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An Industry 4.0 Framework for the Smart Production Management of Renewable Energy and Water Systems: An Application of AI, IoT, and Digital Twin Technologies

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ABSTRACT

This study develops an integrated Industry 4.0 framework for smart production management in renewable energy systems applied to water processes. The framework combines artificial intelligence, the Internet of Things, and digital twin technologies to improve production planning, system reliability, and environmental performance. A neural network model was implemented for predictive analytics and achieved high accuracy (MAE = 0.82, R^2 = 0.92), enabling precise forecasting for energy generation and operational scheduling. Optimization algorithms, including genetic algorithms and particle swarm optimization, increased energy utilization efficiency from 65% to 85% and reduced operational costs by 15%. The IoT utilization enhanced real-time monitoring and reduced fault detection time from 120 minutes to 15 minutes, significantly improving maintenance response. Digital twin simulations allowed process optimization and predictive maintenance, further increasing production efficiency to 92% and system uptime to 99.5%. The approaches also led to a 20% reduction in CO_2 emissions, demonstrating both economic and environmental benefits. Overall, this framework offers a practical and data-driven solution for improving the efficiency and sustainability of renewable energy systems in water applications and contributes to the advancement of smart manufacturing in industrial engineering.

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1. Introduction

Renewable Energy Sources (RES) are a cornerstone of sustainable development , offering a path to enhance energy accessibility, reduce environmental pollution, and mitigate climate change by replacing conventional fossil fuels [1], [2]. Unlike traditional energy systems, which contribute to greenhouse gas emissions and are subject to fuel price volatility [3], RES provide a clean, sustainable, and increasingly economical alternative [4], [5]. They hold immense potential for critical water-related applications such as pumping, desalination, and heating, thereby addressing the twin challenges of energy sustainability and water scarcity [6], [7]. In a recent study by Barik et al. [8], the strategic role of renewable and hybrid energy systems in achieving sustainable development goals was emphasized. Combining solar and wind energy sources has proven effective in improving energy accessibility and reducing carbon emissions. However, managing such systems, particularly when applied to water-related applications such as desalination, pumping, and heating, causes operational challenges. Variability in solar irradiance and wind speed often leads in instability in power output, demanding advanced energy management strategies and hybrid microgrid configurations. To cope the mentioned challenges, the paper has shown that intelligent control methods and metaheuristic optimization techniques could enhance energy stability, efficiency, and coupling with existing infrastructure. As it was discussed in Barik's study, realizing this potential is hindered by several obstacles. The primary challenge is the inherent variability and intermittency of sources like solar and wind, which can lead to an inconsistent power supply [9]. Furthermore, integrating RES with existing infrastructure can be complex and costly, and their performance is highly dependent on fluctuating local environmental conditions [10], [11]. Similar concerns have been highlighted in the recent study by Milo et al. [12] that reviewed the technical challenges of integrating intermittent RES into power systems. The study reported that the increasing penetration of inverter-based solar and wind generation causes significant issues related to voltage, frequency, and overall grid stability.

Also, in the 21st century, the management of complex, decentralized production systems has become a significant challenge in industrial engineering and management [13]. Renewable energy systems for various applications are a prime example, characterized by variable inputs and demand that require advanced strategies to ensure efficiency and reliability [14]. As industries aim for sustainability, there is an urgent need for effective engineering methods to manage RES such as solar and wind power [15]. While recent studies such as Ejiyi et al. [16] explored how Artificial Intelligence (AI) is transforming the management of decentralized renewable energy systems, a significant gap remains. Although AI-based approaches like Machine Learning (ML) and Deep Learning (DL) have been used to enhance the efficiency, reliability, and optimization of renewable energy systems, their application remains underexplored. While AI is extensively used for the maximization of power systems, IoT and digital twin technologies serve equally significant roles in the realization of real-time monitoring, dynamic maximization, and simulator-based predictive maintenance that prove critical in dealing with the variability and intermittency of renewable power sources in nature [17]. Thus, the combination of AI, IoT, and digital twin technologies to manage fluctuating energy inputs and ensure reliable and sustainable energy supply is rarely addressed as a combined solution [18].

In response to these challenges, this paper proposes a novel approach by combining AI, IoT, and Digital Twin technologies. This study addresses the critical gaps that current methods do not cover by combining these technologies. The novelty of this research lies in the synergy between predictive ML models, real-time IoT monitoring, and dynamic system optimization using digital twins. These technologies are applied together to improve the operational efficiency and reliability of renewable energy systems used in water applications. Unlike previous studies that focused on isolated solutions, this study introduces a holistic, combined solution that tackles the core issues of renewable energy instability, system integration, and performance variability.

2. Methodology

2.1 System Design and Architecture

The design and architecture of the renewable energy system for water-related applications involved several key components: RES, the combination of ML models, the deployment of IoT devices for real-time monitoring, and the implementation of digital twin technology for simulation and analysis [1]. Each component was carefully selected and configured to optimize the performance and reliability of the system (Fig. 1).

