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Enhancing Solar Power Efficiency: Smart Metering and ANN-Based Production Forecasting †

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Abstract: This paper presents a comprehensive and comparative study of solar energy forecasting in Morocco, utilizing four machine learning algorithms: Extreme Gradient Boosting (XGBoost), Gradient Boosting Machine (GBM), recurrent neural networks (RNNs), and artificial neural networks (ANNs). The study is conducted using a smart metering device designed for a photovoltaic system at an industrial site in Benguerir, Morocco. The smart metering device collects energy usage data from a submeter and transmits it to the cloud via an ESP-32 card, enhancing monitoring, efficiency, and energy utilization. Our methodology includes an analysis of solar resources, considering factors such as location, temperature, and irradiance levels, with PVSYST simulation software version 7.2, employed to evaluate system performance under varying conditions. Additionally, a data logger is developed to monitor solar panel energy production, securely storing data in the cloud while accurately measuring key parameters and transmitting them using reliable communication protocols. An intuitive web interface is also created for data visualization and analysis. The research demonstrates a holistic approach to smart metering devices for photovoltaic systems, contributing to sustainable energy utilization, smart grid development, and environmental conservation in Morocco. The performance analysis indicates that ANNs are the most effective predictive model for solar energy forecasting in similar scenarios, demonstrating the lowest RMSE and MAE values, along with the highest R^2 value.

Keywords: solar energy; smart city; smart meter; monitoring; artificial intelligence; machine learning; predictive maintenance; photovoltaic fault

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1. Introduction

Monitoring serves as a powerful tool for managing and optimizing solar panels in smart grids [1]. It encompasses a network of connected devices that can gather and share real-time data [2]. Integrating monitoring devices into smart grids enhances the efficiency and performance of solar panel systems. These devices enable effective management of energy generated by solar panels [3]. Smart meters can monitor energy consumption in real time and adjust solar panel output to match demand, thus preventing energy waste and reducing reliance on backup power. Additionally, monitoring photovoltaic production helps predict future energy generation using advanced data analytics and machine learning algorithms [4], optimizing energy usage and improving overall efficiency [5–7]. Moreover, the utilization of artificial intelligence (AI) technology in the domain of renewable energy, particularly in solar power systems, has presented numerous novel possibilities for the identification and resolution of various challenges. These data-based decision-making systems possess an inherent ability to facilitate efficient energy management, thus contributing to the overall optimization of renewable power generation. By harnessing the power of AI, we can effectively address complex issues and unlock greater potential for the advancement of sustainable energy solutions [8,9].

This paper is organized into four sections: the first discusses related works, the second details the simulation steps using the PVSYST tool and validates the study with real data monitored by the proposed data logger, and the third section presents the results of energy generation prediction through a comparative study (RNNs, ANNs, GBM, and XGBoost) to evaluate their effectiveness. The final section concludes the work and explores future perspectives [10].

1.1. Background and Significance

The importance of green or renewable energy sources such as wind, hydro, solar, nuclear, geothermal, and biofuels has been growing very quickly due to a worldwide increase in energy demand [11,12]. Among these, solar energy is regarded as the most sustainable and beneficial source of energy. As many countries are still rural, electrical power for air conditioning and lighting is usually generated by solar energy. Official estimates from IRENA, released in its Renewable Energy Capacity Statistics 2024 report, indicate that the installed solar photovoltaic (PV) capacity of the world as of 2023 was approximately 345.5 GW. However, the actual electricity generated from this capacity is less than the rated capacity due to shading, dust, pollution, aging, and improper operation and monitoring of systems. Thus, solar monitoring and fault detection are very important for increasing electricity output. The use of IoT and machine learning (ML) can monitor and forecast real-time energy output [13,14], increasing the electrical efficiency of a photovoltaic system (PVS). The main limitations of the current state of the art can be summarized as follows. Many of the predictions are made using historical data, leading to the uncertain nature of the actual PV outputs. Additionally, the application of intelligence techniques in PVS may reduce the need for extensive parameter tuning of systems, which involves the use of sophisticated devices. Furthermore, there is a shortage of field experience with PVS. Finally, the available resources do not address the comparison of real-time IoT data with traditional methods to forecast the electrical power output of solar energy.

1.2. Research Objectives

This research has two main goals: first, to create a real-time monitoring system for a large rooftop photovoltaic system, and second, to develop, evaluate, and deploy a precise solar power production forecast algorithm. The monitoring system collects and analyzes data periodically, allowing for remote real-time monitoring and analysis of the PV inverters' electrical status, photovoltaic array temperature, and instantaneous solar radiation. The study brings real-world operational and environmental benefits by optimizing maintenance, identifying potential operation failures, assessing power losses due to degradation factors, and raising public awareness about the benefits of switching to photovoltaic energy. Overall, this paper combines a full-stack smart metering solution for solar system monitoring with a predictive algorithm for energy production. The proposed architecture serves as a secure framework for predictive maintenance. The paper contributes to renewable energy research and development, offering evidence of potential power savings in large PV installations and highlighting power losses that can be improved. The findings can help shape policies and refine designs for residential use by quantifying real-time power losses and by identifying operational inefficiencies in a large test PV plant.

2. Related Work

Organizations and establishments are employing monitoring solutions to oversee solar plants. Solar power monitoring primarily focuses on maintenance activities because the total number of units sold makes it easy to determine the amount of power generated [15,16]. However, we argue that integrating these data with inputs to an artificial neural network (ANN) can provide deeper insights into the operations of solar plants. The ANN can forecast the power that will be generated [17], while the IoT monitoring system can measure the actual power being generated. By combining these data, even minor variations in the output of the inverters can be identified. This section provides a concise and understandable overview of solar power monitoring using both monitoring and machine learning algorithms, which is summarized in Table 1.

Analyzing the field of solar energy forecasting in this specific context is a critical issue that has not been extensively researched. It is also worth noting that the creation of a thorough modeling framework that incorporates simulation methods to evaluate the results, in addition to regularly monitoring energy output combined with forecasting energy production. Thus, it is evident that our pioneering research effectively bridges this gap by providing a conclusive resolution to this urgent matter.

Table 1. Review of solar power optimization combining IoT and ANNs.

