Electricity Need Forecast for The Power Plant Using Non-Renewable Energy Sources Based on Machine Learning Method

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***Abstract*:** This research paper aims to forecast the electricity need for a power plant that uses non-renewable energy sources by incorporating machine learning methods while also considering power consumption and power generation from renewable energy sources. However, the integration of renewable energy sources into power systems can be complex due to their intermittency and variability. As a result, accurate forecasting of electricity needs is crucial for power plant operators to make informed decisions about energy generation and consumption. The study utilizes historical data to train the machine learning models, and several regression models were developed to predict the power consumption and power generation. The research considers various factors that may affect electricity demand and generation. Furthermore, renewable energy sources' generation data is integrated into the models to determine their impact on the accuracy of the electricity demand predictions. The results indicate that incorporating renewable energy sources in the forecasting models can significantly improve the accuracy of the predictions. We have developed the machine learning model and tested the model for data from the western states of the india. The study provides valuable insights into how non-renewable and renewable energy sources can work together to meet the growing demand for electricity in a sustainable way.

Keywords: machine learning, non-renewable energy, forecast, electricity consumption

1. Introduction

The world's growing population and technological advancements have led to a significant increase in the demand for electricity. The majority of the world's electricity generation still depends on non-renewable sources of energy such as coal, natural gas, and oil. This dependence on non-renewable energy sources has led to concerns about their negative impact on the environment, particularly with regards to climate change. In order to ensure a reliable and sustainable supply of electricity, accurate forecasting of electricity demand is crucial for power plants that rely on non-renewable energy sources. Traditional forecasting methods, such as statistical models, have limitations in accurately predicting electricity demand due to the complex and dynamic nature of the electricity market.

Machine learning methods have emerged as a powerful tool for improving the accuracy of electricity demand forecasting. These methods are capable of handling large amounts of data, identifying complex patterns, and making accurate predictions. This research paper aims to explore the use of machine learning methods for forecasting electricity demand for power plants that rely on non-renewable energy sources.

The paper will focus on the development of a machine learning model for predicting electricity demand based on historical data on electricity consumption, weather patterns, and other relevant variables. However, it does emphasize the importance of accurate electricity demand forecasting for power plant operators to make informed decisions about energy generation and consumption. Without accurate forecasting, operators may generate more energy than is actually needed, leading to energy waste and increased costs. On the other hand, if they generate less energy than is needed, there may be power shortages, which can lead to blackouts and other problems. Therefore, accurate forecasting is crucial to optimize energy generation and consumption and reduce energy waste. The model should trained and validated using data from a non-renewable power plant, and its performance will be compared to traditional forecasting methods.

We have developed the machine learning model for the forecast of electricity need. We have tested our model using the data of western states of india. We have used the state wise electricity consumption data and plant wise energy generation data of hydro power plant and nuclear power plant. We also have done the performance analysis of our model and find the accuracy of the model.

The findings of this research paper will have important implications for the energy sector, particularly in terms of improving the efficiency and sustainability of non-renewable power plants. By accurately predicting electricity demand, power plants can optimize their operations, reduce their environmental impact, and ensure a reliable supply of electricity to meet the growing demand.

1.1 Motivation

Increasing demand for electricity worldwide and the urgent need to transition to sustainable energy sources. Power plants that rely on non-renewable energy sources have been the primary sources of electricity for many years. However, these sources of energy have several drawbacks, such as environmental degradation and limited availability. To address these challenges, power plant operators are exploring the integration of renewable energy sources into their power systems. However, renewable energy sources, such as solar and wind, have intermittency and variability, which makes their integration complex. Accurate forecasting of electricity needs is critical for power plant operators to optimize energy generation and consumption and ensure a stable power supply. Therefore, the motivation for this research paper is to develop machine learning models that can accurately forecast electricity needs for power plants that use non-renewable energy sources, while also considering the impact of renewable energy sources on electricity generation. The results of this study will provide insights into how non-renewable and renewable energy sources can work together to meet the growing demand for electricity sustainably.

1.2 Research Contributions

The research paper contributes to the field of energy forecasting and renewable energy integration by developing machine learning models that accurately forecast electricity needs for power plants using non-renewable energy sources while considering the impact of renewable energy sources.

The study considers various factors that affect electricity demand and generation and demonstrates that incorporating renewable energy sources significantly improves the accuracy of the predictions. The research provides valuable insights into how non-renewable and renewable energy sources can work together to meet the growing demand for electricity sustainably.

