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Application of MCDM Methods to Optimal Consensus Protocol Selection for Blockchain-Based IoT Networks

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Abstract: One of the modern areas of blockchain technology application is the Internet of Things (IoT). An important component of blockchain technology is the consensus layer. It includes consensus protocols that are used to establish and maintain consensus, as well as to ensure network security, accuracy, and protection of the registry from unauthorized access. Currently, there are a large number of different consensus protocols, including those for blockchain-based IoT networks. Therefore, choosing the most suitable consensus protocol for a specific distributed ledger system, in particular, for an IoT blockchain solution, is an important task. The problem of optimal blockchain consensus mechanism selection in IoT networks can be considered a multi-criteria decision-making problem. This paper presents the step-by-step development of a conceptual model of a system of optimal consensus protocol selection for blockchain-based IoT networks. Following this step-by-step approach, the final goal is to transform the conceptual framework into a practical, adaptive, and efficient decision-making system for blockchain-based IoT networks. The obtained results can be useful for developers and researchers working in the field of blockchain technology and the Internet of Things and contribute to improving the efficiency and security of IoT networks.

Keywords: consensus protocol; blockchain; internet of things; multi-criteria decision making methods

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1. Introduction

Distributed ledger technologies (DLT) enable the functioning of distributed ledgers, i.e., ledgers that are shared among multiple participants that form a network and synchronize with each other using consensus protocols. When developing distributed ledgers, they are tamper-proof, append-only, and immutable. The ledgers should only contain confirmed and verified transactions. In other words, distributed ledger technologies can provide a high level of security, transparency, and immutability, making them well-suited for use cases involving the transfer of digital assets or the recording of digital transactions. The most well-known and widely used example of distributed ledger technology is the blockchain. Distributed ledger technologies can be used in a wide variety of industries and applications, such as financial services, supply chain management, digital identity, games, and more. Distributed ledger technologies can offer many potential benefits, especially in terms of security, transparency, and decentralization. At the same time, they also have limitations such as scalability and cost. These technologies are still in the process of active development and improvement.

One of the important areas of application for blockchain technology is the Internet of Things (IoT). The Internet of Things refers to a network of physical devices, vehicles, home appliances, and other items that are embedded with electronics, software, sensors, and network connectivity which enables these objects to collect and exchange data. The Internet of Things allows these objects to be sensed or controlled remotely across existing network infrastructure, creating opportunities for more direct integration of the physical world into computer-based systems, resulting in improved efficiency, accuracy, and economic benefit.

The Internet of Things is expanding at a rapid pace; for example, from an analytical report [1], it suggested that the number of IoT devices connected to cellular networks will grow to 4.3 billion by 2026. For comparison, according to results from 2023, this indicator was estimated at 3.3 billion. Currently, most IoT solutions rely on a centralized server–client paradigm, connecting to cloud servers over the Internet. While this solution may work as expected for the time being, the huge growth in connected devices is causing problems in many areas, including data integrity, security, and reliability. Distributed ledger technologies can help solve the problems of traditional IoT applications, including the following:

- Ensuring the integrity of IoT data without the participation of a third party, while maintaining the bandwidth and computing power of IoT devices;
- Ensuring the confidentiality of information transmitted over networks without a centralized server;
- Providing identification and authentication functions while tracking sensor data measurement and transmitting data between IoT peers without a central server;
- Lowering IoT operating costs by allowing smart devices to make automatic micro-transactions.

Currently, one can observe an increase in the number of applications combining blockchain technology and the Internet of Things [2,3]. Several cases illustrate the combined use of blockchain technology and the Internet of Things in the logistics sector. In 2020, major logistics company SF Express began using a blockchain-based tracking system for key shipments. Well-known food manufacturer Nestlé uses blockchain and the Internet of Things to ensure the real-time tracking of agricultural products. Logistics giant DHL uses blockchain and the Internet of Things to improve the transparency and efficiency of its supply chains. German company BayWa Global Produce, a wholesaler and retailer of agricultural and industrial goods, uses the SIGNiT blockchain solution to optimize the logistics of fresh produce in collaboration with Giesecke+Devrient (G+D). Danish company Maersk, a specialist in maritime freight and port terminal services, uses the TradeLens blockchain platform to improve transparency and interoperability in its logistics operations. The world's largest consumer goods company Unilever is using blockchain to provide traceability for raw materials such as palm oil. Amazon is combining its managed blockchain with IoT devices to track shipments in real time. Walmart is using blockchain technology to provide traceability for food products. This is only a partial list of examples.

