidden layers, the number of perceptrons in each layer, the learning rate, and the activation function. Proper selection of hyperparameters is crucial to the effectiveness and efficiency of the network. An example of neural network visualization is shown with Fig. 1.

C. The Characteristic Objects Method

The Characteristic Objects METhod (COMET) is an approach proposed by Sałabun in 2015 to eliminate the paradox

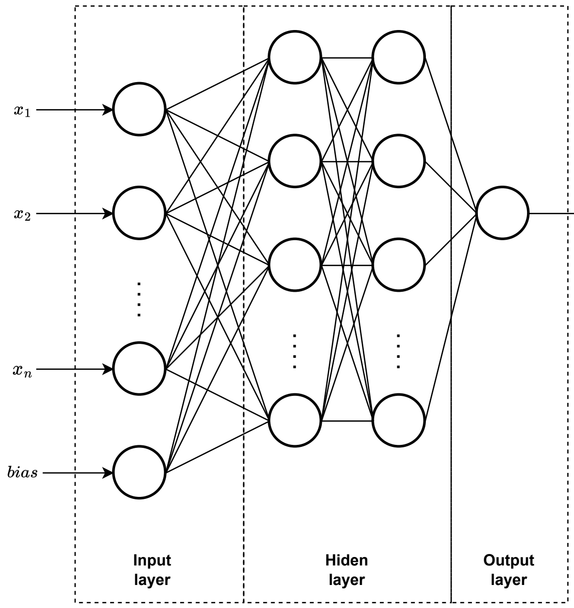

Fig. 1. Example structure of a multilayer perceptron.

of reversed rankings [57]. Here, the evaluation of decision alternatives is done by measuring the distance between them and the characteristic objects that play a key role in the model. In addition, this method has seen many extensions for uncertain environments such as Normalized Interval-Valued Triangular Fuzzy Numbers (NIVTFN) [58], Intuitionistic Fuzzy Sets (IFS) [59] and Hesitant Fuzzy Sets (HFS) [60], For the COMET method, the following sequence of steps is used:

Step 1. Identify the problem's dimensionality. Expert selects r number of criteria and their fuzzy values, which is represented by a Eq. (6).

$$\begin{array}{c} C_1 = \left\{\tilde{C}_{11}, \tilde{C}_{12}, ..., \tilde{C}_{1c_1}\right\} \\ C_2 = \left\{\tilde{C}_{21}, \tilde{C}_{22}, ..., \tilde{C}_{2c_2}\right\} \\ ... \\ C_r = \left\{\tilde{C}_{r1}, \tilde{C}_{r2}, ..., \tilde{C}_{rc_r}\right\} \end{array} \tag{6}$$

where $C_1, C_2, \ldots, C_r$ are the criteria represented by the fuzzy numbers.

Step 2. Creating Characteristic Objects (COs) with the Cartesian product from fuzzy number cores. An example of the construction of characteristic objects can be illustrated by the Eq. (7).

$$CO = \langle C(C_1) \times C(C_2) \times ...C(C_r)\rangle \tag{7}$$

The result is a set of characteristic objects. This set can be expressed as follows:

$$\begin{array}{c} CO_1 = \langle C(\tilde{C}_{11}), C(\tilde{C}_{21}), ..., C(\tilde{C}_{r1})\rangle \\ CO_2 = \langle C(\tilde{C}_{11}), C(\tilde{C}_{21}), ..., C(\tilde{C}_{r2})\rangle \\ ... \\ CO_t = \langle C(\tilde{C}_{1c_1}), C(\tilde{C}_{2c_2}), ..., C(\tilde{C}_{rc_r})\rangle \end{array} \tag{8}$$

Step 3. Formation of Matrix of Expert Judgments (MEJ) using comparisons of characteristic objects among themselves. The Expert Judgment Matrix (MEJ) is represented by the Eq. (9).