2. Literature Survey

Safae Bourhnane et al. [5] have compared several approaches can use to forecast the electricity consumption in smart buildings. They have explained the Auto regression, Moving Average, and different ANN like feedforward or recurrent for time series forecast. They have developed the model using ANN and Genetic algorithm. Using Their model they have achieved 97.5% of accuracy. So In this paper we have also compared the prediction the consumption using this models.

Junfeng Zhang et al. [8] have proposed several steps to achieve accuracy using transformer model and K-nearest Neighbour , Support Vector Machine and Artificial Neural Network. They also checked the accuracy using RSME, NRSME and MAPE. The have compared different approaches to get higher accuracy. Proposed model has an RMSE of 0.73, the Transformer has an RMSE of 0.77, and the LSTM has an RMSE of 0.86.

Swati Sucharita Barik et al. [10] gave explained Conventional Machine Learning, Adaptive Network based Fuzzy Inference System (ANFIS), Extreme Learning Machine (ELM) for electricity consumption prediction in their paper. They gave the details about different machine learning models like Support Vector Regression (SVR), Random Forest (RF), Linear Regression (LR), K-Nearest Neighbour (KNN), ANN, K-means Clustering, ELM can be used to forecast the time series data for electricity consumption prediction.

Mel Keytingan et al. [3] proposes three different methodologies, namely Support Vector Machine, Artificial Neural Network, and k-Nearest Neighbour, for the algorithm of the predictive model. The research focuses on a real-life scenario in Malaysia and considers two tenants from a commercial building as a case study. The collected data is analysed and pre-processed before being utilized for model training and testing. The performance of each method is compared using RMSE, NRMSE, and MAPE metrics.

Dinh Hoa Nguyen et al. [7] introduces a machine learning approach to predict electricity consumption using an improved radial basis function neural network (iRBF-NN). The inputs to the iRBF-NN include time sampling points, temperature, and humidity data associated with the consumption. The parameters of the iRBF-NN are obtained by solving an optimization problem, where four types of cost functions are utilized and compared based on their performances and computational costs. The developed model is then used to forecast future electricity consumption by utilizing hourly temperature and humidity forecasts.

Alexandra Khalyasmaa et al. [9] their paper addresses the problem of short-term renewable energy forecasting. The study proposes a machine learning approach to improve day-ahead forecasting by using retrospective metering data and open source weather information from meteorological services. The paper focuses on the challenges of feature identification and selecting appropriate error metrics. The developed model is tested on a real solar power plant located in the southern region of the Russian Federation, and the mean forecasting accuracy is reported to be around 93%.

Adam Krechowicz et al. [2] have studied many research papers and gave the detailed comparision in their paper and they concluded that Extreme Learning Machine and ensemble methods were the most popular methods used for electricity generation forecasting from RES in the recent years. And most of the research done for the wind systems, 33% researchers preferred for the hybrid models. Moreover, strengths, weaknesses, opportunities, and threats for the analyzed ML forecasting models were identified and presented in this paper.

C. Vennila et al. [6] their study proposes a hybrid model that combines machine learning and statistical approaches for predicting future solar energy generation. To enhance the accuracy of the model, an ensemble of machine learning models was utilized. The simulation results demonstrate that the proposed method significantly reduces placement costs compared to existing methods.

D A Widodo et al. [4] have proposed their paper named "Renewable energy power generation forecasting using deep learning method". The paper aims to develop a Deep Neural Network (DNN) method that employs Long Short-Term Memory (LSTM) as a learning model to provide accurate predictions of electricity use and renewable energy plant performance. The proposed model is evaluated through prediction tests, which utilize Confusion Matrix accuracy values and RMSE error values as performance metrics.

So many research have done for the comparing of the different model to predict the electricity consumption or forecast the Renewable energy generation. We are going to refer different models and try to achieve higher accuracy for different types of data and will compare that which of the model is working with higher accuracy for different forecasting.

3. Methodology

The methodology of the research paper involves testing machine-learning models to forecast electricity needs for power plants using non-renewable energy sources. The study employs several regression models, including random forest, and support vector regression, Support vector, ensemble learning, decision tree and ANN also to predict power consumption and generation.

In section 4 we have tried different Regression models on the electricity consumption dataset. In section 5 we have applied Random Forest and Decision Tree on the electricity generation dataset of Nuclear, Thermal and Hydro power. In section 6 we tried Artificial Neural Network and other models on the solar power plant electricity generation and weather condition dataset. You can see the detailed research and result comparison in respective sections.

4. Electricity Consumption Forecasting

Electricity consumption forecasting is a crucial task for the efficient operation and planning of power systems. Accurate forecasts enable utilities to balance the electricity supply and demand, optimize energy generation and distribution, and reduce costs and carbon emissions. There is a growing interest in developing advanced models for electricity consumption forecasting. In this section, we present a review of some popular models that have been used for electricity consumption forecasting.