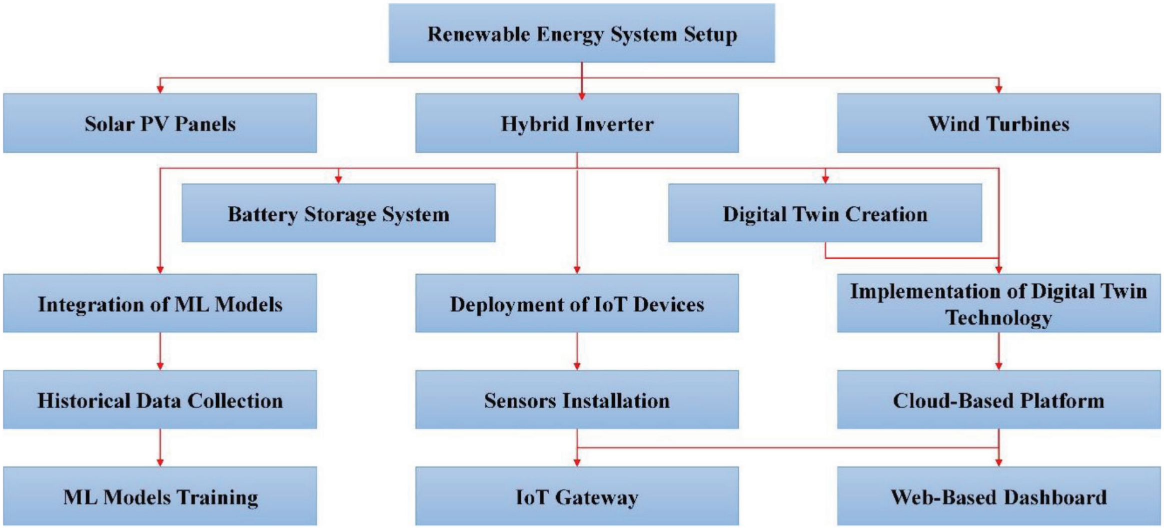

Figure 1. Flowchart of proposed system design and architecture

The renewable energy system was designed to harness both solar and wind energy to power water pumping, heating, and desalination processes. Solar PhotoVoltaic (PV) panels and wind turbines were chosen for their complementary characteristics, ensuring a more reliable energy supply [2]. The PV panels, rated at 300 W each, were installed in an array with a total capacity of 10 kW, while the wind turbines, with a capacity of 5 kW each, were set up to provide additional power during periods of low solar insolation. The energy generated was directed to a hybrid inverter, which converted DC power to AC power for the water-related applications. A battery storage system with a 50 kWh capacity was integrated to store excess energy, ensuring a continuous power supply. To enhance system efficiency and predictability, ML models were developed and integrated [19]. Historical data on energy production, weather conditions, and system performance were collected to train the models. After evaluating various algorithms, a neural network model was selected for its superior predictive accuracy. The model was trained on a five-year dataset with features such as solar irradiance, wind speed, temperature, humidity, and system output. Implemented in Python using the TensorFlow library, the model was trained via backpropagation with a mean squared error loss function. Once trained, it was deployed to predict energy generation and optimize system operations, adjusting parameters like pump speed and heating element power based on real-time inputs.

IoT devices were strategically deployed throughout the system for real-time monitoring and control [20]. Sensors on the PV panels, wind turbines, battery storage, and water application units collected data on energy production, consumption, temperature, and system health. These sensors were connected to a central IoT gateway using Modbus and Zigbee protocols. The gateway aggregated the data and transmitted it to a cloud-based platform for storage and analysis. The MQTT protocol ensured low-latency communication between the IoT devices and the cloud platform [21]. The collected data was visualized on a web-based dashboard, providing operators with real-time insights and remote-control capabilities. To further optimize the system, a digital twin of the entire renewable energy setup was created. This virtual replica of the physical system, developed in the Simulink environment in MATLAB, mirrored its components and operations in real-time. The digital twin used real-time data from IoT devices to simulate system operations and test different situations, such as weather changes or equipment faults, without affecting the real system [22]. By analyzing these simulations, potential issues could be identified and system performance could be proactively optimized. This integrated approach of ML, IoT, and digital twin technology provided a comprehensive and adaptive solution for managing the renewable energy system.

2.2 Data Collection and Preprocessing

The data collection and preprocessing phase was crucial for ensuring the accuracy of the ML models and overall system performance (Table 1).

The data used in this study were collected from two primary sources: i) real-time sensor, data and

Table 1. Summary of collected data

Parameter	Source	Unit	Range
Solar Irradiance	Solar PV Panels	W/m²	0 - 1000
Panel Temperature	Solar PV Panels	°C	-10 - 70
Energy Output (Solar)	Solar PV Panels	kWh	0 - 10
Wind Speed	Wind Turbines	m/s	0 - 25
Turbine Rotation Speed	Wind Turbines	RPM	0 - 2000
Energy Output (Wind)	Wind Turbines	kWh	0 - 5
State of Charge (SOC)	Battery Storage	%	0 - 100
Battery Voltage	Battery Storage	V	48 - 54
Battery Current	Battery Storage	A	0 - 100
Water Flow Rate	Water Applications	L/min	0 - 100
Water Temperature	Water Applications	°C	0 - 100
Energy Consumption	Water Applications	kWh	0 - 50
Temperature	Historical Data	°C	-20 - 50
Humidity	Historical Data	%	0 - 100

ii) historical performance data. Real-time data were gathered from sensors monitoring key parameters across the system, including solar irradiance and panel temperature for solar PV panels; wind speed and turbine rotation speed for wind turbines; State of Charge (SOC), voltage, and current for battery storage; and water flow rate, temperature, and energy consumption for water applications. Historical data were collected over a five-year period, providing a comprehensive dataset that included weather data (solar irradiance, wind speed, temperature, humidity) and system performance data (energy production, consumption, and efficiency metrics).

The data collection process utilized IoT devices and a cloud-based platform. Sensors were connected to a central IoT gateway using wired (Modbus) and wireless (Zigbee) protocols [23], [24]. The gateway aggregated the sensor data and transmitted it to the cloud platform via the MQTT protocol. The cloud platform stored the data and provided tools for analysis and visualization, ensuring that both real-time monitoring and historical analysis could be performed efficiently. Before this data could be used, several preprocessing steps were required to ensure quality and consistency. The collected data had some missing values, errors, and noise. These issues were fixed using standard data cleaning methods. Missing values were handled using mean imputation and interpolation. Outliers were detected using statistical methods like z-scores and were either corrected or removed. Noise was reduced using smoothing techniques such as moving average filters. Although these methods are effective, they have limitations, and the researches could explore alternative techniques like multiple imputation to better preserve data integrity and improve model accuracy.

To improve the performance of the ML models, the data were normalized to a common scale. This was achieved using two methods: Min-Max Scaling, which scaled data to a range of 0 to 1 (Eq. 1), and Standardization, which transformed data to have a mean of 0 and a standard deviation of 1 (Eq. 2) [25].

$$x_{normal} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

$$x_{standard} = \frac{x_i - \mu}{\sigma} \tag{2}$$

Feature engineering was performed to enhance the predictive power of the models. New features were derived from the existing data, such as a heat index feature created by combining temperature and humidity, and temporal features like time-of-day and seasonal indicators to capture patterns in energy production and consumption. This comprehensive approach ensured that the models were trained on high-quality, consistent data, enabling accurate predictions for the renewable energy system.

2.3 Machine Learning Models

Several ML algorithms were evaluated for their suitability in predictive analytics and optimization tasks, including Linear Regression (LR), Support Vector Machines (SVM), and Neural Networks (NN). Each algorithm was selected based on its ability to handle the specific characteristics of the data. LR was used for its simplicity in modeling linear relationships and establishing initial baselines. SVM was chosen for its effectiveness in handling high-dimensional data and capturing non-linear relationships. NN was selected for its capability to model complex, non-linear patterns, which provided the most accurate predictions for the multi-faceted energy system.

