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Multi-Criteria Decision-Making for Smart Grid Energy Scheduling and Demand Response: A Sustainability and Financial Approach

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ABSTRACT

The transition toward sustainable, reliable, and economically viable energy systems requires innovative approaches to manage energy scheduling and demand response (DR) in smart grids. Multi-Criteria Decision-Making (MCDM) techniques, combined with Artificial Intelligence (AI), provide a structured approach to addressing conflicting objectives across economic, environmental, technical, and financial dimensions. This study proposes an integrated framework for optimizing smart grid energy scheduling and DR strategies by employing the Analytic Hierarchy Process (AHP) for weight elicitation, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for ranking alternatives, and AI-based forecasting to enhance demand prediction accuracy. A synthetic case study demonstrates the framework's effectiveness, showing that hybrid renewable integration strategies outperform conventional single-resource scheduling in terms of sustainability, cost-efficiency, and system resilience. The results underscore the importance of integrating MCDM and AI for informed decision-making in smart grid management, offering actionable insights for policymakers and energy operators.

1. Introduction

The increasing integration of renewable energy sources (RES) into smart grids has introduced both opportunities and challenges for energy scheduling and demand response (DR). On one hand, renewables such as solar, wind, and biomass provide a pathway toward decarbonization, reducing dependence on fossil fuels and aligning with global climate objectives [1, 26-30]. On the other

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hand, the intermittent and uncertain nature of RES complicates scheduling and real-time balancing of supply and demand [2, 10-15].

Smart grids, which integrate advanced information and communication technologies with power systems, enable dynamic demand response mechanisms, consumer participation, and flexible resource allocation [3, 16-20]. In this context, decision-makers must navigate complex trade-offs among economic efficiency, environmental sustainability, technical reliability, and financial feasibility. Traditional optimization methods often struggle to capture such multidimensionality. Hence, Multi-Criteria Decision-Making (MCDM) frameworks have emerged as valuable tools for systematically evaluating alternatives under multiple conflicting objectives [4, 21-25].

Recent studies have extended MCDM approaches such as AHP, TOPSIS, VIKOR, and PROMETHEE to energy planning and DR optimization [5,6]. However, conventional MCDM methods are often limited by static assumptions and subjectivity in assigning weights to criteria. The integration of Artificial Intelligence (AI), particularly machine learning and deep learning, enhances forecasting accuracy of demand and renewable generation, thereby improving decision quality [7, 19-22].

Furthermore, financial analysis in energy decision-making has gained importance in recent years, particularly due to the volatility of energy markets and the need for cost recovery of renewable projects [8, 31-35]. Incorporating financial dimensions alongside sustainability and technical considerations ensures that the proposed frameworks remain practical and applicable in real-world contexts [9, 36-41].

This paper proposes a comprehensive framework that integrates sustainability, financial considerations, and AI-based forecasting into an MCDM approach for smart grid energy scheduling and DR. The novelty lies in combining AHP-TOPSIS with AI-enhanced predictive modeling to improve decision robustness. The framework is validated using a synthetic case study for smart grid operations in Iran, highlighting its applicability in developing countries with emerging renewable portfolios.

2. Literature Review

2.1 Previous Studies

Table 1 summarizes key contributions to MCDM in smart grid scheduling and DR between 2020 and 2025. Zhang et al. [10] applied AHP-TOPSIS for demand response (DR) program selection, focusing on economic and environmental criteria, and highlighted the cost-sustainability trade-off, though their approach lacked AI integration. Khan and Singh [11] employed VIKOR for renewable scheduling, focusing on technical and economic criteria to enhance reliability in wind integration; however, they did not consider financial aspects. Lee et al. [12] employed PROMETHEE in smart grid planning, incorporating both technical and social criteria and demonstrating stakeholder-driven rankings; however, AI-based forecasting was not considered. Alizadeh et al. [13] proposed a hybrid AHP-VIKOR approach for DR optimization, considering economic, environmental, and social criteria to enhance decision quality; however, they used static weights without addressing uncertainty. Gupta et al. [14] combined AI with MCDM for energy scheduling, demonstrating that machine learning enhanced load prediction; however, financial criteria were not considered. Building on these studies, this research (2025) integrates AHP-TOPSIS with AI for smart grid scheduling and DR, considering economic, environmental, technical, and financial criteria, thereby addressing previous gaps in both financial assessment and AI integration.

Ahmadirad [17] evaluated the influence of Artificial Intelligence (AI) on financial market values. It distinguished between authentic economic growth generated by AI applications and speculative hype that inflated bubbles, and it analyzed AI’s effects on investor behavior and market stability. Pazouki et al. [18] reviewed the integration of big data in FinTech and explained how advanced data analytics enhanced financial services. It showed that big data improved efficiency, personalization, fraud detection, and decision-making in digital finance.