	Goa	Gujarat	Maharashtra	DNH	Rajasthan
0	12.8	319.5	428.6	18.6	234.1
1	13.7	316.7	419.6	18.2	240.2
2	12.6	301.9	395.8	16.7	239.8
3	13.0	313.2	411.1	17.6	239.1
4	12.9	320.7	408.6	18.6	240.4
...	...	...	...	...	...
474	12.3	312.0	421.6	18.2	219.8
475	8.8	289.7	369.2	17.4	203.2
476	8.8	297.9	395.5	18.3	212.6
477	8.8	296.8	395.5	18.7	225.5
478	10.2	288.7	399.6	18.5	225.7

Figure 1. Sample Dataset of Power Consumed of Western States of India (in Mega Unit)

We have tested different model on the above dataset. We have considered the Western States of the India and all the figures in Mega Unit. Now we will see different models of Machine Learning models tested on this dataset and analysis of the result.

4.1 Decision Tree Regressor

Decision tree regressor is a type of machine learning model that belongs to the family of decision tree algorithms. Decision trees are binary tree structures that recursively partition the input space into subsets based on the most discriminative features or attributes. Each internal node of the tree represents a test on a specific attribute, and each leaf node represents a predicted output value. Decision tree regressor, in particular, is used for continuous target variables, such as electricity consumption.

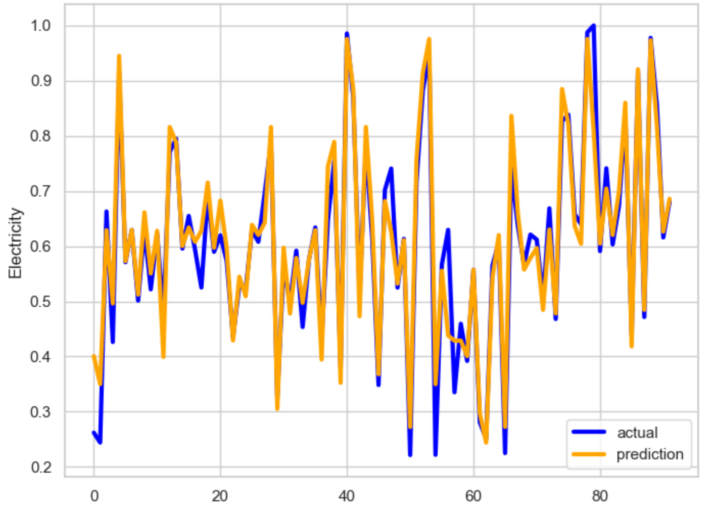

Figure 2. Graph of Actual and Predicted electricity using Decision Tree Regressor

Mean Absolute Error is 15.01 and Accuracy is 0.922 of this model.

4.2 Random Forest Regressor

Random Forest Regressor works by randomly sampling subsets of the training data and features, and constructing decision trees based on these subsets. Each tree is trained using a different subset of the data, and the predictions of all trees are aggregated to obtain the final output. This helps to reduce overfitting and improve the generalization ability of the model.Random Forest Regressor has several advantages, such as its ability to handle high-dimensional data, nonlinear relationships, and interactions between variables. It is also robust to noise, missing values, and outliers in the data.

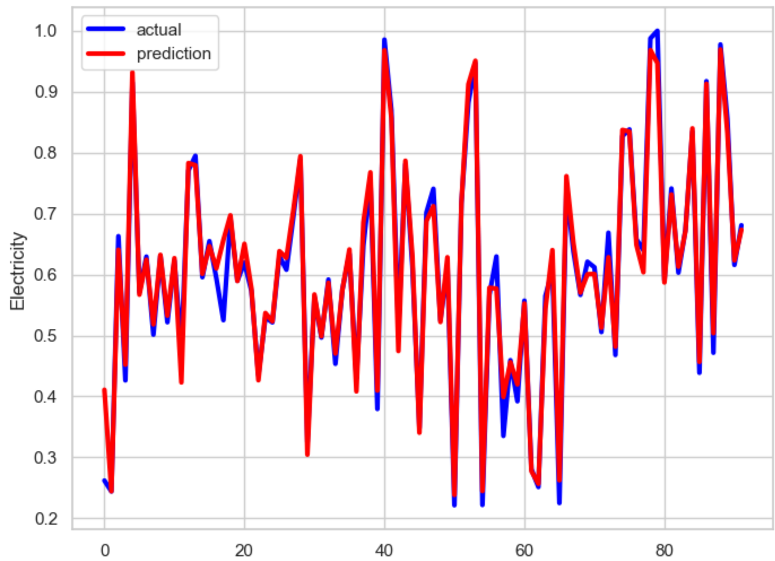

Figure 3. Graph of Actual and Predicted electricity using Random Forest Regressor

Mean Absolute Error is 7.93 and Accuracy is 0.975 of this model.

