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A New Low-Cost IoT Based Monitoring System Design for Stand-Alone Solar Photovoltaic Plant and Power Estimation

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Abstract: This study presents a cost-effective IoT-based remote monitoring system for solar PV energy systems, along with a machine learning-based PV power estimator. Remote access is crucial for tracking PV systems installed in remote areas. In this system, an open-source and IoT-compatible data logger is employed. The data logger collects important performance data of the PV system and transfers it to a server. Real-time visualization of this data is displayed in the designed web and mobile monitoring interfaces. The measured data includes the current, voltage, and temperature information of the PV generator and battery, as well as environmental parameters such as temperature, radiation, humidity, and pressure. Subsequently, this data is used for PV power estimation using machine learning methods. This enables the identification of maintenance requirements and the prediction of potential issues in the PV system. When a problem occurs in the PV system, the user is alerted through the mobile application. Early detection and intervention prevent power loss and damage to system components. When comparing the results of linear regression, SVM, decision trees, random forests, and KNN machine learning methods for power estimation based on performance evaluation criteria, it was observed that the random forests algorithm provided the best results. In conclusion, the developed monitoring and estimation system, along with web and mobile interfaces, is suitable for large-scale PV energy systems.

Keywords: solar PV power; remote monitoring; IoT; power estimation; machine learning

1. Introduction

The awareness regarding the utilization of renewable energy sources in energy production has been steadily increasing worldwide due to factors such as the rising global energy demand, depletion of fossil fuel reserves, and the adverse effects of CO^2 emissions. Among the most widely employed renewable energy sources, solar energy is harnessed through solar panels to convert sunlight into electricity in Photovoltaic (PV) systems. The annual average solar irradiance in Turkey is 1527.46 kWh/m^2/year, with an average sunshine duration of 2741.07 hours, approximately equivalent to 27 million TOE (Tonnes of Oil Equivalent). As of the end of December 2022, the installed capacity of solar power plants in Turkey reached 9,425.4 MW, indicating a growth of 1,609.8 MW compared to the previous year [1]. This global increase in solar energy installation capacity, observed in Turkey as well, brings about the necessity to address aspects such as power control, optimal energy generation, mitigation of power losses, power estimation, and maintenance and repair requirements in solar energy systems.

In this context, the conducted study comprises two fundamental parts. In the first part, a data recording and monitoring system is designed. Particularly crucial is the development of an automation system for remote monitoring of large-scale PV energy systems situated in remote areas, enabling early intervention against potential power losses. Considering the aforementioned attributes, this study designs an Internet of Things (IoT) based data recording and monitoring system to real-time record and monitor parameters obtained from the FV panels, batteries, and energy system within their operational environment. The gathered data is stored in a database and can be tracked in real-time using the designed web and mobile interfaces. The data is presented both

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numerically and graphically to the user. Furthermore, the implemented monitoring system sends alert messages to the user in the event of a malfunction in the energy system, facilitating informed actions to prevent potential power loss through early intervention.

The second part of the study involves power forecasting using the collected data. The power output from PV panels varies based on factors such as geographical location, seasonal changes, and environmental conditions. Accurate power forecasting is essential for the efficient and economical utilization of solar panels as a reliable energy source. This enables the installation of controllable PV energy systems, guides electric companies, manages energy, optimizes energy levels, and identifies necessary panel adaptations to reach maximum production capacity. Moreover, it holds significant importance in terms of time savings and reduction of additional labor costs. Therefore, the estimation of power output values and load trends for renewable power facilities like PV energy systems emerges as a fundamental process [2].

Presently, the prevalent approach for power forecasting in PV energy systems involves analyzing historical data and considering seasonal, daily, and hourly variations to predict future power generation. Artificial neural networks and regression models are among the methods employed for this purpose [3]. In this study, power forecasting is conducted using the data obtained from Karabük province in Turkey's Western Black Sea region, where the annual sunshine duration is 2402 hours, and the annual radiation value is 1369 kW/h per square meter. Meteorological data such as humidity, temperature, pressure, and time information are utilized in power forecasting through machine learning techniques [4]. To determine the most successful machine learning method for power forecasting, linear regression, support vector machines (SVM), decision trees, random forests, and k-nearest neighbors (KNN) algorithms are sequentially employed. The results obtained from each algorithm are presented in a comparative manner. The subsequent section provides an in-depth review of the relevant literature on the topic.

