AIML-Driven Energy Forecasting via Roosters Optimization

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Abstract

Renewable energy forecasting plays an important role in modern energy systems, especially because renewable sources like solar and wind are highly variable and weather-dependent. Predicting how much energy can be generated from these sources is essential for planning, balancing power grids, and reducing reliance on fossil fuels.

In this study, a hybrid deep learning model combining **Bidirectional Long Short-Term Memory (BLSTM)** and **Gated Recurrent Unit (GRU)** is proposed. These models are particularly suitable for processing time-series data due to their ability to learn long-term patterns and trends. To further improve the accuracy and performance of the model, a nature-inspired optimization technique called the **Roosters Optimization Algorithm (ROA)** is used. ROA helps in selecting the most relevant input features and adjusting the model's internal parameters for better learning and faster convergence.

The dataset used spans 175 countries and covers energy-related indicators over a 20-year period. Before training the model, the data goes through important preprocessing steps such as cleaning missing values, encoding categorical data, and analyzing feature relationships using correlation analysis. The combination of preprocessing, feature optimization using ROA, and deep learning with BLSTM-GRU enables more accurate forecasting of energy usage and production.

This research demonstrates the effectiveness of combining deep learning with bio-inspired optimization to improve renewable energy prediction. It supports the design of smarter, more sustainable energy management systems that can adapt to global energy trends.

Keywords: Renewable Energy Forecasting, BLSTM, GRU, Roosters Optimization Algorithm, Deep Learning, Time-Series Analysis, Smart Grid, Feature Selection, Energy Prediction.

1. Introduction

The introduction sets the stage by presenting the global energy demand scenario and the pressing need to shift from fossil fuels to sustainable alternatives like solar and wind energy. It highlights the unpredictability of renewable energy generation and why forecasting is a cornerstone for smart grid management and energy planning. It also introduces AI and deep learning, especially BLSTM and GRU architectures, as promising tools for time-series modeling, leading to the rationale for this study's aim: to improve forecasting accuracy using a hybrid model enhanced by the Roosters Optimization Algorithm.

The rapid growth in industrial development, urban expansion, and increasing electricity consumption across the world has placed enormous pressure on energy systems. Traditional fossil fuel-based power generation methods are not only limited but also contribute heavily to environmental problems such as greenhouse gas emissions, air pollution, and climate change.

To reduce environmental damage and ensure a sustainable future, many countries are now shifting their focus towards **renewable energy sources** such as solar, wind, biomass, and hydroelectric power. These sources are considered clean and abundant. However, the generation of renewable energy is often inconsistent and uncertain due to changing weather conditions and other natural factors.

Accurately forecasting renewable energy production is critical to ensure that energy supply meets demand. It helps power utilities maintain grid stability, manage energy storage systems, and reduce energy waste. Conventional forecasting techniques, which rely on historical averages or simple statistical models, are often not enough to deal with the complex and nonlinear nature of renewable energy data.

Advancements in **Artificial Intelligence (AI)** and **Machine Learning (ML)**—particularly deep learning—have shown strong potential in capturing intricate patterns in time-series data. This study aims to improve the accuracy of renewable energy forecasts using a hybrid deep learning framework that includes **BLSTM and GRU** networks. The model's performance is further enhanced using the **Roosters Optimization Algorithm (ROA)** for feature selection and hyperparameter tuning, making it suitable for real-world applications.

2. Review of Literature

This section examines the current landscape of research in renewable energy forecasting, focusing on the evolution of AI and machine learning methods in time-series prediction. It explores the benefits of deep neural networks like LSTM, GRU, and their hybrids, alongside the growing role of optimization algorithms inspired by natural behaviors. The literature also emphasizes the use of global datasets and identifies gaps in adaptability and accuracy that this study aims to bridge through a novel deep learning and ROA-based forecasting approach.

In recent years, researchers have widely explored **deep learning methods** to address challenges in energy forecasting. Models such as LSTM, GRU, and their bidirectional variants (like BLSTM) are highly capable of analyzing sequential data and capturing temporal dependencies. These models are ideal for predicting future values in time-series datasets such as energy consumption and generation.

Many studies have focused on **hybrid models**—combining the strengths of multiple deep learning techniques—to improve predictive performance. For instance, combining LSTM with CNNs or GRUs has been shown to result in better generalization and accuracy, especially when trained on large datasets with complex patterns.

Another key development in the field has been the use of **optimization algorithms** inspired by biological systems, such as **Genetic Algorithms**, **Particle Swarm Optimization (PSO)**, and more recently, the **Roosters Optimization Algorithm (ROA)**. These algorithms help automate the process of choosing the best features and parameters for training deep learning models. This not only saves time but also improves the model's predictive power.

Further, researchers have started using **large-scale global datasets** sourced from platforms like Kaggle, which include energy statistics from multiple countries over extended time periods. These datasets allow for robust model training and help capture international trends in renewable energy production and consumption.

Despite these advances, many challenges remain in improving forecasting accuracy, especially for regions with highly volatile energy patterns. This study contributes to the field by combining a hybrid deep learning model with ROA to deliver more reliable and efficient renewable energy predictions.