$$MEJ = \begin{pmatrix} \alpha_{11} & \alpha_{12} & \ldots & \alpha_{1t} \\ \alpha_{21} & \alpha_{22} & \ldots & \alpha_{2t} \\ \ldots & \ldots & \ldots & \ldots \\ \alpha_{t1} & \alpha_{t2} & \ldots & \alpha_{tt} \end{pmatrix} \tag{9}$$

where α_{ij} is the degree of preference of comparing one characteristic object to another. If object CO_i is more reflective than object CO_j assign the value 1. If they are equal, assign the value 0.5. If CO_i is less reflective than CO_j assign the value 0. It can be shown by the Eq. as follows:

$$\alpha_{ij} = \begin{cases} 0.0, & f_{expert}(CO_i) < f_{expert}(CO_j) \\ 0.5, & f_{expert}(CO_i) = f_{expert}(CO_j) \\ 1.0, & f_{expert}(CO_i) > f_{expert}(CO_j) \end{cases} \tag{10}$$

Once the expert matrix MEJ is determined, the Summed Judgements (SJ) vector must be determined using Eq. (11).

$$SJ_i = \sum_{j=1}^{t} \alpha_{ij} \tag{11}$$

where t is the number of characteristic objects.

After computing the Summed Judgements (SJ) vector, the vector of preferences (P) for the COs should be computed. This is shown as follows [57].

Step 4. Formation of a rule base from characteristic objects and a preference vector. This can be expressed using an Eq. (12).

$$IF\ C\left(\tilde{C}_{1i}\right)\ AND\ C\left(\tilde{C}_{2i}\right)\ AND\ \ldots\ THEN\ P_i \tag{12}$$

Step 5. Make an inference to compute the scores of the given alternatives. The alternative A_i comprises the values of every criterion, i.e., $A_i = \{\alpha_{1i}, \alpha_{2i}, \ldots, \alpha_{ri}\}$. By employing Mamdani fuzzy inference, a preference P is computed for every alternative according to [61].

IV. PROPOSED APPROACH

This paper proposes an approach to evaluate nodes in a complex network using the MultiLayer Perceptron Regressor (MLP Regressor) and the Characteristic Objects METhod (COMET). This approach aims to construct a multi-criteria model to evaluate network nodes. In traditional expert-based multi-criteria models, problems often arise due to dynamically changing knowledge and the limited availability of experts. Our approach uses MLP Regressor as an artificial expert trained from existing node evaluations. This allows us to avoid relying on experts and obtain node evaluations based on the artificial expert model. After constructing the artificial expert model, we use it to evaluate Characteristic Objects in the COMET approach. Characteristic Objects are reference points with information about the decision maker's preferences. This allows us to construct a multi-criteria model that considers the decision-makers preferences and allows us to evaluate the nodes with these preferences in mind. The approach described in the paper aims to combine machine learning techniques, such as MLP Regressor, with multi-criteria analysis to evaluate nodes in a complex network efficiently. This hybrid approach can be helpful in various fields where there is a need to make decisions based on network analysis considering the decision maker's preferences.

Fig. 2 represent the proposed MLP-COMET approach. The first step in this approach is to determine the set of evaluated decision alternatives, the hyperparameters for the MLP Regressor model, and the decision criteria with their characteristic values needed for the COMET method. This is followed by training the MLP-Regressor model, an artificial expert for this approach. Once a stable model maps the decision maker's preferences to the designated set of decision alternatives created, the decision model is initialized. Then the structure of the COMET method is modeled based on the characteristic values and the reidentification of the decision model using the artificial expert (model: MLP). After determining the preference of Characteristic Objects, the newly created decision options can be evaluated. In the case of this article, the implementation of the entire algorithm was created using the `sklearn` library (class: MLPRegressor) and the `pymcdm` library (class: COMET) [62], [63].

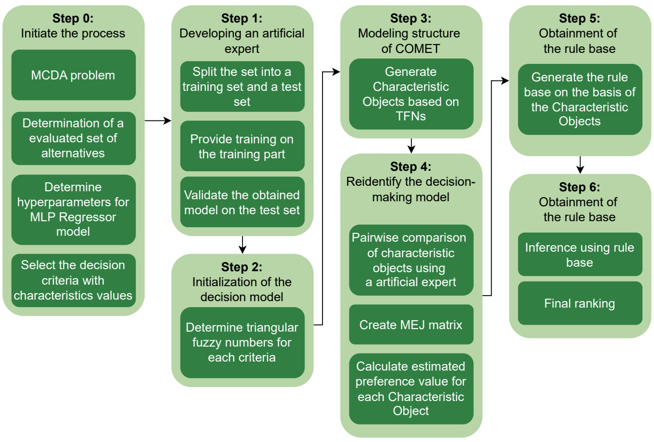

Fig. 2. MLP-COMET approach procedure.

