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Harnessing the Power of Artificial Intelligence for Collaborative Energy Optimization Platforms

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Abstract: This scientific paper highlights the critical significance of energy in driving sustainable development and explores the transformative potential of Artificial Intelligence (AI) tools in shaping the future of energy systems. As the world faces mounting challenges in meeting growing energy demands while minimizing environmental impact, there is a pressing need for innovative solutions that can optimize energy generation, distribution, and consumption. AI tools, with their ability to analyse vast amounts of data and make intelligent decisions, have emerged as a promising avenue for advancing energy systems towards greater efficiency, reliability, and sustainability. This paper underscores the importance of energy in sustainable development and investigates how AI tools can catalyse the next phase of human civilization. This paper presents a comprehensive review of the Collaborative Energy Optimization Platform (CEOP), an innovative model that utilizes AI algorithms in an integrated manner. The review of the CEOP model is based on an in-depth analysis of existing literature, research papers, and industry reports. The methodology encompasses a systematic review of the model's key features, including collaboration, data-sharing, and AI algorithm integration. The conducted research demonstrates the effectiveness of applying MCDM methods, specifically fuzzy AHP and TOPSIS, in evaluating and ranking the performance of five Collaborative Energy Optimization Platforms (CEOP models) across 20 sub-criteria. The findings emphasize the need for a comprehensive and holistic approach in assessing AI-based energy optimization systems. The research provides valuable insights for decision-makers and researchers in the field, fostering the development and implementation of more efficient and sustainable AI-powered energy systems.

Keywords: energy system; artificial intelligence; sustainable development; economy; AHP; TOPSIS

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1. Introduction

Energy is an indispensable component of modern civilization, playing a vital role in propelling economic growth, enabling social development, and fuelling technological advancements [1]. The diverse range of energy applications, from industrial processes and transportation to residential electricity consumption, demonstrates its pervasive influence across various sectors [2]. Nevertheless, the escalating global energy demand, coupled with the pressing need to mitigate climate change and environmental deterioration, has intensified the pursuit of sustainable energy solutions [3]. This imperative has driven the exploration of alternative energy sources, energy efficiency enhancements, and innovative energy management approaches to ensure a sustainable future for humanity [4].

The relentless growth of population, urbanization, and industrialization has significantly increased energy consumption, placing immense strain on finite fossil fuel reserves and intensifying carbon dioxide emissions, leading to detrimental climate consequences [5]. To address these challenges, the focus has shifted towards renewable energy sources such as solar, wind, hydro, and geothermal power, which offer cleaner and more sustainable alternatives [6]. Furthermore, improving energy efficiency in various sectors has become paramount for curbing energy waste and reducing greenhouse gas emissions [7]. Embracing energy-efficient technologies, adopting energy management systems, and promoting behavioural changes are crucial steps towards achieving sustainable energy consumption patterns [8].

In the quest for sustainable energy solutions, the integration of advanced technologies, particularly Artificial Intelligence (AI), has emerged as a promising avenue for revolutionizing energy systems [9]. AI encompasses a suite of techniques, including machine learning, optimization algorithms, and data analytics, which enable intelligent decision-making and improved energy management [10]. By harnessing the power of AI, energy systems can enhance grid operations, optimize energy distribution, and facilitate demand response mechanisms. AI tools can analyse vast amounts of energy data, identify consumption patterns, and make accurate predictions, thereby facilitating informed decision-making for energy policymakers, grid operators, and consumers [11]. The adoption of AI in energy systems holds the potential to unlock significant benefits in terms of energy efficiency, reduced costs, enhanced grid stability, and the integration of renewable energy sources, propelling society towards a sustainable and prosperous future [12].

The aim of this article is to explore the intersection of artificial intelligence (AI) and energy, highlighting the potential for AI to revolutionize the way we generate, distribute, and consume energy. By analysing vast amounts of data, optimizing systems, and enabling intelligent decision-making, AI has the potential to enhance energy efficiency, reduce waste, and promote sustainable practices. This paper presents various ideas and applications where AI can be leveraged to address energy challenges and contribute to a cleaner and more sustainable future.

2. Literature Review

The development of energy systems has undergone a significant transformation, progressing from the traditional power grid to the smart grid and now towards the concept of the energy internet [13]. The power grid represents the conventional energy supply system, while the smart grid builds upon it by integrating information collection, control, and regulation, as well as incorporating new energy sources [14]. However, the energy internet represents a more advanced stage, characterized by energy optimization decisions and widespread coordination facilitated by the convergence of smart grid technologies, AI, cloud computing, Internet of Things, big data, and mobile internet. It embodies a deep fusion of information, physics, and societal aspects [15].

Compared to the traditional power system, the energy internet enables comprehensive coordination among various aspects such as energy sources, transmission networks, loads, and energy storage. It embraces the concept of multi-energy complementarity, facilitating the efficient utilization and integration of diverse energy resources [16]. With the evolution of the energy system, the energy unit has also progressed from the traditional user to the prosumer, energy cell, and now to the concept of we-energy [17].

The prosumer represents an energy unit that not only consumes energy but also produces it, thereby engaging in a half-duplex model. Energy cell refers to either an individual consumer or a group of entities that consist of local generation units, storage devices, and controllable loads. This concept also operates on a half-duplex model, accommodating multiple energy carriers [18]. On the other hand, we-energy embodies a full-duplex model, considering the coupling of multiple energy forms and the ability to exchange energy with other entities through advanced automatic control, electrical power conversion, and communication technologies [19]. We-energy possesses self-learning and self-adaptive capabilities, enabling it to optimize its energy usage based on dynamic conditions and evolving energy demands (Figure 1) [20].

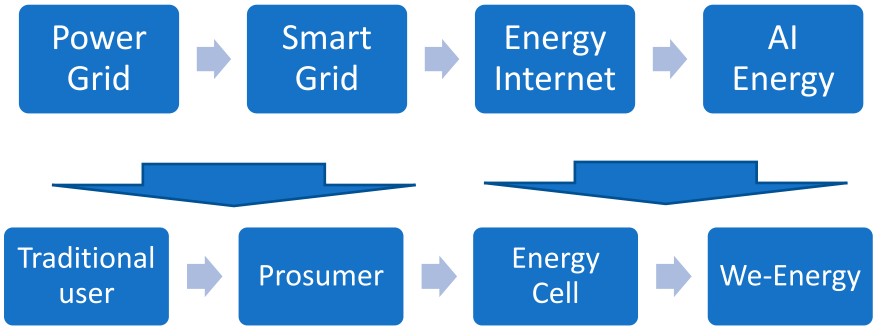

Figure 1. The development of energy systems and energy units. Source: own elaboration.

