Evaluation of Machine Learning Models in Solar Radiation Prediction for Photovoltaic System Design

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Abstract. This research evaluates machine learning models in predicting solar radiation, crucial for designing photovoltaic systems. Accuracy in solar forecasting is key to mitigating climate change and meeting energy demand. Advanced machine learning techniques were applied, surpassing traditional models in precision and efficiency, including SARIMA, Random Forests, SVM, ANN, and LSTM, assessed with metrics such as accuracy, sensitivity, precision, NME, R^2, and execution time. After normalization, the SVM model achieved the highest overall score of 5.86. A photovoltaic system was sized using an SVM model with solar radiation data (2017-2020). Predictions calculated an average daily consumption of 4.89 kWh, a total daily energy of 109.88 kWh, and a solar panel area of 4.42 m^2. The system's peak power is 0.86 kWp, and the inverter power with a safety margin is 1.04 kW.

Keywords: Machine learning, solar radiation, photovoltaic, prediction accuracy.

1 Introduction

The importance of human energy needs for various daily and industrial activities makes it crucial to opt for renewable energies [1] and the transition to renewable energies is essential to meet current needs without compromising the capacity of future generations [2]. Globally, the need to ensure a full and environmentally compatible energy supply is recognized, which has led to legal actions and regulations to address climate change.

In [3] discusses the management of solar photovoltaic energy between 2000 and 2019, which highlights the importance of technological development to improve energy efficiency and also discusses the recent approach such as life cycle assessment and prediction of factors in photovoltaic generation. In [4] mentions that in-creasing energy consumption requires carbon neutral solutions to control CO2. Therefore, in [5] the availability of solar radiation is analyzed and its results indicate high cost- effectiveness for solar applications.

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In [6] reveals the inadequacy and limited accuracy of current methods, highlighting the need for more flexible models for specific applications, due to the variability of the solar resource, influenced by factors such as cloud cover and atmospheric aerosols, which increases reserve costs and the need for auxiliary generators, affecting grid reliability. Solar forecasts, over multiple time horizons, are essential for energy regulation, dispatch and scheduling. Various methods, including remote sens-ing and artificial intelligence models, have been developed to improve the accuracy of these forecasts, addressing the complexity and nonlinearity of the solar resource [7].

Supervised learning techniques (neural networks, Gaussian processes and support vector machines) are evaluated to predict global horizontal solar irradiance (GHI) in comparison with a simple autoregressive model and two naive persistence models. Using data from three French islands, the study finds that machine learning techniques slightly outperform linear models, further highlights the importance of accurate solar predictions for island power grids and discusses the use of statistical models and machine learning techniques to improve forecast performance [8].

In [9] reviews the use of machine learning techniques in solar radiation predic-tion, highlighting its evolution from numerical and analytical methods to hybrid approaches, classifying models according to the type of input data, such as struc-tured, endogenous or exogenous data, and exploring various methodologies, such as Markov processes, fuzzy logic, decision trees and support vector machines (SVM). The importance of data preprocessing, error handling and the appropriate selection of algorithms according to the prediction horizon is highlighted [10].

In addition, a study on the prediction of solar radiation and ambient temperature using recurrent neural networks (RNRE) and recurrent neural networks Jordan (RNRJ) in three meteorological stations located in Ecuador is presented. Data from these stations are used, which are divided into training and validation sets [11].

The models are evaluated using performance indicators such as the mean square error (MSE) and Pearson's correlation coefficient (r) in the validation and prediction stages. The results obtained for each model in terms of r and MSE for solar radiation and temperature are shown [11]. Therefore, it is estimated that the evaluation of machine learning models will allow the selection of the appropriate algorithm which will guarantee the highest accuracy and the lowest error in the prediction of solar radiation.

The purpose of this study is to compare different machine learning models for so-lar radiation prediction, in order to identify the most accurate and efficient one to design a photovoltaic system. The aim is to improve the accuracy of the predictions, minimize errors and optimize the design of the photovoltaic system by selecting the best algorithm.

