International Journal of Applied Power Engineering (IJAPE)
Vol. 12, No. 3, September 2023, pp. 331~340
ISSN: 2252-8792, DOI: 10.11591/ijape.v12.i3.pp331-340

Using machine learning prediction to design an optimized renewable energy system for a remote area in Italy

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Article Info

Article history:

Received Feb 8, 2023
Revised Apr 19, 2023
Accepted May 7, 2023

Keywords:

Hybrid solar/wind system
Machine learning prediction
Power generation
Renewable energy
System advisor model

ABSTRACT

Due to the lack of fossil fuels, there is a significant demand to employ renewable energy systems (RES) worldwide. This paper proposes designing an optimized RES for a remote microgrid that relies solely on solar and wind sources. The proposed RES aims to provide reliable and efficient energy to the microgrid by using machine learning algorithms to forecast the power output of the solar and wind sources. This forecasting will help the system to anticipate and adjust to changes in the weather patterns that may affect the availability of solar and wind. In addition, the system advisor model (SAM) software is used to design the hybrid solar/wind system, considering factors such as the size of the microgrid and the available resources. The system comprises a 60-kW wind system of ten turbines and a 100-kW PV system spread out over the houses. The results show that random forest regression (RFR) models achieved a high level of accuracy in predicting solar power generation, as evidenced by their low mean squared error (MSE) and high R^2 values. Additionally, a proposed hybrid system can generate enough energy to meet the area's needs.

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1. INTRODUCTION

The development of renewable energy sources is crucial due to the energy crisis and environmental pollution [1]. Microgrids are renewable energy systems with two or more power-generating sources to balance each other's strengths and limitations. There are many different kinds of microgrids, including ecologically friendly ones that use wind and solar energy. Most microgrids are linked to the electrical grid, but they can also operate independently and supply various recipients, including one or several houses or huge local communities. The grid-connected system delivers extra power to the grid when the microgrid system generates more power than the receivers. Designing renewable energy systems for remote areas is becoming increasingly important as access to electricity is crucial for economic development and improving the quality of life [2]. Remote areas are often located far from the grid, making it difficult and costly to extend power lines to these areas. Additionally, conventional sources of energy, such as fossil fuels, are often scarce and expensive in remote areas, making renewable energy sources a more viable option. Renewable energy systems can provide reliable and sustainable power to remote areas, reducing dependence on fossil fuels and improving energy security [3]–[5]. These systems can also have positive environmental impacts by reducing carbon emissions and other forms of pollution. In recent years, there have been several studies on the design of renewable energy systems for remote areas. Most of these studies have focused on the optimization of renewable energy systems using mathematical modeling and simulation techniques. For example, Shabestari *et al.* [6] proposes the use of a hybrid renewable energy system consisting of solar and wind power sources, along with energy storage solutions, to provide a reliable and sustainable source of energy to rural areas experiencing frequent power outages. The results show that the proposed system is a viable solution for supplying reliable and sustainable energy to rural areas experiencing power outages, and has the potential to provide significant economic benefits compared to traditional energy sources. Nam *et al.* [7] presents a deep learning-based model for forecasting renewable energy scenarios in Korea. The proposed model uses a long short-term memory (LSTM) neural network to predict renewable energy production and demand in different time horizons. The results show that the proposed model can accurately predict renewable energy production and demand, and can be used to support the development of sustainable energy policies. Khosravi *et al.* [8] presents a case study on the use of machine learning algorithms to predict wind speed time-series data at a wind farm in Osorio, Brazil. The study found that the random forest model outperformed other models in terms of accuracy, with a mean absolute error of 0.82 m/s. The authors suggest that the use of machine learning models for wind speed prediction can help to improve the efficiency and profitability of wind energy systems by enabling more accurate forecasting and better decision-making. Al-Swaiedi *et al.* [9] focuse on the design of a sustainable city in Iraq and the use of the system advisor model (SAM) program to calculate renewable energy potential. The results show that a combination of solar and wind energy can be used to meet the energy demand of the city, with the potential to generate a significant amount of renewable energy. The study concludes that the use of renewable energy sources can lead to significant environmental and economic benefits, and can contribute to the sustainable development of the city. Boretti [10] propose a renewable energy system design for NEOM city, Saudi Arabia. The proposed system integrates solar thermal and photovoltaic, wind, and battery energy storage through artificial intelligence (AI) optimization techniques. The results show that the proposed system can meet the energy demand of NEOM city while reducing the overall cost and CO^2 emissions compared to conventional energy systems. Temiz and Dincer [11] presents a case study of a rural community in India, where a solar and wind-based hydrogen energy system was designed and implemented. The results of the case study showed that the solar and wind-based hydrogen energy system was able to meet the energy demands of the rural community while reducing greenhouse gas emissions and improving energy security. The main goal of this study is to serve isolated, off-grid areas where the expenses of connecting to the long-distance power grid are too expensive with a microgrid system that uses solar and wind energy [12], [13]. Meanwhile, solar and wind power generation systems have their own set of issues. The primary issue with installing a PV system is that it cannot generate power at night or on overcast days. Furthermore, because the wind is unpredictable, the fundamental problem with wind energy is its unreliability [14]–[16]. In order to address these issues, this research offers a hybrid solar/wind energy system. The case study for this paper is a remote area with 20 houses in Italy. Figure 1 indicates the proposed microgrid system.

