World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

(Research Article)

Enhancing Wind and Solar Power Forecasting in Smart Grids Using a Hybrid CNN-LSTM Model for Improved Grid Stability and Renewable Energy Integration

Saeed Hasan Nabil *

Department of Electrical Engineering, Lamar University, Beaumont, TX, United States.

World Journal of Advanced Engineering Technology and Sciences, 2025, 17(03), 213-226

Publication history: Received on 03 November 2025; revised on 09 December 2025; accepted on 11 December 2025

Article DOI: https://doi.org/10.30574/wjaets.2025.17.3.1552

Abstract

The integration of renewable energy sources, such as wind and solar power, into smart grids presents significant challenges due to their inherent variability and intermittency. Accurate forecasting of renewable energy generation is essential for maintaining grid stability, minimizing energy imbalance, and optimizing power distribution. This paper proposes a hybrid deep learning model that combines Convolutional Neural Networks (CNN) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for temporal dependency modeling. The approach is applied to forecast wind and solar power generation using meteorological data from multiple geographical locations. The model's performance is compared to traditional forecasting methods such as ARIMA and standalone LSTM models. Experimental results show superior forecasting accuracy and improved error margins achieved by the hybrid CNN-LSTM model, offering an enhanced solution for real-time energy management and integration into smart grid operations. This research follows the methodology proposed by Fozlur Rayhan in *"A Hybrid Deep Learning Model for Wind and Solar Power Forecasting in Smart Grids"* and builds upon it to demonstrate the practical application and effectiveness of hybrid deep learning models in renewable energy forecasting.

Keywords: Renewable Energy; Wind Power; Solar Power; Forecasting; Deep Learning; Smart Grids; Hybrid Models; CNN; LSTM; Machine Learning

1. Introduction

The global transition to sustainable energy sources is accelerating, with wind and solar power at the forefront of this transformation. These renewable energy sources offer vast potential for reducing reliance on fossil fuels and addressing climate change. However, their integration into the electrical grid presents challenges due to their intermittent nature. Wind and solar power generation depends heavily on weather conditions, which vary both spatially and temporally. This variability introduces uncertainties that must be addressed to ensure the stable operation of modern energy grids. The need for accurate forecasting of renewable energy generation has become more critical as the share of renewables in the energy mix increases. Smart grids, which use advanced sensors, communication systems, and data analytics, offer an ideal platform for integrating renewable energy sources into the grid. However, these grids require sophisticated forecasting models that can dynamically adjust to real-time data and predict energy generation from variable sources.

Current forecasting models often struggle to accurately account for the complex spatial and temporal relationships in renewable energy generation. While statistical models such as ARIMA and machine learning approaches like LSTM networks have shown promise, they are typically limited in their ability to handle both spatial and temporal data simultaneously. To overcome these limitations, this paper proposes a hybrid deep learning model combining Convolutional Neural Networks (CNN) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for temporal dependency modeling. This approach builds on the methodology introduced by Fozlur Rayhan in *"A Hybrid*

* Corresponding author: Saeed Hasan Nabil

Deep Learning Model for Wind and Solar Power Forecasting in Smart Grids" and adapts it for use in real-world smart grid operations.

1.1. Background and Motivation

As the demand for renewable energy grows, integrating variable sources like wind and solar power into existing energy systems becomes more challenging. The intermittent nature of these energy sources requires advanced forecasting models that can accurately predict power generation, preventing energy shortages or surpluses and optimizing grid operations. Smart grids, which rely on real-time data to adjust energy distribution, require sophisticated models that can handle the complexities of renewable energy forecasting. Accurate forecasting plays a crucial role in grid stability, operational efficiency, and cost reduction. Current methods struggle with the non-linear, time-varying relationships between weather conditions and energy generation. Moreover, existing forecasting models tend to treat spatial and temporal data separately, which limits their effectiveness. By integrating CNNs for spatial feature extraction and LSTMs for temporal sequence modeling, the hybrid model proposed in this paper offers a more robust solution for forecasting renewable energy generation.

1.2. Problem Statement

Traditional statistical models, such as ARIMA, fail to capture the non-linear dynamics of renewable energy generation. Machine learning methods, including decision trees and support vector machines, are better suited for modeling complex relationships but often fall short in integrating spatial and temporal data effectively. LSTM networks, which are adept at modeling temporal dependencies in time-series data, struggle with spatial data, which is critical for understanding the geographic variability of renewable energy generation. To address these challenges, a hybrid deep learning model that combines CNNs and LSTMs is proposed. This model integrates the spatial feature extraction capabilities of CNNs with the temporal dependency modeling capabilities of LSTMs, enabling it to more accurately forecast wind and solar power generation. The proposed model aims to improve upon existing methods by handling both spatial and temporal data simultaneously, providing more accurate and reliable predictions.

1.3. Proposed Solution

This paper proposes a hybrid deep learning model that integrates CNNs for spatial feature extraction and LSTMs for temporal dependency modeling. The CNN component processes meteorological data, such as temperature, humidity, wind speed, and cloud cover, to extract spatial features that influence energy generation. These spatial features are then passed to the LSTM network, which captures temporal dependencies in power generation. By combining these two models, the proposed hybrid model can handle both spatial and temporal complexities, resulting in more accurate forecasts of renewable energy generation. The model is tested on real-world data and compared with traditional forecasting methods, such as ARIMA and standalone LSTM models, to demonstrate its superiority in forecasting accuracy.

1.4. Contributions

This paper makes several significant contributions to the field of renewable energy forecasting, specifically in the context of smart grid integration:

1.4.1. Development of a Hybrid Deep Learning Model

The paper introduces a novel hybrid model that integrates Convolutional Neural Networks (CNNs) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for modeling temporal dependencies. This hybrid architecture allows the model to address the complexities of renewable energy generation, which is influenced by both spatial weather patterns and temporal fluctuations.

1.4.2. Enhanced Forecasting Accuracy

By combining CNNs and LSTMs, the proposed model demonstrates superior accuracy in forecasting wind and solar power generation compared to traditional methods, such as ARIMA and standalone LSTM models. The hybrid model is shown to capture both spatial and temporal dependencies more effectively, improving forecasting precision and reducing errors.

1.4.3. Improved Smart Grid Operations

The model contributes to the optimization of smart grid operations by providing more accurate forecasts of renewable energy generation. This is crucial for grid operators who rely on accurate predictions to balance energy supply and demand efficiently, minimize storage costs, and ensure grid stability.

1.4.4. Real-World Data Validation:

The proposed model is validated using real-world data from multiple geographical locations, including meteorological and energy production data. The validation demonstrates the model's practical applicability in diverse operational settings, ensuring its utility for smart grid applications.

1.4.5. Advancement of Hybrid Deep Learning Approaches:

This research extends the work of Fozlur Rayhan by applying the hybrid CNN-LSTM methodology in the context of renewable energy forecasting. It opens new avenues for future research into the integration of additional data sources, such as energy consumption patterns and real-time grid data, to further enhance forecasting accuracy.

