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LARGE EXPERT DATA-BASED Q-LEARNING ASSESSMENT WITH HYBRID MOLECULAR FUZZY MODELLING FOR PEER-TO-PEER ENERGY TRADING USING BLOCKCHAIN TECHNOLOGIES

Gang Kou[1], Serhat Yüksel[2], Hasan Dinçer[2], Ayşe Nur Çırak[3], Serkan Eti[4*]

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[1] School of Business Administration, Faculty of Business Administration, Southwestern University of Finance and Economics, Chengdu, China

[2] School of Business, Istanbul Medipol University, Istanbul, Turkey, Department of Economics and Management, Khazar University, Baku, Azerbaijan

[3] School of Business, Istanbul Medipol University, Istanbul, Turkey

[4] IMU Vocational School, Istanbuledipol University, Istanbul, Turkey

[*]Corresponding Author:
Serkan Eti

Email:
seti@medipol.edu.tr

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ABSTRACT

Peer-to-peer (P2P) energy trading is an industry where energy producers and consumers buy and sell energy directly by using a platform and in most cases, the technology behind P2P energy trading is blockchain. Tracking performance indicators of blockchain-based P2P energy trading is important to evaluate the effectiveness of a project and to help investors manage resources effectively. However, the literature is still scarce, and the risks of strategic decision making are higher. To fill this gap, we present a novel method to prioritize strategies in P2P energy trading. The model combines molecular fuzzy-based cognitive maps with molecular fuzzy ranking. It contributes to the literature by creating a novel method for ranking alternatives across different geometric shapes. So, the testing of reliability of ranking can be done and the accuracy and robustness of the model can be improved. The Q-learning approach also allows expert weights to be calculated objectively which mitigates the subjectivity of the results and helps investors make informed decisions. By providing a reliable framework for strategy development, this study contributes significantly to the literature and thus investors can make well-informed decisions. The results show that blockchain scalability and grid integration are the most critical performance indicators to enhance these projects. Community empowerment through local partnerships for microgrid development is also the most important investment option.

Keywords: *peer-to-peer energy trading, energy economics, energy investments, strategic decision-making, molecular fuzzy sets*

1. INTRODUCTION

Peer-to-peer (P2P) energy trading enables producers and consumers to trade energy through digital platforms without the need for centralized intermediaries (Galici et al., 2025). Blockchain technology is essential for these systems as it provides transparency, records, and price-setting. The performance of blockchain-based P2P energy trading systems is influenced by technological, economic, and regulatory factors. Advances in technology improve the efficiency and security of transactions, thereby increasing the performance of decentralized trading systems as well (Uddin et al., 2025). Similarly, enhanced cybersecurity measures strengthen the security of an energy market against cyber-attacks and reinforce user trust (Sun et al., 2025). The installation of energy generation and storage systems will also improve system efficiency by making it easier for renewable energy to be used and optimizing energy management processes. Meanwhile, economic and institutional conditions are equally important. High transaction fees may deter investors, and the implementation of regulations that are in line with existing energy market structures will boost investor confidence and market adoption (Zheng and Wei, 2025). While there has been increasing interest in blockchain-based P2P energy trading, there is still a lack of a systematic recognition of the performance indicators that impact the success of these platforms (Chen et al., 2026). To evaluate project performance, investors and policymakers need to know the most important indicators to make their decisions. Existing studies have primarily focused on technological architectures and operational mechanisms, while paying limited attention to the relative importance of the factors that drive system performance. This gap creates uncertainty in strategic decision-making related to decentralized energy trading infrastructures. To address this limitation, the present study proposes a novel analytical framework for prioritizing performance indicators and strategic alternatives in blockchain-based P2P energy trading. In this framework, information gain-based attribute selection is employed to identify the most relevant expert specifications, while expert weights are determined through a Q-learning-based assessment. Performance indicators are evaluated using molecular fuzzy-based cognitive maps, and strategic alternatives are ranked through molecular fuzzy ranking. Accordingly, the study addresses two principal research questions: which performance indicators of blockchain-based P2P energy trading systems are the most significant and which strategic investment alternatives should be prioritized by investors. This study contributes to the literature by introducing a novel model for identifying priority investment strategies in blockchain-based P2P energy trading. The model offers two main methodological contributions. First, the integration of molecular fuzzy sets, molecular geometry theory, and fuzzy logic provides an original framework for multi-criteria decision-making. Unlike conventional fuzzy approaches, which are typically grounded in abstract mathematical representations, molecular fuzzy sets incorporate a concrete geometric structure that improves interpretability and supports more precise analysis. This approach enables the ranking of alternatives across different geometric shapes while also allowing the reliability and consistency of the resulting rankings to be tested. As a result, the proposed model enhances both the robustness and the credibility of the evaluation process. Second, the incorporation of Q-learning strengthens the objectivity of expert weighting. In traditional weighting methods, expert importance is often determined through subjective judgment. By contrast, Q-learning provides a dynamic and data-driven mechanism for evaluating expert contributions and performance. Because the algorithm continuously updates itself through feedback, it can adapt to new information and changing conditions, thereby generating more reliable and up to date expert weights. This reduces subjectivity and improves the overall accuracy of the model. Beyond its methodological contribution, the study is also situated within the broader literature on innovation economics and energy transition. Blockchain-based P2P energy trading represents an important dimension of the digital transformation of energy markets. From an innovation systems perspective, decentralized trading platforms create new opportunities for knowledge diffusion, technological experimentation, and broader market participation by enabling small-scale producers and consumers to engage directly in energy exchange. From the perspective of the knowledge economy, the effective operation of these systems depends heavily on digital infrastructure, data management capacity, and interoperability among smart devices and energy networks. Moreover, P2P energy trading supports the transition toward decentralized and flexible energy systems by facilitating the integration of renewable energy sources. By identifying and prioritizing the most critical performance indicators of these platforms, this study contributes to a deeper understanding of how digital technologies are reshaping energy market structures and promoting more resilient and decentralized energy ecosystems. The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on P2P energy trading, blockchain technologies, and performance indicators, while identifying the main research gaps. Section 3 presents the proposed methodology, including the molecular fuzzy-based cognitive maps approach and the Q-learning-based expert weighting procedure. Section 4 reports the empirical findings and presents the ranking of performance indicators and strategic alternatives. Section 5 discusses the results in relation to the existing literature and outlines their implications for investors and researchers. Finally, Section 6 concludes the paper by summarizing the main contributions, practical implications and directions for future research.

2. LITERATURE REVIEW

Blockchain-based peer-to-peer (P2P) energy trading can be situated within the broader literature on innovation diffusion and digital ecosystems. Innovation diffusion theory explains how new technologies spread through the interaction of infrastructure, institutional conditions, and user adoption. In the energy sector, blockchain-based P2P platforms represent a digital innovation that enables decentralized coordination between producers and consumers while reducing dependence on traditional intermediaries. From a digital ecosystem perspective, these platforms rely on interconnected technologies, data exchange, and collaborative networks to create value among multiple actors. In this context, blockchain infrastructure, smart meters, IoT devices, and energy storage systems function as complementary components of an integrated ecosystem. Their effectiveness depends not only on technical feasibility but also on the reliability, scalability and integration capacity of digital infrastructures. Accordingly, identifying and prioritizing the key performance indicators of blockchain-based P2P energy trading is essential for understanding how such innovations are adopted, diffused and sustained in decentralized energy markets.

In essence, P2P energy trading allows energy producers with surplus electricity to sell directly to consumers without the involvement of conventional energy companies. All transactions are recorded through blockchain infrastructure, which increases transparency, reduces transaction costs, and supports the wider use of renewable energy, particularly solar and wind power. Because the system is decentralized, entry and exit are relatively easy, which saves time and improves transactional flexibility. However, its effectiveness depends on several critical conditions. First, blockchain scalability is essential, especially when the number of participants grows and transaction matching becomes more complex. Without sufficient scalability, the system may slow down and transaction costs may increase. Mechanisms such as side chains and sharding can improve speed, reduce congestion, and enable larger-scale and lower-cost operations.

Second, the compatibility of IoT devices and smart meters is crucial for the efficient functioning of blockchain-based P2P trading. Smart meters provide continuous real-time data on energy production and consumption, while IoT devices process this information and facilitate automated trading decisions. Together, these technologies improve pricing accuracy, optimize production and consumption, reduce waste, and enhance the overall efficiency of the system. They also strengthen the underlying blockchain infrastructure, making P2P energy trading more beneficial for both producers and consumers.

