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An Explainable AI–Driven Type-2 Fuzzy Decision Support Framework for Sustainable Energy Management in Smart Grids

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Abstract

The increasing integration of renewable energy resources, distributed energy systems, and intelligent monitoring technologies has transformed traditional power networks into complex smart-grid environments. Although Artificial Intelligence (AI) and Machine Learning (ML) techniques have significantly improved forecasting accuracy and operational efficiency, the lack of transparency in many AI models remains a major challenge for critical energy-management applications. In addition, the inherent uncertainty associated with renewable energy generation, electricity demand, and market conditions further complicates decision-making processes in smart grids. To address these challenges, this paper proposes an Explainable Artificial Intelligence (XAI)–Driven Type-2 Fuzzy Decision Support Framework for sustainable energy management in smart grids. The proposed framework integrates Extreme Gradient Boosting (XGBoost)-based forecasting, SHapley Additive exPlanations (SHAP), and an Interval Type-2 Fuzzy Inference System (IT2FIS) into a unified architecture. First, the forecasting module predicts future electricity demand and renewable energy generation using historical operational and environmental data. Subsequently, SHAP is employed to provide both global and local explanations by quantifying the contribution of input variables to forecasting outcomes. The extracted explainability information is then incorporated into the Type-2 fuzzy decision-support module, which generates interpretable and uncertainty-aware energy-management actions under dynamic operating conditions. The proposed framework aims to simultaneously improve prediction accuracy, enhance transparency, and increase the robustness of decision-making in the presence of uncertainty. Performance evaluation is designed using standard forecasting metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2), together with sustainability-oriented indicators such as Renewable Energy Utilization rate (REU), Peak Load Reduction (PLR), Energy Cost Saving Ratio (CSR), and Carbon Emission Reduction (CER). Compared with conventional ML and Type-1 fuzzy approaches, the proposed framework is expected to provide more reliable predictions, greater interpretability, and improved sustainability performance. The findings of this study contribute to the development of trustworthy and human-centered intelligent energy-management systems and provide a promising pathway toward transparent, resilient, and sustainable smart-grid operation.

Keywords: Explainable artificial intelligence, Smart grid, Sustainable energy management, Type-2 Fuzzy Logic, SHAP, XGBoost, Decision support system, Renewable energy.

1 | Introduction

The global transition toward sustainable and low-carbon energy systems has significantly accelerated the deployment of smart grid technologies over the past decade. The increasing penetration of renewable energy

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resources, including solar photovoltaic systems, wind farms, distributed energy storage, and electric vehicles, has transformed conventional power grids into highly interconnected cyber-physical systems. Smart grids integrate advanced sensing, communication, automation, and computational technologies to improve operational efficiency, reliability, resilience, and sustainability. However, the large-scale integration of intermittent renewable energy sources introduces substantial uncertainty into energy generation, demand forecasting, and grid operation, creating new challenges for energy management and decision-making processes [1].

Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have enabled the development of sophisticated predictive models capable of addressing many of these challenges. Intelligent forecasting systems are increasingly employed to estimate electricity demand, renewable energy production, market prices, and system reliability indicators. Models such as Long Short-Term Memory (LSTM), Extreme Gradient Boosting (XGBoost), Random Forests, and Transformer-based architectures have demonstrated remarkable predictive performance in smart-grid applications. Accurate forecasting allows operators to optimize generation schedules, improve demand-response programs, reduce operational costs, and enhance grid stability [2].

Despite their impressive predictive capabilities, many advanced AI models suffer from a critical limitation: lack of interpretability. Most state-of-the-art ML models operate as black boxes, producing predictions without providing transparent explanations regarding the factors influencing their decisions. In critical infrastructure environments such as smart grids, where operational decisions directly affect economic performance, energy security, and system reliability, stakeholders require understandable and trustworthy explanations before adopting AI-generated recommendations. The absence of transparency can reduce operator confidence, hinder regulatory acceptance, and increase the risk of inappropriate decision-making under uncertain conditions [3].

To address these concerns, Explainable Artificial Intelligence (XAI) has emerged as a rapidly growing research field focused on improving the transparency, interpretability, and trustworthiness of AI systems. XAI techniques seek to reveal how ML models generate predictions and identify the most influential factors affecting decision outcomes. Methods such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), Integrated Gradients, and counterfactual explanations have been widely applied in energy forecasting and smart-grid analytics. These techniques provide valuable insights into model behavior, enabling domain experts to validate predictions, identify anomalies, and gain confidence in automated decision-support systems [4].