1.4.6. Scalability and Future Work:

Future work will focus on improving the scalability of the model, expanding its applicability to other renewable energy sources, and integrating additional features such as energy storage levels and real-time grid data. This will further enhance the robustness of the model and its capacity to handle large-scale energy forecasting in diverse smart grid environments.

2. Related work

Renewable energy forecasting, particularly for wind and solar power, has garnered significant attention in recent years due to its critical importance in optimizing grid operations and ensuring energy stability. Various forecasting techniques, ranging from traditional statistical methods to advanced machine learning approaches, have been proposed to address the complexities of predicting renewable energy generation. This section reviews the existing literature, focusing on traditional methods, machine learning approaches, and hybrid deep learning models, highlighting their strengths, limitations, and how they compare to the proposed hybrid CNN-LSTM model.

2.1. Traditional Forecasting Models

Traditional forecasting models have been widely used for time-series prediction, including models like Auto-Regressive Integrated Moving Average (ARIMA), which capture linear trends in historical data. These models have been applied to renewable energy forecasting, but their ability to handle the non-linear, time-varying patterns of wind and solar energy generation is limited. ARIMA and similar models are often inadequate for modeling the complex relationships between meteorological data and energy production, especially when dealing with the spatial aspects of renewable energy generation [1] [2]. One common approach is the use of regression models to predict solar and wind power output based on weather forecasts. However, these models are limited by their inability to capture temporal dependencies and non-linear relationships in the data, which are critical for accurate forecasting in renewable energy applications. As renewable energy penetration increases, there is a growing need for more sophisticated models that can handle the complexities of energy generation from variable sources [2] [3].

2.2. Machine Learning Approaches for Renewable Energy Forecasting

Machine learning techniques have gained popularity in renewable energy forecasting due to their ability to model complex, non-linear relationships in large datasets. Models such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN) have been applied to forecast wind and solar power generation by learning from historical data. These methods can capture non-linear patterns and interactions between meteorological variables more effectively than traditional statistical methods [4] [5]. SVM, for example, has been used to classify and predict wind and solar power production based on weather data. Random Forests and k-NN models have also been utilized for their ability to handle large datasets and account for complex, non-linear interactions. However, while these machine learning models have shown improvements over traditional approaches, they still face challenges in integrating both spatial and temporal data simultaneously, which limits their accuracy in dynamic environments like smart grids [6] [7]

2.3. Hybrid Deep Learning Models

Hybrid deep learning models that combine the strengths of different neural network architectures, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have emerged as a promising solution for renewable energy forecasting. CNNs excel at capturing spatial features, such as weather patterns and geographic influences, while LSTMs are adept at modeling temporal dependencies in time-series data. By integrating these two techniques, hybrid models are able to better capture the complexities of both spatial and temporal factors, offering superior forecasting accuracy [8] [9]. Fozlur Rayhan's work, *"A Hybrid Deep Learning Model for Wind and Solar Power Forecasting in Smart Grids"*, proposed a CNN-LSTM hybrid model for renewable energy forecasting, demonstrating its superior performance compared to traditional methods. This model leverages CNNs to extract spatial features from weather-related data and LSTMs to capture temporal dependencies in energy production, significantly improving forecasting accuracy for both wind and solar power. The success of Rayhan's approach has inspired further research into hybrid models for renewable energy forecasting, showcasing their potential to optimize smart grid operations and enhance renewable energy integration into power systems [1]. Recent advancements in hybrid deep learning for renewable energy forecasting have demonstrated promising results. For example, hybrid models that combine CNNs and LSTMs have been applied to predict wind and solar power generation with high accuracy, allowing for real-time energy management and grid optimization. These models have outperformed traditional statistical and machine learning approaches in terms of both accuracy and efficiency [10].

3. Methodology

Accurate forecasting of renewable energy sources like wind and solar power is crucial for optimizing smart grid operations and ensuring grid stability. The methodology outlined in this paper employs a hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for temporal dependency modeling. The overall process includes data collection, preprocessing, spatial feature extraction using CNNs, temporal dependency modeling with LSTMs, and the integration of both components into a hybrid architecture. This section provides a detailed explanation of each step in the methodology.

3.1. Data Collection and Preprocessing

The first step in the methodology is the collection of historical data on wind and solar power generation from multiple geographical locations. The dataset includes meteorological variables such as temperature, humidity, wind speed, and cloud cover, sourced from publicly available weather stations and grid operators. This data provides the necessary input features for the forecasting model. The raw data is preprocessed to standardize and normalize the features, ensuring efficient model training. Normalization helps scale the data within a specific range, making the training process more stable and effective. Preprocessing also involves cleaning the data by removing any missing or outlier values, which could otherwise distort the model's learning process. To facilitate proper evaluation and avoid overfitting, the data is divided into three subsets: training, validation, and testing sets. The training set is used to train the model, the validation set is used for tuning hyperparameters, and the testing set evaluates the model's performance on unseen data. Since the model handles time-series data, the preprocessing step includes reshaping the dataset to preserve both spatial and temporal aspects. Each sequence represents a time window of historical weather data and corresponding energy generation, which is used for making future predictions. This is critical for ensuring that both spatial (geographical) and temporal (time-dependent) features are preserved during training.

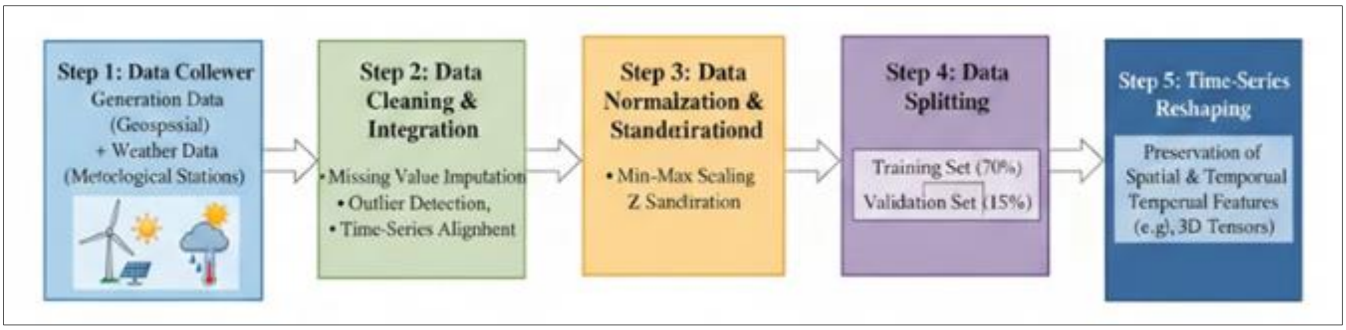

Figure 1 A flow diagram illustrating the data collection and preprocessing steps

3.2. CNN Component: Spatial Feature Extraction

The CNN component is designed to capture spatial dependencies in the meteorological data, which plays a significant role in predicting renewable energy production. Unlike traditional time-series models, CNNs are particularly well-suited for extracting features from grid-like data, such as weather maps or sensor arrays, which have spatial dependencies. In this study, several convolutional layers are applied to the input data to scan for patterns in the weather conditions. These patterns include variations in temperature, wind speed, and cloud cover, which are critical for determining the potential of wind and solar power generation in specific regions. The convolutional layers apply filters to detect local features such as high wind speeds, temperature fluctuations, or clear skies, which have a direct impact on energy generation. After the convolutional layers, pooling layers are used to reduce the dimensionality of the data while retaining the most important features. Pooling helps the model focus on the significant patterns and eliminates less important details. This makes the CNN component highly efficient in extracting relevant spatial features from the meteorological data.