V. Study case

In this section, a study will be conducted related to the proposal of the MLP-COMET approach for evaluating the composite network. First, the dataset associated with the Bitcoin composite network will be described. Then, research on the accuracy of the MLP Regressor model, which will serve as an artificial decision expert, will be conducted. After the research on its accuracy, an example of re-identifying the decision model and examining the similarity of the rankings derived from MLP-COMET at different characteristic values and the size of the learning set demonstrated is.

A. Description of the data

For this article, a complex network related to cryptocurrencies and, more specifically, Bitcoin was chosen [64], [65]. The selected network is people who trust those using this cryptocurrency. The network presented has 5881 nodes and 35592 edges. In addition, the network directed is in this way, and a weight is assigned to each of its edges. For this article, the weights of each edge were taken into account in determining centrality measures such as betweenness and eigenvector. In the case of the present network, nodes will play the role of decision variants. A visualization of the Bitcoin user network is shown in Fig. 3.

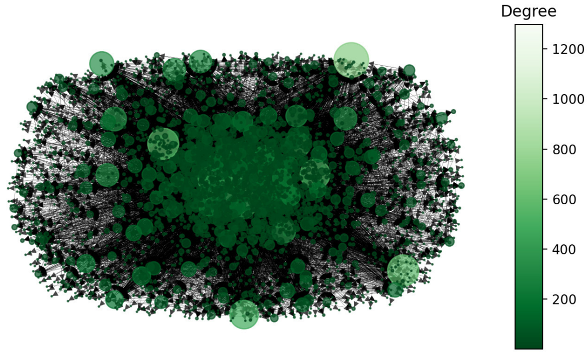

Fig. 3. Complex network of Bitcoin users [64], [65].

To evaluate the nodes of the present complex network, centrality metrics were used as criteria. Five centrality metrics were selected, i.e., betweenness centrality, degree centrality, eigenvector centrality, closeness centrality, and harmonic centrality. These metrics are presented in the Section III-A. Due to the low values found among some centrality metrics, the number of nodes is shown on histograms on a logarithmic scale.

Fig. 4 shows the distribution of values of the betweenness centrality metric, chosen as the first criterion for evaluating nodes (C_1). The minimum value of the centrality measure of indirectness is 2.89182e-08, which means that there are nodes with a shallow indirect role. The mean value of the measure is 0.01798, suggesting that most nodes have a low mediating role. The highest recorded value of the centrality of agency measure is 0.84816, suggesting the existence of a few nodes with a highly high mediating role. The standard deviation value is 0.06324, indicating some variation in the distribution of the centrality measure. The skewness value is 4.39799, indicating that the distribution of the centrality measure of intermediation is skewed to the right. This means there are a few nodes with very high centrality, which may indicate the existence of crucial nodes in the Bitcoin network.

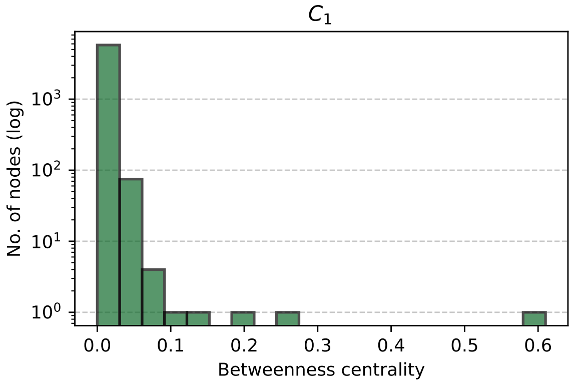

Fig. 4. Distribution of betweenness centrality values for Bitcoin users complex network.

