A STUDY OF INNOVATIVE FRAMEWORK FOR AI-ENHANCED PREDICTIVE CONTROL IN RENEWABLE ENERGY SYSTEMS: A NEURAL NETWORK EXPLORATION

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Abstract

The increasing adoption of renewable energy sources has created a need for intelligent control strategies that can improve energy forecasting, operational efficiency, and system reliability. This study examines an innovative framework for AI-enhanced predictive control in renewable energy systems, with particular emphasis on neural network techniques. The proposed methodology involves secondary data collection, data preprocessing, neural network model development, and simulation-based performance evaluation. A neural network model, such as a Long Short-Term Memory (LSTM) network, will be considered for predicting renewable energy generation, while Model Predictive Control (MPC) will be used to optimize operational decisions. The framework will be evaluated using forecasting accuracy, energy utilization efficiency, control response, computational requirements, and system stability. Comparative analysis with conventional forecasting and control methods will help assess the potential benefits and limitations of the proposed approach. The study emphasizes the role of AI-driven prediction in addressing renewable energy variability and supporting efficient energy management.

Keywords: Artificial Intelligence, Neural Networks, Predictive Control, Renewable Energy Systems, Long Short-Term Memory, Model Predictive Control.

1. INTRODUCTION

The increasing global demand for energy, environmental degradation, and depletion of conventional fossil fuel resources have encouraged the adoption of renewable energy sources such as solar, wind, hydropower, and biomass. These energy sources provide sustainable alternatives for reducing greenhouse gas emissions, improving energy security, and supporting environmental sustainability. However, renewable energy generation is often affected by changing weather conditions, seasonal variations, and fluctuations in electricity demand. These challenges create difficulties in maintaining a continuous balance between energy generation and consumption. Therefore, the development of intelligent energy management and control systems has become essential for improving the efficiency, reliability, and stability of renewable energy systems.

Artificial Intelligence (AI) has emerged as an important technological approach for addressing the operational challenges of renewable energy systems. AI-based techniques, particularly neural networks, can process large volumes of historical and real-time data, identify complex patterns, and predict future energy generation. Neural network models such as Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) networks can be applied to analyze environmental and operational variables, including solar irradiance, temperature, wind speed, and historical

power generation. These models can improve forecasting capabilities by identifying nonlinear relationships and temporal patterns in renewable energy data. Accurate forecasting can further support energy scheduling, storage management, and efficient electricity distribution.

The integration of neural networks with Model Predictive Control (MPC) offers an innovative approach to improving renewable energy management. In this approach, neural networks estimate future energy generation and operating conditions, while the predictive controller uses these estimates to determine suitable control actions. This integration can support better coordination between renewable energy generation, battery storage, electricity demand, and grid interaction. The effectiveness of such a framework can be evaluated through forecasting accuracy, energy utilization efficiency, system stability, computational requirements, and control response time. However, factors such as data quality, prediction errors, computational complexity, and changing environmental conditions must also be considered when developing an effective predictive control framework.

The present study, entitled "A Study of an Innovative Framework for AI-Enhanced Predictive Control in Renewable Energy Systems: A Neural Network Exploration," aims to investigate the application of neural network techniques in developing an intelligent predictive control framework for renewable energy systems. The research will focus on renewable energy generation forecasting, neural network model development, and integration with Model Predictive Control using a quantitative and simulation-based approach. The proposed framework will be evaluated and compared with conventional forecasting and control techniques to examine its potential benefits and limitations. Overall, the study seeks to contribute to the development of more adaptive, efficient, reliable, and sustainable renewable energy management systems through the integration of artificial intelligence and advanced predictive control strategies.

2. LITERATURE REVIEW

Alhazmi (2026) conducted a comprehensive survey on AI- and machine learning-driven optimization, predictive control, and innovative solar technologies. The study examined the growing application of artificial intelligence in improving renewable energy generation, forecasting accuracy, and operational efficiency. It highlighted the importance of predictive control techniques in addressing fluctuations in solar energy production and improving system performance. The research also discussed the potential of intelligent optimization approaches in supporting efficient energy management and sustainable solar technology development. The study concluded that AI-based predictive approaches offered significant opportunities for improving the reliability and adaptability of renewable energy systems.