According to Figure 1, the input sources of energy are solar and wind, using a battery storage system, and the output of the system is a remote area in Italy. The required power converters are a DC-DC converter to charge the battery and an inverter to feed the customers [17], [18]. Additionally, it is vital to forecast the area's potential energy using machine learning algorithms and data analysis before investing any money in a renewable system [19]–[21]. This paper used a linear regression model to forecast both solar and wind energy in the considered remote area.

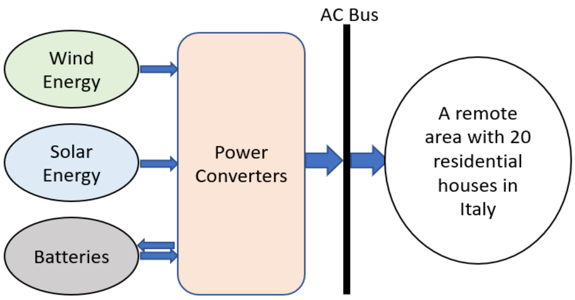


Figure 1. Proposed microgrid system

2. METHOD

The methodology for this paper has three parts. At first the data should be collected and cleaned, in the second part, the machine learning models are explained. Finally in the third part the hybrid solar/wind system is designed.

2.1. Data collection

The first step in the process was to gather data on the weather patterns in the study area, including the temperature, wind direction, wind speed, humidity, and solar radiation. Historical data on energy consumption in the area was also collected to determine the required energy output of the renewable energy system. The collected data was then cleaned and preprocessed to remove any outliers and missing values. Before applying linear regression, it is necessary to clean the data and eliminate the bad data [22]. The bad data such as the NAN values and minus values for the output power. In this process, the bad data of the all features in the dataset are processed and eliminated.

2.2. Machine learning model

A machine learning model was trained to predict the output power of the renewable energy system. The model was trained on the historical data on energy production from the existing renewable energy system, as well as weather data collected from the study area. The model used supervised learning techniques to optimize the energy output of the system. Today, many different machine learning models may be used to estimate the output energy from the sun and wind, thanks to the availability of weather data. The temperature, wind speed, solar radiation, number of overcast days, precipitation, and humidity of the site are six key characteristics that are used in this paper's linear regression model to predict the extracted power of the solar system [23], [24]. Furthermore, the wind speed data and wind direction are the two most significant factors utilized to predict extracted wind power [25], [26]. The predictability of solar power generation is crucial for solar integration into regular electrical grid systems. In the current study, regression models were used to forecast the system's power production. Month, hour, exact time, air pressure, azimuthal angle (A), elevation angle (E), humidity (H), temperature (T), rainfall (R), cloud ceiling (C), wind direction (V), and wind velocity (W) are a few of the variables that affect the generation of solar electricity [27]. Furthermore, so many machine learning models that can be used to model the extracted power. In this paper, as can be seen in (1) and (2) are implemented to forecast the generated power.

$$Extracted\ solar\ power = -131A + 23E + 0.06T - 7.94R - 0.028C \tag{1}$$

$$Extracted\ solar\ power = 0.46\,W + 0.68\,V \tag{2}$$

Based on (1) and (2), humidity and wind velocity are neglected. To ensure that the model is valid for long-term operation, it is important to compare the predicted outputs to actual data over an extended period of time. This can help to validate the accuracy of the model and ensure that it provides useful and reliable predictions. In this study a dataset of one year was evaluated to ensure the validity of the model. The correlation between accessible characteristics and power output is seen in Figure 2.