The distribution of the degree centrality metric's value, which is selected as the second criterion for evaluating nodes (C_2), is shown using Fig. 5. The distribution of degree centrality measure values for users of the Bitcoin comprehensive network is as follows: the minimum value of the degree measure is 0.00017, indicating the existence of nodes with a low degree of connectivity. The average value of the degree measure is 0.00205, implying that most nodes have a lesser degree of connection. However, the highest recorded value of the degree measure is 0.22074, indicating a few nodes with an extremely high degree of connection. The standard deviation is 0.00651, indicating a rather diverse distribution of the degree measure. In addition, the skewness value is 13.84915, implying that the distribution is significantly skewed to the right. This means there are a few nodes with a very high degree of connectivity.

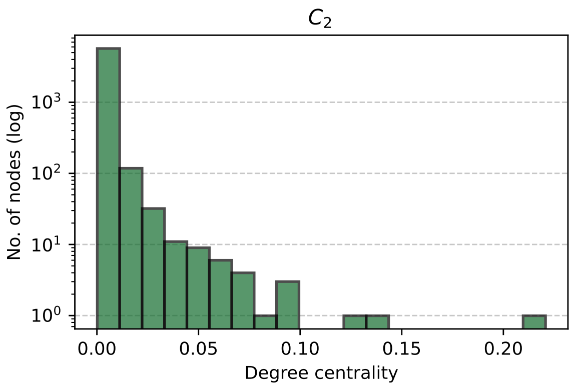

Fig. 5. Distribution of degree centrality values for Bitcoin users complex network.

Eigenvector centrality is another metric used as the third criterion (C_3) for evaluating nodes, and Fig. 6 represents it. The minimum value of the measure is -0.17028, which indicates the presence of negatively influenced nodes in the network. The mean value of the measure is 0.00038, revealing that most nodes have little influence in the network. The highest recorded value of the measure is 0.32039, indicating the existence of a few nodes with high importance in the Bitcoin network. The standard deviation value is 0.01303, which hints at some variation in the distribution of the vector centrality measure. The skewness value is 3.97669, pointing to a skewed distribution to the right.

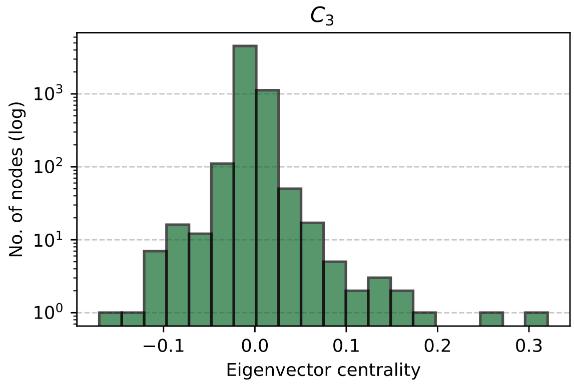

Fig. 6. Distribution of eigenvector centrality values for Bitcoin users complex network.

The closeness centrality metric for evaluating nodes was chosen as the fourth criterion (C_4), and its distribution is shown in Fig. 7. The minimum value of the measure is 0.0, which means there are nodes that not directly connected are to any other node in the network. The average value of the measure is 0.21886, which suggests that most nodes have a moderate degree of proximity to other nodes in the Bitcoin network. The highest recorded value of the measure is 0.33939, indicating that a few nodes exceptionally well connected are to other nodes. The standard deviation value is 0.03196, indicating some variation in the distribution of the proximity centrality measure. The skewness value is -1.65533, indicating that the distribution is slightly skewed to the left.

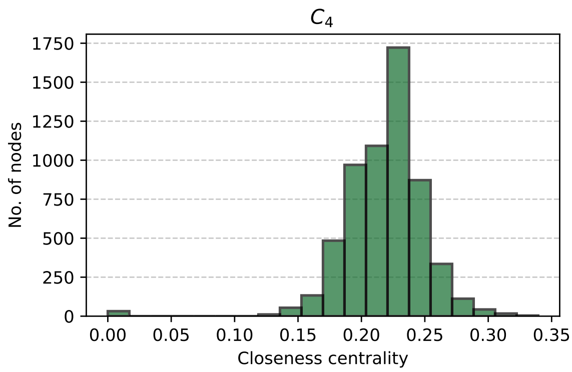

Fig. 7. Distribution of closeness centrality values for Bitcoin users complex network.