The reference architecture for distributed ledger technologies includes the consensus layer. This layer manages the consensus between nodes in the network and ensures that the ledger state is agreed upon by all nodes. It includes consensus protocols that are used to establish and maintain consensus and ensure network security, accuracy, and tamper-proofing of the ledger. Consensus can significantly affect the performance and security of a blockchain system. To date, a wide range of consensus protocols with different concepts and properties have been developed, including for blockchain-based IoT networks [4–16]. However, at the same time, designing and developing optimized consensus protocols for specific scenarios and use cases is usually a labor-intensive and error-prone task, since choices must be made between conflicting requirements and there is a high degree of uncertainty. Most new protocols are variations of existing well-known consensus protocols. At the same time, existing implementations often cannot be reused for their implementation. And, there is a need for their complete reimplementation. This leads to potential new errors and difficulties in applying existing verification results. In this regard, in practical applications and scenarios, such as for blockchain-based IoT networks, developing a new suitable optimal consensus protocol or choosing one from a variety of existing ones is an important task.

A promising modern approach for developing new protocols is the design of modular and composable consensuses. For example, in [17], Sui et al. (2024) presented a flexible framework that allows for the detailed analysis and redesign of existing BFT protocols, and the fairly easy generation of new BFT protocols. The structure of the framework is hierarchical and consists of three levels. All three levels are extensible and allow for innovation. Any level can be modified or expanded to theoretically cover all BFT protocols, known and unknown. In [18], Haas et al. (2025) proposed a new programming model for implementing consensus protocols using replicated data types (RDT). The composability of PRDTs allows for the design of consensus protocols by composing basic consensus blocks and/or simpler protocols, facilitating the construction and verification of consensus protocols. The core components of consensus protocols can be designed as independent PRDTs. These components can then be combined to create complete consensus protocols. Individual components can be modified to adapt existing protocols.

To select optimal consensus protocols from a variety of existing protocols, a suitable approach is to use multi-criteria decision making (MCDM) methods. There are works devoted to the application of such methods in the field of distributed ledger and blockchain technologies, mainly for choosing a blockchain platform, but also for choosing a consensus protocol [6,19–21].

To date, many studies have been conducted on the integration of distributed ledger technologies and the Internet of Things, as well as the application of MCDM methods to problems associated with their joint use. These studies provide a solid basis for the development of practical tools aimed at supporting researchers and practitioners. However, such developments have not yet been undertaken to date. This paper initiates research in this direction with the aim of developing a system for selecting optimal consensus protocols for IoT networks. The blockchain consensus protocol selection is formalized as a multi-criteria decision-making task as follows. The main goal of decision-making is to obtain the best alternative or a list of ranked alternatives using multi-criteria decision-making methods. Once the decision-making task is formulated and a set of consensus protocols is defined, the corresponding criteria for evaluating the alternatives are developed. Next, the most suitable multi-criteria decision-making method is selected using specialized software. Finally, based on the steps taken, the remaining tasks are to design and implement the software for the optimal consensus protocol selection.

The rest of the paper is organized as follows. Section 2 reviews the literature related to the analysis, comparison, and selection of blockchain consensus protocols, and the application of MCDM in the field of DLT and blockchain, in particular, for blockchain consensus protocol selection. Section 3 introduces the main stages of developing a conceptual model of the optimal consensus protocol selection system for blockchain-based IoT networks. Finally, Section 4 concludes the work.

2. Materials and Methods

Multi-criteria decision making is a promising scientific direction of operations research that deals with decisions consisting of selecting the best alternatives from a set of potential solutions, taking into account a set of decision evaluation criteria. The goal of decision makers is to try to select the optimal solution from a certain set of alternative options, without having a priori knowledge about which of these options is the best. In general, the decision-making process can be described as a process consisting of the following several stages. The first stage includes identifying the problem under consideration and structuring it. At this stage, the goals of the decision, cause-and-effect relationships for the decision-making situation, and the criteria by which judgments will be made are determined. The second stage includes systematic development of the formal models of preferences, values, trade-offs, and the goals of decision makers to compare the alternatives or actions under consideration with each other. And finally, the third stage involves the development of action plans. The optimality of actions aimed at achieving a decision affects the effectiveness of the decision-making process itself and leads to the choice of the best solution, that is, a solution in which the positive benefits outweigh possible losses. Efficiently extracting information about a decision problem from available data, generating a solution, and providing a good understanding of the structure of the decision problem are the primary goals of the decision making process. MCDM methods combine objective measurements with value judgments and make the subjectivity explicit.

