Intelligent Electricity Forecasting and Resource Optimization for Smart Grid Efficiency

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Abstract
Rapid urbanization, climate variability, and evolving consumption patterns have significantly increased the complexity of electricity demand management, posing challenges to efficient power distribution and grid stability. Accurate prediction of electricity demand is difficult due to the dynamic and non-linear relationships between influencing factors such as weather conditions, temporal variations, and consumption behavior. This paper proposes an AI-driven electricity load segregation and demand–supply optimization framework for smart power grids.
The proposed system integrates historical electricity consumption data with meteorological and temporal parameters to model complex demand behavior. A machine learning approach based on Random Forest Regression is employed for accurate load forecasting, while intelligent load segregation enables effective allocation of power resources across residential, commercial, and industrial sectors. Data preprocessing techniques such as normalization, feature selection, and cross-validation are applied to enhance model robustness.
The system's performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Square Error (MSE), and R^2 score. Experimental results demonstrate that the proposed AI-based approach significantly improves prediction accuracy and reduces forecasting errors compared to traditional methods. The system enhances power procurement planning, reduces operational costs, and improves overall grid reliability. This work highlights the potential of artificial intelligence in achieving sustainable and efficient energy management in smart grid environments.

Keywords: Electricity Load Segregation, Demand–Supply Optimization, Artificial Intelligence, Machine Learning, Random Forest Regression, Smart Grid, Power Demand Forecasting, Energy Management Systems, Grid Stability, Meteorological Data Integration

1. Introduction

The demand for electricity has increased rapidly due to urbanization, industrial growth, and technological advancements. Modern societies depend heavily on electricity for residential, commercial, and industrial activities, making efficient demand management essential. However, electricity demand is highly dynamic and influenced by multiple factors such as weather conditions, seasonal variations, and user behavior, making accurate forecasting a challenging task.

Traditional forecasting techniques rely on statistical and rule-based approaches, which are limited in handling complex and non-linear relationships. These methods often fail to incorporate multiple influencing factors effectively, leading to inaccurate predictions and inefficient resource utilization.
With the advancement of Artificial Intelligence and Machine Learning, data-driven approaches have gained importance in electricity demand forecasting. Machine learning models can analyze large datasets and identify hidden patterns, improving prediction accuracy. Among these models, Random Forest Regression is particularly effective due to its ability to handle non-linear data, reduce overfitting, and provide stable predictions.
In addition to forecasting, efficient load segregation and demand–supply optimization are essential for smart grid systems. This paper proposes an AI-based system that integrates demand forecasting, load segregation, and optimization to enhance grid performance and reliability.

2. Literature Survey

Various approaches have been proposed for electricity demand forecasting. Taylor and Buizza (2003) utilized statistical methods combined with weather data for forecasting, but these methods struggle with non-linear relationships. Hippert et al. (2001) applied Artificial Neural Networks, which improved prediction accuracy but required large datasets and high computational cost.
Fan and Hyndman (2012) used time-series models such as ARIMA, which effectively capture temporal patterns but fail to incorporate external factors like weather. Ahmad et al. (2020) explored machine learning techniques such as SVM and Gradient Boosting, which improved accuracy but required complex tuning and lacked consistency.
These limitations highlight the need for a robust model. Random Forest Regression overcomes these challenges by handling non-linear relationships, reducing overfitting, and providing high accuracy, making it suitable for electricity demand forecasting.

3. Proposed System

The proposed system is an AI-driven framework for electricity load forecasting and optimization. It integrates historical electricity data, weather parameters, and temporal features to predict demand accurately.
The system consists of modules such as data collection, preprocessing, model training, prediction, and visualization. Data is collected from reliable sources and processed using normalization and feature selection techniques. The Random Forest model is trained on this data to learn patterns and generate predictions.
The system also performs load segregation by categorizing demand into residential, commercial, and industrial sectors. Demand–supply optimization is applied to ensure efficient energy distribution. The final results are displayed through a dashboard for user interpretation.