Correlation matrices can be useful in identifying which variables are most strongly correlated with each other, which can help in understanding the underlying dependencies and relationships within a dataset. For example, in a solar energy case, the correlation matrix may show which variables are most strongly correlated with energy production, such as solar radiation levels or temperature. Figure 2 explains the correlation from the ambient plot temperature, cloud ceiling, and humidity which are the top 3 most correlated features with solar power output [28]. Also, Figure 3 shows the scatter plot of the data variables including radiation, temperature, humidity, and wind-speed.

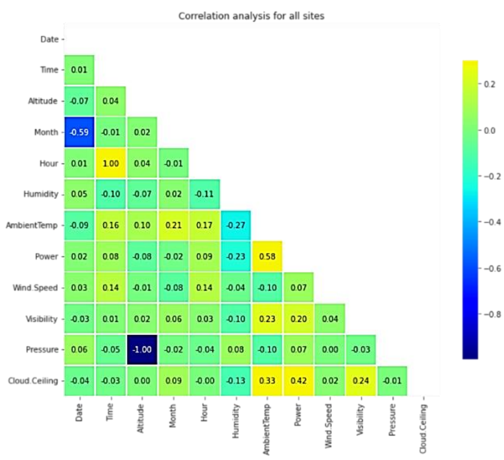


Figure 2. Correlation matrix of the weather dataset

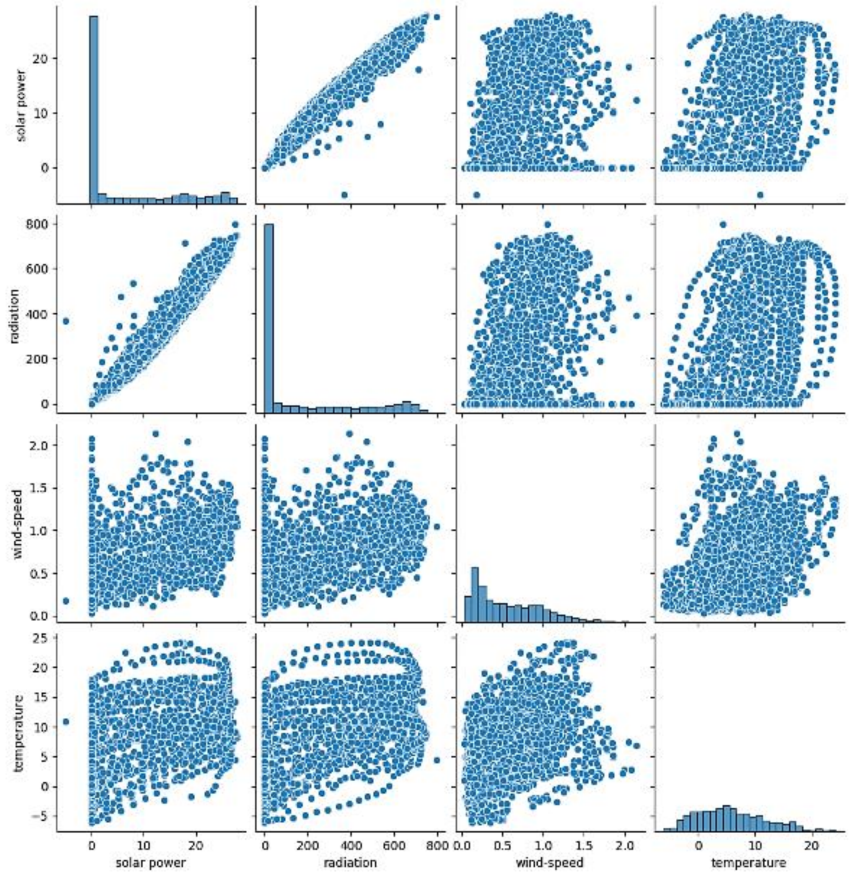


Figure 3. Scatter plot of data variables

The scatter plot of the processed data on the grid is shown in Figure 3, showing that certain variables have outliers and others are highly concentrated. Scatter plot can be used to help visualize and analyze the relationship between the data variables related to solar energy production or usage, and to gain insights that can inform decision-making and optimization of solar energy systems. Figure 4 indicates the power-humidity regression model.

