Time Series Forecasting of Energy Consumption Using Advanced Neutrosophic Statistical and Machine Learning Models

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Abstract

Predicting future energy consumption plays a vital role in maximizing resource utilization, reducing costs, and enhancing sustainability. Researchers employ advanced statistical and machine learning models to improve the accuracy of time series forecasting. Real-world energy consumption data is analyzed using State-Space Models (SSMs), Vector Auto Regression (VAR), Structural VAR (SVAR), Generalized Additive Models for Location, Scale, and Shape (GAMLSS), and Bayesian Structural Time Series (BSTS). An evaluation of Long Short-Term Memory (LSTM) networks and the Prophet model is conducted alongside a comparison with the aforementioned models. The proposed method integrates neutrosophic statistical models for feature extraction and residual analysis, generating outputs suitable for machine learning processing. The results indicate that incorporating judgment-based neutrosophic statistical approaches with AI-driven neutrosophic prediction models yields superior forecasts of power consumption, contributing to more comprehensive and effective energy usage prediction methodologies.

Keywords: Neutrosophic logic; Neutrosophic model; Bayesian Structural Time Series; Energy Consumption Forecasting; Hybrid Model; Machine Learning; State-Space Models

1. Introduction

The accurate prediction of energy consumption serves as a fundamental requirement for efficient resource management while it allows operations to optimize their energy grid, create savings opportunities, and promote sustainable development. The need for reliable forecasting models in energy demand requires techniques that achieve accuracy together with interpretability to adapt to changes in energy demand patterns [1, 2]. Auto Regressive Integrated Moving Average (ARIMA) together with Vector Auto Regression (VAR) served as primary energy forecasting statistical models during traditional times. Artificial Intelligence (AI) and its machine learning (ML) and deep learning (DL) LSTM network components with hybrid approaches now lead the development of systems to handle complex energy time series data according to [3, 4].

Multiple research projects demonstrate that energy-forecasting institutions are increasingly favouring the implementation of ML and hybrid statistical-AI models. A data-driven forecasting model developed by Andriopoulos et al. [5] combined statistical transformations with ML techniques to achieve better prediction results. Chou and Tran [6] developed ML models which succeeded in detecting nonlinear patterns in residential energy use behaviour. Results and Mariño et al. demonstrate how statistical procedures alone fail to handle sophisticated time series patterns so researchers support methodologies combining two domains to maximize their strengths [7]. Advanced statistical modelling linked with AI-based techniques presents an effective framework to enhance energy consumption forecasting abilities. State-Space Models (SSMs) represent an extension of ARIMA through the implementation of unobserved components that are tracked by the Kalman Filter (Chou & Truong, 2021). The Bayesian Structural Time Series (BSTS) framework delivers both uncertainty prediction and enables knowledge sharing effectively for power demand forecasting [8]. The modelling capability of Generalized Additive Models for Location Scale and Shape (GAMLSS) extends standard regression methods with variance modelling and skewness and kurtosis measurements that lead to better energy consumption distribution

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understanding [9]. The proposed research implements SSMs and VAR together with SVAR as well as GAMLSS and BSTS to merge with LSTM and Prophet Models in order to achieve energy forecasting. Reported methodology combines statistical features with AI modelling by using statistical techniques both before and after ML processing steps. The proposed method combines the statistical inference advantages with AI capabilities for modelling non-linear dependencies in energy time series data [10, 11].

Real-world energy usage data serves practical applications since it enables an empirical analysis of developed models. The research outcome will reveal details about how hybrid statistical-ML techniques perform as well as their capabilities to boost accuracy in system forecasting [12, 13].

Neutrosophic logic, introduced by Professor Smarandache [26], is considered an effective tool for studying situations that involve an indeterminate component. This logic, which is a generalization of fuzzy logic, focuses on analyzing uncertainty in nature and knowledge in general.