Decision making typically involves not only selecting the best alternative but also ranking all options in order to allocate resources efficiently or to combine individual preferences to form a collective choice. This involves mathematical methods that quantify or prioritize personal and collective judgments that are inherently subjective and difficult to measure. The different types of alternatives are compared by decomposing the preferences into attributes, assigning weights to them, assessing the relative preferences for each attribute, and then synthesizing them to obtain an overall ranking.

The most important task in decision making is to determine the set of alternatives. A distinction is made between cases where such a set is defined explicitly by a finite list of alternatives, and where the set of alternatives is implicitly specified by a mathematical programming structure. Another important task is to define the set of criteria against which the alternatives are to be compared. This is part of the modeling and problem formulation stage. Sets of criteria are often developed hierarchically, starting with general and vague objectives and refining them to more detailed subgoals. They allow the alternatives to be compared according to a particular point of view. In defining the set of criteria, consideration should be given to their relevance to the objectives of the decision maker, their comprehensiveness, their measurability, their non-redundancy, their evaluative independence, and their balance between comprehensiveness and conciseness. In the course of the development of MCDM, many methods have been developed in different fields with different theoretical bases, dealing with different types of questions, and yielding different types of results. Some MCDM methods are designed to solve specific problems, while other methods are more general and can be used in different fields. The different methods differ from each other in the nature of the model, the information needed, and the way in which the model is used. They share a common goal of creating a more formalized and better-founded decision-making process, as well as the need to define the alternatives to be considered, the evaluation criteria, and the relative importance of the various criteria.

For example, one of the simplest and most widely used MCDM methods is the simple additive weighting (SAW) method [22]. The fundamental idea behind the SAW (simple additive weighting) method involves calculating the total value of the performance ratings, taking into account the weights assigned to each attribute for every alternative. The SAW method necessitates a step where the decision matrix ($X = [x_{ij}]_{m\times n}$) is normalized to a scale that allows for a comprehensive comparison with the ratings of all available alternatives.

The formula to perform the normalization for the benefit attribute is as follows:

$$r_{ij} = \frac{x_{ij}}{Max(x_{ij})}, \quad (1)$$

The formula to perform the normalization for the cost attribute is as follows:

$$r_{ij} = \frac{Min(x_{ij})}{x_{ij}}, \quad (2)$$

Here r_{ij} is the normalized performance rating of the alternatives A_i on attribute C_j; where $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$.

The formula to perform the preference value for each alternative is as follows:

$$V_i = \sum_{j=1}^{n} w_j r_{ij}, \quad (3)$$

Another example is the technique for order of preference by similarity to ideal solution (TOPSIS) [23]. The TOPSIS method is a well-known method of multi-criteria decision making, which is based on calculating the distances between each alternative and the ideal alternative, as well as between each alternative and the anti-ideal alternative. TOPSIS operates on the principle of positive and negative ideal solutions, viewed geometrically through Euclidean distance. Positive ideal solutions represent the cumulative best achievable values for each attribute, while negative ideal solutions comprise the worst values attained for each attribute. By comparing the relative distances, alternative priority rankings can be established. The method is widely applied for practical decision-making due to its simplicity and its ability to gauge the relative performance of decision alternatives in a straightforward mathematical format.

The formula to perform the normalization is as follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}}, \quad (4)$$

One more example is VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [24]. The VIKOR method (Serbian: VIseKriterijumska Optimizacija I Kompromisno Resenje, meaning "Multi-criteria optimization and compromise solution") is also a well-known method of multi-criteria decision making. This method takes into account compromise decisions. It can be useful when there is a set of conflicting criteria. The VIKOR method aims to maximize collective benefits while minimizing individual regret. This approach revolves around devising a solution that aligns closely with the ideal solution within the parameters of alternatives and criteria. VIKOR establishes the compromise ranking list, identifies the compromise solution, and delineates weight stability intervals to ensure preference stability for the compromise solution, determined by the assigned weights.

Additionally, some modifications of these methods can be considered. Fuzzy TOPSIS [25] and fuzzy VIKOR [26] methods are an extension of the TOPSIS method and work with fuzzy data. The method can be used when the criteria are assessed with some degree of uncertainty, i.e., for example, instead of exact numerical values, values such as "low", "medium", or "high" are indicated. The TOPSIS interval method [27] is also an extension of the TOPSIS method, which works with interval data, i.e., when the criteria assessments are expressed not by exact numerical values, but by the ranges of possible values. The TOPSIS interval and fuzzy method [28] is a more complex extension of the TOPSIS method, which works with both interval and fuzzy data.