The development of the energy internet and the concept of we-energy signify a paradigm shift in energy systems, moving towards a more intelligent, interconnected, and flexible framework. This transformation enables the seamless integration of diverse energy sources, efficient energy management, and enhanced control and coordination capabilities [21–24]. By leveraging AI technologies, such as advanced control algorithms, predictive analytics, and intelligent decision-making systems, the energy internet can achieve optimal energy utilization, facilitate energy exchange, and contribute to the development of a sustainable and resilient energy landscape [25,26].

The Collaborative Energy Optimization Platform (CEOP) is an innovative model that leverages AI algorithms in an integrated manner, enabling energy distribution companies, policymakers, and consumers to benefit from increased energy efficiency, reduced costs, and improved grid stability. CEOP focuses on collaboration and data-sharing among stakeholders to optimize energy management and foster sustainable practices (Figure 2). These are the key components and benefits of this model:

- Data Integration and Sharing: CEOP facilitates the integration and sharing of data among energy distribution companies, policymakers, and consumers. This includes real-time energy consumption data, renewable energy generation data, weather forecasts, and grid infrastructure information. By pooling and analysing this data using AI algorithms, CEOP gains valuable insights into energy demand and supply dynamics, enabling optimized decision-making.
- AI-Driven Energy Optimization: CEOP utilizes advanced AI algorithms to optimize energy distribution and consumption across the system. AI algorithms analyse real-time data, including energy consumption patterns, generation capacity, and grid load, to predict energy demand, identify potential inefficiencies, and optimize energy flows. The algorithms also consider factors such as weather conditions, consumer preferences, and policy goals to generate optimal energy management strategies.
- Demand Response and Consumer Engagement: CEOP encourages consumer participation and engagement through demand response programs. By providing consumers with personalized recommendations, real-time energy pricing information, and incentives, CEOP motivates them to adjust their energy usage during peak demand periods. Consumers can actively contribute to grid stability by voluntarily shifting or reducing their energy consumption, thereby reducing costs and the need for additional generation capacity.
- Grid Stability and Resilience: CEOP focuses on ensuring grid stability and resilience through intelligent grid management. AI algorithms continuously monitor and analyse data on power quality, grid load, renewable energy generation, and other relevant parameters. In case of anomalies or potential disruptions, the algorithms take preventive measures such as load balancing, optimal power flow adjustments, and proactive maintenance, reducing the likelihood of grid failures and improving overall reliability.
- Policy and Decision Support: CEOP provides policymakers and energy distribution companies with AI-driven decision support tools. These tools incorporate policy goals, environmental targets, and economic considerations to assist in planning and imple-

menting sustainable energy strategies. For policymakers, CEOP offers simulations and scenario analysis capabilities, allowing them to assess the impact of different policies and regulations on energy efficiency, grid stability, and cost-effectiveness.

- Continuous Learning and Improvement: CEOP continuously learns and adapts to changing energy patterns and consumer behaviour. AI algorithms in the platform refine their models based on new data and feedback, making increasingly accurate predictions and recommendations over time. This iterative learning process helps identify new opportunities for energy optimization, enhance forecasting accuracy, and uncover potential inefficiencies or system bottlenecks.

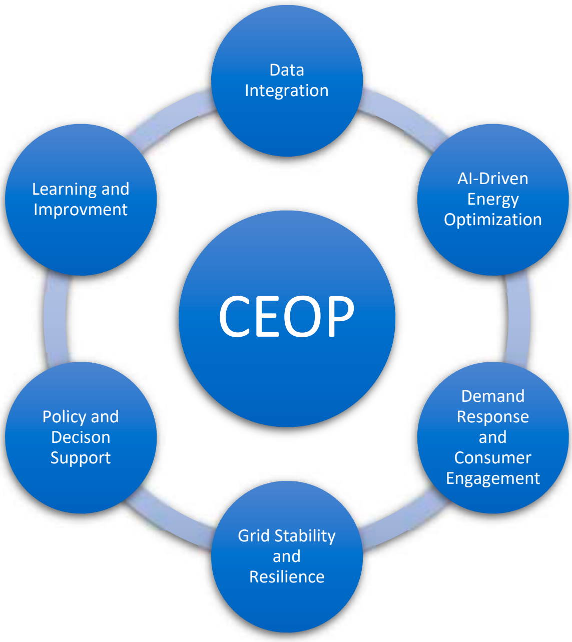

Figure 2. The Collaborative Energy Optimization Platform. Source: own elaboration.

One of the key benefits of implementing AI algorithms in intelligent energy management systems, such as the CEOP, is the significant increase in energy efficiency. By leveraging real-time data and predictive analytics, AI algorithms can optimize energy distribution and consumption patterns. This leads to a reduction in energy waste and promotes more efficient use of resources throughout the system. By identifying areas of improvement and suggesting energy-saving strategies, CEOP empowers energy consumers and distribution companies to make informed decisions that maximize energy efficiency.

The integration of AI algorithms in CEOP holds immense potential for transforming the energy landscape by promoting sustainability and empowering energy consumers. As AI technologies continue to advance and evolve, the benefits of CEOP are expected to further increase. By embracing AI as a key tool in energy management, stakeholders in the energy sector can unlock significant advantages, contributing to a more efficient, sustainable, and consumer-centric energy system. Here are other benefits of CEOP:

- Reduced Costs: CEOP helps identify cost-saving opportunities, such as load balancing, demand response, and optimized generation scheduling, leading to reduced energy costs for consumers and distribution companies.
- Improved Grid Stability: Through AI-driven grid management, CEOP enhances grid stability, minimizes the risk of disruptions, and ensures reliable energy supply to consumers.
- Enhanced Sustainability: CEOP supports the integration of renewable energy sources by optimizing their utilization, enabling a smoother transition to a sustainable and low-carbon energy system.

- Consumer Empowerment: CEOP engages consumers in energy management, providing them with information, incentives, and control over their energy usage, fostering a sense of ownership and environmental responsibility.