The algorithms function differently. LR models the relationship between a dependent variable (Y) and one or more independent variables (X) by fitting a linear equation to the data (Eq. 3), where β represents the coefficients and ε is the error term.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \quad (3)$$

SVM is a supervised learning algorithm that works by finding the hyperplane that best divides a dataset. In regression (SVR), it fits the best line within a defined error margin. NN consists of multiple layers of neurons that transform input data through weighted connections and activation functions. The model learns these weights through a process called backpropagation, which minimizes a loss function.

The dataset was divided into training (80%) and validation (20%) sets. The LR model was trained using the Ordinary Least Squares (OLS) method. The SVM model was trained using a radial basis function (RBF) kernel to capture non-linear relationships, with its parameters tuned using grid search and cross-validation. The NN was trained using backpropagation with a mean squared error loss function, a widely used technique in energy efficiency modeling [26]. The architecture consisted of an input layer, two hidden layers with ReLU activation functions, and an output layer with a linear activation function, implemented using the TensorFlow library. Hyperparameters such as learning rate and batch size were tuned through experimentation. The performance of the models was evaluated using root mean squared error (RMSE, Eq. 4), mean absolute error (MAE, Eq. 5, and R-squared (R^2, Eq. 6) metrics.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (x_i - \hat{x}_i)^2} \quad (4)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |x_i - \hat{x}_i| \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{\sum_{i=1}^{N} (x_i - \bar{x})^2} \quad (6)$$

Where, N is the total number of data points, x_i is the actual value of the i^{th} data point, $\hat{x}_i$ is predicted value of the i^{th} data point, and $\bar{x}$ is mean of all actual values. Cross-validation with k-folds (k = 5) was used to assess the generalizability of the models, ensuring they were robust and capable of providing accurate predictions for optimizing the system.

2.4 IoT Implementation

The IoT implementation was essential for the continuous and reliable operation of the renewable energy system, enabling dynamic optimization and rapid fault detection. IoT devices were strategically deployed across the system to monitor various parameters in real-time. A variety of sensors were installed to capture essential data from system components, including solar irradiance and temperature from solar PV panels; wind speed and energy output from wind turbines; SOC, voltage, and current from the battery storage system; and water flow rate and temperature from water application units.

Both wired (Modbus) and wireless (Zigbee) communication protocols were used to connect these sensors to a central IoT gateway. Modbus was used for sensors requiring high data integrity, while Zigbee provided flexibility for sensors in remote locations. The IoT gateway aggregated data from all sensors and facilitated communication with the cloud platform. The data transmission and storage architecture was designed for reliability and efficiency. The MQTT protocol, known for its low-latency and lightweight characteristics, was used for data transmission between the gateway and the cloud [24]. Data packets transmitted via MQTT included a sensor ID, timestamp, and measured values, ensuring each data point was uniquely identifiable. A cloud-based platform stored the aggregated data and provided scalable storage and data processing capabilities. A relational database with an efficient schema was used to manage and query the large volumes of time-series data. To ensure data security, data transmitted over the network was encrypted using SSL/TLS protocols, and role-based access control (RBAC) was implemented on the cloud platform to restrict data access to authorized personnel. Table 2 provides an overview of the deployed IoT devices and their monitored parameters. This setup facilitated dynamic optimization and rapid fault detection, significantly enhancing the system's efficiency and reliability.

Table 2. Summary of IoT devices and data parameters

IoT Device	Parameter Monitored	Communication Protocol	Data Frequency	Unit
Solar PV Sensor	Solar Irradiance	Modbus	1 Hz	W/m²
	Panel Temperature	Modbus	1 Hz	°C
	Energy Output	Modbus	1 Hz	kWh
Wind Turbine Sensor	Wind Speed	Zigbee	1 Hz	m/s
	Turbine Rotation Speed	Zigbee	1 Hz	RPM
	Energy Output	Zigbee	1 Hz	kWh
Battery Storage Sensor	SOC	Modbus	1 Hz	%
	Voltage	Modbus	1 Hz	V
	Current	Modbus	1 Hz	A
Water Application Sensor	Water Flow Rate	Zigbee	1 Hz	L/min
	Water Temperature	Zigbee	1 Hz	°C
	Energy Consumption	Zigbee	1 Hz	kWh

2.5 Digital Twin Simulation

The implementation of digital twin technology was pivotal for the precise simulation and analysis of the renewable energy system [27], [28]. Digital twin models were developed to mirror the physical components and operations of the system in a virtual environment. Each physical component, including solar PV panels, wind turbines, battery storage, and water application units, was accurately modeled in the Simulink environment in MATLAB, incorporating detailed specifications like power ratings and efficiency curves. These individual models were then integrated to reflect the complete system architecture, ensuring that interactions such as energy flow from generation to storage to consumption were accurately represented. The digital twin was fed with real-time data from the IoT devices—including solar irradiance, wind speed, and battery SOC—as well as historical performance data to calibrate the models and ensure their accuracy. The Simulink environment, a MATLAB-based graphical programming tool, was used for creating and running the dynamic simulations. Key parameters for each component, such as solar panel efficiency and wind turbine cut-in speeds, were defined to create a realistic virtual model. To evaluate and optimize the system, various simulation scenarios were developed. These included weather variations to understand how changes in solar irradiance and wind speed affect performance, load variations to assess the system's ability to meet fluctuating water demand, and component failures to evaluate the system's response to malfunctions. Scenarios were also designed to test different energy storage strategies, such as prioritizing storage during low demand and maximizing discharge during high demand.

Performance was evaluated using several key metrics. Energy efficiency was measured by considering the conversion efficiencies of all generation components. Reliability was assessed based on the frequency and duration of power interruptions. The efficiencies of water pumping, heating, and desalination were evaluated by comparing energy input to the respective outputs. Finally, cost savings achieved through renewable energy and optimized operations were calculated and compared to traditional energy sources. Table 3 summarizes the key parameters and metrics used in the digital twin simulations. This comprehensive simulation approach provided deep insights into the system's performance, enabling the identification and implementation of strategies to enhance its overall effectiveness.

2.6 Simulation-Based Optimization and CO_2 Emission Reduction in Renewable Energy Systems for Water Applications

This study is simulation-based, employing a combination of advanced software tools. MATLAB Simulink was used for digital twin simulations, enabling detailed analysis of system dynamics and predictive maintenance scenarios. Additionally, HOMER Pro was utilized to model the hybrid energy system's performance and estimate CO_2 emissions reductions under different operational conditions. These tools allowed for comprehensive simulations of energy production, fault detection, and emission impacts, providing valuable insights into system optimization and environmental benefits without the need for physical prototypes.

