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

Evaluating and Comparing AI Models for Hourly Energy Demand Prediction

Bhavay Bhaskar Singla[1], N.S. Thakur[2]

[1]Student, Centre for Energy Studies, National Institute of Technology, Hamirpur
[2]Professor, Centre for Energy Studies, National Institute of Technology, Hamirpur

Abstract
This study investigates the application of various AI models to predict energy demand, comparing the performance of four specific models: Decision Tree, Random Forest, Gradient Boosting, and Linear Regression. The evaluation of these models' prediction performance reveals that ensemble methods like Random Forest and Gradient Boosting exhibit promising generalization capabilities, while the Decision Tree model shows high training accuracy but suffers from overfitting. The discussion underscores the importance of ensemble techniques and feature engineering optimization in mitigating overfitting and enhancing forecast accuracy. Furthermore, the study highlights the potential of AI-driven approaches to promote sustainability and resilience in energy systems, emphasizing the need for further optimization and collaboration among stakeholders to achieve a cleaner, more sustainable energy future.

Keywords: Load Forecasting, Smart Microgrids, Artificial Intelligence

1. Introduction

Artificial intelligence (AI) and renewable energy sources combined have enormous potential to transform energy systems and move them toward resilience and sustainability. In the context of smart microgrids, this study focuses on the use of AI-driven methodologies for load forecasting, with a particular focus on the Island of Luzon. Load forecasting is essential for maximizing energy distribution and maintaining grid stability, especially in microgrid systems that use renewable energy sources. This study attempts to assess how well "machine learning models—such as Decision Tree, Random Forest, Gradient Boosting, and Linear Regression"—predict load demand. In order to improve forecast accuracy and reduce problems like overfitting, the study investigates cooperative solutions including ensemble approaches in addition to evaluating the performance of individual models.

By shedding light on the potential of AI-driven strategies to enhance forecast reliability and encourage the uptake of microgrid technologies, our research aims to further sustainable energy systems.

2. Literature Review

[1] This paper presents an AI-enhanced Model Predictive Control (MPC) strategy for an integrated wind-Hydrogen-fuel cell power system within a smart grid. The strategy utilizes a Particle Swarm Optimization (PSO) and Backpropagation (BP) neural network for wind power forecasting, while Genetic Algorithm (GA) optimization iteratively defines optimal solutions over a 24-hour horizon. The State-Space Model (SSM) adjusts operational strategies based on forecasted and measured data. Key findings include a significant increase in wind power utilization (45-90%) through the developed MPC scheme and effective energy storage system management. Future work aims to implement this strategy in practical wind farms, fostering the use of renewable energy sources and fuel cells in power generation and contributing to grid-tied energy system advancement.

[2] This paper provides a concise overview of the applications of Artificial Intelligence (AI) techniques in the context of Smart Grids (SG) and Renewable Energy Sources (RES). It begins with a brief but comprehensive introduction to Evolutionary Strategies (ES), Fuzzy Logic (FL), and Neural Networks (NNW), which are essential branches of AI. The paper then outlines various AI-based applications in these areas, including automatic design, simulation and controller tuning for permanent magnet synchronous generator (PMSG)-based wind generation systems, adaptive neuro-fuzzy Health monitoring wind generation sequence scheduling (ANFIS) using statistical algorithms, spatial vector fault pattern detection in SG by neural mapping, and centralized SG control using supercomputer-based real-time simulation These projects, mainly supercomputer-based centralized control, is tight and fun beyond the limit Furthermore, the described application examples hold the potential for further extensions to encompass various other applications in the field.

[3] In future power systems with extensive distributed generation (DG), efficient energy resource management is essential. This paper introduces an approach for managing Demand Response (DR) programs and contracts using Locational Marginal Prices (LMPs). The method is applied to a 33-bus network with intensive DG, showing that DR programs have a limited impact on LMP values at lower demand levels but significantly reduce both LMP and operation costs at higher demand, especially when renewable energy sources are unavailable. This highlights the importance of tailoring DR programs for higher demand scenarios. Energy efficiency is essential in future energy systems with extensive distributed generation (DG). This paper introduces a methodology for managing demand response (DR) policies and contracts using local marginal pricing (LMPs). The method is applied to a 33-bus network with strong DG, which shows that DR schemes have negligible effect on LMP price at low demand but significantly reduce LMP operating costs at high demand in, especially in the absence of renewable energy This increased demand conditions The need to design DR systems accordingly has been emphasized. The proposed method is computationally efficient, tailored to different player characteristics and DR systems, and can be applied to balancing three-phase medium voltage networks, which are programmed to handle unbalanced connections want to be addressed in the future by methods of symmetric components.