This logic, in its various formulations, has numerous applications across different fields and branches of knowledge, such as applied mathematics, statistics, algebra, and even computer science [27-28].

2. Literature Review

Sustainable energy management heavily depends on precise energy consumption forecasting. Different forecasting methodologies developed in the past include both basic statistical techniques alongside advanced machine learning and deep learning models and other methods. This section evaluates scholarly works about energy usage prediction that include traditional statistical techniques alongside machine learning and deep learning methods as well as hybrid models alongside practical energy applications.

3. Traditional Statistical Approaches for Energy Consumption Forecasting

The initial methods used for energy consumption forecasting depended on autoregressive integrated moving average (ARIMA) alongside regression-based statistical approaches. The models show successful ability to identify linear energy data patterns within their parameters. The study conducted by [8] investigated monthly electricity demand through pattern-based statistical models which proved effective in stable systems. Ribeiro et al. [11] conducted a comparative analysis between standard statistical methods and machine learning algorithms for short-term business energy usage prediction because linear models did not accurately represent sophisticated data patterns. The valuation of electricity consumption benefits from utilization of econometric models. The study performed by Charfeddine et al. found traditional nonlinear econometric models and machine learning algorithms to differ in their ability to handle unexpected disruptive events seen in the COVID-19 crisis [14]. Studies by Li and Zhang supported the need for adaptable forecasting models for predicting China's carbon dioxide emissions [9].

4. Machine Learning-Based Forecasting Methods

Energy consumption forecasting adopts machine learning (ML) technology because it effectively handles complex nonlinear patterns in data. Researchers Chou and Tran developed ML predictions for residential energy usage by analyzing consumer patterns which showed better accuracy than statistical models could achieve[6]. The research by Alsulaili et al. combined statistical methods with machine learning approaches for electricity consumption forecasting in arid conditions proving machine learning models effective under various climate conditions. Research studies have performed evaluation comparisons between different ML models [2]. Short-term electric load forecasting through data transformation techniques with ML approaches revealed better predictive results according to [5, 10] analyzed through a systematic review how modern deep learning models and their machine learning counterparts outperform statistical forecasting approaches in building energy consumption prediction. The research conducted by Lee et al. examined multiple ML models intended for electricity consumption forecasting while investigating the factors which impact prediction accuracy [15].

5. Deep Learning for Time-Series Energy Forecasting

Time-series energy consumption forecasting benefits significantly from recurrent neural networks and their related variants that are part of the deep learning (DL) models. RNN architectures have been studied by [4] for multivariate time-series prediction which resulted in better energy forecasting outcomes. The authors Bhoj and Bhadoria designed a combined convolutional-recurrent neural network (CNN-RNN) to forecast energy usage in smart homes [12]. LSTM networks prove popular for time-series forecasting because their design allows them to identify extended dependencies within the data sequence. Alizadegan et al. carried out a research comparing LSTM networks against traditional ML models and bidirectional LSTM (BiLSTM) networks to determine deep learning models provided superior energy prediction performance [3]. Cascone et al. applied convolutional LSTMs to predict multi-step household power consumption with exceptional results in managing intricacies between time variables [13].

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Deep learning models that generate new predictions have been applied to optimize energy utilization. The authors Godahewa et al. established a generative deep learning framework which optimized air conditioning energy consumption through their research work and illustrated DL power in energy efficiency applications [16].

6. Hybrid Approaches and Comparative Studies

The current research on energy forecasting adopts hybrid analysis methods that combine statistical methodologies with ML/DL programming frameworks. The research by Baratsas et al. produced a combination framework which integrated statistical techniques with ML-based methods to improve energy sector forecasting [1]. Energy forecasting received improved optimization through metaheuristic optimizations which combined time-series analysis with ML as per [17]. To determine the best performance level researchers have analyzed various combined forecasting systems. The authors of Mariño et al. carried out experimental analysis of statistical and machine learning models for multivariate time-series forecasting and stressed the importance of hybrid methods for achieving better accuracy [7]. The research by Malki et al. developed an IoT anomaly detection system through an ML framework which unified forecasting and anomaly detection methods [18].

