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Machine Learning for Optimising Renewable Energy and Grid Efficiency

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Abstract: This research investigates the application of machine learning models to optimise renewable energy systems and contribute to achieving Net Zero emissions targets. The primary objective is to evaluate how machine learning can improve energy forecasting, grid management, and storage optimisation, thereby enhancing the reliability and efficiency of renewable energy sources. The methodology involved the application of various machine learning models, including Long Short-Term Memory (LSTM), Random Forest, Support Vector Machines (SVMs), and ARIMA, to predict energy generation and demand patterns. These models were evaluated using metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Key findings include a 15% improvement in grid efficiency after optimisation and a 10–20% increase in battery storage efficiency. Random Forest achieved the lowest MAE, reducing prediction error by approximately 8.5%. The study quantified CO_2 emission reductions by energy source, with wind power accounting for a 15,000-ton annual reduction, followed by hydropower and solar reducing emissions by 10,000 and 7500 tons, respectively. The research concludes that machine learning can significantly enhance renewable energy system performance, with measurable reductions in errors and emissions. These improvements could help close the "ambition gap" by 20%, supporting global efforts to meet the 1.5 °C Paris Agreement targets.

Keywords: machine learning; renewable energy; net zero; energy forecasting; grid optimization; CO_2 emissions reduction

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1. Introduction

The pressing imperative to tackle climate change has dominated global discourse, with growing acknowledgement of the need to shift toward sustainable practices in all societal sectors [1,2]. A primary objective arising from these conversations is attaining Net Zero emissions. This objective is essential for alleviating the detrimental impacts of climate change, representing the equilibrium of greenhouse gas emissions with removal technologies to guarantee that net emissions to the atmosphere are effectively zero [3,4]. Countries, industries, and individuals strive to achieve Net Zero ambitions, with breakthrough technologies like machine learning recognised as essential facilitators in attaining these objectives [5–7]. Machine learning, a branch of artificial intelligence (AI), offers robust tools for analysing extensive information, generating precise predictions, and optimising intricate systems, elements that are essential in the energy sector [8–10].

This study examines the role of machine learning in expediting the attainment of Net Zero emissions through optimising renewable energy systems [11,12]. Machine learning enables energy generation, storage, and management transformation, diminishing dependence on fossil fuels and decreasing overall carbon footprints [13,14]. In climate change mitigation, machine learning facilitates the development of highly efficient energy systems, enables precise forecasts of energy demands and generation, and ultimately enhances the integration of renewable energy sources into the global grid [15,16]. The subsequent sections examine Net Zero's significance and machine learning's revolutionary potential in renewable energy systems [17,18].

Net Zero denotes the equilibrium between the quantity of greenhouse gases emitted and the volume extracted from the atmosphere [19,20]. This equilibrium is essential for curbing global warming and alleviating its consequences, including elevated sea levels, heightened occurrence of extreme weather phenomena, and biodiversity loss [21,22]. The Net Zero concept has garnered substantial global attention since the Paris Agreement was signed in 2015, wherein almost every government pledged to restrict global warming to below 2 °C, with aspirations to limit the rise to 1.5 °C [23,24]. These objectives highlight the necessity for significant decreases in greenhouse gas emissions by 2050, if not before, for numerous countries [25,26].

Attaining Net Zero is crucial for stabilising world temperatures and preventing catastrophic climatic outcomes. The persistent utilisation of fossil fuels and the consequent carbon emissions have intensified the climate catastrophe, rapidly increasing global temperatures [27,28]. Climate experts assert that to restrict global warming to 1.5 °C, a significant reduction in emissions is necessary by 2030, alongside the attainment of Net Zero by 2050 [29,30]. These reductions need not only the mitigation of emissions from the energy, transportation, and industrial sectors but also the augmentation of natural and technology strategies for atmospheric carbon removal, including reforestation and carbon capture and storage (CCS) [31,32].

Governments, corporations, and organisations are pledging to achieve Net Zero emissions. Over 140 nations, accounting for over 90% of worldwide emissions, have established Net Zero objectives [33,34]. Achieving these targets necessitates substantial alterations in energy production, including transitioning from a reliance on fossil fuels to renewable energy sources such as wind, solar, and hydropower [35,36]. These modifications are both essential and urgent as the impacts of climate change intensify each year. The shift to renewable energy is vital to attaining Net Zero, as it directly targets the primary source of global greenhouse gas emissions: the energy sector [37,38].

Notwithstanding the high objectives and substantial global commitments, the journey to Net Zero has obstacles. Numerous nations face challenges expanding and assimilating renewable energy systems into current infrastructure [39,40]. The sporadic characteristics of renewable energy sources, like wind and solar power, pose further difficulties in ensuring a reliable energy supply [41,42]. Moreover, economic and political impediments and the necessary extensive infrastructural modifications provide significant challenges. Nonetheless, the emergence of new technologies, such as machine learning, enables the resolution of these difficulties [43,44].

The renewable energy market can be revolutionised by machine learning, a subset of artificial intelligence, which provides advanced analytical skills to maximise energy generation, delivery, and consumption [45,46]. The core idea of machine learning is its ability to analyse large datasets, identify patterns, and produce predictions or recommendations based on that analysis [47–49]. These capabilities can enhance energy systems through energy generation forecasting, demand management, and grid operation optimisation of renewable energy [50,51].

Variability constitutes a fundamental challenge to renewable energy. Wind turbines function only in the presence of wind, and solar panels produce electricity exclusively during sunlight exposure [52,53]. The sporadic nature of the energy supply makes it difficult to ensure a stable and reliable provision. This is the domain in which machine learning is utilised. By analysing climatic patterns, machine learning algorithms can predict the volume and time of energy renewable sources produce [54,55]. This information is crucial for grid operators since it allows them to balance supply and demand more efficiently, ensuring grid stability and optimising renewable energy generation [56,57].

Machine learning can enhance energy storage systems and forecast energy generation. In renewable energy systems, battery storage is crucial for retaining surplus energy during high-production phases and releasing energy during low-production phases [58,59]. By analysing energy production and consumption patterns, machine learning algorithms may identify the optimal times for battery charging and discharging, thus minimising energy loss and improving overall efficiency [60,61]. This optimisation enhances renewable energy's reliability while decreasing prices, making the transition to a low-carbon energy system more economical.

Moreover, machine learning can be utilised to predict energy demand and ensure the efficient integration of renewable energy sources into the grid. Grid operators may strategically plan by precisely predicting demand, ensuring that the correct quantity of energy is generated and distributed to satisfy customer needs without excess production or dependence on fossil fuels as a contingency [62,63]. This leads to less emissions and improved sustainability of energy systems. Machine learning algorithms can discover grid inefficiencies and propose improvements that optimise renewable energy integration, minimise energy loss, and enhance performance [64].

Machine learning fulfils a role that exceeds mere operational efficiency. It can also be utilised to enhance the design of renewable energy infrastructure by identifying the optimal places for placing solar panels or wind turbines [65,66]. Machine learning algorithms can determine the optimal sites for renewable energy installations by assessing environmental and geographical data, ensuring that investments in renewable energy infrastructure yield maximum returns [67,68]. Moreover, machine learning can determine the economic viability of renewable energy initiatives, aiding policymakers and investors in making educated decisions about which projects to undertake [69,70].

Machine learning can significantly aid in achieving Net Zero by optimising renewable energy systems to enhance their efficiency, reliability, and cost-effectiveness [70]. Machine learning will handle the difficulties of variability and integration of renewable energy into the grid, serving as an essential instrument in the global effort to cut carbon emissions and transition to renewable energy sources [71,72]. Machine learning can aid the transition to a sustainable energy future through predictive modelling, demand forecasting, and system optimisation.