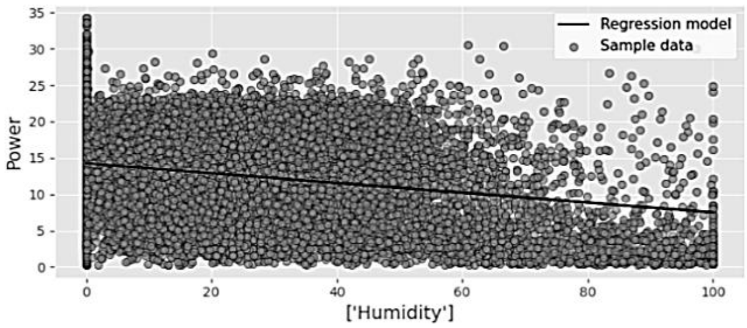


Figure 4. Power-humidity regression model

Figure 4. represents a power-humidity regression model that was developed to predict the power output based on the humidity level. The x-axis of the plot represents the humidity values (%), while the y-axis represents the predicted power output based on the regression equation. As can be observed in Figure 4, the humidity factor has an impact on the power output. In general, higher levels of humidity can decrease the efficiency of power generation or use in some types of systems. In addition, the power-temperature regression model is depicted in Figure 5.

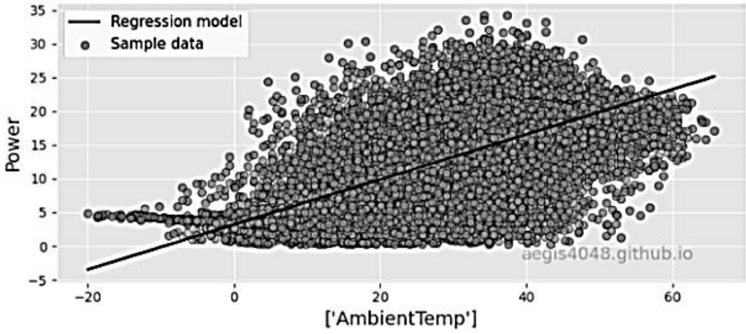


Figure 5. Power-temperature regression model

Figure 5 represents the power-temperature regression model which is developed to predict the output power based on the ambient temperature. The x-axis of the plot represents the temperature values, while the y-axis represents the predicted power output based on the regression equation. Like the power-humidity regression model, the regression line or curve in the plot represents the overall trend of the relationship between temperature and power output.

2.3. System design

The output of the machine learning model was used to design an optimized renewable energy system for the study area. The design of the system included the selection of the most suitable renewable energy technology, the sizing of the system components, and the optimal placement of the components. The proposed power plant uses two renewable energy sources: wind and solar energy. The wind system, which has a rated capacity of 60 kW, comprises 10 wind turbines. Also, the solar system size is 100 kW system mounted on the rooftop of 10 houses in a remote area in Italy. Table 1 shows the characteristics of each solar module in the PV system, which has a nameplate capacity of 100 kW.

Based on Table 1, cells number per module are 96, and the weight is 19.2 kg. The power of each module is 343 W, with the tilt of 44° which is Genova's latitude [29]–[31]. The suggested wind system is made of 10 wind turbines, each of which with a nameplate capacity of 6 kW. Table 2 shows the characteristics of each wind turbine in the wind system. As can be seen from the Table 2, the number of blades for each turbine is 3; the hub height is 30 m and the rotor diameter is 8 m.

Table 1. Solar system features

S.L.	Criteria	Achievement
1	Rated power of each module	343 W
2	Module size	1.98*1.14 m
3	Cells number per module	96
4	Tilt angle	44°
5	Efficiency (η)	20.91%

Table 2. Wind system features

	Criteria	Achievement
1	Blades	3
2	Diameter of rotor	8 m
3	Hub height	30 m
4	Cut-in wind speed (m/s)	3
5	Cut-out wind speed (m/s)	24

3. RESULTS AND DISCUSSION

To assess the viability of the proposed system, economic analysis and simulation results must be conducted. SAM was used to model the proposed hybrid system in this paper. According to SAM, the average yearly power consumption of a residential house is 10820 kWh which is depicted in Figure 6. Summer months require up to 4 kW of power every day because of the usage of air conditioners and other similar devices. The very significant advantage of using solar energy is that the highest solar power generation is synchronized with the highest consumption of power during the summer months. Figure 6 demonstrates the required load for a residential house in Italy.