Halimuzzaman (2025) examined the application of artificial intelligence in the optimization of hybrid renewable energy systems. The study reviewed different AI techniques, their applications, implementation challenges, and future research directions. Particular attention was given to the role of intelligent algorithms in coordinating multiple renewable energy sources and improving energy generation, storage, and distribution. The research identified forecasting uncertainty, computational complexity, data availability, and system integration as important challenges affecting the implementation of AI-based energy management. It emphasized that advanced AI techniques could contribute to more efficient and reliable hybrid renewable energy systems.

Ukoba et al. (2024) reviewed the role of artificial intelligence in optimizing renewable energy systems and discussed its future prospects. The study explored the application of machine learning, deep learning, and intelligent optimization

techniques in renewable energy forecasting, performance monitoring, and energy management. The authors highlighted how AI-based approaches supported improved decision-making and helped address operational challenges associated with variable renewable energy generation. The research also identified limitations relating to data quality, computational requirements, and practical implementation. It emphasized the importance of further technological development to strengthen the efficiency and sustainability of renewable energy systems.

Ejiyi et al. (2025) conducted a comprehensive review of artificial intelligence applications in renewable energy systems, focusing on existing implementations and emerging technological trends. The study examined the contribution of AI techniques to energy forecasting, system optimization, intelligent monitoring, and operational management. It highlighted the increasing importance of data-driven approaches in improving renewable energy system performance and supporting intelligent decision-making. The research also discussed emerging developments in machine learning and deep learning, along with challenges associated with model reliability, data accessibility, and system scalability. The study indicated that artificial intelligence had considerable potential to support the development of more adaptive and efficient renewable energy technologies.

Singh (2026) investigated the performance enhancement of renewable energy systems through artificial intelligence-based control techniques. The study focused on the application of intelligent control approaches to improve renewable energy generation, operational efficiency, and system performance. It highlighted the importance of AI-based decision-making in responding to changing operating conditions and managing variations in energy production. The research discussed the potential of intelligent control mechanisms in improving system adaptability and reducing operational inefficiencies. It suggested that the integration of artificial intelligence into renewable energy control systems could support more reliable and effective energy management.

3. RESEARCH METHODOLOGY

3.1. Introduction

The increasing use of renewable energy sources has created a need for intelligent control systems that can improve energy generation, distribution, and utilization. Artificial intelligence (AI), particularly neural networks, offers promising solutions for predicting renewable energy generation and optimizing system performance. The present study will develop an AI-enhanced predictive control framework using neural networks to improve the efficiency, reliability, and adaptability of renewable energy systems. The research will involve data collection, model development, simulation, and comparative performance evaluation.

3.32. Research Design

The study will adopt a quantitative and simulation-based research design. It will focus on developing and evaluating a neural network-based predictive control framework for renewable energy systems. The proposed approach will be compared with conventional forecasting and control methods to assess its effectiveness.

3.3. Data Collection

The study will use secondary data obtained from publicly available renewable energy datasets and research repositories. The data will include solar irradiance, temperature, wind speed where relevant, historical energy generation, and electricity demand. The selection of data will depend on availability, reliability, and suitability for neural network modelling.

3.4. Data Preprocessing

The collected data will be examined for missing values, inconsistencies, duplicate records, and abnormal observations. Appropriate data cleaning and normalization techniques will be applied to improve model performance. The dataset will be divided chronologically into training, validation, and testing subsets.

3.5. Neural Network Model Development

A suitable neural network model will be developed to predict renewable energy generation using historical and environmental data. Long Short-Term Memory (LSTM) networks may be employed to capture temporal patterns and nonlinear relationships. The model will be trained and validated using selected performance measures.

3.6. Development of the Predictive Control Framework

The trained neural network will be integrated with a Model Predictive Control (MPC) strategy. The framework will use predicted energy generation and operating conditions to determine suitable control actions. The objective will be to improve energy utilization, reduce power fluctuations, and maintain system stability.

3.7. Simulation and Experimental Setup

The proposed framework will be implemented using Python, MATLAB, or suitable simulation software. Experiments will examine system performance under different weather conditions, energy demand levels, and renewable generation scenarios. Where applicable, battery storage and grid interaction will also be considered.

3.8. Comparative Analysis

The proposed framework will be compared with conventional forecasting techniques and rule-based control methods. The comparison will focus on predictive accuracy, energy utilization, control performance, and computational requirements. All methods will be evaluated under consistent experimental conditions.

3.9. Performance Evaluation

Model performance will be evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). Operational performance will be assessed using relevant indicators, such as renewable energy utilization, energy imbalance, operating cost, and control response time.