Reference	Year/Citation	Summary of Paper
[18]	2019/15	This paper introduces a low-cost method using Node-Red, an IoT platform, for tracking and monitoring solar panel performance. By analyzing current, voltage, and power parameters, the approach optimizes solar panel output and enhances energy efficiency, facilitating better decisions for installations and maintenance.
[19]	2023/05	This study, conducted in Iran, focuses on optimizing artificial neural networks (ANNs) for forecasting global solar radiation. The ANN model with three neurons in the hidden layer maintained excellent performance (R^2 > 0.97%).
[20]	2021/36	This paper assesses machine learning models for forecasting photovoltaic power in Colombia and finds that artificial neural networks (ANNs) provide the most accurate predictions, outperforming k-nearest neighbors, linear regression, and support vector machines. The ANN model offers significant improvements in forecasting accuracy, with the lowest RMSE and MAE.
[21]	2022/25	This paper presents various machine learning algorithms to predict energy consumption in open pit mines. The study compares the performance of four ML algorithms: artificial neural network (ANN), support vector machine (SVM), decision tree (DT), and random forest (RF). The models were evaluated, and the results showed that the random forest algorithm was the most effective model for energy forecasting in this particular case.
[22]	2022/14	The authors aim to provide machine learning algorithms for predicting hotel energy consumption in Shanghai. The algorithms studied include SVM, ANN, DT, and RF. The study compares these algorithms to find the best fit. They can be used to estimate energy consumption and costs, aiding in finding solutions for reducing energy usage and integrating DER.
[23]	2019/32	This work presents a system that includes a data gateway, a smartphone application, and data that were accurately collected, with a success rate of 98.49% and submitted to the data gateway. Forecasting energy consumption time series using recurrent neural network in TensorFlow explored various architectural designs and data preprocessing techniques to enhance the accuracy and reliability of the predictions.

Table 1. *Cont.*

Reference	Year/Citation	A Summary of Paper
[24]	2023/09	This paper introduces a day-ahead forecasting method for photovoltaic (PV) power plants using numerical weather prediction (NWP) models and plant specifications, integrated with battery storage for optimal control. The approach reduces dependency on conventional power sources and shows promising results with low error metrics and a strong correlation between predicted and observed power outputs.
[25]	2023/27	This paper presents a comparative study on solar energy production forecasting in Morocco using six machine learning algorithms, with the ANN model proving the most effective. The findings aim to enhance solar energy system optimization and predictive maintenance of photovoltaic systems.
[26]	2023/08	This paper presents a novel photovoltaic (PV) monitoring system combining artificial neural networks (ANN) for fault detection and an Internet of Things (IoT) platform for real-time data analysis. The system enhances energy generation efficiency and reduces maintenance costs by accurately detecting shading and other faults in PV panels.

3. Materials and Methods

This study's first step was to determine, by simulation, the energy to be produced in the site. In our case, we used PVSYST software and, after that, we installed in our system the monitoring solution, supervised our results, and compared them with the estimated output from the simulation. Finally, we used machine learning techniques to predict the future generation. Figure 1 represents the approach followed to carry out a complete study of a photovoltaic system from the installation sizing to the energy production forecasting.

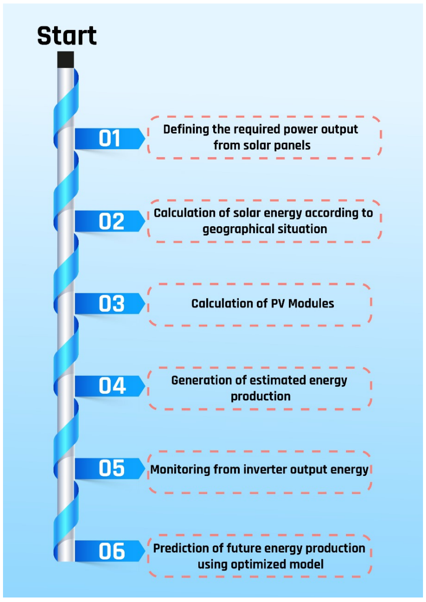


Figure 1. Flowchart of the study.

3.1. PVSYST Overview

PVSYST is a specialized software application designed for architects, engineers, and researchers, offering both practical and educational value. It is equipped with a comprehensive user-friendly menu that clarifies the methodologies and models used within the software. PVSYST supports users throughout the entire project development process, from initial design to final evaluation. Additionally, it enhances its flexibility by allowing the import of meteorological and personal data from diverse sources. It can simulate the performance of bifacial systems, even those mounted on sheds, and provides detailed economic evaluations of projects over their entire lifespan. The software can also simulate three types of solar installations: grid-connected, off-grid, and solar pumping.

Numerous studies have demonstrated the effectiveness of PVSYST in accurately modeling solar energy production. Researchers have used this tool to analyze solar PV system performance in various geographical locations with different levels of solar irradiance and climatic conditions. By integrating meteorological data, PVSYST effectively simulates the real-world behavior of solar panels [27–30].

3.2. Description of the Study Area

A simulation with PVSYST was performed for Benguerir localization (Figure 2). Results show that, to produce 25.44 MWh of energy per year with a specific production of 1051 kWh/kWp/year, the solar PV system requires 44 photovoltaic panels with a total nominal power of 24.20 kWp and a 22.5 kWac inverter. The solar PV system is converting solar energy to electricity efficiently, with only 20.82% energy loss.

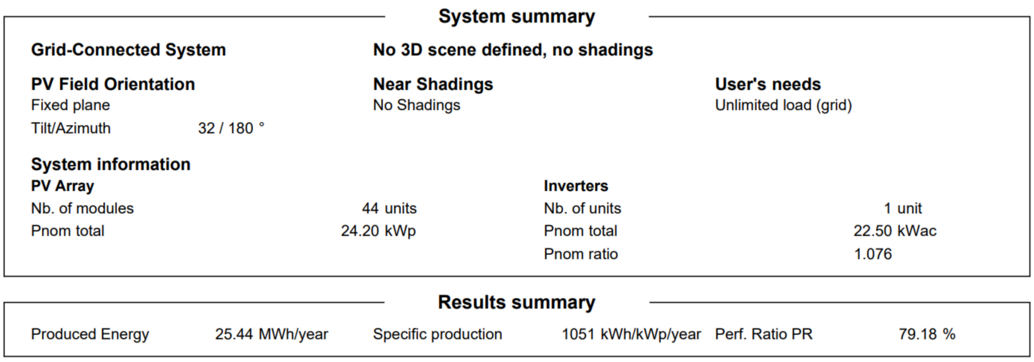


Figure 2. Simulation under PVSYST.