Among existing XAI approaches, SHAP has attracted considerable attention due to its strong theoretical foundation based on cooperative game theory and its ability to provide both local and global explanations. SHAP values quantify the contribution of each input feature to individual predictions, thereby facilitating a comprehensive understanding of model behavior. Recent studies have demonstrated the effectiveness of SHAP-based explanations in renewable energy forecasting, electricity load prediction, demand-response management, and power system monitoring. The integration of SHAP with ML models has been shown to improve transparency while maintaining high predictive accuracy, making it particularly suitable for smart-grid applications [5].

Although explainability improves transparency, smart-grid environments remain inherently uncertain. Renewable energy generation is highly dependent on weather conditions, consumer behavior changes dynamically, and electricity prices fluctuate continuously. Such uncertainties complicate the decision-making process and often reduce the effectiveness of conventional deterministic optimization approaches. Therefore, intelligent decision-support systems must not only provide accurate predictions but also effectively handle ambiguity, vagueness, and uncertainty associated with real-world energy systems [6].

Fuzzy logic has long been recognized as a powerful methodology for modeling uncertain and imprecise information. Unlike classical binary logic, fuzzy systems allow variables to possess varying degrees of membership, enabling the representation of linguistic knowledge and expert reasoning. Fuzzy-based decision-support systems have been successfully applied to energy management, renewable energy integration, load balancing, and demand-side management. However, traditional Type-1 fuzzy systems assume precise membership functions, which may not adequately capture the uncertainties present in modern smart-grid environments [7].

To overcome this limitation, Type-2 Fuzzy Logic Systems (T2FLS) have been introduced as an advanced extension of conventional fuzzy systems. Type-2 fuzzy sets incorporate uncertainty directly into membership functions through a Footprint of Uncertainty (FOU), enabling superior modeling of ambiguity and variability. Numerous studies have demonstrated that Type-2 fuzzy systems outperform Type-1 approaches in complex and uncertain environments, particularly when data quality is limited or expert knowledge is incomplete. Consequently, Type-2 fuzzy inference systems have emerged as promising tools for intelligent energy management and decision support in smart-grid applications [8].

While both XAI and Type-2 fuzzy logic have independently demonstrated significant benefits, relatively limited research has explored their integration within a unified decision-support framework. Most existing studies focus either on improving forecasting accuracy through explainable ML models or enhancing uncertainty management through fuzzy reasoning mechanisms. Few studies have investigated how knowledge extracted from XAI models can be systematically incorporated into Type-2 fuzzy decision-making processes to support sustainable energy management. This gap is particularly important because explainability and uncertainty management are complementary capabilities that can collectively improve decision quality, transparency, and stakeholder trust [9].

Furthermore, the growing emphasis on sustainable development and carbon-neutral energy systems has increased the need for intelligent decision-support frameworks capable of optimizing energy utilization while maintaining transparency and accountability. Smart-grid operators must continuously balance multiple objectives, including minimizing operational costs, maximizing Renewable Energy Utilization (REU), reducing carbon emissions, maintaining system reliability, and ensuring consumer satisfaction. Achieving these objectives requires decision-support systems that can effectively combine predictive intelligence with human-understandable reasoning mechanisms [10].

Motivated by these challenges, this study proposes an XAI–Driven Type-2 Fuzzy Decision Support Framework for Sustainable Energy Management in Smart Grids. The proposed framework integrates ML-based forecasting, SHAP-driven interpretability analysis, and Interval Type-2 Fuzzy Inference Systems (IT2FIS) into a unified architecture for intelligent decision support. The forecasting component predicts future electricity demand and renewable energy generation, while the explainability component identifies the most influential variables affecting predictions. The extracted knowledge is subsequently incorporated into a Type-2 fuzzy decision engine that generates interpretable and uncertainty-aware energy management recommendations.

The primary contributions of this study can be summarized as follows.

I. Development of a hybrid explainable forecasting framework for smart-grid energy management.

II. Integration of SHAP-based explainability mechanisms with ML prediction models.

III. Design of an Interval Type-2 Fuzzy Decision Support System capable of handling uncertainty in energy management scenarios.

IV. Enhancement of transparency and trustworthiness in AI-driven smart-grid decision-making.

V. Promotion of sustainable energy utilization through intelligent and interpretable operational recommendations.

The remainder of this paper is organized as follows. Section 2 reviews recent literature on XAI, smart-grid forecasting, and Type-2 fuzzy systems. Section 3 presents the proposed framework and system architecture. Section 4 describes the mathematical formulation and fuzzy inference mechanism. Section 5 outlines the experimental design and evaluation metrics. Section 6 discusses expected outcomes and performance evaluation, while Section 7 concludes the paper and identifies directions for future research.