Third, grid integration is a fundamental requirement for the safe, stable, and efficient operation of P2P energy trading. It supports uninterrupted energy exchange, enables the storage of excess energy, and enhances flexibility by allowing stored energy to be used or sold during periods of high demand. When combined with smart grids and smart meters, grid integration improves supply-demand matching, increases transparency, reduces storage costs, and supports the expansion of renewable energy use. This not only benefits producers and consumers economically, but also contributes to environmental sustainability by promoting cleaner energy systems and reducing dependence on fossil fuels.

Fourth, cybersecurity is indispensable in blockchain-based P2P energy trading. Although blockchain enhances transparency, decentralization may also expose the system to privacy risks, malicious interference, and information asymmetries (Todorova et al., 2025). User identity data may be compromised, creating both ethical and financial risks. For this reason, strong cybersecurity measures are necessary to ensure trust, prevent losses, and maintain system continuity. Smart contracts, cryptographic signatures, and the distributed architecture of blockchain all play important roles in protecting data, minimizing human-related risks, and enabling early detection and mitigation of cyberattacks.

Overall, the literature shows that blockchain-based P2P energy trading offers significant advantages, including transparency, reliability, speed, and lower costs. However, its broader implementation depends on simultaneously satisfying several demanding criteria, particularly blockchain scalability, IoT and smart meter compatibility, grid integration, and cybersecurity. Meeting all these requirements at once can be difficult and costly for households, communities, or institutions, as it requires substantial research and development capacity, qualified personnel, and advanced technological infrastructure. This challenge represents an important gap in the literature. Existing studies often examine technological, operational, or security-related dimensions separately, but rarely provide a systematic prioritization of the performance indicators that most strongly determine the effectiveness of P2P energy trading systems. The existing literature can generally be grouped into three streams. One focuses on blockchain infrastructure, including transaction security, smart contracts, and system architecture. A second examines operational dimensions such as grid integration, energy storage, and the role of smart meters and IoT in real-time data exchange. A third explores optimization and decision-support models for energy trading platforms. Although these studies provide valuable insights, they often assess individual factors in isolation and frequently rely on conventional multi-criteria decision-making approaches that may not fully capture uncertainty, interdependencies, and expert-related subjectivity. Consequently, the literature still lacks an integrated, decision-oriented framework capable of evaluating technological infrastructure, operational dynamics and expert uncertainty simultaneously. To address this gap, the present study proposes a hybrid analytical framework that combines molecular fuzzy sets, Q-learning, cognitive maps, and optimization techniques. This framework enables a more comprehensive prioritization of performance indicators for blockchain-based P2P energy trading systems, helps identify the most critical factors, and supports the development of more effective policy and investment strategies. In doing so, it contributes to a more efficient allocation of resources and advances the literature on decentralized energy systems.

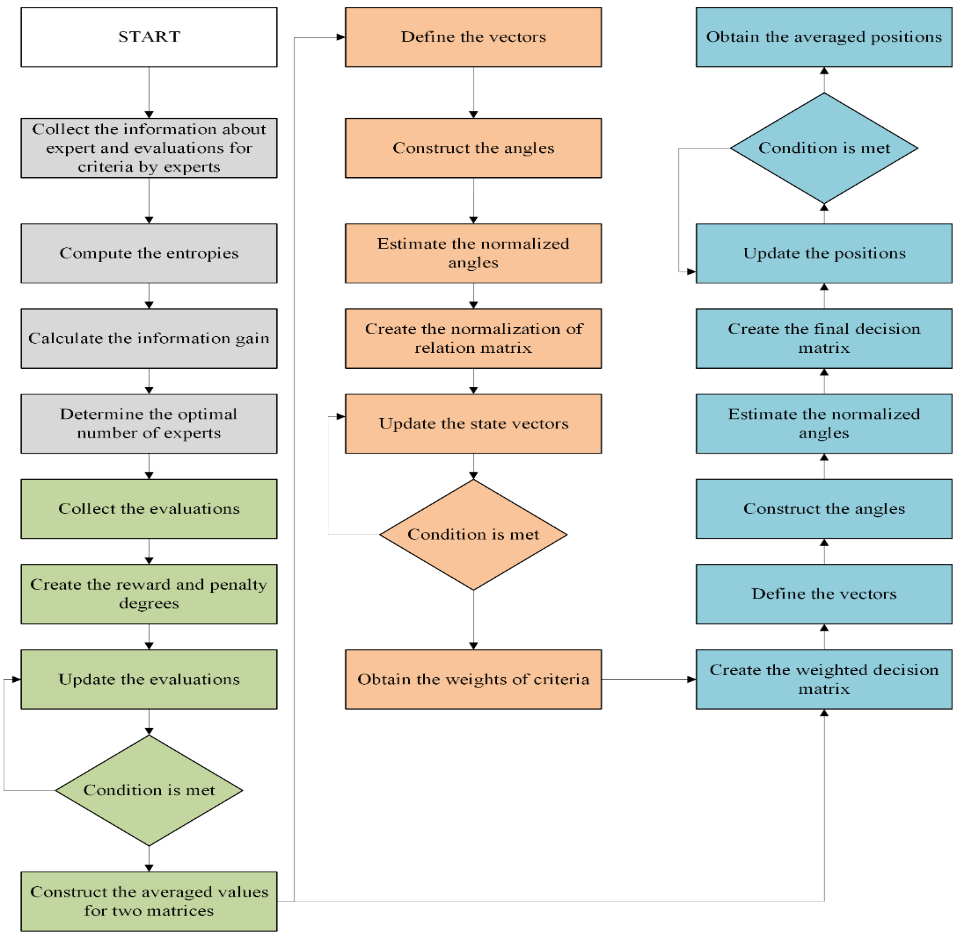
3. METHODOLOGY

The proposed framework integrates molecular fuzzy sets, Q-learning, cognitive maps and multi-objective particle swarm optimization (MOPSO) to address several methodological limitations of conventional multi-criteria decision-making approaches. Traditional models often rely on static expert judgments and simplified representations of uncertainty, which may weaken result reliability in complex technological contexts such as blockchain-based peer-to-peer (P2P) energy trading. In the present framework, each method serves a complementary function. Molecular fuzzy sets provide a more flexible representation of uncertainty by incorporating geometric structures that enable more robust comparisons among alternatives. Q-learning is used to determine expert weights dynamically, thereby reducing the subjectivity associated with traditional weighting procedures. Cognitive maps capture the interdependencies among performance indicators, which is essential for understanding the complex structure of decentralized energy trading systems. Finally, MOPSO enhances the ranking process by identifying optimal solutions within a multidimensional decision space. Taken together, these methods allow the framework to simultaneously address uncertainty, expert reliability, and systemic relationships, offering a more comprehensive and reliable analytical perspective than conventional approaches, which typically consider these dimensions separately.

To clarify the logic of the framework, the methodological process can be interpreted as a structured multi-stage decision model. In the first stage, an information gain-based attribute selection procedure is applied to identify the most relevant experts from the initial expert pool. In the second stage, the evaluations provided by the selected experts are balanced using Q-learning to calculate objective expert weights and reduce subjective bias. In the third stage, molecular fuzzy-based cognitive maps are employed to examine the relationships among performance indicators and determine their relative importance. In the final stage, MOPSO is used to rank the strategic alternatives based on the weighted criteria. This sequential structure enables the integration of expert evaluation, uncertainty modelling, and optimization within a unified analytical framework.

Accordingly, the methodology developed for the analysis of blockchain-based P2P energy trading consists of four interconnected components. First, an information gain-based mass expert selection model is used to identify the most suitable experts from the dataset. Second, the data obtained from these experts are balanced through Q-learning. Third, the criteria used in the feasibility analysis of blockchain-based P2P energy trading are weighted through cognitive maps. Fourth, the strategic alternatives are ranked using MOPSO. Throughout the process, uncertainty is evaluated using molecular fuzzy sets. The overall methodological flow is illustrated in Figure 1.