Several MCDM methods have been developed or refined by various authors in recent decades. The key distinctions among these methods pertain to the algorithm's complexity, criteria weighting techniques, the representation of preference evaluation criteria, the handling of uncertain data, and the type of data aggregation. Furthermore, each type of MCDM method comes with its specific merits and drawbacks that need detailed explanation based on the methodology.

The reference architecture for blockchain technology includes the consensus layer. This layer manages the consensus between the nodes of the network and ensures that the state of the ledger is agreed upon by all nodes. It includes consensus protocols that are used to establish and maintain consensus, as well as to ensure network security, accuracy, and security of the ledger. Consensus can significantly affect the performance and security of a blockchain system. There are currently over a thousand initiatives in the field of blockchain technology, including over a hundred different consensus protocols. In recent years, there has been a noticeable increase in publications devoted to blockchain and distributed ledger technologies. Given that consensus mechanisms are a core aspect of these systems, it is not surprising that an increasing number of studies have been devoted to the design, evaluation, comparison, and selection of consensus protocols. For example, studies such as [4–16], have reviewed, analyzed, and compared various consensus protocols using various criteria. These works provide a comprehensive understanding of the characteristics of the protocols and the factors affecting their performance and security. And, to understand and analyze this huge number of consensus algorithms, researchers create their own classifications, taxonomies, and ontologies.

Several works appeared recently in the literature, where different MCDM approaches were used in the field of DLT and blockchain, mainly for the choice of the blockchain platform, but also for the choice of the consensus protocol, for example [6,19–21].

In Ref. [6] Bouraga (2021) introduced the Boolean decision tree (BDT) technique-based framework based on the results of the classification framework introduced in the article. The proposed decision process starts with the accessibility of the blockchain following the design, performance, and security choices.

In Ref. [19] Bamakan (2020) et al. proposed a new approach to selecting blockchain consensus algorithms using multi-criteria decision-making (MCDM). The authors began by conducting a thorough review of the existing literature on blockchain consensus, identifying the various criteria used to evaluate consensus protocols. From this review, they identified the most important criteria and used a pairwise comparison technique to assign weights to each criterion. They then used a traditional benchmarking technique to compare ten consensus algorithms using a set of criteria in two parts. However, this study was only a starting point for an end-to-end MCDM approach, as further steps were required to define criteria values, select appropriate MCDM techniques, analyze results, and provide guidance for practitioners.

In Ref. [21] Filatovas et al. (2022) developed a MCDM framework to help select the most appropriate consensus protocol for a blockchain system based on its specific requirements. The authors viewed the consensus protocol ranking process as a MCDM problem that evaluated different alternatives (protocols) using decision criteria (features) and considering the defined weights (priorities) by decision-makers (experts). They gathered quantitative and qualitative data on 18 state-of-the-art consensus protocols from various sources and combined it into an open-source data repository. They demonstrated the potential of the framework by using the collected data set to identify the best consensus protocols for public, consortium, and private blockchains. Furthermore, the authors used the proposed framework to determine the most suitable consensus protocol for a blockchain-based bike renting system. The data and tools are freely available, enabling full replicability, reusability, and further development. This MCDM-based decision framework can be a valuable tool for designing real-world blockchain systems based on expert preferences and system requirements. Given the growing interest in blockchain technology worldwide, this framework could be an effective way to assess consensus protocols.

It can be said that at present, there are no works that consider the application of MCDM methods to optimal consensus protocol selection for blockchain-based IoT networks (see Table 1).

Table 1. Comparative table of the works devoted to consensus protocols in light of the IoT and application of MCDM methods. Notation: + considered, - not considered.

Sources	Protocols	IoT	MCDM
[4] Lashkari et al. (2021)	130	-	-
[5] Oyinloye et al. (2021)	15	-	-
[6] Bouraga (2021)	28	-	-
[7] Ismail et al. (2019)	20	-	-
[8] Fu et al. (2020)	18	-	-
[10] Singh et al. (2022)	58	-	-
[12] Auhl et al. (2022)	12	+	-
[13] Khan et al. (2022)	28	+	-
[14] Salimitari et al. (2020)	24	+	-
[16] Wu et al. (2020)	1	+	-
[19] Bamakan et al. (2020)	10	-	-
[21] Filatovas et al. (2022)	18	-	+

This paper takes the first steps toward developing a system of optimal consensus protocol selection for blockchain-based IoT networks using MCDM methods.

3. Results and Discussion

In the context of this study on the issue of applying multi-criteria decision making methods to optimal consensus protocol selection for blockchain-based IoT networks, the following main stages of developing a conceptual model of the selection system can be identified (Figure 1).