2 | Literature Review

2.1 | Explainable Artificial Intelligence in Smart Grids

The rapid adoption of AI and ML technologies in modern smart grids has significantly improved forecasting accuracy, operational efficiency, fault diagnosis, and demand-response management. However, the increasing complexity of DL and ensemble learning models has introduced a major challenge: the lack of interpretability. While advanced models often achieve superior predictive performance, their black-box nature makes it difficult for operators and decision-makers to understand the rationale behind generated predictions and recommendations. This limitation is particularly critical in smart-grid environments where operational decisions directly affect reliability, economic performance, and energy security. Recent reviews have identified explainability as one of the most important requirements for trustworthy AI deployment in energy systems [4].

XAI has emerged as a promising solution to address these concerns. XAI techniques aim to provide transparent explanations regarding how ML models generate predictions and which variables influence decision outcomes. Among existing methods, SHAP and LIME are the most frequently adopted approaches in energy-related applications. SHAP is particularly attractive because it provides both global and local interpretability while maintaining a strong theoretical foundation derived from cooperative game theory. Recent studies have demonstrated the effectiveness of SHAP in electricity demand forecasting, renewable energy prediction, fault detection, and demand-response optimization. These explanations enable operators to validate model outputs and identify influential variables such as weather conditions, electricity prices, and consumer behavior patterns [4].

Furthermore, explainability has become increasingly important because regulatory agencies and energy stakeholders demand transparency in AI-assisted decision-making processes. Interpretable models improve stakeholder trust, facilitate human oversight, and support compliance with emerging AI governance frameworks. Consequently, XAI is now considered a critical component of next-generation smart-grid intelligence systems rather than merely an optional analytical tool [4].

2.2 | Machine Learning for Energy Forecasting and Management

Energy forecasting represents one of the most important applications of AI in smart-grid environments. Accurate prediction of electricity demand, renewable energy generation, and market prices enables grid operators to optimize resource allocation and improve system stability. Recent studies have shown that ML models such as XGBoost, Random Forest, Artificial Neural Networks, and LSTM networks outperform many traditional statistical forecasting methods in terms of prediction accuracy and adaptability to nonlinear energy consumption patterns [11].

Hybrid intelligent systems have gained particular attention because they combine the predictive capabilities of ML with the interpretability of fuzzy logic. For example, Wang and Nishter [11] proposed a neuro-fuzzy framework for real-time load forecasting and adaptive control in smart grids. Their results demonstrated that integrating neural networks with fuzzy reasoning improved forecasting performance while maintaining interpretability and adaptability under dynamic operating conditions. Such findings indicate that hybrid approaches may provide a suitable foundation for developing intelligent decision-support systems in modern energy infrastructures.

Despite these advances, many forecasting models still focus exclusively on predictive accuracy while neglecting interpretability and uncertainty management. As a result, there remains a need for integrated frameworks capable of simultaneously addressing prediction accuracy, explainability, and decision uncertainty.

2.3 | Type-2 Fuzzy Logic for Energy Management

Uncertainty is an inherent characteristic of smart-grid environments due to fluctuating renewable energy production, changing consumer behavior, weather variability, and market dynamics. Conventional optimization methods often struggle to manage these uncertainties effectively. Fuzzy logic has therefore become a widely adopted methodology for energy management because it enables the representation of vague, uncertain, and linguistic information through fuzzy sets and inference rules.

Traditional Type-1 Fuzzy Logic Systems (T1FLS) have demonstrated effectiveness in energy management applications; however, they assume precise membership functions and may be insufficient when uncertainty levels are high. To overcome this limitation, T2FLS were developed. Type-2 fuzzy sets incorporate uncertainty directly into membership functions through the FOU, enabling more robust reasoning under ambiguous conditions [12].

Recent research has demonstrated the advantages of Type-2 fuzzy systems in various smart-energy applications. Aljohani [12] proposed an Intelligent Type-2 Fuzzy Logic Controller for hybrid microgrid energy management with electric vehicle integration. The results showed improved energy utilization, enhanced system stability, and reduced operational costs under uncertain renewable generation conditions. Similarly, robust Type-2 fuzzy controllers have been successfully applied to photovoltaic microgrids and battery energy storage systems, outperforming traditional Type-1 fuzzy approaches in power-quality improvement and uncertainty management.

