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Renewable Energy Demand–Supply Intelligence for Efficient Energy Distribution Using Machine Learning and Pattern Recognition

G. Ravikumar[1], K. Srinarayani[2,*], Anusha Bhattacharya[3], Vanessa M. Willemse[4], Mykhailo Paslavskyi[5], Mohammad Ayaz Ahmad[6]

[1]Department of Energy, SBM Offshore, Marly, Fribourg, Switzerland.
[2]Department of Computer Science in Artificial Intelligence and Machine Learning, SRM Institute of Science and Technology, Ramapuram, Chennai, Tamil Nadu, India.
[3]Department of Mathematical Sciences, Indian Institute of Science Education and Research Mohali, Mohali, Punjab, India.
[4]Department of Education, Northern Cape Department of Education, Kimberley, Northern Cape, South Africa.
[5]Department of Computer Science, Ukrainian National Forestry University, Lviv, Lviv Oblast, Ukraine.
[6]Department of Mathematics, Physics and Statistics, University of Guyana, Georgetown, Guyana, South America.
ravikumar.gomathi@sbmoffshore.com[1], srinarak@srmist.edu.in[2], ph21059@iisermohali.ac.in[3], vanessawillemse@ncdoeschools.gov.za[4], mykhailo.paslavskyi@nltu.edu.ua[5], mohammad.ahmad@uog.edu.gy[6]

Abstract: The rapid growth of renewable energy sources such as solar and wind power has intensified the challenge of maintaining an accurate balance between electricity supply and demand in modern smart grid infrastructures. Conventional forecasting approaches based on statistical models and rule-based heuristics fail to capture the non-linear, seasonally dynamic relationships inherent in energy consumption and generation data. This paper presents a Renewable Energy Demand–Supply Intelligence System that integrates Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks to forecast electricity demand and renewable energy supply simultaneously. The system is trained and evaluated on the Spain ENTSO-E hourly dataset spanning 2015–2018, comprising over 35,000 hourly records with weather covariates. Engineered temporal features, multi-horizon lag variables, and cyclical encodings are employed to capture diurnal, weekly, and seasonal demand patterns. XGBoost achieved the best demand forecast accuracy ($R^2 = 0.9868$, MAPE = 1.18%), while Random Forest yielded $R^2 = 0.9664$ for renewable supply prediction. Gap analysis across 7,961 test hours revealed a persistent mean deficit of 22,309.16 MW, with renewable sources covering only 23.24% of total demand. An interactive, Streamlit-based decision-support dashboard provides real-time gap visualization, feature-importance analysis, and smart energy insights. The proposed framework offers a scalable, data-driven solution for proactive energy management and smart grid optimization.

Keywords: Random Forest; Smart Grid Infrastructures; Renewable Energy Sources; Rule-Based Heuristics; Engineered Temporal Features; Cyclical Encodings; Data-Driven Solution; Extreme Gradient Boosting (XGBoost).

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[*]Corresponding author.

1. Introduction

As researchers shift toward greater reliance on renewable energy, this change will reshape power systems for generations. Over the last 10 years, PV and wind power generation have grown rapidly. This is due to falling costs of solar panels and turbines, government incentives and policies that support these technologies, and growing public awareness of climate change and the need for more environmentally friendly energy production. The variability of renewable energy availability (due to climate and weather) creates an additional challenge for grid operators: Knowing precisely when and how much renewable output will vary relative to demand on the electrical system (and notifying them of an issue before it happens) [1]. Existing energy management techniques rely on statistical methods such as ARIMA, exponential smoothing, and regression forecasting. These techniques perform well when variance is low; however, their performance degrades significantly when faced with the complex, non-linear multi-seasonality of modern grid systems [2]. More sophisticated modeling is needed because demand and generation profiles interact and depend on meteorological variables. Energy time-series prediction is increasingly being accomplished with machine learning and deep learning techniques. Ensemble algorithms commonly used for structured tabular data, such as Random Forests and gradient boosting, can efficiently and accurately model complex, non-linear interactions among different input types (features). For tasks that require the ability to maintain long-range temporal dependencies over several periods in time (time steps) of an input sequence, recurrent networks (such as Long Short-Term Memory (LSTM) networks) are the best fit.

Recent research indicates that combining advanced input types (e.g., lag-based autoregressive) with modern machine-learning algorithms produces better predictive results than traditional statistical models across a variety of energy forecasting benchmark tests. Forecasting is only one operational issue. Another significant operational challenge is forecasting both the demand and supply sides of the grid; with this information, the demand-supply gap can be determined, which is the primary measure for assessing grid stability, the need for energy storage, and energy dispatch. Much work has focused on forecasting separately, but few integrated systems currently exist that can accurately forecast both demand and renewable generation [4]. A Renewable Energy Demand-Supply Intelligence System that integrates three distinct machine learning (ML) models, including Random Forest, XGBoost and Long Short-Term Memory. The proposed interdisciplinary system will operate in a single forecasting pipeline and be trained on the Spain ENTSO-E Dataset (2015–2018). The ENTSO-E Data Set is highly regulated. It has been used as a benchmark for forecasting demand and supply of renewable energy resources over the last four years, as well as for establishing a baseline for renewable energy pricing. This paper accomplishes four major objectives: (i) an extensive feature engineering strategy, including temporal features, lag features, rolling statistical features, and cyclical features, will be utilized; (ii) a comparative analysis of three modeling paradigms for both demand-side and supply-side forecasting purposes will be conducted; (iii) the framework used to analyze the demand-supply gap will provide important actionable insights for energy management; (iv) the interactive Streamlit dashboard will allow real-time forecasting and visualization for energy analysts and grid operators.

