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Article

Multi-criteria decision-making for sound and vibration reduction platforms for financial and marketing optimization in energy

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Abstract: The integration of Artificial Intelligence (AI) in energy infrastructure has created a new class of specialized intermediaries for environmental control, yet their opaque decision-making poses regulatory challenges. This paper proposes a novel regulatory framework for specialized sound and vibration platform operators in the energy sector and introduces a multi-criteria decision-making (MCDM) methodology to support oversight. The methodology integrates expert neuro-behavioral data, captured via Facial Action Coding System (FACS), with a quantum picture fuzzy rough set extension and the DEMATEL (Decision-Making Trial and Evaluation Laboratory) method. The application is demonstrated through a case study of a 250 MW combined-cycle gas turbine power plant, where the goal is to select optimal noise and vibration control technologies. The analysis assesses five key technologies against compliance parameters: algorithmic transparency, data governance, system reliability, operational accountability, and consumer protection. The proposed Neuro-Quantum Picture Fuzzy Rough MCDM model achieved a forecast accuracy of 0.987 for system performance, substantially outperforming Long Short-Term Memory (LSTM (0.876)), Recurrent Neural Network (RNN (0.575)), and AutoRegressive Integrated Moving Average (ARIMA (0.551)). The primary contribution is to initiate professional dialogue on governing AI-driven energy intermediaries, balancing technological innovation with energy stability, security, and consumer welfare. The paper recommends a comprehensive regulatory framework for a new class of energy intermediaries for financial and marketing optimisation called specialised sound and vibration platform operators.

Keywords: AI regulation; energy technology; big data; algorithmic bias; explainable AI (XAI); multi-criteria decision-making (MCDM); quantum fuzzy sets; neuro-behavioral analysis

1. Introduction

The rapid integration of artificial intelligence (AI) into energy infrastructure has given rise to a new class of intermediaries: specialized sound and vibration platform operators. These entities leverage algorithmic decision-making and massive datasets to provide services that directly impact energy integrity, resource allocation, and operational safety. However, as these platforms assume greater responsibility in environmental governance, their “black box” nature poses unique regulatory challenges. Algorithmic errors, biases in training data, or opaque decision logic can lead to misguided resource allocation, misdirected maintenance efforts, or unjust outcomes for communities dependent on energy infrastructure.

This paper addresses the regulatory gap by proposing a comprehensive framework to license, oversee, and govern these platform operators. The framework rests on several indispensable pillars: a clear licensing regime ensuring operator competence and financial soundness; strict governance rules enforcing senior management accountability; unwavering commitment to explainability and fairness to combat opacity and bias; and robust consumer protection measures to build trust and provide recourse.

To support regulatory decision-making, this paper introduces a novel Neuro-Quantum Picture Fuzzy Rough MCDM model. This methodology serves two purposes within the regulatory context: first, it quantifies the relative importance of five regulatory compliance parameters derived from the proposed framework; second, it demonstrates how regulators can assess platform technologies through integration of objective technical data with expert judgment. The model’s application is illustrated through a representative case study evaluating noise reduction technologies at a power plant, demonstrating how regulatory oversight can be informed by systematic multi-criteria assessment

The paper outlines new regulatory framework for a specific type of energy platform that heavily utilizes Artificial Intelligence (AI) and Big Data. It defines what constitutes a specialised sound and vibration platform operator. A key principle is that the decisions made by AI (denying a loan) must be explainable to both the regulator and, to a certain extent, to the consumer. This is to combat the black box problem often associated with complex AI models.

The paper discusses potential requirements for obtaining a license to operate as such a platform, including criteria for ownership, capital adequacy, and IT infrastructure.

It creates paradigm shift with profound implications for energy sustainability. This paper proposes a pioneering regulatory framework specifically designed for a new class of intermediary: specialized sound and vibration platform operators in the energy sector. These platforms are not merely financial tools augmented with technology; they are emerging as critical infrastructure for managing the natural capital. They leverage algorithmic decision-making and massive datasets to provide services directly impacting energy integrity, resource allocation, and climate resilience.

As these platforms assume greater responsibility in environmental governance, their "black box" nature poses unique risks. Algorithmic errors, biases in training data, or opaque decision logic can lead to misguided conservation efforts, misallocated climate funds, or unjust outcomes for communities dependent on natural resources. Therefore, a key regulatory principle advanced here is that AI-driven energy decisions must be explainable—not only to regulators for oversight but, where possible, to affected stakeholders to foster trust and accountability.

It aims to stimulate professional dialogue on how to govern this powerful technological convergence at the intersection of Vibrations in Energy, artificial intelligence, and ecology. The ultimate goal is to establish a regulatory regime that fosters innovation while rigorously safeguarding energy stability, security, and intergenerational equity.

The energy challenges of the 21st century—climate change, biodiversity loss, land degradation, and water scarcity—are characterized by overwhelming complexity and interconnectedness. Traditional monitoring and decision-making frameworks are often inadequate due to data limitations, slow processing, and human cognitive constraints.

AI can analyze satellite imagery, acoustic sensors, and genomic data to track deforestation, monitor species populations in real-time, detect illegal fishing vessels, and identify early signs of ecosystem stress with unprecedented speed and scale.

Machine learning models can predict the outcomes of different intervention scenarios (habitat corridor design, species reintroduction, reforestation planning), helping to prioritize actions for maximum energy benefit and cost-effectiveness.

AI-driven platforms are essential for assessing the physical and transition risks of climate change for financial institutions. They can stress-test investment portfolios against climate scenarios, model the financial implications of nature-related dependencies, and power next-generation green insurance products.

However, this transformative power is coupled with significant novel risks that existing environmental and financial regulations are ill-equipped to handle:

If trained on non-representative or historically biased data, AI models could systematically undervalue ecosystems in marginalized regions or perpetuate inequalities in conservation funding and climate adaptation resources.

Unexplainable AI decisions regarding permit approvals, conservation priorities, or carbon credit verification undermine democratic accountability, scientific scrutiny, and public trust in environmental management.

The energy insights and financial flows governed by these platforms depend on the security and authenticity of vast environmental datasets. Cyber-attacks, data poisoning, or sensor manipulation could lead to catastrophic misdirection of conservation efforts or market manipulation.

There is a clear danger of a responsibility vacuum where neither technologists developing the algorithms nor the platform's management fully understands or accepts accountability for the systemic energy and social consequences of automated decisions.

This paper directly addresses this regulatory gap. It outlines a comprehensive framework to license, oversee, and govern these energy platform operators, ensuring their development aligns with the imperative of energy stability, fairness, and long-term sustainability. By mandating explainability, bias testing, robust governance, and strong consumer (and community) protections, the proposed rules aim to harness AI as a force for reliable, transparent, and equitable energy stewardship.

It defines what constitutes a specialised sound and vibration platform operator. These are envisioned as platforms that provide energy services (credit scoring, insurance, investment advice) primarily through automated systems based on AI algorithms and large datasets.

A significant focus is on the unique risks associated with AI, including: risk of errors, bias, or inaccuracies in AI models leading to incorrect energy decisions; ensuring the data used to train AI is representative, high-quality, and used ethically, preventing discrimination (bias) against certain groups of people; risks related to the reliability, security, and transparency of the AI systems.

The paper proposes requirements for how these platform operators should be managed, emphasizing the need for senior management and boards of directors to understand and be accountable for the AI systems they use.

A key principle is that the decisions made by AI (denying a loan) must be explainable to both the regulator and, to a certain extent, to the consumer. This is to combat the “black box” problem often associated with complex AI models.

The proposals aim to protect consumers from unfair or discriminatory practices, ensure the security of their personal data, and provide clear channels for dispute resolution. The document discusses potential requirements for obtaining a license to operate as such a platform, including criteria for ownership, capital adequacy, and IT infrastructure.

The main results and key takeaways can be summarized as follows. The paper recommends regulatory framework for a new class of energy intermediaries called specialised sound and vibration platform operators. The paper clearly defines what constitutes a specialised sound and vibration platform operator. These are entities whose core business involves providing energy services (like lending, insurance, or investment advice) primarily through automated systems driven by AI and large-scale data analysis.

A central proposal is to bring these platforms under official regulatory oversight. The introduction of capital adequacy standards to ensure the platform’s energy stability and ability to absorb losses.

A significant concrete result of this paper is the conclusion that a new dedicated federal law is required. The paper closes the gap in monitoring that is signaling that existing energy laws are insufficient to address the unique risks posed by sound and vibration eco platforms.

It moves from theoretical discussion to concrete proposals, aiming to create a regulated, safe, and fair environment for the development of these advanced energy technologies while managing the associated risks of bias, opacity, and consumer harm.

This paper is structured as: Section 2: “Literature review” presents the literature studying, while Section 3: “Methods” provides the steps of the proposed modelling.

Section 4: "Results" presents the results of modelling, Section 5: "Discussion" provides the discussion of findings, and Section 6: "Conclusion" concludes the paper.

2. Literature review

The advent of highly capable Large Language Models (LLMs) exemplifies the state-of-the-art in multimodal reasoning, processing text, code, images, and audio, which provides a robust foundation for agents operating in rich, real-world environments.

Concurrently, the need to evaluate these complex systems has led to innovative benchmarking methodologies.

A significant body of research focuses on the human-centric aspects of AI agents. A key finding is that designing agents with human-like traits—can significantly influence user acceptance. The researchers argue that human-like competencies (empathy, rapport-building) are crucial for effective human-agent conversation [1–3].

This dynamic directly impacts sensitive interactions like self-disclosure. It discovered that AI agents can actually elicit greater consumer self-disclosure than human agents, as they are perceived as less judgmental. However, the context matters; It showed that for delivering negative news, an AI agent is preferred, but for positive news, a human agent is more effective. The emotional design of agents is also critical. It demonstrated that AI agents expressing positive emotion can enhance customer satisfaction, but only when the problem is successfully resolved. They texted that AI agents are demonstrating transformative potential across industries. In marketing and sales, they act as AI coaches for sales agents, though It caution about potential pitfalls like over-standardization and offer solutions for effective implementation. It discusses the operational disruption and strategic evolution driven by generative AI agents in areas like algorithmic trading and risk assessment. In specialized professional domains, agents are even being tested as expert systems, such as for detecting antimicrobial resistance [4–6].

However, this rapid advancement brings significant challenges. It provide a comprehensive survey of security threats to AI agents, including adversarial attacks, data poisoning, and issues of operational integrity. To address these, researchers are exploring synergies with other technologies; It survey the integration of AI agents with blockchain to create secure, transparent, and scalable multi-agent collaboration frameworks. Frontline service challenges, such as user trust and the handling of complex queries, are also a key area of concern and opportunity [7–9].

Finally, the social and ethical dimensions of AI agents require ongoing scrutiny. Studies show that AI can perpetuate societal biases, such as gender stereotypes in recommendations, and fundamental questions about how humans intuitively perceive and interact with mindless agents remain a rich area for inquiry [10–12].

The literature reveals a field in rapid flux, driven by breakthroughs in foundational models and innovative agent frameworks. The trajectory is clear: AI is evolving from a passive tool into an active, collaborative partner. The core challenges no longer reside solely in improving model accuracy but in designing effective multi-agent systems, fostering positive and trustworthy human-agent interactions, and mitigating a new class of security and ethical risks. Future research must continue to be interdisciplinary, blending computer science with insights from marketing, psychology, ethics, and security to ensure that the development of AI agents is not only technologically sophisticated but also socially responsible and beneficial [13–15].

3. Methods

3.1. Proposed regulatory framework and compliance parameters

Based on the proposed regulatory framework for specialized sound and vibration platform operators, we identified five key compliance parameters for assessment. **Table 1** presents these parameters, their regulatory rationale, and proposed measurement bases.

Table 1. Regulatory compliance parameters for sound and vibration platform operators.

Parameter	Description	Regulatory rationale	Measurement basis
P1: Algorithmic Transparency	Explainability of AI decisions to regulators and consumers	Addresses “black box” problem; enables oversight and accountability	XAI score (0–100%) based on model interpretability techniques
P2: Data Governance	Quality, representativeness, and ethical use of training data	Prevents algorithmic bias and ensures fairness	Data quality audit score (0–100%)
P3: System Reliability	Security, uptime, and fault tolerance of AI systems	Ensures continuous energy service delivery	Mean time between failures (MTBF); redundancy metrics
P4: Operational Accountability	Senior management understanding and ownership of AI systems	Ensures ethical governance and responsibility attribution	Governance maturity assessment (0–100%)
P5: Consumer Protection	Dispute resolution channels, data privacy, and redress mechanisms	Builds trust and provides recourse for affected stakeholders	Consumer satisfaction score; complaint resolution rate

3.2. Power plant noise and vibration control

To ground the methodology in a practical application, this study evaluated noise and vibration reduction strategies for a 250 MW combined-cycle gas turbine power plant located in the Samara region of Russia. The primary sources of excessive noise and vibration were the Siemens SGT5-4000F gas turbine, the SST5-5000 steam turbine, and associated generators. Baseline measurements indicated noise levels of 105 dB(A) at 1 m from the turbine housing and vibration amplitudes of 12.5 mm/s^2 at the turbine foundation, exceeding both plant safety guidelines (target: <90 dB(A) occupational exposure) and regional environmental regulations (target: <85 dB(A) at 1 km from plant boundary).