Fig. 8 shows the distribution of the value of the harmonic centrality metric, which is chosen as a criterion of the five to evaluate nodes (C_5). Based on statistical information, the minimum value of harmonic centrality in the studied network was 0.0, which means that some nodes did not have an essential role in transmitting the information. The mean value of harmonic centrality was 1346.77502, reflecting that most nodes in the network have moderate importance. The highest value recorded was 2233.24999, indicating that there are a few nodes with a vital role in the complex network. The analysis of the standard deviation of 210.28290 indicates the dispersion of harmonic centrality values in the studied network. This means there are significant variations in the level of centrality between different nodes. The value of the skewness coefficient, amounting to -1.26434, indicates an asymmetric distribution of harmonic centrality values, with a predominance of nodes with lower centrality.

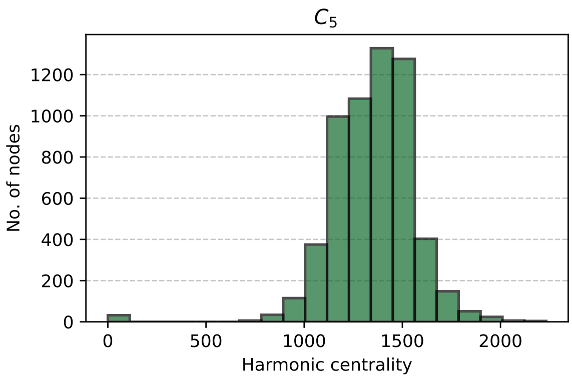

Fig. 8. Distribution of harmonic centrality values for Bitcoin users complex network.

For the studies conducted, min-max normalization was applied to the network centrality metrics. This normalization is intended to scale the values of the metrics within a fixed range to allow comparison and interpretation of the results. The model training process can be sensitive to differences in the scale of metrics values. If no normalization is performed, metrics with a more extensive range of values may significantly impact the training process, and metrics with a smaller range may be ignored. Min-max normalization allows the values of metrics to be adjusted to a range of 0 to 1, eliminating scale differences and ensuring that each metric has an equal impact on the learning process.

B. Artificial expert study: MLP regressor

In this section, a study related to the accuracy of the MLP Regressor model will be conducted. Since the MLP Regressor model will be responsible for evaluating character objects acting as reference preference points of the decision maker, it is necessary to investigate the possibilities related to the model's accuracy concerning the training sample. Therefore, a 10-fold cross-validation was carried out for a given size of the learning set. For the MLP Regressor model, its hyperparameters were adjusted using the `GridSearchCV` class, where the following results were obtained: `max_iter=1000`, `batch_size=64`, `solver= 'lbfgs'`, `hidden_layer_sizes=[1000]`, `activation='relu'`, `alpha=0.0001`.

Using Fig. 9 shows the 10-fold cross-validation on the training set. The dashed line denotes the limiting values obtained for the coefficient of determination obtained for the learning set of the obtained model. In comparison, the solid line with points denotes the average coefficient of determination values. The present results show that as the size of the training set increases, the R^2 values tend to increase. These results indicate that a larger training set size tends to translate into better results for the coefficient of determination. The R^2 values are high for all training set sizes, suggesting that the model can describe the data well.

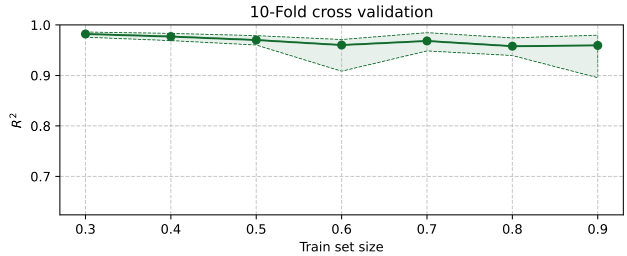

Fig. 9. Relationship between the coefficient of determination and the size of the training set for 10-fold crosvalidation(validated set: train, metric: R^2).