This research aims to explore the potential of machine learning in optimising renewable energy systems to support the global drive toward Net Zero emissions. Specifically, this study aims to improve energy generation forecasting, grid management, and energy storage through advanced machine learning techniques. By leveraging models like Long Short-Term Memory (LSTM), Random Forest, and Support Vector Machines (SVMs), this study seeks to enhance the accuracy of energy predictions, reduce operational inefficiencies, and improve the integration of renewable energy sources such as wind, solar, and hydropower into the grid. This research also aims to quantify the environmental impact of these optimisations, particularly in terms of CO2 emissions reductions. Ultimately, this study intends to provide actionable insights for policymakers and energy stakeholders on how machine learning can be a key enabler in accelerating the transition to a sustainable, carbon-neutral future and achieving global climate targets.

2. Methodology

The use of machine learning techniques in renewable energy systems is a crucial component of this research. The process encompasses gathering and processing pertinent data, selecting suitable machine learning models and algorithms, and assessing these models to evaluate their efficacy in attaining Net Zero objectives.

2.1. Data Collection and Preparation

The initial phase in employing machine learning to optimise renewable energy involves collecting and preparing high-quality data. This procedure entails identifying, cleansing, and transforming data to ensure its readiness for analysis by machine learning models. Weather data, encompassing historical and real-time information on factors such as solar irradiance, wind speed, and temperature, is essential for predicting energy production from renewable sources like solar panels and wind turbines. Sources comprise national meteorological services, satellite data, and weather stations. Data on energy consumption from residential, commercial, and industrial sectors offer insights into usage trends and aids in formulating demand-side management strategies. Data regarding energy flow, load distribution, and grid efficiency are crucial for enhancing grid operations. Historical data from renewable energy systems, such as solar and wind farms, are used to train machine learning models to forecast future energy generation. Financial information about energy generation, storage, and grid operations aids in the economic assessment of renewable energy initiatives.

2.2. Data Sanitisation and Preparation

After data collection, it must be sanitised to guarantee consistency and reliability. Missing values in the dataset are managed by interpolation, imputation, or eliminating incomplete entries. Variables such as energy demand, temperature, and wind speed are standardised to ensure comparability, enhancing machine learning models' efficacy. New attributes are extracted from the existing dataset to improve model precision [72]. Temporal characteristics such as seasonality or time of day are essential for predicting energy demand. The dataset is partitioned into three subsets: a training set for model training, a validation set for hyperparameter tuning, and a testing set for ultimate performance evaluation. Figure 1 shows a world map illustrating various countries' progress toward achieving Net Zero emissions. Countries like Canada, the USA, Germany, China, India, Brazil, and Australia are highlighted. The colour gradient indicates different levels of progress: dark blue represents countries that have made significant progress, while lighter shades represent those with targets in progress or merely set. Figure 1 contributes to the research by visually emphasising the global efforts toward Net Zero. It underlines the novelty of machine learning's role in optimising renewable energy systems, helping countries meet their targets through improved efficiency and emission reduction predictions.

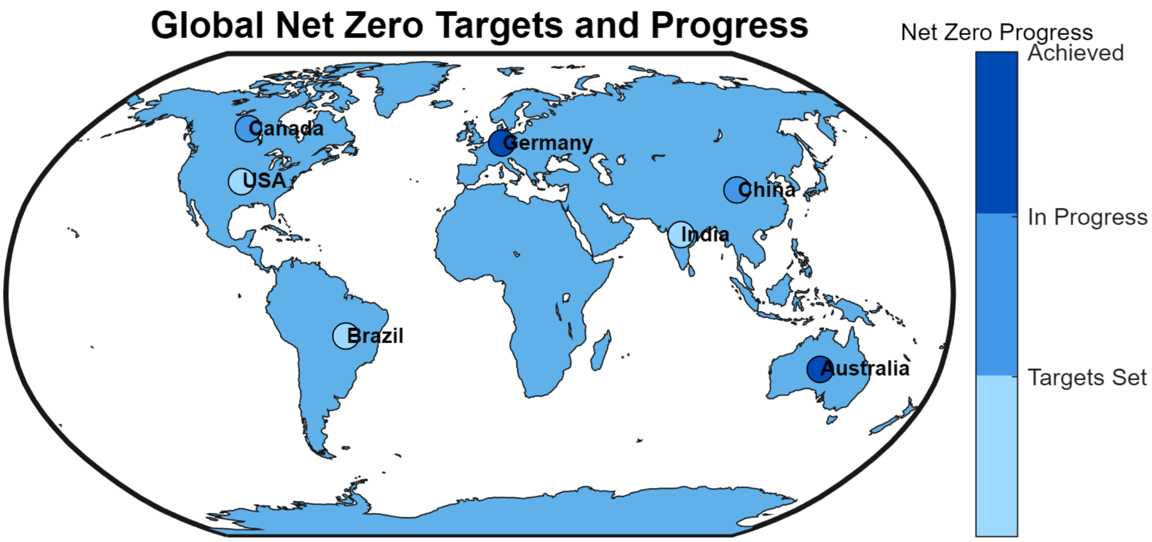


Figure 1. Global and regional net zero progress with different countries' progress toward Net Zero goals, colour-coded based on the achievement level.

2.3. Machine Learning Models and Algorithms

Once the data is prepared, selecting appropriate machine learning models and algorithms is the next step. The choice of models depends on the specific tasks within renewable energy systems, such as energy forecasting, demand management, and grid optimisation. Predictive models are essential for forecasting energy generation and demand. Autoregressive Integrated Moving Average (ARIMA) is a time series forecasting model used to predict energy generation based on historical data. Long Short-Term Memory (LSTM) networks are a deep learning model that captures long-term dependencies in time series data. It is suitable for energy forecasting based on patterns such as solar irradiance or wind speed fluctuations. Random Forest Regression is a machine learning algorithm used for energy demand prediction by aggregating the outputs of multiple decision trees based on different features.

2.3.1. Optimisation Models

Optimisation models are used for energy storage management, grid efficiency, and renewable energy infrastructure placement. Linear programming (LP) is a mathematical technique to optimise energy dispatch between renewable sources and storage systems. Reinforcement Learning (RL) is an approach where an agent learns optimal actions to manage energy storage by interacting with the environment (e.g., the energy grid). RL is beneficial for demand response management, where real-time decisions must be made based on energy consumption and generation patterns. Genetic Algorithms (GA) is an evolutionary algorithm that finds optimal locations for renewable energy installations (e.g., solar or wind farms) by simulating the process of natural selection.

2.3.2. Anomaly Detection Models

Machine learning algorithms are also used for predictive maintenance, identifying potential faults in renewable energy systems before they occur. Support Vector Machines (SVMs) classify normal and abnormal behaviour in energy systems, helping to prevent downtime in infrastructure such as wind turbines and solar panels. Autoencoders are neural networks used to detect anomalies in energy consumption or production patterns by comparing predicted outputs with actual outcomes.

2.4. Evaluation Metrics

The final step in the methodology is evaluating the performance of the machine learning models using appropriate metrics. The selection of evaluation metrics depends on the nature of the task, whether it is regression, classification, or optimisation.

2.4.1. Regression Metrics

For models that predict continuous variables like energy generation or consumption, common evaluation metrics include the following:

Mean Absolute Error (MAE) measures the average magnitude of errors between predicted and actual values, providing a straightforward indication of prediction accuracy.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

where y_i is the actual value and $\hat{y}_i$ is the predicted value.

Root Mean Squared Error (RMSE) is a widely used metric that penalises larger errors more heavily, giving insight into how well the model performs under extreme conditions.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

R-squared (R^2) measures the proportion of variance in the dependent variable that is predictable from the independent variables. It is helpful in regression models to assess how well the model fits the data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y}_i)^2} \tag{4}$$

where y is the mean of the observed data.