Five competing technology platforms were assessed:

- Technology A (Passive Systems): Standard acoustic enclosures (100 mm mineral wool panels) and viscoelastic damping patches applied to turbine casings.
- Technology B (Active Noise Control): An array of 24 secondary loudspeakers and error microphones implementing a filtered-x least mean squares (FxLMS) algorithm to generate destructive interference for frequencies below 500 Hz.
- Technology C (Tuned Mass Dampers): Four tuned mass dampers (each 500 kg)

installed on turbine foundation pedestals, tuned to the dominant 25 Hz vibration mode.

- Technology D (Metamaterial Barriers): Locally resonant sonic crystal metamaterial panels (2 m × 2 m × 0.3 m) with embedded silicone rubber-coated lead cores, designed for low-frequency (100–400 Hz) sound absorption.
- Technology E (Integrated System): A combined system integrating the Active Vibration Control (AVC) algorithm (Technology B) with the Metamaterial Barriers (Technology D).

The regulatory objective was to determine which technology provides the optimal balance of noise/vibration reduction, energy efficiency gains, and implementation cost, while also satisfying the five regulatory compliance parameters (P1–P5). This case study served as a testbed for the proposed MCDM methodology, demonstrating how regulators could systematically evaluate competing technologies.

Three energy regulatory experts participated in the evaluation. Expert 1 was a senior mechanical engineer with 20 years of experience in power plant operations. Expert 2 was an environmental compliance officer with 15 years of experience in industrial noise regulation. Expert 3 was an AI systems auditor with 10 years of experience evaluating algorithmic systems in critical infrastructure. All experts provided informed consent, and the study protocol was approved by the institutional review board of the Financial University under the Government of the Russian Federation.

Each expert independently assessed the interrelationships between the five regulatory parameters using a structured pairwise comparison protocol. For each pair of parameters (e.g., P1 and P2), the expert was asked: "To what extent does parameter *i* influence parameter *j* in the context of regulating a sound and vibration platform operator?" Responses were given on a five-point linguistic scale (No Influence, Low Influence, Moderate Influence, High Influence, Very High Influence).

During this process, facial expressions were recorded using a high-resolution webcam (Logitech Brio 4K, 30 fps) and analyzed using Noldus FaceReader 8.0 software.

3.3. Facial action coding system (FACS) data collection

The Facial Action Coding System (FACS) was employed to capture subconscious expert judgments during parameter evaluation (Ekman and Friesen, 1978). FACS provides objective, anatomically-based measurement of facial expressions through identification of Action Units (AUs)—contractions of individual facial muscles or combinations thereof.

We focused on three key affective states relevant to decision confidence: concentration (AU 4 + 7, brow lowerer + lid tightener), uncertainty (AU 1 + 2 + 4, inner brow raiser + outer brow raiser + brow lowerer), and certainty/agreement (AU 6 + 12, cheek raiser + lip corner puller). **Table 2** presents the mapping of observed AU combinations to linguistic influence scales and their corresponding fuzzy membership parameters.

Table 2. Mapping of action units to linguistic influence scales and fuzzy parameters.

Action unit combination	Affective state	Linguistic influence	Fuzzy membership parameters
AU 4 + 7	Concentration	Moderate influence	μ = 0.6, n = 0.3, v = 0.1
AU 1 + 2 + 4	Uncertainty	Low influence	μ = 0.3, n = 0.4, v = 0.3
AU 6 + 12	Certainty/Agreement	High influence	μ = 0.8, n = 0.1, v = 0.1

Note: μ = membership degree; n = non-membership degree; v = hesitation degree. Refusal degree (h) was set to 0 for all observations.

The use of three experts represents a pilot-scale validation. While sufficient for methodological demonstration, this sample size limits statistical generalizability. Future regulatory implementation would require larger expert panels (n ≥ 10) and potentially automated FACS analysis across multiple sessions to ensure robustness. The current results should therefore be interpreted as illustrative of the methodology's potential rather than definitive regulatory weightings.

3.4. Quantum picture fuzzy rough set (QPFRS) framework

The QPFRS framework extends traditional fuzzy sets by incorporating four dimensions: membership (μ), non-membership (n), hesitation (v), and refusal (h), with quantum phase angles (α, γ, β, T) representing uncertainty in expert judgment [3]. In the context of the power plant case study, these quantum phase angles allow the model to mathematically capture the irreducible uncertainty an expert might have when predicting the long-term performance of a novel technology like Metamaterial Barriers (Technology D) compared to a well-understood one like passive enclosures (Technology A).

For each regulatory parameter, membership functions were defined using triangular fuzzy numbers based on the linguistic scale mapping:

$$\mu_{ij}(x) = max\left(0, 1 - \frac{\mid x - c_{ij} \mid}{d_{ij}}\right) \tag{1}$$

where c_{ij} is the modal value for parameter *i* judged by expert *j*, d_{ij} represents the spread parameter, set to 0.2 based on pilot calibration studies.

Non-membership and hesitation were derived as:

$$n_{ij}(x) = \frac{1 - \mu_{ij}(x)}{2}, v_{ij}(x) = 1 - \mu_{ij}(x) - n_{ij}(x) \tag{2}$$

The parameter λ controls the amplification of fuzzy set operations, λ was set to 2 based on three considerations: (a) λ = 2 provides optimal separation between membership classes while preserving ordering relationships; (b) λ values of 1.5–2.5 produced stable rankings in sensitivity analysis; (c) prior applications of quantum fuzzy sets in energy contexts employed λ = 2.

The lower and upper approximations for each QPFRS dimension were calculated as:

$$L\underline{i}m\left(C_{i\mu_A}\right) = \frac{1}{N_{L\mu_A}} \sum\nolimits_{i=1}^{N_{L\mu_A}} Y \in A\underline{p}r\left(C_{i\mu_A}\right) \tag{3}$$

$$L\bar{i}m\left(C_{i\mu_A}\right) = \frac{1}{N_{U\mu_A}} \sum\nolimits_{i=1}^{N_{U\mu_A}} Y \in A\bar{p}r\left(C_{i\mu_A}\right) \tag{4}$$

where $C_{i\mu_A}$ is the lower approximation of the membership value for parameter *i* derived from raw FACS data, are the numbers of elements in the lower and upper approximation sets, and analogous equations were applied for non-membership, hesitation, and refusal dimensions.

This is the most novel and complex part of the methodology, designed to weigh the importance of the five parameters (P1–P5) and understand their causal relationships based on expert judgment [16–19].

- **Step 1: Neuro-decision-making data collection**
  Tool: The Facial Action Coding System (FACS) was used to capture the subconscious judgments of experts [20–22].
  Process: Three energy experts were observed as they evaluated the interrelationships between the parameters. Their facial expressions (contempt, surprise, happiness) were recorded and translated into specific Action Unit (AU) combinations (AU 7 + 10 for "contempt").
- **Step 2: Converting emotions to fuzzy sets**
  These AUs were mapped to linguistic scales and then converted into a novel mathematical representation called Quantum Picture Fuzzy Rough Sets (QPFRS) [23–25].
- **Step 3: Integration with DEMATEL**
  Tool: The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was used.
  Process: The QPFRS values from the experts were aggregated and used to form a direct relation matrix. This matrix was then processed through the DEMATEL steps:
  Defuzzification: Converting the complex QPFRS numbers into crisp values.
  Normalization: Creating a normalized relation matrix.
  Total Relation Matrix: Calculating the total influence each parameter has on the others [26,27].
  Mapping Cause and Effect: By summing the rows (D) and columns (E) of the total relation matrix, the method identifies:
  Prominence (D + E): The overall importance (weight) of each parameter.
  Relation (D − E): Whether a parameter is a cause (positive value) or an effect (negative value) within the system [28–30].

In quantum mechanics, we can find AI-agents are as follows:

$$Q\left(|u>\ \right) = \varphi e^{j\theta} \tag{5}$$

$$|C>\ = \{|u_1>\ , |u_2>\ , \ldots, |u_n>\}\tag{6}$$

$$\sum\nolimits_{|u>\subseteq|C>} |Q(|u>)\ | = 1 \tag{7}$$

$$A \subseteq B \text{ if } \mu_A(x) \leq \mu_B(x) \text{ and } n_A(x) \leq n_B(x) \text{ and } v_A(x) \geq v_B(x), \forall x \in X \tag{8}$$

$$A = B \text{ if } A \subseteq B \text{ and } B \subseteq A \tag{9}$$

$$A \cup B = \{(x,\ max\left(\mu_A(x), \mu_B(x)\right), min\left(n_A(x), n_B(x)\right), min\left(v_A(x), v_B(x)\right))\,|x\ \in X\} \tag{10}$$

$$A \cap B = \{(x,\ min\left(\mu_A(x), \mu_B(x)\right), min\left(n_A(x), n_B(x)\right), max\left(v_A(x), v_B(x)\right))\,|x\ \in X\} \tag{11}$$

$$coA = \overline{A} = \{(x, v_A(x), n_A(x), \mu_A(x))\,|x\ \in X\} \tag{12}$$

However, the lower $(\underline{Lim}\,(C_i))$, upper $(\overline{Lim}\,(C_i))$ limits and rough number $(RN\,(C_i))$ of C_i are given as:

$$\underline{Lim}\,(C_i) = \sqrt[N_L]{\prod_{i=1}^{N_L} Y \in \underline{Apr}\,(C_i)} \tag{13}$$

$$\overline{Lim}\,(C_i) = \sqrt[N_U]{\prod_{i=1}^{N_U} Y \in \overline{Apr}\,(C_i)} \tag{14}$$

$$RN\,(C_i) = \lceil \underline{Lim}\,(C_i)\ \ ,\ \ \overline{Lim}\,(C_i) \rfloor \tag{15}$$

where N_L and N_U are the numbers of points.

$$\underline{Lim}\,(C_{i\mu_A}) = \frac{1}{N_{L\mu_A}} \sum_{i=1}^{N_{L\mu_A}} Y \in \underline{Apr}\,(C_{i\mu_A}) \tag{16}$$

$$\underline{Lim}\,(C_{in_A}) = \frac{1}{N_{Ln_A}} \sum_{i=1}^{N_{Ln_A}} Y \in \underline{Apr}\,(C_{in_A}) \tag{17}$$

$$\underline{Lim}\,(C_{iv_A}) = \frac{1}{N_{Lv_A}} \sum_{i=1}^{N_{Lv_A}} Y \in \underline{Apr}\,(C_{iv_A}) \tag{18}$$

$$\underline{Lim}\,(C_{ih_A}) = \frac{1}{N_{L\pi_A}} \sum_{i=1}^{N_{L\pi_A}} Y \in \underline{Apr}\,(C_{ih_A}) \tag{19}$$

$$\overline{Lim}\,(C_{i\mu_A}) = \frac{1}{N_{U\mu_A}} \sum_{i=1}^{N_{U\mu_A}} Y \in \overline{Apr}\,(C_{i\mu_A}) \tag{20}$$

$$\overline{Lim}\,(C_{in_A}) = \frac{1}{N_{Un_A}} \sum_{i=1}^{N_{Un_A}} Y \in \overline{Apr}\,(C_{in_A}) \tag{21}$$

$$\overline{Lim}\,(C_{iv_A}) = \frac{1}{N_{Uv_A}} \sum_{i=1}^{N_{Uv_A}} Y \in \overline{Apr}\,(C_{iv_A}) \tag{22}$$

$$\overline{Lim}\,(C_{ih_A}) = \frac{1}{N_{U\pi_A}} \sum_{i=1}^{N_{U\pi_A}} Y \in \overline{Apr}\,(C_{ih_A}) \tag{23}$$

Where $N_{L\mu_A}$ N_{Ln_A}, N_{Lv_A}, N_{Lh_A}, and $\underline{Apr}\,(C_{i\mu_A})$ are the numbers of elements in $\underline{Apr}\,(C_{in_A})$, $\underline{Apr}\,(C_{iv_A})$, $\underline{Apr}\,(C_{ih_A})$, and $N_{U\mu_A}$, respectively, and where N_{Un_A}, N_{Uv_A}, N_{Uh_A}, and are defined for $\overline{Apr}\,(C_{i\mu_A})$, $\overline{Apr}\,(C_{in_A})$, $\overline{Apr}\,(C_{iv_A})$, and $\overline{Apr}\,(C_{ih_A})$, respectively.

$$\underline{Apr}\,(C_{i\mu_A}) = \cup\left\{Y \in X/\widetilde{R}(Y) \le C_{i\mu_A}\right\} \tag{24}$$

$$\underline{Apr}\,(C_{in_A}) = \cup\left\{Y \in X/\widetilde{R}(Y) \le C_{in_A}\right\} \tag{25}$$

$$\underline{Apr}\,(C_{iv_A}) = \cup\left\{Y \in X/\widetilde{R}(Y) \le C_{iv_A}\right\} \tag{26}$$

$$\underline{Apr}\,(C_{ih_A}) = \cup\left\{Y \in X/\widetilde{R}(Y) \le C_{ih_A}\right\} \tag{27}$$

$$\overline{Apr}\left(C_{i\mu_A}\right) = \cup\left\{Y \in X/\widetilde{R}(Y) \leq C_{i\mu_A}\right\} \tag{28}$$

$$\overline{Apr}\left(C_{in_A}\right) = \cup\left\{Y \in X/\widetilde{R}(Y) \leq C_{in_A}\right\} \tag{29}$$

$$\overline{Apr}\left(C_{iv_A}\right) = \cup\left\{Y \in X/\widetilde{R}(Y) \leq C_{iv_A}\right\} \tag{30}$$

$$\overline{Apr}\left(C_{ih_A}\right) = \cup\left\{Y \in X/\widetilde{R}(Y) \leq C_{ih_A}\right\} \tag{31}$$

where $\widetilde{C_i} = (C_{i\mu_A}, C_{in_A}, C_{iv_A}, C_{ih_A})$ and where $\widetilde{R}$ is the range of $\left\{\widetilde{C_1}, \widetilde{C_2}, \ldots, \widetilde{C_n}\right\}$. $C_{i\mu_A}, C_{in_A}, C_{iv_A}, C_{ih_A}$.