2. Related Work

The first part of the literature review addresses the studies related to monitoring of PV energy systems. In the initial research efforts concerning the monitoring of PV energy systems, wired systems utilizing RS232 and RS485 communication protocols were employed for data transmission [5,6]. Due to exposure to environmental factors such as rain, temperature, and humidity, the cables carrying data in these systems necessitated additional maintenance costs. In contrast, wireless monitoring systems are less affected by environmental conditions compared to wired monitoring systems, and especially in real-time applications, they possess a quicker decision-making capability. Additionally, they convey information over a longer range with higher accuracy. In their work, Rouibah et al. [7] developed a low-cost IoT-based tracking system for maximum power point tracking (MPPT) in PV systems. Deshmukh and Bhuyar [8] addressed the automation of solar PV power generation. An IoT platform was utilized to monitor and control solar energy production. Cheddadi et al. [9] aimed to provide a cost-effective and open-source IoT solution using the ESP32 board to intelligently gather and real-time monitor the generated power and environmental conditions of solar stations. Adhya and co-workers [10] discussed an IoT-based, low-cost monitoring system for solar PV installations. Luwes and Lubbe [11] developed an IoT device that individually monitors each PV array and provides feedback on their efficiencies to prevent power losses in large solar farms. Lee and colleagues [12] describe an IoT-based software architecture for continuous monitoring of solar panel efficiency. López-Vargas et al. [13] introduced IoT-based application innovation to a low-cost Arduino microcontroller-based solar data logger. Fernandez et al. [14] propose a fully open-source software-based IoT solution for monitoring PV installations. Gupta et al. [15] systematically present all design stages of a low-cost IoT-based data collection system.

In Nurhafizah's study [16], an IoT-based real-time monitoring system for renewable standalone power plants was discussed. Continuing the literature review, the second part of the study examines the power forecasting methods used in solar PV systems. Lorenz et al. [17] present a comparative study of solar irradiance predictions obtained through multiple linear regression methods and Artificial Neural Networks (ANN) models, revealing PV panel power output characteristics using

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weather data. Wang and colleagues [18], apart from the aforementioned studies, concluded that ANN is the most suitable method for predicting PV power outputs. Shi et al. [19] conducted research using Support Vector Machines (SVM), a machine learning approach, to predict FV system power outputs. Kou et al. [20] utilized a backpropagation-trained ANN structure along with meteorological data to forecast solar panel output power. Zhang et al. [21] hybridized the Particle Swarm Optimization (PSO) evolutionary algorithm with an ANN, incorporating irradiance values as inputs, to obtain solar radiation prediction in their training approach. Qasrawi and Awad [22] designed a multi-layered feedforward ANN using panel outputs from differently located solar panels along with satellite data. Zhu et al. [23] employed wavelet transform to extract useful information from complex PV output power data and constructed an ANN model.

In the studies by Paulin and Praynlin [24], a comparative investigation is presented using a backpropagation-based Artificial Neural Network (ANN) where inputs encompass average ambient temperature, average panel temperature, average inverter temperature, solar irradiance, and wind speed data, while the output consists of power data. Rana et al. [25] offer a comprehensive evaluation of a series of leading methods to forecast solar power output profiles one day in advance. Kwon et al. [26] propose the Naive Bayes (NB) classification method employing publicly available outdoor data (temperature, humidity, dew point, and sky coverage) for solar irradiance prediction. Dinçer and İlhan [27] comparatively employ feedforward-backpropagation artificial neural networks and KNN algorithms using temperature, humidity, pressure, and irradiance values for predicting output power of PV panels. Gumar and Demir [28] utilize metaheuristic algorithms such as Genetic Algorithm (GA), PSO, and Artificial Bee Colony (ABC) in conjunction with an ANN model to predict solar energy outputs.