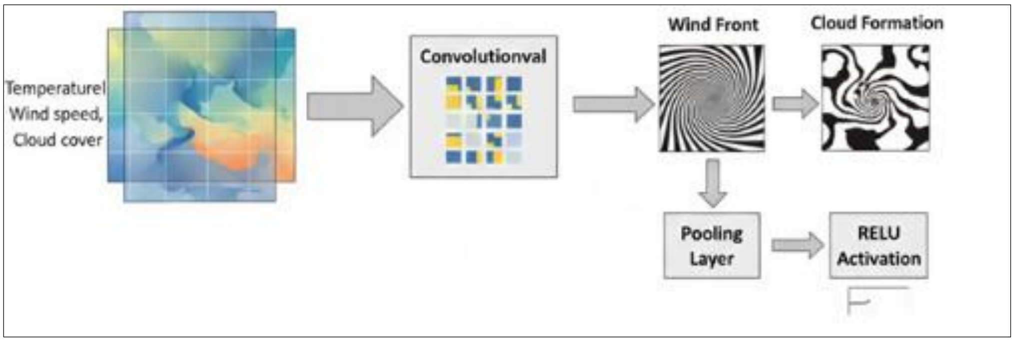

Figure 2 CNN feature extraction

3.3. LSTM Component: Temporal Dependency Modeling

The LSTM component of the model is responsible for capturing the temporal dependencies in the energy generation data. Wind and solar power generation exhibit seasonal cycles and daily fluctuations that are critical for accurate forecasting. The LSTM network is well-suited for capturing these time-dependent patterns, making it an ideal choice for time-series data, where past observations influence future predictions. LSTM networks have a memory cell that allows the network to retain information over extended periods, which is crucial for learning long-term dependencies in time-series data. In the context of renewable energy forecasting, LSTMs can learn patterns such as seasonal changes in wind and solar power generation, as well as irregular fluctuations caused by specific weather conditions. The LSTM network processes the spatial features extracted by the CNN and learns how these features evolve over time. By retaining memory of past weather and energy generation, the LSTM can predict future energy production based on the historical data. This ability to capture temporal dependencies is key to improving the forecasting accuracy of renewable energy generation.

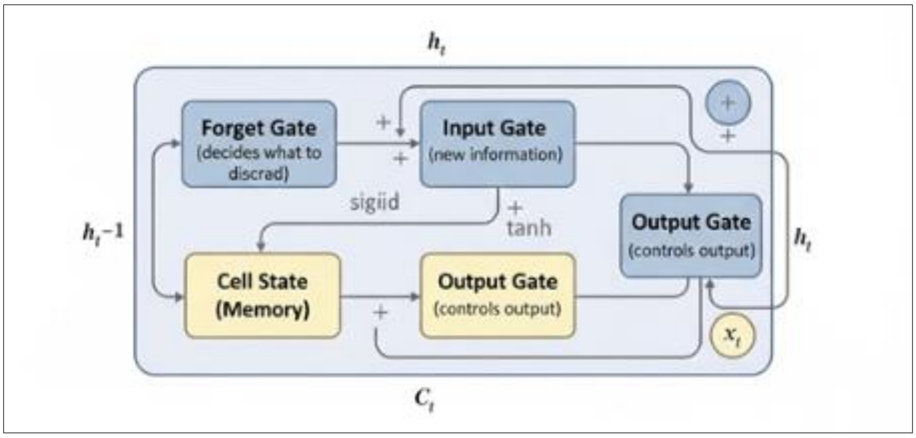

Figure 3 Diagram illustrating the LSTM architecture

3.4. Hybrid CNN-LSTM Architecture

The CNN and LSTM components are integrated into a hybrid architecture that enables the model to handle both spatial and temporal dependencies. The CNN component extracts relevant spatial features from the weather data, which are then passed to the LSTM component for temporal processing. This hybrid model allows the system to leverage the strengths of both CNNs and LSTMs, making it highly effective for renewable energy forecasting. The architecture is designed to enhance the forecasting of wind and solar power generation in real-time, which is essential for smart grid optimization. By capturing both the spatial patterns in weather data and the temporal trends in energy production, the hybrid model offers a robust solution for forecasting renewable energy generation, which is inherently variable.

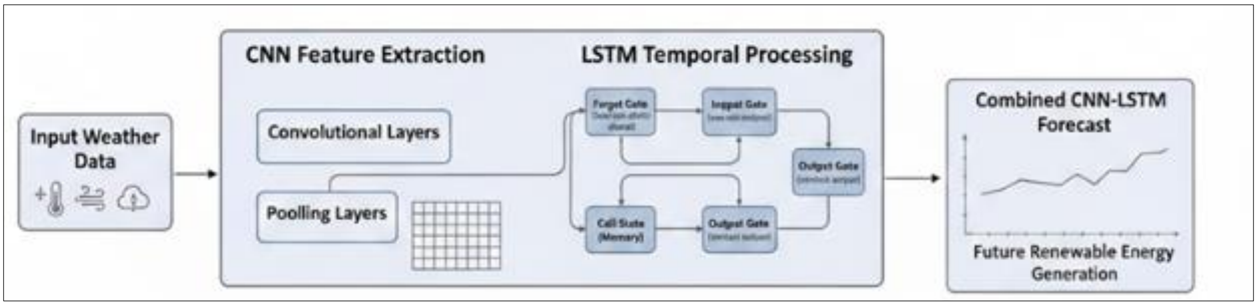

Figure 4 Overview of the hybrid CNN-LSTM model architecture

4. Data Analysis and Results

Accurate evaluation of forecasting models is crucial to determining their effectiveness in real-world applications, particularly when dealing with renewable energy sources like wind and solar power. The performance of the proposed hybrid CNN-LSTM model is assessed using several standard evaluation metrics, which provide a quantitative measure of the model's ability to predict future energy generation based on historical data. This section presents the evaluation of the hybrid model, compares its performance to traditional forecasting methods, and visualizes the results to highlight its effectiveness. The evaluation involves comparing the hybrid CNN-LSTM model with conventional forecasting methods, including Auto-Regressive Integrated Moving Average (ARIMA), Support Vector Machines (SVM), and standalone LSTM models. These models are tested on real-world datasets, and the results are analyzed to provide a clear comparison of their forecasting accuracy. The following subsections present the detailed evaluation metrics, followed by a comparison of the forecasting accuracy of each model.