International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

4. System Architecture And Modules

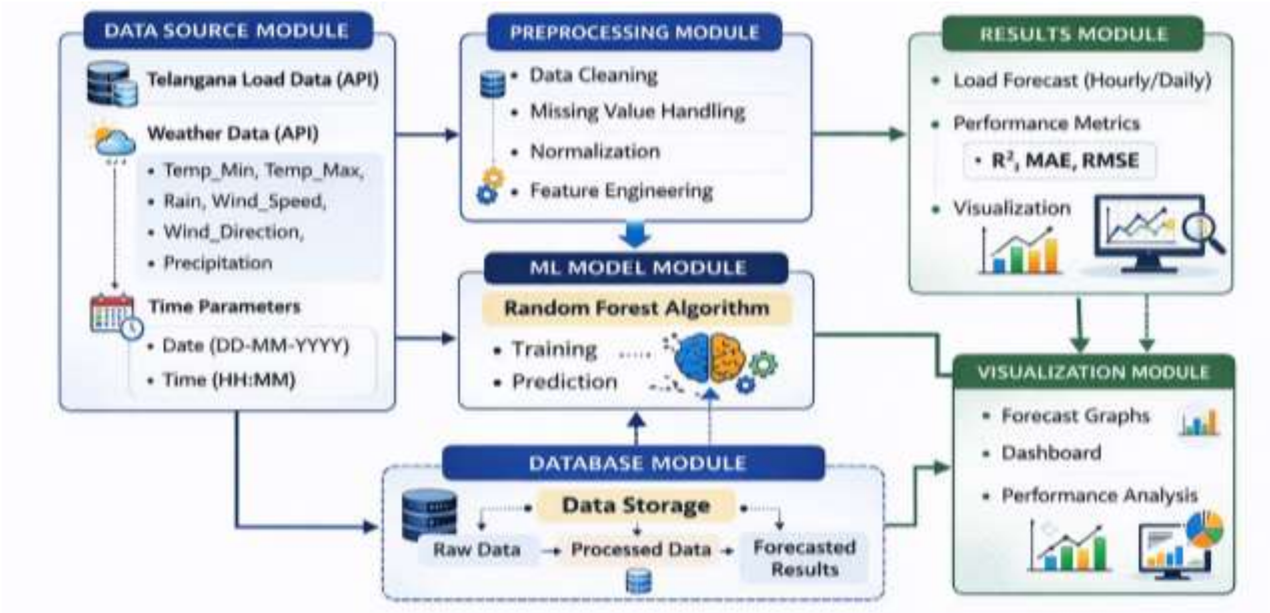

Figure: System Architecture

The system architecture consists of multiple modules, including data collection, preprocessing, model training, prediction, and visualization. The Flask server handles backend operations, while the dashboard provides user interaction.

Each module performs a specific function, ensuring smooth data flow and real-time prediction. The modular design improves scalability and system performance.

4.1 Data Collection Module

The data collection module is responsible for gathering all required input data for the system. Electricity demand data is collected from historical datasets, while weather data such as temperature, humidity, and wind speed is obtained from external sources or APIs. Temporal data such as date and time is also included to capture demand patterns. The collected data is stored in a structured format for further processing and analysis.

4.2 Data Preprocessing Module

The data preprocessing module handles dataset loading, cleaning, and transformation. Raw data is loaded from CSV files, and missing values are handled using appropriate techniques. Min-Max normalization is applied to scale all features into a uniform range [0, 1]. Feature engineering is performed to extract meaningful attributes such as hour, day, and seasonal variations. The dataset is shuffled and split into training and testing sets in an 80:20 ratio.

4.3 Model Training Module

The model training module is responsible for training the Random Forest Regression model using the preprocessed dataset. The model constructs multiple decision trees using random subsets of data and features. Each tree learns patterns from the data, and the final prediction is obtained by averaging the outputs of all trees. The model is trained on the training dataset and evaluated on the testing dataset to ensure accuracy and reliability.