In smart-home environments, Type-2 fuzzy controllers have also been employed to coordinate renewable energy sources, battery storage systems, and electric vehicles. Experimental results demonstrated reductions in electricity consumption, peak demand, and operational costs while maintaining user comfort and system reliability. These findings suggest that Type-2 fuzzy reasoning is particularly suitable for sustainable energy management applications where uncertainty is unavoidable.

2.4 | Integration of Explainable Artificial Intelligence and Fuzzy Decision-Making

Although XAI and Type-2 fuzzy systems have individually demonstrated significant benefits, research integrating these two paradigms remains relatively limited. Existing studies generally focus on either explainable forecasting or uncertainty-aware decision-making. Very few frameworks utilize knowledge extracted from explainable ML models to enhance fuzzy reasoning and decision-support processes.

This gap is particularly significant because explainability and fuzzy reasoning possess complementary characteristics. XAI techniques can identify the most influential variables affecting prediction outcomes, while Type-2 fuzzy systems can use this knowledge to generate transparent and uncertainty-aware decisions. The combination of these approaches has the potential to improve trustworthiness, robustness, and interpretability simultaneously. Recent reviews have identified the integration of XAI, uncertainty quantification, and human-centered decision support as one of the most promising research directions in intelligent energy systems [4].

Therefore, the development of a unified framework that combines ML forecasting, SHAP-based explanations, and IT2FIS represents an important research opportunity. Such a framework can support sustainable energy management by providing accurate predictions, transparent explanations, and robust decisions under uncertainty.

2.5 | Research Gap

Based on the reviewed literature, three major research gaps can be identified:

I. Most smart-grid forecasting studies prioritize prediction accuracy while neglecting explainability.

II. Existing Type-2 fuzzy energy-management systems rarely exploit information extracted from XAI models.

III. Limited research has investigated integrated frameworks that simultaneously address forecasting, interpretability, uncertainty management, and sustainable energy optimization.

To address these limitations, this study proposes an XAI–Driven Type-2 Fuzzy Decision Support Framework that integrates SHAP-based explainability with Interval Type-2 fuzzy reasoning for sustainable smart-grid energy management.

3 | Proposed Framework

3.1 | Framework Overview

The proposed framework aims to develop a transparent, uncertainty-aware, and intelligent decision-support system for sustainable energy management in smart-grid environments. The framework integrates three complementary technologies: ML-based forecasting, XAI, and IT2FIS. The rationale behind this integration is that accurate predictions alone are insufficient for critical energy infrastructures. Instead, decision-makers require both interpretable explanations and robust mechanisms for handling uncertainty.

As illustrated, the proposed architecture consists of four interconnected layers:

I. Data Acquisition and Preprocessing Layer

II. ML Forecasting Layer

III. Explainability Layer

IV. Type-2 Fuzzy Decision Support Layer

The framework continuously collects operational data from smart-grid infrastructures and converts them into actionable energy-management recommendations. This architecture aligns with recent trends in trustworthy AI and explainable smart-grid intelligence, which emphasize transparency, human-centered decision-making, and uncertainty-aware control mechanisms.

3.2 | Data Acquisition and Preprocessing Layer

The first layer gathers real-time and historical information from multiple smart-grid components. The collected variables include:

– *Historical electricity demand*
– *Electricity market prices*
– *Solar irradiance*
– *Wind speed*
– *Ambient temperature*
– *Relative humidity*
– *Battery State of Charge (SOC)*
– *Renewable energy generation output*
– *Electric vehicle charging demand*

Because smart-grid data are typically heterogeneous, noisy, and incomplete, a preprocessing stage is implemented before model training.

The preprocessing pipeline consists of:

Data cleaning: missing values are handled using interpolation or K-nearest neighbor imputation techniques. Outliers are detected through interquartile range analysis and z-score methods.

Feature engineering: additional features are extracted from raw data, including:

- *Hour of day*
- *Day of week*
- *Peak/off-peak indicator*
- *Seasonal index*
- *Renewable penetration ratio*

Data normalization: all variables are normalized using Min-Max scaling:

$$X_{norm}=\frac{X-X_{min}}{X_{max}-X_{min}}$$

This normalization improves learning stability and convergence during model training.

3.3 | Machine Learning Forecasting Layer

The second layer is responsible for predicting future energy conditions. Recent studies indicate that advanced ML models significantly outperform traditional statistical forecasting approaches in smart-grid applications. Hybrid forecasting systems have demonstrated superior performance in capturing nonlinear energy consumption patterns and renewable generation fluctuations.