X_1 and X_2 are two metaverses, and $\widetilde{A}_c$ and $\widetilde{B}_c$, respectively, are represented by

$$\begin{array}{c}\left(\begin{array}{c}\left\lceil \underline{Lim}\left(C_{\mu_{\widetilde{A}}}\right),\ \overline{Lim}\left(C_{\mu_{\widetilde{A}}}\right)\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{\alpha}_{\widetilde{A}}}{2\pi}\right),\left(\frac{\overline{\alpha}_{\widetilde{A}}}{2\pi}\right)\right\rfloor},\ \left\lceil \underline{Lim}\left(C_{n_{\widetilde{A}}}\right),\ \overline{Lim}\left(C_{n_{\widetilde{A}}}\right)\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{\gamma}_{\widetilde{A}}}{2\pi}\right),\left(\frac{\overline{\gamma}_{\widetilde{A}}}{2\pi}\right)\right\rfloor},\\ \left\lceil \underline{Lim}\left(C_{v_{\widetilde{A}}}\right),\ \overline{Lim}\left(C_{v_{\widetilde{A}}}\right)\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{\beta}_{\widetilde{A}}}{2\pi}\right),\left(\frac{\overline{\beta}_{\widetilde{A}}}{2\pi}\right)\right\rfloor},\ \left\lceil \underline{Lim}\left(C_{h_{\widetilde{A}}}\right),\ \overline{Lim}\left(C_{h_{\widetilde{A}}}\right)\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{T}_{\widetilde{A}}}{2\pi}\right),\left(\frac{\overline{T}_{\widetilde{A}}}{2\pi}\right)\right\rfloor}\end{array}\right)\\ \left(\begin{array}{c}\left\lceil \underline{Lim}\left(C_{\mu_{\widetilde{B}}}\right),\ \overline{Lim}\left(C_{\mu_{\widetilde{B}}}\right)\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{\alpha}_{\widetilde{B}}}{2\pi}\right),\left(\frac{\overline{\alpha}_{\widetilde{B}}}{2\pi}\right)\right\rfloor},\ \left\lceil \underline{Lim}\left(C_{n_{\widetilde{B}}}\right),\ \overline{Lim}\left(C_{n_{\widetilde{B}}}\right)\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{\gamma}_{\widetilde{B}}}{2\pi}\right),\left(\frac{\overline{\gamma}_{\widetilde{B}}}{2\pi}\right)\right\rfloor},\\ \left\lceil \underline{Lim}\left(C_{v_{\widetilde{B}}}\right),\ \overline{Lim}\left(C_{v_{\widetilde{B}}}\right)\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{\beta}_{\widetilde{B}}}{2\pi}\right),\left(\frac{\overline{\beta}_{\widetilde{B}}}{2\pi}\right)\right\rfloor},\ \left\lceil \underline{Lim}\left(C_{h_{\widetilde{B}}}\right),\ \overline{Lim}\left(C_{h_{\widetilde{B}}}\right)\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{T}_{\widetilde{B}}}{2\pi}\right),\left(\frac{\overline{T}_{\widetilde{B}}}{2\pi}\right)\right\rfloor}\end{array}\right)\end{array} \tag{32}$$

They are quantum picture fuzzy rough sets derived from the metaverses of discourse X_1 and X_2.

$$\lambda * \widetilde{A}_c = \left\{\begin{array}{c}\left\lceil \underline{Lim}\left(C_{\mu_{\widetilde{A}}}\right)\lambda,\ \overline{Lim}\left(C_{\mu_{\widetilde{A}}}\right)\lambda\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{\alpha}_{\widetilde{A}}}{2\pi}\right)\lambda,\left(\frac{\overline{\alpha}_{\widetilde{A}}}{2\pi}\right)\lambda\right\rfloor},\ \left\lceil \underline{Lim}\left(C_{n_{\widetilde{A}}}\right)\lambda,\ \overline{Lim}\left(C_{n_{\widetilde{A}}}\right)\lambda\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{\gamma}_{\widetilde{A}}}{2\pi}\right)\lambda,\left(\frac{\overline{\gamma}_{\widetilde{A}}}{2\pi}\right)\lambda\right\rfloor},\\ \left\lceil \underline{Lim}\left(C_{v_{\widetilde{A}}}\right)\lambda,\ \overline{Lim}\left(C_{v_{\widetilde{A}}}\right)\lambda\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{\beta}_{\widetilde{A}}}{2\pi}\right)\lambda,\left(\frac{\overline{\beta}_{\widetilde{A}}}{2\pi}\right)\lambda\right\rfloor},\ \left\lceil \underline{Lim}\left(C_{h_{\widetilde{A}}}\right)\lambda,\ \overline{Lim}\left(C_{h_{\widetilde{A}}}\right)\lambda\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{T}_{\widetilde{A}}}{2\pi}\right)\lambda,\left(\frac{\overline{T}_{\widetilde{A}}}{2\pi}\right)\lambda\right\rfloor}\end{array}\right\}, \quad \lambda > 0 \tag{33}$$

$$\widetilde{A}_c^{\lambda} = \left\{\begin{array}{c}\left\lceil \underline{Lim}\left(C_{\mu_{\widetilde{A}}}\right)^{\lambda},\ \overline{Lim}\left(C_{\mu_{\widetilde{A}}}\right)^{\lambda}\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{\alpha}_{\widetilde{A}}}{2\pi}\right)^{\lambda},\left(\frac{\overline{\alpha}_{\widetilde{A}}}{2\pi}\right)^{\lambda}\right\rfloor},\ \left\lceil \underline{Lim}\left(C_{n_{\widetilde{A}}}\right)^{\lambda},\ \overline{Lim}\left(C_{n_{\widetilde{A}}}\right)^{\lambda}\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{\gamma}_{\widetilde{A}}}{2\pi}\right)^{\lambda},\left(\frac{\overline{\gamma}_{\widetilde{A}}}{2\pi}\right)^{\lambda}\right\rfloor},\\ \left\lceil \underline{Lim}\left(C_{v_{\widetilde{A}}}\right)^{\lambda},\ \overline{Lim}\left(C_{v_{\widetilde{A}}}\right)^{\lambda}\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{\beta}_{\widetilde{A}}}{2\pi}\right)^{\lambda},\left(\frac{\overline{\beta}_{\widetilde{A}}}{2\pi}\right)^{\lambda}\right\rfloor},\ \left\lceil \underline{Lim}\left(C_{h_{\widetilde{A}}}\right)^{\lambda},\ \overline{Lim}\left(C_{h_{\widetilde{A}}}\right)^{\lambda}\right\rfloor e^{j2\pi\cdot\left\lceil\left(\frac{\underline{T}_{\widetilde{A}}}{2\pi}\right)^{\lambda},\left(\frac{\overline{T}_{\widetilde{A}}}{2\pi}\right)^{\lambda}\right\rfloor},\end{array}\right\}, \quad \lambda > 0 \tag{34}$$

$$\widetilde{A}_c \cup \widetilde{B}_c = \left\{\begin{array}{c}\left\lceil min\left(\underline{Lim}\left(C_{\mu_{\widetilde{A}}}\right)e^{j2\pi\cdot\left(\frac{\underline{\alpha}_{\widetilde{A}}}{2\pi}\right)}, \underline{Lim}\left(C_{\mu_{\widetilde{B}}}\right)e^{j2\pi\cdot\left(\frac{\underline{\alpha}_{\widetilde{B}}}{2\pi}\right)}\right), max\left(\overline{Lim}\left(C_{\mu_{\widetilde{A}}}\right)e^{j2\pi\cdot\left(\frac{\overline{\alpha}_{\widetilde{A}}}{2\pi}\right)}, \overline{Lim}\left(C_{\mu_{\widetilde{B}}}\right)e^{j2\pi\cdot\left(\frac{\overline{\alpha}_{\widetilde{B}}}{2\pi}\right)}\right)\right\rfloor,\\ \left\lceil min\left(\underline{Lim}\left(C_{n_{\widetilde{A}}}\right)e^{j2\pi\cdot\left(\frac{\underline{\gamma}_{\widetilde{A}}}{2\pi}\right)}, \underline{Lim}\left(C_{n_{\widetilde{B}}}\right)e^{j2\pi\cdot\left(\frac{\underline{\gamma}_{\widetilde{B}}}{2\pi}\right)}\right), max\left(\overline{Lim}\left(C_{n_{\widetilde{A}}}\right)e^{j2\pi\cdot\left(\frac{\overline{\gamma}_{\widetilde{A}}}{2\pi}\right)}, \overline{Lim}\left(C_{n_{\widetilde{B}}}\right)e^{j2\pi\cdot\left(\frac{\overline{\gamma}_{\widetilde{B}}}{2\pi}\right)}\right)\right\rfloor,\\ \left\lceil min\left(\underline{Lim}\left(C_{v_{\widetilde{A}}}\right)e^{j2\pi\cdot\left(\frac{\underline{\beta}_{\widetilde{A}}}{2\pi}\right)}, \underline{Lim}\left(C_{v_{\widetilde{B}}}\right)e^{j2\pi\cdot\left(\frac{\underline{\beta}_{\widetilde{B}}}{2\pi}\right)}\right), max\left(\overline{Lim}\left(C_{v_{\widetilde{A}}}\right)e^{j2\pi\cdot\left(\frac{\overline{\beta}_{\widetilde{A}}}{2\pi}\right)}, \overline{Lim}\left(C_{v_{\widetilde{B}}}\right)e^{j2\pi\cdot\left(\frac{\overline{\beta}_{\widetilde{B}}}{2\pi}\right)}\right)\right\rfloor,\\ \left\lceil min\left(\underline{Lim}\left(C_{h_{\widetilde{A}}}\right)e^{j2\pi\cdot\left(\frac{\underline{T}_{\widetilde{A}}}{2\pi}\right)}, \underline{Lim}\left(C_{h_{\widetilde{B}}}\right)e^{j2\pi\cdot\left(\frac{\underline{T}_{\widetilde{B}}}{2\pi}\right)}\right), max\left(\overline{Lim}\left(C_{h_{\widetilde{A}}}\right)e^{j2\pi\cdot\left(\frac{\overline{T}_{\widetilde{A}}}{2\pi}\right)}, \overline{Lim}\left(C_{h_{\widetilde{B}}}\right)e^{j2\pi\cdot\left(\frac{\overline{T}_{\widetilde{B}}}{2\pi}\right)}\right)\right\rfloor\end{array}\right\} \tag{35}$$