In this study, contemporary technologies are integrated to enable real-time recording and monitoring of electrical data from an IoT-based PV energy system along with meteorological data from its environment, accessible both through the internet and a developed smartphone application. Subsequently, power forecasting of the generated energy in the PV system is carried out using machine learning methods based on these data. The subsequent section presents the developed IoT-based PV monitoring system.

3. Materials and Methods

3.1. Design of an IoT-Based Solar PV Data Measurement, Recording, and Monitoring System

In the designed system, real-time IoT-based condition monitoring of a solar PV panel and a battery charged by this panel is conducted. Issues occurring within the system are identified through the acquired data. Current, voltage, and temperature values of the panel and battery, along with environmental parameters such as humidity, temperature, and irradiance, are measured using relevant sensors. The obtained data is sent to SD cards and Firebase servers through the NodeMCU v2 Wi-Fi microcontroller board and stored. Data tracking can be carried out in real-time through Firebase, as well as via a mobile application and the LCD screen on the designed electronic board. Moreover, various potential errors in the system can also be monitored in real-time through these systems. These errors encompass low panel voltage, low panel current, high panel temperature, low battery voltage, high battery temperature, and PV panel connection fault. The block diagram of the developed IoT-based PV data recording and monitoring system is provided in Figure 1.

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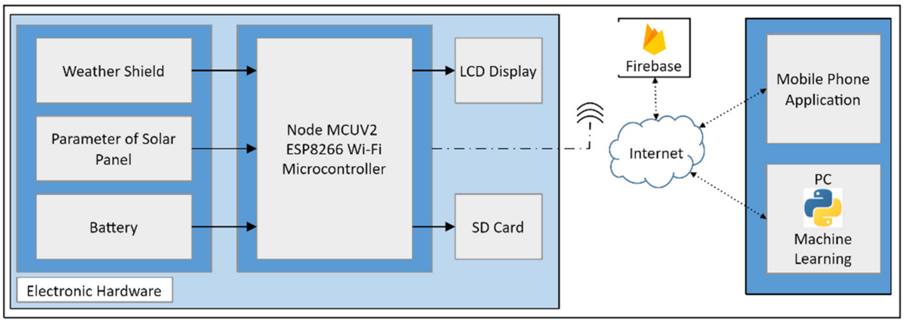
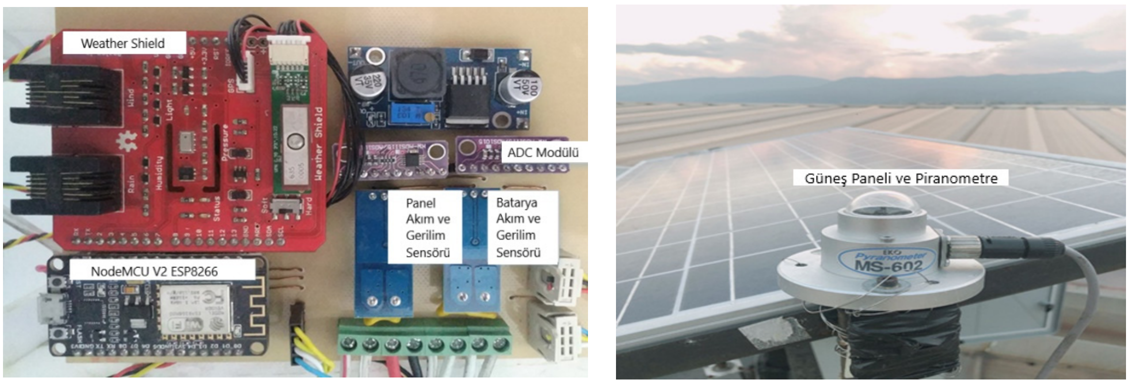


Figure 1. Block diagram of the proposed monitoring and estimation system.