2 Materials and Methods

Component of Solar Photovoltaic Systems. A solar photovoltaic system con-verts solar energy into electricity through key components. Photovoltaic panels, composed of cells that generate a voltage between 0.3 V and 0.5 V, are connected in series to increase voltage and in parallel to increase current. Batteries, essential in off-grid systems, store the energy produced for use when there is no solar generation. They can be lead-acid, nickel-iron or lithium- ion, and their durability depends on the depth of discharge; it is recommended not to discharge more than 40% of their capacity. Charge regulators ensure efficient charging of the batteries, protecting them from overcharging and deep discharges that could reduce their lifetime [12]. The efficiency of the panels varies according to the material, as detailed in Table 1.

Table 1. Efficiency of solar panels [5].

Material	Nominal Efficiency (%)	Real Efficiency (%)
Monocrystalline Silicon	24	14 – 17
Polycrystalline Silicon	18	13 – 15
Amorphous Silicon	13	5 - 7

2.1 Machine learning models.

ARIMA models offer an alternative for time series forecasting, these models are among the most widely used approaches in time series forecasting, providing complementary methods to address this problem, while exponential smoothing models are based on describing the trend and seasonality in the data, ARIMA models focus on describing the autocorrelations present in the data [13].

The SARIMA model uses non-seasonal and seasonal components to capture trends and seasonalities in the data. The ARIMA part includes an autoregressive component as shown in equation (1), which also predicts future values based on past values, and a moving average component given in equation (2), which models the residual error. The seasonal part uses similar terms with a 24-hour SSS periodicity, including the seasonal autoregressive component in equation (3) and the seasonal moving average component in equation (4).

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \epsilon_t \tag{1}$$
$$y_t = c + \epsilon_t + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} \tag{2}$$
$$y_t = \Phi_1 y_{t-S} + \cdots + \Phi_P y_{t-PS} + \epsilon_t \tag{3}$$
$$y_t = \epsilon_t + \Theta_1 \epsilon_{t-S} + \cdots + \Theta_Q \epsilon_{t-QS} \tag{4}$$

2.2 How to create random blocks.

Random forests, introduced by Leo Breiman, are an ensemble learning technique that uses multiple decision trees to improve accuracy and avoid overfitting. Each tree is built from a random subset of data and features, which increases the diversity of the model. It is used in classification and regression problems, such as solar radiation prediction, by combining the predictions of all the trees in the forest [14].

Each decision tree Ti is constructed from a random sample of the training data. A decision tree is a structure where the internal nodes represent tests on a characteristic, where the branches represent the test outcome and the leaves represent the outputs (in this case, predicted radiation values), determined in the equation (5).

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} T_i(x) \tag{5}$$

2.3 Support Vectorial Machines (SVM)

Support vector machines are supervised models that seek to find the hyperplane that maximizes the margin between different classes or, in the case of regression, minimizes the error [15]. SVMs can be used for regression (SVR) and are effective in high-dimensional spaces. An SVM with RBF kernel is used to predict solar radiation [16]. The data is normalized, divided into training and testing, and sequences are generated for training the model. Finally, it performs the prediction for a range of dates to evaluate the model using the confusion matrix and error metrics, which are given in equations (5) and (6).

$$f(x) = w^T x + b \tag{6}$$

$$\text{Loss} = \sum_{i=1}^{N} \max(0, |y_i - f(x_i)| - \epsilon) \tag{7}$$

2.4 The Artificial Neural Network (ANN)

They are based on artificial neurons that receive multiple inputs, process them and produce an output. They are composed of layers: the input layer, which receives initial data; hidden layers, which extract features and patterns; and the output layer, which produces the final result [17]. An Excel file is loaded with the data, verified and displayed, including null values, for indexing dates and radiation values for better data handling. The data set is then divided into training (80%) and test (20%), and normalized using$MinMaxScaler$. A 24-hour time window is defined to create input sequences. The sequential ANN model includes two dense layers of 50 neurons each and is trained with 50 epochs and a batch size of 32. Predictions are denormal-ized and evaluated using metrics such as confusion matrix, precision, sensitivity, accuracy, MSE, NME and R^2. Finally, the confusion matrix and the actual vs. pre-dicted values given by equation (8) are plotted.