In the proposed framework, XGBoost is selected as the primary forecasting model because of its:

- *High predictive accuracy*
- *Computational efficiency*
- *Robustness against overfitting*
- *Compatibility with SHAP explanations*

The forecasting model receives the preprocessed feature vector:

$$X_t = \{D_t, T_t, H_t, P_t, S_t, W_t\}$$

where:

- (D_t) = *historical demand*
- (T_t) = *temperature*
- (H_t) = *humidity*
- (P_t) = *electricity price*
- (S_t) = *solar irradiance*
- (W_t) = *wind speed*

The forecasting function is expressed as:

$$\hat{Y}_{t+1}=f(X_t)$$

where:

$$\hat{Y}_{t+1}$$

represents predicted electricity demand or renewable generation for the next time interval.

The forecasting output serves as the primary input to the explainability and decision-support modules.

3.4 | Explainability Layer

The third layer addresses one of the major limitations of modern ML systems: lack of interpretability.

Recent reviews emphasize that explainability is becoming an essential requirement for trustworthy smart-grid applications because operators must understand why a prediction was generated before taking corrective actions. SHAP has emerged as one of the most reliable explanation techniques in energy forecasting due to its theoretical consistency and ability to provide both local and global interpretations.

The proposed framework adopts SHAP to quantify feature contributions.

For a prediction ($f(x)$), the SHAP explanation is represented as:

$$f(x)=\phi_0+\sum_{i=1}^{M}\phi_i$$

where:

- *(ϕ_0) denotes the average prediction,*
- *(ϕ_i) represents the contribution of feature (i),*
- *(M) is the number of input variables.*

The explainability layer generates:

Global explanations: identification of the most influential variables affecting forecasting performance across the entire dataset.

Local explanations: interpretation of individual predictions.

Temporal explanations: analysis of feature importance changes over time.

The extracted knowledge is subsequently transferred to the fuzzy decision-support module, enabling the incorporation of explainable information into the decision-making process.

3.5 | Interval Type-2 Fuzzy Decision Support Layer

Although explainability improves transparency, uncertainty remains unavoidable in smart-grid operations. Renewable generation, consumer behavior, and electricity prices are inherently uncertain and difficult to model precisely.

To address this challenge, the proposed framework employs an IT2FIS.

Recent studies have shown that Type-2 fuzzy systems outperform conventional Type-1 approaches in energy-management applications because they explicitly represent uncertainty through the FOU. This capability leads to more robust decision-making under dynamic operating conditions.

The fuzzy decision engine receives four inputs:

I. Forecasted Demand
II. Renewable Energy Availability
III. Electricity Price
IV. Battery SOC

The output variable is:

Energy Management Action Level (EMAL): with five linguistic states:

I. Very Low
II. Low
III. Medium
IV. High
V. Critical

Fuzzy rule base: example rules include:

Rule 1.

IF Demand is High

AND Renewable Generation is Low

AND Electricity Price is High

THEN Energy Saving Action is Critical

Rule 2.

IF Demand is Medium

AND Renewable Generation is High

THEN Energy Saving Action is Low

Rule 3.

IF Battery SOC is High

AND Demand is High

THEN Battery Discharge Action is High

The fuzzy reasoning process consists of:

- *Fuzzification*
- *Rule Evaluation*
- *Type Reduction*
- *Defuzzification*

The final crisp output determines the optimal energy-management strategy.

3.6 | Integrated Decision-Making Process

The complete decision-support process operates as follows:

Step 1. Collect smart-grid operational data.

Step 2. Perform preprocessing and feature extraction.

Step 3. Predict future demand and renewable generation using XGBoost.

Step 4. Generate SHAP explanations.

Step 5. Extract influential factors.

Step 6. Feed explainable information into the IT2FIS engine.

Step 7. Generate energy-management recommendations.

Step 8. Execute operational actions and update the system continuously.

This integration enables simultaneous achievement of:

- *High forecasting accuracy,*
- *Explainability,*
- *Uncertainty management,*
- *Sustainable energy utilization.*

3.7 | Expected Advantages of the Proposed Framework

Compared with existing smart-grid decision-support systems, the proposed framework offers several advantages:

- *Improved forecasting accuracy through ML.*
- *Transparent prediction interpretation through SHAP.*
- *Robust uncertainty management using Interval Type-2 Fuzzy Logic.*
- *Increased operator trust and acceptance.*
- *Enhanced REU.*
- *Reduced operational costs and carbon emissions.*

Consequently, the framework provides a comprehensive solution for trustworthy and sustainable smart-grid energy management.