The NodeMCU v2 Wi-Fi microcontroller board, frequently favored in IoT applications, renders the system controllable and monitorable from any location worldwide. The development board possesses features such as a 10-bit ADC, USB-TTL converter, 17 GPIO pins, Wi-Fi module for wireless network connectivity, and ease of programming. In this study, various sensors are utilized to measure values requiring assessment, including FV panel voltage, FV panel current, FV panel temperature, battery voltage, battery current, battery temperature, as well as humidity, temperature, and irradiance values of the ambient air. The ACS712-30A current sensor is employed for measuring the current of both the FV panel and the battery. The LM35 temperature sensor is used for measuring the temperature of the FV panel and the battery. The Sparkfun weather shield is employed for reading temperature, humidity, pressure, and irradiance data from the air. Simultaneously, the GP-735 GPS (Global Positioning System) sensor on the board provides location information. The integration of the weather measurement and microcontroller Wi-Fi boards has resulted in the creation of an electronic circuit board for the IoT-based data recording and monitoring system. The measurement setup, situated within the premises of Karabük University, is depicted in Figure 2.



(a) (b)

Figure 2. (a) IoT-based data recording and monitoring circuit board (b) Experimental setup.

The NodeMCU v2 module within the solar PV data measurement, recording, and monitoring apparatus should initially establish a connection with a wireless network. Once connected, data from the sensors is sequentially measured, displayed on the built-in LCD screen, saved to an SD card, and sent to the Firebase real-time database. The Firebase cloud system is a platform that enables the creation of mobile and web applications for monitoring real-time data, maintaining records and session information, making new announcements, and creating control units. It can be used freely for these purposes. The solar PV data sent to the cloud system can be tracked by end-users via smartphones through the developed mobile application. Additionally, the analysis and visualization of this data in a web-based manner are facilitated through the ThingSpeak IoT platform, where we direct the data flow in the cloud environment. A comparison between the proposed IoT-supported data monitoring system and some existing data monitoring systems is provided in Table 1.

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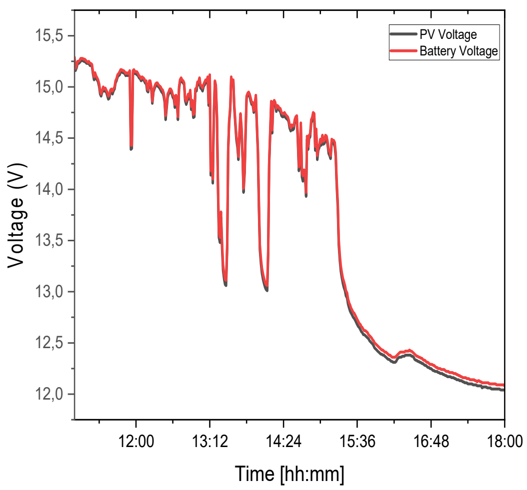
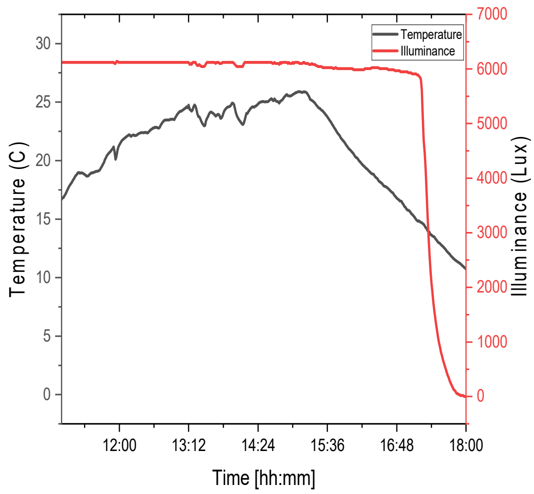
Table 1. Comparison between the proposed solar PV monitoring system and existing solar PV monitoring systems.