$$y = f(W_2 \cdot f(W_1 \cdot X + b_1) + b_2) \tag{8}$$

2.5 Recurrent Neural Network (RNN) with LSTM

It is suitable for time series problems due to its ability to maintain information over time and handle long- term dependencies [11]. A detailed concept of an RNN with LSTM is presented here, followed by a code example and a step-by-step expla-nation. The Excel file with solar radiation data is loaded and verified, indexing dates and values for efficient handling. Then, the data set is divided into training (80%) and test (20%), normalizing them with MinMaxScaler. The 24-hour sequences for the LSTM model with Dropout are created and trained with 40 epochs and a batch size of 16. The mathematical model is described in the equations from (9) to (13).

$$h_t = \sigma(W \cdot [h_{t-1}, x_t] + b) \tag{9}$$
$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \tag{10}$$
$$\tilde{c}_t = tanh\,(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{11}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{12}$$
$$h_t = o_t \cdot tanh\,(c_t) \tag{13}$$

2.6 The confusion matrix

It is a tool used to evaluate the performance of a classification model, showing true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN). Elements on the diagonal of the matrix represent correct predictions, while off-diagonal elements indicate classification errors. The matrix reveals information such as precision (proportion of correct positive predictions), sensitivity (proportion of correctly identified true positives) and accuracy (proportion of correct predictions overall) [11].

2.7 Coefficient of Determination (R^2, R-squared)

Evaluation of machine learning models includes SARIMA, Random Forests, SVM, ANN and LSTM, tested on specific data. Metrics such as precision, sensitivity, accuracy, NME, R^2 and runtime are recorded. Metric normalization ensures comparable values: each metric is divided by its maximum value, except NME and runtime, where the minimum value divided by the current value is used. This balances the metrics and allows for an objective evaluation. The total score of each model, based on the normalized metrics, allows a comprehensive comparison of its performance in predictive accuracy, generalization and computational efficiency [18].

Finally, the models are ranked according to their total scores to identify the best model. This helps in making informed decisions on which model to adopt for a spe-cific problem, balancing predictive performance with computational efficiency and other relevant factors already mentioned above and are described by equations (14) to (17).

$$\text{Normalized Metric } = \frac{\text{Value of Metric}}{max(\text{ Value of Metric })} \tag{14}$$

$$\text{Normalized NME } = \frac{min(\text{ NME })}{\text{NME Value}} \tag{15}$$

$$\text{Normalized Time } = \frac{min(\text{ Execution Time })}{\text{Execution Time}} \tag{16}$$

2.8 Calculation of the Photovoltaic Panel

To determine the required area of solar panels in a PV system, one must first calculate the total daily energy required [19]. This includes the average daily consumption per customer, which is obtained by dividing the total monthly consumption by the number of customers and then dividing this value by 30 days. In addition, the energy required by the luminaires, calculated by multiplying the luminaire power by the total number of luminaires and by the daily operating hours, must be considered. The total daily energy is the sum of the average daily consumption per customer and the daily energy of the luminaires. Then, this total energy is divided by the daily average solar radiation to obtain the energy required from the solar panels [20]. Finally, by dividing this energy by the efficiency of the solar panels, the total required area of the solar panels is obtained. Mathematically, these are represented in equations (18) to (20).

$$\mathrm{EDR} = \frac{\mathrm{CMT}}{\mathrm{N}} \times \frac{1}{30} + \mathrm{PL} \times \mathrm{NL} \times \frac{12}{1000} \tag{15}$$

$$\mathrm{EP} = \frac{\mathrm{EDR}}{\mathrm{RD}} \tag{19}$$

$$\mathrm{A} = \frac{\mathrm{EP}}{\eta} \tag{20}$$

2.9 Battery Capacity Calculations

To ensure the autonomy of the system on days without sun, the total battery capacity and energy required must be calculated. First, multiply the total daily energy required by the number of days of autonomy desired. Then, divide this value by the depth of discharge of the batteries to obtain the useful capacity of the battery. Finally, the battery capacity in ampere-hours is calculated by dividing the useful battery capacity by the system voltage [24]. The corresponding equations are (27) to (29).