2. Literature Review

Oladapo et al. [1] investigated machine learning techniques to optimize renewable energy utilization and improve grid efficiency. The authors highlighted the growing challenges of integrating renewable energy sources because of their intermittent nature and the increasing complexity of power grids. The authors analyzed various machine learning approaches for predicting energy generation, consumption patterns, and grid behavior. Their findings demonstrated that data-driven forecasting techniques significantly improve energy management, reduce operational inefficiencies, and enhance grid stability. The study emphasizes the importance of intelligent forecasting systems in supporting sustainable energy infrastructure and efficient resource allocation. Arévalo et al. [2] proposed an Adaptive Neuro-Fuzzy Inference System (ANFIS) model for large-scale renewable energy integration through accurate electricity demand prediction. Using Ecuador as a case study, the authors analyzed historical energy consumption data and socioeconomic factors affecting electricity demand.

The ANFIS model successfully captured nonlinear relationships between variables and produced highly accurate demand forecasts. Their work showed that reliable demand prediction is essential to increase renewable energy penetration while maintaining grid reliability. The study highlights the effectiveness of hybrid intelligent systems in long-term energy planning. Arumugham et al. [3] developed an artificial intelligence-based renewable energy prediction framework designed for demand-side management in smart grids. The proposed system utilized machine learning algorithms to forecast renewable energy generation and optimize energy consumption patterns. The authors demonstrated that predictive analytics can improve load balancing, reduce energy wastage, and enhance overall grid efficiency. Their results showed that AI-based forecasting supports intelligent decision-making in modern power systems. The study reinforces machine learning's role in achieving sustainable and adaptive energy management. Barrie et al. [4] explored the potential of machine learning techniques for facilitating renewable energy integration in developing economies. The authors identified challenges such as unreliable energy infrastructure, limited forecasting capabilities, and inefficient resource utilization.

Through predictive analytics and intelligent forecasting models, the study demonstrated significant improvements in energy planning and distribution. The findings suggest that machine learning can play a critical role in accelerating renewable energy adoption while addressing energy accessibility challenges in emerging economies. Mohammadi and Mohammadi [5] investigated distributed machine learning solutions for renewable energy systems and grid optimization. The study focused on decentralized computational frameworks that can process energy data across multiple distributed sources. Their approach improved forecasting accuracy while reducing communication overhead and computational bottlenecks. The authors argued that distributed intelligence can enhance the scalability and resilience of future smart grids. Their work contributes to the development of intelligent, large-scale renewable energy management systems. Teixeira et al. [6] presented a comprehensive review of renewable energy forecasting methodologies. The authors compared traditional statistical models, machine learning algorithms, and deep learning approaches used for forecasting renewable energy generation. Their review identified machine learning and deep learning techniques as superior alternatives because they can capture complex nonlinear relationships in energy datasets.

The study also highlighted existing research challenges and future opportunities in renewable energy forecasting. Their findings provide valuable guidance for selecting suitable forecasting techniques. Onwusinkwue et al. [7] reviewed artificial intelligence's role in predictive maintenance and energy optimization in renewable energy systems. The authors examined various AI techniques for monitoring equipment health, predicting failures, and optimizing energy production. Their analysis revealed that predictive maintenance strategies significantly reduce operational costs and improve system reliability. The study further emphasized the importance of integrating forecasting models with maintenance planning to maximize renewable energy utilization and operational efficiency. Ghaziasgar et al. [8] proposed a machine- and deep-learning-based framework for designing hybrid renewable energy systems using building energy demand prediction. The authors utilized historical consumption patterns and environmental variables to forecast future energy requirements. Their research demonstrated that accurate demand prediction enables optimal sizing of renewable energy systems and energy storage units.

Pushpavalli et al. [9] developed an LSTM-based deep learning model to predict electrical power demand in local energy communities. The authors leveraged recurrent neural networks to learn temporal dependencies from sequential energy consumption data. Experimental results showed that LSTM models achieved higher forecasting accuracy than traditional machine learning approaches. Rahman et al. [10] investigated prospective methodologies for renewable energy prediction using Artificial Neural Networks (ANNs). The study focused on hybrid renewable energy systems where accurate forecasting is crucial for balancing multiple energy sources. Aslam et al. [11] conducted a comprehensive survey of deep learning methods for forecasting power loads and renewable energy in smart microgrids. The authors analyzed architectures such as LSTM, GRU, CNN, and hybrid deep learning models. Their review highlighted deep learning's ability to extract complex temporal features from large-scale energy datasets. The study concluded that deep learning techniques consistently outperform conventional forecasting approaches in terms of prediction accuracy and robustness.