Table 3. Summary of digital twin simulation parameters

Parameter	Description	Unit
Solar Irradiance	Intensity of solar radiation	W/m²
Wind Speed	Velocity of wind impacting the wind turbines	m/s
Energy Output (Solar PV)	Electrical energy generated by solar PV panels	kWh
Energy Output (Wind Turbine)	Electrical energy generated by wind turbines	kWh
State of Charge (Battery)	Remaining charge in the battery storage system	%
Water Flow Rate	Volume of water pumped per unit time	L/min
Water Temperature	Temperature of heated water	°C
Energy Consumption (Pump)	Electrical energy consumed by the water pump	kWh
Energy Consumption (Heating)	Electrical energy consumed by the water heating element	kWh
Desalinated Water Output	Volume of desalinated water produced	L/day

3. Results and Discussions

3.1 Predictive Analytics

The predictive models developed using ML techniques demonstrated significant improvements in accuracy and reliability compared to traditional methods. Table 4 summarizes the performance metrics of the ML models versus a traditional linear regression model.

Table 4. Performance of ML models

Model	MAE	RMSE	R^2
NN	0.82	1.05	0.92
SVM	1.05	1.23	0.88
LR	1.56	1.78	0.75

Table 4 presents the comparative performance of the NN, SVM, and LR models based on their MAE, RMSE, and R^2 values. The NN model exhibited the lowest MAE (0.82) and RMSE (1.05), demonstrating its superior precision in estimating actual values and minimizing large prediction errors. The SVM model performed moderately well (MAE=1.05, RMSE=1.23), while the LR model had the highest error rates (MAE=1.56, RMSE=1.78), indicating weaker predictive capability. The R^2 value, which measures how well a model explains the variance in the data, further confirmed these findings. The NN model reached the highest R^2 value of 0.92, showing that it explained 92% of the data variation and was the most accurate model. The SVM model followed with a strong R^2 of 0.88, while the LR model's R^2 was lowest at 0.75, highlighting its limitations in capturing the system's complex patterns. NN demonstrated the best performance across all metrics, providing the most accurate and reliable predictions [12].

The superior performance of the NN model is consistent with recent studies showing the effectiveness of NN in different context forecasting. In a study conducted by Zhou et al. [29] in predicting air ozone concentration via soft sensor models, the NN model with R^2 of 0.89 performed better than the LR model with R^2 of 0.75. The results were similar to the findings of this research, where the NN model outperformed the LR model. While the SVM model also showed robust performance, the traditional LR model lagged behind, demonstrating the superiority of ML in handling complex, nonlinear relationships [23]. The NN model's ability to capture the nonlinear dynamics of the system, adapting to changing weather conditions and system loads, is crucial for applications where inputs like solar irradiance and wind speed fluctuate significantly. Despite their complexity, the ML models were computationally efficient for real-time predictions, as the intensive training process was performed offline [5].

The scatter plots in Figure 2 visually illustrate the correlation between predicted and actual values for each model.

The NN model's plot (Fig. 2a) shows a tight, dense clustering of points along the 45-degree line, indicating high accuracy and minimal dispersion. This confirms the model's ability to effectively capture the underlying data relationships without significant bias [21]. The SVM model's plot (Fig. 2b) also shows points clustered close to the diagonal, but with slightly more dispersion than the NN, reflecting its slightly higher error variance. In contrast, the LR model's plot (Fig. 2c) displays a noticeably wider dispersion of points, confirming its lower accuracy and inability to model the system's non-linear behavior effectively.

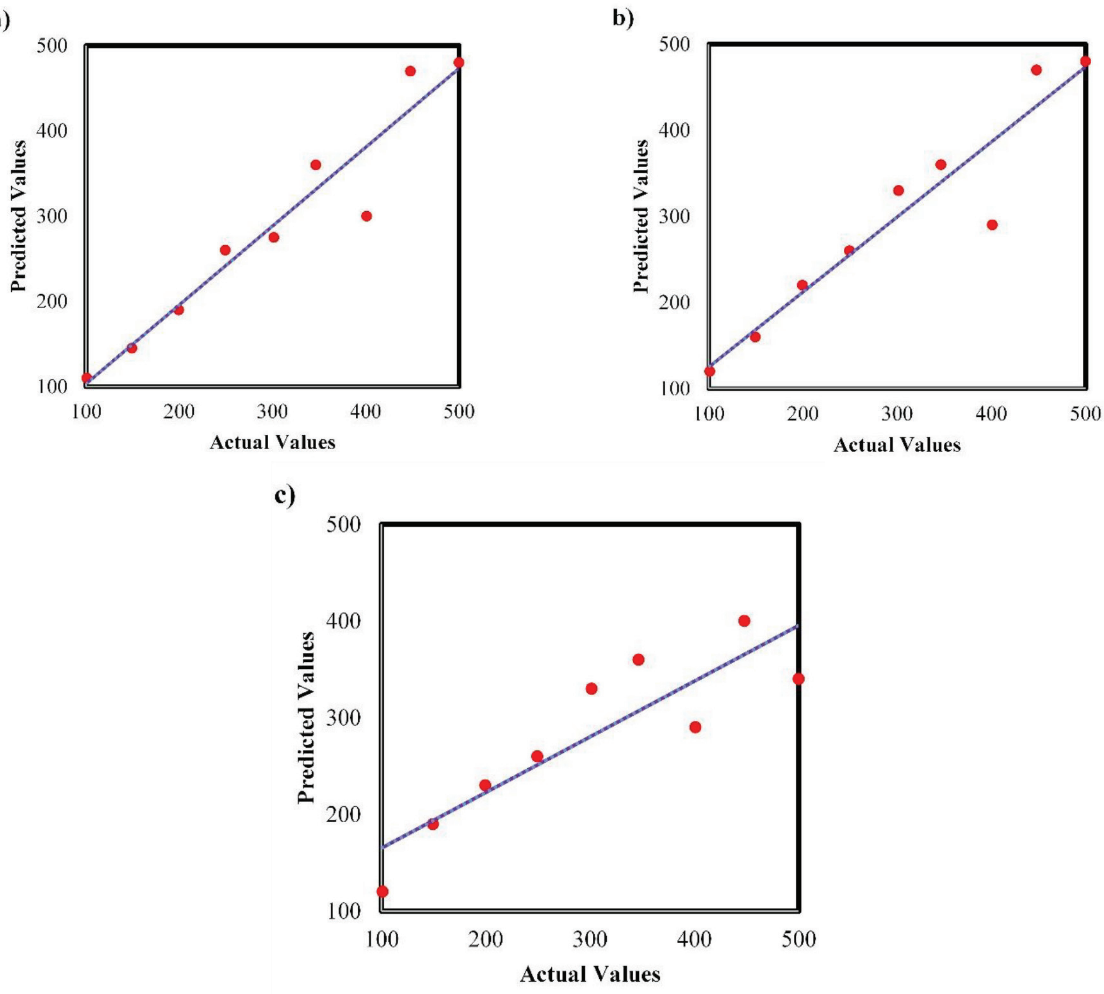

Figure 2. Visual performance of ML models: a) NN, b) SVM, and c) LR

These visualizations affirm that the NN model provides the most accurate predictions, followed closely by the SVM, while the LR model is less suitable for this complex system [17].