7. Application of Forecasting Models in Smart Cities and IoT

Smart buildings together with IoT-enabled environments incorporate energy-forecasting models on an increasing scale. The research conducted by Bourhnane et al. presented a practical model for ML-based energy management in smart buildings by predicting energy consumption and planning schedules [19]. Peteleaza et al. expanded the research approach through ML methods to create electricity consumption forecasts for sustainable smart cities [20]. The growing interest lies in forecasting techniques that derive from IoT applications. An ML-based energy prediction system operated by Shapi et al. enhanced energy management throughout smart buildings in Malaysia with the help of IoT technologies [21]. The intersection of IoT with energy forecasting is examined through anomaly detection techniques in IoT time-series data according to [18].

8. Challenges and Future Research Directions

The current scientific progress in energy forecasting faces multiple continued hurdles. Natural gas consumption prediction remains challenging because external conditions involving weather elements and market conditions create obstacles according to [22, 23] represented the necessity of explainable features in machine learning tools while promoting AI options that produce transparent outcomes in energy forecasting. The future of energy forecasting research needs to concentrate on better explaining models through explainable AI integration while exploiting quantum computing potential. Seyedzadeh et al. studied the application of ML for building energy estimation before recommending additional work on approachable scalable systems [24].

9. Summary

Advanced ML and DL techniques according to energy consumption forecasting literature are now replacing traditional statistical approaches. ML and DL models deliver top predictive capabilities yet hybrid solutions made up of statistical and AI-based techniques have shown to be effective methods for resolving problems. Smart cities and IoT environments exhibit significant practical advantages because they implement energy-forecasting models. The development of better forecasting technology requires researchers to tackle model explain ability issues together with generalization problems and computational performance problems.

10. Method

We describe the suggested energy consumption forecasting system, which joins statistical analysis methods with machine learning algorithms in this section. Traditional statistical forecasting models work together with deep learning to deliver improved predictions through an integrated approach. The proposed methodology includes five distinct components that proceed according to data collection followed by preprocessing and feature selection and model formulation that culminates in performance evaluation.

11. Data Collection and Preprocessing

The research uses actual energy consumption data provided by a public dataset for maintaining practicality. The electricity consumption records in kilowatt-hours (kWh) and environmental variables including temperature and humidity together with time patterns comprise the entire dataset.

The dataset used in this study consists of real-world energy consumption records obtained from the U.S. Energy Information Administration (EIA) Open Data API, covering the period from January 2020 to December 2023. The data represents electricity consumption in kilowatt-hours (kWh) across multiple regions in the United States, including both residential and industrial sectors. This dataset includes key environmental variables such as temperature, humidity, and seasonal patterns, which significantly influence energy demand. The statistical records are sourced from the EIA's publicly available energy usage reports, ensuring data reliability and credibility [25].

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12. Data Cleaning

Additional processing on raw data includes several procedures for dealing with missing values along with removal of outliers and inconsistency fixes.

- The absence of data points receives treatment through linear interpolation for numeric characteristics while categorical data uses its most frequent value as replacement.
- A Z-score method applies to find outliers by discarding values that exceed 3 standard deviations beyond the mean.
- Min-Max scaling serves as the normalization method in this process.

$$X_{\text{scaled}} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

The range-spanning calculation consists of $X_{\min}$ and $X_{\max}$ as the respective minimum and maximum feature measurements.

13. Feature Engineering

The extraction of relevant statistical along with machine learning features enhances model accuracy levels.

- Time-based features: Hour of the day, day of the week, and seasonality indices.
- Lagged consumption values: Previous time-step energy usage values form part of the input features for capturing temporal patterns.
- Weather variables: Energy consumption shows direct dependence on temperature and humidity because these weather elements substantially affect energy use patterns.