4.3 Support Vector Regressor

SVR works by finding a hyperplane that best separates the data points into different categories. In the case of regression, the hyperplane is chosen such that the error between the predicted values and the actual values is minimized. The hyperplane is defined by a subset of the training data, called support vectors, which are the data points closest to the hyperplane.

SVR has several advantages, such as its ability to handle high-dimensional data, nonlinear relationships, and outliers in the data. It is also memory-efficient, as it only requires a subset of the training data to be stored in memory.

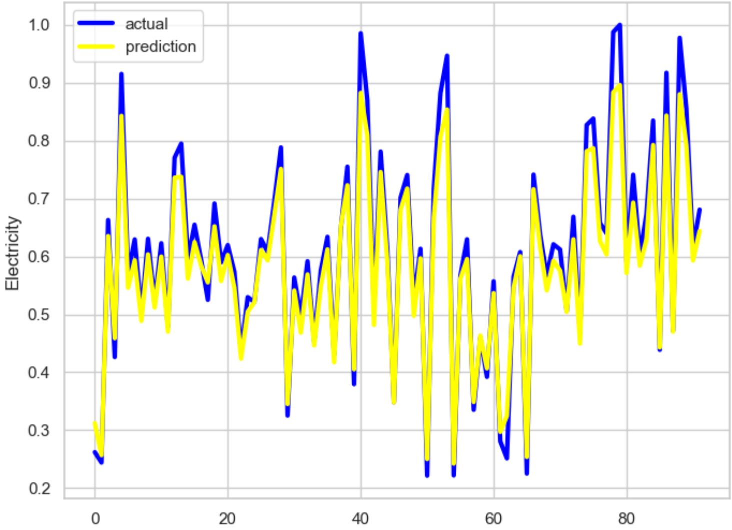

Figure 4. Graph of Actual and Predicted electricity using Support Vector Regressor

Mean Absolute Error is 0.03 and Accuracy is 0.95 of this model.

4.4 Ensemble Learning

Ensemble learning is a machine learning technique that involves combining multiple models to improve the accuracy and robustness of predictions. The idea behind ensemble learning is that a group of models can often produce more accurate predictions than a single model.

Ensembling is a technique where multiple models are combined to improve the accuracy and robustness of predictions. Some ways to ensemble models include taking the simple average of predictions, giving more weight to certain models, stacking predictions as input to a higher-level model, or using bagging to train multiple instances of the same model on different subsets of the data.

In our model we have preferred to use the voting regressor. In this, each model predicts a probability distribution over the possible values, and the final prediction is the weighted average of the predicted distributions.

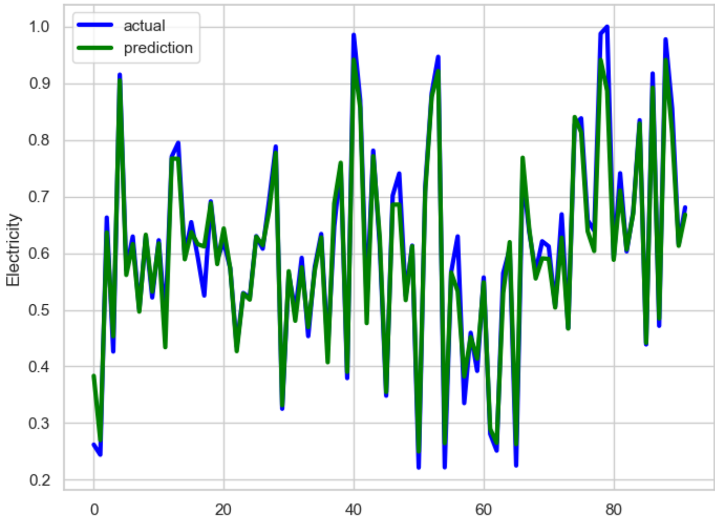

Figure 4. Graph of Actual vs Predicted electricity using Ensemble Method

Mean Absolute Error is ---- and Mean Absolute Error is ---- of this model.

4.5 Comparison of the result of different Models

Model Name	Mean Absolute Error	Accuracy
Decision Tree Regressor	15.016	0.922
Random Forest Regressor	7.932	0.975
Support Vector Regressor	0.031	0.954
Ensemble Learning	0.019	0.9747

Table 1. Comparison of Mean Absolute Error and Accuracy of different Model

After experimenting with different models and analyzing the results shown in the table 1, it is evident that the Random Forest Regressor and Ensemble Method have yielded the highest accuracy for predicting electricity consumption. As a result, we can conclude that the Random Forest Regressor and Ensemble model are the preferred choices for predicting electricity consumption.