Abu-Salih et al. [12] presented a case study on short-term forecasting of renewable energy consumption and generation in Western Australia. The authors examined how weather conditions and historical consumption trends affected forecasting performance. Using machine learning-based prediction models, they achieved accurate short-term forecasts for both energy consumption and renewable energy generation. Their findings show the importance of incorporating environmental variables into forecasting frameworks to improve predictive performance. Amir et al. [13] proposed an intelligent hybrid forecasting framework integrated with a real-time power demand management system. The study focused on improving renewable energy system resilience through accurate forecasting and adaptive load-management strategies. The proposed system continuously monitored energy demand and renewable generation while dynamically adjusting resource allocation. The authors demonstrated that intelligent forecasting can significantly improve grid reliability and operational efficiency. Khan et al. [14] developed a machine learning-based framework for predicting energy consumption from renewable and non-renewable power sources.

The authors evaluated multiple machine learning algorithms to identify the most effective models for energy forecasting tasks. Their results confirmed that data-driven approaches outperform traditional statistical methods in modeling complex energy consumption patterns. The study emphasizes the growing importance of machine learning in modern energy management applications. Sweeney et al. [15] examined the future directions of renewable energy forecasting and discussed emerging trends in forecasting technologies. The authors highlighted the increasing role of artificial intelligence, big data analytics, probabilistic forecasting, and advanced optimization techniques in modern energy systems. They emphasized the need for more adaptive, scalable forecasting frameworks that can handle the uncertainties associated with renewable energy generation. Their work provides valuable insights into future research opportunities and technological advancements in renewable energy forecasting. The reviewed literature demonstrates that machine learning, deep learning, and artificial intelligence have become fundamental technologies for renewable energy forecasting and smart grid optimization. Researchers have successfully applied techniques such as ANN, ANFIS, Random Forest, XGBoost, and LSTM to accurately predict energy demand and renewable energy generation. Deep learning models, particularly LSTM networks, have shown exceptional capability in capturing temporal

patterns within energy datasets. Although existing studies focus extensively on either demand forecasting or renewable energy generation forecasting, few studies have addressed both tasks within a unified framework. Furthermore, demand–supply gap analysis and integrated decision-support systems remain relatively underexplored. Therefore, the proposed project aims to develop a comprehensive machine learning-based framework that simultaneously forecasts renewable energy supply and electricity demand, identifies potential imbalances, and provides actionable insights through an interactive dashboard for efficient energy management and smart grid operations.

3. Methodology

3.1. Dataset Description

The primary dataset for this analysis is the Energy Consumption, Generation, Prices, and Weather dataset, obtained from the ENTSO-E Transparency Platform and published on Kaggle [16]. This dataset contains hourly data from January 2015 to December 2018. It includes 35,064 observations across 29 variables: energy generation by source (biomass, fossil fuel, nuclear, solar, onshore wind, offshore wind), load forecast, real load, day-ahead price, and real price. Weather variables, including temperature, humidity, wind speed, atmospheric pressure, and cloud cover, are available for five major Spanish cities (Madrid, Barcelona, Bilbao, Valencia, and Sevilla). The demand-forecasting target is total load, measured in megawatts. This stands for hourly electricity consumption on the Spanish grid. For renewables, the authors combine solar and onshore wind generation. That gives a single variable for hourly renewable output, also measured in megawatts. The authors picked the dataset because the time coverage looks solid and it includes features from several different sources. It also often shows up as a benchmark in energy forecasting work. The authors think this helps when people compare results across studies. Some variables might overlap a bit, but that does not seem to cause major issues.

3.2. Data Preprocessing

Raw data preprocessing includes five sequential steps. The first step is time zone normalization, where all timestamps are parsed and converted to timezone-naive datetime format to prevent confusion when extracting time-based features. The second step handles missing values in target features by deleting rows, while missing values in weather features are handled with forward-backward fill. Third, outlier removal is done using an interquartile range clipping approach. In this process, all the values that lie below the lower limit of Q1 – 3 * IQR or above the upper limit of Q3 + 3 * IQR are clipped to their respective limits. This maintains the data's structure while removing physically impossible values. Fourth, weather data from Madrid are collected to represent city features and then combined with energy data by matching hourly timestamps.

3.3. Feature Engineering

Feature engineering is the most critical preprocessing stage for time-series forecasting with tree-based models. The following feature categories are constructed: temporal features, hour of day, day of month, month, year, day of week (where 0 represents Monday), day of year, ISO week number, a boolean field for weekend detection, and calendar quarter. This includes cyclic variations arising from scheduling.