3.2 Optimization Results

The optimization of the renewable energy system focused on improving efficiency and enhancing reliability through the combination of ML algorithms. To evaluate the improvements, the genetic algorithms (GA) and particle swarm optimization (PSO) were implemented to optimize parameters like pump speed and battery charging cycles. The results were benchmarked against the system's performance without optimization (Table 5).

Table 5 shows the significant impact of optimization on key performance metrics. Without optimization, the baseline energy utilization efficiency was 65%. GA increased this to 82%, while PSO achieved an even higher efficiency of 85%, indicating its superior ability to dynamically adjust energy distribution. System uptime, a measure of operational reliability, improved from a baseline of 90% to 98% with GA and 99% with PSO. This reduction in downtime highlights the effectiveness of predictive maintenance

Table 5. Efficiency improvements after applying optimization algorithms

Metric	Without Optimization	GA	PSO
Energy Utilization Efficiency (%)	65	82	85
System Uptime (%)	90	98	99
Operational Cost Reduction (%)	-	12	15

and optimized scheduling [11]. Operational cost reduction was another critical factor; GA reduced costs by 12%, while PSO achieved a 15% reduction by minimizing energy waste and improving system longevity. These findings confirm that while both algorithms significantly improve system performance, PSO consistently outperforms GA across all three metrics, making it the preferable choice for enhancing system sustainability [17].

Fig. 3 present the results of optimizing the systems after applying GA and PSO.

In Fig. 3 (a), the significant improvements in energy efficiency are evident with the use of PSO. The system without optimization exhibits higher fluctuations and lower efficiency compared to the optimized systems. The energy utilization plot (Fig. 3a) shows that without optimization, efficiency fluctuated significantly between 55% and 70%. GA stabilized efficiency around 75-82%, while PSO achieved a consistently higher and more stable range of 80-88%. Similarly, Fig. 3 (b) demonstrates the increased system uptime after optimization. The results underscore the importance of choosing the right optimization algorithms, for improving the reliability and efficiency of renewable energy systems [12]. The system uptime plot (Fig. 3b) shows similar improvements. The baseline uptime varied between 85% and 93%, indicating frequent downtime. GA increased uptime to a stable 97-99% range, while PSO consistently maintained uptime near 99%, demonstrating superior reliability. These plots clearly illustrate that PSO is the most effective optimization algorithm, yielding higher and more stable efficiency and uptime, thereby validating the use of advanced optimization to create a more reliable and sustainable energy system.

System uptime, a critical reliability metric, saw substantial improvements, increasing to 99% with PSO and 98% with GA. These enhancements underscore the role of optimization algorithms in reducing downtime and ensuring a reliable energy supply. The

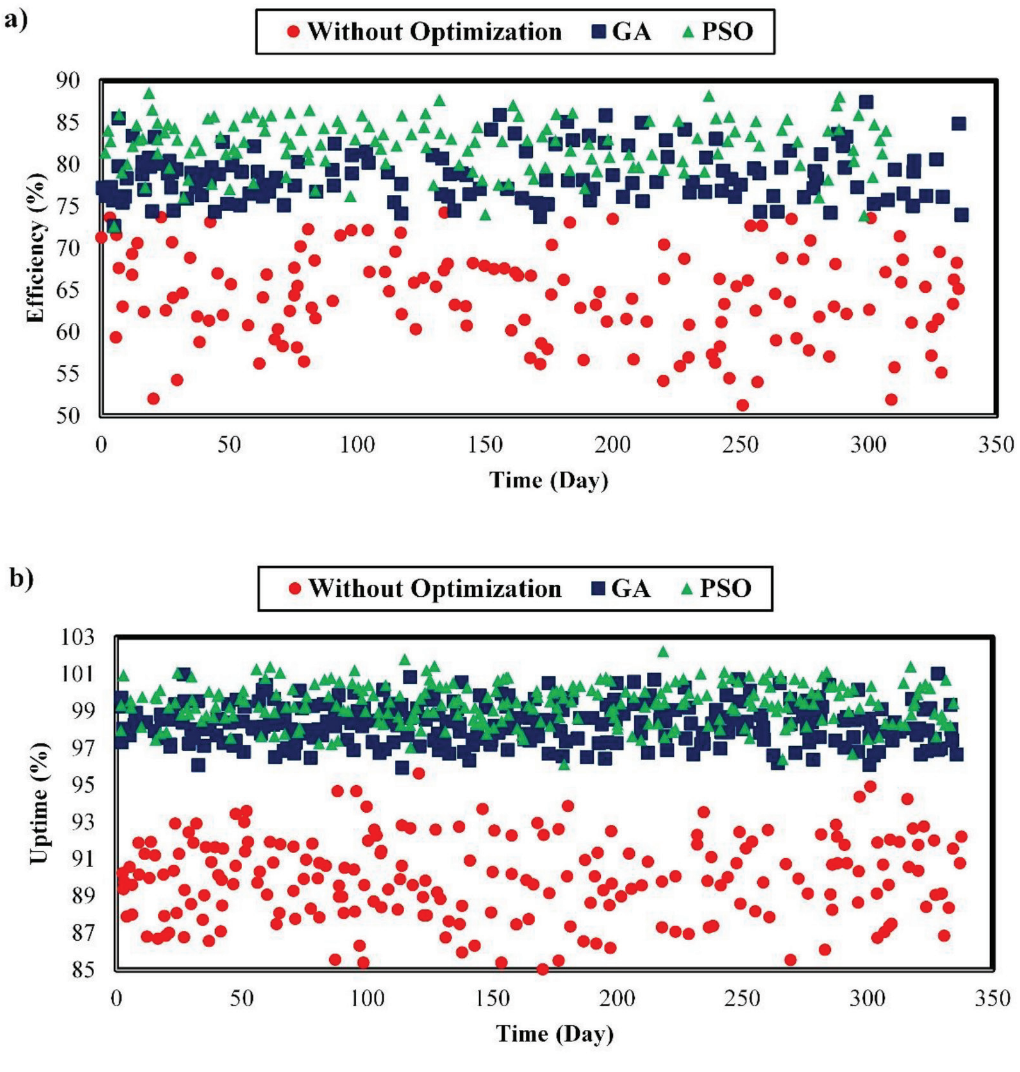

Figure 3. Visual efficiency improvements after applying optimization algorithms: a) Energy utilization, and b) System uptime