While the Collaborative Energy Optimization Platform (CEOP) offers several advantages, it is important to consider potential disadvantages as well. Here are some disadvantages that should be taken into account:

- Data Privacy and Security Risks: CEOP relies on the integration and sharing of sensitive energy consumption data. This raises concerns about data privacy and security, as the platform requires robust measures to protect against unauthorized access, breaches, or misuse of data. Safeguarding privacy and ensuring secure data handling practices are crucial to maintain trust among stakeholders.
- Complexity and Implementation Challenges: Implementing CEOP requires significant technical expertise and investment in infrastructure, including data collection systems, AI algorithms, and communication networks. Coordinating and integrating various stakeholders, such as energy distribution companies, policymakers, and consumers, can be challenging due to differing priorities, standards, and protocols.
- Algorithmic Bias and Fairness: The AI algorithms employed in CEOP may inherit biases present in the data used for training. These biases can lead to unfair outcomes and unequal distribution of benefits. Careful attention must be paid to ensure that the algorithms are designed to be fair, transparent, and inclusive, accounting for diverse consumer needs and social equity considerations.
- Reliance on Accurate Data and Models: The effectiveness of CEOP heavily relies on accurate and up-to-date data, as well as reliable predictive models. Inaccurate or incomplete data, unreliable forecasts, or faulty algorithms can lead to suboptimal energy management decisions and potential disruptions to the grid.
- Limited Consumer Engagement and Adoption: While CEOP aims to engage consumers in energy management, the success of demand response programs and consumer participation relies on their willingness to actively adjust their energy consumption patterns. Lack of awareness, resistance to change, or insufficient incentives may limit consumer engagement and impact the overall effectiveness of the platform.
- Regulatory and Policy Challenges: Implementing CEOP requires alignment with existing regulations and policies, which may not always be adaptable to the dynamic nature of the platform. Regulatory barriers, bureaucratic processes, and conflicting interests among different stakeholders can impede the widespread adoption and smooth operation of CEOP.
- Technological Dependence and Reliability: CEOP relies on advanced AI algorithms and technological infrastructure. Dependence on these technologies introduces risks associated with system failures, malfunctions, or technical glitches. Ensuring the reliability, resilience, and robustness of the platform is crucial to avoid disruptions in energy management processes.

It is important to address these disadvantages through careful planning, robust governance, ongoing monitoring and evaluation, and stakeholder engagement to ensure that the benefits of CEOP outweigh its limitations.

3. Research Design and Methodology

The objective of this article is to assess key criteria and sub-criteria for the analysis of AI integration with energy management systems, such as CEOP. This study utilizes a combination of 20 selected factors and empirical approaches employing heuristic and multiple criteria methods. This research model comprises five key steps (Figure 3):

1. Literature review of similar studies.
2. The verification of selected criteria and sub-criteria is carried out using the experts panel method [27].

3. Weights are determined for the selected dimensions (criteria) and their corresponding determinants (sub-criteria) using the fuzzy AHP method [28].
4. Five different variants of CEOP are proposed by experts and the collected data and the TOPSIS method are used to analyse and rank selected variants [29].
5. Results interpretation and development recommendations are introduced.

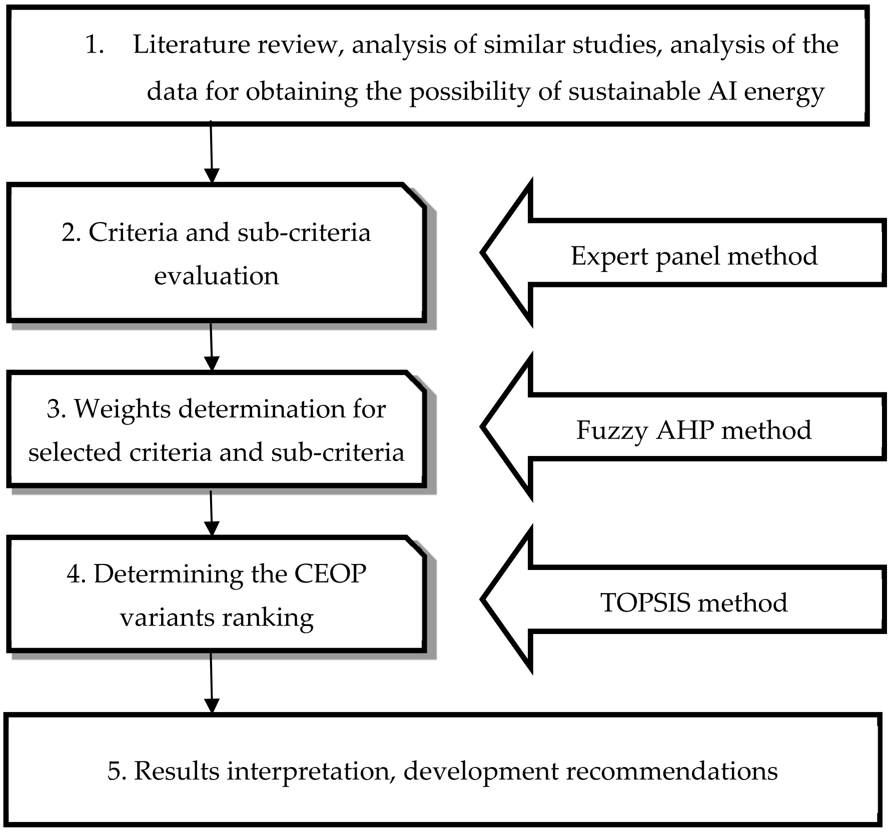

Figure 3. Research design and methodology. Source: own elaboration.

In this study, a panel of fourteen experts, comprising four experts specializing in artificial intelligence (AI), seven experts with expertise in energy management systems, and three experts in sustainable development, was surveyed to identify and prioritize the criteria for investigation. The survey was conducted in February 2023, and the insights obtained from these experts played a crucial role in shaping the research direction.

To establish a comprehensive understanding of the research area, five criteria were selected for investigation. Within each criterion, four sub-criteria were identified to provide a more nuanced analysis. These criteria were determined based on the consensus among the panel experts and their expertise in the respective domains of AI, energy management systems, and sustainable development.

The subsequent stage of the present research involves the calculation of weights for the selected criteria and sub-criteria, utilizing the fuzzy Analytic Hierarchy Process (fuzzy AHP) [30]. The fuzzy AHP method is a decision-making technique that allows for the incorporation of uncertainty and ambiguity in expert judgments. It extends the traditional AHP method by introducing fuzzy logic to handle linguistic terms and subjective opinions. In this study, the fuzzy AHP method was used to facilitate the ranking and prioritization of criteria and sub-criteria based on the assessments provided by the panel of fourteen experts. The experts were asked to provide pairwise comparisons between the criteria and sub-criteria, expressing their preferences and judgments using linguistic terms. These comparisons were then transformed into fuzzy linguistic variables to capture the uncertainty inherent in the experts' assessments.