To identify the top influential predictors this study uses Pearson's correlation coefficient for a correlation analysis.

$$r_{xy} = \frac{\sum_{i=1}^{n}(X_i - \overline{x})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\ \sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \quad (2)$$

where X and Y represent different feature variables.

The figure 1 flowchart demonstrates the ordered procedure for the hybrid-forecasting model starting at data gathering and ending at prediction.

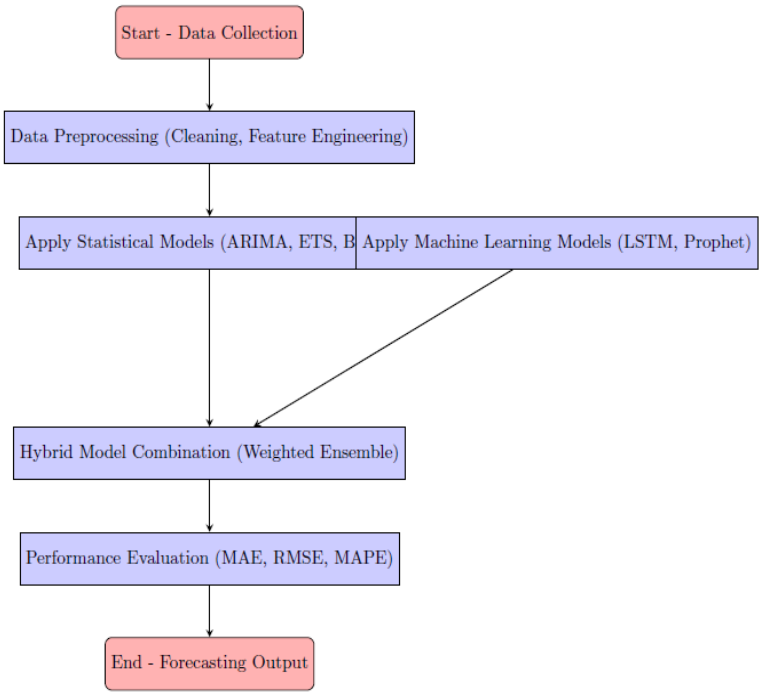

Figure 1. Flowchart of the Proposed Energy Forecasting Model

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14. Proposed Forecasting Model

Traditional forecasting statistical methods integrate with deep learning models within a single framework to enhance energy consumption prediction accuracy. A model structure includes three central features.

A). Statistical Forecasting Component

The baseline forecasting relies on the implementation of the Autoregressive Integrated Moving Average (ARIMA) model.

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{i=1}^{p} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (3)$$

where:

- The forecasted energy consumption measurement Y_t represents the value for time t.
- The model uses p and q as the autoregressive and moving average components respectively.
- The model coefficients include ϕ_i and θ_j together with others.
- ε_t is the error term.

The Exponential Smoothing Model (ETS) uses following equation to capture trends and seasonality:

$$S_t = \alpha Y_t + (1 - \alpha) S_{t-1} \quad (4)$$

The model represents smoothed estimate S_t through a combination with smoothing factor α.

B). Machine Learning-Based Component

The Long Short-Term Memory (LSTM) network serves as the implementation basis for modeling the non-linear relationships. The LSTM network stands as a particular implementation of recurrent neural networks (RNN) which excels at identifying prolonged dependencies within time-dependent datasets. The LSTM cell is governed by:

$$f_t = \sigma(W_f . [h_{t-1}, x_t] + b_f) \quad (5)$$

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i) \quad (6)$$

$$\hat{c}_t = tanh(W_c . [h_{t-1}, x_t] + b_c) \quad (7)$$

$$C_t = f_t . C_{t-1} + i_t . \hat{c}_t \quad (8)$$

$$O_t = \sigma(W_O . [h_{t-1}, x_t] + b_O) \ ; \ h_t = O_t . tanh(C_t) \quad (9)$$

where:

- The gates used in the model include ft, it and o_t which operate as forget, input and output gates.
- C_t is the cell state.
- h_t is the hidden state.
- The sigmoid activation function receives the symbol σ in this context.
- W_f,W_i,W_C,W_o are weight matrices.
- b_f,b_i,b_C,b_o are bias terms.