Therefore, for the proposed case study with ten residential houses, the total load is 108200 kWh. Monthly solar energy production both for each house and for the whole case study is also depicted in Figure 7. For the PV system, the monthly generated power is more significant during the summer season, as shown in Figure 7(a), due to more peak solar hours and a smaller number of cloudy days. For the wind system, the monthly energy output is almost similar but a little more during the fall and winter months, as shown in Figure 7(b), due to more cloudy days and windy hours.

According to Figure 7, for the presented PV system, the monthly energy output is more significant during the summer months, due to more peak solar hours and a smaller number of cloudy days. Furthermore, monthly wind energy production both for each house and for the whole case study is also depicted in Figure 8. Figure 8(a) shows the output wind energy for each turbine and Figure 8(b) shows the total wind energy output. For the wind system, the monthly energy output is almost similar but a little more during the fall and winter months, as shown in Figure 8(b), due to more cloudy days and windy hours. Also, Figure 9 depicts the hybrid system for one residential house in comparison with the needed load for the same house. Figure 9(a) shows the extracted solar energy versus the needed load, and Figure 9(b) shows the generated wind power versus the needed load for the same house.

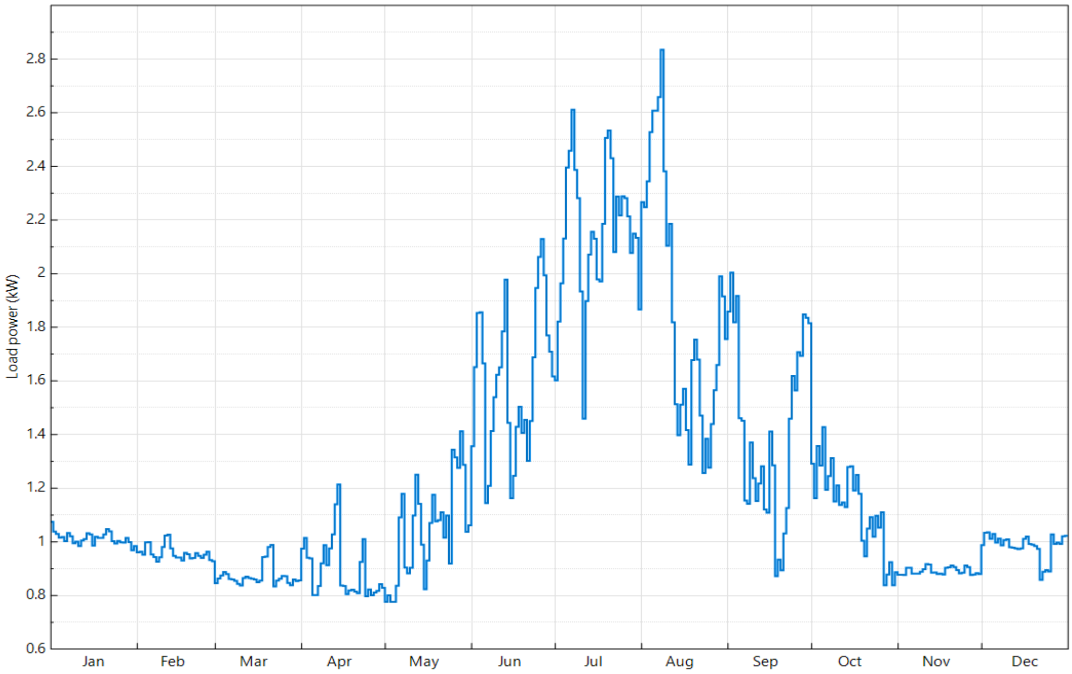
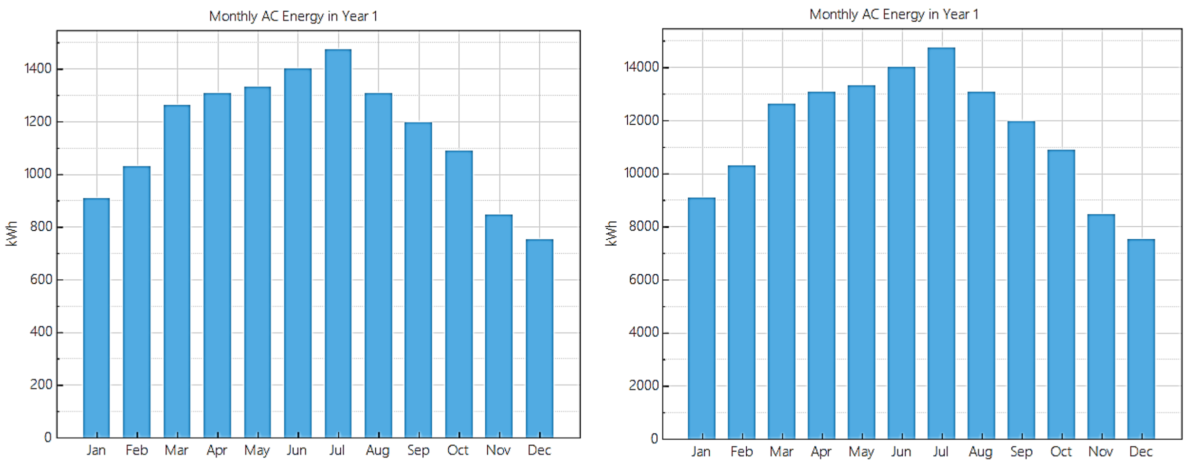


