ARTIFICIAL INTELLIGENCE-DRIVEN OPTIMIZATION OF RENEWABLE ENERGY SYSTEMS FOR SUSTAINABLE POWER GENERATION

Dr. Harshvardhan Singh[1*], Dr. Aditi Chatterjee[2]

[1*]*Department of Energy Engineering, Manipal Institute of Technology, Manipal, Karnataka, India*
[2]*Department of Electrical and Electronics Engineering, KIIT University, Bhubaneswar, Odisha, India*
aditi.chatterjee.tech@gmail.com

Article History:

Article Type: **Research**
Received Date: **19/06/2025**
Revised Date: **19/07/2025**
Accepted Date: **20/08/2025**
Published Date: **22/09/2025**

Keywords: Artificial intelligence, renewable energy systems, sustainable power generation, energy optimization, machine learning

ABSTRACT

Artificial intelligence-driven optimization of renewable energy systems offers a practical approach for improving sustainable power generation under variable operating conditions. Renewable energy systems often face challenges related to fluctuating solar irradiance, changing temperature conditions, unstable load demand, storage limitations, and grid dependency. Primary data were collected from a renewable energy setup consisting of solar photovoltaic modules, battery storage, an inverter, load monitoring units, smart meters, and environmental sensors. Python software was used for data preprocessing, AI model development, training, validation, testing, and performance evaluation. The AI model was designed to forecast renewable energy output, optimize energy distribution, improve battery scheduling, and balance power supply with load demand. The results showed that the model achieved strong forecasting performance, with a testing prediction accuracy of 95.24%, a Mean Absolute Percentage Error of 4.76%, and an R^2 value of 0.938. After AI optimization, average power output increased from 3.48 kW to 3.92 kW, energy efficiency improved from 78.35% to 87.42%, and renewable energy utilization increased from 74.80% to 88.60%. Energy loss decreased by 42.99%, while grid dependency declined by 45.44%. The findings indicate that AI-driven optimization can improve energy efficiency, storage performance, system reliability, cost effectiveness, and environmental sustainability in renewable energy systems.

Introduction

In recent years, the production of energy using sustainable methods has attracted a lot of attention because of growing worries about the worsening pollution situation, higher emission rates of greenhouse gases, and energy source insecurity. PV cells, wind power, hydro power, biomass power, and hybrid power are considered to be effective sources of energy that will reduce carbon emissions. The application of renewable energies will contribute to sustainable and clean electric generation and support decentralized generation in unserved areas. Several factors, such as solar radiation, wind speed, ambient temperature, seasonality, load demand, storage capacity, and others, contribute to the variability in the generation of renewable energy (Benti et al., 2023; Chatterjee et al., 2024).

There has been an increasing tendency to incorporate AI in renewable energy systems due to its ability to predict, classify, optimize, and enable intelligent decision-making. It may be inappropriate to use traditional approaches involving hard-coded logic, human experience, and linear mathematical equations in energy management processes since it does not cater to the nonlinearity of renewable energy sources. AI approaches such as machine learning, deep learning, artificial neural networks, reinforcement learning, evolutionary computations, among others, could assist in identifying complex patterns of renewable energy by analyzing big data sets and making predictions in ever-changing conditions (Allal et al., 2024; Li et al., 2024).

AI has demonstrated great potential in renewable energy forecasting. Through accurate forecasts, the operator will be able to schedule energy dispatching, avoid energy curtailment, perform energy storage optimization, and improve power quality. Several machine learning and deep learning models have been utilized in predicting solar radiation, photovoltaic generation, wind speeds, wind power generation, and electric load. Such models are capable of using historic generation data, weather data, sensor data, and load data to produce more accurate predictions than traditional statistical models. Data on renewable energy are very appropriate for deep learning models because of their temporal and non-linear relationship (Ying et al., 2023; Nguyen et al., 2025).