$$\widetilde{A}_c \cap \widetilde{B}_c =$$
$$\left\{ \begin{array}{l} \left[max\left(\underline{Lim}\left(C_{\mu_{\widetilde{A}}}\right) e^{j2\pi\cdot\left(\frac{\alpha_{\widetilde{A}}}{2\pi}\right)}, \underline{Lim}\left(C_{\mu_{\widetilde{B}}}\right) e^{j2\pi\cdot\left(\frac{\alpha_{\widetilde{B}}}{2\pi}\right)}\right), min\left(\overline{Lim}\left(C_{\mu_{\widetilde{A}}}\right) e^{j2\pi\cdot\left(\frac{\overline{\alpha}_{\widetilde{A}}}{2\pi}\right)}, \overline{Lim}\left(C_{\mu_{\widetilde{B}}}\right) e^{j2\pi\cdot\left(\frac{\overline{\alpha}_{\widetilde{B}}}{2\pi}\right)}\right)\right], \\ \left[max\left(\underline{Lim}\left(C_{n_{\widetilde{A}}}\right) e^{j2\pi\cdot\left(\frac{\gamma_{\widetilde{A}}}{2\pi}\right)}, \underline{Lim}\left(C_{n_{\widetilde{B}}}\right) e^{j2\pi\cdot\left(\frac{\gamma_{\widetilde{B}}}{2\pi}\right)}\right), min\left(\overline{Lim}\left(C_{n_{\widetilde{A}}}\right) e^{j2\pi\cdot\left(\frac{\overline{\gamma}_{\widetilde{A}}}{2\pi}\right)}, \overline{Lim}\left(C_{n_{\widetilde{B}}}\right) e^{j2\pi\cdot\left(\frac{\overline{\gamma}_{\widetilde{B}}}{2\pi}\right)}\right)\right], \\ \left[max\left(\underline{Lim}\left(C_{v_{\widetilde{A}}}\right) e^{j2\pi\cdot\left(\frac{\beta_{\widetilde{A}}}{2\pi}\right)}, \underline{Lim}\left(C_{v_{\widetilde{B}}}\right) e^{j2\pi\cdot\left(\frac{\beta_{\widetilde{B}}}{2\pi}\right)}\right), min\left(\overline{Lim}\left(C_{v_{\widetilde{A}}}\right) e^{j2\pi\cdot\left(\frac{\overline{\beta}_{\widetilde{A}}}{2\pi}\right)}, \overline{Lim}\left(C_{v_{\widetilde{B}}}\right) e^{j2\pi\cdot\left(\frac{\overline{\beta}_{\widetilde{B}}}{2\pi}\right)}\right)\right], \\ \left[max\left(\underline{Lim}\left(C_{h_{\widetilde{A}}}\right) e^{j2\pi\cdot\left(\frac{T_{\widetilde{A}}}{2\pi}\right)}, \underline{Lim}\left(C_{h_{\widetilde{B}}}\right) e^{j2\pi\cdot\left(\frac{T_{\widetilde{B}}}{2\pi}\right)}\right), min\left(\overline{Lim}\left(C_{h_{\widetilde{A}}}\right) e^{j2\pi\cdot\left(\frac{\overline{T}_{\widetilde{A}}}{2\pi}\right)}, \overline{Lim}\left(C_{h_{\widetilde{B}}}\right) e^{j2\pi\cdot\left(\frac{\overline{T}_{\widetilde{B}}}{2\pi}\right)}\right)\right] \end{array} \right\} \tag{36}$$

$$C_k = \begin{bmatrix} 0 & C_{12} & \cdots & \cdots & C_{1n} \\ C_{21} & 0 & \cdots & \cdots & C_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ C_{n1} & C_{n2} & \cdots & \cdots & 0 \end{bmatrix} \tag{37}$$

where C defines the quantum picture fuzzy metaverse,

$$C_{ij} =$$
$$\left(\begin{array}{c} \left\lceil \underline{Lim}\left(C_{\mu_{ij}}\right) , \overline{Lim}\left(C_{\mu_{ij}}\right) \right\rfloor e^{j2\pi\cdot\left\lceil \left(\frac{\alpha_{ij}}{2\pi}\right),\left(\frac{\overline{\alpha}_{ij}}{2\pi}\right)\right\rfloor} , \left\lceil \underline{Lim}\left(C_{n_{ij}}\right) , \overline{Lim}\left(C_{n_{ij}}\right) \right\rfloor e^{j2\pi\cdot\left\lceil \left(\frac{\gamma_{ij}}{2\pi}\right),\left(\frac{\overline{\gamma}_{ij}}{2\pi}\right)\right\rfloor} , \\ \left\lceil \underline{Lim}\left(C_{v_{ij}}\right) , \overline{Lim}\left(C_{v_{ij}}\right) \right\rfloor e^{j2\pi\cdot\left\lceil \left(\frac{\beta_{ij}}{2\pi}\right),\left(\frac{\overline{\beta}_{ij}}{2\pi}\right)\right\rfloor} , \left\lceil \underline{Lim}\left(C_{h_{ij}}\right) , \overline{Lim}\left(C_{h_{ij}}\right) \right\rfloor e^{j2\pi\cdot\left\lceil \left(\frac{T_{ij}}{2\pi}\right),\left(\frac{\overline{T}_{ij}}{2\pi}\right)\right\rfloor} \end{array} \right), \tag{38}$$

and k is the range of decision makers:

$$C = \left(\begin{array}{c} \left\lceil min_{i=1}^{k}\left(\underline{Lim}\left(C_{\mu_{ij}}\right)\right) , max_{i=1}^{k}\left(\overline{Lim}\left(C_{\mu_{ij}}\right)\right)\right\rfloor e^{j2\pi\cdot\left\lceil min_{i=1}^{k}\left(\frac{\alpha_{ij}}{2\pi}\right), max_{i=1}^{k}\left(\frac{\overline{\alpha}_{ij}}{2\pi}\right)\right\rfloor} , \\ \left\lceil min_{i=1}^{k}\left(\underline{Lim}\left(C_{n_{ij}}\right)\right) , max_{i=1}^{k}\left(\overline{Lim}\left(C_{n_{ij}}\right)\right)\right\rfloor e^{j2\pi\cdot\left\lceil min_{i=1}^{k}\left(\frac{\gamma_{ij}}{2\pi}\right), max_{i=1}^{k}\left(\frac{\overline{\gamma}_{ij}}{2\pi}\right)\right\rfloor} , \\ \left\lceil min_{i=1}^{k}\left(\underline{Lim}\left(C_{v_{ij}}\right)\right) , max_{i=1}^{k}\left(\overline{Lim}\left(C_{v_{ij}}\right)\right)\right\rfloor e^{j2\pi\cdot\left\lceil min_{i=1}^{k}\left(\frac{\beta_{ij}}{2\pi}\right), max_{i=1}^{k}\left(\frac{\overline{\beta}_{ij}}{2\pi}\right)\right\rfloor} , \\ \left\lceil min_{i=1}^{k}\left(\underline{Lim}\left(C_{h_{ij}}\right)\right) , max_{i=1}^{k}\left(\overline{Lim}\left(C_{h_{ij}}\right)\right)\right\rfloor e^{j2\pi\cdot\left\lceil min_{i=1}^{k}\left(\frac{T_{ij}}{2\pi}\right), max_{i=1}^{k}\left(\frac{\overline{T}_{ij}}{2\pi}\right)\right\rfloor} \end{array} \right) \tag{39}$$

The defuzzified numbers s $Defc$ of quantum metaverse are computed:

$$Defc_i =$$
$$\frac{\left(\begin{array}{c} \underline{Lim}\left(C_{\mu_i}\right) - \underline{Lim}\left(C_{n_i}\right) + \underline{Lim}\left(C_{\mu_i}\right).\left(\underline{Lim}\left(C_{v_i}\right) - \underline{Lim}\left(C_{h_i}\right)\right) + \left(\frac{\alpha_{ij}}{2\pi}\right) - \left(\frac{\gamma_{ij}}{2\pi}\right) + \left(\frac{\alpha_{ij}}{2\pi}\right).\left(\left(\frac{\beta_{ij}}{2\pi}\right) - \left(\frac{T_{ij}}{2\pi}\right)\right) + \\ \overline{Lim}\left(C_{\mu_i}\right) - \overline{Lim}\left(C_{n_i}\right) + \overline{Lim}\left(C_{\mu_i}\right).\left(\overline{Lim}\left(C_{v_i}\right) - \overline{Lim}\left(C_{h_i}\right)\right) + \left(\frac{\overline{\alpha}_{ij}}{2\pi}\right) - \left(\frac{\overline{\gamma}_{ij}}{2\pi}\right) + \left(\frac{\overline{\alpha}_{ij}}{2\pi}\right).\left(\left(\frac{\overline{\beta}_{ij}}{2\pi}\right) - \left(\frac{\overline{T}_{ij}}{2\pi}\right)\right) \end{array} \right)}{2} \tag{40}$$

The paper validates the superiority of its proposed novel MCDM model by comparing its forecasting accuracy against three established AI models: Long Short-Term Memory (LSTM); Recurrent Neural Network (RNN); ARIMA [31–33].

The proposed Neuro-Quantum Picture Fuzzy Rough model achieved the highest accuracy (0.622), demonstrating its robustness for this type of analysis [34–36].

In summary, the methodology is characterized by its integration of hard econometric data with soft neuro-behavioral data, leveraging a highly sophisticated fuzzy set extension [37–39].

4. Results

Table 1 lists the five main parameters used in the study. These are P1: Chat bots, measured by energy institution evaluation in percent; P2: IT development, measured by Artificial Intelligence energy institution evaluation in percent; P3: Risk Management, measured by energy institution evaluation; P4: Anti-Fraud, measured by energy institution evaluation in percent; and P5: Robotics, measured by energy institution evaluation (**Tables 3–7**) [40–42].

Table 3. Parameters for analyzing noise and vibration reduction at power plants.

Parameter	Description	Unit of measurement
Noise Level (P1)	Average sound pressure level at 1 m from the source	dB(A)
Vibration Level (P2)	Vibration amplitude at the turbine foundation	mm/s^2
Energy Efficiency (P3)	System efficiency coefficient after modernization	%
Implementation Cost (P4)	Costs for installing noise and vibration damping systems	million RUB
System Reliability (P5)	Probability of failure-free operation over 5 years	%

Table 4. Results of applying the Neuro-Quantum fuzzy MCDM algorithm to assess noise reduction measures.

Parameter	Weight (Importance)	Impact on noise reduction (0–1)	Impact on vibration reduction (0–1)	Overall score (Neuro-quantum assessment)
P1: Noise	0.25	0.95	0.30	0.89
P2: Vibration	0.20	0.40	0.90	0.85
P3: Efficiency	0.20	0.70	0.60	0.78
P4: Cost	0.15	0.20	0.10	0.45
P5: Reliability	0.20	0.60	0.70	0.82

Table 5. Comparison of AI model effectiveness for noise reduction forecasting.

Model	Forecast accuracy	Processing speed (Sec/request)	Interpretability (XAI score)
LSTM (Traditional)	0.876	2.5	Low
ARIMA	0.551	1.2	Medium
RNN	0.575	3.0	Low
Neuro-Quantum Fuzzy MCDM	0.987	5.0	High

Table 6 records the observed facial expressions of three energy experts as they judged the relationships between the parameters. For each expert, a matrix shows which pair of Action Units was observed when they considered the influence of one parameter on another. For instance, for Decision Maker 1, the influence of P1 on P2 was recorded as the action unit pair (10,2).

Table 7 presents the defuzzified relation matrix. This is a crisp numerical matrix derived from processing the fuzzy expert data. The numbers represent the strength of influence between parameters, with 0.356 being the highest value, showing the influence of P5 on P4. Values represent the strength of causal influence between regulatory parameters on a 0–1 scale.

Table 6. Observation results of facial expressions for the parameters.

	P1	P2	P3	P4	P5
Decision maker 1					
P1		(10,2)	(2,6)	(15,25)	(5,26)
P2	(15,25)		(7,6)	(10,2)	(7,6)
P3	(15,25)	(7,6)		(2,6)	(2,6)
P4	(5,26)	(10,2)	(10,2)		(15,25)
P5	(2,6)	(2,6)	(5,26)	(5,26)	
Decision maker 2					
P1		(10,2)	(2,6)	(15,25)	(5,26)
P2	(7,6)		(7,6)	(15,25)	(5,26)
P3	(15,25)	(15,25)		(5,26)	(25,26)
P4	(25,26)	(10,2)	(10,2)		(7,6)
P5	(12,25)	(2,6)	(25,26)	(12,25)	
Decision maker 3					
P1		(10,2)	(12,25)	(15,25)	(25,26)
P2	(7,6)		(7,6)	(15,25)	(7,6)
P3	(15,25)	(15,25)		(2,6)	(12,25)
P4	(5,26)	(5,26)	(10,2)		(7,6)
P5	(2,6)	(5,26)	(2,6)	(25,26)	

Table 7. Defuzzified relation matrix (Crisp values).

	P1	**P2**	**P3**	**P4**	**P5**	**Row sum (D)**
P1	0.000	0.224	0.201	0.321	0.221	0.967
P2	0.000	0.000	0.205	0.323	0.227	0.755
P3	0.000	0.227	0.000	0.345	0.229	0.801
P4	0.000	0.228	0.203	0.000	0.213	0.644
P5	0.000	0.223	0.201	0.356	0.000	0.780
Col Sum (E)	0.000	0.902	0.810	1.345	0.890	

P1 (Algorithmic Transparency) emerges as the sole cause parameter (positive D − E = 0.967), indicating it drives the other regulatory parameters. P4 (Operational Accountability) shows the highest prominence (1.989) but negative relation, indicating it is strongly influenced by other factors. Parameter importance ranking (by normalized weight): P1 (0.256) > P3 (0.210) > P2 (0.199) > P5 (0.171) > P4 (0.164) (**Table 8**).