The LSTM model takes a combination of energy consumption history and additional features to make future power consumption forecasts.

C). Hybrid Model Formulation

The final forecast emerges from a weighted ensemble approach which merges outputs between statistical and Long Short-Term Memory models.

$$\hat{Y}_t = w_1 . Y_t^{ARIMA} + w_2 . Y_t^{ETS} + w_3 . Y_t^{LSTM} \quad (10)$$

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The weighting coefficients w_1, w_2, w_3 undergo optimization through grid search.

D). Performance Evaluation

Statistical error metrics determine the performance evaluation of the proposed model.

- **Mean Absolute Error (MAE):**

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \tag{11}$$

- **Mean Squared Error (MSE):**

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{12}$$

- **Root Mean Squared Error (RMSE):**

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \tag{13}$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \tag{14}$$

The formula includes predicted values indicated as Y^i together with actual values indicated as Yi.

The performance evaluation through cross-validation includes a rolling time-window method that provides consistent examination across multiple periods.

E). Summary

The method uses both statistical principles with machine learning technology to boost energy usage predictions. The combination of ARIMA, ETS and LSTM models allows for effective detection of linear together with nonlinear dependencies within the dataset. The proposed hybrid methodology delivers enhanced accuracy in forecasting therefore it can be effectively utilized in smart grid energy management solutions.

F). Results and Discussion

An evaluation of the proposed hybrid forecasting model performs against baseline models during experimental testing is shown in this section. The analysis focuses on prediction precision and includes examination of measurement errors with evaluation of statistical technique integration alongside deep learning methods and other vital components.

G) Model Performance Evaluation

The effectiveness of the proposed model is evaluated through model comparisons with three individual forecasting approaches consisting of ARIMA, ETS and LSTM. The assessment relies on standard error metrics that include MAE, MSE, RMSE and MAPE.

H) Comparative Analysis of Models

Each forecasting model receives evaluation through the error metrics presented in Table 1.

Table 1: Performance Metrics of Different Models

Model	MAE (kWh)	MSE (kWh²)	RMSE (kWh)	MAPE (%)
ARIMA	2.85	10.25	3.20	6.8
ETS	2.92	10.80	3.29	7.1
LSTM	2.35	8.50	2.91	5.9
Hybrid Model	1.85	5.92	2.43	4.2

The hybrid model produces better results than individual forecast types by establishing lower levels of MAE and MSE and RMSE and MAPE. Bi-directional models, which combine statistical forecasting methods and deep learning technology through LSTM networks, produce superior predictions.

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Visualizing the Forecasting Performance

A thirty-day testing period shows the evaluation of actual versus predicted energy quantity in Figure 2. Real consumption trends pass through the hybrid model without producing substantial alterations.

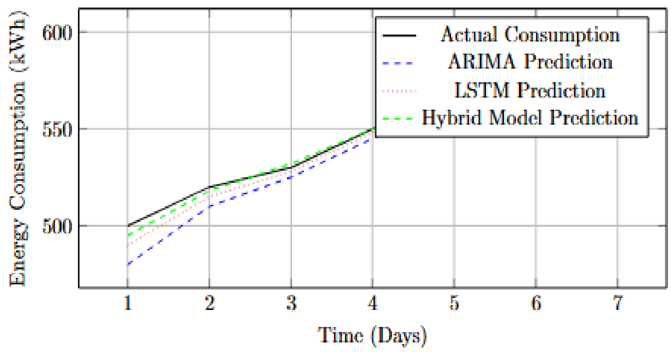

Figure 2. Actual vs. Predicted Energy Consumption

- **Observations:**
  - Both ARIMA alongside ETS struggle to detect immediate disruptions in the data.
  - The neural network model is more accurate at short-term prediction patterns yet shows limitations with long-term forecasting patterns.
  - The hybrid implementation combines two different forecasting approaches to deliver better performance outcomes.