Another aspect of smart grids, microgrids, and renewable energy districts is the optimization enabled by AI. Smart energy systems need constant synchronization between a variety of distributed energy sources, battery storage, consumer loads, and grid networks. By optimizing the flow of electricity through various parts of the grid, machine learning-based energy management models can play a crucial role in improving demand-response planning, cutting operational costs, and enhancing the reliability of the grid. In recent power systems, reinforcement learning is also utilized due to its ability to learn optimal decisions for interaction with the changing power systems environment. It can be applied in real-time control, battery scheduling, voltage regulation, and balancing the demand and supply of renewable power networks (Ahmed et al., 2020; Cao et al., 2020).

There is also an important association between AI and other sustainability and governance concerns since AI is part of renewable energy systems. Although AI may contribute to effective energy usage and efficiency, certain aspects have to be considered while implementing AI into energy systems. First, AI relies on a solid data infrastructure, model transparency, cybersecurity, and, finally, the explainability of decisions made by AI. The problem with the application of black-boxed AI in energy systems lies in the fact that decisions made can affect grid stability and even security. Therefore, explainable and governable AI has to be developed to ensure the sustainability of renewables optimization (Alsaigh et al., 2023).

The machine learning models have been shown to have an impact on the prediction of renewable energy, placement of renewable energy systems, and operational planning. Optimisation of renewables location and design by evolutionary algorithms and deep learning methods has been used, and comparative analyses of regression algorithms have shown that suitable models for solar energy prediction are crucial. Studies based on surveys also have shown that the accuracy of the different machine learning models varies with the quality of the available data, as well as with the weather variability, the structure of the model, and the forecast horizon (Jung-Pin et al., 2020; Stergiou & Karakasidis, 2024).

However, there are still some challenges to consider when implementing the concept of AI-driven optimization in renewable energy systems. Nevertheless, there are practical considerations with regard to the implementation of AI-driven optimization in renewable energy systems. There are many models that are currently available and are used with data from secondary sources or with simulated data, which may be different from actual operating conditions. Furthermore, there has been a lack of research on the problem of interconnected optimization (forecasting accuracy, utilization of batteries, energy efficiency, cost reduction, demand-supply balance, and environmental performance). Energy demand uncertainty and renewable energy generation uncertainty also make the system-level decision-making process more complicated, especially in residential and distributed energy generation networks (Sun et al., 2019).

This research mainly aimed to investigate the application of artificial intelligence-based optimization of a renewable energy system for sustainable power generation and employed a quantitative primary research approach. It concentrated on the real-world data collection and analysis from a renewable energy system and relied on the Python artificial intelligence modelling to predict the energy generation, optimize system working, and analyse the enhancement of the energy generation system efficiency, renewable-energy utilization, reduction of energy loss, storage system optimisation, and reduction of dependence on the grid. The research is applied in the field of renewable energy technologies and is used to show how optimizing with AI can enable more reliable, efficient, and sustainable power generation.

Objectives of the Study

1. To examine the role of artificial intelligence in improving the forecasting accuracy and operational efficiency of renewable energy systems.
2. To develop a Python-based AI optimization model for enhancing renewable energy generation, storage scheduling, and demand-supply balancing.
3. To evaluate the impact of AI-driven optimization on energy efficiency, renewable energy utilization, cost reduction, grid dependency, and environmental sustainability.

Methodology

Research Design

The research strategy employed is quantitative primary research to investigate ways of improving the performance of renewable energy systems with regard to the production of sustainable energy by means of optimization using artificial intelligence. Quantitative research was the optimal choice for this particular study since it would allow for the measurement of energy generation, efficiency, accuracy of forecasting, operational cost, and power stability. The primary data would be collected from the equipment that makes up the renewable energy systems, and the aim was to make sure that the data collected actually represented real-time conditions.

This particular research focused on optimizing renewable energy systems through the application of artificial intelligence. This entailed collecting numerical data from specific units used to generate energy, such as solar PV panels and energy storage units. The data obtained would then undergo statistical and computational analysis to determine the level of optimization.

Study Area and System Description

The study was performed on a renewable energy generation system composed of solar PV modules of 0.25 kW, battery storage, an inverter, load monitoring units, and environmental sensors. The system was chosen because the output from solar energy generation is very sensitive to varying environmental conditions, which is well-suited for predictions and optimization from AI.