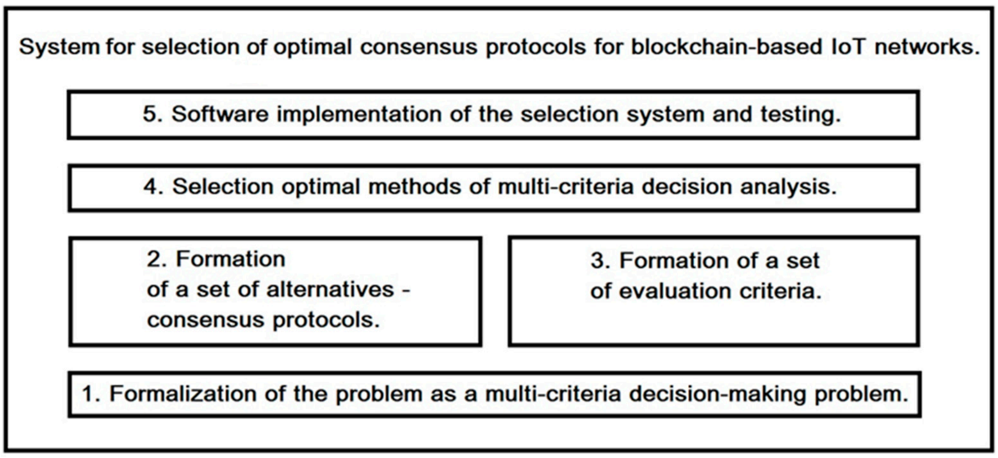

Figure 1. System for optimal consensus protocol selection for blockchain-based IoT networks.

Stage 1. Formalization of the problem as a multi-criteria decision-making problem.

The Internet of Things environment is characterized by its diversity, incorporating a broad range of hardware and software solutions that must meet strict requirements related to power consumption, storage, and computational capabilities. In addition, IoT devices operate in dynamic environments where sensors generate constant data, and they must function in ad hoc networks that involve going online and offline depending on their power requirements. As a result of their flexibility, IoT devices are widely used in various applications, such as smart cities, supply chains, and healthcare. Consensus mechanisms are a critical component of blockchain deployments, and their selection is particularly important in IoT-targeted blockchain deployments. However, all blockchains have trade-offs, and there is no perfect blockchain solution. Some are more resource-intensive, while others are faster or more centralized. To compare various blockchains, this paper establishes a set of requirements to better understand their usability and impact in IoT environments. These requirements include processor usage, security, decentralization, storage, and transactions per second (TPS). Processor usage is critical in determining how IoT devices will agree on the content and order of the blockchain. Security is a vital factor to consider, given that blockchain implementations may offer stronger security guarantees than traditional IoT networks with central points of failure. Decentralization is a choice that operates on a sliding scale and affects the speed and scalability of the network. Storage is a crucial consideration for security and decentralization aspects, as IoT devices do not have the capacity to store large amounts of blockchain data. Finally, transactions per second is another important trade-off, where a higher number of nodes participating in consensus could result in lower speed but higher decentralization, and a lower number of nodes could lead to increased transaction throughput and lower block times, which is generally desirable for IoT devices.

When choosing a consensus protocol, requirements are first determined that take into account a specific use case. The choice of the blockchain consensus protocol is formalized as an MCDM task as follows [21]. Let $A = \{A_1, A_2, ..., A_m\}$, which is the set of alternatives (consensus protocols). Let $C = \{C_1, C_2, ..., C_n\}$, which is the set of criteria. Let $W = \{w_1, w_2, ..., w_n\}$, which is the set of the weights of corresponding criteria, such that $w_j \in [0, 1]$, $\sum_{j=1}^{n} w_j = 1$. Let $= [x_{ij}]_{m \times n}$, which is the decision matrix, where its elements represent the performance of the alternative A_i with respect to criterion C_j.

Stage 2. Formation of a set of alternatives (consensus protocols).

The main goal of decision making is to get the best alternative or a list of ranked alternatives using MCDM methods based on the decision matrix X, criteria weights, and other constraints (if any). As a rule, the number of alternatives is not limited. However, some MCDM methods can only be effectively applied to a few criteria and alternatives. Therefore, compiling the most appropriate list of alternatives is a responsible task. The scientific literature and documentation of blockchain consensus protocols can be used to solve this. A large number of works are devoted to consensus protocols for blockchain-based IoT networks, for example [12–16].