Figure 1. The Flow of the Process



Source: Authors

3. 1. DEFINITIONS OF THE MFS

MFS is constructed by integrating fuzzy sets with molecular geometry, which are used for the spatial arrangement of atoms in molecular subjects. An element of a MFS with degrees of membership, non-membership and hesitant satisfies the condition in Eq (1) (Dinçer et al., 2024).

$$\mu_X(x) + v_X(x) + \xi_X(x) = 1 \quad (1)$$

Eq (2) identifies the membership of the MFS according to the normalized angles from molecular geometry shapes.

$$\mu_X(x) = \mathrm{f}(\theta_x) = 1 - \frac{\theta_x}{\theta^*} \quad (2)$$

Where θ^* is equals to maximum angle, π, $2\pi/3$, $\pi/2$, $2\pi/5$ and $\pi/3$ respect to general, linear, trigonal planar, tetrahedral, trigonal bipyramidal and octahedral shapes, respectively. Similarly, Eq (3) defines the non-membership of the MFS.

$$V_X(x) = \frac{\theta_x}{\theta^*} \quad (3)$$

Finally, Eq (4) determines the hesitant of the MFS.

$$\xi_X(x) = 1 - \left(\left(1 - \frac{\theta_x}{\theta^*}\right) + \frac{\theta_x}{\theta^*}\right) \quad (4)$$

3. 2. INFORMATION GAIN-BASED MASS EXPERT SELECTION

Selecting the most appropriate experts from a large pool remains a major challenge in multi-criteria decision-making methods. To address this issue, the present study adopts a model based on information gain between input and output variables. In this framework, experts' education, experience, salary, and age are treated as input variables, while their evaluations of the problem criteria are used as output variables. Based on these input-output relationships, Eq. (5) is employed to calculate the entropy of each output (Feng et al., 2024). The initial expert pool consists of eight individuals, reflecting the interdisciplinary nature of the subject, which requires integrated knowledge of energy markets, blockchain infrastructure, digital platforms, and project evaluation. Experts were included only if they satisfied at least one domain-related criterion, such as direct experience in renewable energy or smart grid projects, blockchain or digital platform implementation, or academic and policy work on energy systems, as well as one seniority-related criterion, including substantial professional experience or demonstrated decision-making responsibility. Within this framework, education, experience, salary, and age are not interpreted as normative indicators of expertise. Rather, they are used as observable proxies for analytical training, accumulated sectoral exposure, organizational responsibility, and professional maturity. The purpose of the information-gain filter is therefore to determine which observable characteristics explain criterion assessments most strongly and, in turn, to identify the experts who provide the most information-rich judgments for the decision model.

$$\mathcal{E}(C) = -\sum_{i=1}^{n} x_i \log_2(x_i) \quad (5)$$

Then, the information gain is obtained for each input attribute that defines the expert specification. In this process, the partitioning is done according to each input and the calculations are repeated. Eq (6) is related to the compute of the information gain.

$$g(F,C) = \mathcal{E}(C) - \sum_{i \in F} \frac{|C_i|}{|C|} \mathcal{E}(C_i) \quad (6)$$

Next, the weighted entropy is estimated for each output. The weight of the expert input in the total expert team is used as the weight. Similarly, this computing is performed for all partitions. In the final stage, the most suitable expert with the biggest information gain value for each criterion is determined.

3. 3. DECISION MAKING MODEL INCLUDING Q-LEARNING, COGNITIVE MAPS AND MOPSO WITH MFS

Following the balancing of expert evaluations, the decision-making framework is used to weight the criteria and rank the alternatives. For this purpose, the model incorporates three distinct algorithms. The integrated three-stage structure of the model, based on molecular fuzzy numbers (MFNs), is presented in Table 1.

Table 1. The pseudo-code of decision-making model

Input: Criteria and Alternatives Evaluations of Experts, $C^i_{n\times n}$ and $A^i_{m\times n}$; m is the number of alternatives; n is the number of criteria; the weights of the experts W Output: Ranking Results of Alternatives $p_i, i \in [1, m]$
Begin (1) Collecting evaluations from each expert about criteria and alternatives $C^i = [c]$ $A^i = [a]$ (2) Transforming linguistic evaluations into MFN $Q_C^{lead} \leftarrow \max_w C$ $Q_C^{others} \leftarrow \text{others}_w\, C$ $Q_A^{lead} \leftarrow \max_w A$ $Q_A^{others} \leftarrow \text{others}_w\, A$ (3) Defining reward and penalty factors according to expert weights (4) Computing the reward degrees among the experts $RC_{s,a} \leftarrow r \cdot (Q_C^{lead} - Q_C^{others})$ $RA_{s,a} \leftarrow r \cdot (Q_A^{lead} - Q_A^{others})$ (5) Calculating the penalty degrees among the experts $PC_{s,a} \leftarrow p \cdot (Q_C^{others} - Q_C^{lead})$ $PA_{s,a} \leftarrow p \cdot (Q_A^{others} - Q_A^{lead})$ (6) Updating the evaluations $Q`_{s,aC} \leftarrow Q_C^{lead} + \alpha \cdot (RC_{s,a} - PC_{s,a})$ $Q`_{s,aA} \leftarrow Q_A^{lead} + \alpha \cdot (RA_{s,a} - PA_{s,a})$ (7) Obtaining the maximum value of absolute differences $\Delta_{max}{}^C \leftarrow \max \{\lvert Q`_{s,aC} - Q_{s,aC}\rvert\}$ $\Delta_{max}{}^A \leftarrow \max \{\lvert Q`_{s,aA} - Q_{s,aA}\rvert\}$ (8) If the maximum values are less than threshold value, then go to (9) Else go to (6)

(9) Estimating the averaged values for relation and decision matrices

$$M_C \leftarrow \left(\frac{1}{k}\sum_{i=1}^{k} \mu_{C_i}(x), \frac{1}{k}\sum_{i=1}^{k} v_{C_i}(x), \frac{1}{k}\sum_{i=1}^{k} \xi_{C_i}(x)\right)$$

$$M_A \leftarrow \left(\frac{1}{k}\sum_{i=1}^{k} \mu_{A_i}(x), \frac{1}{k}\sum_{i=1}^{k} v_{A_i}(x), \frac{1}{k}\sum_{i=1}^{k} \xi_{A_i}(x)\right)$$

(10) Constructing the fuzzy vectors for relation matrix

$$u_i \leftarrow [(\mu_{i1}, v_{i1}, \xi_{i1}), (\mu_{i2}, v_{i2}, \xi_{i2}), \dots (\mu_{i(n-1)}, v_{i\,(n-1)}, \xi_{i\,(n-1)})\,]_{M_C}$$

(11) Creating the angles for relation matrix

$$\theta_{u_i,u_j} \leftarrow cos^{-1}\left(\frac{(u_i.u_j)}{\|u_i\|.\|u_j\|}\right)$$

(12) Determining the normalized angles for relation matrix

(13) Computing the normalization of relation matrix

$$NR \leftarrow \left[\frac{\frac{1}{norm\left(\theta_{u_i,u_j}\right)}}{\sum_{j=1}^{n}\frac{1}{norm\left(\theta_{u_i,u_j}\right)}}\right]$$

(14) Identifying the state vectors

$$A(t) \leftarrow [a_1(t), a_2(t), \dots, a_n(t)]$$

(15) Updating the state vectors

$$A(t+1) \leftarrow \frac{1}{1+e^{-A(t)\cdot NR}}$$

(16) If $fA(s+1) = fA(s)$ Then go to (17) Else go to (15)

(17) Weighting the criteria

$$W_j \leftarrow \frac{fA(s)_j}{\sum_{j=1}^{n} fA(s)_j}$$

(18) Creating the weighted decision matrix

$$B_{ij} \leftarrow (w_{j.}\,\mu_{ij}, w_{j.}\,v_{ij}, w_{j.}\,\xi_{ij})_{M_A}$$

(19) Constructing the fuzzy vectors for weighted decision matrix

$$y_i \leftarrow [(\mu_{i1}, v_{i1}, \xi_{i1}), (\mu_{i2}, v_{i2}, \xi_{i2}), \dots (\mu_{im}, v_{im}, \xi_{im})]_B$$

(20) Creating the angles for decision matrix

$$\theta_{y_i,y_j} \leftarrow cos^{-1}\left(\frac{(y_i.y_j)}{\|y_i\|.\|y_j\|}\right)$$

(21) Determining the normalized angles for decision matrix

(22) Computing the final decision matrix

$$\mathrm{F} \leftarrow \left[\frac{\frac{1}{norm\left(\theta_{y_i,y_j}\right)}}{\sum_{j=1}^{m}\frac{1}{norm\left(\theta_{y_i,y_j}\right)}}\right]$$

(23) Defining the particle presentation

$$X_i = \{ x_{i1}, x_{i2}, \ldots, x_{in} \}$$

(24) Updating the velocity of each particle and positions

$$V_{ij}(t+1) \leftarrow \omega V_{ij}(t) + c_1 r_1 (P_{ij}(t) - X_{ij}(t)) + c_2 r_2 (P_{gb_j}(t_i - X_{ij}(t))$$

$$X_{ij}(t+1) \leftarrow X_{ij}(t) + V_{ij}(t+1)$$

(25) If the differences the global positions are lower than threshold Then go to (26) Else go to (24)

(26) Obtaining the ranking results

$$p_i \leftarrow \frac{1}{m} \sum_{i=1}^{m} P_{ij}$$

End

Source: Authors

4. ANALYSIS

Within the scope of Eq (1), fuzzy number equivalents of linguistic expressions are constructed and analyzed. Also, Eqs (2)-(4) are taken into consideration in the construction of numbers. The results are presented under subheadings.