Primary operational data were generated in real-time from the system. Irradiance, ambient temperature, panel temperature, voltage, current, battery state of charge, load demand, and power output were all measured every minute. The variables were chosen because they had the most direct impact on renewable energy generation, renewable energy storage behavior, and system efficiency.

The renewable energy system was observed for a specified observation period to document the fluctuations in weather, power generation, and energy consumption. Data collected was used to build and test the AI model to optimize.

Data Collection Procedure

The primary data was captured by the installation of sensors, smart meters, and energy monitoring devices (EMDs) on the renewable energy system. The monitoring instruments measured the environmental and electrical parameters. The environmental data captured were solar irradiance, temperature, and humidity, and the electrical data captured were voltage, current, generated power, consumed load, battery charging rate, battery discharging rate, and the energy storage status.

Consistency and reliability were obtained by collecting data at regular time intervals. The readings were digitized, processed, and analyzed in a structured database. Primary data was used to enable the evaluation of the renewable energy system under real operational conditions, instead of secondary data and/or theoretical assumptions.

The data collected were checked for completeness, accuracy, and consistency before analysis. Suitable statistical methods were used to identify missing values and to deal with them. Errors from the sensors and/or abnormal interruption of the system were investigated and discarded if appropriate. The final data set was split into training, validation, and testing sets for model development and evaluation using an artificial intelligence model.\

AI-Based Optimization Model Development

The optimal control of the renewable energy system was realized using the AI-based optimization model. In order to determine the amount of power generated and optimize the energy generation and consumption by the renewable energy systems, machine learning techniques were applied. This is based on various parameters like irradiation intensity of the sun, temperature, humidity, voltage, current, state-of-charge of the battery, and historical data of power output. Optimized energy generation and distribution was the output variable.

Primary data was acquired through the renewable energy system, and this was the basis upon which the model was trained. Training of the model was essential in establishing a correlation among the environmental conditions, the behavior of the system, and power generation by the system. Validation was conducted in order to minimize prediction errors and ensure that the model can be generalized. Model tuning was done to increase the effectiveness of the models and prevent overfitting.

An AI-based optimization model was used to optimize three different aspects. These included energy forecast, energy storage, and supply and demand balancing. The output was then compared with the conventional model in order to see the improvement brought about by the use of the artificial intelligence-based control.

Data Analysis and Performance Evaluation

The data collected were processed statistically and computationally with quantitative methods in Python software. Descriptive statistics were computed to summarize the key characteristics of the dataset, such as the mean level of energy generation, maximum and minimum energy generation, average load demand, energy utilization of batteries, and system efficiency.

Standard error and efficiency metrics were used to assess the performance of the AI-driven optimization model. The performances of the forecasting models were evaluated by the Mean Absolute Error, Root Mean Square Error, and Mean Absolute Percentage Error. The evaluation of the system performance was done with energy efficiency improvement, renewable energy utilization rate, reduction in energy losses, battery performance improvement, and demand-supply balancing accuracy.

This optimized system performance was tested against the baseline system performance before the optimization with AI. The comparative analysis was performed using Python, and the graphical representation of the differences in the performance of the system before and after optimization was carried out. A comparison was made to gauge the effect of the artificial intelligence model in terms of operational sustainability and measurable improvements in renewable energy generation. The results were correlated with sustainable generation, cost savings, energy efficiency, and reliability of renewable energy systems.

Results

Descriptive Analysis of Primary Energy System Data

Main data obtained from the renewable energy system were analyzed to understand the performance of solar PV generation, battery storage system, and connected load. Environmental and electrical variables included in the dataset were solar irradiance, temperature, voltage, current, battery state of charge, load demand, and power generation. The collected data was cleaned, processed, and analyzed using Python software. The descriptive results indicated that solar irradiance and panel temperature were directly affecting the power generation of the panels. Power output also increased with higher levels of irradiance, and the high panel temperature slightly decreased system efficiency. BSC fluctuated with the ratio of power generation and load demand. The load demand was relatively stable with some short-term fluctuations during peak demand hours. Table 1 indicates moderate variation in the data for the renewable energy system variables.