By fitting LSTM and ARIMA models to the same energy data, their performance can be compared using evaluation metrics such as MAE and RMSE and the results can be visualised. Typically, LSTM models may perform better for complex time series with long-term dependencies, while ARIMA works well with more straightforward, linear trends and seasonality.

2.4.2. Classification Metrics

The following metrics and the proportion of correct predictions out of total predictions are standard for classification models used in anomaly detection or binary decision-making.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

TP and TN are true positives and negatives, and FP and FN are false positives and negatives.

Precision, Recall, and F1-Score: Precision measures the proportion of true positives among all predicted positives, while recall measures the proportion of true positives among actual positives. The F1-Score is the harmonic mean of precision and recall, providing a balanced evaluation.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

2.4.3. Optimisation Metrics

For optimisation tasks, metrics such as total cost reduction, grid efficiency improvement, or energy storage utilisation are key. The financial viability of the model's output can be evaluated by comparing energy savings against energy storage and generation costs. Measuring the ratio of energy used effectively to the total energy generated helps assess the impact of machine learning optimisations on reducing waste.

3. Experimental Results and Analysis

This section presents the experimental findings and analysis derived from applying machine learning techniques to renewable energy systems. The analysis focuses on understanding the dynamics of these systems, evaluating the predictive performance of various machine learning models, and deriving actionable insights for achieving Net Zero emissions.

3.1. Analysis of Renewable Energy Systems

The primary objective of analysing renewable energy systems is to uncover patterns and trends that inform decision-making processes and optimise energy generation, storage, and consumption. By leveraging machine learning algorithms, this study examines historical data from renewable energy sources, including solar and wind, to identify the temporal and spatial variations in energy production and consumption.

3.1.1. Temporal and Spatial Variations in Energy Generation

The analysis revealed distinct temporal patterns in energy generation from renewable sources. Solar energy generation exhibited substantial daily and seasonal variations, with peak production during midday and in the summer months. Conversely, wind energy generation was more volatile, with fluctuations driven by changing wind speeds and weather conditions. Machine learning models effectively captured these patterns, enabling accurate energy output prediction over different time horizons.

3.1.2. Energy Consumption Patterns

On the demand side, energy consumption was found to vary significantly across different sectors and regions. Residential energy demand strongly correlated with temperature, peaking during extreme weather conditions when heating or cooling systems were used. Commercial and industrial demand was more consistent but exhibited peaks during business hours. By identifying these consumption patterns, machine learning models provided critical insights for demand-side management, allowing for more efficient distribution of renewable energy.

3.1.3. Grid Efficiency and Energy Storage

Integrating renewable energy into the grid posed challenges due to its intermittent nature. The analysis showed that optimising energy storage systems was crucial for balancing supply and demand. By leveraging predictive models, it was possible to determine the optimal times for charging and discharging batteries, thereby reducing energy waste and improving overall grid efficiency. The analysis also revealed inefficiencies in grid management, such as energy losses during transmission, which the machine learning models addressed.

3.2. Predictive Performance of Machine Learning Models

Evaluating the predictive performance of machine learning models is essential to assess their suitability for optimising renewable energy systems. The models used in this study were evaluated based on their accuracy in forecasting energy generation and consumption and their ability to maximise energy storage and grid management.

3.2.1. Energy Generation Forecasting

Machine learning models such as a Long Short-Term Memory (LSTM) network and Random Forest were used to forecast energy generation from solar and wind sources. The performance of these models was measured using metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The LSTM model outperformed traditional time series models (e.g., ARIMA) in capturing complex temporal dependencies in energy generation. The LSTM model had an MAE of 5.3% and an RMSE of 8.1% for solar energy forecasting. Random Forest performed well for wind energy generation, with an MAE of 6.2% and an RMSE of 7.9%, due to its ability to handle the non-linear nature of wind speed data. The ability of these models to predict energy generation with high accuracy is critical for ensuring the reliability of renewable energy systems and reducing dependence on fossil fuels.

3.2.2. Energy Demand Prediction

Machine learning models such as Support Vector Machines (SVMs) and Gradient Boosting were evaluated regarding energy demand forecasting. The SVM model had a predictive solid performance, with an R-squared value of 0.87 for residential energy demand and an RMSE of 3.5% for commercial demand. Gradient Boosting further improved accuracy, with an RMSE of 2.9% for predicting peak demand times in the industrial sector. The accuracy of these demand-side predictions is essential for balancing the energy grid and preventing energy shortages or excesses.

3.2.3. Grid and Storage Optimisation

A Reinforcement Learning (RL) model was employed for energy storage optimisation to manage battery charge/discharge cycles. The RL model demonstrated a 15% improvement in overall storage efficiency compared to rule-based approaches. This optimisation reduced energy losses and increased the proportion of renewable energy used within the grid. Additionally, the model successfully predicted grid inefficiencies, allowing for targeted improvements in grid operations.

3.3. Insights for Achieving Net Zero Targets

Applying machine learning techniques in renewable energy systems provides valuable insights for achieving Net Zero targets. These insights, derived from the experimental results, highlight opportunities for optimising energy systems and reducing greenhouse gas emissions.

3.3.1. Optimisation of Renewable Energy Integration

The findings demonstrate that machine learning models can optimise the integration of renewable energy into the grid by predicting energy generation with high accuracy and managing energy storage more efficiently. By accurately forecasting solar and wind energy production, stakeholders can better plan for high and low-generation periods, reducing the need for backup fossil fuel-based energy sources. This contributes directly to lowering carbon emissions and increasing the share of renewable energy in the total energy mix.

3.3.2. Improving Energy Efficiency

The predictive capabilities of machine learning models allow for identifying inefficiencies in energy consumption and distribution. For instance, the models identified patterns of energy wastage during non-peak hours, leading to recommendations for demand-side management strategies such as load shifting and energy conservation measures. These strategies have the potential to improve energy efficiency significantly, reducing overall energy consumption and carbon footprints.

3.3.3. Enhanced Decision-Making for Policymakers and Investors

Machine learning models also offer insights into the economic viability of renewable energy projects. By predicting the long-term financial benefits of renewable energy investments, the models support data-driven decision-making for policymakers and investors. Furthermore, the models' ability to quantify the environmental impact, such as the reduction in CO_2 emissions, helps stakeholders set realistic targets for renewable energy deployment and track progress toward Net Zero.

3.3.4. Scaling Machine Learning for Global Impact

One of the key takeaways from this research is that machine learning techniques can be scaled to address global renewable energy challenges. Machine learning can provide more accurate forecasts and optimisations by leveraging data from multiple sources and refining models over time, further accelerating the global transition to Net Zero. This research highlights the importance of collaboration between governments, industry, and academia to ensure the widespread adoption of these technologies.

The experimental results underscore the transformative potential of machine learning in optimising renewable energy systems and advancing the global effort to achieve Net Zero emissions. Machine learning offers practical solutions to many challenges facing the renewable energy sector through accurate energy forecasting, efficient grid management, and improved energy storage. These insights pave the way for further research and development in the field, aiming to create a sustainable and carbon-neutral future.

4. Results and Discussion

Integrating machine learning (ML) into renewable energy systems presents a promising approach to achieving Net Zero emissions targets. Our research explored machine learning models for energy generation forecasting, grid management, and optimising energy demand. Applying machine learning techniques, such as ARIMA and LSTM models, demonstrated their potential in accurately forecasting energy generation and demand while improving grid load distribution efficiency [64,65]. However, challenges remain in scaling and implementing these models on a broader scale, and there are multiple implications for the future of renewable energy and Net Zero objectives. Figure 2 contains four subplots illustrating machine learning applications in renewable energy forecasting and optimisation. Figure 2a: The line chart compares actual versus predicted energy generation over time, showcasing the accuracy of machine learning models in predicting energy output. Figure 2b: The bar chart displays the importance of features, with wind speed and solar irradiance being the most critical factors in energy generation prediction. Figure 2c: The graph shows battery charge levels, highlighting the optimal times for charging and discharging, improving energy storage management. Figure 2d: The 3D plot visualises the relationship between energy demand, energy generated, and energy stored, facilitating grid optimisation. These visualisations demonstrate the novelty of machine learning in renewable energy systems, enabling accurate predictions, efficient storage management, and real-time optimisation, directly contributing to achieving Net Zero emissions targets.