[4] This paper offers a thorough analysis of anomaly detection techniques for building energy consumption, including a methodical categorization based on application situations, artificial intelligence models, detection thresholds, and computing platforms. But there are issues that must be resolved, like platforms for repeatability, uniform metrics, and data availability. Robust models require the inclusion of extra elements such as ambient conditions and occupancy. Scalability, decentralization, low power consumption, and privacy protection are some of the future directions. Collaborations with industry partners are vital to realize the commercial potential of anomaly detection technology in residential buildings. **[5]** Over the past decade, Deep Learning (DL) has emerged as a promising model to revolutionize the Smart Grid (SG). In this comprehensive review, we investigate the application of DL in power systems in detail, shedding light on its important applications. Notably, we highlight distributed DL, edge intelligence, and federated learning as state-of-the-art examples. DL contributions span a variety of areas within SG, including energy forecasting, fault detection, cybersecurity, forecasting, and quality, all designed to meet leading-edge technical requirements for energy systems a safe and secure operations as well , we address current cyber challenges and propose mitigation measures. We examine emerging challenges, needs, and future research directions between the SG and DL models. Our future work will place special emphasis on Explainable DL (XDL) algorithms, highlighting their potential to provide insight and comprehensiveness in SG systems. **[6]** This special issue contains eleven papers on topics and methodologies in AI for smart and sustainable energy systems and applications, with a research article Guest editors summarize each work briefly and they focus on four emerging topics in the energy industry. The guest editors express their gratitude to all contributors and reviewers and express hope that virtual AI techniques will be widely used and adopted in the energy industry in the near future.

[7] As the traditional electric grid system evolves into a smart grid, it faces challenges in handling the vast amounts of data generated. To address this, Artificial Intelligence (AI) techniques have been applied to critical smart grid areas, such as load forecasting, power grid stability assessment, fault detection, and security. This paper provides a comprehensive survey of recent AI applications in these domains, highlighting their role in enhancing smart grid reliability. While AI shows promise, challenges like data privacy, security, and the interpretability of AI methods remain. The survey aims to foster discussions and exchange of ideas in these areas, emphasizing AI's contribution to smart grid resilience. Future research will explore the impact of AI's "black box" nature on smart grid operations. **[8]** The dynamism of consumer power requirements profoundly influences grid stability. Leveraging machine learning, this study addresses power consumption prediction and grid stability. Utilizing the Kaggle smart grid stability dataset, various machine learning models were trained and tested. The Support Vector Machine (SVM) classifier exhibited superior accuracy across precision, recall, F-score, and overall accuracy metrics, validated by the AUC score. Future enhancements could incorporate environmental and geographical factors, while deep learning classifiers hold potential for further accuracy improvements. **[9]** Electricity market reform, renewable energy integration, and demand response introduce openness, uncertainty, and complexity to power systems. Consequently, the development and adoption of smart grids are gaining momentum. Artificial intelligence (AI) plays a key role in the technical support of the digital power grid. AI applications of the smart grid include power delivery, scheduling optimization, user behavior analysis, fault diagnosis, and more. While challenges like limited data, reliability, infrastructure, and domain-specific algorithms persist, AI remains a potent catalyst for advancing smart grids into the next generation of power systems and energy networks **[10]** Artificial Neural Networks (ANNs) excel at replicating complex system behaviours and learning through experience. Despite mathematical complexity and data demands, ANNs find utility in uncovering knowledge with elusive, nonlinear relationships. They thrive when employing a wide range of variables and necessitate robust procedures and data systems for result documentation and reproduction. Flexibility outweighs precision. This paper introduces ANNs' potential in assessing renewable energy plant reliability, promising significant cost savings and enhanced service quality. Future work could explore integrating other AI tools like “deep learning, SVM, T-Bastes, Random Forest, and Boosting” as data quality and quantity improve.

3. Methodology

3.1. Gathering and Preparing Data:

- For Luzon, hourly load statistics and information were gathered between May and July of 2020.
- Preprocessing entails controlling missing numbers, spotting anomalies, and normalizing data.