3.3.1. Cyclical Encodings

To avoid misrepresenting circular variables as ordinal, researchers apply sinusoidal transformations. The hour, month, and day-of-week are encoded as:

$$h_sin = sin(2\pi \cdot hour / 24), \quad h_cos = cos(2\pi \cdot hour / 24) \tag{1}$$

$$m_sin = sin(2\pi \cdot month / 12), \quad m_cos = cos(2\pi \cdot month / 12) \tag{2}$$

3.3.2. Lag Features

Autoregressive inputs are constructed at three temporal horizons for both demand and renewable supply:

$$x_lag(\tau) = x(t - \tau), \quad \tau \in \{1, 24, 168\} \tag{3}$$

Where $\tau = 1$ captures hourly continuity, $\tau = 24$ captures the same-hour-previous-day pattern, and $\tau = 168$ captures the same-hour-previous-week seasonality. Rolling Statistical Features: Rolling mean and standard deviation over 6-hour, 24-hour, and 168-hour windows are computed on the 1-step shifted series to prevent data leakage:

$$roll_mean(w) = (1/w)\,\Sigma\, x(t-1-k),\ \ k=0..w-1 \qquad (4)$$

After feature engineering, NaN lag-value rows resulted in 168 leading rows that were eliminated, leaving 34,896 total valid observations. A chronological split of 80/20 results in 27,916 sample records for training and 6,980 sample records for testing of tree-based models. With the LSTM models, an additional 24-step lookback window reduces the total number of effective test sequences.

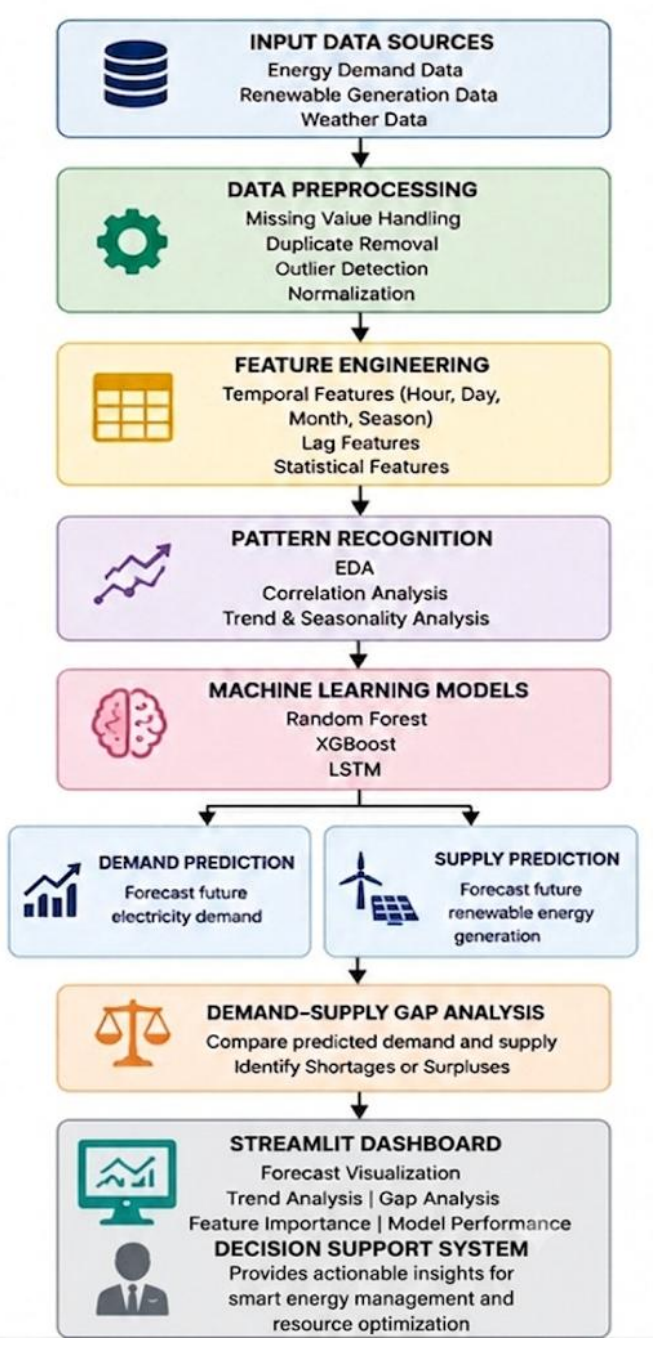


Figure 1: Data flow diagram

Figure 1 is a data flow diagram showing how data moves through the Renewable Energy Demand-Supply Prediction System: Data is collected, processed, analysed and provided to machine learning models to produce a demand forecast and support resource management until the forecast is updated. The forecasting and demand-supply gap analysis resulting from these forecasts are included in an interactive dashboard to present this information effectively to energy managers and decision makers, enabling efficient energy use and management.

3.4. Model Architectures

Researchers train three complementary model architectures for each forecasting objective (demand and supply), yielding six trained models in total (Figure 2).