Author	Network	Hardware	Software
Koutroulis and Kalaitzakis [10]	Wired	NI DAQ	LabView
Chouder et al. [23]	Wired	Agilent 34902A	LabView
Ferdoush and Li [24]	Wireless	Arduino UNO	Arduino IDE
Rezk et al. [25]	Wired	DAQ NI6009	LabView
Proposed IoT Based System	Wireless	ESP8266	Arduino IDE

In this study, following the integration of IoT-based electronic hardware, the ThingSpeak platform, and the mobile application, experimental measurements were conducted. The data from the experimental measurements were recorded and monitored through internet and mobile platforms. The prototype system, which was purposefully designed and cost-effective, utilized NodeMCU v2 microcontroller board, Sparkfun WeatherShield weather measurement board, ADS1115 ADC module, ACS712-30A current sensor, LCD screen, LM35 temperature sensor, and GP-735 GPS receiver. The approximate budget spent on creating this prototype system was around 3000 TL. Examining the results obtained from the testing process, it was observed that the developed system accurately measured and transmitted data. Electrical and meteorological measurements were corroborated through comparison with diverse sources. The mentioned measurements in the study were repeated and recorded at five-minute intervals. Daily variation graphs for the output voltage of the monitored PV panel, battery voltage, daily irradiance, and ambient temperature are provided in Figure 3.



(a)



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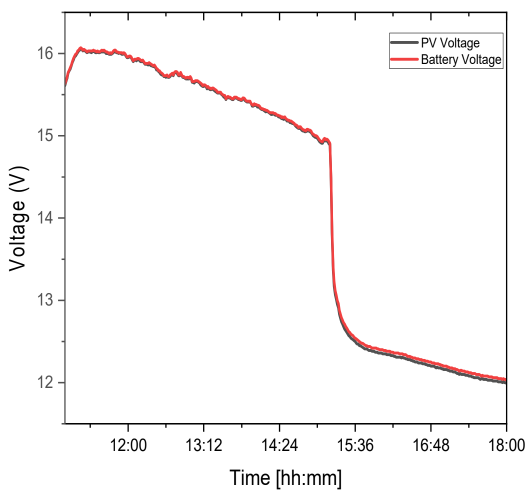
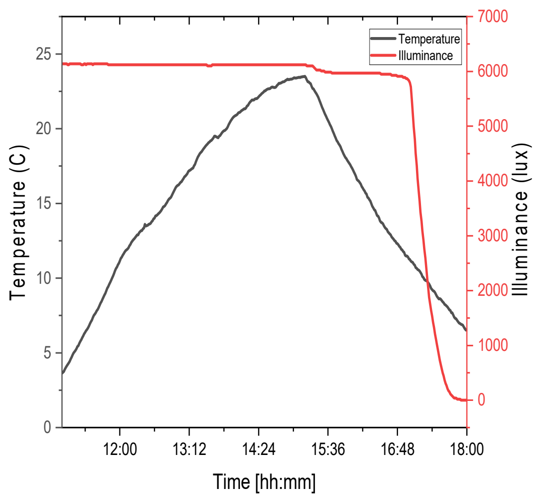


(c)



(d)

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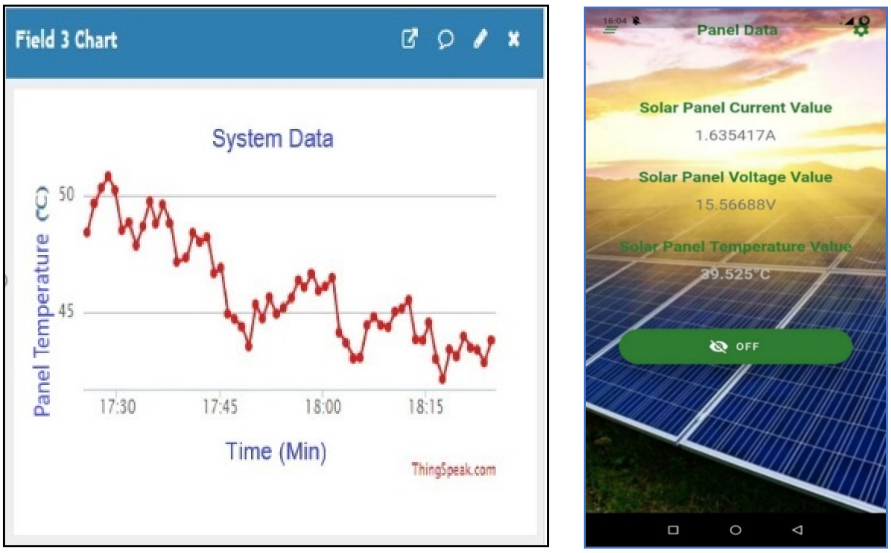
Figure 3. Voltage, illuminance, and ambient temperature measured in a, b) Karabuk (9/11/2021) c,d) Karabuk (16/11/2021).