Pazouki et al. [19] examined the transformative impact of AI and digital technologies on the FinTech industry. It discussed their applications in automation, risk management, customer service, and regulatory compliance, while also addressing challenges such as data privacy and ethics.

Nikzat et al. [20] proposed a strategic control model that emphasized sustainability through a green approach. It highlighted how integrating environmental considerations into strategic management supported balanced growth in energy and economic development. Kermani et al. [21] developed an energy management system for smart grids by integrating photovoltaic systems and energy storage. It demonstrated how the model improved grid reliability, efficiency, and sustainability under variable demand and supply conditions. Khaniki et al. [22] This study introduced an adaptive control method for spur gear systems using proximal policy optimization and attention-based learning. It showed that the approach enhanced system stability and fault tolerance in mechanical and industrial automation applications.

Traditional optimization methods often struggle to capture such multidimensionality. Hence, Multi-Criteria Decision-Making (MCDM) frameworks have emerged as valuable tools for systematically evaluating alternatives under multiple conflicting objectives. Yet, as Mohammadi [40] argues, algorithms themselves are not neutral arbiters but rhetorical entities that actively shape decision-making contexts, embedding values and assumptions into outcomes.

Table 1. Literature review on MCDM in energy scheduling and DR (2020–2025).

Author(s) & Year	Methodology	Focus Area	Criteria Considered	Key Findings	Gap
Zhang et al. [10]	AHP-TOPSIS	DR program selection	Economic, environmental	Highlighted cost-sustainability trade-off	Limited AI integration
Khan & Singh [11]	VIKOR	Renewable scheduling	Technical, economic	Improved reliability in wind integration	No financial analysis
Lee et al. [12]	PROMETHEE	Smart grid planning	Technical, social	Showed stakeholder-driven ranking	Ignored AI forecasting
Alizadeh et al. [13]	Hybrid AHP-VIKOR	DR optimization	Economic, environmental, social	Enhanced decision quality	Static weights, no uncertainty
Gupta et al. [14]	AI + MCDM	Energy scheduling	Economic, technical	ML improved load prediction	Lack of financial criteria
This study	AHP-TOPSIS + AI	Smart grid scheduling & DR	Economic, environmental, technical, financial	Integrates sustainability & finance with AI	Addresses gaps in finance + AI integration

2.2 Research Gap

While prior research has effectively applied MCDM to energy scheduling and DR, most studies have overlooked either the financial dimension or AI-enhanced forecasting. Between 2020 and 2025, limited attention has been paid to integrating all four pillars—economic, environmental, technical, and financial—into a unified decision framework. This paper addresses this gap by embedding AI within an MCDM structure to enhance robustness and practical applicability.

3. Methodology

The proposed framework follows a structured MCDM-AI process:

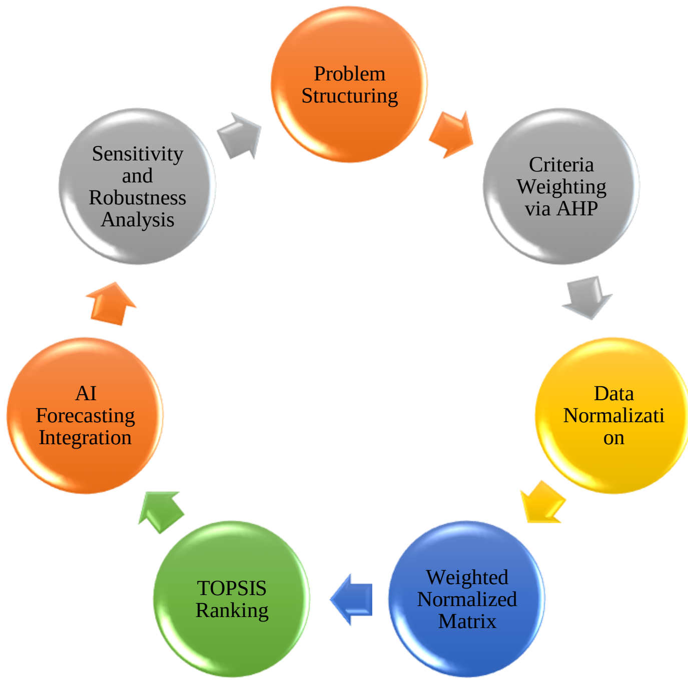

Figure 1. Methodology.