$$\mathrm{ET} = \mathrm{EDR} \times \mathrm{DA} \tag{16}$$

$$\mathrm{Cu} = \frac{\mathrm{ET}}{\mathrm{DOD}} \tag{17}$$

$$\mathrm{Cb} = \frac{\mathrm{Cu}}{\mathrm{Vs}} \tag{18}$$

2.10 Investor Calculations

The inverter must be able to handle the peak power of the PV system, which is obtained by multiplying the total required area of the panels by the rated power of each solar panel. In addition, an overload factor and a safety margin must be considered to ensure that the inverter can handle variations in power production and demand. The final power output of the inverter is calculated by multiplying the peak power by the overload factor and then by the safety margin [21]. This is given by equations (30) (31) and (32).

$$\mathrm{Ppico} = N \times \mathrm{Pnom} \tag{19}$$

$$\mathrm{Pinversor} = \mathrm{Ppico} \times FS \tag{20}$$

$$\mathrm{Pinversor\ final} = \mathrm{Pinversor} \times (1 + MS) \tag{21}$$

2.11 Programming Structure

The script loads solar radiation data from an Excel file and prepares it for modeling. It performs data cleaning and transformation, creating a time index. Use a time window to create sequences of data for training. Train a Support Vector Machine (SVM) model and make solar radiation predictions. Compares predictions to actual values and plots the results. Calculates evaluation metrics such as confusion matrix, MSE, NME and R^2 (See Figure 1).

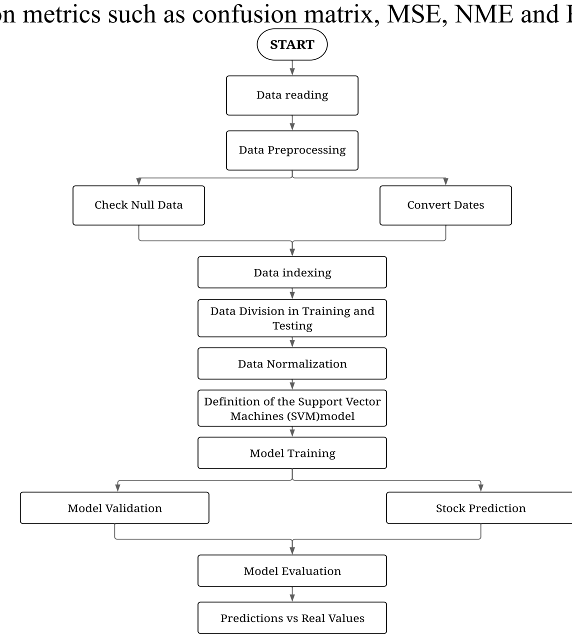

Fig. 1. Programming structure for the machine learning model.

2.12 Code structure for Photovoltaic System Calculations

The code describes the methodology for sizing a PV system, starting with general data such as energy consumption and solar radiation. It calculates the average monthly and daily consumption per customer, adding the energy required by the luminaires. From the average daily radiation, determine the energy needed from the solar panels and their required area, considering the efficiency. Then, it calculates the total energy required from the battery for several days of autonomy and the useful capacity based on the depth of discharge. In addition, it estimates the battery capacity in Ah and the peak power of the PV system, adjusting with an overload factor and safety margin for the inverter. Finally, it saves the results in an Excel file (See Figure 2).

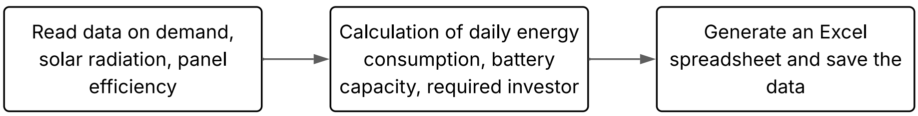

Fig. 2. Photovoltaic System Calculations.