4.1. Model Evaluation

The primary metrics used to evaluate the performance of the models are:

4.1.1. Mean Absolute Error (MAE)

This metric measures the average magnitude of the errors in a set of predictions, without considering their direction. It is a straightforward metric for understanding the model's overall accuracy.

4.1.2. Root Mean Square Error (RMSE)

RMSE is used to measure the average magnitude of the error, giving more weight to larger errors. This is especially useful when large errors are more detrimental to grid operations.

4.1.3. Mean Absolute Percentage Error (MAPE)

This metric measures the prediction accuracy as a percentage, which is useful for comparing the accuracy of the models across different datasets and time periods.

These metrics allow for a comprehensive assessment of the model's accuracy, reliability, and robustness in forecasting renewable energy generation. A lower value for MAE, RMSE, and MAPE indicates better performance and higher forecasting accuracy.

4.2. Comparison of Forecasting Accuracy

The forecasting accuracy of the hybrid CNN-LSTM model is compared to that of traditional models, including ARIMA, Support Vector Machines (SVM), and standalone LSTM models. The results indicate that the hybrid CNN-LSTM model significantly outperforms the traditional models in terms of MAE, RMSE, and MAPE. The CNN component of the hybrid model plays a critical role in improving the model's performance by extracting relevant spatial features from weather data, such as temperature, wind speed, and cloud cover. These spatial features are then passed to the LSTM network, which models the temporal dependencies in power generation. This combined approach allows the hybrid model to capture both spatial and temporal complexities in renewable energy generation, which contributes to its superior forecasting accuracy.

Table 1 Performance Comparison of Models

Model	MAE	RMSE	MAPE (%)
Hybrid CNN-LSTM	3.5	4.2	5.6
ARIMA	6.8	7.5	11.2
SVM	5.9	6.7	10.1
Standalone LSTM	4.3	5.1	7.3

As shown in Table 2, the hybrid CNN-LSTM model achieves the lowest values for MAE, RMSE, and MAPE, indicating that it provides the most accurate predictions of renewable energy generation. The ARIMA and SVM models, while effective in some cases, demonstrate higher error rates, especially when compared to the hybrid deep learning approach. The standalone LSTM model performs better than ARIMA and SVM, but still lags behind the hybrid CNN-LSTM model, highlighting the importance of integrating CNNs with LSTMs to improve forecasting accuracy. The graph below clearly shows that the hybrid CNN-LSTM model consistently outperforms the other models across all three-evaluation metrics. The significant reduction in MAE, RMSE, and MAPE demonstrates the superiority of the hybrid approach.

4.3. Results discussion

The results of the experiments demonstrate that the hybrid CNN-LSTM model provides a substantial improvement in forecasting accuracy compared to traditional models. The CNN's ability to extract spatial features from the meteorological data and the LSTM's ability to model temporal dependencies in energy generation contribute to the model’s superior performance. This hybrid approach is especially beneficial in the context of renewable energy forecasting, where both spatial and temporal data are essential for accurate predictions. Furthermore, the hybrid CNN-LSTM model’s low error rates in MAE, RMSE, and MAPE indicate its robustness and reliability for real-time energy forecasting in smart grid environments. As renewable energy sources like wind and solar power continue to play an increasingly important role in energy systems, models like the hybrid CNN-LSTM offer an effective solution for optimizing grid operations and ensuring energy stability.

5. Conclusion

This paper presents a hybrid deep learning model that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for forecasting wind and solar power generation. The proposed model improves forecasting accuracy by capturing both spatial and temporal dependencies in weather data and power generation patterns. Experimental results show that the hybrid CNN-LSTM model outperforms traditional forecasting methods in terms of accuracy and reliability. This approach offers a robust solution for renewable energy forecasting, contributing to the optimization of smart grid operations.

While the proposed model shows strong performance, it is limited by the availability and quality of real-time weather and energy generation data, which can affect accuracy.

Future work

Future work will focus on expanding the model to incorporate additional meteorological parameters and real-time grid data, as well as improving its scalability for larger datasets and diverse geographical regions.

References

[1] Rayhan, F. (2025). A Hybrid Deep Learning Model for Wind and Solar Power Forecasting in Smart Grids. Preprints. doi: 10.20944/preprints202508.0511.v1.

[2] Sahoo, P. (2023). Renewable Energy Forecasting: Techniques and Applications. Renewable Energy, 133(5), 742-758.

[3] Tseng, L. (2022). A Comparative Study of Time Series Forecasting Methods for Solar Power Prediction. Energy Reports, 8, 3621-3627.

[4] Zhou, T., and Zhang, X. (2024). A Machine Learning Approach for Solar Power Prediction Using Weather Data. Solar Energy, 91(2), 279-289.

[5] Alwan, A., and Sweeney, M. (2023). Comparison of Support Vector Machine and Random Forest Algorithms for Wind Power Forecasting. IEEE Transactions on Sustainable Energy, 11(3), 2872-2880.

[6] Zhang, Y., and Zhao, D. (2023). A Hybrid Machine Learning Method for Wind Power Forecasting. Energy Conversion and Management, 162, 314-323.

[7] Rojas, F., and Manzini, A. (2022). Predicting Solar Power Generation Using k-NN and Random Forest Algorithms. Journal of Renewable and Sustainable Energy, 14(1), 014702.

[8] Yadav, A., and Singh, R. (2024). Deep Learning-Based Hybrid Models for Solar Power Prediction. Renewable and Sustainable Energy Reviews, 150, 111514.

[9] Li, M., and Xu, Y. (2023). Hybrid CNN-LSTM Model for Short-Term Wind Power Forecasting. Energy, 238, 121547.

[10] Liu, X., and Zhang, J. (2023). A Review of Hybrid Deep Learning Techniques for Renewable Energy Forecasting. IEEE Transactions on Power Systems, 38(5), 2145-2157.