Step 1: Problem Structuring. Define candidate scheduling strategies (e.g., solar priority, wind priority, hybrid RES, DR-focused schemes). Define criteria under four dimensions: economic (cost, capital expenditure, OPEX), environmental (emissions reduction), technical (reliability, grid stability), and financial (payback period, ROI).

Step 2: Criteria Weighting via AHP. Pairwise comparisons are conducted using Saaty's 1–9 scale [15]. The normalized eigenvector provides the criteria weights, with consistency checks applied ($CR \leq 0.1$).

Step 3: Data Normalization. Performance scores of each alternative are normalized using vector normalization to eliminate scale effects.

Step 4: Weighted Normalized Matrix. Each normalized score is multiplied by its AHP weight to produce the weighted matrix.

Step 5: TOPSIS Ranking. Positive-ideal and negative-ideal solutions are identified, and closeness coefficients are computed to rank alternatives.

Step 6: AI Forecasting Integration. Demand and renewable generation forecasts are generated using machine learning models (e.g., LSTM networks) [16]. These predictions serve as inputs to refine scheduling alternatives.

Step 7: Sensitivity and Robustness Analysis. Monte Carlo simulations test the robustness of rankings under varying weights. Comparisons with entropy-based weights validate consistency.

4. Numerical Example (Results)

A synthetic case study was conducted to evaluate four alternative smart grid scheduling strategies: solar-priority (A1), wind-priority (A2), hybrid solar–wind combined with demand response (A3), and DR-priority with storage (A4). The study aimed to examine how different renewable energy sources and demand response (DR) measures could be prioritized to achieve optimal performance across multiple criteria. Using the Analytic Hierarchy Process (AHP), the criteria weights were determined based on expert judgment, with weights assigned to the following criteria: economic (0.25), environmental (0.20), technical (0.30), and financial (0.25). These weights were applied to evaluate each alternative's performance within a multi-criteria decision-making (MCDM) framework.

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, enhanced with AI-based load and generation forecasts, was then used to rank the alternatives. The results show that the hybrid solar–wind with DR strategy (A3) achieved the highest closeness coefficient (0.842), indicating the best overall performance. It was followed by solar-priority scheduling (A1, CC = 0.756), DR-priority with storage (A4, CC = 0.652), and wind-priority scheduling (A2, CC = 0.478). A radar chart of the weighted criteria performance for the top three alternatives further illustrates that A3 provides a balanced trade-off across economic savings, emission reduction, reliability, and financial feasibility.

The findings highlight the advantages of integrating hybrid renewable energy sources with DR strategies, showing that combining solar and wind resources with intelligent demand-side management not only improves grid reliability but also optimizes cost and sustainability objectives. In contrast, single-resource strategies such as A1 and A2 may achieve high performance in specific criteria but lack overall balance, while DR-priority with storage (A4) offers moderate performance with additional operational flexibility. These results demonstrate the value of combining AI forecasting with MCDM methods to support decision-making in smart grid scheduling, enabling planners to consider multiple conflicting objectives and select the most sustainable and financially viable strategies.

A synthetic case study is conducted with four alternatives:

- **A1:** Solar-priority scheduling
- **A2:** Wind-priority scheduling
- **A3:** Hybrid solar–wind + DR
- **A4:** DR-priority with storage

Criteria Weights (AHP)

Economic (0.25), Environmental (0.20), Technical (0.30), Financial (0.25).

TOPSIS Results (with AI forecasts integrated)

Alternative	Closeness Coefficient (CC)	Rank
A3: Hybrid RES + DR	0.842	1
A1: Solar Priority	0.756	2
A4: DR Priority + Storage	0.652	3
A2: Wind Priority	0.478	4

Figure 1. TOPSIS ranking of smart grid scheduling strategies.

Figure 2. Radar chart of weighted criteria performance for top-3 alternatives.

Interpretation: The hybrid solar–wind with DR strategy (A3) achieved the best overall performance, balancing economic savings, emission reduction, reliability, and financial feasibility.

5. Conclusion

This study proposed a novel MCDM framework integrated with AI to support sustainable energy scheduling and demand response strategies in smart grids. By incorporating economic, environmental, technical, and financial perspectives, the framework ensures that decision-making aligns with both sustainability goals and market realities.

The numerical example demonstrated that hybrid renewable integration combined with DR significantly outperforms single-resource strategies in terms of efficiency and resilience. The integration of AI enhanced forecast accuracy, leading to more reliable decision outcomes.

Policy implications suggest that energy operators and regulators should adopt AI-enabled MCDM tools to evaluate future scheduling strategies under multiple conflicting objectives. Future research may extend this framework using fuzzy MCDM methods, real-world datasets, and blockchain-enabled DR mechanisms.

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