Table 2 shows data on the daily ambient temperature, irradiation, and photovoltaic production rates. The temperature has a direct impact on the efficiency of the photovoltaic system, as higher temperatures result in lower system performance. The irradiation data show the amount of solar energy received by the system, and higher levels lead to greater energy production rates. The photovoltaic production rate data represent the amount of energy generated by the system on a daily basis. The data presented in Table 2, which are derived from PVSYST simulations, offer a broad overview of energy production trends on a monthly basis. This long-term perspective is valuable for understanding seasonal variations and the overall performance of the solar power system over extended periods. In contrast, the 10-minute interval data obtained through smart metering devices provide high-resolution insights into real-time energy production. This granularity is crucial for capturing short-term fluctuations in power generation, allowing for more precise monitoring and forecasting of solar energy output. The choice of a 10 min interval is particularly effective, as it is sufficiently detailed to study the behavior of energy production while also ensuring that the database is not overloaded with excessive data points.

Table 2. Simulation results from PVSYST.

Month	Temperature (°C)	Irradiation (kWh/M^2)	PV_Production (kWh)
January	11.49	0.99	18.83
February	13.25	1.79	33.10
March	16.76	3.16	63.70
April	18.55	4.82	102.76
May	22.33	5.94	127.32

Table 2. *Cont.*

Month	Temperature (°C)	Irradiation (kWh/M^2)	PV_Production (kWh)
June	25.67	6.87	146.36
July	29.16	6.54	137.48
August	29.39	5.37	111.77
September	25.20	3.78	76.26
October	22.47	2.3	43.35
November	16.16	1.16	20.83
December	12.89	0.77	15.09

3.3. Monitoring of Energy Production

Solar panels are the primary component of an on-grid PV system, and Figure 3 depicts the essential parts of our system. They typically consist of photovoltaic cells, which use sunshine to produce power. Additionally, there is an inverter, a component that transforms the DC electricity produced by the solar panels into AC electricity that may be supplied back onto the grid. The monitoring system also tracks the performance of the on-grid PV installation. It can offer details on the amount of electricity generated, the quantity of electricity supplied back into the grid, and the general effectiveness of the system. The data-gathering frequency can be set to an average of every 10 min for monitoring-only purposes. Therefore, the data should be gathered more regularly when local control functions are necessary. An on-site control system employs the gathered information to operate the electrical installation equipment effectively and efficiently. The most effective set points for the nearby energy sources and manageable loads can be provided by algorithms and analytics. Moreover, cloud-based software uses the acquired data for visualization, analysis, and reporting.

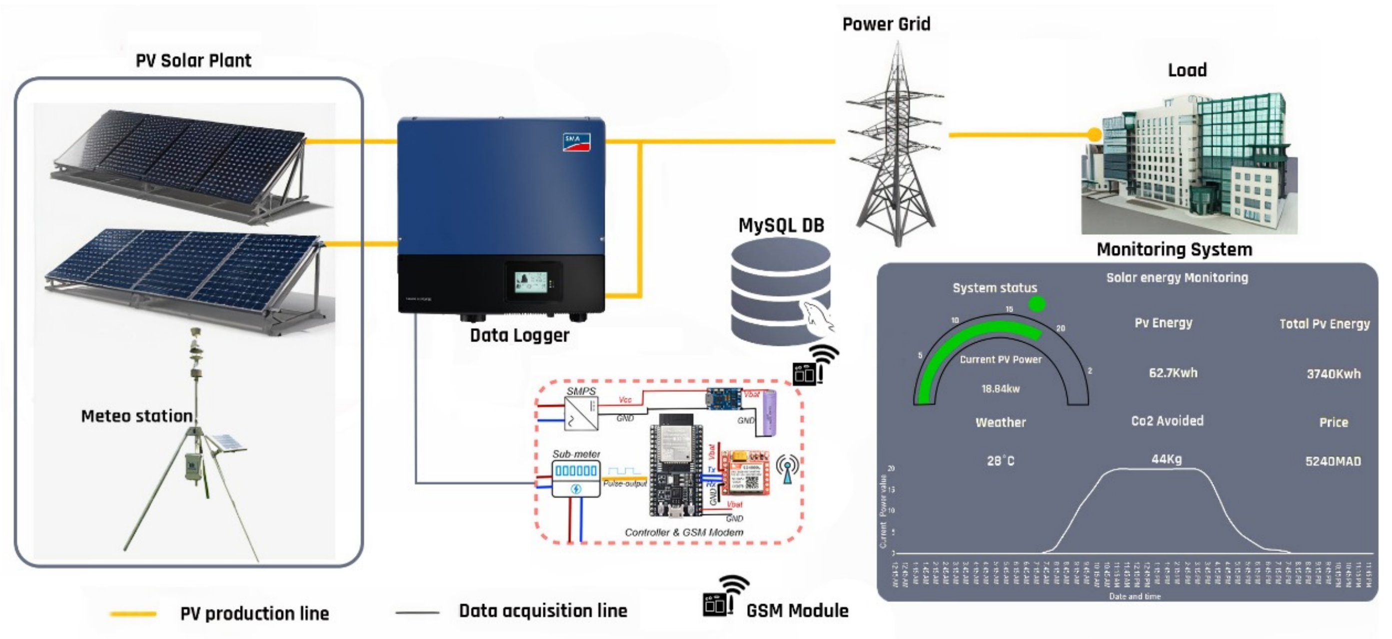
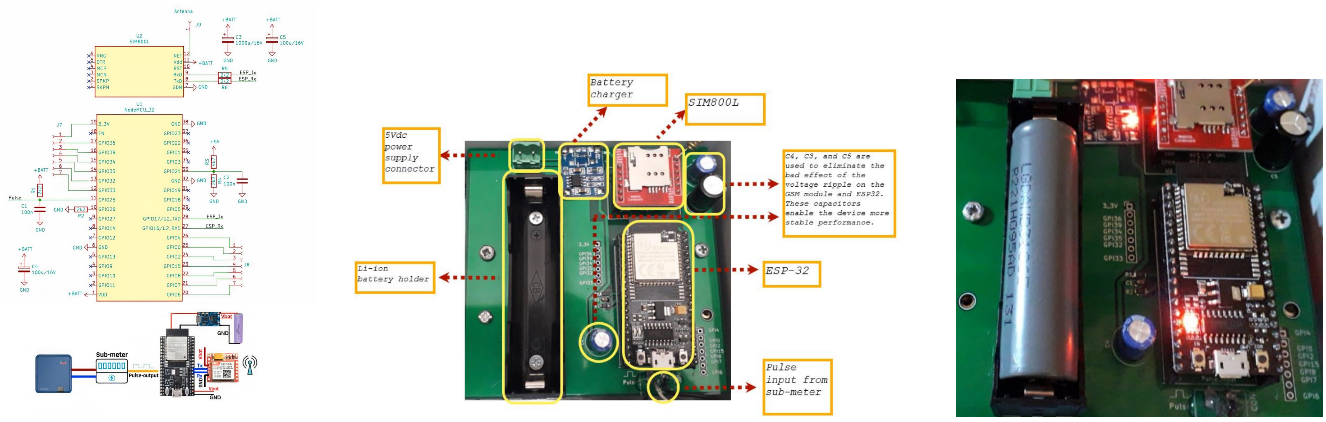