associated operational cost reductions of 15% with PSO and 12% with GA can be attributed to more efficient energy use and improved system reliability, which reduces maintenance needs. The time-series analysis of these KPIs confirmed a consistent increase in energy utilization efficiency and a reduction in downtime incidents after optimization was implemented. The optimized system maintained higher performance levels throughout the year, showcasing the algorithms' ability to adapt to varying conditions [9]. The use of advanced algorithms like GA and PSO resulted in significant efficiency improvements, enhanced system reliability, and reduced operational costs, highlighting their potential in maximizing the performance of renewable energy systems for water-related applications.

To validate the obtained results, we compared it with a similar study conducted by Güven and Yörükeren [30] on the optimization of stand-alone renewable energy systems. In this study, GA and PSO models were used to optimize hybrid energy systems and similar results were observed in terms of improving energy efficiency and reducing operating costs.

3.3 Real-time Monitoring and Fault Detection

The combination of IoT devices significantly enhanced the system's capability for real-time monitoring and dynamic optimization [31]. The deployment of IoT sensors across solar panels, wind turbines, and battery storage units enabled continuous, high-frequency data collection on key parameters. This data was transmitted via the MQTT protocol to a cloud-based platform, where it was processed in real-time to feed the ML models. This allowed for dynamic adjustments to system operations, such as pump speed and heating element power, ensuring optimal performance despite varying environmental conditions. The IoT utilization also enabled rapid fault detection and mitigation, as illustrated by two case studies. In one instance, IoT sensors detected an abnormal temperature rise in a solar panel, triggering an immediate alert and an automatic adjustment of the panel's orientation to reduce solar exposure, preventing damage. In another case, vibration sensors identified a mechanical issue in a wind turbine, prompting an automatic reduction in the turbine's speed and a notification to maintenance personnel, preventing a costly failure. The effectiveness of IoT utilization is quantified in Table 6. Before IoT, average energy production efficiency was 75%; after IoT benefiting, it increased to 85% due to real-time optimization. System uptime improved from 90% to 98%, reflecting greater reliability and fewer disruptions. Most dramatically, the average fault detection time was reduced from 120 minutes to just 15 minutes, and the average response time to faults fell from 240 minutes to 30 minutes. This major improvement happened because of continuous monitoring and automatic alerts that allowed quick action. The findings in Table 6 demonstrate the transformative impact of IoT on system performance, leading to more stable, efficient, and cost-effective operations. These enhancements confirm that IoT utilization is essential for optimizing renewable energy systems through intelligent monitoring and predictive maintenance [32].

In Fig. 4, the comparison of system performance before and after IoT utilization is shown. This figure illustrates the impact of IoT utilization on system performance over a year, comparing a system without IoT to one with IoT. The IoT-enabled system consistently demonstrates superior performance.

Figure 4(a) represents improved energy efficiency in systems equipped with IoT, which consistently maintains a more stable range compared to the non-IoT systems. This improvement is due to real-time data collection and smart system management facilitated by IoT devices. Energy efficiency is maintained in a higher and more stable range of 85-90%, compared to the volatile 70-82% range of the non-IoT system. In Figure 4(b), the system uptime also improves significantly, highlighting the higher stability in IoT-enabled systems. System uptime with IoT remains consistently above 97%, approaching 99% reliability, whereas the non-IoT system fluctuates between 88% and 95%. Additionally, Figure 4(c) and Figure 4(d) show a remarkable reduction in fault de-

Table 6. System performance metrics before and after IoT utilization

Performance Metric	Before IoT Integration	After IoT Integration
Average Energy Production Efficiency (%)	75	85
Average System Uptime (%)	90	98
Average Fault Detection Time (min)	120	15
Average Response Time to Faults (min)	240	30