5. Testing Model on Thermal, Nuclear and Hydro dataset

In this we have consider the one year Electricity generation data of Thermal, Nuclear and Hydro and Applied Random Forest Regressor and Ensemble Learning.

	index	Date	Region	Thermal Generation Actual (in MU)	Thermal Generation Estimated (in MU)	Nuclear Generation Actual (in MU)	Nuclear Generation Estimated (in MU)	Hydro Generation Actual (in MU)	Hydro Generation Estimated (in MU)
1	1	2017-09-01	Western	1,106.89	1,024.33	25.17	3.81	72.0	21.53
6	6	2017-09-02	Western	1,106.89	1,050.91	25.17	3.83	72.0	23.97
11	11	2017-09-03	Western	1,106.89	1,066.73	25.17	3.80	72.0	13.94
16	16	2017-09-04	Western	1,106.89	1,115.43	25.17	3.81	72.0	37.38
21	21	2017-09-05	Western	1,106.89	1,131.78	25.17	3.83	72.0	28.78

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df.tail()
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	index	Date	Region	Thermal Generation Actual (in MU)	Thermal Generation Estimated (in MU)	Nuclear Generation Actual (in MU)	Nuclear Generation Estimated (in MU)	Hydro Generation Actual (in MU)	Hydro Generation Estimated (in MU)
4921	286	2020-07-28	Western	1,182.24	1,282.43	42.37	36.80	29.75	25.94
4926	291	2020-07-29	Western	1,182.24	1,271.90	42.37	36.65	29.75	21.91
4931	296	2020-07-30	Western	1,194.97	1,279.02	42.37	36.62	29.75	24.46
4936	301	2020-07-31	Western	1,199.28	1,288.65	42.37	36.68	29.75	19.26
4941	306	2020-08-01	Western	1,116.00	1,262.10	42.37	36.63	54.67	20.28

Figure 5. Sample Dataset of the generated Electricity using Thermal, Nuclear and Hydro energy

We have applied the model on dataset shown in figure 5. We have applied Random Forest Regressor and Ensemble learning

5.1 Result Comparison

	Thermal	Hydro	Nuclear
Decision Tree Regressor	289.787	1.156	0.106
Random Forest Regressor	242.69	1.23	0.145

Table 2. Mean Squared Error of different model

	Thermal	Hydro	Nuclear
Decision Tree Regressor	0.96	0.98	0.99
Random Forest Regressor	0.96	0.98	0.99

Table 3. R2 Score of different model

	Thermal	Hydro	Nuclear
Decision Tree Regressor	0.96	0.98	0.998
Random Forest Regressor	0.97	0.978	0.997

Table 4. Accuracy on different model

As we can see in the Table 2, Table 3 and Table 3 that for the hydro, thermal and nuclear. Both the model are performing equal. But the Decision tree regressor is performing slight better. And it can be helpful when we are forecasting for large amount of electricity.

6. Testing Model on solar Power Generation and Weather Condition dataset

	DATE_TIME	PLANT_ID	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD
0	15-05-2020 00:00	4135001	1BY6WEcLGh8j5v7	0.0	0.0	0.0	6259559.0
1	15-05-2020 00:00	4135001	1IF53ai7Xc0U56Y	0.0	0.0	0.0	6183645.0
2	15-05-2020 00:00	4135001	3PZuoBAID5Wc2HD	0.0	0.0	0.0	6987759.0
3	15-05-2020 00:00	4135001	7JYdWkrLSPkdwr4	0.0	0.0	0.0	7602960.0
4	15-05-2020 00:00	4135001	McdE0feGgRqW7Ca	0.0	0.0	0.0	7158964.0

Figure 6. Sample dataset of electricity generation of Solar Plant

	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE	IRRADIATION	DATE	TIME
24	24.088446	22.206757	0.005887	2020-05-15	06:00:00
25	24.011635	22.353459	0.022282	2020-05-15	06:15:00
26	23.976731	22.893282	0.049410	2020-05-15	06:30:00
27	24.218990	24.442444	0.095394	2020-05-15	06:45:00
28	24.537398	27.185653	0.141940	2020-05-15	07:00:00

Figure 7. Sample dataset of weather conditions of the Solar Plant

As shown Figure 6 and Figure 7 we have the electricity generation dataset of the solar plant and the weather conditions of the solar plant. We have applied different model to compare the accuracy of the forecast values. We have tried Artificial Neural Network, Ensemble Method, Decision Tree, and SVM on the data.