Figure 3. Key components of the system.

The smart meter, shown in Figure 4, is built around an ESP-32 controller, which manages and processes the data. The controller uses a GSM module to transmit the calculated energy consumption information to a cloud-based MySQL database, enabling real-time monitoring and secure data storage. Additionally, the smart meter is designed to remain functional during power outages. When the main power is off, the controller runs on a backup battery, ensuring continuous recording and transmission of energy consumption data. In the schematic diagram, capacitors C3, C4, and C5 are used to mitigate the adverse effects of voltage ripple on the controller and GSM module. These capacitors enable the device to achieve more stable performance.



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

Figure 4. System schematic diagram (**a**), SmartMeter PCB (**b**), and real system implementation (**c**).

PV energy generation forecasting [31] is essential for grid operators, energy traders, and consumers. This crucial process helps optimize energy production and consumption, leading to a more efficient and sustainable energy ecosystem [32]. Accurate forecasting of energy generation enables more efficient planning and management of energy resources. By predicting future energy output, utilities and grid operators can optimize energy distribution, reducing the risk of supply shortages or surpluses. This leads to improved grid stability and reliability. Forecasting also supports better integration of renewable energy sources, such as solar and wind, by anticipating their variable outputs and allowing for more effective balancing with other power sources. Additionally, accurate forecasts help in reducing operational costs by minimizing the need for expensive peak-time energy generation and enabling better maintenance scheduling. They also contribute to environmental sustainability by facilitating the more effective use of clean energy sources and reducing reliance on fossil fuels. Overall, energy generation forecasting enhances operational efficiency, economic performance, and environmental impact, leading to a more sustainable and resilient energy system [33–35]

To achieve this, the suggested approach is outlined below. After monitoring the solar site data from the inverter, the dataset was cleaned to remove corrupted and missing values. The main dataset was then split into training, testing, and validation sets. The scikit-learn library was used to run the datasets through four machine learning algorithms: XGBoost, GBM, RNNs, and ANNs. The predicted energy output was evaluated using three metrics: root mean square error (RMSE), mean absolute error (MAE), and R-squared (R^2). The methodology, as depicted in Figure 5, provides a comprehensive overview of the process used to select the best-performing algorithm. The following sections describe the dataset and the different ML models leveraged in this study.

3.3.1. Data Acquisition and Processing

After installing our system and monitoring the daily production for one year from 1 January 2023 to 31 December 2023, we were able to acquire a database of our site that contains the daily energy (kWh), total energy (MWh), irradiation (kWh/m^2/day) and the temperature (°C).

- Data Resolution: Energy produced was recorded every 10 min, capturing the power output from the solar panels with a high level of granularity. This resolution allows for a detailed analysis of production patterns throughout the day.
- Nature of the Data: Energy produced represents the electrical output (in kilowatt hours) generated by the solar panels. It is a direct measure of the system's performance

under varying environmental conditions. This energy is highly correlated with the temperature, as shown in Figure 6.