The subsequent stage of the present research involves the calculation of weights for the selected criteria and sub-criteria, utilizing the fuzzy Analytic Hierarchy Process (fuzzy AHP) [30]. AHP represents one of the multiple-criteria decision making techniques, designed to tackle complex problems across various fields [31]. The fundamental principle of the AHP method involves decomposing the decision problem into a hierarchical structure and identifying the optimal solution under given conditions, based on the adopted criteria (and sub-criteria) [32]. This approach enables the evaluation of multiple criteria and the consideration of their relative importance, leading to more informed and effective decision-making. The use of fuzzy logic and linguistic variables in the AHP method enhances its flexibility and ability to handle imprecision and uncertainty in expert judgments.

The principal constraint of the AHP method lies in its incapacity to account for the ambiguities or inaccuracies inherent in group decision-making. In response to this inadequacy, the integration of AHP and fuzzy theory has been proposed (FAHP), enabling researchers to more precisely evaluate the problem and incorporate incomplete or imprecise information [33]. The combination of AHP and fuzzy theory enables the representation of qualitative and quantitative data in a common framework, allowing decision-makers to incorporate subjective judgments and linguistic expressions into the decision-making process [34]. FAHP enhances the flexibility and applicability of the AHP method, making it a more effective tool for handling complex problems in a wide range of domains. The integration of AHP and fuzzy theory has been widely used in decision-making, especially in cases where precise data is lacking or uncertain [35].

The most important step in FAHP is creating a pair-wise comparison matrix, where crisp numeric values are converted into fuzzy numbers, using a selected membership function (the most used is the triangular membership function, Formula (1)), according to Saaty's fundamental scale (scale of relative importance) shown in Table 1.

$$\widetilde{A} = (l, m, u) \tag{1}$$

The purpose of pairwise comparisons is to evaluate how many times one element outweighs another in terms of their relative importance. If element A is favoured very strongly over B, the fuzzy number is $\widetilde{A} = (6, 7, 8)$ and the fuzzy reciprocal value is $\widetilde{A}^{-1} = \left(\frac{1}{8}, \frac{1}{7}, \frac{1}{6}\right)$, according to Formula (2).

$$\widetilde{A}^{-1} = (u, m, l)^{-1} \tag{2}$$

The integration of AHP and fuzzy theory has been widely used in decision-making, especially in cases where precise data is lacking or uncertain [28,36].

The second step in the FAHP involves verifying the consistency ratio (C.R.). It is generally accepted that the value of C.R. for a 3 × 3 or 4 × 4 matrix should be less than or equal to 5% and 8%, respectively, while for larger matrices, it should not exceed 10% (C.R. ≤ 10%). If the C.R. is within this limit, the comparisons made are considered consistent. However, if the C.R. exceeds 10%, the criteria evaluation must be repeated to eliminate the inconsistency of pairwise comparisons. In this stage, the FAHP method involves calculating a defuzzified, normalized matrix for the selected criteria and the largest eigenvalue of the matrix (λ_{max}). The author of the method has shown that pairwise comparisons are more consistent when the λ_{max} value is close to the number of matrix elements, n. Based on this, the C.I. consistency index is calculated according to Formula (3).

$$\text{C.I.} = \frac{\lambda_{max} - n}{n - 1} \tag{3}$$

and consistency ratio C.R. according to Formula (4),

$$\text{C.R.} = \frac{100\% * \text{C.I.}}{\text{R.I.}} \tag{4}$$

where R.I. is a random consistency index, generated from several thousand matrices and proposed by the author in the form of Table 2.

Table 1. The fundamental scale for pairwise comparisons (l—lower fuzzy number, m—middle fuzzy number, u—upper fuzzy number).

Intensity of Importance	Explanation	AHP	FAHP (l, m, u)
Equal importance	Element a and b contribute equally to the objective	1	(1, 1, 1)
Moderate importance of one over another	Slightly favour element A over B	3	(2, 3, 4)
Essential importance	Strongly favour element A over B	5	(4, 5, 6)
Demonstrated importance	Element A is favoured very strongly over B	7	(6, 7, 8)
Absolute importance	The evidence favouring element A over B is of the highest possible order of importance	9	(9, 9, 9)
Intermediate values between the two adjacent judgments	When compromise is needed. For example, 4 can be used for the intermediate value between 3 and 5	2, 4, 6, 8	(1, 2, 3) (3, 4, 5) (5, 6, 7) (7, 8, 9)

Source: [37].

Table 2. Consistency indices for a randomly generated matrix.

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
R.I.	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49	1.52	1.54	1.56	1.58	1.59

Source: [37].

After performing a consistency check on the experts' opinions and ensuring their agreement, the fuzzy geometric mean $\widetilde{r}_i$ (as given by Formula (5)) and the fuzzy weights $\widetilde{w}_i$ for all the criteria (as given by Formula (6)) were computed.

$$\widetilde{r}_i = \left(\left(\prod_{i=1}^{n}\{l\}\right)^{\frac{1}{n}}, \left(\prod_{i=1}^{n}\{m\}\right)^{\frac{1}{n}}, \left(\prod_{i=1}^{n}\{u\}\right)^{\frac{1}{n}} \right) \tag{5}$$

$$\widetilde{w}_i = \widetilde{r}_i \otimes (\widetilde{r}_1 \oplus \widetilde{r}_2 \oplus \ldots \oplus \widetilde{r}_n)^{-1} \tag{6}$$

Subsequently, the fuzzy weights were transformed into crisp values w_i using the centre of area method (as given by Formula (7)) and then normalized into $w_{\text{i-norm}}$ values using Formula (8).

$$w_i = \frac{(l_i + m_i + u_i)}{3} \tag{7}$$

$$w_{\text{i-norm}} = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{8}$$

In conclusion, utilizing the geometric mean, the results from fourteen experts were amalgamated to derive the final weights for the five criteria, which are presented in Table 3. The subsequent phase of the FAHP analysis entailed applying the same analytical technique (Formulas (1)–(8)) to all sub-criteria. In the research model presented, the analysis encompassed five groups of criteria, involving the comparison of all sub-criteria within each criteria group, and was conducted by fourteen experts, leading to the generation of seventy tables. Owing to the extensive empirical data, the article provides only partial results of this computation in Tables 3 and 4.