6.1 Artificial Neural Network

Using an ANN for solar power generation forecasting is a great application of machine learning. The dataset should include weather conditions and electricity generation output as input and target variables, respectively. The ANN model is trained using a portion of the dataset, and another portion is used for validation. The trained model can then make predictions on new data, which would be future weather conditions. The accuracy of the model's predictions depends on the quality of the input data, the complexity of the model, and the size of the training dataset. Careful selection of input variables and model parameters is crucial for achieving optimal performance.

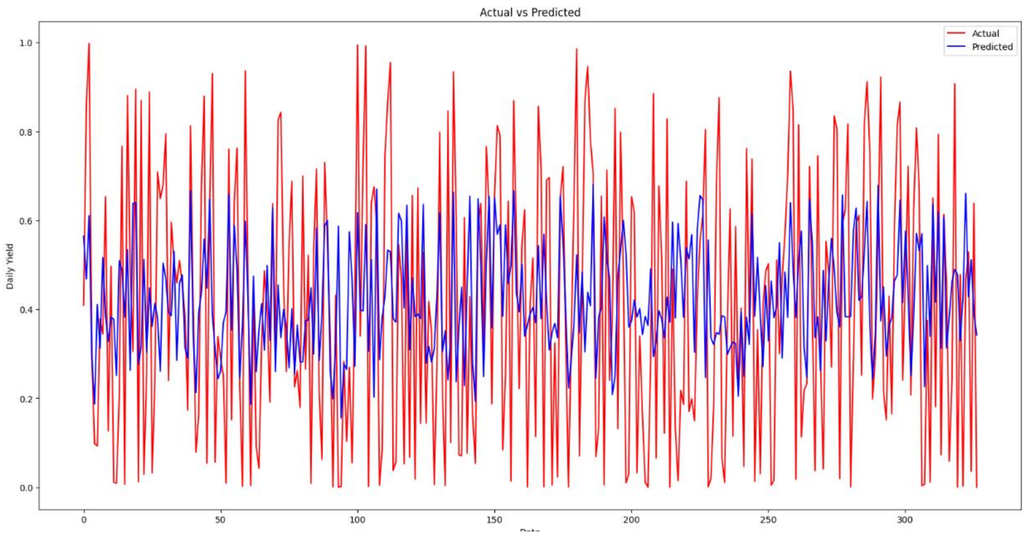

Figure 8. Graph of Actual and Predicted electricity using ANN

6.2 SVM, Decision Tree and Ensemble learning Model on dataset

We have applied the different models on the same dataset of solar electricity generation and weather conditions.