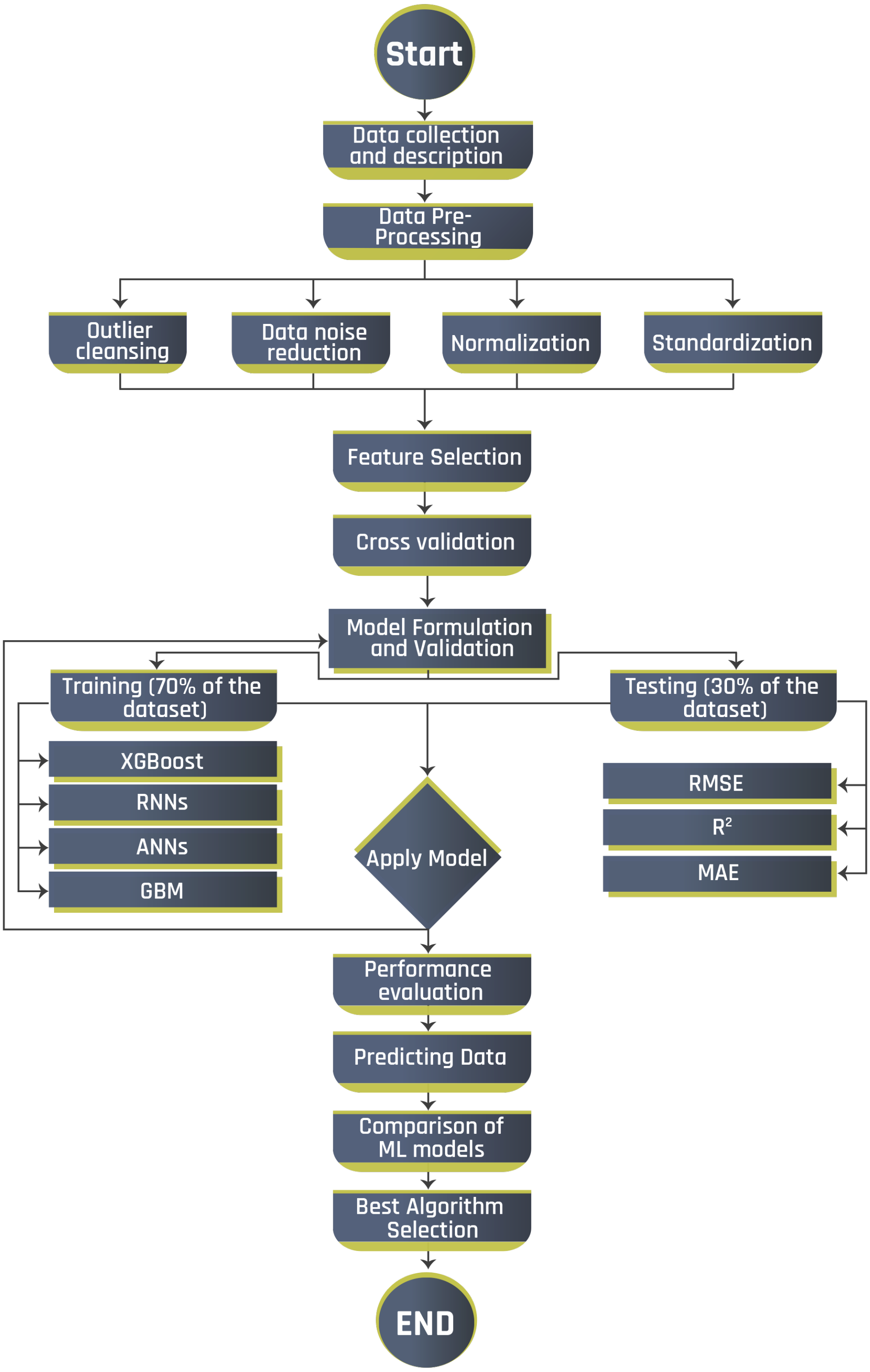


Figure 5. Methodology used to select the best prediction algorithm.

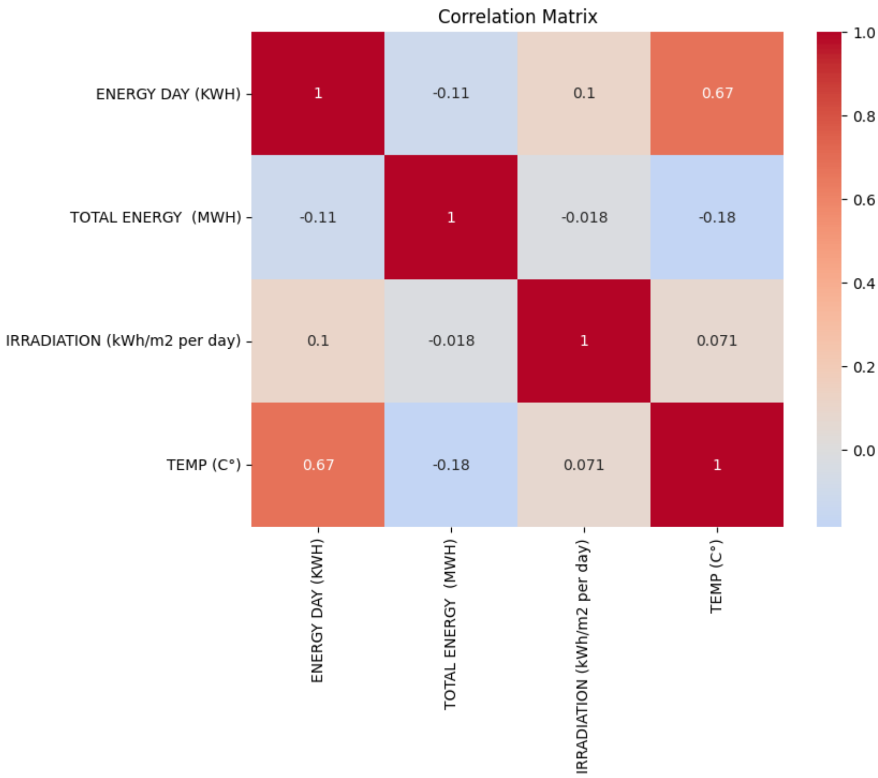


Figure 6. Correlation matrix.

3.3.2. Artificial Neural Networks

Artificial neural networks (ANNs) consist of artificial neurons called "units" organized into layers. ANNs have input, output, and hidden layers, as depicted in Figure 7. Each node or unit is connected to others and has a weight and threshold value. When a node's output exceeds its threshold, it becomes activated and transmits data to the subsequent layer. If the output does not surpass the threshold, the data are not forwarded. ANNs rely on training data to enhance their performance and accuracy over time. Data are processed through the hidden layers, allowing the output layer to generate a response [36]. ANNs learn from data through a process called learning by adjusting weights and biases. ANNs can adapt and make predictions, making them suitable for various applications in many fields such as robotics, healthcare, medicine, energy, and transportation.

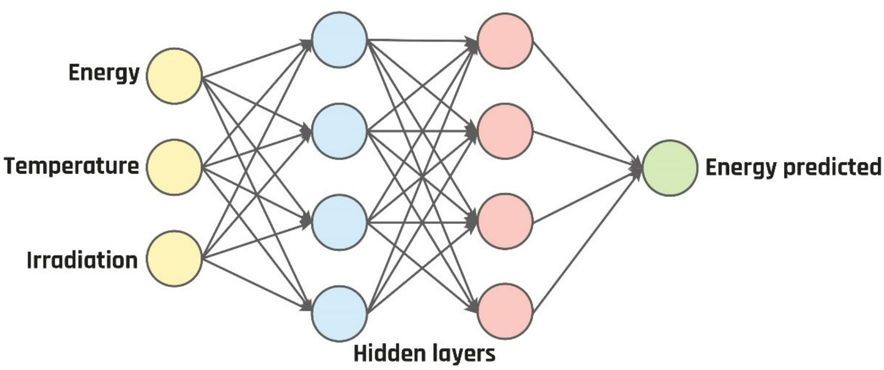


Figure 7. ANN architecture.

3.3.3. Recurrent Neural Networks

Recurrent neural networks (RNNs) are specialized neural network architectures that incorporate hidden states and feedback connections to handle sequences of data. Unlike traditional neural networks, RNNs can use information from previous outputs as inputs for processing current data, enabling them to capture and learn temporal dependencies and patterns in sequential data. This functionality makes RNNs particularly effective for tasks involving time series data or language modeling. As illustrated in Figure 8, the architecture of RNNs involves nodes that maintain hidden states, which are updated with each new input. This design allows RNNs to continuously integrate past information to influence future predictions, enhancing their ability to manage and interpret complex sequences of data.