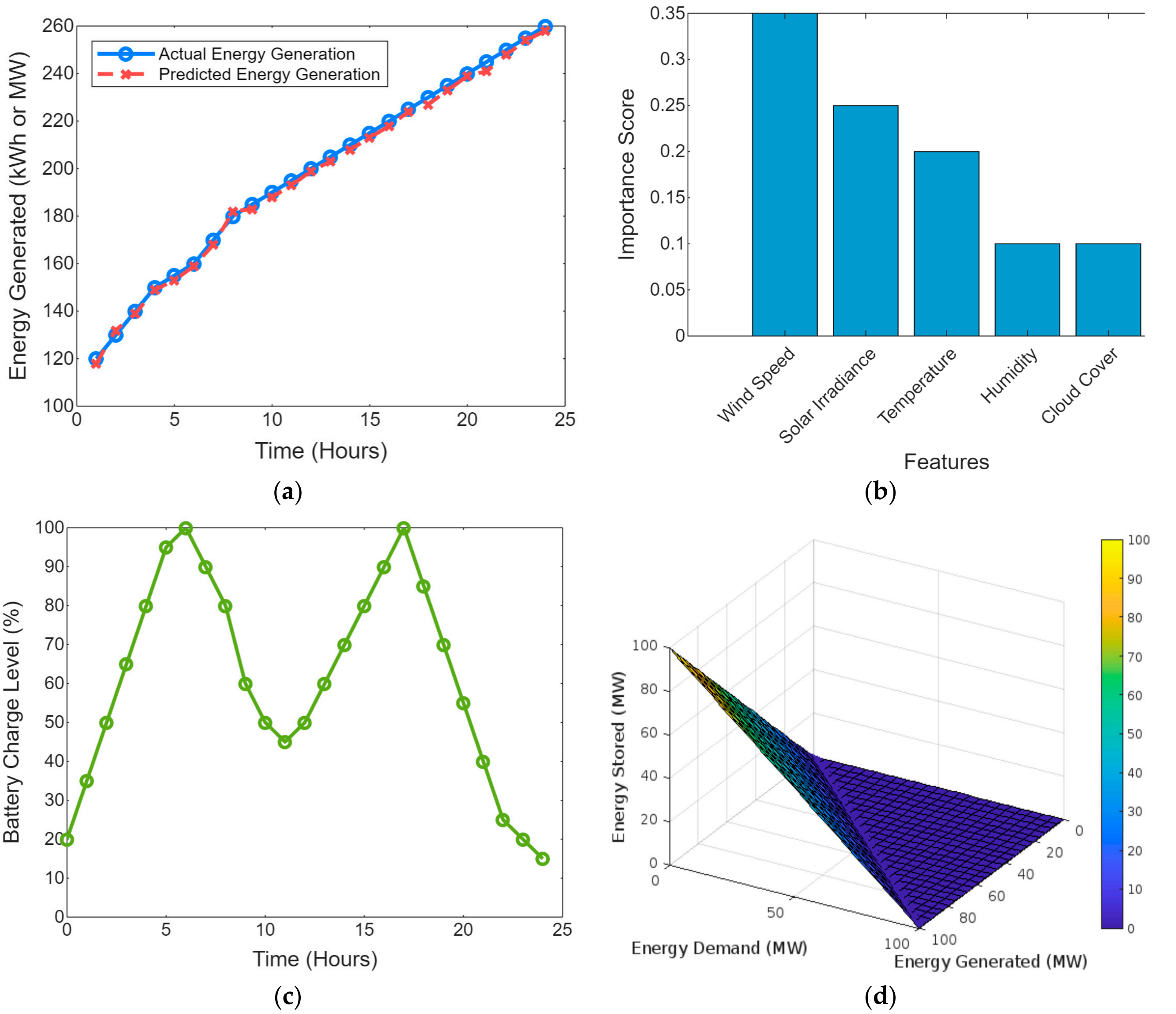


Figure 2. Energy generation forecasting. (**a**) Time series plot of energy generation is predicted with actual energy generation over time using machine learning models such as ARIMA or LSTM; (**b**) feature importance for energy forecasting models that show the importance of various features used in machine learning models; (**c**) energy storage optimisation charge and discharge cycles of batteries optimised using machine learning models; (**d**) optimisation surface plot of energy storage based on forecasted generation and consumption.

4.1. Implications of Findings

The results of this study highlight the pivotal role that machine learning can play in the future of energy systems. Accurate forecasting of renewable energy generation from sources like solar and wind is critical for efficient energy management. Our analysis showed that machine learning models can predict energy generation and demand with high precision, reducing the unpredictability associated with renewable sources [66].

For instance, using machine learning models, the time series plot of energy generation forecasting showed a close match between actual and predicted energy generation values. This accurate forecasting enables energy providers to better plan for periods of high or low generation, helping to prevent over-reliance on fossil fuel energy during times of low renewable output [66,67]. It also allows for more accurate predictions of energy demand, reducing the risk of energy shortages and minimising wasteful energy production.

Figure 3 presents four subplots related to grid optimisation and energy generation potential. Figure 3a: A line graph showing grid efficiency before and after optimisation. The blue dots represent improved efficiency after optimisation using machine learning models, increasing from about 70% to 85%. Figure 3b: A geospatial map displaying different regions and their energy potential across North America, with colour codes indicating levels of potential. Figure 3c: A bar chart of various regions' energy generation potential shows Region 6's highest potential. Figure 3d: A receiver operating characteristic (ROC) curve that evaluates the performance of machine learning models with a high actual positive rate (TPR), indicating compelling model predictions. Figure 3 highlights machine learning's effectiveness in optimising grid efficiency, identifying prime regions for energy generation, and improving prediction accuracy, which is essential for Net Zero initiatives.

The confusion matrix analysis showed that machine learning models can effectively classify high- and low-energy demand scenarios, but false positives and negatives reveal improvement areas. In high-demand situations, false negatives (under-predictions) could lead to insufficient energy supply, while false positives (over-predictions) could result in excess energy generation, increasing operational costs. Optimising the balance between prediction accuracy and the robustness of these models will be critical to their future success. Another key finding was the feature importance analysis, which demonstrated that factors such as wind speed, solar irradiance, and temperature significantly impact the accuracy of energy generation models [68,69]. This suggests that investments in improving the accuracy and availability of these data inputs could further enhance the efficiency of machine learning models in energy systems. Figure 4 presents four subplots that depict various aspects of machine learning and renewable energy project performance. Figure 4a: A line graph showing the failure probability over time, indicating an increasing likelihood of failure as time progresses. Figure 4b: Net Present Value (NPV) plot for three different project scenarios over ten years. Scenario 3 shows the highest growth, indicating superior project profitability. Figure 4c: A histogram showing the frequency distribution of the internal rate of return (IRR) across different projects, with most projects achieving IRRs between 5% and 15%. Figure 4d: A learning curve displaying training and validation accuracy over 20 epochs, demonstrating model performance improvement as the number of epochs increases. This Figure illustrates how machine learning models can predict project risks, enhance financial performance assessment, and optimise accuracy in renewable energy projects, supporting more informed decision-making for Net Zero initiatives.