4 | Mathematical Formulation

4.1 | Overview of the Mathematical Framework

The proposed XAI–Driven Type-2 Fuzzy Decision Support Framework integrates three mathematical components: 1) ML-based forecasting, 2) SHAP-based explainability analysis, and 3) IT2FIS-based decision-making. The objective is to transform raw smart-grid data into interpretable and uncertainty-aware energy management recommendations. Recent studies emphasize that future smart-grid intelligence systems should combine predictive accuracy, explainability, and uncertainty quantification within a unified framework to support trustworthy operational decision-making.

Let the smart-grid input vector at time (t) be defined as:

[
X_t = [D_t, T_t, H_t, S_t, W_t, P_t, SOC_t]
]

where:

- *(D_t): electricity demand,*
- *(T_t): ambient temperature,*

- *(H_t): relative humidity,*
- *(S_t): solar irradiance,*
- *(W_t): wind speed,*
- *(P_t): electricity price,*
- *(SOC_t): battery state of charge.*

The objective of the forecasting model is to estimate future demand and renewable generation:

$$\hat{Y}_{t+1}=f(X_t)$$

where ($f(\cdot)$) denotes the ML forecasting function.

4.2 | Forecasting Model Formulation

In the proposed framework, XGBoost is employed as the forecasting engine because of its robustness, scalability, and compatibility with explainability techniques. XGBoost constructs an ensemble of regression trees and generates predictions by minimizing a regularized objective function.

The prediction model is expressed as:

$$\hat{Y}_{i}=\sum_{k=1}^{K} f_k(X_i)$$

where:

- *(K) represents the number of decision trees,*
- *(f_k) denotes the prediction generated by tree (k).*

The corresponding optimization objective is:

$$Obj=\sum_{i=1}^{n}l(y_i,\hat{y}_i)+\sum_{k=1}^{K}\Omega(f_k)$$

where:

- *($l(\cdot)$) denotes the loss function,*
- *($\Omega(\cdot)$) represents the regularization term used to control model complexity.*

The forecasting model generates:

- *Predicted electricity demand.*
- *Predicted renewable energy generation.*
- *Predicted energy imbalance indicators.*

Accurate forecasting provides the foundation for subsequent explainability and decision-support processes. Recent smart-grid forecasting studies demonstrate that ML models significantly improve prediction accuracy when compared with conventional statistical approaches.

4.3 | SHAP-Based Explainability Formulation

To improve transparency and trustworthiness, the framework employs SHAP.

SHAP quantifies the contribution of each feature to a prediction based on Shapley values derived from cooperative game theory. Recent reviews identify SHAP as one of the most reliable and widely adopted explainability techniques in energy forecasting and smart-grid intelligence.

For an instance (x), the prediction is represented as:

$$
f(x)=\phi_0+\sum_{i=1}^{M}\phi_i
$$

where:

- *(ϕ_0) is the average model prediction,*
- *(ϕ_i) is the contribution of feature (i),*
- *(M) is the number of input features.*

The Shapley value is calculated as:

$$
\phi_i=\sum_{S\subseteq N\setminus \{i\}} \frac{|S|!(M-|S|-1)!}{M!} [f(S\cup \{i\})-f(S)]
$$

where:

- *(S) represents a subset of input features,*
- *(N) is the complete feature set.*

The resulting SHAP values provide:

Global importance:

$$
GI_i=\frac{1}{n}\sum_{j=1}^{n}|\phi_{ij}|
$$

which measures the overall influence of feature (i) across all observations.

Local importance:

$$
LI_i=\phi_i
$$

which explains a specific prediction.

The obtained SHAP information is transferred to the fuzzy decision-support layer, enabling explainability-aware decision-making.

4.4 | Interval Type-2 Fuzzy Set Representation

Although explainability provides transparency, smart-grid environments remain highly uncertain due to renewable intermittency, weather variability, and consumer behavior fluctuations.

To model uncertainty explicitly, the framework employs Interval Type-2 Fuzzy Sets (IT2FS). Recent energy-management studies demonstrate that IT2FLS provides superior robustness compared with Type-1 fuzzy systems under uncertain operating conditions.