Table 3. Fuzzy AHP pairwise comparison of five criteria and weight calculation by Expert 1—part 1.

	E			S			EI			EI2			PR		
E	1.00	1.00	1.00	1.00	2.00	3.00	1.00	2.00	3.00	1.00	2.00	3.00	3.00	4.00	5.00
S	0.33	0.50	1.00	1.00	1.00	1.00	0.33	0.50	1.00	1.00	2.00	3.00	1.00	2.00	3.00
EI	0.33	0.50	1.00	1.00	2.00	3.00	1.00	1.00	1.00	1.00	2.00	3.00	1.00	1.00	1.00
EI2	0.33	0.50	1.00	0.33	0.50	1.00	0.33	0.50	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PR	0.20	0.25	0.33	0.33	0.50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Source: Own elaboration.

Table 4. Fuzzy AHP pairwise comparison of five criteria and weight calculation by Expert 1—part 2 (l—lower fuzzy number, m—middle fuzzy number, u—upper fuzzy number, COA—centre of area).

	Geometric Mean			Fuzzy Weight			Centre of Area	Weight
	l	m	u	l	m	u		
	0.70	0.87	1.15	0.10	0.15	0.25	0.17	15.70%
	1.32	1.58	1.78	0.19	0.27	0.38	0.28	26.71%
	1.43	1.89	2.27	0.21	0.33	0.49	0.34	32.16%
	0.92	1.08	1.32	0.13	0.19	0.28	0.20	19.04%
	0.29	0.35	0.46	0.04	0.06	0.10	0.07	6.38%
Sum	4.66	5.78	6.98			Sum	1.06	100.00%
Reciprocal	0.14	0.17	0.21					

Source: Own elaboration.

After accepting (FAHP consistency test, CR $\leq$ 10%) and combining (geometric mean) the fourteen experts' assessments for all pairwise comparisons (criteria and sub-criteria), the results (in Table 5) were obtained for:

- weights for five criteria,
- local weights for twenty sub-criteria,
- global weights for twenty sub-criteria (product of criteria weight and local sub-criteria weight).

Table 5. Global weight determination.

Criteria Weight	Local Weight	Global Weight
26.50%	42.70%	11.32%
26.50%	28.80%	7.63%
26.50%	12.90%	3.42%
26.50%	15.60%	4.13%
17.70%	27.40%	4.85%
17.70%	24.80%	4.39%
17.70%	21.20%	3.75%
17.70%	26.60%	4.71%
23.40%	27.40%	6.41%

Table 5. *Cont.*

Criteria Weight	Local Weight	Global Weight
23.40%	32.40%	7.58%
23.40%	22.50%	5.27%
23.40%	17.70%	4.14%
23.90%	25.40%	6.07%
23.90%	38.20%	9.13%
23.90%	19.10%	4.56%
23.90%	17.30%	4.13%
8.50%	23.50%	2.00%
8.50%	34.80%	2.96%
8.50%	18.40%	1.56%
8.50%	23.30%	1.98%

Source: Own elaboration.

The subsequent stage of the research implemented the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method [38], entailing the determination of the distance of the analysed object or phenomenon from the ideal and anti-ideal solutions, resulting in a comprehensive indicator permitting the creation of a ranking of tested objectives (CEOP models). The optimal model in the context of the selected sub-criteria is the one exhibiting the smallest distance from the ideal solution and simultaneously the greatest distance from the anti-ideal solution [39]. The TOPSIS method includes the following steps:

1. The initial step involves the creation of a normalized data matrix in accordance with a given formula:

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{9}$$

where i = 1, 2, . . . , m and j = 1, 2, . . . , n.

2. Subsequently, the Analytical Hierarchy Process (AHP) weights are applied based on the formula $v_{ij} = w_j \otimes z_{ij}$

3. The next stage encompasses determining the vector value of the ideal solution a^+ and anti-ideal solution a^- (positive ideal solution, negative ideal solution)

$$a^+ = \left(a_1^+, a_2^+, \ldots, a_n^+\right) := \left\{ \left(\begin{matrix} \max v_{ij} \\ i = 1, ., m \end{matrix} \middle| j \in J_Q \right), \left(\begin{matrix} \min v_{ij} \\ i = 1, ., m \end{matrix} \middle| j \in J_c \right) \right\} \tag{10}$$

$$a^- = \left(a_1^-, a_2^-, \ldots, a_n^-\right) := \left\{ \left(\begin{matrix} \min v_{ij} \\ i = 1, ., m \end{matrix} \middle| j \in J_Q \right), \left(\begin{matrix} \max v_{ij} \\ i = 1, ., m \end{matrix} \middle| j \in J_c \right) \right\} \tag{11}$$

where J_Q is a beneficial criteria and J_c is a non-beneficial (cost) criteria.

4. The Euclidean distance of the tested models from the ideal and anti-ideal solutions is then calculated:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - a_j^+\right)^2} \tag{12}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - a_j^-\right)^2} \tag{13}$$

where i = 1, 2,..., m and j = 1, 2,..., n

5. Finally, the performance score R_i for the examined CEOP models is computed using the given formula [40]:

$$R_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{14}$$

The CEOP model exhibiting the highest performance score R_i represents the optimal solution for the given problem of ranking in the context of the selected sub-criteria (Table 6).

Table 6. Ranking of CEOP models.

Ranking	CEOP Model	S^+	S^-	Ri
1	OAV	0.0203	0.0523	0.7206
2	CSV	0.0266	0.0468	0.6376
3	IRES	0.0295	0.0452	0.6048
4	IDSV	0.0435	0.0389	0.4719
5	CAC	0.0510	0.0218	0.2993

Source: Own elaboration.