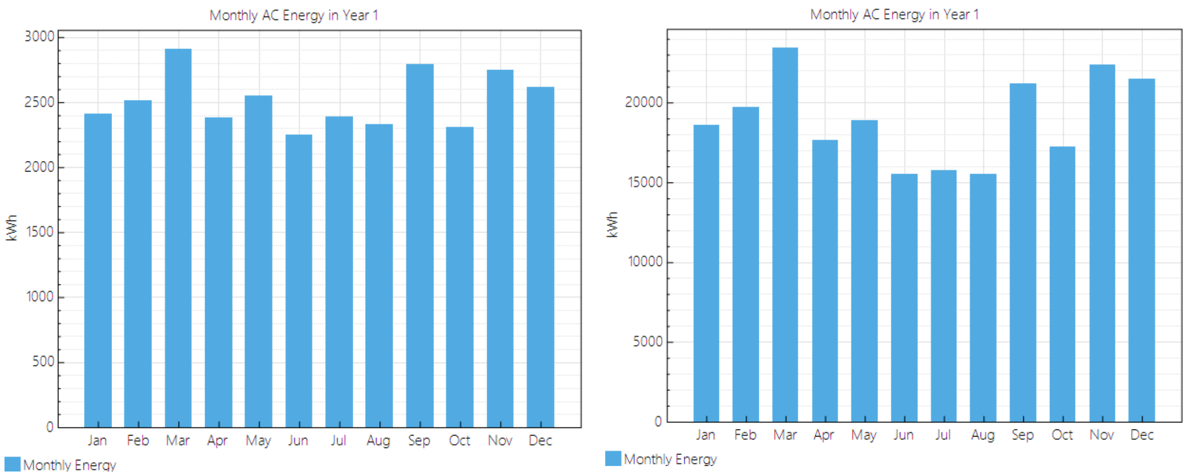
Figure 6. Needed load for a residential house



(a) (b)