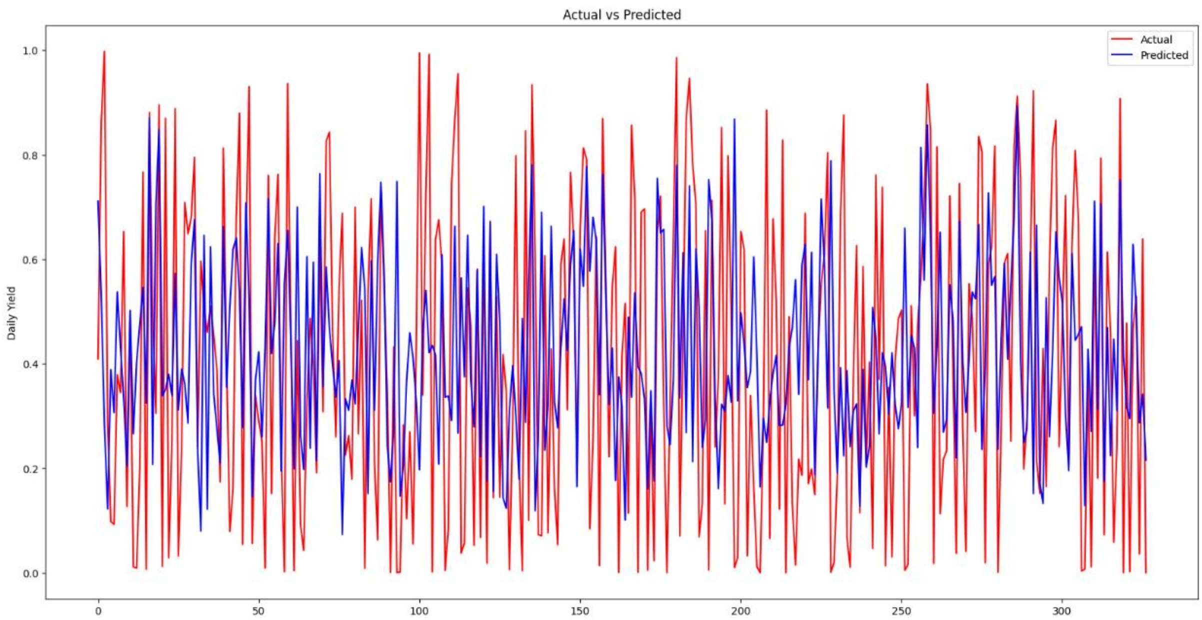

Figure 9. Graph of Actual and Predicted electricity using Ensemble Learning

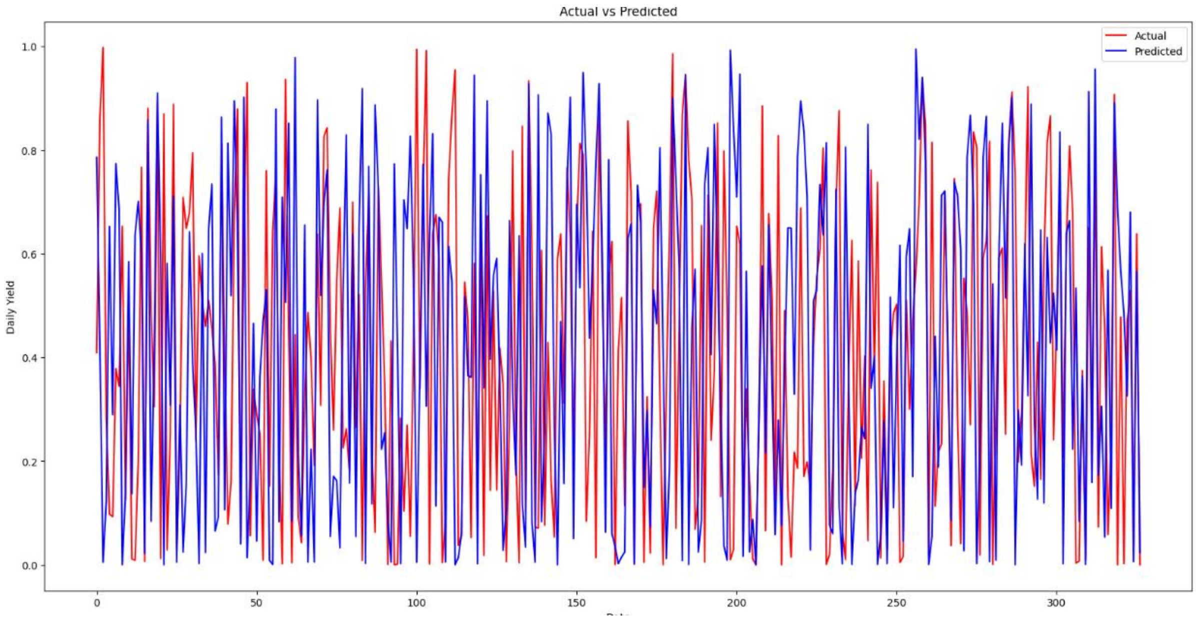

Figure 10. Graph of Actual and Predicted electricity using Decision Tree

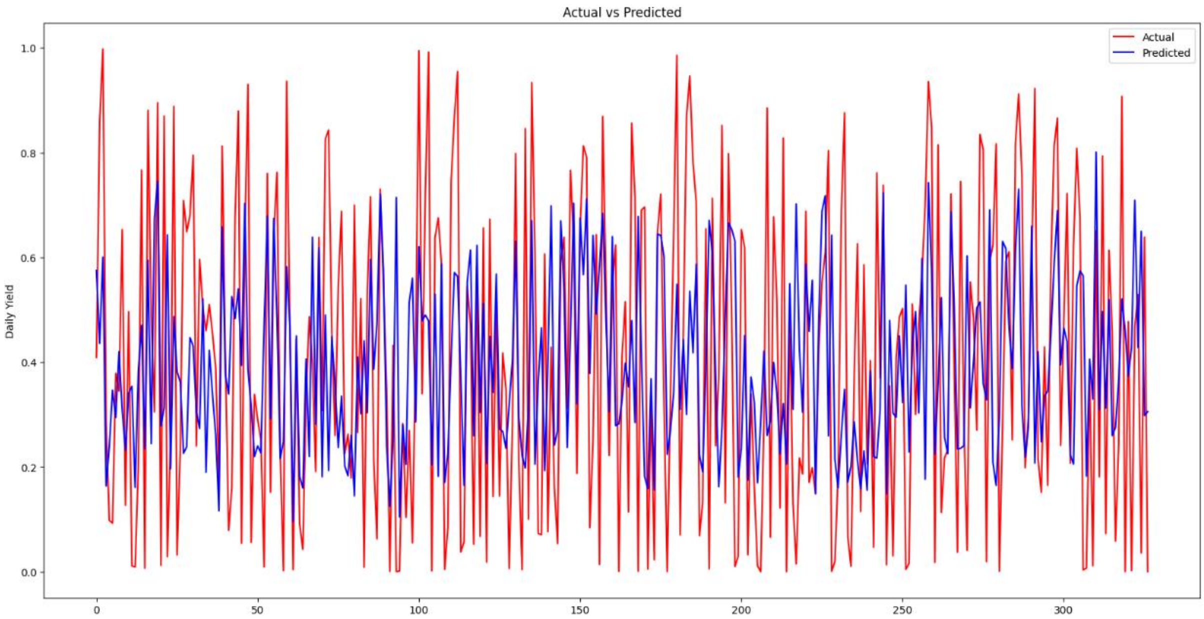

Figure 11. Graph of Actual and Predicted electricity using SVM

6.3 Result Comparison

	Mean Squared Error	RMSE	Accuracy
Artificial Neural Network	0.077	0.277	99.92
Ensemble Learning	0.087	0.29	99.91
Decision Tree Regressor	0.148	0.38	99.85
SVM	0.079	0.28	99.92

Table 5. Comparison of MSE, RMSE and Accuracy of different model

After experimenting with different models and analyzing the results shown in table 5 that Support vector machine and Artificial Neural Network have better result that other models. So for the forecast of the solar power generation the SVM model is performing better as it is less computing model that ANN. As a result, we can conclude that the Support vector machine and Artificial Neural Network are the preferred choices for predicting Solar Electricity Generation Forecast.

7. Combine Models for Electricity Need Forecasting

To forecast the electricity need using generation and consumption prediction models, we first need to generate predictions for both the electricity generation and consumption. Once we have these predictions, we can subtract the predicted consumption from the predicted generation to obtain the forecasted electricity need.

Generate predictions for electricity consumption using the relevant dataset and machine learning model. This could involve using electricity consumption datasets with ANN, SVM, Ensemble learning, DTR, or other models to generate predictions for electricity consumption. We have tried different models on the electricity consumption dataset in section 3.1 and you can see the result comparison in table1.

Generate predictions for electricity generation using the relevant dataset and machine learning model. This could involve using solar, wind, hydro, and non-renewable sources-based power plant generation datasets along with ANN, SVM, Ensemble learning, DTR, or other models to generate predictions for electricity generation. We have tried different models on the electricity generation dataset in section 3.2 and 3.3 In section 3.2, we have generated the prediction using past electricity generation dataset. In section 3.3, we have generated the prediction using past electricity generation as well as weather condition dataset. And we can see the results in table 2, 3, 4.