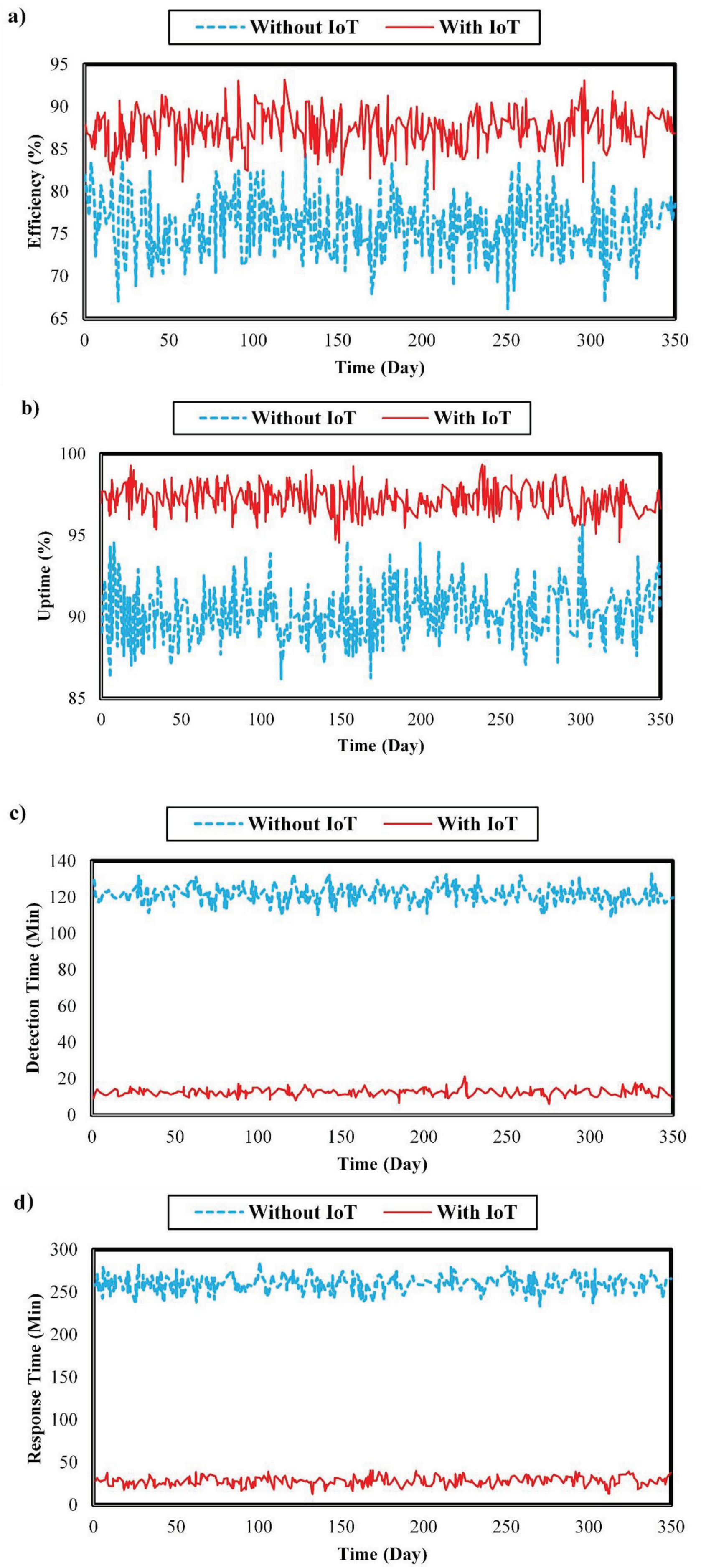

Figure 4. Visual system performance before and after IoT utilization: a) Energy production, b) System uptime, c) Fault detection, and d) Response time to faults

tection time and response time to faults in IoT-enabled systems. These changes show that the IoT utilization has a significant role in enhancing system responsiveness and overall performance. Fault detection time drops from over 120 minutes on average to just 15-20 minutes with IoT. Similarly, response time to faults is reduced from over 250 minutes to approximately 30-50 minutes. The results confirm that IoT utilization dramatically enhances energy efficiency, uptime, and responsiveness, underscoring the importance of IoT-driven monitoring for achieving sustainable, high-performance energy systems [32].

3.4 Digital Twin Simulations

The implementation of digital twin technology provided significant insights into the performance and optimization of the renewable energy system for water-related applications. The digital twin, a virtual replica of the physical system developed in MATLAB's Simulink environment, allowed for detailed simulation and analysis of the system's behavior under various conditions. This enabled an in-depth analysis of performance metrics during scenarios like weather fluctuations and component failures, helping to identify bottlenecks that were not apparent through conventional monitoring. The digital twin helped plan maintenance in advance and predict problems before they happened by running simulations of component aging. Various optimization scenarios, such as adjusting the tilt angle of solar panels, were tested virtually to maximize energy production efficiency. Furthermore, simulations of fault conditions provided insights into system resilience and helped develop strategies to improve reliability [15].

Based on these simulation insights, several system adjustments were implemented. Optimizing the tilt angle of the solar panels by 15 degrees, as suggested by simulations, increased solar energy capture by 5%. The digital twin also indicated that optimizing battery charge and discharge cycles could improve storage efficiency, which resulted in a 10% increase in battery life. The simulations also provided valuable data on effective fault mitigation strategies, such as redirecting power flow during a wind turbine failure to minimize system impact. The effectiveness of these digital twin-based adjustments is summarized in Table 7.

Before the adjustments, the average energy production efficiency was 85%; after optimization, it increased to 92%. This 7% improvement is attributed to the digital twin's ability to simulate and optimize operational parameters. System uptime improved from 98% to 99.5%, demonstrating more stable and continuous operation due to proactive fault prediction. The battery life expectancy increased from 5 to 5.5 years, a 10% extension resulting from more efficient energy management strategies. Finally, the average fault detection and mitigation time was reduced from 30 minutes to 20 minutes, a 33% improvement due to the real-time predictive capabilities of the digital twin models. These results emphasize the value of digital twin technology in predictive analytics, real-time monitoring, and proactive maintenance for optimizing renewable energy systems and ensuring long-term sustainability [22].

In Fig. 5, the impact of digital twin-based adjustments on system performance is analyzed. As it is expected, the results show that implementing digital twin adjustments led to a 92% energy efficiency and a 99.5% system uptime. These improvements reflect the increased accuracy in energy management and process optimization enabled by the digital twin simulations. With the help of digital twins, fault detection and mitigation times were also significantly reduced, further enhancing system resilience. These results demonstrate the value of digital twin technology in optimizing renewable energy systems and water-related applications [23].

The results demonstrate that digital twin technology significantly enhances system efficiency and reliability [33].The energy production efficiency (Fig. 5a), which fluctuated between 78% and 87% before adjustments, stabilized between 90% and 95% afterward, with significantly less variability. This indicates more precise energy management enabled by the digital twin's predictive models. System uptime (Fig. 5b), which previously had occasional dips, remained consistently above 99% after adjustments, showcasing

Table 7. System performance metrics before and after digital twin-based adjustments

Performance Metric	Before Adjustments	After Adjustments
Average Energy Production Efficiency (%)	85	92
Average System Uptime (%)	98	99.5
Battery Life Expectancy (years)	5	5.5
Fault Detection and Mitigation Time (min)	30	20