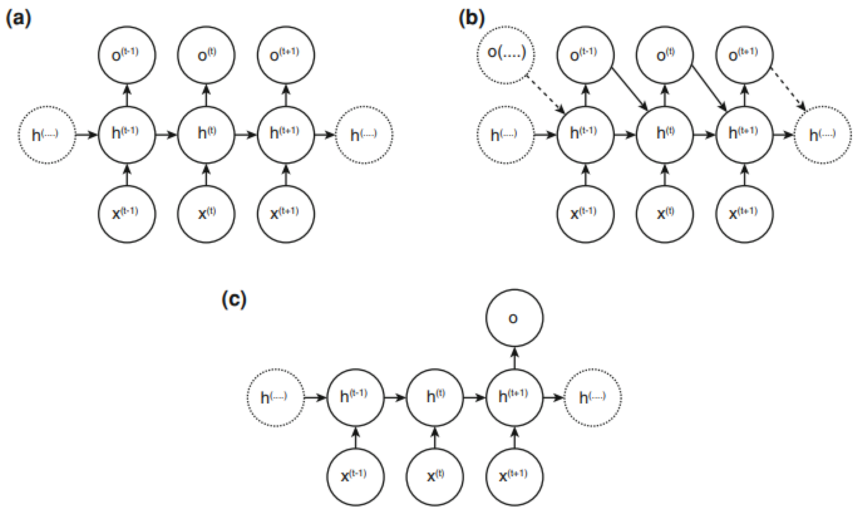


Figure 8. Types of simple RNN architectures include: (**a**) connections between hidden units, (**b**) connections from output to hidden units, and (**c**) connections that process the entire sequence to produce a single output [37].

3.3.4. Extreme Gradient Boosting: XGBoost

XGBoost is a highly efficient and scalable gradient boosting framework featuring a linear model solver and tree learning algorithm. It supports various objective functions for regression, classification, and ranking and allows for custom objectives. It is designed to maximize computational efficiency and model performance. Unlike GBDT, XGBoost builds trees in parallel rather than sequentially. It uses a level-wise strategy to evaluate split quality by scanning gradient values and partial sums across the training set, as shown in Figure 9.

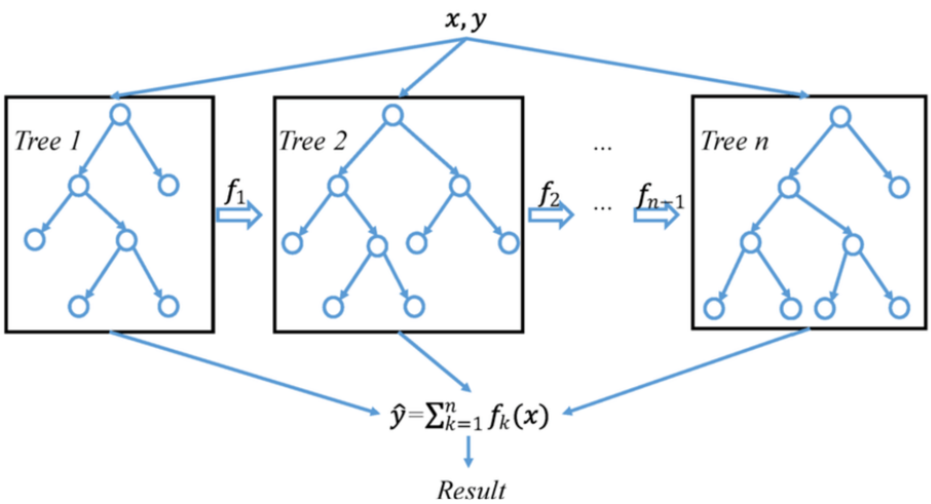


Figure 9. General architecture of XGBoost [38].

3.3.5. Gradient Boosting Machine: GBM

GBM is a powerful ensemble learning algorithm used for regression and classification tasks. As depicted in Figure 10, it builds predictive models by combining multiple weak learners, typically decision trees, into a single strong model. GBM works iteratively: each new tree corrects the errors of the previous ones, and the final prediction is made by aggregating the outputs of all the trees. This approach improves predictive performance by focusing on difficult-to-predict instances and reducing model errors. GBM is valued for its accuracy and ability to handle various types of data.

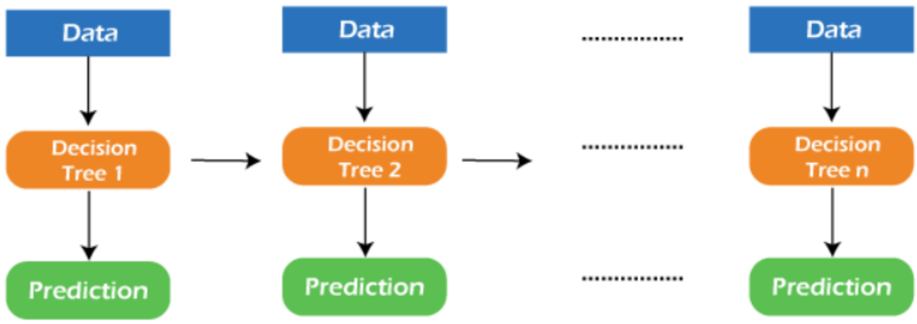


Figure 10. General architecture of GBM.

3.3.6. Scikit-Learn

Scikit-learn [39], commonly known as sklearn, is a widely used Python package for machine learning. It provides a range of tools for data analysis and various machine learning methods, including dimensional reduction, clustering, regression, and classification. Built on Matplotlib, SciPy, and NumPy, scikit-learn is known for its ease of use and effectiveness. It is a popular library for tasks such as predictive maintenance and solar panel production forecasting.

The performance and effectiveness of the four compared algorithms were rigorously evaluated using three key metrics: mean absolute error (MAE), R-squared (R^2), and root mean square error (RMSE).

3.3.7. Mean Absolute Error

MAE serves as a measure for assessing how well a predictive model is performing. By taking the average absolute difference between the predicted values and the actual values, the MAE provides insight into the average magnitude of errors in a set of predictions. A lower MAE indicates a higher level of performance for the model.

3.3.8. Root Mean Square Error

RMSE calculates the typical difference between values that a model predicts and actual values. It gives an estimate of the model's predictive power for the desired value (accuracy). The better the model is, the lower the root mean square error is. The root mean square error would be zero in a perfect model, which is a hypothetical model that always predicts the exact expected value.