4. 1. DETECTING THE RELEVANT EXPERT SPECIFICATIONS USING THE INFORMATION GAIN-BASED ATTRIBUTE SELECTION

For the selection of the most appropriate experts, Eqs. (5) and (6) are applied within the proposed framework. First, the expert group, the relevant expert information, and the initial output feedback are identified. Table A1 presents the background information of the experts together with their initial criterion evaluations. Subsequently, the output entropies are calculated, and the entropy value for each criterion is reported in Table A2. Using the obtained E values, the criterion entropies are further decomposed according to expert characteristics, after which the g values are computed. Table A3 reports the entropies of BS separated by expert information. The results show that salary has the highest g value among the expert characteristics for BS, indicating that it is the most influential expert attribute for this criterion. The same procedure is then repeated for the remaining criteria. Table A4 presents the g values corresponding to the expert characteristics for each criterion. According to these results, experience has the highest importance for BS and CD, education is the most influential expert attribute for GI, and salary and age are equally the most influential characteristics for CYB. Based on the decision rules derived from the g values, the most relevant expert group is identified. Expert 5 is selected as the most representative expert, matching four input attributes, while Experts 2 and 4 each match three relevant expert attributes. Since Expert 5 has the highest priority by satisfying four matching conditions, and Experts 2 and 4 have equal relevance, the final expert team consists of Experts 5, 2, and 4, with Experts 2 and 4 assigned equal weight. Their linguistic evaluations are then used to construct the relation and decision matrices.

4. 2. ANALYZING STRATEGY CHOICES USING DECISION MAKING MODEL

The proposed method, consisting of three integrated models, is applied to the evaluation of strategic alternatives for blockchain-based P2P energy trading. The strategic options considered are market diversification of P2P energy trading through Vehicle-to-Grid and Vehicle-to-Vehicle systems (MRK); leveraging blockchain capabilities through tokenized renewable energy assets (STR); community empowerment through local partnerships for microgrid development (PTR); customization of investment tools via decentralized lending platforms

(DECNT); and the provision of energy-as-a-service models to enhance the accessibility of P2P trading networks (SRV). The evaluations of criteria and strategic alternatives are obtained from the three experts identified in Section 4.1. Table A5 presents the linguistic assessments of both the criterion relationships and the alternatives. Expert weights are assigned based on their relative importance within the selected expert group. Accordingly, Expert 5 is treated as the lead expert and assigned a weight of 0.4, while Experts 2 and 4 are each assigned a weight of 0.3. These linguistic evaluations are then transformed into molecular fuzzy numbers (MFNs).

Subsequently, reward degrees are calculated for both matrices, and the corresponding results are reported in Table A6. Penalty degrees are then computed, as shown in Table A7. Using a learning rate of 0.1, the matrix elements are updated, and the revised matrices are presented in Table A8. Because the method involves iterative learning, the stopping condition is tested after each iteration. The absolute differences obtained in the first iteration are reported in Table A9. Since some matrix elements remain above the threshold value of 0.02, the iterative process continues. The convergence condition is satisfied after four iterations, and the resulting balanced evaluation matrices are presented in Table A10. The expert evaluations are then averaged to obtain the aggregated matrix values, which are summarized in Table A11. Following this, the u_i values are generated, and the angles for the molecular cognitive maps are constructed. Table A12 reports the angles for MC. The normalized angles are then determined for different geometric shapes, after which the relation matrix is normalized. Table A13 presents the normalized matrix for the linear form. Finally, the iterative state vectors are identified and updated. The corresponding results for the linear form are shown in Table A14, while Table 2 summarizes the findings for the other geometric shapes.

Table 2. The Priorities of Criteria According to Others

:0.1	First	Second	Third	Fourth	Fifth
BS	1	1	1	1	1
CD	3	3	3	3	3
GI	2	2	2	2	2
CYB	4	4	4	4	4
:0.5	First	Second	Third	Fourth	Fifth
BS	1	1	1	1	1
CD	3	3	3	3	3
GI	2	2	2	2	2
CYB	4	4	4	4	4
:1	First	Second	Third	Fourth	Fifth
BS	1	1	1	1	1
CD	3	3	3	3	3
GI	2	2	2	2	2
CYB	4	4	4	4	4

Source: Authors

Across different geometric shapes and learning rates, the priority ranking of the criteria remains unchanged, indicating the robustness of the results. In all cases, BS emerges as the most important criterion. In the next stage, the elements of MA are multiplied by the criterion weights to construct the weighted decision matrix. Table A15 presents the resulting B matrix.

Subsequently, the y_i values are generated and the angles for B are constructed. Table A16 reports these angles. The normalized angles for B are then calculated for different geometric shapes, after which the final decision matrix is obtained. Table A17 presents this matrix for the linear form. In the following step, the velocity and position of each particle are iteratively updated. During this process, the convergence condition is checked at each iteration. The condition is satisfied at the end of the fifth iteration, and the iterative results for the linear form are summarized in Table A18.

Finally, the average position values are calculated for the strategic alternatives. The corresponding values are 0.1101, 0.1294, 0.1393, 0.1127, and 0.1307, respectively. Accordingly, the strategic alternatives are ranked in descending order as follows: PTR, SRV, STR, DECNT, and MRK. Table 3 presents the corresponding results for the other geometric shapes.

Table 3. The Ranks of Strategic Choices According to Others

:0.1	First	Second	Third	Fourth	Fifth
MRK	5	5	5	5	5
STR	3	3	3	3	3
PTR	1	1	1	1	1
DECNT	4	4	4	4	4
SRV	2	2	2	2	2
:0.5	First	Second	Third	Fourth	Fifth
MRK	5	5	5	5	5
STR	3	3	3	3	3
PTR	1	1	1	1	1
DECNT	4	4	4	4	4
SRV	2	2	2	2	2
:1	First	Second	Third	Fourth	Fifth
MRK	5	5	5	5	5
STR	3	3	3	3	3
PTR	1	1	1	1	1
DECNT	4	4	4	4	4
SRV	2	2	2	2	2

Source: Authors

According to different shapes and learning rates in Table 3, the ranks of the strategic choices are the same. So, the best strategic choice is community empowerment with the local partnership for developing microgrids.

4. 3. ROBUSTNESS, SENSITIVITY, AND IMPLEMENTATION SCENARIOS

The proposed analysis enables a clearer interpretation of the stability of the findings. As shown in Tables 16 and 21, the rankings of both the criteria and the strategic alternatives remain unchanged across different molecular shapes and under varying learning-rate assumptions (= 0.1, 0.5, 1.0). This indicates that the identification of blockchain scalability and grid integration as the most important criteria, as well as PTR as the leading strategy, is not dependent on a specific model parameterization. Such consistency strengthens the robustness and credibility of the proposed framework.

To further examine robustness and demonstrate practical applicability, a comprehensive sensitivity analysis was conducted using four distinct scenarios. These scenarios were constructed by systematically varying the criterion weights in the decision matrix to reflect different real-world conditions and policy priorities. In addition, the results were compared with those obtained from the Extended TOPSIS method to assess the consistency of the rankings. The full comparative results are presented in Table 4.

Table 4. Comparative Ranking Results with Sensitivity Analysis (:0.5)

Proposed Model					
Case 1	First	Second	Third	Fourth	Fifth
MRK	5	5	5	5	5
STR	3	3	3	3	3
PTR	1	1	1	1	1
DECNT	4	4	4	4	4
SRV	2	2	2	2	2
Case 2	First	Second	Third	Fourth	Fifth
MRK	5	5	5	5	5
STR	3	3	3	3	3
PTR	1	1	1	1	1
DECNT	4	4	4	4	4
SRV	2	2	2	2	2
Case 3	First	Second	Third	Fourth	Fifth
MRK	5	5	5	5	5
STR	3	4	4	3	3
PTR	1	1	1	1	1
DECNT	4	3	3	4	4
SRV	2	2	2	2	2
Case 4	First	Second	Third	Fourth	Fifth
MRK	5	5	5	5	5
STR	3	4	4	3	3
PTR	1	1	1	1	1
DECNT	4	3	3	4	4
SRV	2	2	2	2	2
Extended TOPSIS					
Case 1	First	Second	Third	Fourth	Fifth
MRK	5	5	5	5	5
STR	3	3	3	3	3
PTR	1	1	1	1	1
DECNT	4	4	4	4	4
SRV	2	2	2	2	2
Case 2	First	Second	Third	Fourth	Fifth
MRK	5	5	5	5	5
STR	3	3	3	3	3
PTR	1	1	1	1	1
DECNT	4	4	4	4	4
SRV	2	2	2	2	2
Case 3	First	Second	Third	Fourth	Fifth
MRK	5	5	5	5	5
STR	3	4	4	3	3
PTR	1	1	1	1	1
DECNT	4	3	3	4	4
SRV	2	2	2	2	2
Case 4	First	Second	Third	Fourth	Fifth
MRK	5	5	5	5	5
STR	3	3	3	3	3
PTR	1	1	1	1	1
DECNT	4	4	4	4	4
SRV	2	2	2	2	2