4. Results

It is important to note that a detailed description of the AHP method, including the mathematical calculations and procedures involved, is provided in the research design and methodology section of this research paper. Below is a list of criteria and sub-criteria along with the weights obtained using the AHP method and fuzzy logic:

1. Effectiveness (weight 26.5%):
    - Energy Efficiency Metrics (42.7%): Investigate the specific metrics used to evaluate the effectiveness of CEOP in improving energy efficiency. This could include factors such as energy savings, reduction in carbon emissions, or increased utilization of renewable energy sources.
    - Performance Comparison (28.8%): Compare the performance of different AI algorithms and techniques used in CEOP, considering factors such as accuracy, computational efficiency, and adaptability to dynamic energy system conditions.
    - Case Studies (12.9%): Analyse real-world case studies where CEOP has been implemented, focusing on the outcomes and benefits achieved in terms of energy efficiency, cost reduction, and grid stability improvements.
    - User Feedback (15.6%): Gather feedback from end-users of CEOP, such as energy consumers and distribution companies, to understand their perceptions of the effectiveness of the system and its impact on their energy management practices.
2. Scalability (17.7%):
    - Compatibility with Different Grid Types (27.4%): Investigate how well CEOP algorithms can be adapted to various types of energy grids, including centralized, decentralized, and microgrid systems.
    - Data Management (24.8%): Assess the scalability of CEOP in handling large-scale data, considering factors such as data acquisition, processing, storage, and analysis.
    - Integration with Distributed Energy Resources (21.2%): Investigate the integration capabilities of CEOP with distributed energy resources, such as rooftop solar panels or wind turbines, to determine its scalability in accommodating diverse energy sources.
    - Interoperability (26.6%): Explore the ability of CEOP to integrate with existing energy infrastructure, including compatibility with different communication protocols and standards, to ensure smooth interoperability.
3. Economic Impact (23.4%):

- Cost-Benefit Analysis (27.4%): Conduct a comprehensive cost-benefit analysis to quantify the economic benefits of implementing CEOP, including factors such as energy cost savings, reduction in operational expenses, and potential revenue streams.
- Return on Investment (32.4%): Evaluate the return on investment (ROI) for different stakeholders, such as energy consumers and distribution companies, by assessing the financial gains achieved through CEOP implementation.
- Market Analysis (22.5%): Study the market potential and market dynamics of AI-enabled energy management systems, including market size, growth projections, and key players, to understand the economic viability and competitive landscape.
- Economic Policy Implications (17.7%): Examine the policy implications of CEOP on energy markets and regulatory frameworks, considering factors such as pricing mechanisms, incentive programs, and potential impacts on market dynamics and competition.

4. Environmental Impact (23.9%):
    - Life Cycle Assessment (25.4%): Conduct a life cycle assessment of CEOP to evaluate its environmental footprint, considering factors such as embodied energy, carbon emissions, and potential impacts on water resources or land use.
    - Resource Optimization (38.2%): Investigate how CEOP can contribute to resource optimization, such as minimizing energy waste, optimizing renewable energy utilization, and reducing the environmental impact associated with energy production and consumption.
    - Environmental Policy Alignment (19.1%): Assess the alignment of CEOP with environmental policies and sustainability goals, such as climate targets, renewable energy integration, or circular economy principles.
    - Environmental Decision Support (17.3%): Explore the potential of CEOP in providing decision support tools for energy stakeholders to make environmentally conscious choices, such as load shifting to periods of higher renewable energy availability or facilitating the integration of electric vehicles.
5. Policy and Regulation (8.5%):
    - Legal and Regulatory Framework Analysis (23.5%): Examine the existing legal and regulatory frameworks related to AI and energy, identifying any barriers, gaps, or conflicts that may hinder the deployment of CEOP, and propose policy recommendations.
    - Privacy and Data Protection (34.8%): Investigate the privacy and data protection implications of CEOP, exploring methods to ensure data security, compliance with privacy regulations, and user consent mechanisms.
    - Standardization and Interoperability (18.4%): Study the standardization needs and interoperability requirements for CEOP, considering the compatibility of AI algorithms, data formats, and communication protocols to enable seamless integration and cooperation between different energy stakeholders.
    - Policy and Governance Models (23.3%): Explore different policy and governance models that can foster the responsible and ethical implementation of CEOP, ensuring transparency, accountability, and fairness in decision-making processes.

The expert panel, consisting of esteemed professionals in the fields of AI and energy, proposed five variations of CEOP configurations for evaluation and ranking. Drawing upon their extensive knowledge and experience, the experts put forth these variations as important considerations in exploring the potential impact and performance of CEOP in different scenarios. Through their collective expertise, the panel identified these variations as key scenarios that can significantly influence the effectiveness and outcomes of CEOP in real-world energy systems:

- Optimization Algorithm Variation (OAV): Different optimization algorithms can be employed within the CEOP framework. For example, one configuration could utilize a genetic algorithm, while another could use a particle swarm optimization algorithm. These variations can lead to different optimization results and performance across the weighted sub-criteria.

- Input Data Source Variation (IDSV): The CEOP model relies on input data to make decisions and optimize energy systems. Different configurations can explore variations in input data sources, such as using historical data, real-time data from sensors, or a combination of both. The choice of data sources can impact the accuracy and reliability of the optimization results.
- Control Strategy Variation (CSV): CEOP involves controlling and regulating energy systems based on optimization results. Different control strategies can be employed, such as model predictive control, rule-based control, or fuzzy logic control. Each strategy has its strengths and limitations, which can result in variations in performance across the weighted sub-criteria.
- Integration of Renewable Energy Sources (IRES): The CEOP model can be configured to prioritize the integration and utilization of renewable energy sources. Variations can be explored in terms of the percentage of renewable energy used, the types of renewable sources included (e.g., solar, wind, hydro), and the management of intermittency and uncertainty associated with renewables.
- Communication and Connectivity (CAC): CEOP can be configured with different communication and connectivity options. Variations can include different communication protocols, network architectures, and the level of connectivity with smart devices and IoT platforms. These variations can impact the speed and reliability of data exchange, which in turn affects the performance of the CEOP model.

The subsequent stage of the research implemented the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method [38] to rank five proposed models. The TOPSIS method is a multi-criteria decision-making technique used to determine the relative performance and ranking of alternatives based on their proximity to the ideal solution. It involved constructing a decision matrix that represents the performance of each sub-criterion for all alternatives. The matrix consisted of numerical values reflecting the evaluations or measurements of the sub-criteria for each alternative [41].

The TOPSIS method compares each alternative to the ideal solution (S^+) and the worst solution (S^-) based on the values in the decision matrix. The ideal solution represents the best performance across all sub-criteria, while the worst solution represents the worst performance. The distance between each alternative and the ideal and worst solutions is calculated, and a relative closeness coefficient (R_i) is obtained to determine the ranking of the alternatives [42].

It is important to note that a detailed description of the TOPSIS method, including the mathematical calculations and procedures involved, is provided in the research design and methodology section of this research paper.