A 10-fold cross-validation on the test set is shown using Fig. 10. In the graph, the dashed line marks the limit values of the coefficient of determination obtained for the test set, and the solid line with points marks the average values of the coefficient of determination. Analysis of the results indicates that the model can significante explain variation in the data. The average values of the coefficient of determination are high, indicating a good fit of the model to the data. The maximum values of the coefficient of determination are also high, which means that in some cases, the model achieves a significant fit for the data.

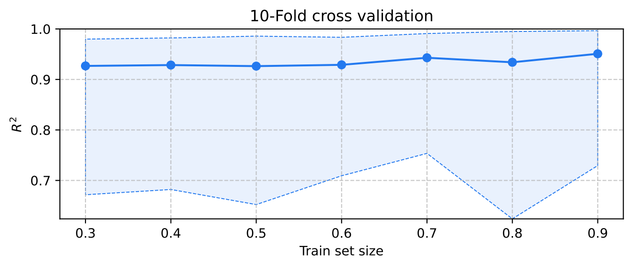

Fig. 10. Relationship between the coefficient of determination and the size of the training set for 10-fold crosvalidation(validated set: test, metric: R^2).

Using Table II, the results of 10-fold cross-validation on the learning set for different sizes of the training set are presented. Analyzing the results for a training set of size 0.3, the lowest R^2 value is 0.9859, indicating a high fit of the model to the data. In contrast, for a training set of 0.9, the lowest R^2 value is 0.8955, indicating a lower model fit to the data than other training set sizes. The average R^2 value ranges from 0.9579 to 0.9820, depending on the size of the training set. The standard deviation is most significant for a training set size of 0.9, suggesting greater variability in results for this set size.

TABLE II
10-FOLD CROSVALIDATION ON THE TRAINING SET FOR ITS PARTICULAR SIZE (VALIDATED SET: TRAIN, METRIC: R^2).

Stats	Train set size						
	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Min	0.9757	0.9689	0.9602	0.9083	0.9485	0.9393	0.8955
Mean	0.9820	0.9770	0.9701	0.9601	0.9682	0.9579	0.9594
Max	0.9859	0.9832	0.9788	0.9711	0.9847	0.9743	0.9797
Std	0.0034	0.0047	0.0063	0.0176	0.0088	0.0109	0.0229

The Table III shows the results of 10-fold cross-validation on the learning set for different training set sizes, using the R^2 metric on the test set. The minimum values of R^2 range from 0.6522 to 0.7536, depending on the size of the training set. The average values of R^2 are high, ranging from 0.9263 to 0.9508 for different training set sizes. The maximum values of R^2 range from 0.9798 to 0.9966, indicating a high fit of the model to the data for some cases. The standard deviation of R^2 measures the variability of the results and ranges from 0.0679 to 0.1050.

TABLE III
10-FOLD CROSVALIDATION ON THE TRAINING SET FOR ITS PARTICULAR SIZE (VALIDATED SET: TEST, METRIC: R^2).

Stats	Train set size						
	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Min	0.6716	0.6820	0.6522	0.7092	0.7536	0.6239	0.7294
Mean	0.9268	0.9284	0.9263	0.9289	0.9429	0.9339	0.9508
Max	0.9798	0.9821	0.9857	0.9834	0.9909	0.9949	0.9966
Std	0.0883	0.0854	0.0944	0.0768	0.0679	0.1050	0.0754

Based on the results presented above, the MLP Regressor model is stable to perform its function in the present problem as an artificial expert.

C. Study of the stability: MLP-COMET

The study will focus on the similarity of the rankings obtained from the MLP-COMET approach. In order to test the applicability of the MLP model for evaluating the characteristic objects of the COMET method, a study related to the evaluation of 15 selected nodes of a complex network derived from a test set was conducted. In this study, a division of the set into a train set (size: 80%) and a test set (size: 20%) was used to test the MLP-COMET model. The same set was used for the hyperparameters for the MLP model, as shown in the previous study. On the other hand, for the COMET method, 2 characteristic values were selected for each criterion based on the limit values of the normalized criteria.