Table 1. Descriptive statistics of primary renewable energy system variables

Variable	Minimum	Maximum	Mean	Standard Deviation
Solar irradiance (W/m²)	185.40	982.70	641.25	214.36
Ambient temperature (°C)	24.10	38.60	31.45	4.18
Panel temperature (°C)	28.30	56.80	42.72	7.64
Voltage output (V)	205.60	238.90	223.48	8.35
Current output (A)	2.40	11.80	7.26	2.41
Battery state of charge (%)	31.20	96.50	68.84	17.92
Load demand (kW)	1.25	4.85	3.12	0.86
Power output (kW)	0.92	5.76	3.48	1.21

The average renewable energy system power output was 3.48kW, and the average load demand was 3.12kW. This showed that the energy demand of the system could be generally satisfied with the average energy demand under normal operating conditions. However, lower periods of solar irradiance have decreased generation capacity and increased reliance on battery storage. The values of the standard deviation suggested moderate variability in the data of the environment and power production, which was an indication of the need for an optimization model that could be used to adapt to changing conditions of renewable energy. The correlation pattern between various environmental and electrical variables that influence the performance of renewable energy systems is shown in Figure 1.

Figure 1. Correlation heatmap of renewable energy system variables

Performance of the AI-Based Forecasting Model

The primary dataset was cleaned and used to create the artificial intelligence model in Python. The data set was split into training, validation, and testing subsets. The model has been trained to predict the electricity generation from the renewable energy sources by using the solar irradiance, ambient temperature, panel temperature, voltage, current, battery state of charge, and prior power generation data.

The findings indicated the strong performance of the AI-based forecasting model. The model results in reduced prediction errors after hyperparameter tuning, which shows that it can learn from primary system data better. Three statistical measures, namely Mean Absolute Error, Root Mean Square Error, and Mean Absolute Percentage Error, were used to evaluate forecasting accuracy. Table 2 indicates that the forecasting model based on Artificial Intelligence gave good predictability with low error values.

Table 2. Performance evaluation of the AI-based forecasting model

Evaluation Metric	Training Set	Validation Set	Testing Set
Mean Absolute Error (kW)	0.118	0.146	0.162
Root Mean Square Error (kW)	0.157	0.189	0.214
Mean Absolute Percentage Error (%)	3.42	4.18	4.76
Coefficient of Determination, R^2	0.972	0.951	0.938
Prediction accuracy (%)	96.58	95.82	95.24

The testing result revealed a Mean Absolute Percentage Error of 4.76%, which means the AI model has high accuracy in predicting the renewable energy output. The model accounted for the highest percentage of the renewable power output variation, with an R^2 of 0.938. While the slight difference in performance between the training and testing sets indicated that significant overfitting was not occurring, it is still possible that the model was overfitting.

Next, it was found that solar irradiance, battery state of charge, and panel temperature had the greatest influence on the prediction of the output of renewable energy. The generation capacity showed the highest positive correlation with solar irradiance, whereas high panel temperature showed a negative effect on energy conversion efficiency.

Comparison of System Performance Before and After AI Optimization

The working ability of the renewable energy system before and after applying the AI-driven optimization model was compared. The "baseline system" was the conventional operation method; the "optimized system" was the method after introducing the AI-based forecasting, storage scheduling, and demand-supply balancing.

The results of the comparison were more than just a few positive gains in energy efficiency, renewable energy use, battery operation, and power stability after implementing AI optimization. The percentage improvements and comparative analytical outputs were created using Python. Based on the analysis of Table 3, it is suggested that the application of AI optimization enhanced power output, energy efficiency, renewable use, and demand-supply balance.

Table 3. Comparison of renewable energy system performance before and after AI optimization

Performance Indicator	Before AI Optimization	After AI Optimization	Improvement
Average power output (kW)	3.48	3.92	12.64%
Energy efficiency (%)	78.35	87.42	11.58%
Renewable energy utilization rate (%)	74.80	88.60	18.45%
Energy loss (%)	15.70	8.95	42.99% reduction

Battery utilization efficiency (%)	72.40	84.75	17.06%
Demand-supply balancing accuracy (%)	81.25	93.40	14.95%
Power fluctuation index	0.184	0.097	47.28% reduction
Average operating cost per kWh	0.142	0.119	16.20% reduction

The results showed that, after the application of AI, the average power output increased from 3.48 kW to 3.92 kW. The energy efficiency increased from 78.35 to 87.42%, and the share of renewable energy has risen from 74.80 to 88.60%. This enhancement was attributed to the optimization of power dispatch and the reduction of power mismatch between generation, storage, and load demand using the AI model.