An IT2FS ($\tilde{A}$) is defined as:

$$\tilde{A}=\left\{(x,u),\mu_{\tilde{A}}(x,u)\right\}$$

where:

$$u\in J_x\subseteq[0,1]$$

The uncertainty is represented through the FOU:

$$FOU(\tilde{A})=\bigcup_{x\in X}J_x$$

The FOU is bounded by:

Upper Membership Function (UMF):

$$\overline{\mu}_{A}(x)$$

Lower Membership Function (LMF):

$$\underline{\mu}_{A}(x)$$

The interval between UMF and LMF captures uncertainty associated with linguistic variables.

4.5 | Fuzzification Process

The fuzzy decision-support system utilizes four inputs:

$$I=[D_f,R_g,P_e,SOC]$$

where:

- *(D_f): forecasted demand,*
- *(R_g): renewable generation,*
- *(P_e): electricity price,*
- *(SOC): battery state of charge.*

Each variable is represented by five linguistic terms:

$$\{VL, L, M, H, VH\}$$

corresponding to:

- *Very Low,*
- *Low,*
- *Medium,*
- *High,*
- *Very High.*

Gaussian interval Type-2 membership functions are employed:

$$\mu(x)=\exp\left(-\frac{(x-c)^2}{2\sigma^2}\right)$$

where:

- *c is the center,*
- *σ is the standard deviation.*

4.6 | Fuzzy Rule Inference

The fuzzy knowledge base consists of expert-defined IF–THEN rules.

A typical rule is:

$$R_i: IF\ D_f\ is\ High \ AND R_g\ is\ Low \ AND P_e\ is\ High \ THEN EMAL\ is\ Critical$$

The firing strength of *Rule 1* is computed as:

$$w_i= \mu_{D_f}$$

\cdot
\mu_{R_g}
\cdot
\mu_{P_e}
\cdot
\mu_{SOC}
]

For interval Type-2 systems:

[
w_i=
[\underline{w_i},\overline{w_i}]
]

where:

– *(\underline{w_i}) denotes lower firing strength,*
– *(\overline{w_i}) denotes upper firing strength.*

4.7 | Type Reduction Using Karnik–Mendel Algorithm

A unique characteristic of Type-2 fuzzy systems is the type-reduction stage.

The framework employs the Karnik–Mendel (KM) algorithm, which remains the most widely adopted approach for centroid type reduction in interval Type-2 fuzzy systems. Recent studies continue to improve computational efficiency of KM-based procedures while preserving accuracy.

The left and right centroids are computed as:

[
Y_L=
\frac{\sum_{i=1}^{N}x_iw_i^{L}}
{\sum_{i=1}^{N}w_i^{L}}
]
[
Y_R=
\frac{\sum_{i=1}^{N}x_iw_i^{R}}
{\sum_{i=1}^{N}w_i^{R}}
]

The type-reduced interval is:

[
Y_{TR}=[Y_L,Y_R]
]

4.8 | Defuzzification

The final crisp decision output is obtained through centroid averaging:

[
Y=

\frac{Y_L+Y_R}{2}
]

The resulting value corresponds to the EMAL.

Table 1. Decision levels.

EMAL Range	Decision Action
0–20	Very Low
20–40	Low
40–60	Medium
60–80	High
80–100	Critical

4.9 | Multi-Objective Sustainability Index

To evaluate the effectiveness of the proposed framework, a sustainability index is introduced:

[
SI=
w_1REU+
w_2PCR+
w_3CER+
w_4CSR
]

where:

- *REU = Renewable Energy Utilization,*
- *PCR = Peak Consumption Reduction,*
- *CER = Carbon Emission Reduction,*
- *CSR = Cost Saving Ratio.*

Subject to:

[
\sum_{i=1}^{4}w_i=1
]

This index provides a unified measure of sustainability performance and enables comparison with benchmark energy-management approaches.

4.10 | Computational Workflow

The complete mathematical workflow can be summarized as follows:

- *Acquire smart-grid data.*
- *Forecast future demand and renewable generation using XGBoost.*
- *Generate SHAP explanations and feature importance values.*
- *Transform prediction outputs into fuzzy linguistic variables.*
- *Execute Interval Type-2 fuzzy inference.*
- *Apply KM type reduction.*
- *Perform defuzzification.*
- *Generate final energy-management recommendations.*

This formulation establishes a mathematically rigorous and explainable framework capable of supporting sustainable smart-grid energy management under uncertainty.

5 | Experimental Design

To validate the proposed XAI–Driven Type-2 Fuzzy Decision Support Framework, experiments are conducted using publicly available smart-grid datasets containing electricity demand, renewable energy generation, weather variables, and electricity price information.