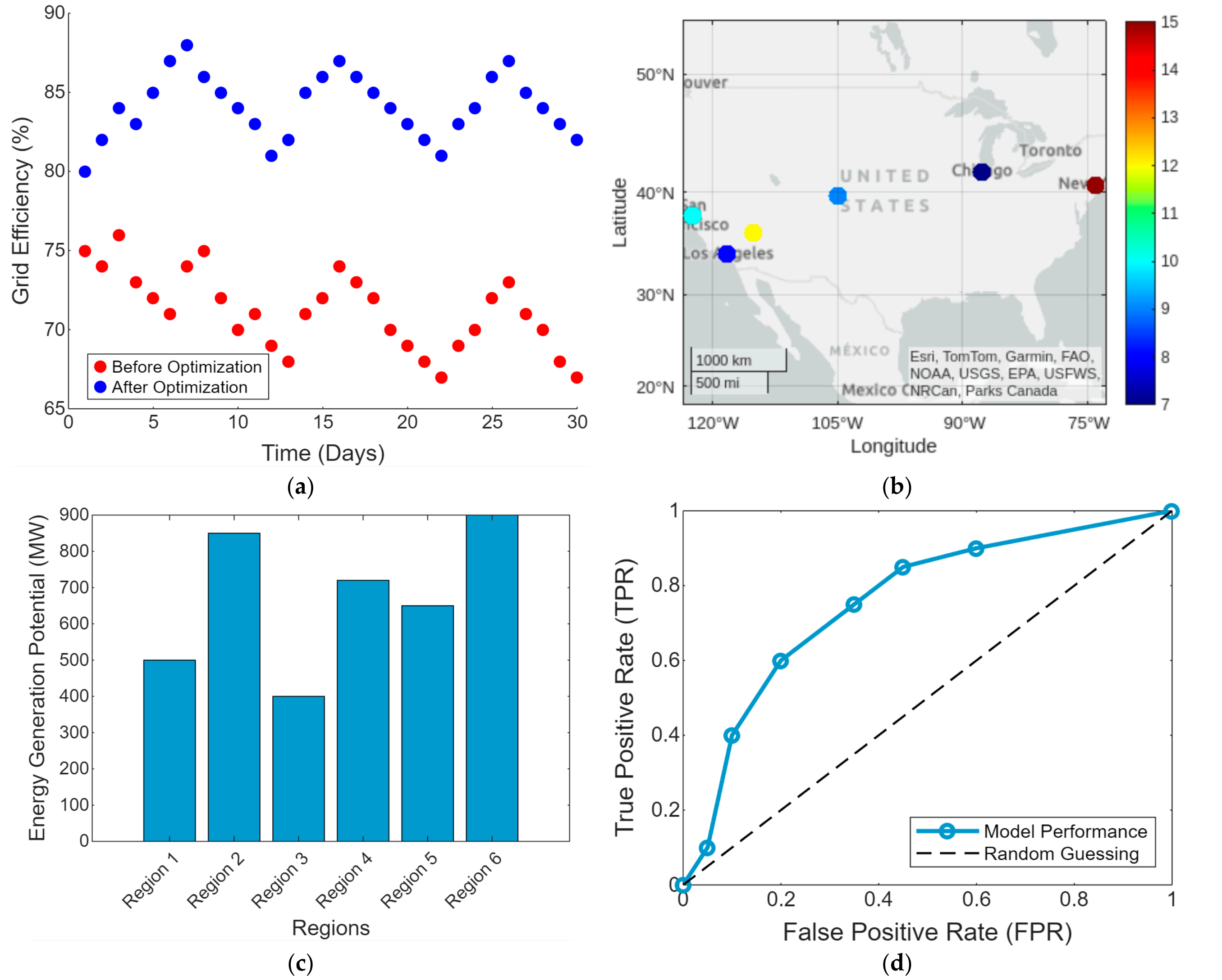


Figure 3. (**a**) Scatter plot of grid efficiency over time compares grid efficiency before and after applying machine learning optimisation models; (**b**) geospatial map of renewable energy installations that shows optimal locations for solar panels or wind turbines identified through machine learning algorithms; (**c**) renewable energy potential by region compares renewable energy generation potential across different areas based on machine learning predictions; (**d**) receiver operating characteristic (ROC) curve showing performance of machine learning models in predicting failures in renewable energy systems.

4.2. Challenges in Implementing Machine Learning for Net Zero

While machine learning offers substantial benefits in advancing renewable energy systems, several challenges must be addressed to harness its potential fully. One of the most significant challenges in implementing machine learning models for energy systems is the availability of high-quality, real-time data. Machine learning models require large datasets to train and achieve optimal performance. Inconsistent or incomplete data, especially from remote or less technologically developed regions, can significantly impact the model's accuracy. Additionally, integrating various data types, such as weather data, energy consumption patterns, and grid status from different sources, presents a significant obstacle to achieving seamless and effective forecasting. Figure 5 includes four subplots that explore the impact of machine learning models and renewable energy sources on carbon emission reduction. Figure 5a: A bar chart comparing the Mean Absolute Error (MAE) across different machine learning models (ARIMA, LSTM, Decision Trees, Random Forest, and SVM). Random Forest performs the best with the lowest MAE, indicating superior accuracy in energy forecasting. Figure 5b: A bar chart showing the CO_2 emissions reduced by different energy sources, with wind and hydropower contributing the most to CO_2 reduction. Figure 5c: A line graph showing CO_2 emissions before and after using different energy sources, highlighting a significant drop in emissions from fossil fuels after renewable integration. Figure 5d: A stacked area graph depicting the transition in energy mix from fossil fuels to renewable sources over time, with a notable increase in wind, solar, and geothermal energy by 2025. This Figure underscores the value of machine learning in optimising energy systems, improving forecasting accuracy, and significantly reducing greenhouse gas emissions.