Combine the predicted electricity generation and predicted electricity consumption data to calculate the forecasted electricity need. To do this, subtract the predicted consumption from the predicted generation. The resulting value will be the forecasted electricity need.

By using machine learning models to forecast electricity generation and consumption, you can obtain more accurate and reliable predictions of the electricity need. This can help power plants and energy companies to better manage their electricity generation and distribution and avoid potential power shortages or overloads.

8. Analysis and Discussion

The study tests several regression models to predict power consumption and generation and integrates renewable energy sources' generation data into the models to determine their impact on the accuracy of the predictions. The results show that incorporating renewable energy sources in the forecasting models can significantly improve the accuracy of the predictions.

The research provides insights into how non-renewable and renewable energy sources can work together to meet the growing demand for electricity sustainably. The study demonstrates that integrating renewable energy sources into power systems can enhance the accuracy of electricity demand forecasting and optimize energy generation and consumption.

However, the study acknowledges that the integration of renewable energy sources into power systems can be complex due to their intermittency and variability. The research highlights the importance of accurately forecasting electricity needs for power plant operators to make informed decisions about energy generation and consumption.

9. Conclusion and Future Scope

This research paper studied different machine-learning models that accurately forecast electricity needs for power plants using non-renewable energy sources while considering the impact of renewable energy sources. The study demonstrates that incorporating renewable energy sources into power systems can significantly improve the accuracy of electricity demand forecasting and optimize energy generation and consumption. The study provides valuable insights into the potential of machine learning models to inform energy policies that promote the integration of renewable energy sources into power systems.

Future research can explore the application of machine learning models to forecast electricity needs for power plants using a combination of renewable energy sources and integrate energy storage systems to enhance the stability and reliability of renewable energy sources' integration into power systems.

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