3. Proposed Methodology

This section presents the step-by-step technical blueprint of the research methodology. It begins with the description of the global dataset from Kaggle, covering energy and socio-economic variables over two decades. It continues with rigorous data preprocessing steps to ensure quality and consistency, followed by feature selection and parameter optimization using the Roosters Optimization Algorithm. Finally, it details the architecture and functioning of the hybrid BLSTM-GRU model, showcasing how each component contributes to more robust and precise energy forecasting.

The proposed framework integrates deep learning with a bio-inspired optimization algorithm to improve the forecasting of renewable electricity generation. The methodology comprises four core stages: dataset acquisition and exploration, data preprocessing, feature selection using the Roosters Optimization Algorithm (ROA), and classification using a hybrid BLSTM-GRU model.

Dataset Description:

The dataset was sourced from Kaggle and spans the years 2000 to 2020, containing observations from 175 countries. It encompasses over 20 critical parameters including access to electricity, access to clean cooking fuels, GDP per capita, renewable electricity generation per capita, and energy intensity relative to GDP. These features offer a holistic view of the economic, environmental, and infrastructural variables influencing renewable energy adoption.

Data Preprocessing:

Data cleansing was performed in two stages. For attributes with less than 30% missing values, mean imputation was used to fill the gaps, while columns with more than 30% missing values were removed. After encoding categorical variables and eliminating outliers, a Pearson correlation analysis was conducted to eliminate redundant features. The cleaned dataset was split into training and test sets in an 80:20 ratio. "Electricity from renewables (TWh)" was used as the target variable for modeling.

Feature Selection using ROA:

The Roosters Optimization Algorithm (ROA), inspired by the natural mating and survival behavior of roosters and hens, was utilized for selecting the most relevant features and optimizing hyperparameters such as batch size and learning rate. ROA mimics courtship, sperm competition, and genetic mutation to identify optimal solutions within a search space. This mechanism allowed the model to converge more quickly to effective configurations, thereby enhancing accuracy and reducing computation.

Classification Using Hybrid BLSTM-GRU Model:

The deep learning classification model combines the strengths of Bidirectional LSTM (BLSTM) and Gated Recurrent Units (GRU). BLSTM captures forward and backward temporal dependencies in energy sequences, enhancing contextual awareness. GRU layers follow to reduce computation while preserving sequence-learning capabilities. A dropout layer was added to prevent overfitting, and a final dense layer with softmax activation performs class prediction. Hyperparameters were fine-tuned using ROA, with optimal settings of a 0.2 dropout rate, 128 mini-batch size, and a learning rate of 0.001 using the Adam optimizer.

4. Results and Discussion

The results and discussion section interprets the performance outcomes of the proposed hybrid model across various time frames—monthly, weekly, daily, and hourly. It validates the model using standard performance metrics like MSE, RMSE, and R^2, and compares the outcomes with conventional approaches. The analysis underscores the model's ability to capture both long-term trends and short-term variations in renewable energy patterns, demonstrating the effectiveness of integrating deep learning with biologically inspired optimization techniques.