For example, the paper [13] presents a new approach to surveying blockchain consensus algorithms that are suitable for resource-limited IoT systems. The authors introduce an ontology, which is a tool for organizing and explaining knowledge, that is specifically designed to classify consensus algorithms in terms of their adaptability to IoT. The ontology is divided into two parts: CONB for generic consensus algorithms and CONIoT for algorithms proposed for IoT. Using this ontology, the article provides a detailed analysis of major consensus algorithms and their suitability for IoT based on their design and implementation goals. The authors also discuss open research challenges and future directions for research in this area.

The paper [14] explored the potential use of blockchain to ensure data security and integrity in IoT networks. It focused on the current consensus methods and their feasibility for IoT devices and networks with limited resources. The article discussed the advantages and disadvantages of current blockchain implementations and suggested that private blockchains and Tangle may be better suited for IoT networks than public blockchains. Among the discussed implementations, Hyperledger Fabric, Sawtooth, Iota, and Ethereum were considered to be the most promising for IoT applications, as they had addressed some of the existing limitations of the blockchain. However, none of them had fully addressed all the limitations to an acceptable degree. The authors suggested that a hybrid framework combining multiple existing frameworks or a modified method of consensus may be necessary to achieve a large-scale, low-latency blockchain-based IoT network.

Ref. [15] aimed to provide researchers with an overview of blockchain consensus mechanisms and their applications in IoT networks. The authors classified the consensus mechanisms into four categories based on their focus on security, scalability, energy efficiency, and performance improvement. They analyzed the advantages and disadvantages of each of these consensus mechanisms and suggested future directions for the development of blockchain consensus mechanisms, with a focus on security, scalability, performance improvement, and resource consumption. It is likely that in the future, the combination of blockchain and the Internet of Things will seek more secure, energy-efficient, highly scalable, and efficient blockchain consensus mechanisms.

In the considered works, benchmarking, i.e., comparison and testing in accordance with a set of specific evaluation criteria, was used as the main decision-making method when comparing and choosing consensus protocols.

The choice could involve the use of existing surveys and studies of blockchain consensus mechanisms for IoT networks. Among such examples were protocols which are suitable or partially suitable for IoT [12–16]: Proof of Stake (PoS), Delegated Proof of Stake (DPoS), Proof of Importance (PoI), Proof of Supply Chain Share (PoSCS), Credit-Based Proof of Work (CBPoW), RapidChain, OmniLedger, Raft, Practical Byzantine Fault Tolerance (PBFT), dPBFT, Proof of Elapsed Work and Luck (PoEWAL), Microchain, Proof of Elapsed Time (PoET), Tangle, Ripple Protocol Consensus Algorithm (RPCA), Steller Consensus Protocol (SCP), CBCIoT [29], Proof of Block & Trade (PoBT) [30], Proof of Accumulated Trust (PoAT) [31], hierarchical and location-aware consensus protocol LH-Raft [32], Proof of Chance (PoCh) [33], Honesty-based Distributed Proof of Authority (HDPoA) [34], Proof of Reputation X [35], and Proof of X-repute [36].

Stage 3. Formation of a set of evaluation criteria.

The next critical task was to develop evaluation criteria against which alternatives could be tested. Typically, MCDM divides criteria into two main categories: benefit criteria, which should be maximized, i.e., higher values are preferred, and cost criteria, which should be minimized, i.e., lower values are preferred. Again, the academic literature and research papers could be used. There were already studies in the literature aimed at finding criteria for evaluating consensus protocols. In this paper, the results of works [12,13,19,21] were studied and used in the process of finding criteria. The selected criteria were common to any blockchain-based systems, including in the case of IoT networks. The criteria were among the most well-known solutions for consensus protocols. And their relevance was confirmed by various sources, including various white papers and specialized online resources on distributed ledger technologies.

The choice involved the enumeration of the following criteria that could be divided into five groups: throughput, decentralization, incentives, sustainability, and security [21]. For each group, the corresponding criteria (metrics) were taken into account [13]: throughput (C_1—transactions per second (TPS), C_2—transaction latency (s), C_3—finalization (Probabilistic/Deterministic)), Decentralization (C_4—number of consensus nodes, C_5—number of network nodes), Incentivization (C_6—transaction fees (USD/tx), C_7—Reward (USD/day)), Sustainability (C_8—power consumption (Low/Medium/High), C_9—hardware dependency (No/Yes), C_10—storage), Security (C_11—fault-tolerance, C_12—51% attack (Vulnerable/Safe), C_13—double spending (Vulnerable/Difficult/Safe)). Since some multi-criteria decision-making methods can only work with quantitative criteria, the qualitative criteria were converted into quantitative measures. For this purpose, appropriate conversion scales were used. For example, in the case of the criterion "power consumption", its qualitative values Low, Medium, and High took quantitative values of 1, 5, and 9, respectively, on the Saaty scale (see Table 2).