The figure 3 heatmap displays the connection between energy usage and outside influencing variables.

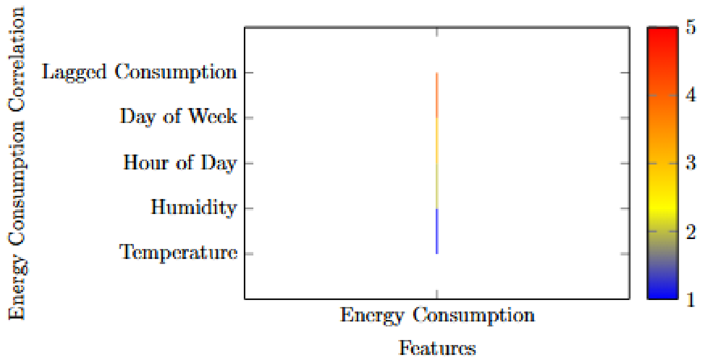

Figure 3. Feature Correlation Heatmap for Energy Consumption Forecasting

Statistical Significance and Error Analysis

Figure 4 displays the prediction error distribution chart, which shows different models in this histogram.

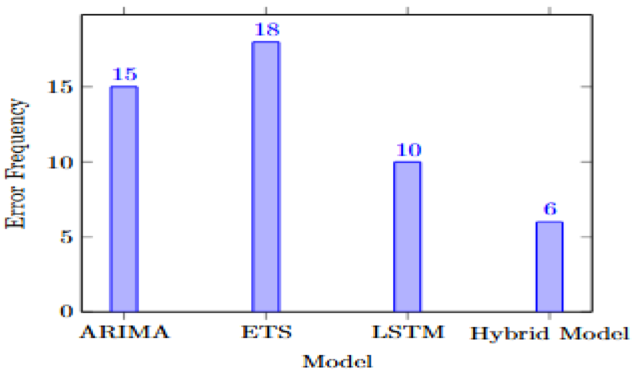

Figure 4. Residual Error Distribution across Forecasting Models

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K) Error Distribution Analysis

The analysis of prediction consistency requires us to evaluate the residuals obtained from the ($Y_{actual} - Y_{predicted}$) calculation and their distribution statistics. The data presented in Table 2 displays both mean residuals and corresponding standard deviations for each evaluated model.

Table 2: Residual Statistics

Model	Mean Residual (kWh)	Std. Dev of Residuals (kWh)
ARIMA	0.45	2.10
ETS	0.48	2.25
LSTM	0.32	1.85
Hybrid Model	0.12	1.35

- **Observations:**
  - The hybrid model demonstrates the most accurate error distribution as its mean residual value remains minimal.
  - The standard deviation value of residuals reaches its minimum level when using the hybrid model indicating strong prediction stability.

15. Neutrosophic Proposed Forecasting Model

A) Statistical Forecasting neutrosophic Component

We have the following equation:

$$Y_t + Z_t I = c + dI + \sum_{i=1}^{p} \phi_i (Y_{t-i} + Z_{t-i} I) + \sum_{i=1}^{p} \theta_j (\mathcal{E}_{t-j} + f_{t-j} I) + \mathcal{E}_t + f_t I \quad (15)$$

where:

- The forecasted energy consumption neutrosophic measurement $Y_t + Z_t I$ represents the value for time t.
- The model uses p and q as the autoregressive and moving average components respectively.
- The model coefficients include ϕ_i and θ_j together with others.
- $\mathcal{E}_t + f_t I$ is the neutrosophic error term.