3 Results and Discussion

Solar Radiation Data: these data were provided by the Geological and Energy Re-search Institute from three meteorological stations located in the Provinces of Pichincha and Tungurahua, the study site was determined in Cayambe, the location is given in UTM coordinates (816851.00 m E; 4872.00 m N); for a number of 21 residential users, with 6 sodium luminaires with a power of 100 watts and an average energy consumption of 3080.46 in kWh, data were obtained from the Argis of Empresa Eléctrica Quito. The database is from January 1, 2017 at seven o'clock in the morning, until December 31, 2020. That is, a total amount of 18994 of data, of which 80% were taken for the training of the evaluated models and 20% for the validation of the same.

Figure 3 shows the comparison between actual and predicted solar radiation during the prediction period, providing a clear view of the accuracy of the SVM model used. The data were obtained from an Excel file, normalized and divided into training and test sets. With a 24-hour time window, the model was trained and predictions were made. The plot reveals the correlation between actual and predicted values, highlighting both trends and discrepancies. Evaluation of the model using the coefficient of determination (R^2) and normalized mean square error (NME) confirms the effectiveness of the approach. Visual comparison on the graph facilitates the interpretation of model performance in terms of solar radiation.

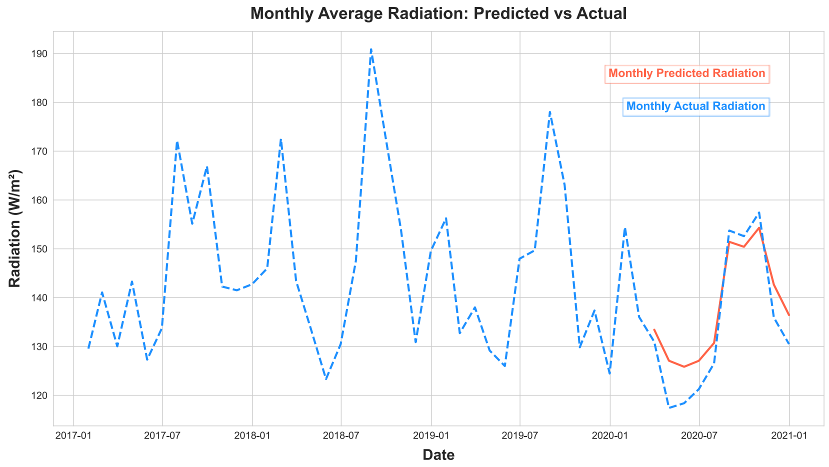

Fig. 3. Comparison between Actual and Predicted radiation in the prediction time frame.

Figure 4 "Predicted vs Actual Average Daily Radiation" shows the comparison between predicted and actual solar radiation values recorded during the 2020 period. Using an SVM model trained with historical radiation data (2017-2020), daily pre-dictions were generated and compared to the observed values. The blue line represents the predicted radiation, while the green line shows the actual radiation. The graph reveals the accuracy of the model in capturing daily solar radiation trends. This analysis is crucial to evaluate the effectiveness of the model in predicting solar radiation, which is essential for sizing PV systems in rural areas without access to electricity.