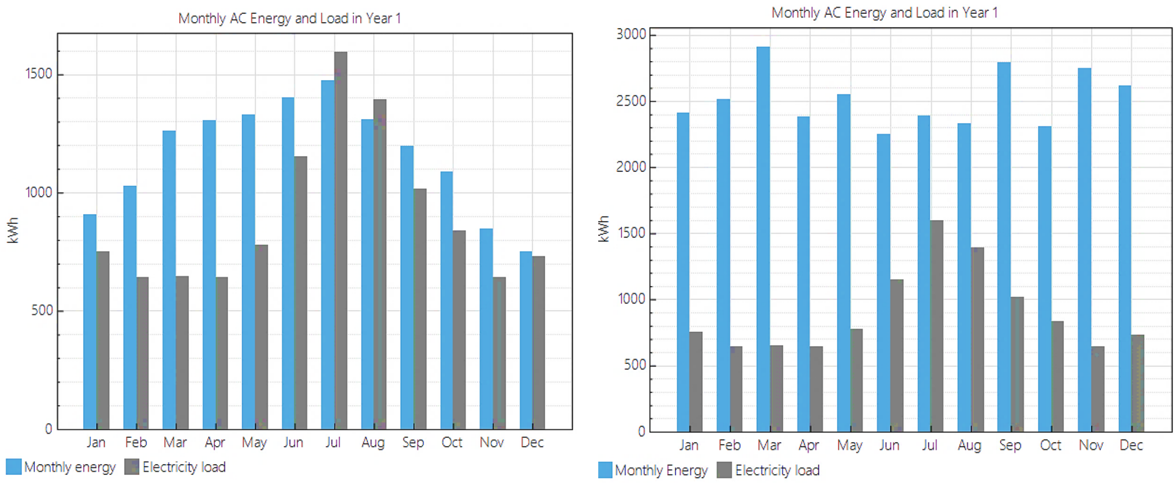
Figure 7. Monthly energy production (a) solar output per each house and (b) total solar output

Based on Figure 9, it is quite obvious that each system can cover the entire load separately. Here are quite a few machines learning (ML) models which have been used for forecasting weather data. In this paper, linear regression (LR), polynomial regression (PR), and random forest regression (RFR) are utilized to forecast the generated power of the system in the future. Figure 10 indicates the actual and predicted power production of the solar system for a random day and a random week. Figure 10(a) depicts the prediction of the power over one random day and Figure 10(b) depicts the prediction of the solar power over a random week.



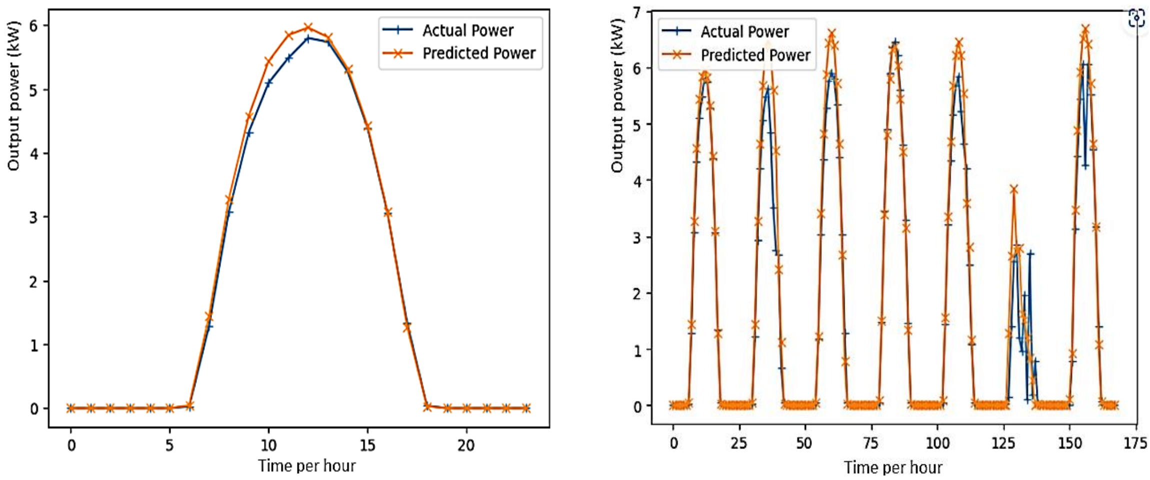
(a) (b)

Figure 8. Monthly energy production (a) wind energy per each turbine and (b) total wind energy output



(a) (b)

Figure 9. Energy production vs load (a) solar energy vs load and (b) wind energy vs load



(a) (b)

Figure 10. Predicted and actual generated power (a) one day and (b) one week

According to Figure 10, the ML models were able to predict the solar power with a very good accuracy. Figure 11 indicates the actual and predicted power production of the wind system for a random day and a random week. According to Figure 11, the ML models were able to predict the solar power with a high precision. Figure 11(a), predicts the power over one random day and Figure 11(b), predicts over a random week. In this work, the performance of machine learning models for forecasting was assessed using the mean squared error (MSE) and R-squared (R2) metrics, which are frequently used to assess the performance of ML models. Table 3 shows the performance of each model on the testing set.