Source: Authors

The four scenarios presented in Table 4 reflect alternative strategic environments that investors and policymakers may encounter. Case 1 represents the baseline scenario, in which all criteria retain the weights derived from the original model. This scenario reflects a balanced investment environment in which blockchain scalability (BS), compatibility of IoT devices (CD), grid integration (GI), and cybersecurity (CYB) are considered according to their empirically estimated importance. It serves as the benchmark for comparison with the other cases. Case 2 represents a technology-focused scenario. In this case, the weights assigned to the technical criteria, namely BS and CD, are increased by 20%, while the weights of GI and CYB are reduced proportionally. This scenario captures an environment in which technological advancement and device interoperability are prioritized, such as a technologically advanced region with an already well-established grid infrastructure. Case 3 reflects an infrastructure-security balanced scenario, in which GI and CYB are assigned equal importance, while the weights of BS and CD are slightly reduced. This setting represents a policy context in which grid failures or security incidents have shifted regulatory attention toward grid stability and data protection. Case 4 corresponds to an extreme cybersecurity priority scenario. Here, the weight of CYB is increased substantially, by 40%, while the weights of the remaining criteria are reduced proportionally. This scenario reflects a high-risk environment, such as one following a major cyberattack on energy infrastructure, where investor and consumer confidence depends heavily on strong security measures. The results show that PTR (community empowerment through local partnerships for microgrid development) ranks first in all four scenarios and across all five iterations within each case. This high degree of stability indicates that community-based microgrid development is the most robust strategic option, regardless of changes in criterion weights. For investors, this finding suggests that local partnership-based strategies represent the most reliable and resilient investment choice under varying market and policy conditions. By contrast, STR (leveraging blockchain strengths through tokenized renewable energy assets) and DECNT (customization of investment tools through decentralized lending platforms) display minor fluctuations in Cases 3 and 4, occasionally exchanging third and fourth positions. This variation suggests that when grid integration and cybersecurity receive greater emphasis, decentralized financial mechanisms may temporarily gain relative importance over tokenization-based strategies. However, these shifts do not affect the top-ranked alternatives. The results obtained from the Extended TOPSIS method largely confirm these findings. In Cases 1, 2, and 4, the rankings are identical to those produced by the proposed model. In Case 3, the same minor fluctuation between STR and DECNT is observed. This consistency between two methodologically different approaches, namely the proposed molecular fuzzy-based framework and Extended TOPSIS, provides further evidence that the rankings are not merely artifacts of a single method, but instead reflect stable underlying strategic priorities. From a practical perspective, these findings offer clear guidance for both investors and policymakers. For investors, the persistence of PTR as the top-ranked strategy across all scenarios indicates that community partnerships for microgrid development constitute a no-regret investment option, remaining valuable under different technological, regulatory, and security conditions. For policymakers, the results provide a useful basis for adaptive regulation and policy prioritization, particularly in designing frameworks that support resilient and decentralized energy trading systems.

5. DISCUSSION

As the number of users participating in P2P energy trading increases, a growing volume of transactions is recorded within the blockchain system. This expansion in transaction activity may gradually create operational challenges, including slower processing speeds, system disruptions, and inaccuracies in transaction calculations. To prevent such problems, blockchain scalability becomes essential as transaction volume rises in blockchain-based P2P energy trading systems (Shinde et al., 2024). The priority analysis conducted in this study identifies blockchain scalability as the most important criterion for enhancing blockchain-based P2P energy trading. Because these systems operate without intermediary institutions or profit-oriented firms, transactions occur directly between producers and consumers, significantly reducing costs (Rao et al., 2024). At the same time, the growing adoption of renewable energy, particularly among households, has increased interest in participating in P2P trading networks. As a result, the blockchain system must process not only a higher number of transactions, but also a broader range of operational data, including the volume of energy produced and demanded, peak and off-peak consumption periods, storage status, usage rates, and transaction timing (Lincopinis and Llantos, 2024; Dhulavvagol et al., 2024). Wang and Guo (2024) further note that user-related information is recorded in increasingly detailed form as participation expands, which may eventually slow system performance and create operational inefficiencies. In this regard, Huang and Scott (2024) emphasize the importance of blockchain scalability in preventing such disruptions. Scalability solutions such as sharding divide the blockchain network into smaller sections, enabling parallel transaction processing and improving speed. Similarly, sidechains can operate alongside the main blockchain and become active in the event of disruptions (Egunjobi, 2024). These solutions not only reduce operational costs and save time, but also lower energy waste, facilitate the participation of small-scale producers, and support the wider expansion of blockchain-based energy trading. According to the priority analysis, grid integration is the second most important criterion for the development of blockchain-based P2P energy trading. The effective distribution and use of energy depend heavily on the integration of grid networks (Khalid, 2024). Without proper integration, energy cannot be distributed efficiently, energy-related production activities may decline, and negative consequences such as energy waste may emerge. For this reason, grid integration is essential for avoiding such inefficiencies and ensuring system stability (Bokopane et al., 2024). Since P2P energy trading operates through a blockchain-based infrastructure, the growth in participation also leads to a greater volume of data that must be processed accurately. At this point, smart meters remain crucial because they record data continuously and verify production, consumption, and payment calculations in real time (Ashrafi et al., 2024). In this sense, smart meters function as a key subcomponent of effective grid integration. Accurate data recording is especially important in P2P trading to ensure fairness and prevent losses for both producers and consumers (Yang et al., 2024). Feili et al. (2024) further argue that grid integration significantly reduces energy waste, particularly because small producers are also included in the system. The renewable energy generated by these producers must be stored efficiently, and grid integration enables this process. Liao et al. (2024) show that stored excess energy can later be sold during periods of lower production, thereby protecting small producers from economic losses. Moreover, grid integration contributes substantially to reducing the carbon footprint. Renewable energy technologies such as wind turbines and solar panels can be deployed in geographically disadvantaged areas, where locally generated energy can first serve nearby communities before being distributed more widely (Zhu et al., 2024). This increases the use of renewable energy, reduces dependence on fossil fuels, and supports green growth. Collectively, these developments further strengthen interest in blockchain-based P2P energy trading. The findings of this study have important implications for both the academic literature and practical decision-making in energy markets. First, the identification of blockchain scalability and grid integration as the two most critical performance indicators is consistent with earlier studies emphasizing the central role of technological infrastructure in decentralized energy systems. Previous research has shown that the growing number of participants and transactions in P2P trading platforms creates significant scalability challenges for blockchain networks. The present findings reinforce this argument by demonstrating that scalability improvements are essential for maintaining efficiency and reliability in decentralized trading environments. Likewise, the strong importance assigned to grid integration supports prior evidence that the effective connection of distributed renewable energy sources to existing grid infrastructures is fundamental to the sustainability of decentralized energy markets. From a policy perspective, the results suggest that regulators and policymakers should prioritize investments aimed at strengthening the technological infrastructure of decentralized energy systems. Policies that support blockchain scalability solutions, smart grid development, and the integration of distributed renewable energy resources may significantly accelerate the growth of P2P energy trading platforms. Regulatory frameworks that encourage innovation and support decentralized energy communities may also promote wider market adoption. The findings additionally offer valuable insights for investors and market participants. The identification of community-based microgrid partnerships as the most effective strategic alternative suggests that collaborative investment structures are likely to play a decisive role in the future expansion of decentralized energy markets. Investors may therefore benefit from prioritizing projects that strengthen local energy communities, expand renewable energy production, and incorporate blockchain-based trading infrastructures. In practical terms, the proposed hybrid decision-making framework may serve as a useful decision-support tool for energy companies, investors, and policymakers in evaluating strategic alternatives and identifying the key factors that shape the success of P2P energy trading initiatives.