Table IV shows the selected 15 nodes of the network composed of the test set and their rankings obtained from the MLP-COMET model and the reference expert model. For this study, a high similarity between the two rankings can be observed, as the difference in positions occurs only for four decision variants, i.e., A_1, A_{12}, A_{13} and A_{14}. In addition, the differences in ranking positions are slight and occur mainly at the end of the ranking, which may have a negligible effect on the order.

TABLE IV
SAMPLE NODES OF THE COMPLEX NETWORK SELECTED FROM THE TEST SET AND THEIR CRITERION VALUES (C_1-C_5) AND RANKINGS.

A_i	C_1	C_2	C_3	C_4	C_5	Obt.	Ref.
A_1	0.0003	0.00154	0.34915	0.66337	0.61881	7	8
A_2	0.0001	0.00231	0.32911	0.69508	0.65103	3	3
A_3	0.0009	0.00616	0.34907	0.61402	0.56985	12	12
A_4	0.0001	0.00000	0.34738	0.59391	0.54956	14	14
A_5	0.0001	0.00000	0.34791	0.69165	0.65592	5	5
A_6	0.0001	0.00000	0.34703	0.54707	0.50306	15	15
A_7	0.0003	0.00693	0.37048	0.73539	0.69548	2	2
A_8	0.0003	0.00693	0.35113	0.75381	0.71646	1	1
A_9	0.0006	0.00462	0.34813	0.69907	0.66312	4	4
A_{10}	0.00056	0.00385	0.38118	0.69595	0.65366	6	6
A_{11}	0.00036	0.00077	0.34609	0.60992	0.56510	13	13
A_{12}	0.05522	0.00539	0.34817	0.63432	0.59286	9	10
A_{13}	0.00091	0.00771	0.34825	0.65936	0.61782	8	7
A_{14}	0.00065	0.00616	0.34797	0.64370	0.60106	10	9
A_{15}	0.00036	0.00077	0.34792	0.63731	0.59520	11	11

* where: 'Obt.' - MLP-COMET rank, 'Ref.' - reference model rank.

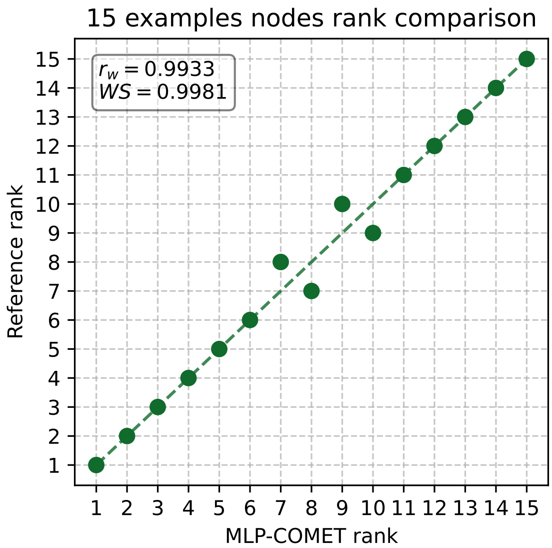

Fig. 11. Relationship between the ranking obtained from the MLP-COMET model and the reference ranking of the expert model for 15 nodes from the test set.

With the help of Fig. 11, the relationship between the ranking obtained from the MLP-COMET model and the reference ranking of the expert model is shown for 15 selected nodes of the composite network. The nodes usually occupy the same positions in both rankings, indicating high similarity. In addition, high similarity can also be observed by analyzing the similarity metrics of the rankings, such as r_w (weighted Spearman correlation coefficient) and WS (ranking similarity coefficient). The values of these metrics were 0.9933 for r_w and 0.9981 for WS, respectively.

After a sample study related to the applicability of the MLP model as an artificial expert for evaluating characteristic objects in the COMET method was performed, it was necessary to investigate the effect of the number of characteristic values on the similarity of rankings depending on the size of the training set. For this study, the r_w measure was used as a metric of ranking similarity for each case studied.

Fig. 12 shows the similarity matrix of node rankings derived from the training set for a given size of the training set and several characteristic values for each criterion. As can be seen from the heatmap, a very stable model was obtained based on samples from the training set. The values of the coefficient r_w were in the range [0.98,1.00], which shows the high similarity of the rankings. The most stable models were obtained for the learning set of 50% and 80% of the initial set and the number of characteristic values 6, 7, 8. In contrast, the slightest similarity was obtained for the learning set of 30% of the initial set.