Energy loss was reduced from 15.70% to 8.95%, which is a 42.99% reduction. This reduction demonstrated the benefits of using renewables generated by the AI control. The efficiency of battery utilization also increased from 72.40% to 84.75%, indicating an improvement in charging and discharging schedules as a result of the AI model. After optimization, the output stability improved by reducing the power fluctuation index. Figure 2 shows the benefits of AI optimisation on key renewable energy system performance metrics.

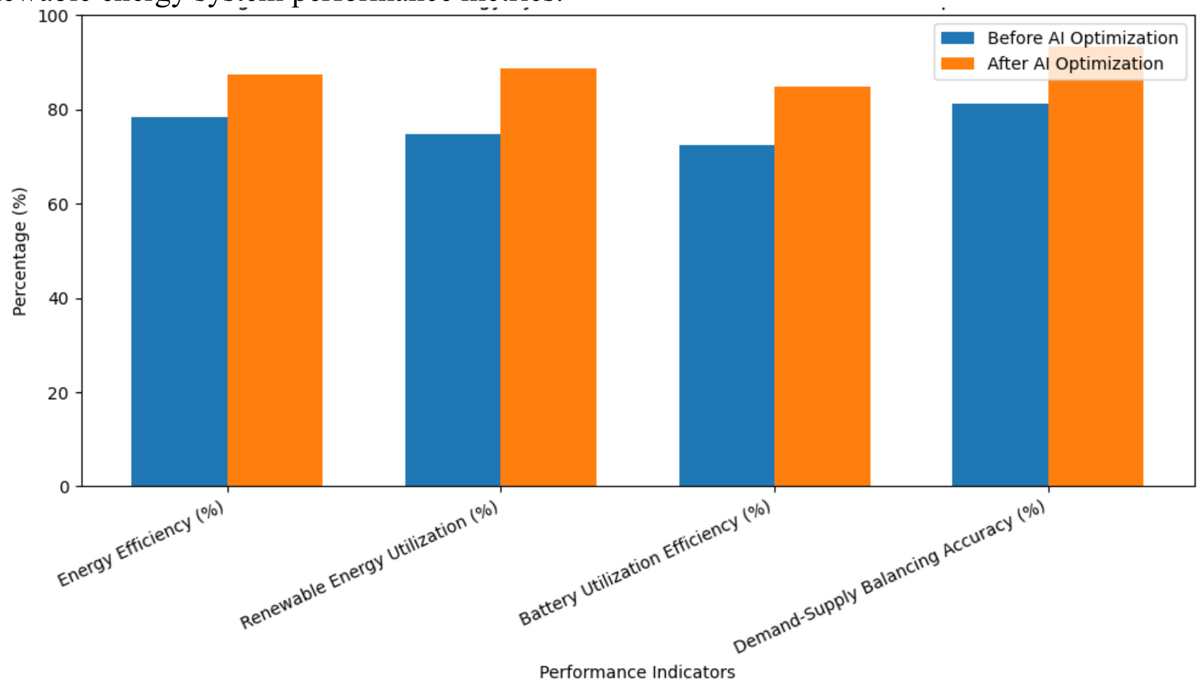

Figure 2. Renewable energy system performance before and after AI optimization

Environmental and Operational Impact of AI Optimization

The energy saving, carbon emission reduction, cost reduction, and system reliability indicators were used to assess the environmental and operational effects of the optimization model developed using AI. The optimized system demonstrated better sustainability performance than the baseline system due to the following reasons: Table 4 indicates that AI optimization decreased reliance on the grid, increased reliability, and helped to maintain a sustainable environment.