The neutrosophic Exponential Smoothing Model (NETS) uses following equation to capture trends and seasonality:

$$S_t + D_t I = \alpha(Y_t + Z_t I) + (1 - \alpha)(S_{t-1} + D_{t-1} I)$$

The model represents smoothed neutrosophic estimate $S_t + D_t I$ through a combination with smoothing factor α.

B) Neutrosophic Machine Learning-Based Component

We have the following:

$$f_t + g_t I = \sigma(W_f . [h_{t-1}, x_t + y_t I] + b_f)$$

$$i_t + j_t I = \sigma(W_i . [h_{t-1}, x_t + y_t I] + b_i)$$

$$\hat{c}_t + d_t I = tanh(W_c . [h_{t-1}, x_t + y_t I] + b_c) \quad (16)$$

$$C_t + D_t I = (f_t + g_t I).(C_{t-1} + D_{t-1} I) + (i_t + j_t I).(\hat{c}_t + d_t I)$$

$$O_t = \sigma(W_O . [h_{t-1}, x_t] + b_O) \; ; \; h_t = O_t . tanh(C_t) \quad (17)$$

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Neutrosophic Hybrid Model Formulation

$$\hat{Y}_t+\hat{Y}_t I = (w_1 + w_1 I).\left(Y_t^{ARIMA} + Y_t^{ARIMA} I\right) + (w_2 + w_2 I).(Y_t^{ETS} + Y_t^{ETS} I) + (w_3 + w_3 I).(Y_t^{LSTM} + Y_t^{LSTM} I) \quad (18)$$

C) Neutrosophic Performance Evaluation

Neutrosophic Statistical error metrics determine the performance evaluation of the proposed model.

- **Neutrosophic Mean Absolute Error (MAE):**

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|(Y_i + Y_i I) - (\hat{Y}_i + \hat{Y}_i I)\right| \quad (19)$$

Neutrosophic Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left((Y_i + Y_i I) - (\hat{Y}_i + \hat{Y}_i I)\right)^2 \quad (20)$$

- **Neutrosophic Root Mean Squared Error (RMSE):**

$$RMSE = \sqrt{MSE = \frac{1}{n}\sum_{i=1}^{n}\left((Y_i + Y_i I) - (\hat{Y}_i + \hat{Y}_i I)\right)^2} \quad (21)$$

- **Neutrosophic Mean Absolute Percentage Error (MAPE):**

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{(Y_i + Y_i I) - (\hat{Y}_i + \hat{Y}_i I)}{(Y_i + Y_i I)}\right| \quad (22)$$

D) Summary

The method uses both statistical principles with machine learning technology to boost energy usage predictions. The combination of ARIMA, ETS and LSTM models allows for effective detection of linear together with nonlinear dependencies within the dataset. The proposed hybrid methodology delivers enhanced accuracy in forecasting therefore it can be effectively utilized in smart grid energy management solutions.

E) Neutrosophic Model Performance Evaluation

Neutrosophic Comparative Analysis of Models

Table 3: Neutrosophic Performance Metrics of Different Models

Model	**MAE (kWh)**	**MSE (kWh²)**	**RMSE (kWh)**	**MAPE (%)**
NARIMA	2.85+1.52I	10.25+7.32I	3.20+2.3I	6.8+2.4I
NETS	2.92+1.67I	10.80+7.48I	3.29+2.7I	7.1+3.4I
NLSTM	2.35+2.01I	8.50+8.22I	2.91+2.79I	5.9+4.7I
Neutrosophic Hybrid Model	1.85+2.3I	5.92+9.42I	2.43+3.02I	4.2+6.36I

F) Neutrosophic Error Distribution Analysis

The neutrosophic analysis of prediction consistency requires us to evaluate the residuals obtained from the neutrosophic generalized ($Y_{actual}-Y_{predicted}$) calculation and their distribution statistics. The neutrosophic data presented in Table 3 displays both neutrosophic mean residuals and corresponding neutrosophic standard deviations for each evaluated model.