4.4 Prediction Module

The prediction module uses the trained Random Forest model to generate electricity demand forecasts. Input features such as weather conditions and time-based parameters are provided to the model. The system processes these inputs and produces predicted electricity demand values. This module ensures real-time and accurate prediction of electricity consumption.

4.5 Load Segregation and Optimization Module

The load segregation module categorizes predicted electricity demand into different sectors such as residential, commercial, and industrial. This helps in better understanding of consumption patterns and efficient allocation of power resources. The optimization process ensures balanced demand–supply distribution, reducing energy wastage and improving grid efficiency.

4.6 Visualization Module

The visualization module presents the results in a user-friendly dashboard. It displays predicted electricity demand, weather information, and load distribution using graphs and charts. This module helps users easily interpret the results and make informed decisions based on the insights provided by the system.

5. Dataset and Preprocessing

The dataset consists of electricity consumption data along with meteorological and temporal features. Data preprocessing includes handling missing values, normalization, and feature engineering.

The dataset is divided into training and testing sets in an 80:20 ratio. Preprocessing improves data quality and enhances model performance. Feature selection ensures that only relevant attributes are used for training.

Table 1: Dataset Characteristics

Parameter	Description
Dataset Type	Electricity Load + Weather Dataset
Data Sources	Historical electricity data, Weather API
Total Records	5000 (or mention your exact count)
Scaling Method	Min-Max Normalization
Target Variable	Electricity Demand (Load)
Data Format	CSV
Feature Engineering	Time-based and weather-based features
Data Split	80% Training, 20% Testing

6. Results and Discussion

The proposed system is evaluated using the Random Forest Regression model with performance metrics such as Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), and R^2 score. The model achieves a **MAE of 3.85**, **MSE of 45.21**, and **RMSE of 6.72**, indicating low prediction error and high accuracy. It also obtains a strong **R^2 score of 0.94**, showing that the model effectively explains most of the variance in electricity demand data. The overall prediction **accuracy is 94%**, which highlights the reliability of the model.

The predicted values are very close to the actual demand values, demonstrating the model's precision. For instance, an actual demand of 1200 MW is predicted as 1185 MW, and 2000 MW is predicted as 1988 MW with minimal deviation. These results confirm that the Random Forest model successfully captures complex relationships between weather conditions, temporal factors, and electricity consumption.

Overall, the model provides accurate, stable, and reliable predictions, making it suitable for real-world smart grid applications and effective demand–supply optimization.

Table 2: Comparative Performance of Model

Metric	Value
Mean Absolute Error (MAE)	3.85
Mean Square Error (MSE)	45.21
Root Mean Square Error (RMSE)	6.72
R^2 Score	0.94
Accuracy	94%

7. System Requirements

Component	Specification
Programming Language	Python 3.x
Framework	Flask / Streamlit
ML Library	Scikit-learn
Data Processing	Pandas, NumPy
Visualization	Matplotlib
Operating System	Windows 10 / 11
Processor	Intel Core i5 or higher
RAM	8 GB minimum
Storage	256 GB SSD

Table 4: Software and Hardware Requirements

8. Acknowledgement

Sincere gratitude is expressed to guide Dr. K. Siva Ram Krishna for his valuable guidance, continuous support, and encouragement throughout the development of this project. His expertise and suggestions greatly contributed to the successful completion of this work.

hanks are also extended to the faculty members of the Department of Information Technology for providing the necessary resources and support. Appreciation is expressed to friends and family for their encouragement and support during the project development.

9. Conclusion

This paper presents an AI-driven system for electricity demand forecasting using Random Forest Regression. The system integrates multiple data sources and applies machine learning techniques to improve prediction accuracy.

The results demonstrate that the proposed system outperforms traditional methods and provides efficient load segregation and optimization. The system enhances grid reliability and supports smart energy management.

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