Table 4. Environmental and operational impact of AI-driven optimization

Impact Indicator	**Baseline System**	**AI-Optimized System**	**Net Change**
Daily usable renewable energy (kWh/day)	27.84	31.36	+3.52 kWh/day

Monthly energy saving (kWh/month)	0.00	105.60	+105.60 kWh/month
Estimated monthly cost saving (%)	0.00	16.20	+16.20%
Estimated carbon emission reduction (kg CO_2/month)	0.00	74.45	+74.45 kg CO_2/month
Battery discharge during peak load (%)	64.30	78.85	+22.63%
Grid dependency (%)	25.20	13.75	45.44% reduction
System reliability (%)	84.60	94.25	+11.41%
Fault detection response accuracy (%)	79.40	91.70	+15.49%

The system optimized by AI increased the usable renewable energy by 3.52 kWh/day on a daily basis. This equates to an extra 3.52 kWh/day of usable renewable energy. The energy saving was estimated as 105.60 kWh/month per month, showing that the use of available renewable resources is improved through the use of AI-based optimization.

The reduction in carbon emissions was estimated to be 74.45kg CO_2/month due to the lower dependence on traditional grid electricity. This resulted in a reduction in the degree of grid dependency from 25.20% to 13.75%, which is 45.44%. This result indicated that the optimized system used a greater proportion of locally generated renewable energy.

In this regard, after the optimization of AI, there has been an increase in the reliability of the system, which now stands at 94.25%, compared to its initial value of 84.60%. Furthermore, the accuracy of the response to fault detection has also been increased from 79.40% to 91.70%. From these results, it can be seen that AI helps optimize the use of energy while also contributing to the reliability of the system, sustainability, and efficient renewable energy management.

Discussion

The results indicated that the optimisation of renewable energy systems using AI technology boosted their performance in several areas: power generation, accuracy of energy predictions, minimization of energy losses, optimisation of battery utilisation, and reduction of dependence on the grid. The findings show that AI-based models can facilitate adapting the management of renewable energy more effectively than a traditional rule-based approach. The generation of renewable energies is variable because of the dependence on irradiance, temperature, the condition of storage, and the demand for load. In this study, the efficiency of the prediction accuracy has been improved, which indicates that there is a non-linear relationship between solar irradiance and temperature, battery state of charge, voltage, current, and power output. This is consistent with the previous studies that demonstrated the use of advanced neural network models for better forecasting of renewable energy by learning complex temporal and environmental patterns from energy data (Nascimento et al., 2023; Al-Dahidi et al., 2021).

One of the significant results of the study was the forecasting ability of the AI model. The model achieved low error values and high accuracy in predicting renewable power, demonstrating the effectiveness of using AI modelling with Python for renewable power estimation. Accurate forecasting is crucial as renewable energy is unpredictable and weather-dependent. Battery charging and discharging, load scheduling, and providing grid support can be managed more efficiently if power generation is predicted accurately in the future. The results are in accordance with previous studies, indicating that deep learning and ensemble ANT approaches can alleviate uncertainty in renewable energy forecasting and optimize energy system operation (Nascimento et al., 2023; Al-Dahidi et al., 2021).

The power output and energy efficiency of the system before and after optimization revealed a positive impact of AI optimization. This baseline-to-optimized performance comparison demonstrated that AI optimization boosts the average power output and enhances energy efficiency. This improvement is probably due to improved coordination between power generation, energy storage, and load demand. Traditional ways of managing renewable energy systems react to changes in the system after they happen, whereas AI-based systems can predict the system and make the best decision before it happens. This forecast power is beneficial for renewable energy systems, where energy needs and energy supply fluctuate during the day. Reinforcement learning (RL) has also been found to be a suitable approach for dynamic energy decision making as it allows a model to learn optimal control actions when the system conditions change (Perera & Kamalaruban, 2021).

AI optimization of batteries also led to better utilization. The finding is significant as energy storage is a critical component to the reliability of renewable energy. If the storage management is poor, then during the high generation period, power will be wasted and, during the low generation period, dependence on the grid will be increased. The AI model enhanced battery scheduling, enabling optimal charging and discharging decisions. This result aligns with previous works that have demonstrated the application of deep reinforcement learning (DRL) to optimize the use of battery storage under different operating conditions for hybrid battery systems (Li et al., 2021). Other methods, such as AI-based approaches, have been employed to enhance battery state of charge and battery state of health estimation, which are crucial for safe and efficient battery management (Shi et al., 2023).