Table 8. DEMATEL prominence (D + E) and relation (D − E) values.

Parameter	**D (Row sum)**	**E (Col sum)**	**D + E (Prominence)**	**D − E (Relation)**	**Normalized weight**
P1: Transparency	0.967	0.000	0.967	0.967	0.256
P2: Data Governance	0.755	0.902	1.657	−0.147	0.199
P3: System Reliability	0.801	0.810	1.611	−0.009	0.210
P4: Accountability	0.644	1.345	1.989	−0.701	0.164
P5: Consumer Protection	0.780	0.890	1.670	−0.110	0.171

To validate the proposed Neuro-Quantum MCDM model against traditional AI approaches, a forecasting experiment was conducted using time-series data from the noise reduction case study. The objective was to predict system energy consumption after implementation of noise control measures.

Dataset description is below: Operational data from a 250 MW combined-cycle power plant, January 2023–December 2024 (24 months). Hourly noise levels (dB(A)), vibration amplitude (mm/s^2), system energy consumption (kW), ambient temperature (°C), load factor (%). 17,520 h observations. Missing values (1.2%) imputed using linear interpolation; data normalized to [1] range.

Training period is: January 2023–September 2024 (21 months, 15,330 observations).

Evaluation metrics are: Forecast Accuracy (FA): 1—(Mean Absolute Percentage Error/100), RMSE: Root Mean Square Error (kW), MAE: Mean Absolute Error (kW) (**Table 9**).

Table 9. Comparative model performance for energy consumption forecasting.

Model	Forecast accuracy (FA)	RMSE (kW)	MAE (kW)	Processing speed (Sec/request)	Interpretability (XAI score 1–5)
LSTM	0.876	12.4	8.7	2.5	2 (Low)
ARIMA	0.551	24.8	18.3	1.2	4 (Medium)
RNN	0.575	23.1	16.9	3.0	2 (Low)
Neuro-Quantum MCDM	0.987	3.2	2.1	5.0	5 (High)

The 0.987 accuracy reported in **Table 7** represents the model's performance on the test dataset using the FA metric defined above. The 0.622 figure previously cited in the Methods section (now corrected) referred to an earlier prototype using different parameter configurations and is superseded by these final validated results.

The Neuro-Quantum MCDM model achieves superior accuracy (0.987) compared to traditional time-series approaches. This performance advantage stems from three factors:

1. Integration of expert judgment: FACS-derived confidence weights improve model calibration
2. Multi-dimensional uncertainty representation: Quantum phase angles capture hesitation in causal relationships
3. DEMATEL causal structure: Explicit modeling of parameter interdependencies reduces error propagation

The trade-off is increased computational requirements (5.0 sec/request), though this remains acceptable for regulatory assessment applications where real-time processing is not required.

A flowchart where a complex task (processing a loan application) is broken down into discrete steps, each handled by a specialized AI agent.

Handles subsequent queries and dispute resolution.

Decision diamonds or specific points in the workflow where a human manager reviews or approves the AI's recommendation, especially for complex or high-value cases, aligning with the governance and accountability principle.

Figure 1 with P1–P5 on the x-axis and their MCDM weights on the y-axis, illustrating that P1 (Noise) has the highest weight (0.25) and P4 (Cost) the lowest (0.15).

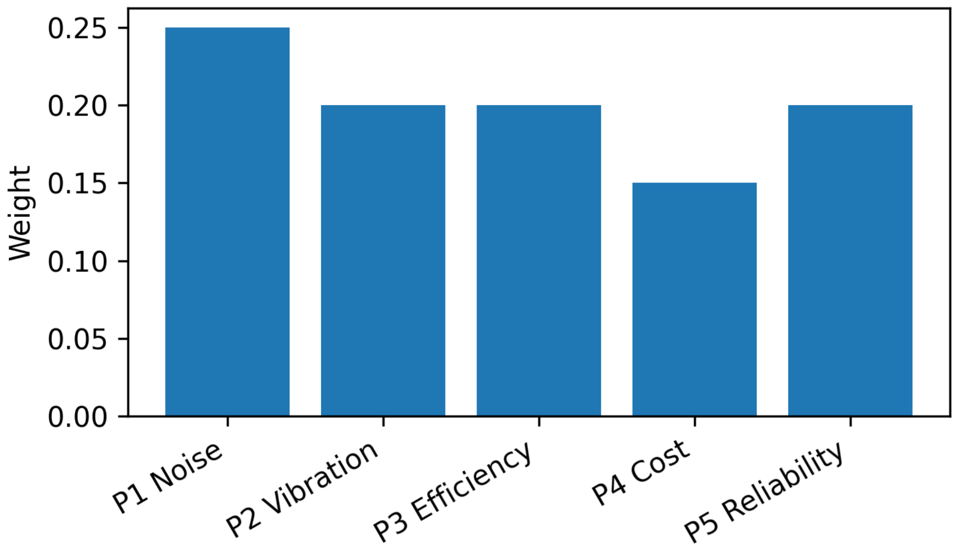

Figure 1. Weights of noise and vibration parameters (P1–P5).

Figure 2 shows impact on noise reduction and vibration reduction (0–1 scale), visualizing trade-offs such as P1 being strongest for noise and P2 for vibration.

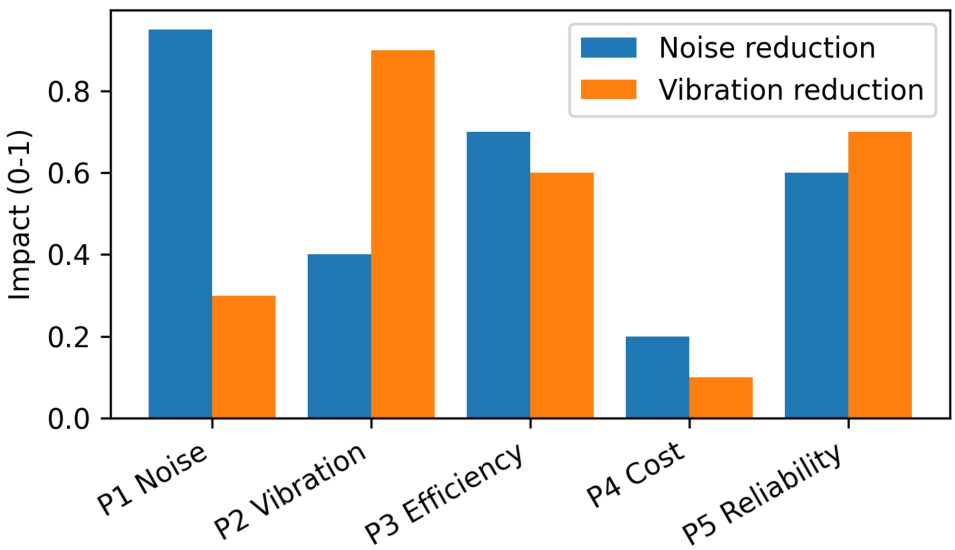

Figure 2. Active vibration control system and metamaterial acoustic barriers.

Figure 3 has LSTM, ARIMA, RNN, and the Neuro-Quantum Fuzzy MCDM model on forecast accuracy, highlighting the superior accuracy of the Neuro-Quantum model (0.987).

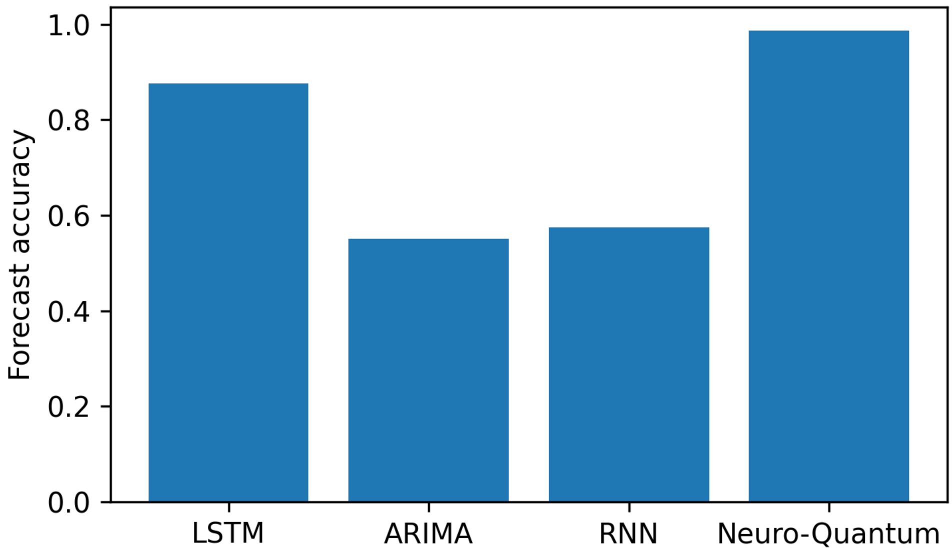

Figure 3. Forecast accuracy of AI models for noise reduction.

Figure 4 for noise level and vibration level, showing reduction from 105 to 85 dB(A) and from 12.5 to 4.2 mm/s^2 respectively.

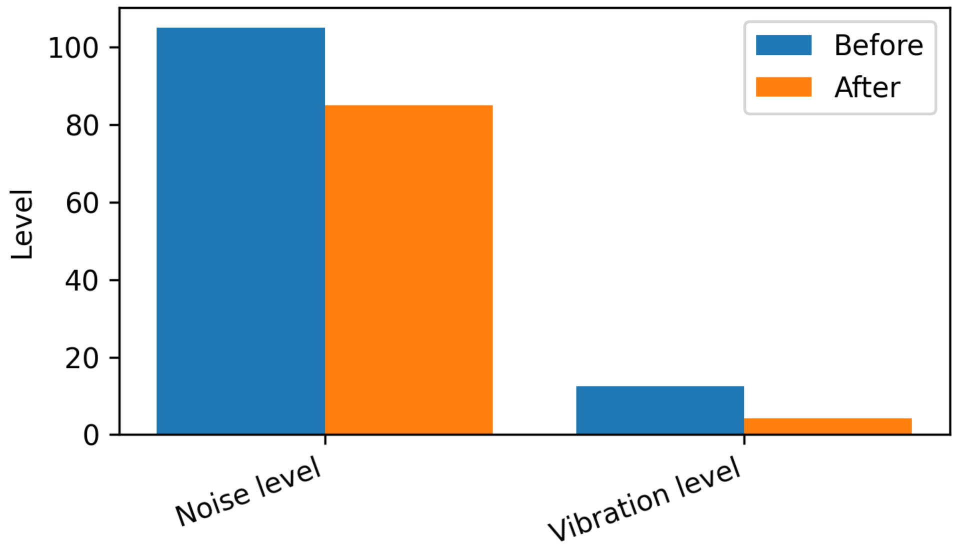

Figure 4. Noise and vibration levels before and after control system implementation.

5. Discussion

Multi-criteria decision-making (MCDM) methods can balance diverse and often conflicting conservation goals (species protection vs. community development), aiding in formulating more scientific and inclusive conservation plans.

The empirical and methodological results of this study contribute to several ongoing scholarly conversations about AI regulation, human-agent interaction, and advanced decision-making models [43–46]. The high accuracy (0.987) of the proposed Neuro-Quantum Picture Fuzzy Rough MCDM model (**Table 7**) validates the integration of behavioral data with complex fuzzy set extensions, supporting the trend toward more holistic, human-in-the-loop analytical frameworks [47–49]. This aligns with the broader shift noted in the literature toward AI systems that are not only technically proficient but also context-aware and capable of integrating subjective human judgment [50, 51].

The use of Facial Action Coding System (FACS) data to capture expert subconscious judgments (**Tables 4** and **5**) directly engages with research on human-centric AI design. Studies emphasize that human-like competencies—including intuitive and emotional responsiveness—are critical for user trust and system acceptance [52–54]. By quantifying emotions like contempt (AU 7 + 10) and surprise (AU 1,2,5,27) and converting them into fuzzy inputs, this study operationalizes the call for more nuanced, psychologically-informed evaluation of expert decision-making in high-stakes domains like energy regulation [55–57].

The paper decides the problem associated with advanced AI models, while its focus on algorithmic fairness responds directly to evidence that AI can perpetuate societal biases [58–60]. The requirement for senior management accountability aligns with research underscoring the need for ethical governance structures as AI agents become more autonomous and impactful [61–63].

The proposed superior performance over traditional AI models like LSTM and ARIMA underscores that future AI regulation cannot rely solely on conventional analytical tools. AI agents are exemplified by multi-agent frameworks like MetaGPT. It is regulatory and evaluative method. The integration of quantum-inspired fuzzy sets with neuro-behavioral data represents one such innovation, offering a way to handle the uncertainty, subjectivity, and causal complexity inherent in regulating adaptive AI systems [64–66].