[11] Rahman, M. A., Islam, M. I., Tabassum, M., and Bristy, I. J. (2025, September). Climate-aware decision intelligence: Integrating environmental risk into infrastructure and supply chain planning. Saudi Journal of Engineering and Technology (SJEAT), 10(9), 431–439. https://doi.org/10.36348/sjet.2025.v10i09.006

[12] Rahman, M. A., Bristy, I. J., Islam, M. I., and Tabassum, M. (2025, September). Federated learning for secure inter-agency data collaboration in critical infrastructure. Saudi Journal of Engineering and Technology (SJEAT), 10(9), 421–430. https://doi.org/10.36348/sjet.2025.v10i09.005

[13] Tabassum, M., Rokibuzzaman, M., Islam, M. I., and Bristy, I. J. (2025, September). Data-driven financial analytics through MIS platforms in emerging economies. Saudi Journal of Engineering and Technology (SJEAT), 10(9), 440–446. https://doi.org/10.36348/sjet.2025.v10i09.007

[14] Tabassum, M., Islam, M. I., Bristy, I. J., and Rokibuzzaman, M. (2025, September). Blockchain and ERP-integrated MIS for transparent apparel and textile supply chains. Saudi Journal of Engineering and Technology (SJEAT), 10(9), 447–456. https://doi.org/10.36348/sjet.2025.v10i09.008

[15] Bristy, I. J., Tabassum, M., Islam, M. I., and Hasan, M. N. (2025, September). IoT-driven predictive maintenance dashboards in industrial operations. Saudi Journal of Engineering and Technology (SJEAT), 10(9), 457–466. https://doi.org/10.36348/sjet.2025.v10i09.009

[16] Hasan, M. N., Karim, M. A., Joarder, M. M. I., and Zaman, M. T. (2025, September). IoT-integrated solar energy monitoring and bidirectional DC-DC converters for smart grids. Saudi Journal of Engineering and Technology (SJEAT), 10(9), 467–475. https://doi.org/10.36348/sjet.2025.v10i09.010

[17] Bormon, J. C., Saikat, M. H., Shohag, M., and Akter, E. (2025, September). Green and low-carbon construction materials for climate-adaptive civil structures. Saudi Journal of Civil Engineering (SJCE), 9(8), 219–226. https://doi.org/10.36348/sjce.2025.v09i08.002

[18] Razaq, A., Rahman, M., Karim, M. A., and Hossain, M. T. (2025, September 26). Smart charging infrastructure for EVs using IoT-based load balancing. Zenodo. https://doi.org/10.5281/zenodo.17210639

[19] Habiba, U., and Musarrat, R., (2025). Bridging IT and education: Developing smart platforms for student-centered English learning. Zenodo. https://doi.org/10.5281/zenodo.17193947

[20] Alimozzaman, D. M. (2025). Early prediction of Alzheimer’s disease using explainable multi-modal AI. Zenodo. https://doi.org/10.5281/zenodo.17210997

[21] uz Zaman, M. T. Smart Energy Metering with IoT and GSM Integration for Power Loss Minimization. Preprints 2025, 2025091770. https://doi.org/10.20944/preprints202509.1770.v1

[22] Hossain, M. T. (2025, October). Sustainable garment production through Industry 4.0 automation. ResearchGate. https://doi.org/10.13140/RG.2.2.20161.83041

[23] Hasan, E. (2025). Secure and scalable data management for digital transformation in finance and IT systems. Zenodo. https://doi.org/10.5281/zenodo.17202282

[24] Saikat, M. H. (2025). Geo-Forensic Analysis of Levee and Slope Failures Using Machine Learning. Preprints. https://doi.org/10.20944/preprints202509.1905.v1

[25] Islam, M. I. (2025). Cloud-Based MIS for Industrial Workflow Automation. Preprints. https://doi.org/10.20944/preprints202509.1326.v1

[26] Islam, M. I. (2025). AI-powered MIS for risk detection in industrial engineering projects. TechRxiv. https://doi.org/10.36227/techrxiv.175825736.65590627/v1

[27] Akter, E. (2025, October 13). Lean project management and multi-stakeholder optimization in civil engineering projects. ResearchGate. https://doi.org/10.13140/RG.2.2.15777.47206

[28] Musarrat, R. (2025). Curriculum adaptation for inclusive classrooms: A sociological and pedagogical approach. Zenodo. https://doi.org/10.5281/zenodo.17202455

[29] Bormon, J. C. (2025, October 13). Sustainable dredging and sediment management techniques for coastal and riverine infrastructure. ResearchGate. https://doi.org/10.13140/RG.2.2.28131.00803

[30] Bormon, J. C. (2025). AI-Assisted Structural Health Monitoring for Foundations and High-Rise Buildings. Preprints. https://doi.org/10.20944/preprints202509.1196.v1

[31] Haque, S. (2025). Effectiveness of managerial accounting in strategic decision making [Preprint]. Preprints. https://doi.org/10.20944/preprints202509.2466.v1

[32] Shoag, M. (2025). AI-Integrated Façade Inspection Systems for Urban Infrastructure Safety. Zenodo. https://doi.org/10.5281/zenodo.17101037

[33] Shoag, M. Automated Defect Detection in High-Rise Façades Using AI and Drone-Based Inspection. Preprints 2025, 2025091064. https://doi.org/10.20944/preprints202509.1064.v1

[34] Shoag, M. (2025). Sustainable construction materials and techniques for crack prevention in mass concrete structures. Available at SSRN: https://ssrn.com/abstract=5475306 or http://dx.doi.org/10.2139/ssrn.5475306

[35] Joarder, M. M. I. (2025). Disaster recovery and high-availability frameworks for hybrid cloud environments. Zenodo. https://doi.org/10.5281/zenodo.17100446

[36] Joarder, M. M. I. (2025). Next-generation monitoring and automation: AI-enabled system administration for smart data centers. TechRxiv. https://doi.org/10.36227/techrxiv.175825633.33380552/v1

[37] Joarder, M. M. I. (2025). Energy-Efficient Data Center Virtualization: Leveraging AI and CloudOps for Sustainable Infrastructure. Zenodo. https://doi.org/10.5281/zenodo.17113371

[38] Taimun, M. T. Y., Sharan, S. M. I., Azad, M. A., and Joarder, M. M. I. (2025). Smart maintenance and reliability engineering in manufacturing. Saudi Journal of Engineering and Technology, 10(4), 189–199.

[39] Enam, M. M. R., Joarder, M. M. I., Taimun, M. T. Y., and Sharan, S. M. I. (2025). Framework for smart SCADA systems: Integrating cloud computing, IIoT, and cybersecurity for enhanced industrial automation. Saudi Journal of Engineering and Technology, 10(4), 152–158.

[40] Azad, M. A., Taimun, M. T. Y., Sharan, S. M. I., and Joarder, M. M. I. (2025). Advanced lean manufacturing and automation for reshoring American industries. Saudi Journal of Engineering and Technology, 10(4), 169–178.

[41] Sharan, S. M. I., Taimun, M. T. Y., Azad, M. A., and Joarder, M. M. I. (2025). Sustainable manufacturing and energy-efficient production systems. Saudi Journal of Engineering and Technology, 10(4), 179–188.