6. CONCLUSION

This study addresses an important gap in the literature by proposing a novel decision-making framework for prioritizing strategies in blockchain-based peer-to-peer (P2P) energy trading. The proposed model integrates molecular fuzzy-based cognitive maps, molecular fuzzy ranking, Q-learning, and multi-objective particle swarm optimization to provide a comprehensive analytical framework for evaluating project effectiveness and guiding investment decisions. In contrast to conventional decision-making approaches, which often rely on static expert judgments and simplified representations of uncertainty, the proposed framework enables a more robust assessment by simultaneously incorporating uncertainty, expert reliability, and interdependencies among criteria. The findings indicate that blockchain scalability and grid integration are the most critical performance indicators for improving blockchain-based P2P energy trading systems. In addition, community empowerment through local partnerships for microgrid development emerges as the most important strategic investment alternative. The incorporation of molecular fuzzy sets represents a distinctive methodological contribution, as it extends conventional fuzzy logic by integrating geometric properties, thereby improving the reliability and accuracy of the ranking results. Accordingly, the study contributes to the literature both theoretically and practically by offering a more effective and reliable decision-making framework for complex decentralized energy systems. Beyond its methodological contribution, the study also provides practical implications for energy policy and investment strategies. The results suggest that improving blockchain scalability and strengthening grid integration should be treated as priority areas in the development of decentralized energy trading platforms. Policymakers may support the expansion of P2P energy markets by encouraging investments in smart grid infrastructure and regulatory frameworks that facilitate decentralized energy communities. Similarly, investors and energy companies may benefit from prioritizing community-based microgrid projects and digital energy platforms that combine renewable energy generation with blockchain-based trading mechanisms. Such efforts may contribute to the development of more efficient, transparent, and sustainable decentralized energy markets.

Despite these contributions, the study has several limitations. First, the expert evaluations and data used in the analysis may be limited to a specific geographic context, industry setting, or field of expertise, which may restrict the generalizability of the findings. Future studies could improve the external validity of the model by incorporating broader datasets and expert opinions from different regions, sectors, and disciplinary backgrounds. Second, blockchain technology and P2P energy trading are dynamic and rapidly evolving fields, meaning that the performance indicators considered in this study may change over time. Future research may therefore develop adaptive models capable of updating performance indicators dynamically in response to technological and market developments. Finally, the present study focuses primarily on technical performance indicators. Subsequent research could examine the influence of economic, social and political factors in greater detail to provide a more comprehensive understanding of the determinants of success in blockchain-based P2P energy trading systems.

Appendix

Table A_1. The Information about the Experts and Feedback

Experts	Inputs				Outputs			
	Education	Experience (year)	Salary (USD)	Age	Blockchain scalability (BS)	Compatibility of IoT devices and smart meters (CD)	Grid integration (GI)	Cybersecurity (CYB)
Expert 1	PhD	25	4500	52	High	High	High	High
Expert 2	Master	20	4000	49	Moderate	High	Significant	High
Expert 3	Master	15	3500	45	Significant	High	Moderate	High
Expert 4	Master	18	4250	47	High	Low	Moderate	Significant
Expert 5	PhD	19	5000	48	Significant	High	Moderate	Low
Expert 6	PhD	21	4500	54	Significant	High	Low	Significant
Expert 7	Bachelor	24	3500	56	Moderate	Significant	Low	High
Expert 8	Bachelor	22	2500	44	Significant	Significant	Low	Significant

Source: Authors

Table A_2. The Entropy of Each Criterion

	Probability Degrees					
	N	L	M	S	H	
BS	.000	.000	.250	.500	.250	1.500
CD	.000	.125	.000	.250	.625	.924
GI	.000	.375	.375	.125	.125	1.811
CYB	.000	.125	.000	.375	.500	1.031

Source: Authors

Table A_3. The Entropies of BS

Education								
	Probability Degrees					$\mathcal{E}$	Overall $\mathcal{E}$	$\mathcal{g}$
	N	L	M	S	H			
PhD	.000	.000	.000	.750	.250	.811	.906	.594
Master	.000	.000	.500	.000	.500	1.000		
Bachelor	.000	.000	.500	.500	.000	1.000		
Experience								
	Probability Degrees					$\mathcal{E}$	Overall $\mathcal{E}$	$\mathcal{g}$
	N	L	M	S	H			
0-15	.000	.000	.000	1.000	.000	.000	1.344	.156
16-20	.000	.000	.333	.333	.333	1.585		
21-	.000	.000	.250	.500	.250	1.500		
Salary								
	Probability Degrees					$\mathcal{E}$	Overall $\mathcal{E}$	$\mathcal{g}$
	N	L	M	S	H			
Less than 3000	.000	.000	.000	1.000	.000	.000	.844	.656
3000-4000	.000	.000	.667	.333	.000	.918		
More than 4000	.000	.000	.000	.500	.500	1.000		
Age								
	Probability Degrees					$\mathcal{E}$	Overall $\mathcal{E}$	$\mathcal{g}$
	N	L	M	S	H			
Ages below 45	.000	.000	.000	1.000	.000	.000	1.344	.156
Ages between 45 and 50	.000	.000	.250	.500	.250	1.500		
Ages above 50	.000	.000	.333	.333	.333	1.585		

Source: Authors

Table A$_4$. g for the Information About Experts of Each Criterion

Education												
	BS			CD			GI			CYB		
	ε	Overall ε	g	ε	Overall ε	g	ε	Overall ε	g	ε	Overall ε	g
PhD	.811			.000			1.500			1.500		
Master	1.000	.906	.594	1.000	.250	.674	1.000	1.000	.811	.500	1.125	-.094
Bachelor	1.000			.000			.000			1.000		
Experience												
	BS			CD			GI			CYB		
	ε	Overall ε	g	ε	Overall ε	g	ε	Overall ε	g	ε	Overall ε	g
0-15	.000			.000			.000			.000		
16-20	1.585	1.344	.156	.918	.844	.079	.918	.750	1.061	1.585	1.094	-.064
21-	1.500			1.000			.811			1.000		
Salary												
	BS			CD			GI			CYB		
	ε	Overall ε	g	ε	Overall ε	g	ε	Overall ε	g	ε	Overall ε	g
Less than 3000	.000			.000			.000			.000		
3000-4000	.918	.844	.656	.918	.750	.174	1.585	1.344	.467	.000	.750	.281
More than 4000	1.000			.811			1.500			1.500		
Age												
	BS			CD			GI			CYB		
	ε	Overall ε	g	ε	Overall ε	g	ε	Overall ε	g	ε	Overall ε	g
Ages below 45	.000			.000			.000			.000		
Ages between 45 and 50	1.500	1.344	.156	.811	.750	.174	.811	.750	1.061	1.500	1.094	-.064
Ages above 50	1.585			.918			.918			.918		

Source: Authors

Table A_5. The Linguistic Terms of Criteria Relations and Alternatives

Expert 5	BS	CD	GI	CYB
BS		H	H	H
CD	S		S	H
GI	S	H		H
CYB	H	S	H	
Expert 2	BS	CD	GI	CYB
BS		M	H	H
CD	M		S	H
GI	M	M		S
CYB	H	S	H	
Expert 4	BS	CD	GI	CYB
BS		H	H	H
CD	S		S	S
GI	S	H		S
CYB	H	S	H	
Expert 5	BS	CD	GI	CYB
MRK	S	H	H	H
STR	H	H	H	S
PTR	H	S	S	H
DECNT	H	H	H	H
SRV	H	H	S	S
Expert 2	BS	CD	GI	CYB
MRK	S	M	M	H
STR	S	S	S	S
PTR	S	S	H	S
DECNT	M	H	H	H
SRV	S	H	S	H
Expert 4	BS	CD	GI	CYB
MRK	S	S	S	S
STR	S	H	H	S
PTR	H	S	S	S
DECNT	S	S	H	H
SRV	S	H	S	S

Source: Authors

Table A_6. Rewards of Two Matrices Among the Experts

Expert 5-Expert 2	BS	CD	GI	CYB
BS	(.00, .00, .00)	(-.11, .08, .03)	(.00, .00, .00)	(.00, .00, .00)
CD	(-.06, .05, .02)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
GI	(-.06, .05, .02)	(-.11, .08, .03)	(.00, .00, .00)	(-.05, .03, .02)
CYB	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
Expert 5-Expert 4	BS	CD	GI	CYB
BS	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
CD	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(-.05, .03, .02)
GI	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(-.05, .03, .02)
CYB	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
Expert 5-Expert 2	BS	CD	GI	CYB
MRK	(.00, .00, .00)	(-.11, .08, .03)	(-.11, .08, .03)	(.00, .00, .00)
STR	(-.05, .03, .02)	(-.05, .03, .02)	(-.05, .03, .02)	(.00, .00, .00)
PTR	(-.05, .03, .02)	(.00, .00, .00)	(.05, -.03, -.02)	(-.05, .03, .02)
DECNT	(-.11, .08, .03)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
SRV	(-.05, .03, .02)	(.00, .00, .00)	(.00, .00, .00)	(.05, -.03, -.02)
Expert 5-Expert 4	BS	CD	GI	CYB
MRK	(.00, .00, .00)	(-.05, .03, .02)	(-.05, .03, .02)	(-.05, .03, .02)
STR	(-.05, .03, .02)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
PTR	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(-.05, .03, .02)
DECNT	(-.05, .03, .02)	(-.05, .03, .02)	(.00, .00, .00)	(.00, .00, .00)
SRV	(-.05, .03, .02)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)