The benefits of optimizing renewable energy systems in terms of energy reduction prove the effectiveness of AI in energy system control in practice. Losses can happen due to poor dispatch, lack of good demand-supply matching, unstable power flow, and poor storage operation. With the optimized system, these losses were minimized by optimizing energy allocation and reinforcing the balance between energy produced and consumed. In renewable storage systems, forecast-based control can help with the decision-making process, as it is possible to make decisions based not only on the current state of the system but also on its future availability. This enables research on AI agents and deep reinforcement learning to forecast for renewable energy storage systems (Dreher et al., 2022).

Furthermore, the study found that AI optimization made it possible to reduce the dependence on the grid and increase reliability. Lowering the dependence on the grid implies that less external energy will be required to operate the system and that more renewable energy will be produced within the region. This can also lead to cost savings and reduced greenhouse gas emissions. It also shows that AI optimization contributed towards making the system stable by reducing any fluctuation in its operation. Despite the usefulness of the AI-based optimization approach in improving power system flexibility and resilience, it has several shortcomings. Although the AI-based optimization strategy proved effective in improving power system flexibility, resilience, and operational efficiency in HR power systems, there are some drawbacks associated with its application.

As observed from the environmental results, there is an evident positive influence of AI-driven optimization in improving sustainable electricity production through increased renewable energy utilization and decreased electricity usage from the grid. This resulted in lower carbon dioxide emissions. The use of AI in renewable energy production and the application of intelligent technologies in optimizing energy production and consumption have been discussed in the literature on sustainable energy production (Shelare et al., 2023).

The results of the study should be considered in the context of the scope of the study. The conclusions have been made based on the primary data collected from a certain renewable energy system, and such data may not apply to other large-scale systems connected to a grid and different weather conditions. Moreover, factors like the quality of sensors used, volume of data, weather variability, design of the model, and computation power could impact the performance of the AI optimization strategy. There is also a need to validate the model for a variety of renewable energy sources, periods of observation, and geographic areas. Explainable AI, cybersecurity, and frameworks for real-time implementation are among the aspects to investigate. Based on the analysis, an AI optimization strategy could improve prediction accuracy, energy efficiency, use of batteries, reliability, and sustainability of renewable energy sources.

Conclusion

This study concluded that artificial intelligence-driven optimization significantly improved the performance of renewable energy systems for sustainable power generation. From the results, it is evident that the use of the AI model created in Python led to an increase in the forecast accuracy, average power generation, energy efficiency, reduction in energy losses, and improved demand and supply balance. In addition, the use of AI helped in optimising the system's battery usage through optimising the battery charging and discharging rates, thus reducing dependence on the system grid in situations when the generation of energy was at its lowest level. Moreover, the results revealed that the use of the AI optimization strategy led to environmental sustainability by maximising the amount of renewable energy generated while minimising carbon emissions. Therefore, the results suggest that there are opportunities for the use of AI in controlling renewable energy systems since the system variability and complexities could be controlled through AI. Furthermore, the study found that the creation of models capable of providing forecasts and controlling energy systems could be accomplished using primary data with the help of AI. Although this research has made several important contributions in this field, the current findings are only applicable to the current energy system and can differ with changes in system scale, climate, and grid environment.

