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Supervised Machine Learning for Renewable Energy Forecasting

Authors: [1]Noman Mazher, [2]Hadia Azmat

Corresponding Author: nauman.mazhar@uog.edu.pk

Abstract:

Renewable energy forecasting is a critical challenge in the transition to sustainable energy systems. The variability of renewable energy sources such as solar and wind necessitates accurate forecasting methods to enhance grid stability, optimize energy distribution, and reduce reliance on fossil fuels. Supervised machine learning (ML) techniques have emerged as powerful tools for addressing these challenges, leveraging historical data to predict energy generation with improved accuracy. This paper provides an in-depth analysis of supervised machine learning models applied to renewable energy forecasting, covering methodologies, challenges, and experimental results. Various algorithms, including decision trees, support vector machines (SVM), artificial neural networks (ANN), and ensemble models, are explored in the context of energy prediction. A comprehensive experiment is conducted using real-world datasets, comparing model performance based on accuracy metrics such as mean absolute error (MAE) and root mean square error (RMSE). The results demonstrate that ensemble methods and deep learning-based approaches outperform traditional statistical techniques, highlighting the importance of advanced ML strategies. This research contributes to the ongoing development of efficient renewable energy forecasting methods, ultimately supporting the integration of clean energy into power systems.

Keywords: Renewable Energy Forecasting, Supervised Machine Learning, Artificial Neural Networks, Support Vector Machines, Energy Grid Stability, Time-Series Prediction

[1]Department of Information Technology, University of Gujrat, Punjab, Pakistan

[2]University of Lahore, Punjab, Pakistan

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I. Introduction

The global shift toward renewable energy sources is driven by the need for sustainable and environmentally friendly alternatives to fossil fuels. However, the inherent variability and intermittency of renewable energy sources such as solar and wind pose significant challenges to their widespread adoption [1]. Efficient forecasting mechanisms are required to ensure energy grid stability, facilitate energy storage, and optimize distribution networks. Traditional forecasting techniques, such as statistical and physics-based models, often fail to capture complex patterns in energy generation data. In contrast, machine learning approaches have demonstrated superior performance in extracting nonlinear relationships and handling large-scale datasets [2]. Supervised machine learning plays a crucial role in renewable energy forecasting by learning from historical data and making predictions based on labeled examples. These models utilize various input features such as weather conditions, historical power output, and geographical data to predict future energy generation with high accuracy. Different supervised learning algorithms, including regression models, decision trees, and deep learning architectures, have been successfully applied to renewable energy forecasting problems. Despite their advantages, machine learning models require careful feature selection, model tuning, and validation to achieve optimal performance [3].

The application of supervised learning in renewable energy forecasting is an evolving field that integrates domain knowledge from meteorology, energy systems, and computer science. Researchers and industry professionals continuously develop and refine models to improve prediction accuracy and computational efficiency. The availability of high-quality datasets and advancements in ML frameworks has significantly contributed to the progress in this domain. However, challenges such as data scarcity, overfitting, and model interpretability still hinder the widespread deployment of ML-based forecasting systems. This paper explores the role of supervised machine learning in renewable energy forecasting, focusing on its advantages, challenges, and implementation techniques. A thorough review of commonly used ML models is provided, along with experimental results demonstrating their effectiveness. The study also discusses the integration of ML-based forecasting systems into energy management frameworks to enhance their practical applicability. Furthermore, ethical considerations and sustainability

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implications of ML-driven energy forecasting are examined to ensure responsible AI development.

In the subsequent sections, we delve into the methodologies used in supervised learning-based energy forecasting, analyzing different model architectures and training approaches. We then present an experimental study where multiple supervised learning models are applied to real-world energy datasets to evaluate their prediction performance. The results are discussed in detail, highlighting the strengths and weaknesses of each approach. Finally, the conclusion summarizes the key findings and suggests future research directions in this rapidly evolving field.

II. Methodologies in Supervised Learning for Energy Forecasting

Supervised learning in renewable energy forecasting involves training models on historical data with labeled outcomes to predict future energy generation. The first step in this process is data collection and preprocessing. Reliable datasets are obtained from energy monitoring stations, satellite imagery, and meteorological sensors [4]. The collected data typically includes time-series records of solar radiation, wind speed, temperature, humidity, and past energy production values. Since real-world datasets often contain missing values and noise, preprocessing techniques such as interpolation, normalization, and outlier removal are applied to enhance data quality. Feature selection and engineering are critical for improving model accuracy [5]. Advanced feature engineering techniques, including principal component analysis (PCA) and autoencoders, are often employed to extract meaningful patterns from high-dimensional data.