Table 2. Qualitative criteria.

Criteria	Qualitative Measures	Quantitative Measures
C_3—finalization	Probabilistic/Deterministic	1/9
C_8—power consumption	Low/Medium/High	1/5/9
C_9—hardware dependency	No/Yes	1/9
C_12—51% attack	Vulnerable/Safe	1/9
C_13—double spending	Vulnerable/Difficult/Safe	1/5/9

Stage 4. Selection of optimal methods of multi-criteria decision analysis.

Currently, there are many different methods of multi-criteria analysis. In addition, new methods appear, and the existing ones continue to develop. In such conditions, it seems very important to correctly determine the most appropriate method of multi-criteria decision making for the problem under consideration. It was assumed that such a correct choice would provide greater confidence in objectivity and accuracy in assessing and making decisions. This was also important, given that the problem under consideration was characterized by a large number of alternatives (many different consensus protocols) and a large number of criteria (e.g., energy consumption, throughput, resistance to attacks, transaction processing delay, etc.). Currently, there are open software tools designed to automate the process of selecting the most appropriate methods of multi-criteria decision making. Such decision support systems help analysts and researchers in various areas of multi-criteria analysis application. In this paper, the specialized tools MCDA Methods Selection Software (MCDA-MSS) [37] and Weighting Methods Selection Software (WEMSS) [38] were used to select the optimal methods of multi-criteria decision making.

The process of working with the MCDA-MSS program was as follows. In order to determine which method or, possibly, several methods of multi-criteria decision making were suitable for the problem under consideration, it was necessary to answer a series of questions consisting of four groups. Each question had several answer options, including the answer "I don't know" (i.e., it is possible that the user may not know how to answer the question at the time of working with the tool). The questions and answers had descriptions explaining their meaning. When choosing answers to some questions or to all questions, a list of methods that the system recommended for the problem under consideration automatically appeared. Moreover, for each method, a description was given with a list of answers to questions corresponding to this method. The selected answers would be highlighted in bold. The first group of questions was called "Problem Formulation". The answers to these helped determine what type the problem under consideration belonged to and what structure it had. The second group of questions is called "Preference Model". These helped to find out what type of model should be applied to the problem under consideration. The third group of questions was called "Preference Elicitation". The questions of this group were designed to determine the type, modality, and frequency of the model preferences. The last group of questions was called "Using the Preference Relationship Given by the Preference Model". It defined the strategy used to obtain and improve decision recommendations. Thus, as a result of receiving the answers to the questions of the above groups, the user could receive a list of recommended methods. However, there may be a case when the list is empty. Currently, the MCDA-MSS database contains more than 205 multi-criteria decision making methods and 156 key decision characteristics. MCDA-MSS can be useful for researchers and practitioners working in the field of multi-criteria decision making [39–41]. When working with the WEMSS system, the user similarly answered a number of interactive questions grouped into three sections. As a result of receiving answers, the user received a list of recommended weighting methods. Currently, the WEMSS database contains 35 weighting methods and 50 key decision characteristics.

In the process of working with the MCDA-MSS tool, answering the questions proposed by the system, the main characteristics that the selected method of multi-criteria decision making should satisfy were determined. As a result, the system proposed the following options: TOPSIS, fuzzy TOPSIS, TOPSIS interval, TOPSIS interval and fuzzy, VIKOR, and fuzzy VIKOR.

The nature of the input data in the considered multi-criteria decision-making problem affects the final choice of the methods proposed by the MCDA-MSS system. If the available input data were clear and deterministic, and it was necessary to find an alternative closest to the ideal alternative, then the TOPSIS method could be selected. If the input data were clear and deterministic, and it was important to take into account the trade-off between the criteria, then the VIKOR method could be selected. If the input data were fuzzy, and strict ordering of the criteria was required, then the fuzzy TOPSIS method could be selected. If the input data were fuzzy, and trade-off solutions were important, then the fuzzy VIKOR method could be selected. If the data were intervals, then the TOPSIS interval method could be selected. If the data included both interval and fuzzy data, then the TOPSIS interval and fuzzy method could be selected.

In the process of working with the WEMSS tool, the optimal method for weighing the criteria was determined. In the context of this problem, the best choice turned out to be the Analytic Hierarchy Process (AHP) method [42].

Stage 5. Software implementation of the selection system and testing.