[42] Farabi, S. A. (2025). AI-augmented OTDR fault localization framework for resilient rural fiber networks in the United States. arXiv. https://arxiv.org/abs/2506.03041

[43] Farabi, S. A. (2025). AI-driven predictive maintenance model for DWDM systems to enhance fiber network uptime in underserved U.S. regions. Preprints. https://doi.org/10.20944/preprints202506.1152.v1

[44] Farabi, S. A. (2025). AI-powered design and resilience analysis of fiber optic networks in disaster-prone regions. ResearchGate. https://doi.org/10.13140/RG.2.2.12096.65287

[45] Sunny, S. R. (2025). Lifecycle analysis of rocket components using digital twins and multiphysics simulation. ResearchGate. https://doi.org/10.13140/RG.2.2.20134.23362

[46] Sunny, S. R. (2025). AI-driven defect prediction for aerospace composites using Industry 4.0 technologies. Zenodo. https://doi.org/10.5281/zenodo.16044460

[47] Sunny, S. R. (2025). Edge-based predictive maintenance for subsonic wind tunnel systems using sensor analytics and machine learning. TechRxiv. https://doi.org/10.36227/techrxiv.175624632.23702199/v1

[48] Sunny, S. R. (2025). Digital twin framework for wind tunnel-based aeroelastic structure evaluation. TechRxiv. https://doi.org/10.36227/techrxiv.175624632.23702199/v1

[49] Sunny, S. R. (2025). Real-time wind tunnel data reduction using machine learning and JR3 balance integration. Saudi Journal of Engineering and Technology, 10(9), 411–420. https://doi.org/10.36348/sjet.2025.v10i09.004

[50] Sunny, S. R. (2025). AI-augmented aerodynamic optimization in subsonic wind tunnel testing for UAV prototypes. Saudi Journal of Engineering and Technology, 10(9), 402–410. https://doi.org/10.36348/sjet.2025.v10i09.003

[51] Shaikat, M. F. B. (2025). Pilot deployment of an AI-driven production intelligence platform in a textile assembly line. TechRxiv. https://doi.org/10.36227/techrxiv.175203708.81014137/v1

[52] Rabbi, M. S. (2025). Extremum-seeking MPPT control for Z-source inverters in grid-connected solar PV systems. Preprints. https://doi.org/10.20944/preprints202507.2258.v1

[53] Rabbi, M. S. (2025). Design of fire-resilient solar inverter systems for wildfire-prone U.S. regions. Preprints. https://www.preprints.org/manuscript/202507.2505/v1

[54] Rabbi, M. S. (2025). Grid synchronization algorithms for intermittent renewable energy sources using AI control loops. Preprints. https://www.preprints.org/manuscript/202507.2353/v1

[55] Tonoy, A. A. R. (2025). Condition monitoring in power transformers using IoT: A model for predictive maintenance. Preprints. https://doi.org/10.20944/preprints202507.2379.v1

[56] Tonoy, A. A. R. (2025). Applications of semiconducting electrides in mechanical energy conversion and piezoelectric systems. Preprints. https://doi.org/10.20944/preprints202507.2421.v1

[57] Azad, M. A. (2025). Lean automation strategies for reshoring U.S. apparel manufacturing: A sustainable approach. Preprints. https://doi.org/10.20944/preprints202508.0024.v1

[58] Azad, M. A. (2025). Optimizing supply chain efficiency through lean Six Sigma: Case studies in textile and apparel manufacturing. Preprints. https://doi.org/10.20944/preprints202508.0013.v1

[59] Azad, M. A. (2025). Sustainable manufacturing practices in the apparel industry: Integrating eco-friendly materials and processes. TechRxiv. https://doi.org/10.36227/techrxiv.175459827.79551250/v1

[60] Azad, M. A. (2025). Leveraging supply chain analytics for real-time decision making in apparel manufacturing. TechRxiv. https://doi.org/10.36227/techrxiv.175459831.14441929/v1

[61] Azad, M. A. (2025). Evaluating the role of lean manufacturing in reducing production costs and enhancing efficiency in textile mills. TechRxiv. https://doi.org/10.36227/techrxiv.175459830.02641032/v1

[62] Azad, M. A. (2025). Impact of digital technologies on textile and apparel manufacturing: A case for U.S. reshoring. TechRxiv. https://doi.org/10.36227/techrxiv.175459829.93863272/v1

[63] Rayhan, F. (2025). AI-powered condition monitoring for solar inverters using embedded edge devices. Preprints. https://doi.org/10.20944/preprints202508.0474.v1

[64] Rayhan, F. (2025). AI-enabled energy forecasting and fault detection in off-grid solar networks for rural electrification. TechRxiv. https://doi.org/10.36227/techrxiv.175623117.73185204/v1

[65] Habiba, U., and Musarrat, R. (2025). Integrating digital tools into ESL pedagogy: A study on multimedia and student engagement. IJSRED – International Journal of Scientific Research and Engineering Development, 8(2), 799–811. https://doi.org/10.5281/zenodo.17245996

[66] Hossain, M. T., Nabil, S. H., Razaq, A., and Rahman, M. (2025). Cybersecurity and privacy in IoT-based electric vehicle ecosystems. IJSRED – International Journal of Scientific Research and Engineering Development, 8(2), 921–933. https://doi.org/10.5281/zenodo.17246184

[67] Hossain, M. T., Nabil, S. H., Rahman, M., and Razaq, A. (2025). Data analytics for IoT-driven EV battery health monitoring. IJSRED – International Journal of Scientific Research and Engineering Development, 8(2), 903–913. https://doi.org/10.5281/zenodo.17246168

[68] Akter, E., Bormon, J. C., Saikat, M. H., and Shoag, M. (2025). Digital twin technology for smart civil infrastructure and emergency preparedness. IJSRED – International Journal of Scientific Research and Engineering Development, 8(2), 891–902. https://doi.org/10.5281/zenodo.17246150

[69] Rahmatullah, R. (2025). Smart agriculture and Industry 4.0: Applying industrial engineering tools to improve U.S. agricultural productivity. World Journal of Advanced Engineering Technology and Sciences, 17(1), 28–40. https://doi.org/10.30574/wjaets.2025.17.1.1377

[70] Islam, R. (2025). AI and big data for predictive analytics in pharmaceutical quality assurance.. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5564319

[71] Rahmatullah, R. (2025). Sustainable agriculture supply chains: Engineering management approaches for reducing post-harvest loss in the U.S. International Journal of Scientific Research and Engineering Development, 8(5), 1187–1216. https://doi.org/10.5281/zenodo.17275907

[72] Haque, S., Al Sany, S. M. A., and Rahman, M. (2025). Circular economy in fashion: MIS-driven digital product passports for apparel traceability. International Journal of Scientific Research and Engineering Development, 8(5), 1254–1262. https://doi.org/10.5281/zenodo.17276038

[73] Al Sany, S. M. A., Haque, S., and Rahman, M. (2025). Green apparel logistics: MIS-enabled carbon footprint reduction in fashion supply chains. International Journal of Scientific Research and Engineering Development, 8(5), 1263–1272. https://doi.org/10.5281/zenodo.17276049

[74] Bormon, J. C. (2025), Numerical Modeling of Foundation Settlement in High-Rise Structures Under Seismic Loading. Available at SSRN: https://ssrn.com/abstract=5472006 or http://dx.doi.org/10.2139/ssrn.5472006