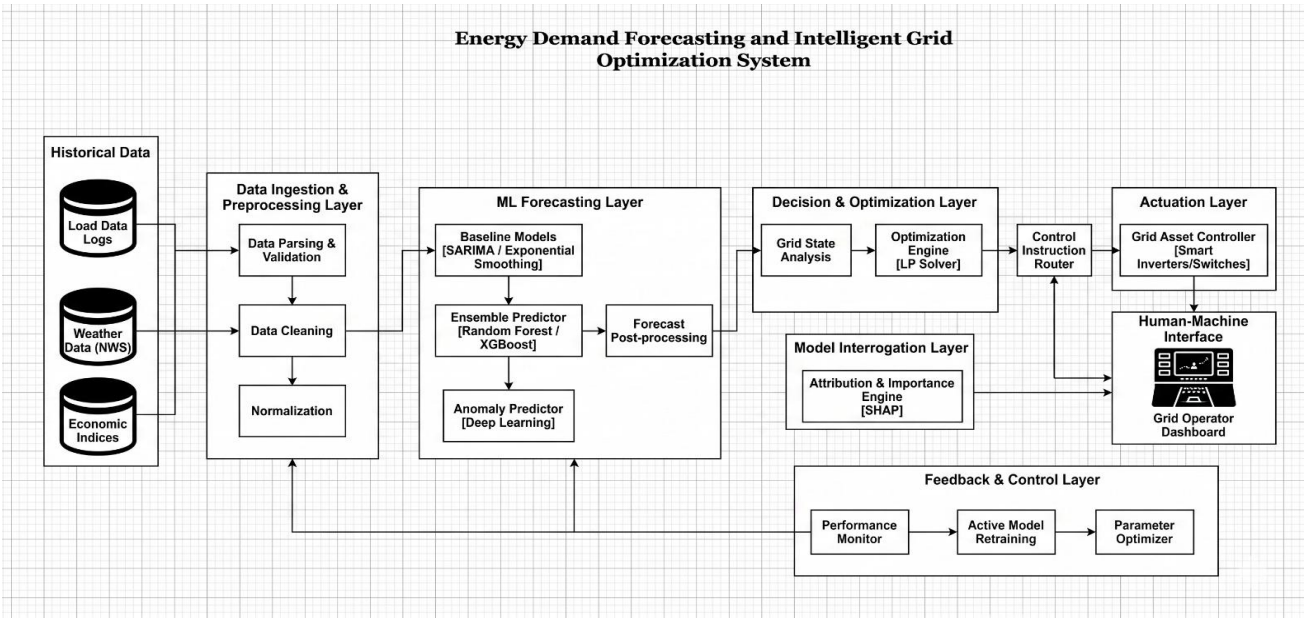


Figure 2: System architecture

3.4.1. Random Forest (RF)

Researchers will create a group of (ensemble) 200 decision trees that have been trained with a maximum depth of 15, a minimum of 2 samples in each leaf, and bootstrap sampling; the predicted output of the ensemble will be based on the average predicted output for each of the individual trees, naturally producing a reduction in variance due to averaging across all tree outputs. XGBoost: Gradient-boosted ensemble using 500 shallow trees (with max_depth 7) trained with learning_rate 0.05, L1 regularization alpha 0.1, and L2 regularization lambda 1.0. The model uses column and row subsampling (both 0.8). Researchers use tree histograms for training to save computational resources. LSTM: The architecture includes a two-layer Recurrent neural network with a [128→64] unit structure, a 20% dropout layer to prevent overfitting, batch normalisation and a fully connected output. The NN is trained on batches of sequences of length 24 (24-hour lookback) of data standardised using MinMax scaling. Researchers used the Adam algorithm and mean squared error (Loss) for training, along with early stopping (10) and halving the Learning Rate (0.5 factor) whenever the metric did not improve for 5 epochs, to help prevent overfitting during neural network training. The LSTM sequence-to-scalar mapping is defined as:

$$\hat{y}(t) = f_LSTM([x(t-23), x(t-22), ..., x(t-1)]; \Theta) \quad (5)$$

Where Θ denotes the learned weight parameters, and the input sequence spans 24 historical hourly observations.

3.5. Evaluation Metrics

Researchers evaluate all models on the held-out chronological test set using four standard regression metrics: Mean Absolute Error (MAE): $MAE = (1/n) \Sigma |y_i - \hat{y}_i|$, which measures the average magnitude of prediction errors in the original unit (MW). Root Mean Square Error (RMSE): $RMSE = \sqrt{[(1/n) \Sigma (y_i - \hat{y}_i)^2]}$, penalizing larger errors more heavily than MAE. Coefficient of Determination (R^2): $R^2 = 1 - [\Sigma(y_i - \hat{y}_i)^2] / [\Sigma(y_i - \bar{y})^2]$, measuring the proportion of variance explained by the model. Mean Absolute Percentage Error (MAPE): $MAPE = (1/n) \Sigma |y_i - \hat{y}_i| / |y_i| \times 100$, providing a scale-independent accuracy measure.