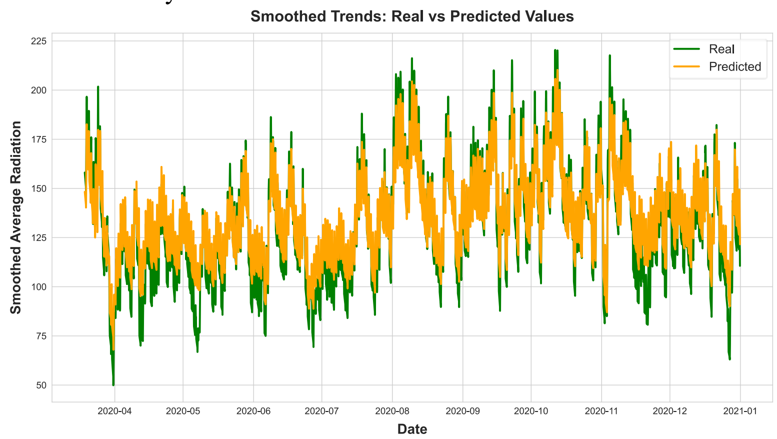

Fig. 4. Predicted vs. Actual Daily Average Radiance

Figure 5 presents the Confusion Matrix generated to evaluate the performance of the SVM model in predicting solar radiation. The analysis was based on radiation data between 2017 and 2020, processed and normalized appropriately. The confusion matrix shows the relationship between model predictions and actual values the amount of data for validation is 3774, classifying the instances into true positives, true negatives, false positives and false negatives. The results indicate a precision of 98%, a sensitivity of 97% and an accuracy of 99%

Fig. 5. Confusion Matrix

Figure 6 presents an analysis of the five machine learning models: SARIMA, Random Forests, SVM, ANN, and LSTM, which were evaluated based on metrics such as precision, sensitivity, accuracy, NME (Normalized Mean Error), R^2 and exe-cution time. After normalization, the SVM model obtained the highest total score of 5.86, standing out as the best model. This model showed a balance between accuracy (97.25%) and execution time (12.33 seconds). Although SARIMA had the highest accuracy (99.25%), its long run time (244.25 seconds) and lower total score (3.72) relegated it. These results underscore the importance of balancing accuracy and time efficiency in the selection of the optimal model, detailed in Figure 6.

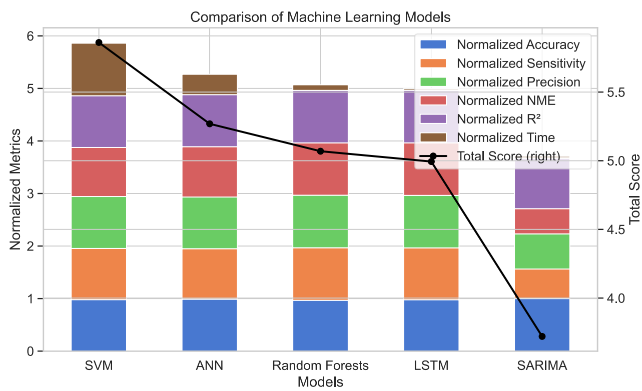

Fig. 6. Results of the comparison of the machine learning models

Figure 7 details the results of the calculations for sizing a PV system. Using an SVM model trained with solar radiation data from 2017 to 2020, daily and monthly radiation was predicted. These results allow determining the average energy consumption per customer and the total daily energy required, considering both residential and luminaire consumption. In addition, the energy required and the area of solar panels required were calculated, as well as the useful and total capacity of the batteries in kWh and Ampere-hours. Finally, the peak power of the photovoltaic system and the inverter power were determined, incorporating an overload factor and a safe-ty margin, ensuring an adequate sizing of the system (See Figure 8).