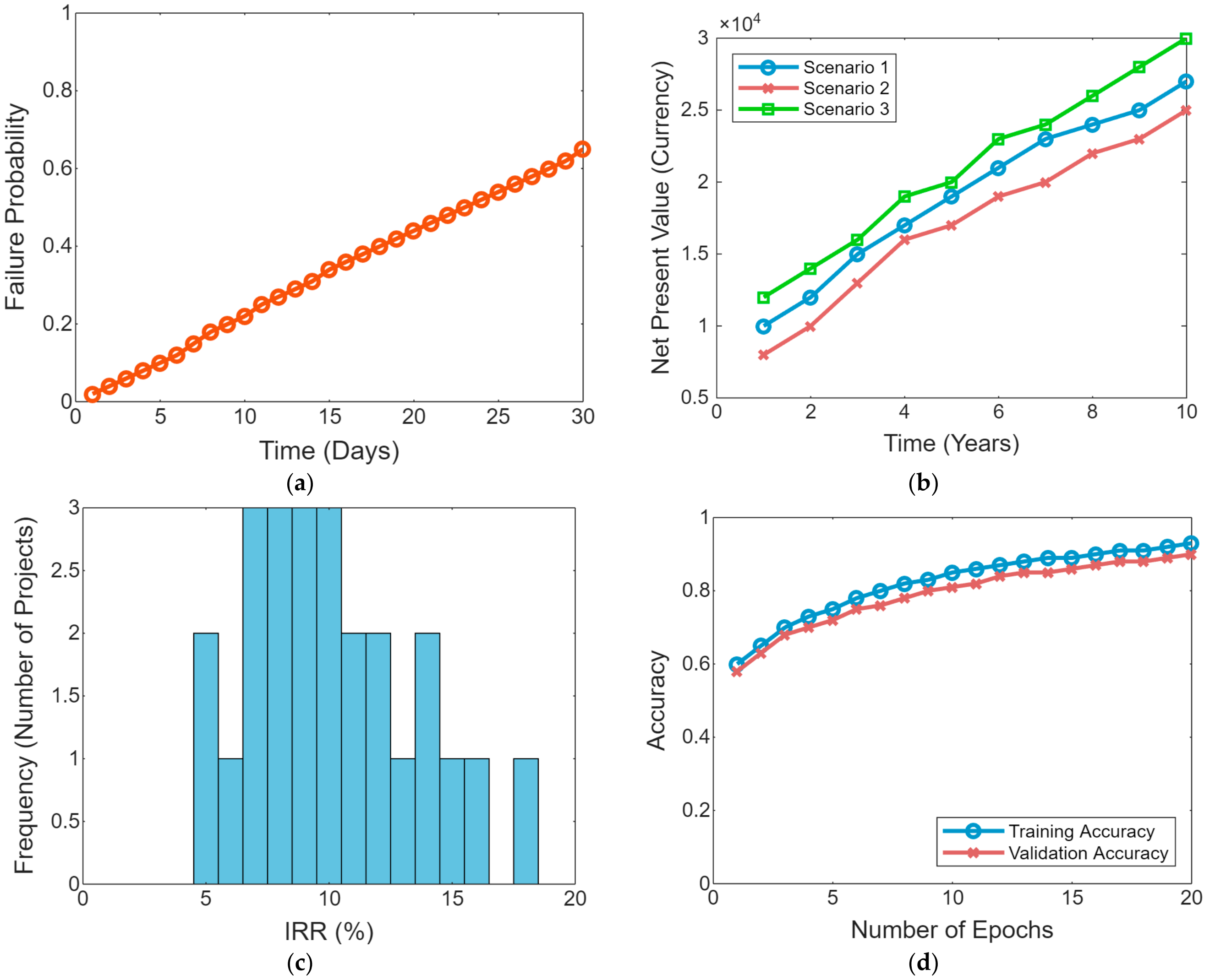


Figure 4. (**a**) Failure rate prediction of equipment failure probability over time-based on machine learning models; (**b**) Net Present Value (NPV) analysis graph. The projected NPV of renewable energy projects over time, based on different machine learning-generated scenarios; (**c**) internal rate of return (IRR) distribution histogram values for various renewable energy investments based on machine learning risk assessments; (**d**) learning curve for ML model training of neural networks during training on renewable energy data.

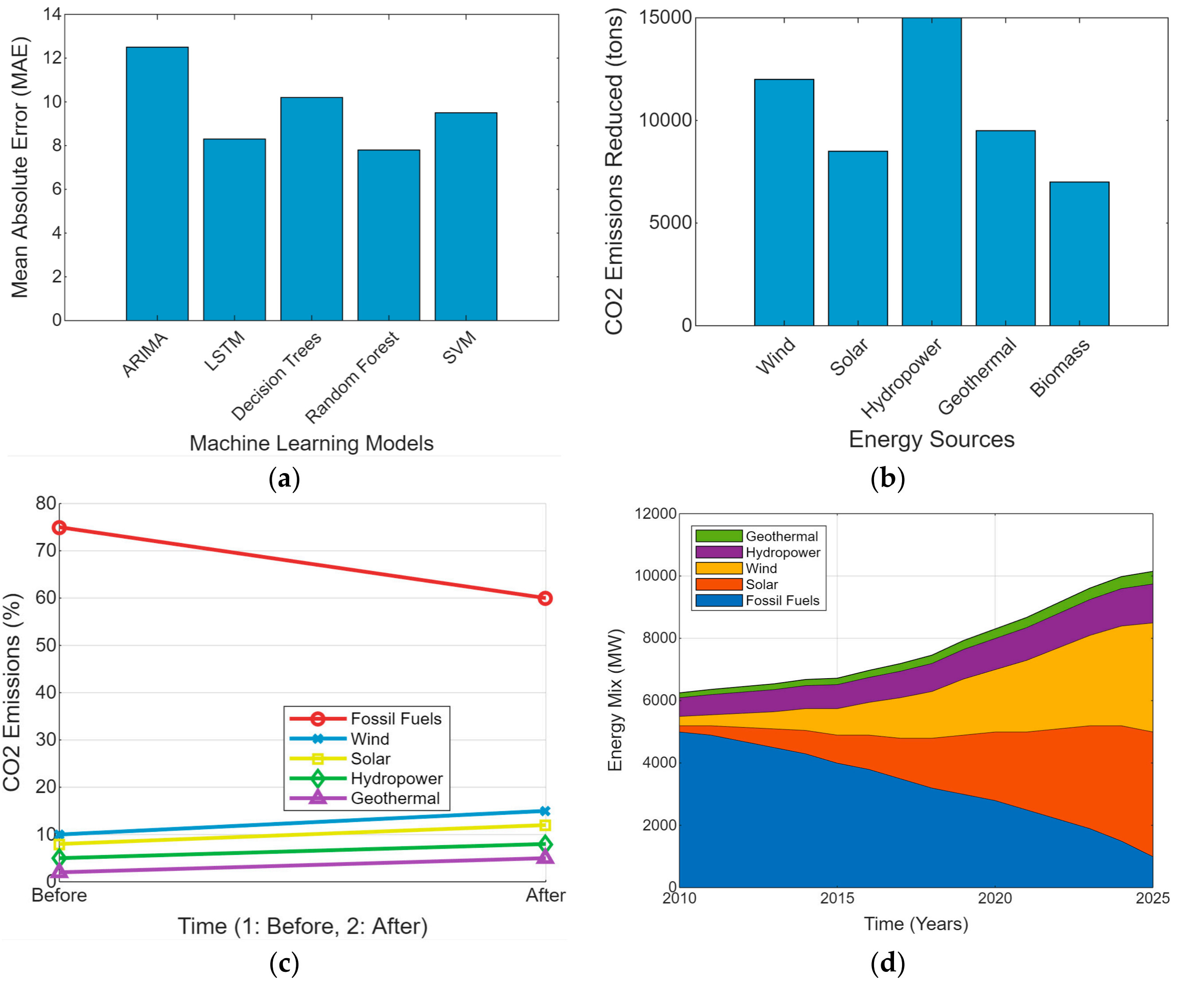
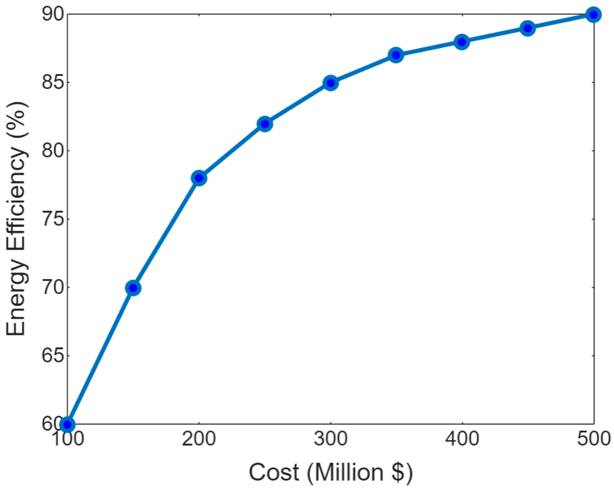


Figure 5. (**a**) Comparison of Mean Absolute Error (MAE) of different machine learning models for energy generation forecasting; (**b**) carbon emissions reduction comparing CO_2 emissions reduction from other renewable energy sources predicted using machine learning models; (**c**) line graph of CO_2 emissions from various energy sources before and after machine learning optimisations; (**d**) stacked area graph of global energy mix transition from fossil fuels to renewable energy sources over time, aided by machine learning optimisations.