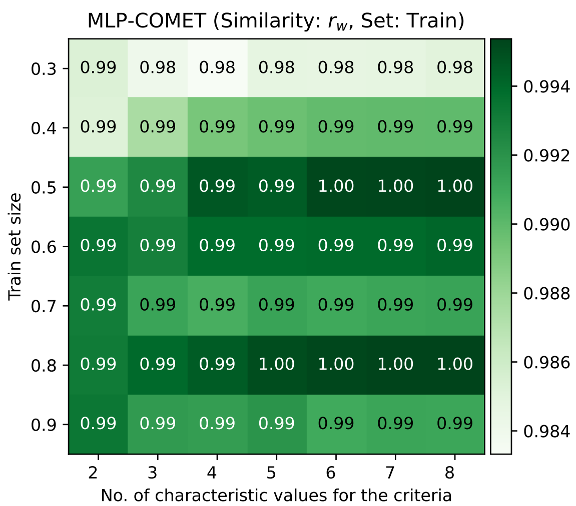

Fig. 12. Ranking similarity matrix for given learning set size and number of characteristic values (MLP-COMET, metric: r_w, studied set: train).

Using Fig. 13, the similarity matrix of node rankings derived from the test set is shown for a given size of the train set and several characteristic values for each criterion. As in the case of the learning set, the high similarity of rankings derived from comparisons of MLP-COMET rankings and reference rankings was shown on the test set. The range of obtained values of the coefficient r_w is [0.98, 1.00], which indicates a high mapping of the rankings of the complex network nodes by the MLP-COMET model. The highest similarity of rankings was obtained for a learning set of size 50% of the base set and 6,7,8 numbers of characteristic values for all considered criteria.

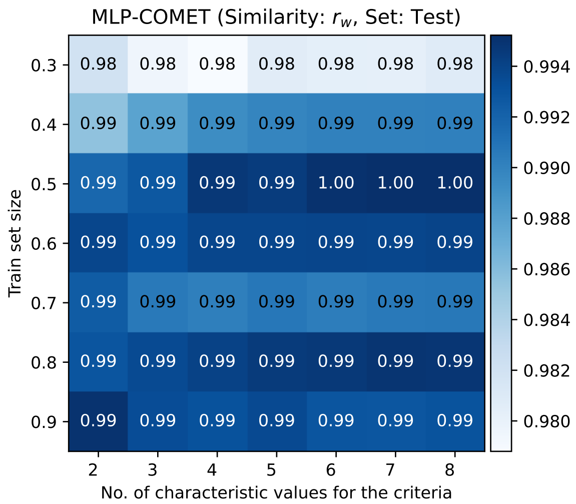

Fig. 13. Ranking similarity matrix for given learning set size and number of characteristic values (MLP-COMET, metric: r_w, studied set: test).

VI. Conclusions and Future works

This paper presents a study on applying the MLP-COMET approach to evaluating the nodes of a complex network of Bitcoin users. The accuracy of the representation of the decision maker's preferences in the decision-making process investigated was using the MLP Regressor model, which achieved high accuracy on both the test set and the training set. Therefore, another study conducted was con the MLP-COMET model, where the results indicate that the MLP-COMET model reproduces well the ranking obtained from the reference expert model, suggesting that it can be an effective tool in evaluating the nodes of a complex network.

The effect of the training sample size and the number of characteristic objects on the similarity of rankings between MLP-COMET and the reference rankings was also investigated. Similar results were obtained, where the similarity measured using the r_w metric for both the train and test sets was in the range [0.98, 1.00]. This demonstrates the tested model's high stability and applicability to the tested complex network to evaluate its nodes.

Future research directions of the proposed approach include other complex networks or multi-criteria decision-making problems. In addition, it would also be appropriate to consider a study related to the consistency of the obtained MEJ matrices of the MLP-COMET approach. Also, more research on its accuracy and consideration of the uncertain environment would need to be conducted. In addition, future research should focus on other cryptocurrencies such as Ethereum.

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