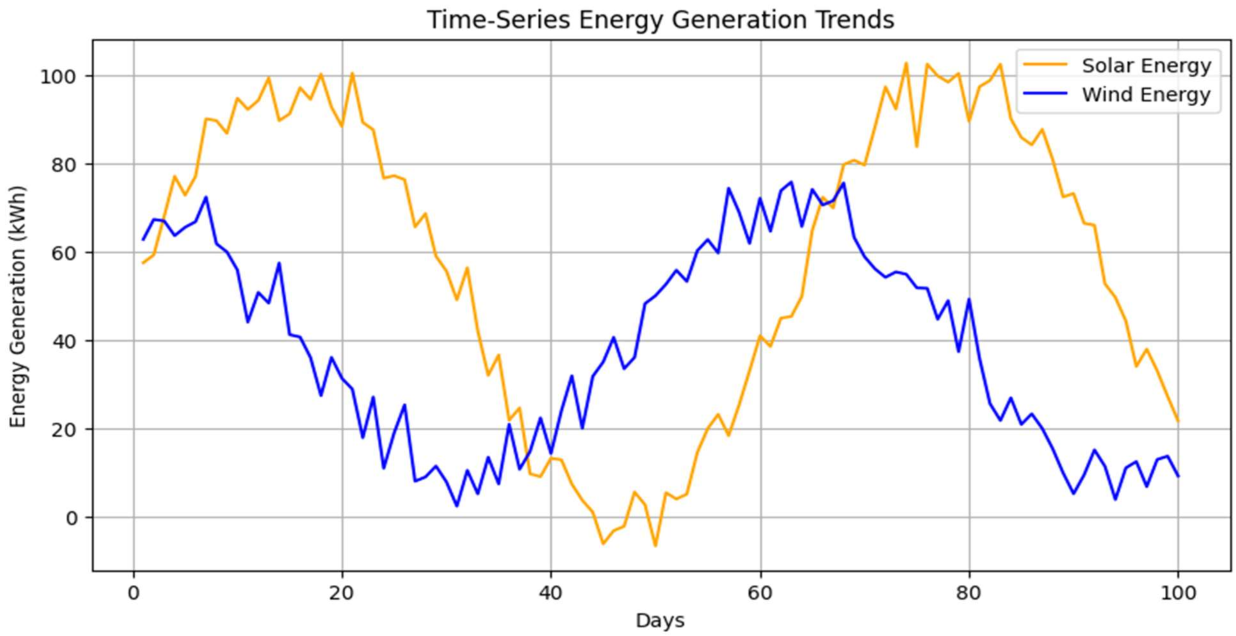

Figure 1 helps understand energy trends over time.

Once the dataset is preprocessed, supervised learning models are trained using historical input-output pairs. Regression models, such as linear regression and support vector regression (SVR), are commonly used for energy prediction tasks. However, these models may struggle with nonlinear relationships in data. Decision trees, random forests, and gradient boosting methods (e.g., XGBoost) offer improved predictive capabilities by capturing intricate dependencies between input features and target values [6]. Deep learning models, such as artificial neural networks (ANN) and long short-term memory (LSTM) networks, have gained popularity due to their ability to learn complex temporal patterns. ANN models, consisting of multiple hidden layers, enable automatic feature extraction, while LSTM networks are specifically designed for sequential data modeling, making them well-suited for time-series forecasting.

To ensure model generalization, training data is split into training, validation, and test sets. Cross-validation techniques, such as k-fold cross-validation, are used to assess model performance and prevent overfitting. Hyperparameter tuning is conducted using grid search or Bayesian optimization to optimize learning rates, network architectures, and regularization parameters. Model evaluation metrics such as mean absolute error (MAE), root mean square error (RMSE), and R-squared (R^2) scores are used to quantify predictive accuracy [7].

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III. Experimental Study and Results

In our experimental study, we applied multiple supervised learning models to forecast solar and wind energy generation using publicly available datasets [8]. The dataset used for solar energy forecasting included historical weather records and PV system output from the National Renewable Energy Laboratory (NREL). The wind energy dataset was obtained from the Global Energy Forecasting Competition (GEFCom), featuring wind speed, direction, and past energy production records. We evaluated the performance of various supervised learning models, including linear regression, decision trees, random forests, support vector regression, and LSTM networks. The models were trained using 80% of the data and validated using the remaining 20%. Feature selection techniques were applied to identify the most significant predictors for each energy source.