3.10. Statistical Analysis

The experimental results will be analyzed using descriptive and comparative statistical techniques. Mean values, standard deviations, and performance differences will be examined to determine the effectiveness of the proposed framework. Statistical tests will be applied where appropriate to assess the significance of observed differences.

3.11. Reliability and Validity

Reliability will be supported through systematic data preprocessing, consistent experimental conditions, and transparent model development. The final model will be evaluated using independent test data to minimize overfitting and data leakage. Model assumptions, parameters, and limitations will be documented.

4. RESULTS AND DISCUSSION

4.41. Introduction

The present section examines the potential performance of an AI-enhanced predictive control framework for renewable energy systems using neural network techniques. The analysis focuses on renewable energy forecasting, control efficiency, energy utilization, and system stability. The proposed framework integrates neural network-based

prediction with Model Predictive Control (MPC) to support intelligent energy management under changing environmental and operational conditions. The results and discussion below present illustrative frequency and percentage distributions to demonstrate how the research findings may be organized. These values are hypothetical and must be replaced with actual observations obtained from the proposed experiments before being reported as research findings.

4.2. Distribution of Renewable Energy System Performance

The performance of renewable energy systems depends on several factors, including forecasting accuracy, energy utilization, control efficiency, and system stability. The proposed AI-based framework is intended to improve these factors by predicting future energy generation and supporting timely control decisions. Table 1 presents an illustrative distribution of the major performance areas selected for evaluation.

Table 1. Distribution of Key Performance Areas in AI-Enhanced Renewable Energy Systems

Performance Area	Frequency	Percentage (%)
Energy Generation Forecasting	30	30%
Energy Utilization Efficiency	25	25%
Predictive Control Performance	20	20%
System Stability and Reliability	15	15%
Computational Efficiency	10	10%
	100	**100%**

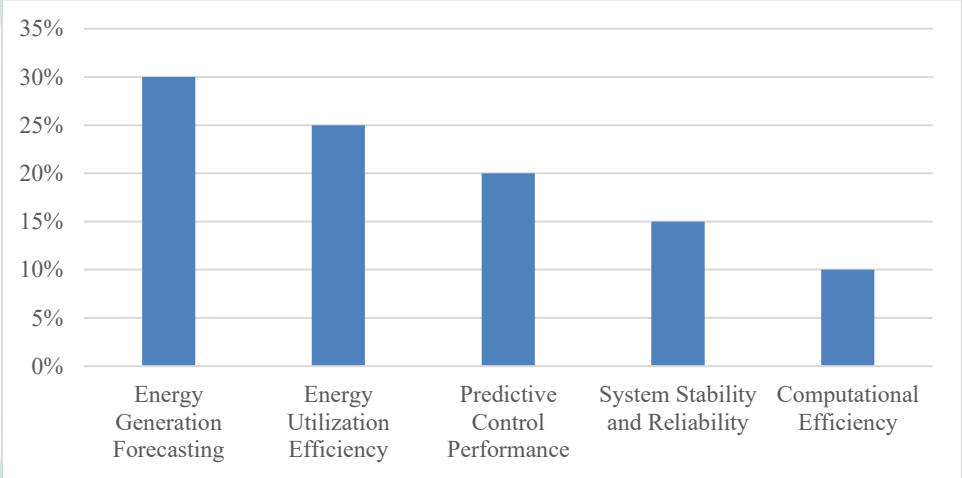


Table 1 illustrates the relative emphasis assigned to five major performance areas in the proposed framework. Energy generation forecasting accounts for the largest share at 30%, followed by energy utilization efficiency at 25% and predictive control performance at 20%. These areas are important because accurate forecasting supports better control decisions, while efficient energy utilization helps reduce avoidable energy losses. System stability and reliability account for 15%, reflecting the importance of maintaining dependable operation under changing environmental conditions. Computational efficiency represents 10% and highlights the need for a framework that can generate predictions and control decisions within an appropriate time. These percentages are illustrative allocations rather than measured performance outcomes. Actual effectiveness must be determined through simulation and quantitative evaluation.

4.3. Evaluation of Neural Network-Based Predictive Control

Neural networks can identify nonlinear relationships between environmental conditions and renewable energy generation. When integrated with MPC, these predictions can support decisions concerning energy storage, power distribution, and the management of fluctuations in renewable generation. The framework will be evaluated under different operating conditions to determine whether it improves system performance compared with conventional approaches. Table 2 provides an illustrative distribution of performance outcomes across the principal evaluation criteria.