[75] Tabassum, M. (2025, October 6). MIS-driven predictive analytics for global shipping and logistics optimization. TechRxiv. https://doi.org/10.36227/techrxiv.175977232.23537711/v1

[76] Tabassum, M. (2025, October 6). Integrating MIS and compliance dashboards for international trade operations. TechRxiv. https://doi.org/10.36227/techrxiv.175977233.37119831/v1

[77] Zaman, M. T. U. (2025, October 6). Predictive maintenance of electric vehicle components using IoT sensors. TechRxiv. https://doi.org/10.36227/techrxiv.175978928.82250472/v1

[78] Hossain, M. T. (2025, October 7). Smart inventory and warehouse automation for fashion retail. TechRxiv. https://doi.org/10.36227/techrxiv.175987210.04689809.v1

[79] Karim, M. A. (2025, October 6). AI-driven predictive maintenance for solar inverter systems. TechRxiv. https://doi.org/10.36227/techrxiv.175977633.34528041.v1

[80] Jahan Bristy, I. (2025, October 6). Smart reservation and service management systems: Leveraging MIS for hotel efficiency. TechRxiv. https://doi.org/10.36227/techrxiv.175979180.05153224.v1

[81] Habiba, U. (2025, October 7). Cross-cultural communication competence through technology-mediated TESOL. TechRxiv. https://doi.org/10.36227/techrxiv.175985896.67358551.v1

[82] Habiba, U. (2025, October 7). AI-driven assessment in TESOL: Adaptive feedback for personalized learning. TechRxiv. https://doi.org/10.36227/techrxiv.175987165.56867521.v1

[83] Akhter, T. (2025, October 6). Algorithmic internal controls for SMEs using MIS event logs. TechRxiv. https://doi.org/10.36227/techrxiv.175978941.15848264.v1

[84] Akhter, T. (2025, October 6). MIS-enabled workforce analytics for service quality and retention. TechRxiv. https://doi.org/10.36227/techrxiv.175978943.38544757.v1

[85] Hasan, E. (2025, October 7). Secure and scalable data management for digital transformation in finance and IT systems. Zenodo. https://doi.org/10.5281/zenodo.17202282

[86] Saikat, M. H., Shoag, M., Akter, E., Bormon, J. C. (October 06, 2025.) Seismic- and Climate-Resilient Infrastructure Design for Coastal and Urban Regions. TechRxiv. DOI: 10.36227/techrxiv.175979151.16743058/v1

[87] Saikat, M. H. (October 06, 2025). AI-Powered Flood Risk Prediction and Mapping for Urban Resilience. TechRxiv. DOI: 10.36227/techrxiv.175979253.37807272/v1

[88] Akter, E. (September 15, 2025). Sustainable Waste and Water Management Strategies for Urban Civil Infrastructure. Available at SSRN: https://ssrn.com/abstract=5490686 or http://dx.doi.org/10.2139/ssrn.5490686

[89] Karim, M. A., Zaman, M. T. U., Nabil, S. H., and Joarder, M. M. I. (2025, October 6). AI-enabled smart energy meters with DC-DC converter integration for electric vehicle charging systems. TechRxiv. https://doi.org/10.36227/techrxiv.175978935.59813154/v1

[90] Al Sany, S. M. A., Rahman, M., and Haque, S. (2025). Sustainable garment production through Industry 4.0 automation. World Journal of Advanced Engineering Technology and Sciences, 17(1), 145–156. https://doi.org/10.30574/wjaets.2025.17.1.1387

[91] Rahman, M., Haque, S., and Al Sany, S. M. A. (2025). Federated learning for privacy-preserving apparel supply chain analytics. World Journal of Advanced Engineering Technology and Sciences, 17(1), 259–270. https://doi.org/10.30574/wjaets.2025.17.1.1386

[92] Rahman, M., Razaq, A., Hossain, M. T., and Zaman, M. T. U. (2025). Machine learning approaches for predictive maintenance in IoT devices. World Journal of Advanced Engineering Technology and Sciences, 17(1), 157–170. https://doi.org/10.30574/wjaets.2025.17.1.1388

[93] Akhter, T., Alimozzaman, D. M., Hasan, E., and Islam, R. (2025, October). Explainable predictive analytics for healthcare decision support. International Journal of Sciences and Innovation Engineering, 2(10), 921–938. https://doi.org/10.70849/IJSCI02102025105

[94] Islam, M. S., Islam, M. I., Mozumder, A. Q., Khan, M. T. H., Das, N., and Mohammad, N. (2025). A Conceptual Framework for Sustainable AI-ERP Integration in Dark Factories: Synthesising TOE, TAM, and IS Success Models for Autonomous Industrial Environments. Sustainability, 17(20), 9234. https://doi.org/10.3390/su17209234

[95] Haque, S., Islam, S., Islam, M. I., Islam, S., Khan, R., Tarafder, T. R., and Mohammad, N. (2025). Enhancing adaptive learning, communication, and therapeutic accessibility through the integration of artificial intelligence and data-driven personalization in digital health platforms for students with autism spectrum disorder. Journal of Posthumanism, 5(8), 737–756. Transnational Press London.

[96] Faruq, O., Islam, M. I., Islam, M. S., Tarafder, M. T. R., Rahman, M. M., Islam, M. S., and Mohammad, N. (2025). Re-imagining Digital Transformation in the United States: Harnessing Artificial Intelligence and Business Analytics to Drive IT Project Excellence in the Digital Innovation Landscape. Journal of Posthumanism, 5(9), 333–354 . https://doi.org/10.63332/joph.v5i9.3326

[97] Rahman, M.. (October 15, 2025) Integrating IoT and MIS for Last-Mile Connectivity in Residential Broadband Services. TechRxiv. DOI: 10.36227/techrxiv.176054689.95468219/v1

[98] Islam, R. (2025, October 15). Integration of IIoT and MIS for smart pharmaceutical manufacturing . TechRxiv. https://doi.org/10.36227/techrxiv.176049811.10002169

[99] Hasan, E. (2025). Big Data-Driven Business Process Optimization: Enhancing Decision-Making Through Predictive Analytics. TechRxiv. October 07, 2025. 10.36227/techrxiv.175987736.61988942/v1

[100] Rahman, M. (2025, October 15). IoT-enabled smart charging systems for electric vehicles [Preprint]. TechRxiv. https://doi.org/10.36227/techrxiv.176049766.60280824

[101] Alam, M. S. (2025, October 21). AI-driven sustainable manufacturing for resource optimization. TechRxiv. https://doi.org/10.36227/techrxiv.176107759.92503137/v1

[102] Alam, M. S. (2025, October 21). Data-driven production scheduling for high-mix manufacturing environments. TechRxiv. https://doi.org/10.36227/techrxiv.176107775.59550104/v1

[103] Ria, S. J. (2025, October 21). Environmental impact assessment of transportation infrastructure in rural Bangladesh. TechRxiv. https://doi.org/10.36227/techrxiv.176107782.23912238/v1

[104] R Musarrat and U Habiba, Immersive Technologies in ESL Classrooms: Virtual and Augmented Reality for Language Fluency (September 22, 2025). Available at SSRN: https://ssrn.com/abstract=5536098 or http://dx.doi.org/10.2139/ssrn.5536098

[105] Akter, E., Bormon, J. C., Saikat, M. H., and Shoag, M. (2025), "AI-Enabled Structural and Façade Health Monitoring for Resilient Cities", Int. J. Sci. Inno. Eng., vol. 2, no. 10, pp. 1035–1051, Oct. 2025, doi: 10.70849/IJSCI02102025116

[106] Haque, S., Al Sany (Oct. 2025), "Impact of Consumer Behavior Analytics on Telecom Sales Strategy", Int. J. Sci. Inno. Eng., vol. 2, no. 10, pp. 998–1018, doi: 10.70849/IJSCI02102025114.