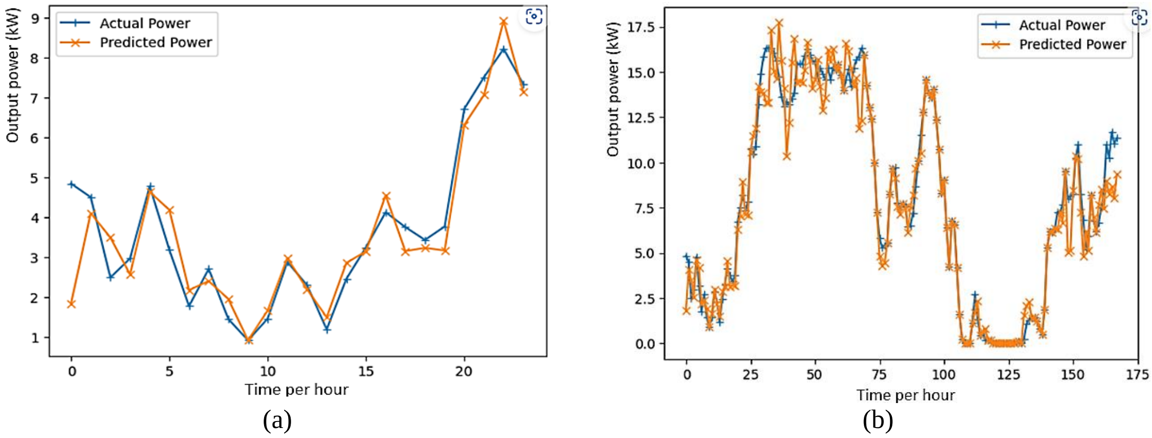


Figure 11. Predicted and actual generated power (a) one day and (b) one week

Table 3. Performance of the ML models

ML Model	MSE	R^2
LR	1.12	0.9612
PR	1.01	0.9745
RFR	0.17	0.9975

The results show that all seven ML models were able to predict solar PV power generation with good accuracy, as evidenced by the high R^2 values and low MSE values. The RFR models performed well, achieving lower MSE and higher R^2 values than others. At the end, the extracted power is demonstrated in Table 4. The solar system spreads out equally on the rooftop of 10 residential houses.

Table 4 shows that the proposed system is a combination of a 60 kW WIND system and 100 kW solar system. According to the results, the total system's extracted power is around 375350 kWh annually, 236330 kWh comes from the wind system and 139020 kWh comes from the solar system. The total load of the proposed case study in this paper is 108200 kWh. This suggests that the system is very dependable and can readily provide the area's energy needs. The potential of the suggested system to decrease hazardous gasses from the environment, hence supporting environmental sustainability, is one of its key benefits. Utilizing green energy sources like solar and wind energy can assist to lessen greenhouse gas emissions and slow down climate change. By lowering the cost of energy usage, the system also helps consumers financially. However, there are several limitations in the suggested system that must be fixed. The intermittent nature of wind and solar electricity is one of the major drawbacks. It might be challenging to match the energy demand since the power production of solar and wind systems changes with the weather and time of day. Therefore, to provide a steady supply of electricity, energy storage solutions like batteries may be necessary. The expensive initial cost of installation is another limitation. Although renewable energy systems have long-term financial advantages, they might demand a sizable upfront expenditure. This can discourage some users from implementing the suggested system.

Table 4. Hybrid system extracted power

S.L.	Criteria	Wind	Solar	Proposed hybrid system
1	System size (kW)	60	100	160
2	Generated power per each house (kWh)	23633	13902	37535
3	Total generated power (kWh)	236330	139020	375350

4. CONCLUSION

The results of this paper demonstrate that machine learning models can effectively forecast solar power generation with a high level of accuracy. The RFR models performed particularly well in this regard, achieving low MSE values and high R^2 values. The proposed hybrid system consisting of a 60 kW wind system and a 100 kW solar system can generate a total of 375350 kWh annually, which is more than sufficient to meet the area's energy needs. Moreover, the use of renewable energy sources can contribute to environmental sustainability and reduce the cost of energy usage for consumers. However, the intermittent nature of wind and solar power and the high initial installation costs are major limitations that must be addressed. Energy storage solutions such as batteries may be necessary to ensure a steady supply of electricity, and efforts should be made to make renewable energy systems more affordable for consumers.

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