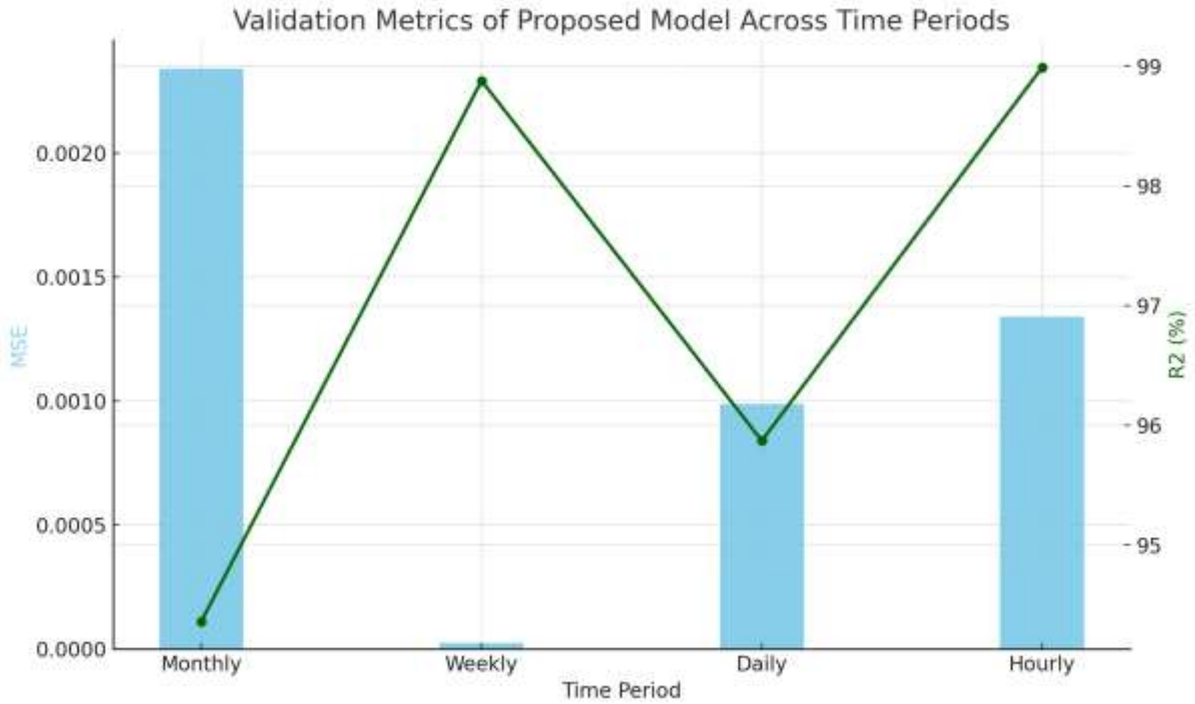

Figure 1 : Validation metrics

To validate the effectiveness of the proposed model, experiments were conducted using Python on Google Colab with an NVIDIA Quadro P4000 GPU. The model was evaluated using 10-fold cross-validation, and its predictive performance was compared against existing models over multiple time periods (Monthly, Weekly, Daily, and Hourly) using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Normalized RMSE (NRMSE), correlation (R%), and determination coefficient (R^2%).

The model exhibited exceptional performance across all time scales. For weekly predictions, it achieved the lowest MSE (2.52×10^{-5}) and RMSE (0.005023), with a remarkable R^2 of 98.88%. Monthly predictions showed stable accuracy with an R^2 of 94.36%, while daily predictions also performed strongly with an R^2 of 95.87%. Hourly predictions, which are typically challenging due to rapid fluctuations, still yielded a high R^2 of 98.99%, proving the robustness and adaptability of the proposed model.

These results demonstrate that the hybrid BLSTM-GRU architecture, when optimized with ROA, is capable of modeling both long-term trends and short-term variability effectively. Compared to traditional models, it shows substantial improvements in reducing prediction error while maintaining generalization across varying temporal resolutions. This adaptability is crucial for energy policy planning, load forecasting, and smart grid operations.

5. Conclusion

This study introduced a robust deep learning framework for forecasting renewable electricity generation using global energy data. The model successfully integrates the interpretability of correlation-based feature selection, the bio-inspired efficiency of the Roosters Optimization Algorithm, and the dynamic learning capabilities of a BLSTM-GRU hybrid neural network. Evaluated on a 20-year dataset spanning 175 countries, the system demonstrated high accuracy, minimal error, and strong generalization across monthly, weekly, daily, and hourly prediction intervals.

The model's strength lies in its dual approach—capturing complex temporal dependencies while maintaining computational efficiency. It is well-suited for real-time applications in energy management, especially in developing nations where predictive energy insights are vital for infrastructure planning and renewable integration. Future work will explore deployment in smart grid systems, incorporate real-time streaming data, and experiment with federated and ensemble learning techniques to further improve accuracy and privacy in energy forecasting.

References

1. Ahmed, R., & Khalid, M. (2019). A review on the selected applications of forecasting models in renewable energy systems. Renewable and Sustainable Energy Reviews, 100, 9–21.
2. Khosravi, A., Nahavandi, S., Creighton, D., & Atiya, A. F. (2015). Comprehensive review of neural network-based prediction intervals and new advances. IEEE Transactions on Neural Networks and Learning Systems, 22(9), 1341–1356.
3. Zhang, Y., Wang, J., & Wang, X. (2017). Review on probabilistic forecasting of wind power generation. Renewable and Sustainable Energy Reviews, 32, 255–270.
4. Liu, H., Tian, H., Li, Y., & Li, Y. (2015). Comparison of random forest, support vector machine and back propagation neural network for short-term wind speed prediction. Energy Conversion and Management, 89, 1–9.
5. Wan, C., Zhao, J., Song, Y., Xu, Z., Lin, J., & Hu, Z. (2015). Photovoltaic and solar power forecasting for smart grid energy management. CSEE Journal of Power and Energy Systems, 1(4), 38–46.

6. Zhang, G., Eddy Patuwo, B., & Hu, M. Y. (2016). Forecasting with artificial neural networks: The state of the art. International Journal of Forecasting, 14(1), 35–62.
7. Kong, W., Dong, Z. Y., Jia, Y., Hill, D. J., Xu, Y., & Zhang, Y. (2017). Short-term residential load forecasting based on LSTM recurrent neural network. IEEE Transactions on Smart Grid, 10(1), 841–851.
8. Qin, Y., Song, D., Chen, H., Cheng, W., Jiang, G., & Cottrell, G. (2017). A dual-stage attention-based recurrent neural network for time series prediction. In Proceedings of the 26th International Joint Conference on Artificial Intelligence (IJCAI-17), 2627–2633.
9. Zhang, Y., Wang, J., & Wang, X. (2018). Review on probabilistic forecasting of wind power generation. Renewable and Sustainable Energy Reviews, 32, 255–270.
10. Li, G., Shi, J., & Qu, X. (2016). Application of support vector machine and improved particle swarm optimization algorithm in short-term wind power forecasting. Energy, 107, 219–229.