References

1. Ahmed, W., Ansari, H., Khan, B., Ullah, Z., Ali, S. M., Mehmood, C. A. A., ... & Nawaz, R. (2020). Machine learning-based energy management model for smart grid and renewable energy districts. *IEE Access*, *8*, 185059-185078.
2. Al-Dahidi, S., Baraldi, P., Zio, E., & Montelatici, L. (2021). Bootstrapped ensemble of artificial neural networks technique for quantifying uncertainty in prediction of wind energy production. *Sustainability*, *13*(11), 6417.
3. Allal, Z., Noura, H. N., Salman, O., & Chahine, K. (2024). Machine learning solutions for renewable energy systems: Applications, challenges, limitations, and future directions. *Journal of Environmental Management*, *354*, 120392.
4. Alsaigh, R., Mehmood, R., & Katib, I. (2023). AI explainability and governance in smart energy systems: A review. *Frontiers in Energy Research*, *11*, 1071291.
5. Benti, N. E., Chaka, M. D., & Semie, A. G. (2023). Forecasting renewable energy generation with machine learning and deep learning: Current advances and future prospects. *Sustainability*, *15*(9), 7087.
6. Cao, D., Hu, W., Zhao, J., Zhang, G., Zhang, B., Liu, Z., ... & Blaabjerg, F. (2020). Reinforcement learning and its applications in modern power and energy systems: A review. *Journal of modern power systems and clean energy*, *8*(6), 1029-1042.
7. Chatterjee, S., Khan, P. W., & Byun, Y. C. (2024). Recent advances and applications of machine learning in the variable renewable energy sector. *Energy Reports*, *12*, 5044-5065.
8. Dreher, A., Bexten, T., Sieker, T., Lehna, M., Schütt, J., Scholz, C., & Wirsum, M. (2022). AI agents envisioning the future: Forecast-based operation of renewable energy storage systems using hydrogen with Deep Reinforcement Learning. *Energy Conversion and Management*, *258*, 115401.
9. Jung-Pin, L., Yu-Ming, C., Chieh-Huang, C., & Pai, P. F. (2020). A survey of machine learning models in renewable energy predictions. *Applied Sciences*, *10*(17), 5975.
10. Krishnamurthy, S., Adewuyi, O. B., & Salimon, S. A. (2026). Recent advances in artificial intelligence-based optimization for power system applications: A review of techniques, challenges, and future directions. *Renewable and Sustainable Energy Reviews*, *226*, 116340.
11. Li, W., Cui, H., Nemeth, T., Jansen, J., Uenluebayir, C., Wei, Z., ... & Sauer, D. U. (2021). Deep reinforcement learning-based energy management of hybrid battery systems in electric vehicles. *Journal of Energy Storage*, *36*, 102355.
12. Li, Y., Ding, Y., He, S., Hu, F., Duan, J., Wen, G., ... & Zeng, Z. (2024). Artificial intelligence-based methods for renewable power system operation. *Nature Reviews Electrical Engineering*, *1*(3), 163-179.
13. Nascimento, E. G. S., de Melo, T. A., & Moreira, D. M. (2023). A transformer-based deep neural network with wavelet transform for forecasting wind speed and wind energy. *Energy*, *278*, 127678.

14. Nguyen, H. N., Tran, Q. T., Ngo, C. T., Nguyen, D. D., & Tran, V. Q. (2025). Solar energy prediction through machine learning models: A comparative analysis of regressor algorithms. *PloS one*, *20*(1), e0315955.
15. Perera, A. T. D., & Kamalaruban, P. (2021). Applications of reinforcement learning in energy systems. *Renewable and Sustainable Energy Reviews*, *137*, 110618.
16. Shelare, S. D., Belkhode, P. N., Nikam, K. C., Jathar, L. D., Shahapurkar, K., Soudagar, M. E. M., ... & Rehan, M. (2023). Biofuels for a sustainable future: Examining the role of nano-additives, economics, policy, internet of things, artificial intelligence and machine learning technology in biodiesel production. *Energy*, *282*, 128874.
17. Shi, D., Zhao, J., Wang, Z., Zhao, H., Eze, C., Wang, J., ... & Burke, A. F. (2023). Cloud-based deep learning for co-estimation of battery state of charge and state of health. *Energies*, *16*(9), 3855.
18. Stergiou, K., & Karakasidis, T. (2024). Optimizing Renewable Energy Systems Placement Through Advanced Deep Learning and Evolutionary Algorithms. *Applied Sciences*, *14*(23), 10795.
19. Sun, M., Zhang, T., Wang, Y., Strbac, G., & Kang, C. (2019). Using Bayesian deep learning to capture uncertainty for residential net load forecasting. *IEEE Transactions on Power Systems*, *35*(1), 188-201.
20. Ying, C., Wang, W., Yu, J., Li, Q., Yu, D., & Liu, J. (2023). Deep learning for renewable energy forecasting: A taxonomy, and systematic literature review. *Journal of Cleaner Production*, *384*, 135414.