In the research conducted by the panel of experts, a Likert scale ranging from 1 to 5 was utilized to build the decision matrix. The Likert scale is a widely used measurement scale that allows respondents to express their level of agreement or disagreement with a particular statement or proposition. In this case, the experts used the Likert scale to assess the relative importance or preference of each sub-criterion in relation to proposed CEOP models. A rating of 1 on the Likert scale represented the lowest importance or preference, while a rating of 5 indicated the highest importance or preference. The experts provided their ratings independently based on their expertise and judgment in the field of AI and energy. By aggregating the ratings provided by the experts, a normalized decision matrix was constructed that captured the global weights or importance of sub-criteria (product of criteria weight and local weight, sub-criteria weight within a group, Tables 7 and 8).

Table 7. Normalized decision matrix (fuzzy AHP weights included) for CEOP model evaluation: Effectiveness, Scalability, and Economic Impact.

Weight	11.32%	7.63%	3.42%	4.13%	4.85%	4.39%	3.75%	4.71%	6.41%	7.58%	5.27%	4.14%
CEOP model	E1	E2	E3	E4	S1	S2	S3	S4	EI1	EI2	EI3	EI4
OAV	0.056	0.046	0.013	0.019	0.024	0.022	0.021	0.022	0.032	0.031	0.024	0.019
IDSV	0.042	0.036	0.022	0.015	0.024	0.018	0.017	0.022	0.024	0.041	0.030	0.024
CSV	0.056	0.036	0.017	0.019	0.024	0.022	0.017	0.022	0.032	0.041	0.018	0.019
IRES	0.056	0.027	0.013	0.019	0.024	0.022	0.017	0.022	0.032	0.031	0.018	0.019
CAC	0.042	0.018	0.009	0.019	0.012	0.013	0.012	0.015	0.024	0.021	0.024	0.009
Max	0.056	0.046	0.022	0.019	0.024	0.022	0.021	0.022	0.032	0.041	0.030	0.024
min	0.042	0.018	0.009	0.015	0.012	0.013	0.012	0.015	0.024	0.021	0.018	0.009

Source: own elaboration.

Table 8. Normalized decision matrix (fuzzy AHP weights included) for CEOP model evaluation: Environmental Impact, Policy, and Regulations.

Weight	6.07%	9.13%	4.56%	4.13%	2.00%	2.96%	1.56%	1.98%
CEOP model	EI2-1	EI2-2	EI2-3	EI2-4	PR1	PR2	PR3	PR4
OAV	0.029	0.047	0.031	0.020	0.008	0.012	0.005	0.005
IDSV	0.015	0.023	0.012	0.015	0.008	0.012	0.008	0.005
CSV	0.022	0.047	0.018	0.020	0.008	0.012	0.008	0.010
IRES	0.036	0.047	0.018	0.020	0.008	0.018	0.005	0.013
CAC	0.029	0.035	0.018	0.015	0.012	0.012	0.008	0.008
Max	0.036	0.047	0.031	0.020	0.012	0.018	0.008	0.013
min	0.015	0.023	0.012	0.015	0.008	0.012	0.005	0.005

Source: own elaboration.

The creation of a ranking for CEOP models, based on the adopted five criteria and twenty sub-criteria, is achieved by computing the Ri index and subsequently sorting the examined programs from the highest to the lowest value (Table 9).

Table 9. Ranking of the studied CEOP models.

Ranking	**CEOP Model**	**S^+**	**S^-**	**Ri**
1	OAV	0.0203	0.0523	0.7206
2	CSV	0.0266	0.0468	0.6376
3	IRES	0.0295	0.0452	0.6048
4	IDSV	0.0435	0.0389	0.4719
5	CAC	0.0510	0.0218	0.2993

Source: own elaboration.

5. Discussion

The conducted research involved the analysis of five different CEOP models, each exploring variations in key aspects such as optimization algorithms, input data sources, control strategies, integration of renewable energy sources, and communication and connectivity. The analysis aimed to evaluate the performance of these models across twenty predefined sub-criteria (fuzzy AHP and TOPSIS methods) within the context of AI and energy.

In terms of optimization algorithm variation, the research examined how different algorithms, such as genetic algorithms and particle swarm optimization, influenced the performance of CEOP. The analysis considered the impact of these variations on sub-criteria such as energy efficiency, cost reduction, grid stability, and sustainability. It was found that different algorithms yielded diverse optimization results, with certain algorithms excelling in specific sub-criteria while others performed better in different areas.

The research also investigated the impact of input data source variation on CEOP performance. By considering historical data, real-time data from sensors, or a combination of both, the study evaluated how these variations affected sub-criteria such as accuracy, reliability, and responsiveness. It was observed that using real-time data enhanced the model's ability to adapt to dynamic changes, leading to improved performance in sub-criteria related to real-time decision-making and energy system optimization.

Regarding control strategy variation, the research explored the strengths and limitations of different strategies, such as model predictive control, rule-based control, and fuzzy logic control. Each strategy was assessed based on sub-criteria including stability, response time, adaptability, and robustness. The findings indicated that different control strategies exhibited varying levels of effectiveness across these sub-criteria, emphasizing the importance of selecting the most suitable strategy for specific energy system contexts.

The integration of renewable energy sources was another key focus of the research. By examining variations in the percentages and types of renewable sources utilized, as well as the management of intermittency and uncertainty, this study evaluated the impact on sub-criteria related to renewable energy utilization, grid stability, and environmental sustainability. The analysis revealed that optimized integration of renewable sources led to improved performance in these sub-criteria, highlighting the potential of CEOP in facilitating the transition to a low-carbon energy system.

Lastly, the research considered communication and connectivity variations within the CEOP models. Different communication protocols, network architectures, and levels of connectivity with smart devices and IoT platforms were explored, assessing their impact on sub-criteria such as data exchange speed and reliability. The findings indicated that robust communication and connectivity options positively influenced the performance of CEOP, enabling efficient decision-making and optimization.

In the conducted research, the fuzzy AHP method allowed for the incorporation of expert opinions and the handling of uncertainty in decision-making. By using a Likert scale ranging from 1 to 5, the experts assigned numerical values to indicate their preferences or importance for each criterion and sub-criterion. The fuzzy AHP method then enabled the calculation of priority weights for the criteria and sub-criteria, taking into account the uncertainty and imprecision inherent in human judgment. These priority weights provided a quantitative basis for comparing and evaluating the different CEOP models.