Source: Authors

Table A_7. Penalties of Two Matrices Among the Experts

Expert 5-Expert 2	BS	CD	GI	CYB
BS	(.00, .00, .00)	(.14, -.10, -.04)	(.00, .00, .00)	(.00, .00, .00)
CD	(.08, -.06, -.02)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
GI	(.08, -.06, -.02)	(.14, -.10, -.04)	(.00, .00, .00)	(.06, -.04, -.02)
CYB	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
Expert 5-Expert 4	BS	CD	GI	CYB
BS	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
CD	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.06, -.04, -.02)
GI	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.06, -.04, -.02)
CYB	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
Expert 5-Expert 2	BS	CD	GI	CYB
MRK	(.00, .00, .00)	(.14, -.10, -.04)	(.14, -.10, -.04)	(.00, .00, .00)
STR	(.06, -.04, -.02)	(.06, -.04, -.02)	(.06, -.04, -.02)	(.00, .00, .00)
PTR	(.06, -.04, -.02)	(.00, .00, .00)	(-.06, .04, .02)	(.06, -.04, -.02)
DECNT	(.14, -.10, -.04)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
SRV	(.06, -.04, -.02)	(.00, .00, .00)	(.00, .00, .00)	(-.06, .04, .02)
Expert 5-Expert 4	BS	CD	GI	CYB
MRK	(.00, .00, .00)	(.06, -.04, -.02)	(.06, -.04, -.02)	(.06, -.04, -.02)
STR	(.06, -.04, -.02)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
PTR	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.06, -.04, -.02)
DECNT	(.06, -.04, -.02)	(.06, -.04, -.02)	(.00, .00, .00)	(.00, .00, .00)
SRV	(.06, -.04, -.02)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)

Source: Authors

Table A_8. The Updated Matrices

Expert 5-Expert 2	BS	CD	GI	CYB
BS	(.00, .00, .00)	(.93, .07, .01)	(.95, .05, .00)	(.95, .05, .00)
CD	(.79, .16, .05)	(.00, .00, .00)	(.80, .15, .05)	(.95, .05, .00)
GI	(.79, .16, .05)	(.93, .07, .01)	(.00, .00, .00)	(.94, .06, .00)
CYB	(.95, .05, .00)	(.80, .15, .05)	(.95, .05, .00)	(.00, .00, .00)
Expert 5-Expert 4	BS	CD	GI	CYB
BS	(.00, .00, .00)	(.95, .05, .00)	(.95, .05, .00)	(.95, .05, .00)
CD	(.80, .15, .05)	(.00, .00, .00)	(.80, .15, .05)	(.94, .06, .00)
GI	(.80, .15, .05)	(.95, .05, .00)	(.00, .00, .00)	(.94, .06, .00)
CYB	(.95, .05, .00)	(.80, .15, .05)	(.95, .05, .00)	(.00, .00, .00)
Expert 5-Expert 2	BS	CD	GI	CYB
MRK	(.80, .15, .05)	(.93, .07, .01)	(.93, .07, .01)	(.95, .05, .00)
STR	(.94, .06, .00)	(.94, .06, .00)	(.94, .06, .00)	(.80, .15, .05)
PTR	(.94, .06, .00)	(.80, .15, .05)	(.81, .14, .05)	(.94, .06, .00)
DECNT	(.93, .07, .01)	(.95, .05, .00)	(.95, .05, .00)	(.95, .05, .00)
SRV	(.94, .06, .00)	(.95, .05, .00)	(.80, .15, .05)	(.81, .14, .05)
Expert 5-Expert 4	BS	CD	GI	CYB
MRK	(.80, .15, .05)	(.94, .06, .00)	(.94, .06, .00)	(.94, .06, .00)
STR	(.94, .06, .00)	(.95, .05, .00)	(.95, .05, .00)	(.80, .15, .05)
PTR	(.95, .05, .00)	(.80, .15, .05)	(.80, .15, .05)	(.94, .06, .00)
DECNT	(.94, .06, .00)	(.94, .06, .00)	(.95, .05, .00)	(.95, .05, .00)
SRV	(.94, .06, .00)	(.95, .05, .00)	(.80, .15, .05)	(.80, .15, .05)

Source: Authors

Table A_9. The First Iteration's Absolute Difference for Matrices

Expert 5-Expert 2	BS	CD	GI	CYB
BS	(.000,.000,.000)	(.025,.018,.007)	(.000,.000,.000)	(.000,.000,.000)
CD	(.014,.011,.004)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
GI	(.014,.011,.004)	(.025,.018,.007)	(.000,.000,.000)	(.011,.007,.004)
CYB	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
Expert 5-Expert 4	BS	CD	GI	CYB
BS	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
CD	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.011,.007,.004)
GI	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.011,.007,.004)
CYB	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
Expert 5-Expert 2	BS	CD	GI	CYB
MRK	(.000,.000,.000)	(.025,.018,.007)	(.025,.018,.007)	(.000,.000,.000)
STR	(.011,.007,.004)	(.011,.007,.004)	(.011,.007,.004)	(.000,.000,.000)
PTR	(.011,.007,.004)	(.000,.000,.000)	(.011,.007,.004)	(.011,.007,.004)
DECNT	(.025,.018,.007)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
SRV	(.011,.007,.004)	(.000,.000,.000)	(.000,.000,.000)	(.011,.007,.004)
Expert 5-Expert 4	BS	CD	GI	CYB
MRK	(.000,.000,.000)	(.011,.007,.004)	(.011,.007,.004)	(.011,.007,.004)
STR	(.011,.007,.004)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)
PTR	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)	(.011,.007,.004)
DECNT	(.011,.007,.004)	(.011,.007,.004)	(.000,.000,.000)	(.000,.000,.000)
SRV	(.011,.007,.004)	(.000,.000,.000)	(.000,.000,.000)	(.000,.000,.000)

Source: Authors

Table A_{10}. The Balanced Evaluation Matrices

Expert 5	BS	CD	GI	CYB
BS	(.00, .00, .00)	(.95, .05, .00)	(.95, .05, .00)	(.95, .05, .00)
CD	(.80, .15, .05)	(.00, .00, .00)	(.80, .15, .05)	(.95, .05, .00)
GI	(.80, .15, .05)	(.95, .05, .00)	(.00, .00, .00)	(.95, .05, .00)
CYB	(.95, .05, .00)	(.80, .15, .05)	(.95, .05, .00)	(.00, .00, .00)
Expert 2	BS	CD	GI	CYB
BS	(.00, .00, .00)	(.86, .11, .03)	(.95, .05, .00)	(.95, .05, .00)
CD	(.75, .19, .06)	(.00, .00, .00)	(.80, .15, .05)	(.95, .05, .00)
GI	(.75, .19, .06)	(.86, .11, .03)	(.00, .00, .00)	(.91, .08, .01)
CYB	(.95, .05, .00)	(.80, .15, .05)	(.95, .05, .00)	(.00, .00, .00)
Expert 4	BS	CD	GI	CYB
BS	(.00, .00, .00)	(.95, .05, .00)	(.95, .05, .00)	(.95, .05, .00)
CD	(.80, .15, .05)	(.00, .00, .00)	(.80, .15, .05)	(.80, .15, .05)
GI	(.80, .15, .05)	(.95, .05, .00)	(.00, .00, .00)	(.80, .15, .05)
CYB	(.95, .05, .00)	(.80, .15, .05)	(.95, .05, .00)	(.00, .00, .00)
Expert 5	BS	CD	GI	CYB
MRK	(.80, .15, .05)	(.95, .05, .00)	(.95, .05, .00)	(.95, .05, .00)
STR	(.95, .05, .00)	(.95, .05, .00)	(.95, .05, .00)	(.80, .15, .05)
PTR	(.95, .05, .00)	(.80, .15, .05)	(.80, .15, .05)	(.95, .05, .00)
DECNT	(.95, .05, .00)	(.95, .05, .00)	(.95, .05, .00)	(.95, .05, .00)
SRV	(.95, .05, .00)	(.95, .05, .00)	(.80, .15, .05)	(.80, .15, .05)
Expert 2	BS	CD	GI	CYB
MRK	(.80, .15, .05)	(.86, .11, .03)	(.86, .11, .03)	(.95, .05, .00)
STR	(.91, .08, .01)	(.91, .08, .01)	(.91, .08, .01)	(.80, .15, .05)
PTR	(.91, .08, .01)	(.80, .15, .05)	(.84, .12, .04)	(.91, .08, .01)
DECNT	(.86, .11, .03)	(.95, .05, .00)	(.95, .05, .00)	(.95, .05, .00)
SRV	(.91, .08, .01)	(.95, .05, .00)	(.80, .15, .05)	(.84, .12, .04)
Expert 4	BS	CD	GI	CYB
MRK	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)
STR	(.80, .15, .05)	(.95, .05, .00)	(.95, .05, .00)	(.80, .15, .05)
PTR	(.95, .05, .00)	(.80, .15, .05)	(.80, .15, .05)	(.80, .15, .05)
DECNT	(.80, .15, .05)	(.80, .15, .05)	(.95, .05, .00)	(.95, .05, .00)
SRV	(.80, .15, .05)	(.95, .05, .00)	(.80, .15, .05)	(.80, .15, .05)