3.3.9. R-Squared

R^2 is a measure that reflects how well a regression model fits the data. The ideal value for R^2 is 1, meaning that the model fits perfectly. As the R^2 value gets closer to 1, it indicates that the model explains a larger portion of the variability in the dependent variable. This suggests that the model's predictions are more precise and dependable. Thus, achieving a high R^2 value in regression analysis is crucial. Furthermore, R^2 can be used to compare different models.

4. Results and Discussion

4.1. Simulation Results

Table 3 presents the results obtained from the simulation using PVSYST software. The comprehensive analysis conducted demonstrates that a PV system requiring a total installed capacity of 24,200 watts-peak (Wp) can be seamlessly developed by utilizing an assemblage of 44 PV panels. Moreover, the integration of a 22.5 kWac inverter ensures the smooth operation of the converting DC to AC.

Table 3. Main simulation results in PVSYST.

Power Required	**24,200 Wc**
PV modules	44 panels
Power inverter	22,500 Wac
Energy produced	25,440 kWh/year
Specific production	1051 kWh/kWp/year
Performance index (PR)	79.18%

To ensure enhanced visualization and a more comprehensive understanding of our remarkable findings, state-of-the-art 3D modeling techniques were diligently employed, as illustrated in Figure 11.

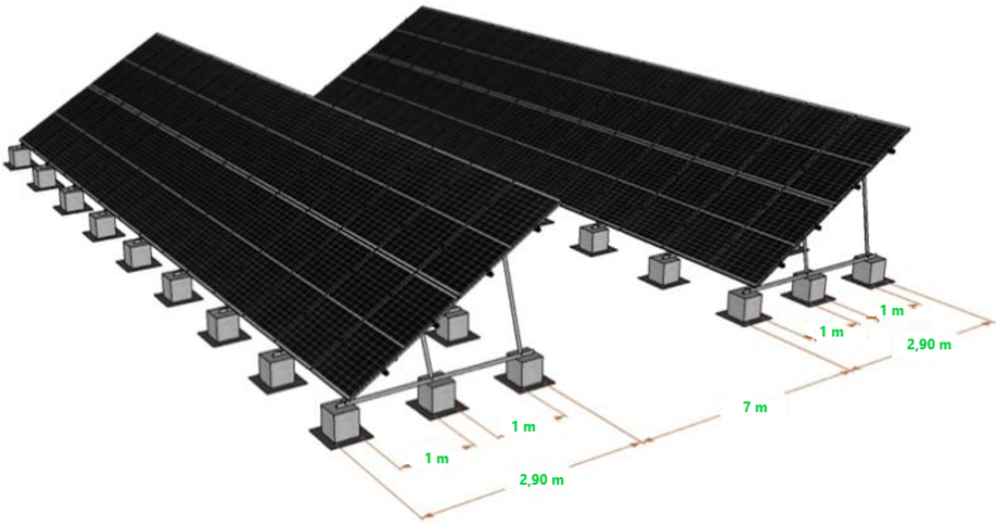


Figure 11. 3D design of the installation.

The comparison of RNNs, ANNs, GBM, and XGBoost models for energy generation forecasting, using data from a 24 kWp solar plant over one year, revealed that the ANN model achieved the best performance. Among the four models, ANNs provided the highest values across all assessment metrics, including visualizations and performance indicators. The performance metrics RMSE, MAE, and R^2 for each model are summarized in Table 4 and Figure 12. The artificial neural networks algorithm offered the most accurate energy forecasting results, followed by the XGBoost algorithm. This comparison aligns with the study's objective to evaluate and select the best forecasting model.

The ANN validates its importance and usefulness in predictive analysis, accurately predicting future solar energy production, minimizing errors, and providing valuable insights for decision-making processes in order to enhance predictive maintenance for solar plants and optimize their lifespan.

Table 4. Performance results of compared ML algorithms.

Model	Metric	Validation Set
XGBoost	RMSE MAE R^2	18.21 3.44 0.4
GBM	RMSE MAE R^2	18.89 3.85 0.31
RNNs	RMSE MAE R^2	19.88 3.83 0.06
ANNs	RMSE MAE R^2	15.6 3.3 0.62

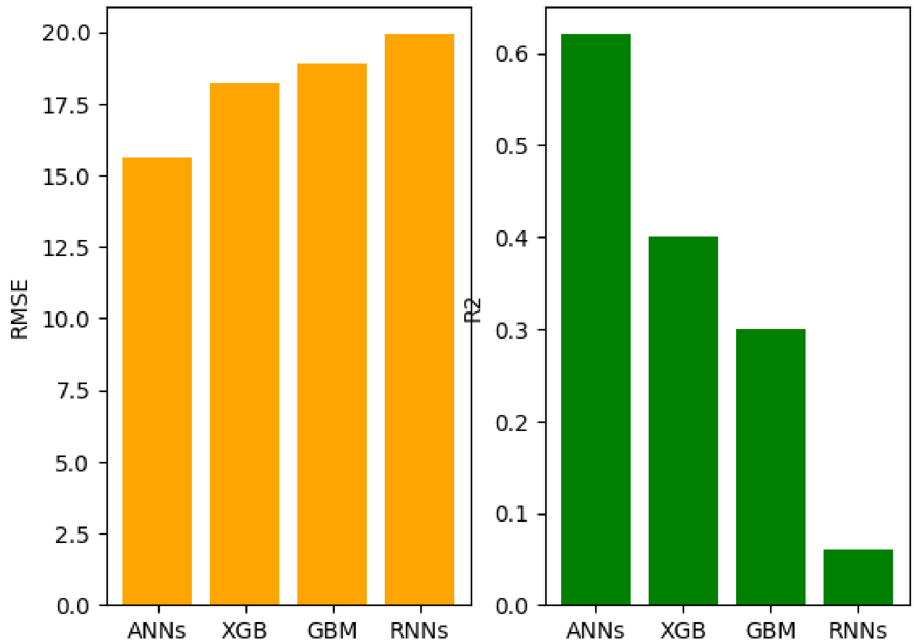


Figure 12. Comparative performance results of the four ML algorithms.

4.2. MySQL

MySQL is a well-known open source relational database system that is commonly used for storing and organizing data. In recent years, there has been a notable increase in the popularity of cloud-based database services. These services offer great scalability, flexibility, and cost-effectiveness, making them appealing to many organizations. By using cloud-based database services, businesses can easily adjust to changing data storage needs and effectively manage their data without spending too much. This shift towards cloud-based solutions has transformed the way data are stored and managed, enabling businesses to concentrate on their main activities while ensuring the security and accessibility of their important data [40].