For practical application of the framework, it was assumed that its software implementation would be developed, for example, as a web application. The functionality of the proposed software tool included a regularly updated database of the names of known consensus protocols suitable for use in the Internet of Things networks, a list of criteria for evaluating alternatives, and a set of relevant methods for multi-criteria decision making. To use it, the user must select the appropriate settings in accordance with a specific case of using the framework. It should be noted that there were a number of problems and limitations for the practical application of the framework. Firstly, the system was programmed based on built-in algorithms, and obviously could not completely replace expert analysis. As such, in the event of a discrepancy between the analyzed task and the algorithms embedded in the system, erroneous recommendations of the system were possible. Secondly, the functioning of the systems directly depended on the user's initial data, and, therefore, any erroneous data could lead to incorrect recommendations of the system. Thirdly, the functioning of the systems depends on databases that may become outdated due to the fact that new protocols, criteria, and methods will appear, and existing ones are developed. And if these databases are not updated in a timely manner, then erroneous and outdated recommendations of the system would be possible. It was also necessary to take into account the increase in complexity with the growth of the number of alternatives and evaluation criteria under consideration. Thus, working with these systems requires their user to understand the basic principles of operation of the multi-criteria decision-making methods, to conduct a preliminary study of the functionality of the systems, as well as apply a critical attitude to the received recommended systems. To overcome these problems, regular data updating and system maintenance are necessary. And it was also necessary to take into account the possibility of scaling and future maintainability of the system. This approach has a number of advantages, such as automation of the method selection process, the ability to take into account many different parameters, and flexibility. However, there were also some limitations: dependence of the system operation on built-in algorithms, dependence on the user's initial data, and dependence on the relevance of the system databases. In general, the approach considered showed the potential of using such software tools to solve complex selection problems in the field of distributed registry technologies for IoT. It can be considered that this could be useful in the development of specialized intelligent decision support systems in the field of distributed registry technologies. Future integration with artificial intelligence technologies is also possible, which will increase the efficiency and adaptability of the decisions made, especially in conditions of high data uncertainty and changing requirements for consensus protocols in IoT networks.

The feasibility and practicality are demonstrated by the following example. In Ref. [21] Filatovas et al. (2022) described a use case for the methods with the most suitable consensus protocol for a bike sharing system. A total of 18 alternative consensus protocols were considered for evaluation. The TOPSIS method was used as the main method for all calculations.

4. Conclusions

The Internet of Things is one of the important application areas of distributed ledger and blockchain technologies. Distributed ledger technologies can provide effective ways to solve the problems of traditional IoT applications. An important component of the reference architecture of distributed ledger technologies is the consensus layer. This layer manages the consensus between network nodes and ensures the agreement of the ledger state by all nodes, as well as ensures network security, accuracy, and security of the ledger. Consensus can significantly affect the performance and security of the blockchain system. To date, a wide range of consensus protocols with different concepts and properties have been developed, including for blockchain-based IoT networks. Therefore, choosing the most suitable consensus protocol for a particular distributed ledger system, in particular, for the IoT blockchain, is an important task. However, at the same time, it is a complex task, since the choice has to be made between conflicting requirements and there is a high degree of uncertainty. In this paper, the first steps were made in this direction with the aim of developing a system for the selection of optimal consensus protocols for blockchain-based IoT networks. This work was carried out to develop a conceptual model of the selection system, consisting of several successive stages:

1. Formalization of the problem as a multi-criteria decision-making problem.
2. Formation of a set of alternatives (consensus protocols).
3. Formation of a set of evaluation criteria.
4. Selection of the optimal methods of multi-criteria decision analysis.
5. Software implementation of the selection system and testing.

The proposed approach can serve as a basis for future research, and the next step is to move from the concept to practical implementation. To achieve this goal, it is intended to create a software implementation of the system for selecting optimal consensus protocols, and its subsequent testing in various use cases. It will then be necessary to explore ways to solve a number of problems and limitations in its further application. It should be taken into account that the developed system cannot completely replace expert analysis. It cannot exclude possible erroneous recommendations. This is due to the fact that the algorithms embedded in the system may not correspond to the analyzed problem. Or, the initial data of the system user may be initially erroneous. In addition, the system databases containing information on the protocols, criteria, and methods may become outdated over time. It is also necessary to take into account the increase in complexity with the increase in the number of alternatives and evaluation criteria considered. In the future, regular data updates, system maintenance, solving of the issues of scaling, and maintainability of the system are necessary.

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Abbreviations

The following abbreviations are used in this manuscript:

DLT	Distributed ledger technologies
IoT	Internet of Things
MCDM	Multi-criteria decision making methods
SAW	Simple additive weighting
TOPSIS	Technique for order of preference by similarity to ideal solution
VIKOR	VIseKriterijumska Optimizacija I Kompromisno Resenje

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