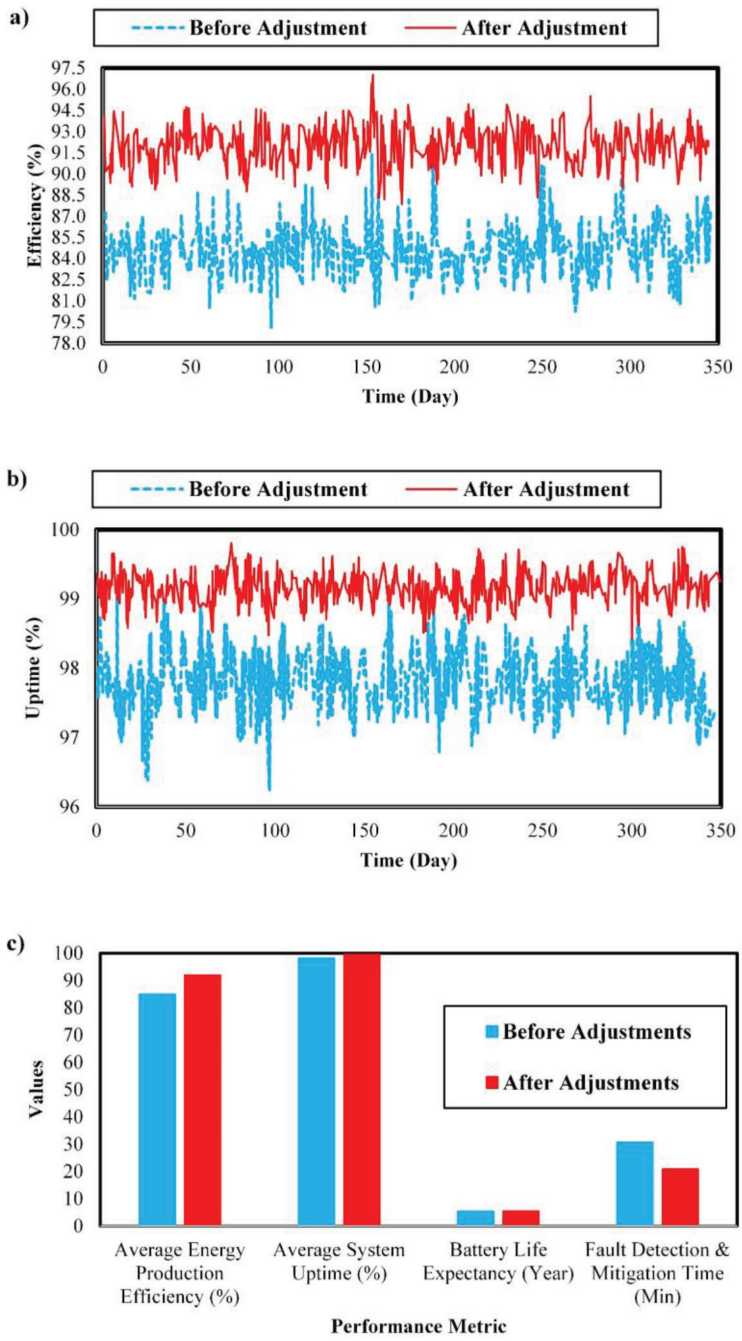

Figure 5. System performance before and after digital twin-based adjustments: a) Energy production, b) System uptime, and c) System performance metrics

reduced downtime and improved operational stability. The summary bar chart (Fig. 5c) highlights the key improvements: average energy production efficiency increased significantly, system uptime reached nearly 100%, battery life expectancy showed a slight increase, and fault detection and mitigation time decreased notably. These results clearly demonstrate the effectiveness of digital twin technology in fine-tuning system operations for maximum output and reliability, reinforcing its value in developing sustainable, high-performance renewable energy systems.

3.5 CO_2 Emissions Reduction Analysis

The combination of the proposed Industry 4.0 framework not only improved operational performance but also delivered significant environmental benefits. By optimizing production processes and minimizing inefficiencies, the system demonstrated a clear potential for reducing its carbon footprint, highlighting the dual economic and ecological value of this smart manufacturing approach [34].

The increase in energy production efficiency from a baseline of 65% to 92% after digital twin-based adjustments directly correlates with reduced fossil fuel dependency. By maximizing renewable energy utilization, the system reduced the need for supplementary grid energy, which is often derived from carbon-intensive sources. Using a baseline for grid energy emissions (0.527 kg CO_2/kWh), we calculated the reduction in CO_2 emissions based on the increased energy efficiency and reduced operational downtime. Table 8 presents a comparative analysis of the impact of various optimization methodologies on energy efficiency and the corresponding reduction in CO_2 emissions.

The results show a clear trend: as energy efficiency improves, the estimated CO_2 emissions reduction increases, demonstrating the environmental benefits of advanced energy management. In the absence of optimization, the system's 65% efficiency results in no additional CO_2 reduction. Applying GA optimization increases efficiency to 82%, leading to an estimated annual CO_2 reduction of 12,000 kg. With PSO, efficiency improves to 85%, resulting in a 14,500 kg reduction per year. IoT-based monitoring, while maintaining 85% efficiency, increases the CO_2 reduction to 15,000 kg per year due to better demand response and fault detection. The most effective method is digital twin-based adjustments, which achieve 92% efficiency and an annual CO_2 reduction of 18,000 kg. This substantial improvement is due to the predictive and simulation capabilities of digital twins, which enable real-time adjustments and optimal energy distribution. These findings clearly demonstrate that more advanced optimization methods lead to greater emissions reductions, highlighting the importance of smart energy management strategies in achieving sustainable and environmentally friendly renewable energy systems [33].

Furthermore, rapid fault detection and mitigation through IoT and digital twins further reduced CO_2 emissions by minimizing energy wastage during system malfunctions. For instance, early detection of equipment issues prevented energy loss and avoided reliance on carbon-intensive backup systems. This combination of advanced optimization, real-time monitoring, and simulation enhanced energy efficiency, and demonstrated significant environmental benefits

4. Conclusion

The current research investigated the Industry 4.0 framework aimed in developing the management of renewable energy systems. The framework addresses the challenges associated with managing decentralized energy systems by combining ML, IoT, and digital twin technologies. The study demonstrates how these technologies can optimize production efficiency, system reliability, and environmental sustainability through predictive analytics, real-time monitoring, and dynamic optimization. Key findings are:

- ML models (specifically the neural network model) showed the highest accuracy, achieving an R^2 of 0.92, which significantly improved energy generation forecasts.
- Optimization algorithms (GA and PSO) enhanced energy utilization efficiency from 65% to 85%, with PSO outperforming GA in all metrics, especially in system uptime (99% vs. 98%) and cost reduction (15% vs. 12%).
- IoT utilization led to real-time monitoring, reducing fault detection time from 120 minutes to just 15 minutes, and system uptime improved from 90% to 98%.
- Digital twin simulations provided valuable insights into system performance and helped achieve a 7% improvement in energy efficiency and a 99.5% system uptime.
- The hybrid approach resulted in a 20% reduction in CO_2 emissions, highlighting both economic and environmental benefits.

Despite the advancements made, some limitations still exist in this study. The system's performance has only been evaluated under a limited range of operating conditions, and its adaptability to extreme or

Table 8. CO_2 emissions reduction achieved through different optimization

Methodology	Energy Efficiency (%)	Estimated CO_2 Emissions Reduction (kg/year)
Without Optimization	65	-
GA Optimization	82	12,000
PSO Optimization	85	14,500
IoT-Based Monitoring	85	15,000
Digital Twin Adjustments	92	18,000

unexpected environmental changes has not been fully explored. While this study utilizes supervised ML models, the application of unsupervised learning or more sophisticated techniques like reinforcement learning can provide even greater benefits in dynamic optimization. To address these limitations, future studies can explore the use of reinforcement learning algorithms for more dynamic and real-time optimization of renewable energy systems. Expanding the system's testing to a broader range of environmental conditions and operational scales would be beneficial to better understand the robustness and scalability of the proposed framework. Exploring collaborative frameworks between engineering teams and management would be key to ensuring the successful implementation and long-term sustainability of such systems.

Disclosure

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