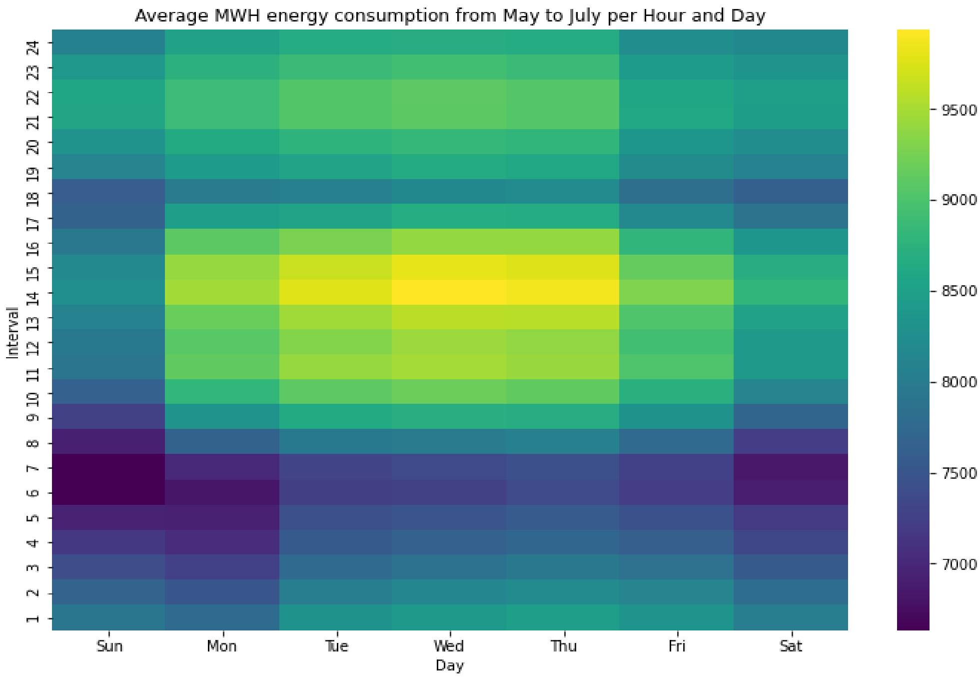

Figure 1: Average MWH Energy Consumption from May 2020 to June 2020 per Hour per Day

3.2. Engineering and Feature Selection:
- Features chosen in accordance with their predictive capacity and relationship to the target variable (load).
- Temporal trends are captured by the incorporation of seasonal indicators and time-based features.
- Historical load data is represented via the inclusion of lag factors.

3.3. Model Choice:
- Models including Decision Trees, AdaBoost, Gradient Boosting, Random Forest, and Linear Regression are taken into consideration.
- Cross-validation is employed to assess baseline performance.

3.4. Adjusting Hyperparameters:
- Grid search or random search are used for hyperparameter adjustment, which improves model performance.
- The robustness and generalizability of the models are guaranteed by cross-validation.

3.5. Validation and Training of Models:
- Models that were trained using preprocessed data, with some kept for validation.
- Metrics such as "Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE)" are used to evaluate performance.

4. Results

The study assesses the efficacy of 'Decision Tree, Random Forest, Gradient Boosting, and Linear Regression" as machine learning models for load forecasting on the Island of Luzon. The Decision Tree model exhibits a large decline in test accuracy, suggesting possible overfitting, even though all models show high training accuracy.

When compared to standalone models, ensemble techniques such as Random Forest and Gradient Boosting exhibit superior generalization performance. Regularization methods, ensemble learning approaches, and feature engineering are some suggestions for enhancing the Decision Tree model. A comparative investigation reveals that ensemble models perform better than standalone models, highlighting the significance of correcting overfitting in order to achieve accurate load forecasting.

Table 1: Test and Train Accuracy

Sr. No.	Regression Method	Train Accuracy	Test Accuracy
1	Decision Tree	0.998673	0.786566
2	Random Forest	0.998673	0.899319
3	Gradient Boosting	0.975089	0.890778
4	Linear Regression	0.798363	0.744686

5. Discussion

The problem of overfitting in individual models, especially the Decision Tree model, is revealed by the evaluation of “machine learning models” for load forecasting on the Island of Luzon. This emphasizes how crucial it is to deal with overfitting in order to enhance generalization capabilities. Better generalization performance is shown by ensemble techniques like Random Forest and Gradient Boosting, indicating the importance of cooperative approaches in model creation. Feature engineering, regularization methods, and investigating ensemble learning approaches are some recommendations for enhancing the Decision Tree model.

The study emphasizes how crucial precise load forecasting is to fostering resilience and sustainability in energy systems. To maximize model performance and expand the use of artificial intelligence in load forecasting for smart microgrids, more study and cooperation are needed.

References

1. Bose B.K., "Artificial Intelligence Techniques in Smart Grid and Renewable Energy Systems - Some Example Applications", 2017.
2. Chui M.D., "The Recent Development of Artificial Intelligence for Smart and Sustainable Energy Systems and Applications", 2019.
3. Hugo P.F. Morais, "Demand Response Design and Use Based on Network Locational Marginal Prices", 2014.
4. Jesús J.F. Ferrero Bermejo, "A Review of the Use of Artificial Neural Network Models for Energy and Reliability Prediction. A Study of the Solar PV, Hydraulic and Wind Energy Sources", 2019.
5. Jiao J., "Application and Prospect of Artificial Intelligence in Smart Grid", 2020.
6. Mohamed H. A.-R. Massaoudi, "Deep Learning in Smart Grid Technology: A Review of Recent Advancements and Future Prospects", 2021.
7. Niu O.A., "Artificial Intelligence Techniques in Smart Grid: A Survey", 2021.
8. Shamik A. J. Tiwari, "Machine Learning-Based Model for Prediction of Power Consumption in Smart Grid - Smart Way Towards Smart City", 2021.
9. Xiangping W. C. Chen, "Artificial Intelligence-Aided Model Predictive Control for a Grid-Tied Wind-Hydrogen-Fuel Cell System", 2020.
10. Yassine K. G. Himeur, "Artificial Intelligence-Based Anomaly Detection of Energy Consumption in Buildings: A Review, Current Trends and New Perspectives", 2021.