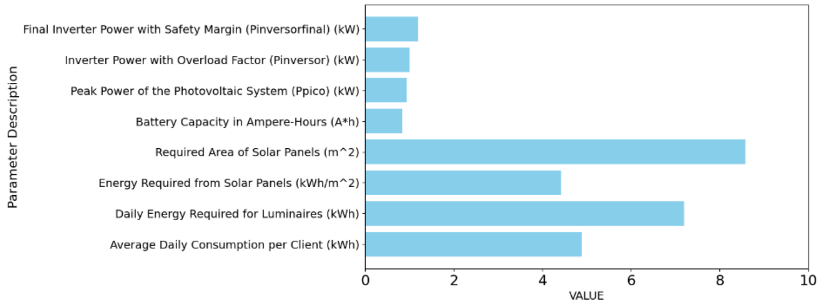

Fig. 7. Photovoltaic System Results

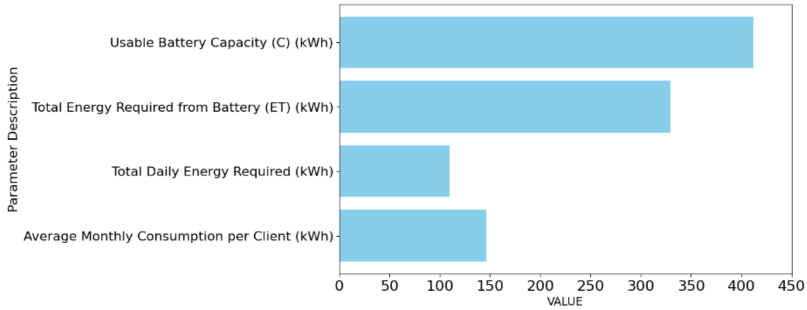

Fig. 8. Results of the photovoltaic system output

4 Conclusions

The transition to renewable energy is important to meet current and future energy needs in a sustainable manner, in order to reduce carbon emissions and address cli-mate change, as discussed in several previous studies.

The efficiency of solar PV systems depends on several key components, including panels, batteries, charge controllers and inverters. Proper selection and sizing of these components is essential to maximize production, in addition to energy storage.

Data preprocessing, including outlier identification and handling, normalization and feature selection, is critical to improving the performance of machine learning models in solar radiation prediction.

The Support Vector Machine (SVM) model was the most effective for predicting solar radiation, achieving a balance between accuracy and computational complexi-ty. SVM obtained an MSE of 0.015 and an R^2 of 0.92, outperforming SARIMA, Ran-dom Forests and neural networks, who's average MSEs were 0.025 and average R^2 was 0.85.

The PV system design shows an average monthly consumption of 146.69 kWh per customer and a total daily energy requirement of 109.88 kWh. An area of 4.42 m^2 of solar panels with an efficiency of 0.796 kWh/m^2 is required. The useful capacity of the battery is 412.06 kWh, and the final power of the inverter is 1.04 kW.

References

1. Hoang, A.T., Pham, V.V., Nguyen, X.P.: Integrating renewable sources into energy system for smart city as a sagacious strategy towards clean and sustainable process. Journal of Cleaner Production. 305, 127161 (2021). https://doi.org/10.1016/j.jclepro.2021.127161