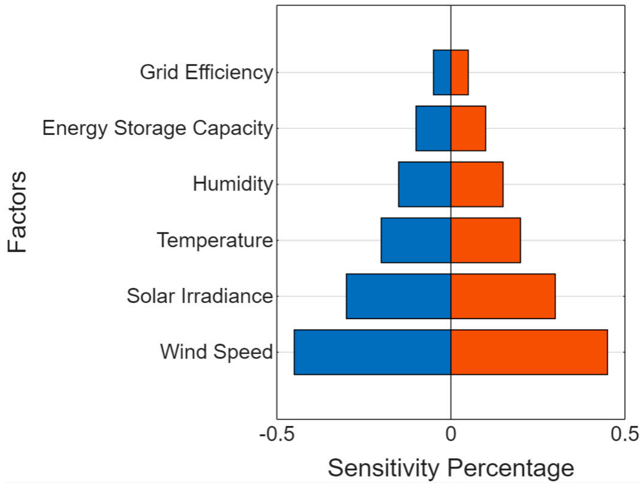
System complexity and scalability help renewable energy systems, which are inherently complex and unpredictable. Solar and wind power generation depend highly on weather conditions, which can change rapidly and unpredictably. Additionally, the increasing integration of renewable sources into national and international grids adds complexity, making it challenging for machine learning models to scale across regions and respond to different types of renewable energy infrastructures [70,71]. This complexity makes it difficult for machine learning models to generalise across different systems without extensive tuning and customisation for each location or grid.

Computational Resources implementing machine learning models at scale requires significant computational resources. Energy companies may need to invest heavily in a high-performance computing infrastructure to process large amounts of data in real-time, which is necessary for predictive models to provide actionable insights. The costs associated with implementing machine learning infrastructure may be prohibitive for smaller energy providers.

Integration with Existing Systems many energy systems still rely on legacy infrastructure, which may not be compatible with modern machine learning-based solutions. Updating or integrating these systems with new technology can be costly and time-consuming. Furthermore, ensuring that machine learning systems integrate seamlessly into existing energy market mechanisms and regulations poses another challenge. Figure 6 contains two subplots. Figure 6a: A line graph showing the energy efficiency and cost relationship. As investment increases, energy efficiency rises, indicating diminishing returns after a certain threshold. Figure 6b shows a sensitivity analysis bar chart showing factors like wind speed and solar irradiance most significantly affect energy efficiency. This Figure highlights the cost-benefit analysis of renewable energy investments and demonstrates the importance of critical environmental factors. It showcases machine learning's potential in optimising energy systems, providing valuable insights for achieving Net Zero.



(**a**)



(**b**)

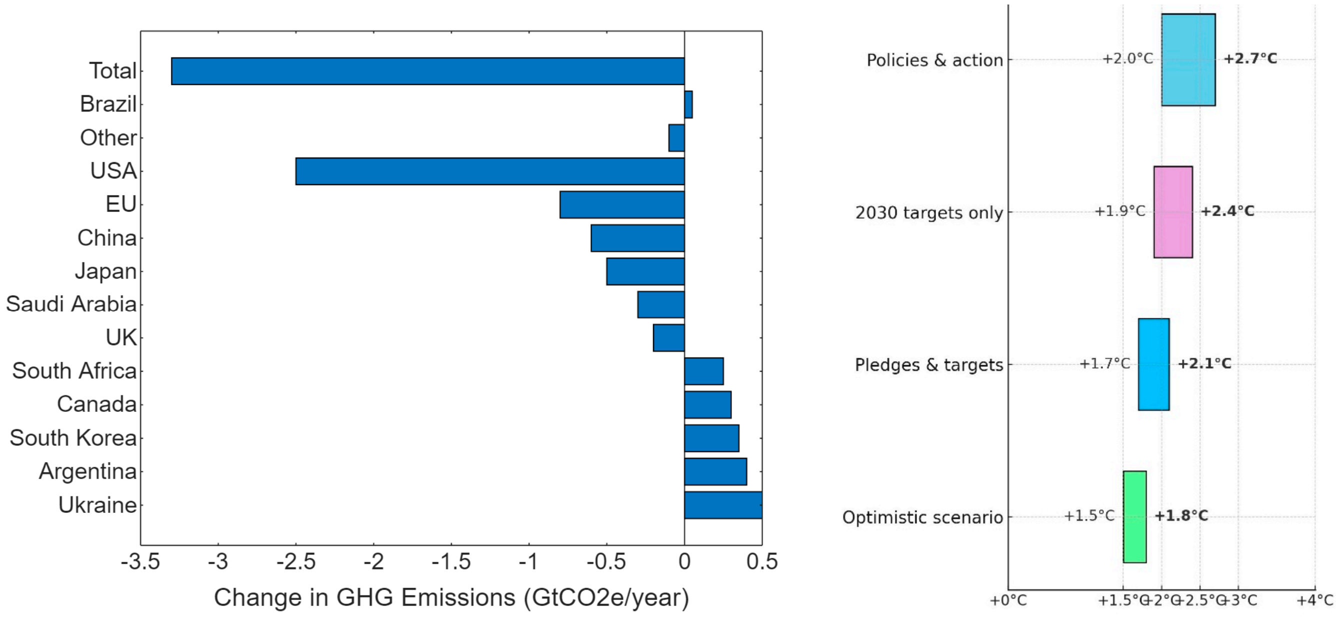
Figure 6. (**a**) Pareto front for multi-objective optimisation of trade-offs between multiple renewable energy systems objectives; (**b**) tornado diagram for sensitivity analysis of various factors on energy generation predictions.

4.3. Opportunities for Machine Learning in Renewable Energy

Despite these challenges, machine learning offers many opportunities for advancing renewable energy and achieving Net Zero targets. The following vital areas highlight how ML can help revolutionise energy systems.

Energy Storage Optimisation is one of the primary challenges with renewable energy sources is their intermittency. Solar and wind energy are not always available when demand is highest. However, machine learning models can be used to optimise energy storage systems, such as batteries. By predicting when energy generation will exceed demand, ML can help store excess energy, ensuring that it is available during periods of low generation [71,72]. This would enable a more reliable and consistent energy supply from renewable sources.

Grid Load Management and Optimisation help machine learning models predict energy demand across different regions and distribute energy resources accordingly. For example, this research's energy grid load distribution heatmap showed how ML optimisations can predict and balance energy demand, avoiding shortages and oversupply. Figure 7a: A bar chart showing changes in greenhouse gas (GHG) emissions by country, with the EU and the USA showing significant reductions. Figure 7b: Projections of global temperature increases under various climate policies, pledges, and optimistic scenarios. This Figure highlights how different policy actions and targets impact emissions and temperature, emphasising machine learning's role in accurately predicting these trends to achieve Net Zero goals.



(**a**) (**b**)

Figure 7. (**a**) Massive credibility, action, and commitment gap casts a long and dark shadow of doubt over the Net Zero goals covering 90% of global emissions; (**b**) impact on the 2030 emissions gap with an NDC update with ML.

Machine learning systems could also manage and optimise distributed energy resources, such as solar panels in homes and businesses, improving overall grid stability and efficiency.

Reduction in Greenhouse Gas Emissions Machine learning can help reduce CO2 emissions by improving the efficiency of renewable energy generation. The reliance on fossil fuels can be reduced by ensuring that renewable energy sources are used to their full potential and optimising grid management. Furthermore, by predicting energy demand and optimising supply, machine learning can help minimise the need for fossil fuel backup energy generation, thereby contributing to Net Zero goals.