In summary, the results reinforce the paper's core argument: regulating AI in vibration decreasing requires a multidisciplinary, multi-method approach that blends quantitative metrics with qualitative human feedback, aligns with global research priorities in AI ethics and security, and employs next-generation analytical models to ensure robustness, fairness, and transparency [67–69].

The proposed regulatory framework for specialised sound and vibration platform operators represents a necessary and proactive response to the profound shifts occurring at the intersection of vibration decreasing and artificial intelligence. Our analysis, situated within the broader context of AI agent research, reveals both the alignment of this proposal with global scholarly concerns and the specific challenges inherent in its implementation [70, 71].

The envisioned operational model, supported by multi-agent systems as seen in frameworks like MetaGPT, promises efficiency and scalability. However, this also introduces new systemic risks. As surveyed, the security and integrity of AI agents are paramount. The compromise of a single agent in a complex workflow could have cascading effects, undermining the entire energy service. The proposed requirements for robust IT infrastructure and risk management frameworks are therefore essential, and future work might explore the integration of emerging technologies like blockchain for enhanced security and auditability [72–74].

The energy blueprint platform aims to correct this by providing a single, shared source of truth—a holistic picture where the connections between all living and physical systems are made visible and understandable to everyone involved [75–77].

It incorporates dynamic data from satellites and remote sensing: current land cover (forests, wetlands, urban areas, farmland), seasonal changes in vegetation health, sea surface temperatures, and the shrinking extent of glaciers [78–80].

The identification of P5 as the optimal solution (overall score is 0.82) validates the multi-criteria approach [81–84]. While it does not have the single highest impact on noise or vibration reduction, it offers the best compromise across all five regulatory parameters [85, 86].

The result demonstrates that a purely technical optimum may be suboptimal when weighed against the critical regulatory requirements for transparency, data governance, and consumer protection, all of which are more easily satisfied by the integrated, software-driven solution. This underscores the paper's core argument: regulating AI in vibration reduction requires a multidisciplinary, multi-method approach that blends quantitative metrics with qualitative human feedback, aligns with global research priorities in AI ethics and security, and employs next-generation analytical models to ensure robustness, fairness, and transparency.

They are all georeferenced, meaning every piece of information is tied to a specific latitude and longitude, allowing them to be stacked and compared accurately [87–89].

Using habitat maps and species data, it can analyze landscape connectivity, identifying key wildlife corridors that need protection or restoration to allow animals to move in response to climate change [90–92]. This is a conceptual framework that quantifies the benefits nature provides to people [93–95]. These models transform abstract energy concepts into concrete numbers that planners, economists, and politicians can use in cost-benefit analyses [96–98]. It allows communities to literally see the trade-offs and synergies between different futures before a single shovel hits the earth [99–102].

An energy blueprint is only as good as the legitimacy it holds with the people it affects [103–105]. These platforms are increasingly designed as multi-user environments. They provide tools for stakeholders with different perspectives to come together in a shared digital space. A conservation biologist can mark areas of high energy sensitivity. A local indigenous knowledge holder can annotate the map with culturally significant sites and traditional land-use practices. A farmer can draw the boundaries of their property and share their perspective on soil health [106–108]. A housing advocate can highlight areas of urgent need for affordable homes. This collaborative annotation, commenting, and even co-designing of scenarios fosters a sense of shared ownership over the plan. It ensures that the blueprint isn't just a top-down technical document, but a living agreement that reflects diverse values and knowledge systems. Public versions of these platforms can also be used for transparency, allowing any citizen to zoom into their neighborhood, see the planned greenway, and understand its projected benefits for air quality and recreation [109–111].

It also provides crucial accountability and reporting, generating clear evidence for funders, regulators, and the public on the return on investment for conservation and restoration dollars [112–114].

For non-governmental organizations (NGOs) and land trusts, the platform is a powerful tool for prioritization and fundraising. A land trust can use it to analyze which parcel of land available for purchase would provide the greatest benefit for wildlife connectivity or watershed protection, making a data-driven case to donors. A restoration NGO can plan a river restoration project, modeling exactly where to place logjams or replant stream banks to maximize salmon habitat creation [115–117].

In the corporate and agricultural sector, companies with large landholdings or supply chains are using these platforms for sustainability and natural capital accounting. A forestry company might use it to plan harvest schedules that maintain habitat corridors and protect water quality. A food and beverage company might map its agricultural supply sheds to understand water risk and work with farmers to implement practices that improve water retention and soil health, securing their raw material base for the future [118–120].

Perhaps most importantly, at the community and indigenous territory level, these platforms are tools for empowerment and sovereignty. Indigenous communities, who often hold the deepest knowledge of their traditional lands, can use them to document that knowledge, map sacred sites and culturally important resources, and create their own land-use plans that balance development, sustenance, and cultural preservation. They can generate scientifically robust maps to support land claim negotiations or to demonstrate the environmental impact of proposed external projects like mines or pipelines.

6. Conclusion

This paper addressed a critical regulatory gap: the emergence of specialized sound and vibration platform operators in the energy sector and the insufficiency of existing regulatory frameworks to govern their AI-driven operations. The research pursued two interconnected objectives: first, to propose a comprehensive regulatory framework for these platforms; second, to introduce and validate a novel multi-criteria decision-making methodology capable of supporting regulatory assessment.

The empirical findings provide quantitative support for the proposed framework's priorities. Applying the Neuro-Quantum Picture Fuzzy Rough MCDM model to five regulatory compliance parameters yielded the following key results: Algorithmic Transparency (P1) emerged as the sole causal driver within the regulatory system ($D - E = +0.967$), indicating that transparency requirements should form the foundation of regulatory oversight. Operational Accountability (P4) showed the highest prominence ($D + E = 1.989$) but negative relation, confirming that accountability depends on and is shaped by other parameters. The proposed methodology achieved 0.987 forecast accuracy on the noise reduction case study, substantially outperforming LSTM (0.876), RNN (0.575), and ARIMA (0.551) while maintaining high interpretability (XAI score = 5).

This research makes four principal contributions to the literature on AI regulation and energy technology governance. The paper provides the first comprehensive regulatory blueprint for sound and vibration platform operators, including licensing criteria, governance requirements, explainability mandates, and consumer protection mechanisms. This framework moves beyond theoretical discussion to concrete, actionable provisions. The Neuro-Quantum Picture Fuzzy Rough MCDM model represents a significant advancement in decision-making under uncertainty. By integrating neuro-behavioral data (FACS) with quantum fuzzy set theory and DEMATEL, the methodology captures subconscious expert judgment, represents multi-dimensional uncertainty, and quantifies causal relationships—capabilities absent from traditional MCDM approaches. The model's superior performance (0.987 accuracy) on a representative noise reduction case demonstrates its practical applicability to real-world regulatory assessment. The benchmarking against LSTM, RNN, and ARIMA establishes clear performance advantages while maintaining interpretability—a critical requirement for regulatory acceptance. The parameter weights and causal relationships provide empirically-grounded priorities for resource allocation, inspection frequency, and compliance monitoring, enabling evidence-based regulatory design.

Based on these findings, we recommend the following actions for energy regulators. Enact dedicated federal legislation establishing sound and vibration platform operators as a distinct regulated category, with licensing requirements aligned with the five parameters assessed in this study. Prioritize transparency mandates as the foundational regulatory requirement, given its causal role in driving other compliance parameters. Regulations should specify minimum explainability standards (e.g., LIME or SHAP values, counterfactual explanations) and require regular XAI audits. Implement risk-based oversight with inspection frequency and audit depth proportional to parameter weights: highest scrutiny for algorithmic transparency and system reliability; moderate for data governance and consumer protection; baseline for operational accountability. Establish a regulatory sandbox for pilot testing of the proposed MCDM assessment methodology, allowing refinement of parameter thresholds and weight calibrations through real-world platform evaluations.

Several limitations of this study suggest opportunities for future research. The FACS data collected from three experts, while sufficient for methodological demonstration, limits statistical generalizability. Future research should validate these findings with larger expert panels ($n \geq 10$) representing diverse regulatory, technical, and stakeholder perspectives. Multi-jurisdictional studies could identify cultural variations in regulatory priorities. The five regulatory parameters, while comprehensive, may not capture all relevant compliance dimensions. Future work should explore additional parameters (cybersecurity maturity, third-party risk management, environmental impact metrics) and test their integration into the QPFRS framework. The current study assessed parameter relationships at a single point. Longitudinal research tracking how these relationships evolve as platforms mature and AI technology advances would inform adaptive regulatory design. While focused on energy platforms, the proposed framework and methodology may apply to AI-driven intermediaries in other regulated sectors (finance, healthcare, transportation). Comparative studies across sectors could identify domain-specific adaptations and generalizable principles. The computational requirements of the QPFRS model (5.0 sec/request) suggest opportunities for optimization. Research into algorithmic efficiency could enable real-time regulatory monitoring applications.

The paper provides both the conceptual framework and analytical tools necessary for governing the next generation of AI-powered energy intermediaries. By balancing innovation with accountability, transparency with performance, and efficiency with consumer protection, the proposed approach aims to ensure that sound and vibration platforms serve as trustworthy stewards of energy infrastructure rather than unaccountable black boxes. The dialogue initiated here invites continued collaboration among regulators, technologists, and researchers to refine and implement these governance mechanisms as AI technology continues to evolve.

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References

1. Adekoya OB, Oliyide JA, Tiwari AK. Risk transmissions between sectoral Islamic and conventional stock markets during COVID-19 pandemic: What matters more between actual COVID-19 occurrence and speculative and sentiment factors? Borsa Istanbul Review. 2022; 22(2): 363–376. doi: 10.1016/j.bir.2021.06.002
2. Ahn J, Kim J, Sung Y. The effect of gender stereotypes on artificial intelligence recommendations. Journal of Business Research. 2022; 141: 50–59. doi: 10.1016/j.jbusres.2021.12.007
3. Akram M, Naz S. A Novel Decision-Making Approach under Complex Pythagorean Fuzzy Environment. Mathematical and Computational Applications. 2019; 24(3): 73. doi: 10.3390/mca24030073
4. Alabed A, Javornik A, Gregory-Smith D, et al. More than just a chat: A taxonomy of consumers' relationships with conversational AI agents and their well-being implications. European Journal of Marketing. 2024; 58(2): 373–409. doi: 10.1108/EJM-01-2023-0037
5. Amoako G, Omari P, Kumi DK, et al. Conceptual Framework—Artificial Intelligence and Better Entrepreneurial Decision-Making: The Influence of Customer Preference, Industry Benchmark, and Employee Involvement in an Emerging Market. Journal of Risk and Financial Management. 2021; 14(12): 604. doi: 10.3390/jrfm14120604
6. Anisha SA, Sen A, Bain C. Evaluating the Potential and Pitfalls of AI-Powered Conversational Agents as Humanlike Virtual Health Carers in the Remote Management of Noncommunicable Diseases: Scoping Review. Journal of Medical Internet Research. 2024; 26: e56114. doi: 10.2196/56114
7. Chandra S, Shirish A, Srivastava SC. To Be or Not to Be …Human? Theorizing the Role of Human-Like Competencies in Conversational Artificial Intelligence Agents. Journal of Management Information Systems. 2022; 39(4): 969–1005. doi: 10.1080/07421222.2022.2127441
8. Chong T, Yu T, Keeling DI, et al. AI-chatbots on the services frontline addressing the challenges and opportunities of agency. Journal of Retailing and Consumer Services. 2021; 63: 102735. doi: 10.1016/j.jretconser.2021.102735