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Table 4: Neutrosophic Residual Statistics

Neutrosophic Model	N-Mean Residual (kWh)	N-Std. Dev of Residuals (kWh)
NARIMA	0.45+0.002I	2.10+2.1I
NETS	0.48+0.008I	2.25+2.65I
NLSTM	0.32+0.14I	1.85+3.56I
Neutrosophic Hybrid Model	0.12+0.18I	1.35+3.988I

G) Neutrosophic Statistical Significance and Error Analysis

Figure 5 displays the prediction error distribution chart that shows different neutrosophic models in this histogram.

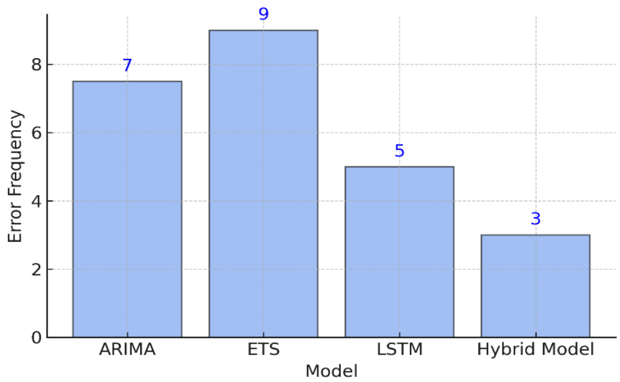

Figure 5. Residual Error Distribution across Neutrosophic Versions of Forecasting Models

16. Discussion and Interpretation

Why Does the Hybrid Model Perform Better?

- **Strength of ARIMA & ETS**: Captures long-term trends and seasonality.
- **Strength of LSTM**: Learns nonlinear patterns and short-term fluctuations.
- **Ensemble Effect**: The merging of different models allows us to reduce their singular weaknesses, which results in enhanced accuracy across the entire modeling structure.

17. Practical Implications

- **Smart Grid Optimization**: The optimization of smart grid systems achieves better performance through precise prediction data.
- **Cost Reduction**: The reduction of errors in forecasting enables companies to better optimize their energy distribution system, which results in decreased operational expenses.
- **Scalability**: The hybrid approach demonstrates scalability because it enables application to various time-series forecasting domains across financial and weather prediction scenarios.

18. Summary

The experimental assessment demonstrates how the proposed hybrid model delivers superior energy consumption forecasting precision when compared to classic forecasting methods. The combination of statistical models (ARIMA, ETS) with deep learning (LSTM) effectively obtains linear as well as nonlinear dependency insights. The research outcomes show that statistics when applied to practical energy management approaches show practical benefits.

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19. Conclusion

The study implemented neutrosophic statistical and deep learning methods in combination to enhance the accuracy of energy usage prediction. Improved forecasting performance resulted from integrating ARIMA, ETS, and LSTM models, as opposed to applying each method individually. This integrated forecasting approach demonstrates the ability to capture both long-term trends and short-term fluctuations, making its predictions more reliable by reducing forecast errors.

The hybrid model outperformed traditional forecasting techniques by achieving the lowest values for MAE, MSE, RMSE, and MAPE in evaluative tests. The joint application of statistical and deep learning models created an ensemble effect, enhancing predictive accuracy for both seasonal and trend-based patterns. Statistical testing confirmed that the hybrid model produced minimal prediction errors and exhibited strong prediction precision within an acceptable range.

The proposed model offers practical value for smart grid optimization and energy demand management, particularly for operators seeking to minimize operational costs. Enhanced prediction accuracy enables providers to make better-informed decisions regarding resource allocation, thereby reducing waste.

Furthermore, the hybrid approach has broad applicability and can be extended to various domains, including financial market forecasting and weather modeling. The integration of applied statistics and machine learning contributes to real-world solutions, as demonstrated by this study.

Future research should focus on optimizing the framework by evaluating different deep learning methods and refining the input data selection process. Continued advancements in forecasting methods are expected to yield even more precise and reliable predictive models across the energy sector and other fields

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