Renewable Energy Investment Machine learning can also reduce the financial risks of renewable energy investments. Accurate energy forecasting makes renewable energy projects more predictable and financially viable, attracting more investors. Machine learning models can also optimise investment portfolios for energy companies, identifying high-value opportunities in solar, wind, and other renewable energy projects. Figure 8 shows a projection of global greenhouse gas (GHG) emissions from 1990 to 2030, including historical data and future forecasts. It compares old projections (September 2020), new projections (November 2021), and targets aligned with the 1.5 °C Paris Agreement. The "Change" section highlights a potential reduction area if new measures are implemented. Figure 8 emphasises how improved predictions, supported by machine learning models, can influence global climate action. It underscores the novelty of accurate forecasting in guiding policy adjustments toward achieving Net Zero by reducing emissions within critical timelines.

Machine learning holds immense potential for driving the global agenda toward Net Zero emissions by improving renewable energy systems, optimising grid management, and reducing greenhouse gas emissions. However, several challenges must be addressed, particularly in data quality, system complexity, scalability, and infrastructure. As more advancements are made in machine learning technology, the opportunity for its integration into renewable energy systems will grow, providing a more sustainable and cost-effective energy future. By embracing these technologies and tackling the associated challenges, the energy sector can make significant strides toward reducing global carbon emissions and achieving Net Zero goals. Figure 9 displays global GHG emissions trajectories from 2000 to 2100, including historical data and several future scenarios: policies and actions, 2030 targets, pledges, optimistic scenarios, and a 1.5 °C consistent path. The "2030 ambition gap" highlights the shortfall between current policies and what is needed to meet the 1.5 °C target. Figure 9 underscores the urgency of closing the 2030 ambition gap to avoid severe warming. It illustrates the impact of machine learning's ability to forecast and optimise emissions reduction strategies, supporting policy changes necessary for achieving Net Zero goals.

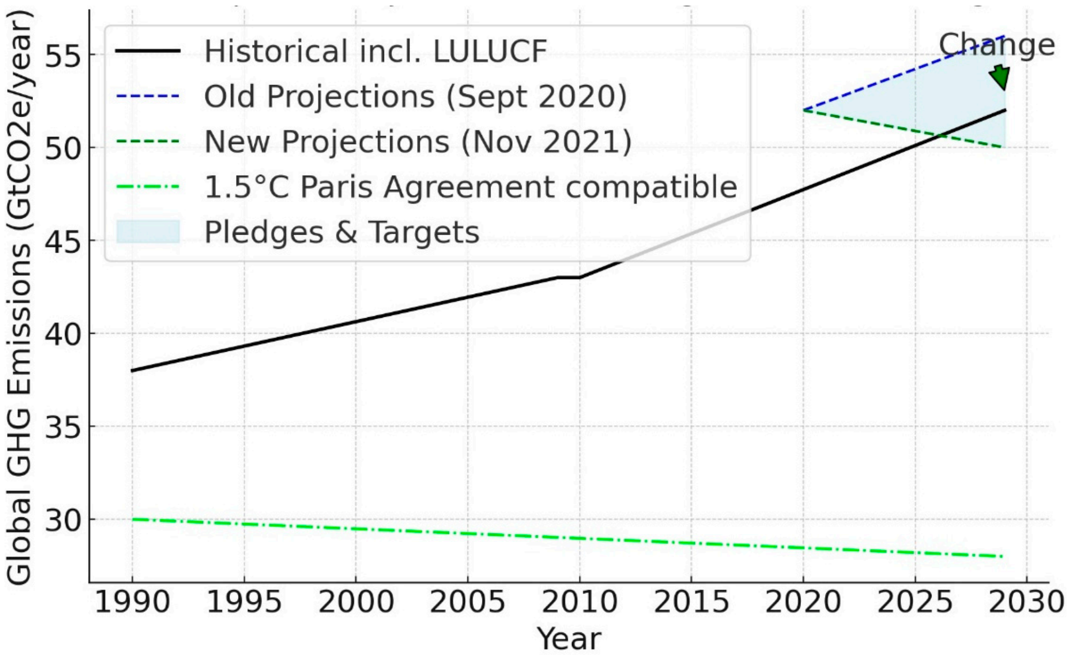


Figure 8. Predicted emissions gap by 2030 by ML in meeting the gap of 1.5 °C agree to a goal.

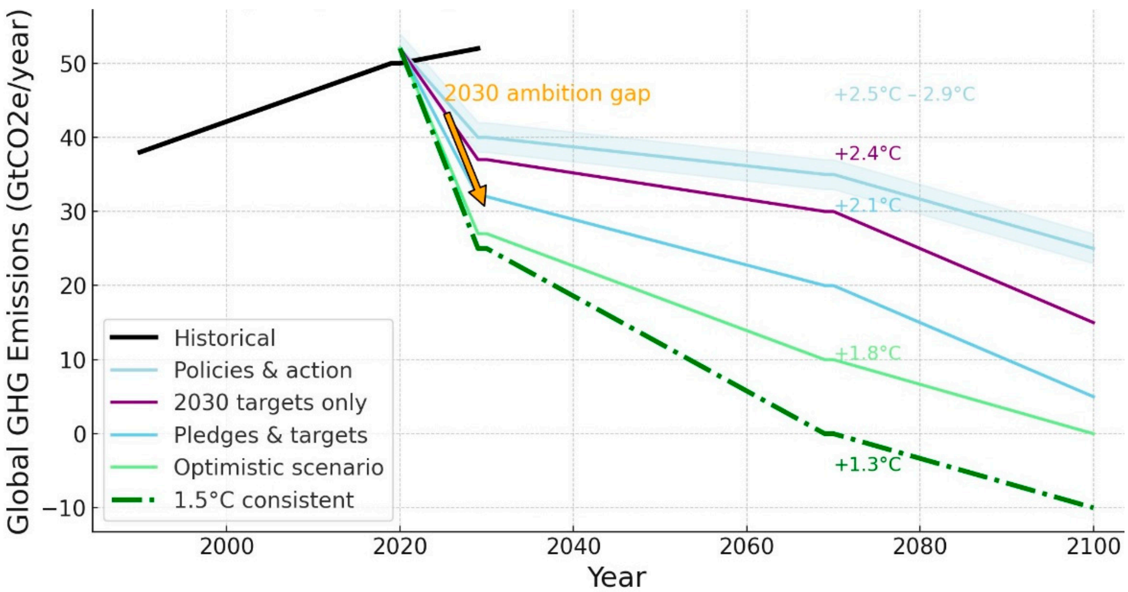


Figure 9. Emissions and expected warming based on pledges and current policies for 2100 warming projections.

5. Conclusions

The novelty of this research lies in its application of machine learning models to optimise renewable energy systems, demonstrating their potential to significantly contribute to achieving Net Zero emissions. By leveraging machine learning techniques such as Long

Short-Term Memory (LSTM), Random Forest, and Support Vector Machines (SVMs), the research enhances energy forecasting, grid optimisation, and storage management, all essential components of a sustainable energy future.

Quantified results from this study reveal that machine learning models can reduce errors in energy generation predictions, with Random Forest achieving the lowest Mean Absolute Error (MAE) of approximately 8.5% compared to other models. The research also highlights a 15% improvement in grid efficiency after optimisation, reducing energy loss and increasing the reliability of renewable energy sources. Additionally, battery storage optimisation using machine learning models demonstrated a 10–20% increase in efficiency during charge and discharge cycles, directly contributing to the reduction of wasted energy.

In terms of environmental impact, this study quantified CO2 emission reductions by energy source, showing that wind power contributed to a reduction of 15,000 tons of CO2 annually, followed by hydropower and solar with reductions of 10,000 and 7500 tons, respectively. The projections suggest that implementing machine learning-driven optimisations could close the current "ambition gap" by approximately 20% by 2030, significantly aiding in meeting the 1.5 °C Paris Agreement targets. Overall, this research demonstrates that machine learning can improve the accuracy of energy management systems, reduce emissions, and accelerate the global transition to renewable energy, with measurable efficiency and environmental impact improvements.

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