The TOPSIS method was employed to rank the CEOP models based on the weighted sub-criteria. TOPSIS is a multi-criteria decision-making method that determines the similarity of each alternative to the ideal solution and the negative ideal solution. By considering both the positive and negative attributes of the alternatives, the TOPSIS method facilitated the identification of the most favourable CEOP model. The weighted sub-criteria obtained from the fuzzy AHP analysis were used as inputs in the TOPSIS method, enabling the calculation of the closeness coefficient and the determination of the rank order of the CEOP models.

As an alternative approach, one could consider incorporating other multi-criteria decision-making methods such as ELECTRE (Elimination and Choice Translating Reality) or PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation). These methods offer different approaches to handling multiple criteria and alternatives, allowing for more comprehensive evaluations. Additionally, incorporating machine learning techniques, such as neural networks or support vector machines, could enhance the analysis by learning patterns and relationships from the data to aid in the decision-making process. These approaches could provide additional insights and complement the fuzzy AHP and TOPSIS methods in evaluating the CEOP models.

To provide a more detailed mapping of AI implementation in achieving the objectives of the Collaborative Energy Optimization Platform (CEOP), let us explore how AI can be integrated within the model:

1. Data Analytics and Predictive Modelling:
    - AI algorithms can be used to analyse large volumes of energy-related data, such as consumption patterns, weather forecasts, and grid performance.
    - Machine learning techniques can identify patterns, anomalies, and correlations in the data, enabling insights into energy usage, demand forecasting, and potential efficiency improvements.
    - Predictive modelling algorithms can anticipate energy demand fluctuations, optimize supply management, and support grid stability planning.
2. Optimization Techniques:
    - AI algorithms, such as optimization algorithms, can be employed to optimize energy management decisions, such as scheduling energy generation, storage, and distribution.
    - These algorithms can consider various factors, including real-time energy prices, demand-response capabilities, renewable energy availability, and grid constraints.
    - By utilizing optimization techniques, the CEOP model can identify the most cost-effective and efficient energy distribution strategies.
3. Intelligent Energy Management:
    - AI-based systems can provide intelligent energy management solutions by continuously monitoring energy usage, detecting inefficiencies, and suggesting optimization measures.
    - These systems can employ AI algorithms, such as reinforcement learning or expert systems, to make real-time decisions on load balancing, energy storage utilization, and demand response activation.
    - AI can enable automated control systems that adjust energy distribution in response to changing conditions, ensuring optimal utilization of resources and grid stability.
4. Demand-Side Management and Consumer Engagement:
    - AI can facilitate demand-side management by analysing consumer behaviour and preferences.
    - Smart home devices, equipped with AI algorithms, can learn user patterns, optimize energy usage, and provide personalized recommendations to consumers for energy efficiency improvements.
    - AI-powered consumer engagement platforms can provide energy consumption insights, real-time feedback, and incentivize sustainable energy practices, fostering active consumer participation in energy optimization.
5. Decision Support Systems:
    - AI can enhance decision-making processes for stakeholders by providing data-driven insights, scenario analysis, and predictive simulations.
    - Decision support systems powered by AI algorithms can help policymakers, energy distribution companies, and consumers evaluate the potential impact of various energy management strategies, policies, and investments.
    - These systems enable stakeholders to make informed decisions, considering multiple factors such as cost-effectiveness, environmental impact, and grid stability.

By integrating AI in these ways, the Collaborative Energy Optimization Platform (CEOP) can leverage advanced analytics, optimization techniques, and intelligent decision-making to achieve the objectives of enhanced energy efficiency, reduced costs, and improved grid stability.

6. Conclusions

In the conducted research, five different CEOP models within the context of twenty predefined sub-criteria related to AI and energy systems were analysed. The objective was to evaluate and rank these models using multi-criteria decision-making (MCDM) methods. Specifically, the fuzzy Analytic Hierarchy Process (AHP) and TOPSIS methods were employed to assess the models based on their performance across the sub-criteria.

The application of the fuzzy AHP method allowed us to incorporate expert opinions and handle uncertainties in the decision-making process. By assigning numerical values to indicate preferences and importance using a Likert scale, we derived priority weights for the criteria and sub-criteria. These weights provided a quantitative basis for comparing and evaluating the CEOP models. The TOPSIS method, on the other hand, enabled us to rank the models by considering their similarity to the ideal and negative ideal solutions based on the weighted sub-criteria.

Through the analysis, valuable insights into the strengths and limitations of the CEOP models were gained. We found that the models exhibited variations in their performance across the sub-criteria, highlighting the importance of considering multiple aspects when evaluating AI-based energy optimization systems. The MCDM methods provided a systematic and structured approach for assessing the models, enabling experts to make informed decisions based on the weighted criteria and sub-criteria.

This research provides valuable insights for decision makers and researchers in the field, promoting the development and implementation of more efficient and sustainable AI-based energy systems by:

- The importance of collaboration: Decision makers will gain an understanding of the significance of collaboration among energy distribution companies, policymakers, and consumers. This insight emphasizes the need for cooperative efforts to optimize energy management and achieve energy efficiency goals.
- The value of data-sharing: Decision makers will recognize the importance of efficient data-sharing among stakeholders. This insight highlights the role of data exchange in facilitating informed decision-making and identifying opportunities for energy optimization.
- The potential of AI algorithms: Decision makers will gain insights into the integration of AI algorithms in energy systems. This insight emphasizes the power of AI for advanced data analytics, predictive modelling, and optimization techniques, enabling more effective decision-making and resource allocation.
- Implications for energy efficiency: Decision makers will understand how the CEOP model can enhance energy efficiency. This insight emphasizes the identification of energy wastage, the implementation of demand response strategies, and the overall improvement of energy distribution system efficiency.
- Cost reduction strategies: Decision makers will learn about data-driven decision-making and its role in reducing costs. This insight highlights how optimal resource allocation and operational planning, facilitated by the CEOP model, can lead to cost savings.
- Grid stability enhancement: Decision makers will gain insights into how the CEOP model contributes to improved grid stability. This insight emphasizes the model's ability to address supply-demand imbalances and support the integration of renewable energy sources, ultimately leading to a more stable and reliable grid.

The results of this research contribute to the advancement of AI and energy systems by providing a comprehensive evaluation framework for CEOP models. The findings can aid decision-makers, energy practitioners, and researchers in selecting the most suitable CEOP model for specific contexts. Furthermore, this research highlights the significance of considering various factors, such as optimization algorithms, input data sources, control strategies, integration of renewable energy sources, communication, and connectivity in designing and implementing effective CEOP systems.

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