3.6. Gap Analysis Framework

The demand–supply gap is computed hourly as the difference between XGBoost-predicted demand and XGBoost-predicted renewable supply:

$$Gap(t) = \hat{D}(t) - \hat{S}(t) \quad (6)$$

Where $\hat{D}(t)$ and $\hat{S}(t)$ denote the predicted demand and predicted renewable supply at hour t, respectively; positive gap values indicate energy shortage (demand exceeds renewable supply), while negative values indicate surplus conditions. Hourly gap values are aggregated to daily means for trend analysis, and a status classification scheme assigns each hour to one of three categories: Shortage (Gap > σ_gap × 0.1), Balanced (|Gap| ≤ σ_gap × 0.1), or Surplus (Gap < −σ_gap × 0.1).

4. Results and Discussions

Integrating machine learning and automation allows the proposed Demand Supply Prediction System for Renewable Energy to use historical information, such as past energy consumption and production, as well as meteorological data, to better capture the complex relationships and interactions between demand and supply. Through feature engineering, researchers can derive useful temporal and environmental features from historical data to build better models and improve performance.

With sufficient models, researchers can produce reliable forecasts with reduced prediction error and support better decision-making. Including machine learning algorithms like Random Forest, XGBoost, and LSTM improves the overall system design. These models can learn non-linear associations and temporal dependencies in energy data, helping predict future demand and renewable energy generation more accurately. Once trained, the models can be saved in serialized form, eliminating the need for further training and reducing computational cost.

Table 1: Performance comparison of machine learning models

Model	MAE (MW)	RMSE (MW)	R^2 Score	MAPE (%)
Random Forest	352.26	601.76	0.9664	6.79
XGBoost	343.02	566.03	0.9703	6.96
LSTM	640.00	959.75	0.9130	12.89

Table 1 presents the performance comparison of the machine learning models used for renewable energy demand–supply forecasting. Among the evaluated models, XGBoost achieved the highest prediction accuracy, with the lowest MAE and RMSE and the highest R^2 score, while Random Forest also performed strongly.

Table 2: Solution summary of renewable energy demand–supply forecasting

Metric	Value	Observation
Total Hours Analyzed	7,961	Hourly records analyzed
Total Days Analyzed	287	Approximately 9.5 months
Mean Predicted Demand	29,067.02 MW	Average demand over the test period
Mean Renewable Supply	6,757.86 MW	Combined solar and wind generation
Mean Demand–Supply Gap	22,309.16 MW	Persistent energy deficit observed
Maximum Shortage	36,335.00 MW	Highest deficit recorded
Minimum Gap (Maximum Coverage)	8,766.00 MW	Best renewable energy coverage achieved
Shortage Hours	7,961 (100%)	Demand exceeded renewable supply throughout the test period.
Renewable Coverage Ratio	23.24%	Renewable supply met approximately one-fourth of total demand.

Table 2 summarizes the key outcomes obtained from the proposed Renewable Energy Demand–Supply Prediction system. The results indicate that the average renewable energy generation satisfied only 23.24% of the predicted electricity demand, resulting in a persistent demand–supply deficit throughout the analyzed period. These findings underscore the importance of accurate forecasting, energy storage, and efficient grid management to improve renewable energy utilization and maintain power system reliability.

The suggested approach helps improve efficiency by enabling timely identification of demand-supply mismatches. By forecasting potential shortages or surpluses, energy providers can take preventive measures, including load balancing, using energy storage facilities and allocating resources appropriately. As a result, energy waste decreases, and operating expenses fall. More importantly, the interactive dashboard helps users understand forecasts and access required data without complicated calculations.