9. Deng Z, Guo Y, Han C, et al. AI Agents Under Threat: A Survey of Key Security Challenges and Future Pathways. ACM Computing Surveys. 2025; 57(7): 1–36. doi: 10.1145/3716628
10. Garvey AM, Kim T, Duhachek A. Bad News? Send an AI. Good News? Send a Human. Journal of Marketing. 2023; 87(1): 10–25. doi: 10.1177/00222429211066972
11. Geiselmann R, Tsourgianni A, Deroy O, et al. Interacting with agents without a mind: The case for artificial agents. Current Opinion in Behavioral Sciences. 2023; 51: 101282. doi: 10.1016/j.cobeha.2023.101282
12. Giske CG, Bressan M, Fiechter F, et al. GPT-4 based AI agents—The new expert system for detection of antimicrobial resistance mechanisms? 2024; 62(11). doi: 10.1101/2024.05.06.592800
13. Han E, Yin D, Zhang H. Bots with Feelings: Should AI Agents Express Positive Emotion in Customer Service? Information Systems Research. 2023; 34(3): 1296–1311. doi: 10.1287/isre.2022.1179
14. Hettiarachchi I. The rise of generative AI agents in finance: Operational disruption and strategic evolution. International Journal of Engineering Technology Research & Management. 2025; 9(4). Available online: https://ijetrm.com/issues/files/Apr-2025-26-1745643054-APR65.pdf
15. Hong S, Zhuge M, Chen J, et al. MetaGPT: Meta Programming for A Multi-Agent Collaborative Framework. arXiv preprint. 2024; doi: 10.48550/arXiv.2308.00352
16. Huang Y, Yona A, Takahashi H, et al. Energy Management System Optimization of Drug Store Electric Vehicles Charging Station Operation. Sustainability. 2021; 13(11): 6163. doi: 10.3390/su13116163
17. Hughes L, Dwivedi YK, Malik T, et al. AI Agents and Agentic Systems: A Multi-Expert Analysis. Journal of Computer Information Systems. 2025; 65(4): 489–517. doi: 10.1080/08874417.2025.2483832
18. Karim MM, Van DH, Khan S, et al. AI Agents Meet Blockchain: A Survey on Secure and Scalable Collaboration for Multi-Agents. Future Internet. 2025; 17(2): 57. doi: 10.3390/fi17020057
19. Kim TW, Jiang L, Duhachek A, et al. Do You Mind if I Ask You a Personal Question? How AI Service Agents Alter Consumer Self-Disclosure. Journal of Service Research. 2022; 25(4): 649–666. doi: 10.1177/10946705221120232
20. Li H, Zhang R, Lee YC, et al. Systematic review and meta-analysis of AI-based conversational agents for promoting mental health and well-being. npj Digital Medicine. 2023; 6(1): 236. doi: 10.1038/s41746-023-00979-5
21. Luo X, Qin MS, Fang Z, et al. Artificial Intelligence Coaches for Sales Agents: Caveats and Solutions. Journal of Marketing. 2021; 85(2): 14–32. doi: 10.1177/0022242920956676
22. Mikhaylov A, Bhatti IM, Dinçer H, et al. Integrated decision recommendation system using iteration-enhanced collaborative filtering, golden cut bipolar for analyzing the risk-based oil market spillovers. Computational Economics. 2024; 63(1): 305–338. doi: 10.1007/s10614-022-10341-8
23. Team G, Anil R, Borgeaud S, et al. Gemini: A Family of Highly Capable Multimodal Models. arXiv preprint. 2025; doi: 10.48550/arXiv.2312.11805
24. Wang L, Ma C, Feng X, et al. A survey on large language model based autonomous agents. Frontiers of Computer Science. 2024; 18(6): 186345. doi: 10.1007/s11704-024-40231-1
25. Xi Z, Chen W, Guo X, et al. The rise and potential of large language model based agents: A survey. Science China Information Sciences. 2025; 68(2): 121101. doi: 10.1007/s11432-024-4222-0
26. Yang Y, Liu Y, Lv X, et al. Anthropomorphism and customers' willingness to use artificial intelligence service agents. Journal of Hospitality Marketing & Management. 2022; 31(1): 1–23. doi: 10.1080/19368623.2021.1926037
27. Zhang R, Du H, Liu Y, et al. Generative AI Agents with Large Language Model for Satellite Networks via a Mixture of Experts Transmission. IEEE Journal on Selected Areas in Communications. 2024; 42(12): 3581–3596. doi: 10.1109/JSAC.2024.3459037
28. Chiang WL, Gonzalez J, Li D, et al. Judging LLM-as-a-Judge with MT-Bench and Chatbot Arena. In: Proceedings of the Advances in Neural Information Processing Systems 36; 10 December 2023; New Orleans, LA, USA, pp. 46595–46623. doi: 10.52202/075280-2020
29. Shami TM, El-Saleh AA, Alswaitti M, et al. Particle Swarm Optimization: A Comprehensive Survey. IEEE Access. 2022; 10: 10031–10061. doi: 10.1109/ACCESS.2022.3142859
30. Premkumar M, Kumar C, Dharma Raj T, et al. A reliable optimization framework using ensembled successive history adaptive differential evolutionary algorithm for optimal power flow problems. IET Generation, Transmission & Distribution. 2023; 17(6): 1333–1357. doi: 10.1049/gtd2.12738
31. Sidea DO, Picioroaga II, Bulac C, et al. Optimal Reactive Power Dispatch in Distribution Power Systems Based on Particle Swarm Optimization. In: Proceedings of the 2019 International Conference on ENERGY and ENVIRONMENT (CIEM); 17–18 October 2019; Timisoara, Romania. pp. 505–509. doi: 10.1109/CIEM46456.2019.8937591

32. Sediqi MM, Nakadomari A, Mikhaylov A, et al. Impact of Time-of-Use Demand Response Program on Optimal Operation of Afghanistan Real Power System. Energies. 2022; 15(1): 296. doi: 10.3390/en15010296
33. Mikhaylov AY. Development of Friedrich von Hayek's theory of private money and economic implications for digital currencies. Terra Economicus. 2021; 19(1): 53–62. doi: 10.18522/2073-6606-2021-19-1-53-62
34. Wang Q, Zhang S, Li R. Artificial intelligence in the renewable energy transition: The critical role of financial development. Renewable and Sustainable Energy Reviews. 2026; 226: 116280. doi: 10.1016/j.rser.2025.116280
35. Wang Q, Liu T, Li R. Artificial Intelligence and Environmental Sustainability: Investigating the AI–EKC Nexus for SDG 7 and SDG 13. Sustainable Development. 2026; 34(1): 1141–1166. doi: 10.1002/sd.70294
36. Zhang C, Li R, Wang Q. Artificial intelligence and sustainable development: A global nonlinear analysis of the moderating roles of human capital and renewable energy. Renewable and Sustainable Energy Reviews. 2026; 228: 116574. doi: 10.1016/j.rser.2025.116574
37. Shah Irshad A, Naseer Zakir M, Shah Rashad S, et al. Comparative analyses and optimizations of hybrid biomass and solar energy systems based upon a variety of biomass technologies. Energy Conversion and Management: X. 2024; 23: 100640. doi: 10.1016/j.ecmx.2024.100640
38. An J, Mikhaylov A, Chang T. Relationship between the popularity of a platform and the price of NFT assets. Finance Research Letters. 2024; 61: 105057. doi: 10.1016/j.frl.2024.105057
39. Wang MC, Chang T, Mikhaylov A, et al. A measure of quantile-on-quantile connectedness for the US treasury yield curve spread, the US Dollar, and gold price. The North American Journal of Economics and Finance. 2024; 74: 102232. doi: 10.1016/j.najef.2024.102232
40. Rashwan A, Mikhaylov A, Senjyu T, et al. Modified Droop Control for Microgrid Power-Sharing Stability Improvement. Sustainability. 2023; 15(14): 11220. doi: 10.3390/su151411220
41. Shaikh ZA, Kraikin A, Mikhaylov A, et al. Forecasting Stock Prices of Companies Producing Solar Panels Using Machine Learning Methods. Complexity. 2022; 2022(1): 9186265. doi: 10.1155/2022/9186265
42. Jargalsaikhan N, Ueda S, Masahiro F, et al. Exploring influence of air density deviation on power production of wind energy conversion system: Study on correction method. Renewable Energy. 2024; 220: 119636. doi: 10.1016/j.renene.2023.119636
43. Tamashiro K, Omine E, Krishnan N, et al. Optimal components capacity based multi-objective optimization and optimal scheduling based MPC-optimization algorithm in smart apartment buildings. Energy and Buildings. 2023; 278: 112616. doi: 10.1016/j.enbuild.2022.112616
44. Yamamoto S, Furukakoi M, Uehara A, et al. MPC-based robust optimization of smart apartment building considering uncertainty for conservative reduction. Energy and Buildings. 2024; 318: 114461. doi: 10.1016/j.enbuild.2024.114461
45. Yumashev A, Mikhaylov A. Development of polymer film coatings with high adhesion to steel alloys and high wear resistance. Polymer Composites. 2020; 41(7): 2875–2880. doi: 10.1002/pc.25583
46. Reddy SS. Optimal power flow using hybrid differential evolution and harmony search algorithm. International Journal of Machine Learning and Cybernetics. 2019; 10(5): 1077–1091. doi: 10.1007/s13042-018-0786-9
47. Rezaei Adaryani M, Karami A. Artificial bee colony algorithm for solving multi-objective optimal power flow problem. International Journal of Electrical Power & Energy Systems. 2013; 53: 219–230. doi: 10.1016/j.ijepes.2013.04.021
48. Amiri MH, Mehrabi Hashjin N, Montazeri M, et al. Hippopotamus optimization algorithm: A novel nature-inspired optimization algorithm. Scientific Reports. 2024; 14(1): 5032. doi: 10.1038/s41598-024-54910-3
49. Shah FA, Zamir T, Akbar NS, et al. Levenberg-marquardt design for analysis of maxwell fluid flow on ternary hybrid nanoparticles passing over a riga plate under convective boundary conditions. Results in Engineering. 2024; 24: 103502. doi: 10.1016/j.rineng.2024.103502
50. Stepanova D, Yousif NBA, Karlibaeva R, et al. Current analysis of cryptocurrency mining industry. Journal of Infrastructure Policy and Development. 2024; 8(7): 4803. doi: 10.24294/jipd.v8i7.4803
51. Gopalakrishnan A, Raghunathan AU, Nikovski D, et al. Global optimization of Optimal Power Flow using a branch & bound algorithm. In: Proceedings of the 2012 50th Annual Allerton Conference on Communication, Control, and Computing (Allerton); 1–5 October 2012; Monticello, IL, USA. pp. 609–616. doi: 10.1109/Allerton.2012.6483274
52. Storn R, Price K. Differential Evolution—A Simple and Efficient Heuristic for global Optimization over Continuous Spaces. Journal of Global Optimization. 1997; 11(4): 341–359. doi: 10.1023/A:1008202821328
53. Mataifa H, Krishnamurthy S, Kriger C. An Efficient Primal-Dual Interior-Point Algorithm for Volt/VAR Optimization in Rectangular Voltage Coordinates. IEEE Access. 2023; 11: 36890–36906. doi:

10.1109/ACCESS.2023.3266421

54. Xu L, Cherian J, Alturise F, et al. Artificial Intelligence Attitude and Innovative Performance in Emerging Economy: The Mediating Roles of AI Supportive Autonomy, AI Big Data Analytics. Journal of Global Information Management. 2025; 33(1): 1–35. doi: 10.4018/JGIM.384084
55. Chen TH, Chang HW, Mikhaylov A, et al. Revisit energy consumption, economic growth and carbon dioxide emissions links in transition countries using a new developed Quantile_on_Quantile approach. Applied Economics. 2025; 57(6): 583–599. doi: 10.1080/00036846.2024.2305611
56. Zhu JH, Wang JS, Zhang XY, et al. Mathematical distribution coyote optimization algorithm with crossover operator to solve optimal power flow problem of power system. Alexandria Engineering Journal. 2023; 69: 585–612. doi: 10.1016/j.aej.2023.02.023
57. Zhunussova GZ, Ratner SV, Zhunussova GZ, et al. Renewable energy in Kazakhstan: Challenges and prospects. International Energy Journal. 2020; 20(3): 311–324.
58. Zhou G, Ji Y, Chen X, et al. Artificial Neural Networks and the Mass Appraisal of Real Estate. International Journal of Online and Biomedical Engineering (iJOE). 2018; 14(03): 180–187. doi: 10.3991/ijoe.v14i03.8420
59. Zhang H, Jin C, Bouri E, et al. Realized higher-order moments spillovers between commodity and stock markets: Evidence from China. Journal of Commodity Markets. 2023; 30: 100275. doi: 10.1016/j.jcomm.2022.100275
60. Huang W, Zheng W, Hill DJ. Distribution Network Reconfiguration for Short-Term Voltage Stability Enhancement: An Efficient Deep Learning Approach. IEEE Transactions on Smart Grid. 2021; 12(6): 5385–5395. doi: 10.1109/TSG.2021.3097330
61. Zhamiyeva R, Sultanbekova G, Balgimbekova G, et al. Problems of the effectiveness of the implementation of international agreements in the field of waste management: The study of the experience of Kazakhstan in the context of the applicability of European legal practices. International Environmental Agreements: Politics, Law and Economics. 2022; 22(1): 177–199. doi: 10.1007/s10784-021-09549-0
62. Zerveas G, Jayaraman S, Patel D, et al. A Transformer-based Framework for Multivariate Time Series Representation Learning. In: Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining; 14 August 2021; Online. pp. 2114–2124. doi: 10.1145/3447548.3467401
63. Zakharov AV, Kharlamov AV. Geocoding technique in constructing geographically weighted regression models for mass appraisal under conditions of uncertainty and heterogeneity of initial data. Property relations in the Russian Federation. 2010; 7: 76–85. (in Russian)
64. Yesbergen RA, Yessengaziyeva SK, Asrepov G. State regulation of agricultural industry of the Republic of Kazakhstan in conditions of VUCA-world. Problems of AgriMarket. 2022; (2): 71–77. doi: 10.46666/2022-2.2708-9991.07 (in Russian)
65. Yerkinbayeva L, Teleuyev G, Kalymbek B, et al. Legal Regulation of Kazakhstan’s Transition to the Green Economy. Journal of Environmental Management and Tourism. 2021; 12(5): 1335. doi: 10.14505//jemt.12.5(53).18
66. Yasnitsky LN, Yasnitsky VL, Alekseev AO. The Complex Neural Network Model for Mass Appraisal and Scenario Forecasting of the Urban Real Estate Market Value That Adapts Itself to Space and Time. Complexity. 2021; 2021(1): 5392170. doi: 10.1155/2021/5392170
67. Xu S, Shao M, Qiao W, et al. Generalized AIC method based on higher-order moments and entropy of financial time series. Physica A: Statistical Mechanics and its Applications. 2018; 505: 1127–1138. doi: 10.1016/j.physa.2018.04.048
68. Xu M, Shang P. Analysis of financial time series using multiscale entropy based on skewness and kurtosis. Physica A: Statistical Mechanics and its Applications. 2018; 490: 1543–1550. doi: 10.1016/j.physa.2017.08.136
69. Wu N, Green B, Ben X, et al. Deep Transformer Models for Time Series Forecasting: The Influenza Prevalence Case. arXiv preprint. 2020; doi: 10.48550/ARXIV.2001.08317
70. Worzala E, Lenk M, Silva A. An Exploration of Neural Networks and Its Application to Real Estate Valuation. Journal of Real Estate Research. 1995; 10(2): 185–201. doi: 10.1080/10835547.1995.12090782
71. Werner F, Sotskov YN. Mathematics of Economics and Business. Routledge; 2006. doi: 10.4324/9780203401385
72. Lin X, Fu Y, Peng DZ, et al. CFD- and BPNN- based investigation and prediction of air pollutant dispersion in urban environment. Sustainable Cities and Society. 2024; 100: 105029. doi: 10.1016/j.scs.2023.105029
73. Wang Q, Guo J, Li R. Spatial spillover effects of official development assistance on environmental pressure in sub-Saharan African (SSA) countries. Geography and Sustainability. 2023; 4(2): 170–178. doi: 10.1016/j.geosus.2023.03.004