2. Potrč, S., Čuček, L., Martin, M., Kravanja, Z.: Sustainable renewable energy supply networks optimization – The gradual transition to a renewable energy system within the European Union by 2050. Renewable and Sustainable Energy Reviews. 146, 111186 (2021). https://doi.org/10.1016/j.rser.2021.111186
3. Ahmed, S., Ali, A., Ahmed Ansari, J., Abdul Qadir, S., Kumar, L.: A Comprehensive Review of Solar Photovoltaic Systems: Scope, Technologies, Applications, Progress, Challenges, and Recommendations. IEEE Access. 13, 69723–69750 (2025). https://doi.org/10.1109/ACCESS.2025.3558539
4. Kou, G., Pamucar, D., Yüksel, S., Dinçer, H., Deveci, M., Umar, M.: Evaluation of Multidimensional Carbon Neutrality Policies in Transportation Using a Novel Quantum Picture Fuzzy Rough Modeling. IEEE Transactions on Engineering Management. 71, 7681–7700 (2024). https://doi.org/10.1109/TEM.2024.3374385
5. Vodapally, S.N., Ali, M.H.: A Comprehensive Review of Solar Photovoltaic (PV) Technologies, Architecture, and Its Applications to Improved Efficiency. Energies. 16, 319 (2023). https://doi.org/10.3390/en16010319
6. Ruiz-Arias, J.A.: Aerosol transmittance for clear-sky solar irradiance models: Review and validation of an accurate universal parameterization. Renewable and Sustainable Energy Reviews. 145, 111061 (2021). https://doi.org/10.1016/j.rser.2021.111061
7. Travieso-González, C.M., Cabrera-Quintero, F., Piñán-Roescher, A., Celada-Bernal, S.: A Review and Evaluation of the State of Art in Image-Based Solar Energy Forecasting: The Methodology and Technology Used. Applied Sciences. 14, 5605 (2024). https://doi.org/10.3390/app14135605
8. Suanpang, P., Jamjuntr, P.: Machine Learning Models for Solar Power Generation Forecasting in Microgrid Application Implications for Smart Cities. Sustainability. 16, 6087 (2024). https://doi.org/10.3390/su16146087
9. Jannah, N., Gunawan, T.S., Yusoff, S.H., Hanifah, M.S.A., Sapihie, S.N.M.: Recent Advances and Future Challenges of Solar Power Generation Forecasting. IEEE Access. 12, 168904–168924 (2024). https://doi.org/10.1109/ACCESS.2024.3496120
10. Jahin, M.A., Shovon, M.S.H., Shin, J., Ridoy, I.A., Mridha, M.F.: Big Data—Supply Chain Management Framework for Forecasting: Data Preprocessing and Machine Learning Techniques. Arch Computat Methods Eng. 31, 3619–3645 (2024). https://doi.org/10.1007/s11831-024-10092-9
11. Achig, R.S., Gonzales, J.A., Hidalgo, C.A.: Flow Prediction for Hydropower Generation using LMST Neural Networks. J. Phys.: Conf. Ser. 2609, 012006 (2023). https://doi.org/10.1088/1742-6596/2609/1/012006
12. Kurzweil, P., Frenzel, B., Scheuerpflug, W.: A Novel Evaluation Criterion for the Rapid Estimation of the Overcharge and Deep Discharge of Lithium-Ion Batteries Using Differential Capacity. Batteries. 8, 86 (2022). https://doi.org/10.3390/batteries8080086
13. Abdullah, Sarpong-Streetor, R.M.N.Y., Sokkalingam, R., Othman, M., Azad, A.S., Syahrantau, G., Yusriwarti, Arifin, Z.: Intelligent Hybrid ARIMA-NARNET Time Series Model to Forecast Coconut Price. IEEE Access. 11, 48568–48577 (2023). https://doi.org/10.1109/ACCESS.2023.3275534
14. Barreñada, L., Dhiman, P., Timmerman, D., Boulesteix, A.-L., Van Calster, B.: Understanding overfitting in random forest for probability estimation: a visualization and simulation study. Diagn Progn Res. 8, 14 (2024). https://doi.org/10.1186/s41512-024-00177-1
15. Tanveer, M., Rajani, T., Rastogi, R., Shao, Y.H., Ganaie, M.A.: Comprehensive review on twin support vector machines. Ann Oper Res. 339, 1223–1268 (2024). https://doi.org/10.1007/s10479-022-04575-w

16. Belmahdi, B., Louzazni, M., El Bouardi, A.: Comparative optimization of global solar radiation forecasting using machine learning and time series models. Environ Sci Pollut Res. 29, 14871–14888 (2022). https://doi.org/10.1007/s11356-021-16760-8
17. Vilone, G., Longo, L.: Classification of Explainable Artificial Intelligence Methods through Their Output Formats. Machine Learning and Knowledge Extraction. 3, 615–661 (2021). https://doi.org/10.3390/make3030032
18. Ullah, K., Ahsan, M., Hasanat, S.M., Haris, M., Yousaf, H., Raza, S.F., Tandon, R., Abid, S., Ullah, Z.: Short-Term Load Forecasting: A Comprehensive Review and Simulation Study With CNN-LSTM Hybrids Approach. IEEE Access. 12, 111858–111881 (2024). https://doi.org/10.1109/ACCESS.2024.3440631
19. Kumar, R., Rajoria, C.S., Sharma, A., Suhag, S.: Design and simulation of standalone solar PV system using PVsyst Software: A case study. Materials Today: Proceedings. 46, 5322–5328 (2021). https://doi.org/10.1016/j.matpr.2020.08.785
20. Liu, F., Wang, X., Sun, F., Wang, H.: Correct and remap solar radiation and photovoltaic power in China based on machine learning models. Applied Energy. 312, 118775 (2022). https://doi.org/10.1016/j.apenergy.2022.118775
21. Nasr, M.-A., Hooshyar, A.: Power Swing in Systems With Inverter-Based Resources—Part II: Impact on Protection Systems. IEEE Transactions on Power Delivery. 39, 1903–1917 (2024). https://doi.org/10.1109/TPWRD.2024.3382843