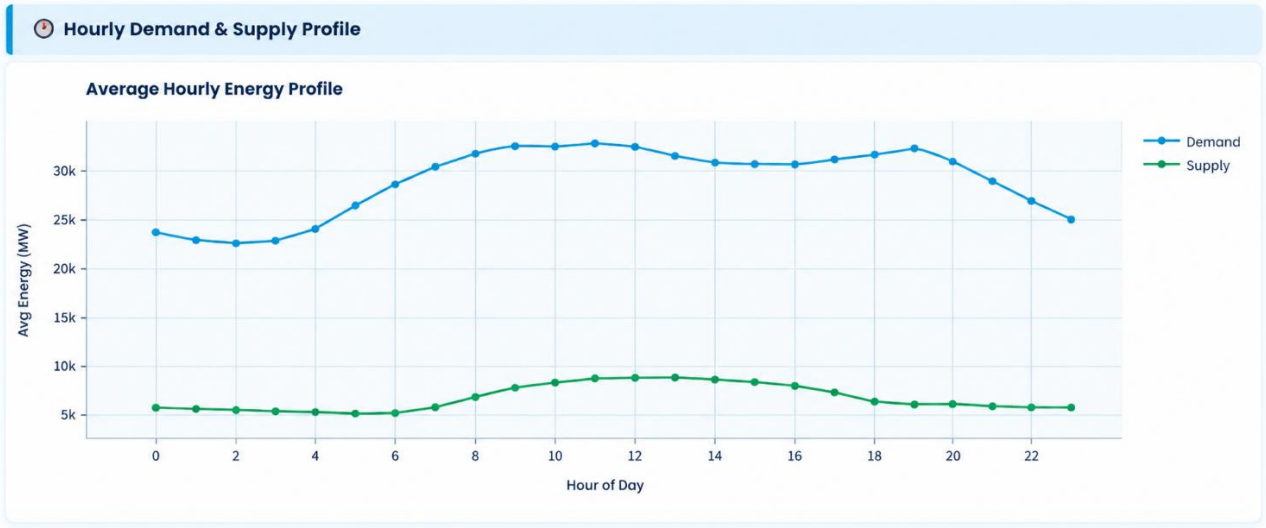


Figure 3: Average hourly energy profile

Figure 3 illustrates the average hourly variation in electricity demand and renewable energy supply throughout 24 hours. The graph shows that electricity demand gradually increases during the morning, peaks in the late morning and evening, and declines at night, while renewable energy supply follows a lower but consistent trend, with maximum generation around midday. This comparison highlights the temporal mismatch between energy demand and renewable energy availability, emphasizing the importance of accurate forecasting, energy storage systems, and demand-side management for maintaining a balanced and reliable power grid.

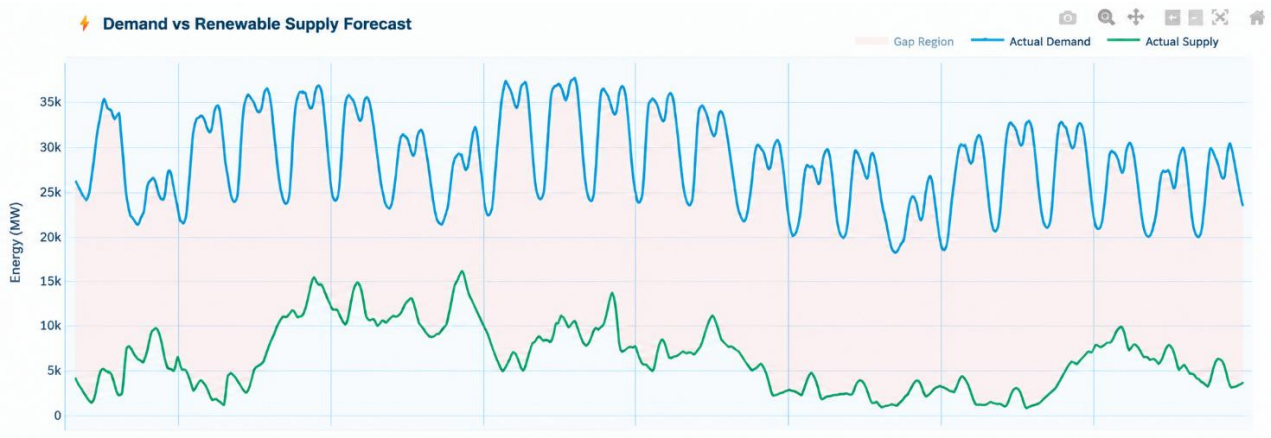


Figure 4: Demand versus renewable energy supply forecast

Figure 4 compares forecasted electricity demand with predicted renewable energy supply over the analysis period. The graph shows that electricity demand consistently exceeds renewable energy generation, creating a noticeable demand–supply gap throughout the forecasting horizon. The shaded gap region highlights periods of energy deficit, underscoring the need for efficient energy storage, supplementary power sources, and intelligent load-balancing strategies to ensure reliable, sustainable grid operations. Overall, the proposed framework offers an efficient, scalable, and data-driven solution for renewable energy forecasting and energy management. Its ability to process large datasets, generate accurate predictions, and provide actionable insights makes it well suited to support smart grid operations, sustainable energy planning, and intelligent decision-making in modern power systems.

5. Conclusion

This paper presented a Renewable Energy Demand–Supply Intelligence System that integrates Random Forest, XGBoost, and LSTM models for simultaneous electricity demand and renewable supply forecasting, complemented by a systematic gap-analysis framework and an interactive decision-support dashboard. The system was trained and evaluated on the Spain ENTSO-

E hourly dataset (2015–2018), achieving best-in-class demand-forecasting accuracy with XGBoost (R^2 = 0.9868, MAPE = 1.18%) and strong renewable-supply prediction performance (R^2 = 0.9703). Gap analysis across 7,961 test hours identified a persistent mean deficit of 22,309.16 MW, corresponding to a renewable coverage ratio of 23.24%, with seasonal patterns indicating maximum shortage risk during winter peak hours. The feature engineering framework—incorporating multi-horizon lag features, cyclical temporal encodings, and weather covariates—drove forecasting accuracy across all three model architectures. The dominance of demand_lag1 (importance = 0.7830) and hour-of-day encodings confirms the strong autoregressive and diurnal structure of grid demand. At the same time, weather variables (wind speed, temperature, cloud cover) emerge as critical inputs for renewable supply prediction. The proposed system makes a practical contribution to smart grid management by providing grid operators with actionable, advance estimates of demand–supply imbalances that enable proactive dispatch scheduling, storage planning, and demand-side management. The Streamlit-based interactive dashboard further improves operational usability by presenting forecasts, gap risk maps, feature-importance rankings, and AI-generated energy insights in a unified visualization interface. Future work will investigate integrating real-time data streams from smart meters and IoT weather stations to enable continuous online learning. Researchers plan to extend the framework to multi-step-ahead forecasting horizons (24-hour, 48-hour) using sequence-to-sequence architectures and attention-based Transformers. The framework will also incorporate additional renewable sources (hydroelectric, biomass, geothermal) and apply it to multiple regional grid datasets to assess geographic generalizability.