The results showed that tree-based ensemble models, such as random forests and gradient boosting, outperformed traditional regression techniques, achieving lower RMSE values. Deep learning models, particularly LSTMs, demonstrated superior performance for long-term forecasting due to their ability to capture temporal dependencies in sequential data. Furthermore, hybrid models that combined multiple techniques exhibited promising results, suggesting that ensemble approaches can enhance predictive robustness [9]. However, deep learning models required substantial computational resources and longer training times, highlighting the trade-off between accuracy and efficiency.

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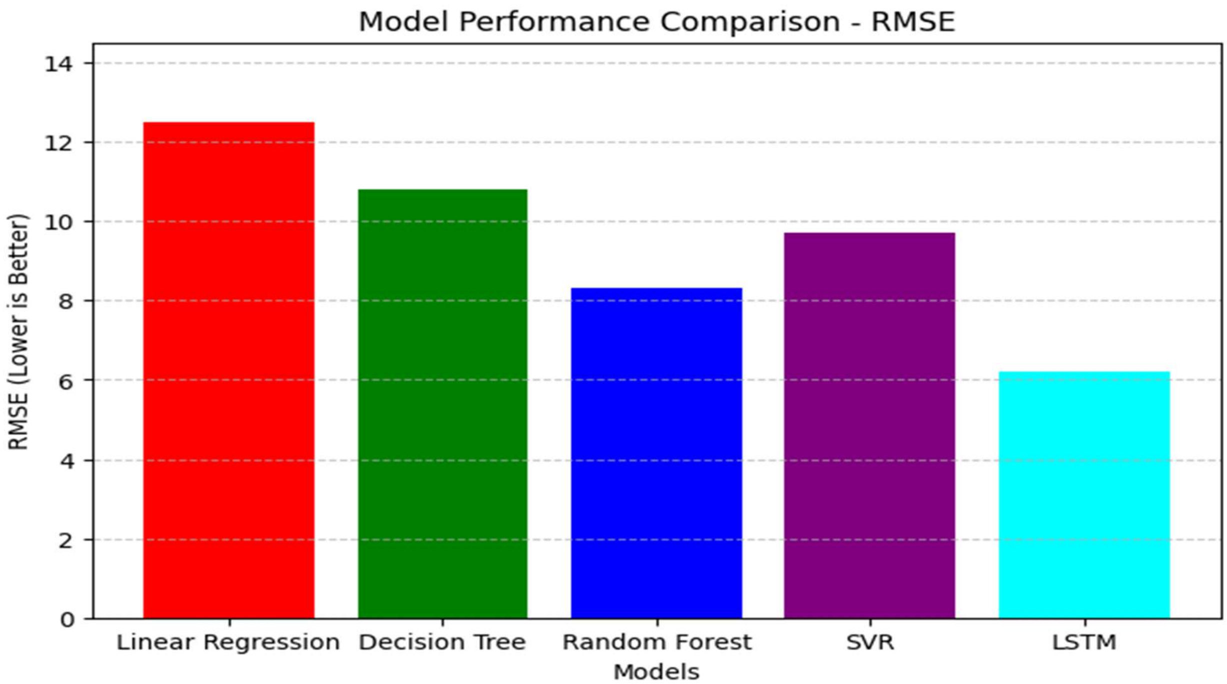

Figure 2 compares different supervised learning models based on their RMSE values.

Overall, the study confirmed that supervised machine learning offers significant improvements over conventional forecasting techniques [10]. The findings emphasize the importance of selecting appropriate algorithms based on data characteristics and prediction time horizons [5].

IV. Conclusion

This research highlights the critical role of supervised machine learning in renewable energy forecasting, demonstrating its ability to enhance prediction accuracy and improve energy grid management. Experimental results indicated that ensemble-based models and LSTM networks offered superior predictive performance, while simpler models provided efficient yet less accurate solutions. Despite these advancements, challenges such as data quality, computational complexity, and model interpretability remain areas of concern. Future research should focus on improving model explainability, integrating hybrid forecasting techniques, and leveraging real-time data for adaptive learning models. Additionally, the ethical and sustainability implications of AI-driven energy forecasting should be considered to ensure responsible and equitable deployment. In conclusion, supervised machine learning holds immense potential for optimizing

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renewable energy utilization, supporting grid stability, and accelerating the transition to sustainable energy systems. With continuous improvements in data availability and algorithmic development, ML-driven forecasting will play an increasingly vital role in shaping the future of energy management.

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