The dataset is divided into training (70%), validation (15%), and testing (15%) subsets. After data preprocessing, the XGBoost model is employed to predict future electricity demand and renewable energy generation. SHAP is then applied to explain model predictions and identify the most influential features affecting forecasting performance. The extracted explainability information is subsequently incorporated into the IT2FIS to generate energy management decisions. Recent studies have highlighted the effectiveness of combining XAI and intelligent energy management techniques in smart-grid environments.

Evaluation Metrics

The forecasting performance is assessed using four commonly adopted metrics:

I. Mean Absolute Error (MAE)

II. Root Mean Square Error (RMSE)

III. Mean Absolute Percentage Error (MAPE)

IV. Coefficient of Determination ((R^2))

The decision-support module is evaluated using sustainability-oriented indicators:

I. REU

II. Peak Load Reduction (PLR)

III. Energy Cost Saving Ratio (CSR)

IV. Carbon Emission Reduction (CER)

The proposed framework is compared with three benchmark approaches:

I. Conventional XGBoost forecasting model.

II. Type-1 fuzzy decision-support system.

III. Rule-based energy management strategy.

Finally, a sensitivity analysis is performed under different renewable energy penetration levels, electricity price variations, and battery storage capacities to evaluate the robustness of the proposed framework under uncertain operating conditions. The expected outcome is improved forecasting accuracy, enhanced interpretability, better uncertainty management, and more sustainable energy utilization compared with existing approaches.

6 | Expected Results

The proposed XAI–Driven Type-2 Fuzzy Decision Support Framework is expected to improve forecasting accuracy, decision transparency, and uncertainty management in smart-grid environments. By integrating XGBoost forecasting, SHAP-based explainability, and Interval Type-2 fuzzy reasoning, the framework can provide more reliable and interpretable energy management recommendations compared with conventional approaches. Recent studies have emphasized that combining XAI with intelligent energy-management systems enhances trustworthiness and supports more effective operational decision-making in smart grids.

From the forecasting perspective, the proposed model is expected to achieve lower MAE, RMSE, and MAPE values than traditional ML models due to its ability to capture nonlinear relationships among demand, weather conditions, renewable generation, and electricity prices. In addition, SHAP analysis is expected to identify the most influential variables affecting energy demand and renewable energy generation, thereby improving model interpretability and supporting human-centered decision-making.

The IT2FIS is expected to improve decision quality under uncertain operating conditions. By explicitly modeling uncertainty through the FOU, the framework can generate more robust energy-management actions when renewable generation fluctuates or demand patterns change unexpectedly. This capability is particularly important in smart grids with high penetration of renewable energy resources.

Furthermore, the proposed framework is expected to increase REU, reduce peak-load demand, lower operational costs, and contribute to CER. The integration of explainability and uncertainty-aware reasoning can also increase operator confidence and facilitate the adoption of AI-based decision-support systems in critical energy infrastructures. Overall, the proposed approach is anticipated to provide a transparent, sustainable, and trustworthy solution for next-generation smart-grid energy management.

7 | Conclusion

This study proposed an XAI–Driven Type-2 Fuzzy Decision Support Framework for sustainable energy management in smart grids. The framework integrates XGBoost-based forecasting, SHAP explainability, and an IT2FIS to provide accurate, transparent, and uncertainty-aware decision support. By combining predictive intelligence with explainable reasoning, the proposed approach addresses two major challenges of modern smart-grid systems: the lack of transparency in AI models and the presence of uncertainty in energy management processes. Recent studies emphasize that explainability, trustworthiness, and uncertainty management are becoming essential requirements for the deployment of AI in critical energy infrastructures.

The proposed framework is expected to improve forecasting performance, enhance operator trust through interpretable predictions, and support more robust decision-making under fluctuating renewable energy generation and dynamic demand conditions. Furthermore, the integration of SHAP explanations with Type-2 fuzzy reasoning enables the transformation of ML outputs into human-understandable and actionable energy-management recommendations. This capability can contribute to increased REU, reduced operational costs, improved grid reliability, and lower carbon emissions.

Future research may focus on real-time implementation of the framework in practical smart-grid environments, integration with reinforcement learning and digital-twin technologies, and extension toward multi-agent energy management systems. In addition, investigating distributed and edge-based XAI architectures could further improve scalability, responsiveness, and resilience in next-generation smart grids.

Overall, the proposed framework provides a promising foundation for the development of trustworthy, explainable, and sustainable intelligent energy management systems capable of supporting the ongoing transition toward smart and low-carbon power networks.

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