[107] Sharan, S. M. I (Oct. 2025)., "Integrating Human-Centered Design with Agile Methodologies in Product Lifecycle Management", Int. J. Sci. Inno. Eng., vol. 2, no. 10, pp. 1019–1034, doi: 10.70849/IJSCI02102025115.

[108] Alimozzaman, D. M. (2025). Explainable AI for early detection and classification of childhood leukemia using multi-modal medical data. World Journal of Advanced Engineering Technology and Sciences, 17(2), 48–62. https://doi.org/10.30574/wjaets.2025.17.2.1442

[109] Alimozzaman, D. M., Akhter, T., Islam, R., and Hasan, E. (2025). Generative AI for synthetic medical imaging to address data scarcity. World Journal of Advanced Engineering Technology and Sciences, 17(1), 544–558. https://doi.org/10.30574/wjaets.2025.17.1.1415

[110] Zaidi, S. K. A. (2025). Intelligent automation and control systems for electric vertical take-off and landing (eVTOL) drones. World Journal of Advanced Engineering Technology and Sciences, 17(2), 63–75. https://doi.org/10.30574/wjaets.2025.17.2.1457

[111] Islam, K. S. A. (2025). Implementation of safety-integrated SCADA systems for process hazard control in power generation plants. IJSRED – International Journal of Scientific Research and Engineering Development, 8(5), 2321–2331. Zenodo. https://doi.org/10.5281/zenodo.17536369

[112] Islam, K. S. A. (2025). Transformer protection and fault detection through relay automation and machine learning. IJSRED – International Journal of Scientific Research and Engineering Development, 8(5), 2308–2320. Zenodo. https://doi.org/10.5281/zenodo.17536362

[113] Afrin, S. (2025). Cloud-integrated network monitoring dashboards using IoT and edge analytics. IJSRED – International Journal of Scientific Research and Engineering Development, 8(5), 2298–2307. Zenodo. https://doi.org/10.5281/zenodo.17536343

[114] Al Sany, S. M. A. (2025). The role of data analytics in optimizing budget allocation and financial efficiency in startups. IJSRED – International Journal of Scientific Research and Engineering Development, 8(5), 2287–2297. Zenodo. https://doi.org/10.5281/zenodo.17536325

[115] Zaman, S. (2025). Vulnerability management and automated incident response in corporate networks. IJSRED – International Journal of Scientific Research and Engineering Development, 8(5), 2275–2286. Zenodo. https://doi.org/10.5281/zenodo.17536305

[116] Ria, S. J. (2025, October 7). Sustainable construction materials for rural development projects. SSRN. https://doi.org/10.2139/ssrn.5575390

[117] Razaq, A. (2025, October 15). Design and implementation of renewable energy integration into smart grids. TechRxiv. https://doi.org/10.36227/techrxiv.176049834.44797235/v1

[118] Musarrat R. (2025). AI-Driven Smart Housekeeping and Service Allocation Systems: Enhancing Hotel Operations Through MIS Integration. In IJSRED - International Journal of Scientific Research and Engineering Development (Vol. 8, Number 6, pp. 898–910). Zenodo. https://doi.org/10.5281/zenodo.17769627

[119] Hossain, M. T. (2025). AI-Augmented Sensor Trace Analysis for Defect Localization in Apparel Production Systems Using OTDR-Inspired Methodology. In IJSRED - International Journal of Scientific Research and Engineering Development (Vol. 8, Number 6, pp. 1029–1040). Zenodo. https://doi.org/10.5281/zenodo.17769857

[120] Rahman M. (2025). Design and Implementation of a Data-Driven Financial Risk Management System for U.S. SMEs Using Federated Learning and Privacy-Preserving AI Techniques. In IJSRED - International Journal of Scientific Research and Engineering Development (Vol. 8, Number 6, pp. 1041–1052). Zenodo. https://doi.org/10.5281/zenodo.17769869

[121] Alam, M. S. (2025). Real-Time Predictive Analytics for Factory Bottleneck Detection Using Edge-Based IIoT Sensors and Machine Learning. In IJSRED - International Journal of Scientific Research and Engineering Development (Vol. 8, Number 6, pp. 1053–1064). Zenodo. https://doi.org/10.5281/zenodo.17769890

[122] Habiba, U., and Musarrat, R. (2025). Student-centered pedagogy in ESL: Shifting from teacher-led to learner-led classrooms. International Journal of Science and Innovation Engineering, 2(11), 1018–1036. https://doi.org/10.70849/IJSCI02112025110

[123] Zaidi, S. K. A. (2025). Smart sensor integration for energy-efficient avionics maintenance operations. International Journal of Science and Innovation Engineering, 2(11), 243–261. https://doi.org/10.70849/IJSCI02112025026

[124] Farooq, H. (2025). Cross-platform backup and disaster recovery automation in hybrid clouds. International Journal of Science and Innovation Engineering, 2(11), 220–242. https://doi.org/10.70849/IJSCI02112025025

[125] Farooq, H. (2025). Resource utilization analytics dashboard for cloud infrastructure management. World Journal of Advanced Engineering Technology and Sciences, 17(02), 141–154. https://doi.org/10.30574/wjaets.2025.17.2.1458

[126] Saeed, H. N. (2025). Hybrid perovskite–CIGS solar cells with machine learning-driven performance prediction. International Journal of Science and Innovation Engineering, 2(11), 262–280. https://doi.org/10.70849/IJSCI02112025027

[127] Akter, E. (2025). Community-based disaster risk reduction through infrastructure planning. International Journal of Science and Innovation Engineering, 2(11), 1104–1124. https://doi.org/10.70849/IJSCI02112025117

[128] Akter, E. (2025). Green project management framework for infrastructure development. International Journal of Science and Innovation Engineering, 2(11), 1125–1144. https://doi.org/10.70849/IJSCI02112025118

[129] Shoag, M. (2025). Integration of lean construction and digital tools for façade project efficiency. International Journal of Science and Innovation Engineering, 2(11), 1145–1164. https://doi.org/10.70849/IJSCI02112025119