Source: Authors

Table A_{11}. The Averaged Numbers for Two Matrices

M_c	BS	CD	GI	CYB
BS	(.00, .00, .00)	(.92, .07, .01)	(.95, .05, .00)	(.95, .05, .00)
CD	(.78, .16, .05)	(.00, .00, .00)	(.80, .15, .05)	(.90, .08, .02)
GI	(.78, .16, .05)	(.92, .07, .01)	(.00, .00, .00)	(.89, .09, .02)
CYB	(.95, .05, .00)	(.80, .15, .05)	(.95, .05, .00)	(.00, .00, .00)
M_A	BS	CD	GI	CYB
MRK	(.80, .15, .05)	(.87, .10, .03)	(.87, .10, .03)	(.90, .08, .02)
STR	(.89, .09, .02)	(.94, .06, .00)	(.94, .06, .00)	(.80, .15, .05)
PTR	(.94, .06, .00)	(.80, .15, .05)	(.81, .14, .05)	(.89, .09, .02)
DECNT	(.87, .10, .03)	(.90, .08, .02)	(.95, .05, .00)	(.95, .05, .00)
SRV	(.89, .09, .02)	(.95, .05, .00)	(.80, .15, .05)	(.81, .14, .05)

Source: Authors

Table A_{12}. The Angles for M_C

	θ_{u1}	θ_{u2}	θ_{u3}	θ_{u4}
θ_{u1}		.126	.096	.113
θ_{u2}	.126		.094	.122
θ_{u3}	.096	.094		.170
θ_{u4}	.113	.122	.170	

Source: Authors

Table A_{13}. The Normalization for Linear

	BS	CD	GI	CYB
BS	0	.153	.200	.170
CD	.153	0	.205	.158
GI	.200	.205	0	.114
CYB	.170	.158	.114	0

Source: Authors

Table A_{14}. The Iterative State Results for Linear

	$A(0)$	$A(1)$	$f(A(1))$	$f(A(2))$	$f(A(3))$	$f(A(4))$	$f(A(5))$	$f(A(6))$	W
BS	1	.523	.628	.580	.575	.574	.574	.574	.2514
CD	1	.516	.626	.579	.574	.573	.573	.573	.2509
GI	1	.519	.627	.580	.574	.574	.574	.574	.2511
CYB	1	.442	.609	.569	.564	.563	.563	.563	.2466

Source: Authors

Table A_{15}. The B Matrix

	BS	CD	GI	CYB
MRK	(.20, .04, .01)	(.22, .03, .01)	(.22, .03, .01)	(.22, .02, .00)
STR	(.22, .02, .01)	(.24, .01, .00)	(.24, .01, .00)	(.20, .04, .01)
PTR	(.24, .01, .00)	(.20, .04, .01)	(.20, .04, .01)	(.22, .02, .01)
DECNT	(.22, .03, .01)	(.23, .02, .00)	(.24, .01, .00)	(.23, .01, .00)
SRV	(.22, .02, .01)	(.24, .01, .00)	(.20, .04, .01)	(.20, .03, .01)

Source: Authors

Table A_{16}. The Angles for B

	θ_{y1}	θ_{y2}	θ_{y3}	θ_{y4}	θ_{y5}
θ_{y1}		.110	.119	.061	.117
θ_{y2}	.110		.146	.103	.094
θ_{y3}	.119	.146		.122	.126
θ_{y4}	.061	.103	.122		.136
θ_{y5}	.117	.094	.126	.136	

Source: Authors

Table A_{17}. The F for Linear

	MRK	STR	PTR	DECNT	SRV
MRK		.098	.090	.176	.092
STR	.098		.074	.104	.114
PTR	.090	.074		.088	.085
DECNT	.176	.104	.088		.079
SRV	.092	.114	.085	.079	

Source: Authors

Table A_{18}. The Iterative Positions for Linear

	MRK $((V_1)(1))$	STR $((V_2)(1))$	PTR $((V_3)(1))$	DECNT $((V_4)(1))$	SRV $((V_5)(1))$	MRK $((P_1)(1))$	STR $((P_2)(1))$	PTR $((P_3)(1))$	DECNT $((P_4)(1))$	SRV $((P_5)(1))$	$((P_{gb})(1))$	$((P_{gb})(t))$ - $(P_{gb})(t\text{-}1)$
MRK		.116	.119	.002	.111	.00	.21	.21	.18	.20	.18	-
STR	.028		.053	.013	.004	.13	.00	.13	.12	.12	.11	-
PTR	.001	.023		.002	.007	.09	.10	.00	.09	.09	.09	-
DECNT	.009	.102	.126		.132	.18	.21	.21	.00	.21	.18	-
SRV	.030	.005	.044	.049		.12	.12	.13	.13	.00	.11	-
	MRK $((V_1)(2))$	STR $((V_2)(2))$	PTR $((V_3)(2))$	DECNT $((V_4)(2))$	SRV $((V_5)(2))$	MRK $((P_1)(2))$	STR $((P_2)(2))$	PTR $((P_3)(2))$	DECNT $((P_4)(2))$	SRV $((P_5)(2))$	$((P_{gb})(2))$	$((P_{gb})(t))$ - $(P_{gb})(t\text{-}1)$
MRK		.11	.13	.00	.13	.00	.20	.21	.18	.21	.18	.000
STR	.03		.07	.02	.00	.12	.00	.13	.12	.12	.12	.005
PTR	.00	.03		.01	.00	.09	.10	.00	.09	.09	.09	.003
DECNT	-.01	.12	.14		.13	.18	.20	.21	.00	.22	.18	.007
SRV	.04	.00	.04	.06		.12	.12	.13	.13	.00	.11	.000
	MRK $((V_1)(3))$	STR $((V_2)(3))$	PTR $((V_3)(3))$	DECNT $((V_4)(3))$	SRV $((V_5)(3))$	MRK $((P_1)(3))$	STR $((P_2)(3))$	PTR $((P_3)(3))$	DECNT $((P_4)(3))$	SRV $((P_5)(3))$	$((P_{gb})(3))$	$((P_{gb})(t))$ - $(P_{gb})(t\text{-}1)$
MRK		-.08	-.08	.01	-.08	.00	.20	.21	.18	.21	.21	.03
STR	-.02		-.04	-.01	-.01	.12	.00	.14	.12	.12	.13	.01
PTR	.00	-.02		.00	-.01	.09	.10	.00	.10	.09	.10	.01
DECNT	.00	-.07	-.09		-.11	.18	.22	.22	.00	.22	.22	.03
SRV	-.02	.00	-.03	-.03		.13	.12	.13	.13	.00	.13	.01
	MRK $((V_1)(4))$	STR $((V_2)(4))$	PTR $((V_3)(4))$	DECNT $((V_4)(4))$	SRV $((V_5)(4))$	MRK $((P_1)(4))$	STR $((P_2)(4))$	PTR $((P_3)(4))$	DECNT $((P_4)(4))$	SRV $((P_5)(4))$	$((P_{gb})(4))$	$((P_{gb})(t))$ - $(P_{gb})(t\text{-}1)$
MRK		-.13	-.15	.01	-.15	.00	.20	.21	.21	.21	.21	.001
STR	-.03		-.08	-.02	.00	.12	.00	.14	.13	.13	.14	.001
PTR	.00	-.03		-.01	-.01	.10	.10	.00	.10	.09	.10	.000
DECNT	.00	-.13	-.16		-.18	.20	.22	.22	.00	.22	.22	.000
SRV	-.04	.00	-.05	-.07		.13	.13	.13	.13	.00	.13	.000

Source: Authors

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