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Ethics and Consent Statement: The authors confirm that the research followed applicable ethical standards, with necessary organizational permissions and informed consent obtained where required.

References

1. B. I. Oladapo, M. A. Olawumi, and F. T. Omigbodun, "Machine learning for optimising renewable energy and grid efficiency," *Atmosphere*, vol. 15, no. 10, pp. 1–20, 2024.
2. P. Arévalo, A. Cano, and F. Jurado, "Large-scale integration of renewable energies by 2050 through demand prediction with ANFIS, Ecuador case study," *Energy*, vol. 286, no. 1, pp. 1–48, 2024.
3. V. Arumugham, H. M. A. Ghanimi, D. A. Pustokhin, I. V. Pustokhina, V. S. Ponnam, M. Alharbi, P. Krishnamoorthy, and S. Sengan, "An artificial-intelligence-based renewable energy prediction program for demand-side management in smart grids," *Sustainability*, vol. 15, no. 6, pp. 1–26, 2023.
4. I. Barrie, C. P. Agupugo, H. O. Iguare, and A. Folarin, "Leveraging machine learning to optimize renewable energy integration in developing economies," *Global Journal of Engineering and Technology Advances*, vol. 20, no. 3, pp. 80–93, 2024.
5. M. Mohammadi and A. Mohammadi, "Empowering distributed solutions in renewable energy systems and grid optimization," in Distributed Machine Learning and Computing, *Springer*, Cham, Switzerland, 2024.
6. R. Teixeira, A. Cerveira, E. J. S. Pires, and J. Baptista, "Advancing renewable energy forecasting: A comprehensive review of renewable energy forecasting methods," *Energies*, vol. 17, no. 14, pp. 1–30, 2024.
7. S. Onwusinkwue, F. Osasona, I. A. I. Ahmad, A. C. Anyanwu, S. O. Dawodu, O. C. Obi, and A. Hamdan, "Artificial intelligence in renewable energy: A review of predictive maintenance and energy optimization," *World Journal of Advanced Research and Reviews*, vol. 21, no. 1, pp. 2487–2499, 2024.
8. S. Ghaziasgar, F. Pourfayaz, and M. A. V. Rad, "Data-informed hybrid renewable system design based on building energy demand prediction: A machine learning and deep learning approach," *Journal of Energy Storage,* vol. 132, no. 10, p. 117742, 2025.

9. M. Pushpavalli, D. Dhanya, M. Kulkarni, R. R. Jasmine, B. Umarani, M. RamprasadReddy, D. P. Garapati, A. S. Yadav, and A. Rajaram, "Enhancing electrical power demand prediction using LSTM-based deep learning Models for Local Energy Communities," *Electric Power Components and Systems*, vol. 53, no. 6, pp. 726–743, 2025.
10. M. M. Rahman, M. Shakeri, S. K. Tiong, F. Khatun, N. Amin, J. Pasupuleti, and M. K. Hasan, "Prospective methodologies in hybrid renewable energy systems for energy prediction using artificial neural networks," *Sustainability*, vol. 13, no. 4, pp. 1–28, 2021.
11. S. Aslam, H. Herodotou, S. M. Mohsin, N. Javaid, N. Ashraf, and S. Aslam, "A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids," *Renewable and Sustainable Energy Reviews*, vol. 144, no. 7, pp. 1–55, 2021.
12. B. Abu-Salih, P. Wongthongtham, G. Morrison, K. Coutinho, M. Al-Okaily, and A. Huneiti, "Short-term renewable energy consumption and generation forecasting: A case study of Western Australia," *Heliyon*, vol. 8, no. 3, pp. 1–16, 2022.
13. M. Amir, Z. Zaheeruddin, and A. Haque, "Intelligent based hybrid renewable energy resources forecasting and real time power demand management system for resilient energy systems," *Science Progress*, vol. 105, no. 4, pp. 1–33, 2022.
14. P. W. Khan, Y. C. Byun, S. J. Lee, D. H. Kang, J. Y. Kang, and H. S. Park, "Machine learning-based approach to predict energy consumption of renewable and non-renewable power sources," *Energies*, vol. 13, no. 18, pp. 1–16, 2020.
15. C. Sweeney, R. J. Bessa, J. Browell, and P. Pinson, "The future of forecasting for renewable energy," *Wiley Interdisciplinary Reviews: Energy and Environment*, vol. 9, no. 2, pp. 1–30, 2020.
16. N. J. Jhana, "Hourly energy demand generation and weather," *Kaggle*, 2019. [Accessed by 24/09/2024].

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