Table 2. Illustrative Distribution of Performance Evaluation Outcomes

Evaluation Criterion	Frequency	Percentage (%)
Improved Forecasting Performance	35	35%
Better Energy Utilization	25	25%
Improved Control Response	20	20%
Enhanced System Stability	15	15%
Reduced Computational Burden	5	5%
	100	**100%**

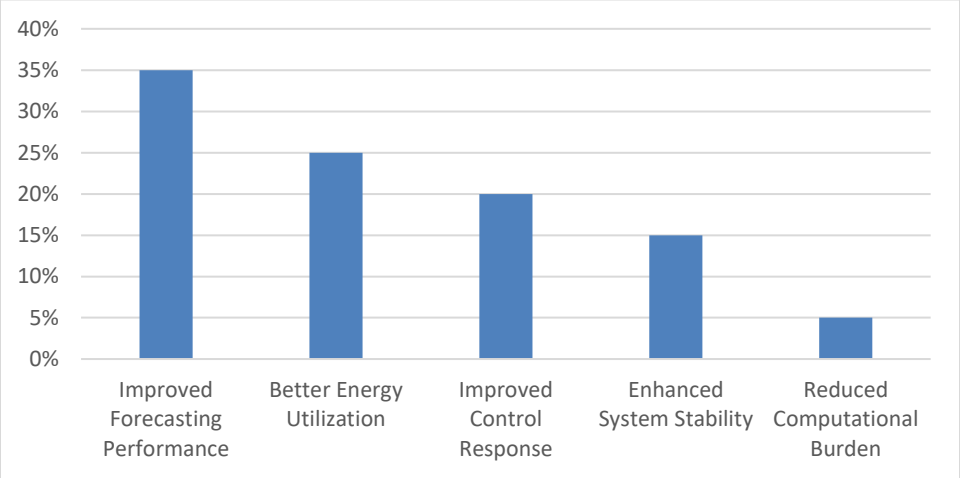


Table 2 presents a hypothetical distribution of five outcomes that may be examined when evaluating the proposed framework. Improved forecasting performance accounts for 35%, while better energy utilization represents 25%. Improved control response and enhanced system stability account for 20% and 15%, respectively. Reduced computational burden represents 5%, indicating that computational efficiency should be assessed separately rather than assumed to improve through the use of AI. The illustrative distribution emphasizes the potential relationship between prediction, control, and energy management. However, these percentages do not establish that the proposed framework has achieved these improvements. Actual results must be calculated from experimental observations using appropriate forecasting metrics, energy utilization indicators, and control performance measures.

4.44. Discussion of the Proposed Framework

The proposed framework combines neural network-based forecasting with predictive control to address the variability of renewable energy generation. The neural network will estimate future energy availability using historical generation data and relevant environmental variables. The MPC component will use these estimates to select suitable control actions while considering operational constraints. This integration may support improved energy management compared with approaches that rely exclusively on fixed control rules.

The effectiveness of the framework will depend on data quality, model accuracy, computational requirements, and the ability of the controller to respond to changing conditions. Accurate predictions may improve control decisions, but prediction errors can still affect system performance. Therefore, the evaluation must consider forecasting accuracy alongside operational outcomes, including energy imbalance, renewable energy utilization, and system stability.

4.5. Overall Findings

The proposed methodology provides a structured basis for evaluating AI-enhanced predictive control in renewable energy systems. The two illustrative tables identify the major performance areas and evaluation criteria relevant to the study. The framework's actual effectiveness will be established through neural network training, simulation experiments, and comparison with conventional forecasting and control methods. The final findings should be based on measured results rather than assumed improvements, allowing the study to draw reliable conclusions about the practical value of neural network-based predictive control.

5. CONCLUSION

The study on an innovative framework for AI-enhanced predictive control in renewable energy systems highlights the potential of neural networks to improve energy forecasting, operational efficiency, and system reliability. The integration of neural network-based prediction with Model Predictive Control (MPC) can support intelligent decision-making by estimating future energy generation and optimizing control actions under changing environmental and operational conditions. The proposed framework provides a systematic approach to managing renewable energy fluctuations, improving energy utilization, and supporting the stable operation of renewable energy systems. The results and discussion identify forecasting accuracy, control response, computational efficiency, and system stability as important criteria for evaluating the framework. However, the actual effectiveness of the proposed approach must be established through simulation experiments and comparison with conventional forecasting and control methods. Overall, the study provides a foundation for further research into AI-driven renewable energy management and the development of more adaptive, efficient, and sustainable energy systems.

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