To finalize our project, we set up a MySQL database and connected the data logger to it, sending data every 10 min. The energy generated is stored in the capacity field, which allows us to accurately track and analyze the efficiency of our system. With the help of PHP, IT development language, the Laravel framework, and open source technology, we created a robust and innovative IT solution to seamlessly interact with the MySQL database for this research. Through extensive testing and iterative development, we have ensured that our program is highly reliable and secure.

Figure 13, showcased below, presents the user-friendly web interface of our program. It provides a seamless experience for users, allowing them to effortlessly input their email and password for authentication purposes. This innovative feature enhances the overall accessibility and user experience, ensuring that our system meets the highest standards of convenience and security [41].

We meticulously designed a comprehensive network of interconnected tables specifically tailored for our online platform. These tables are responsible for storing a multitude of detailed information, not only about the users and proprietors of solar sites but also about the sites themselves. From the precise location of the site to the intricate details regarding the number of panels installed and the specific style of installation, our tables leave no stone unturned.

Of utmost importance is the ultimate table, aptly named "energy", which serves as the central repository for invaluable data. This table houses crucial information regarding the inverters utilized and the storage outcomes derived from the database. It is within this table that the true power of our platform is showcased.

Figure 13. Authentication page.

The illustration presented in Figure 14 exemplifies the remarkable effectiveness of our site when seamlessly linked to a sole inverter. The synergy between our platform and the inverter results in an unparalleled level of performance, efficiency, and overall success.

NO.	Date	Daily energy (KWH)	Total energy (MWH)	Power (KW)	Invert
1	2022-12-13	21	12.2	50	inverter_1234 _ 12
2	2022-12-15	25	21	56	inverter_6786 _ 21
3	2023-02-01	30	24	18	inverter_1234 _ 12
4	2023-02-02	25	25	17	inverter_1234 _ 12
5	2023-02-03	23	25	19	inverter_1234 _ 12
6	2023-02-04	24	26	18	inverter_1234 _ 12
7	2023-02-06	22	28	19	inverter_1234 _ 12
8	2023-02-07	24	29	18	inverter_1234 _ 12

Figure 14. Data visualization.

Contrasting the projected and actual daily output of a photovoltaic (PV) system can reveal any differences between the expected and true performance of the system. This analysis is crucial for verifying the accuracy of the simulation and determining the effectiveness of the approach utilized. In Figure 15, a visual representation of this contrast is depicted, affirming the reliability and precision of the methodology utilized in this study. Notably, the implementation of a smart metering device based on an ESP 32 card has facilitated real-time monitoring of energy production, enabling a comprehensive assessment of the system's performance. The integration of this cutting-edge technology has enhanced the accuracy of data collection, allowing for more informed decision-making and precise evaluation of the system's efficiency. This device serves as a vital tool for ensuring optimal performance, monitoring any fluctuations in energy production, and identifying potential areas of improvement. With this innovative solution in place, energy production can be tracked and analyzed in real time, providing invaluable insights into the actual performance of the photovoltaic system.

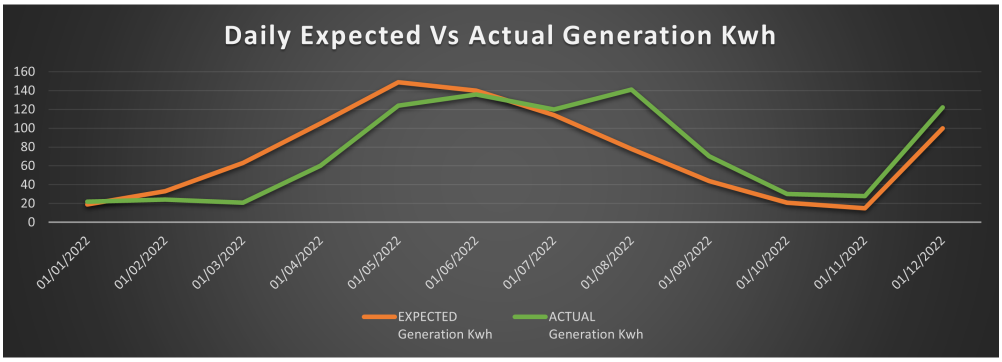


Figure 15. Comparison between daily and expected PV generation.

The generated solar energy production forecast serves the purpose of predicting energy output at a specific site. This prediction proves to be extremely beneficial in the field of predictive maintenance, as it enables users to receive alerts regarding potential malfunctions in the power plant. Additionally, an edge device that centralizes and monitors data production can incorporate a production prediction model. If the forecasted results deviate from the expected values, alerts can be triggered to initiate predictive maintenance. This approach is particularly relevant in smart grids that can replace conventional power grids.

5. Conclusions and Future Work

The utilization of smart metering devices within smart grids featuring solar panels can greatly enhance the efficiency and performance of solar panel systems. By enabling real-time collection and analysis of data, they have the ability to optimize solar panel performance and effectively manage the energy generated.

The current project focuses on the examination and development of an on-grid station powered by photovoltaic panels. It involves the implementation of a monitoring system to track the consumption of solar panels and accurately assess their production levels. This monitoring procedure uses the ANN algorithm for energy production forecasting, chosen after a comparative study with RNNs, XGBoost, and GBM. The ANN's capabilities allow for accurate predictions and better identification of potential system failures, thereby enhancing efficiency and extending the lifespan of the solar panel system.

Looking ahead, our ultimate objective is to integrate an edge device into the system. This device will process the data locally before transmitting them to a central server or cloud platform. By adopting this approach, we aim to achieve seamless monitoring and accurate energy production prediction while ensuring timely notifications for predictive maintenance. It is crucial to implement a comprehensive set of predictive measures to guarantee the continuous functionality and utmost safety of the entire solar panel system.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
ANN	Artificial neural network
IRENA	International Renewable Energy Agency
CNN	Convolutional neural network
DER	Distributed Energy Resources
DL	Deep learning
GBM	Gradient boosting machine
IoT	Internet of Things
kW	Kilowatt
kWh	Kilowatt hour
MAE	Mean absolute error
ML	Machine learning
NumPy	Numerical Python
PCB	Printed circuit board
PVS	Photovoltaic system
R^2	R-squared
RMSE	Root mean square error
Sklearn	Scikit-learn
XGBoost	Extreme gradient boosting

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