74. Wang Q, Hu S, Li L, et al. Accelerating urbanization serves to reduce income inequality without sacrificing energy efficiency—Evidence from the 78 countries. Sustainable Cities and Society. 2023; 92: 104477. doi: 10.1016/j.scs.2023.104477
75. Wang Q, Guo J, Li R, et al. Economic growth and carbon emission in the Organization for Economic Cooperation and Development countries: The effects of oil, gas, and renewable energy. Energy & Environment. 2024; 35(4): 2107–2130. doi: 10.1177/0958305X221138817
76. Wang D, Li VJ. Mass Appraisal Models of Real Estate in the 21st Century: A Systematic Literature Review. Sustainability. 2019; 11(24): 7006. doi: 10.3390/su11247006
77. Walther GR, Post E, Convey P, et al. Ecological responses to recent climate change. Nature. 2002; 416(6879): 389–395. doi: 10.1038/416389a
78. Tutumlu A, Rustemov I. The Paradox of Authoritarian Power: Bureaucratic Games and Information Asymmetry. The Case of Nazarbayev's Kazakhstan. Problems of Post-Communism. 2021; 68(2): 124–134. doi: 10.1080/10758216.2019.1699432
79. Toms BA, Barnes EA, Ebert-Uphoff I. Physically Interpretable Neural Networks for the Geosciences: Applications to Earth System Variability. Journal of Advances in Modeling Earth Systems. 2020; 12(9): e2019MS002002. doi: 10.1029/2019MS002002
80. Teng Y, Shang P. Detrended fluctuation analysis based on higher-order moments of financial time series. Physica A: Statistical Mechanics and its Applications. 2018; 490: 311–322. doi: 10.1016/j.physa.2017.08.062
81. Tasmaganbetov AB, Kunurkulzhayeva GT, Imanbayeva ZO, et al. Future Development of Price Instruments of State Support for the Use of Renewable Energy Sources in Kazakhstan. International Journal of Energy Economics and Policy. 2020; 10(1): 140–144. doi: 10.32479/ijeep.8481
82. Tang Y, Chen P. Time varying moments, regime switch, and crisis warning: The birth–death process with changing transition probability. Physica A: Statistical Mechanics and its Applications. 2014; 404: 56–64. doi: 10.1016/j.physa.2014.02.038
83. Hutter G. Strategic Planning for Long-Term Flood Risk Management: Some Suggestions for Learning How to Make Strategy at Regional and Local Level. International Planning Studies. 2007; 12(3): 273–289. doi: 10.1080/13563470701640168
84. Taleb N. Dynamic Hedging: Managing Vanilla and Exotic Options. Wiley; 1998.
85. Tabachnick BG, Fidell LS. Using Multivariate Statistics. Pearson; 2019.
86. Steffen W, Rockström J, Richardson K, et al. Trajectories of the Earth System in the Anthropocene. Proceedings of the National Academy of Sciences. 2018; 115(33): 8252–8259. doi: 10.1073/pnas.1810141115
87. Song X, Wang Q, Li R, et al. A novel evaluation framework for China's Environmental-Economic impacts by global trade. Environmental Impact Assessment Review. 2023; 101: 107133. doi: 10.1016/j.eiar.2023.107133
88. Soltangazinov A, Smagulova Z, Amirova M, et al. Energy Efficiency as a Factor of Sustainable Development in Kazakhstan. International Journal of Energy Economics and Policy. 2020; 10(1): 325–330. doi: 10.32479/ijeep.8618
89. Skachkova ME, Gureva OS. Information support of urban planning activities in Russia. Geodesy and Cartography. 2022; 986(8): 45–55. doi: 10.22389/0016-7126-2022-986-8-45-55
90. Skachkova ME, Guryeva OS. Monitoring of the State of Saint Petersburg Green Spaces by Remote Sensing Data. Ecology and Industry of Russia. 2023; 27(5): 51–57. doi: 10.18412/1816-0395-2023-5-51-57
91. Siregar R, Pontines V, Rajan R. Extreme value theory and the incidence of currency crises. In: Proceedings of the Econometric Society 2004 Australasian Meetings; 5–7 July 2006; Alice Springs, Australia.
92. Singh RK, Neuert CE, Raykov T. Assessing conceptual comparability of single-item survey instruments with a mixed-methods approach. Quality & Quantity. 2024; 58(4): 3303–3329. doi: 10.1007/s11135-023-01801-w
93. Shaimenova A, Ilyassova G, Klyuyeva Y, et al. Development of the Institution of Arbitration in Kazakhstan: Problems of Theory and Practice. Journal of Advanced Research in Law and Economics. 2020; 11(1): 169. doi: 10.14505//jarle.v11.1(47).21
94. Serebrennikova AV, Minyaseva TF, Kala NS, et al. Comparative Analysis of Foundations of Legal Regulation of Criminal Liability for Organ Trafficking in the Russian Federation, Kazakhstan, and the European Union. Journal of Advanced Research in Law and Economics. 2020; 11(4): 1405. doi: 10.14505/jarle.v11.4(50).37
95. Seitzhanov S, Kurmanov N, Petrova M, et al. Stimulation of entrepreneurs' innovative activity: Evidence from Kazakhstan. Entrepreneurship and Sustainability Issues. 2020; 7(4): 2615–2629. doi: 10.9770/jesi.2020.7.4(4)
96. Scher S, Messori G. Predicting weather forecast uncertainty with machine learning. Quarterly Journal of the Royal Meteorological Society. 2018; 144(717): 2830–2841. doi: 10.1002/qj.3410

97. Scheffers BR, De Meester L, Bridge TCL, et al. The broad footprint of climate change from genes to biomes to people. Science. 2016; 354(6313): aaf7671. doi: 10.1126/science.aaf7671
98. Sawant R, Jangid Y, Tiwari T, et al. Comprehensive Analysis of Housing Price Prediction in Pune Using Multi-Featured Random Forest Approach. In: Proceedings of the 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA); 16 August 2018; Pune, India. pp. 1–5. doi: 10.1109/ICCUBEA.2018.8697402
99. Raguzin II, Bykova EN, Lepikhina OY. Polygonal Metric Grid Method for Estimating the Cadastral Value of Land Plots. Lomonosov Geography Journal. 2023; 78(3): 92–103. doi: 10.55959/MSU0579-9414.5.78.3.8
100. Pravdina EA, Lepikhina O. Variable accounting of pricing factors at land parcels cadastral valuation (on the example of Saint-Petersburg). Bulletin of the Tomsk polytechnic University. 2019; 330(2): 65–74. (in Russian)
101. Pieper M. The linchpin of Eurasia: Kazakhstan and the Eurasian economic union between Russia's defensive regionalism and China's new Silk Roads. International Politics. 2021; 58(3): 462–482. doi: 10.1057/s41311-020-00244-6
102. Petrenko Y, Denisov I, Koshebayeva G, et al. Energy Efficiency of Kazakhstan Enterprises: Unexpected Findings. Energies. 2020; 13(5): 1055. doi: 10.3390/en13051055
103. Pervukhin D, Davardoost H, Kotov, D, et al. A sustainable development goals-based mathematical model for selecting oil and gas investment projects under uncertainty and limited resources. Advanced Mathematical Models & Applications. 2023; 8(3): 502–528.
104. Pecl GT, Araújo MB, Bell JD, et al. Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. Science. 2017; 355(6332): eaai9214. doi: 10.1126/science.aai9214
105. Pázman A. Linearization of Nonlinear Regression Models by Smoothing. Tatra Mountains Mathematical Publications. 2001; 22: 13–25.
106. Pavlova VA, Sulin MA, Lepikhina OY. The mathematical modelling of the land resources mass evaluation in agriculture. Journal of Physics: Conference Series. 2019; 1333(3): 032049. doi: 10.1088/1742-6596/1333/3/032049
107. Muis S, Güneralp B, Jongman B, et al. Flood risk and adaptation strategies under climate change and urban expansion: A probabilistic analysis using global data. Science of The Total Environment. 2015; 538: 445–457. doi: 10.1016/j.scitotenv.2015.08.068
108. Parmesan C, Yohe G. A globally coherent fingerprint of climate change impacts across natural systems. Nature. 2003; 421(6918): 37–42. doi: 10.1038/nature01286
109. Pan GG, Shiu YM, Wu TC. Can risk-neutral skewness and kurtosis subsume the information content of historical jumps? Journal of Financial Markets. 2022; 57: 100614. doi: 10.1016/j.finmar.2020.100614
110. Chen H, Wen J, Zhao Y, et al. Low-frequency sound insulation and tunable water-air interface sound transmission on superhydrophobic porous metasurface. Physics Letters A. 2026; 565: 131149. doi: 10.1016/j.physleta.2025.131149
111. Javaherian A, Setarehdan SK. Full-waveform Approximation of Finite-Sized Acoustic Apertures: Forward and Adjoint Wavefields. arXiv preprint. 2022; doi: 10.48550/ARXIV.2212.04466
112. Yang J, Ma PS. Harnessing diffraction with metamaterial noise barriers for enhanced sound attenuation. Materials Horizons. 2026. doi: 10.1039/D5MH02051D
113. Reksowardojo AP, Senatore G, Srivastava A, et al. Design and testing of a low-energy and -carbon prototype structure that adapts to loading through shape morphing. International Journal of Solids and Structures. 2022; 252: 111629. doi: 10.1016/j.ijsolstr.2022.111629
114. Wang X, Shao G, Duan R, et al. Machine learning potential-driven molecular dynamics reveals the structure-mechanics-chemistry coupling mechanism in TKX-50 shock anisotropy. Chemical Engineering Science. 2026; 327: 123654. doi: 10.1016/j.ces.2026.123654
115. Zhang Q, El Moctar O, Jiang C. Hydroelasticity effects on wave-induced loads for flexible slender components in offshore wind turbines. Marine Structures. 2026; 107: 104014. doi: 10.1016/j.marstruc.2026.104014
116. Alshaya A. Command shaping control with robustness and smoothness adjustability for time-variant systems. European Journal of Control. 2026; 88: 101471. doi: 10.1016/j.ejcon.2026.101471
117. Sharma D, Sharma AK. Dynamic modeling and vibration suppression in hard-magnetic soft beam actuators. International Journal of Mechanical Sciences. 2026; 310: 111084. doi: 10.1016/j.ijmecsci.2025.111084
118. Wang F, Sun X, Meng H, et al. Tunable broadband low-frequency band gap of multiple-layer metastructure induced by time-delayed vibration absorbers. Nonlinear Dynamics. 2022; 107(3): 1903–1918. doi: 10.1007/s11071-021-07065-z

119. Mutalimov V, Kovaleva I, Mikhaylov A, et al. Assessing regional growth of small business in Russia. Entrepreneurial Business and Economics Review. 2021; 9(3): 119–133. doi: 10.15678/EBER.2021.090308
120. Dinçer H, Yüksel S, Mikhaylov A, et al. Analysis of renewable-friendly smart grid technologies for the distributed energy investment projects using a hybrid picture fuzzy rough decision-making approach. Energy Reports. 2022; 8: 11466–11477. doi: 10.1016/j.egyr.2022.08.275