Figure 4 illustrates the visualization of the data transferred to the Firebase real-time database and sent to the cloud platform, where it is displayed via the ThingSpeak server and the developed mobile application.



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

Figure 4. Visualization of solar data transferred to cloud environment (a) ThingSpeak server (b) Developed mobile monitoring application.

The subsequent section addresses the analysis of collected data with the aim of utilizing machine learning methods to predict the future performance of the solar PV system.

3.2. Solar PV Power Estimation using Machine Learning Methods

For solar PV power estimation, we have a dataset containing time, temperature, pressure, and humidity data. This dataset is based on five-minute weather measurements. In order to investigate the relationship between solar energy and meteorological data, certain weather parameters have been collected, aiming to accurately predict FV power generation. The steps related to this part of the study involve acquiring and preprocessing the dataset, followed by splitting the data into training and testing sets, applying classification techniques, and making predictions based on the results. Data preprocessing is necessary to clean the data and prepare it for the utilization of various learning models, thus enhancing accuracy and efficiency. Training and testing data are separated from the preprocessed data. The model is trained using the training data and its predictions are verified using the testing data. Data splitting generally refers to dividing the available data into two parts for cross-validation purposes. The first dataset is used to build a prediction model, while the second dataset is used to evaluate the model's performance. The training percentage is set at 80%, while the testing percentage is set at 20%. Solar PV power generation is predicted using machine learning methods such as linear regression, SVM, decision trees, random forests, and KNN, as proposed in the article. Linear regression is one of the fundamental and commonly used regression methods [32]. Linear prediction functions are used to represent the relationship between input and output variables, and the method of least squares is employed to estimate unknown model parameters from the data. An iterative method, such as a series of linear equations or gradient descent, can be used to estimate parameter values. In the study, a scaling process was applied to standardize the input data, followed by feature provisioning and then scaling for feature standardization. The sensitivity of SVM depends on the kernel function and other variables. The Grid Search approach was employed to find optimal settings. Methods such as decision trees and random forests are commonly used in various data

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science challenges. The random forests method is a tree-based machine learning approach that can be used for regression and classification. It also conducts dimensionality reduction, checks for missing and abnormal values, and performs various additional data exploration activities. The bagging approach is used to train random forests. This method allows for the use of a large number of examples during training since the data set is sampled with replacement. The KNN algorithm is a distance-based classifier extensively utilized in artificial intelligence, especially in pattern recognition. In KNN-based classification, distances between training and test data are calculated to select the nearest K samples to the test example. Subsequently, the class of the test example is determined through majority voting based on the class information of the selected K samples [33]. In this study, prediction models mentioned above were constructed using the scikit-learn library to predict solar PV power output based on multiple meteorological parameters. To evaluate the performance of the models on the test set, metrics including mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and R-squared values were calculated. The equations for MAE, MSE, RMSE, and R-squared performance measurement methods are given as Equation 1, Equation 2, Equation 3, and Equation 4, respectively.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}| \quad (1)$$

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

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2} \quad (3)$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \quad (4)$$

Here, n represents the number of data points, y is the true value, $\hat{y}$ is the predicted value, and $\bar{y}$ is the mean value. The comparison of the performance of the prediction models based on these performance measurement criteria is presented in the results section.

4. Result and Discussion

In order to comprehensively observe the solar PV power generation process based on meteorological data, a matrix consisting of correlation coefficient pairs was constructed. This enabled the identification of collinearity between the existing features and the power output. The data used in this study were obtained from research project numbered KBU-21-DS-018 and titled "IoT-Based Condition Monitoring and Fault Analysis of Solar Panels". Figure 5 provides the correlation between the existing features and solar PV power output.

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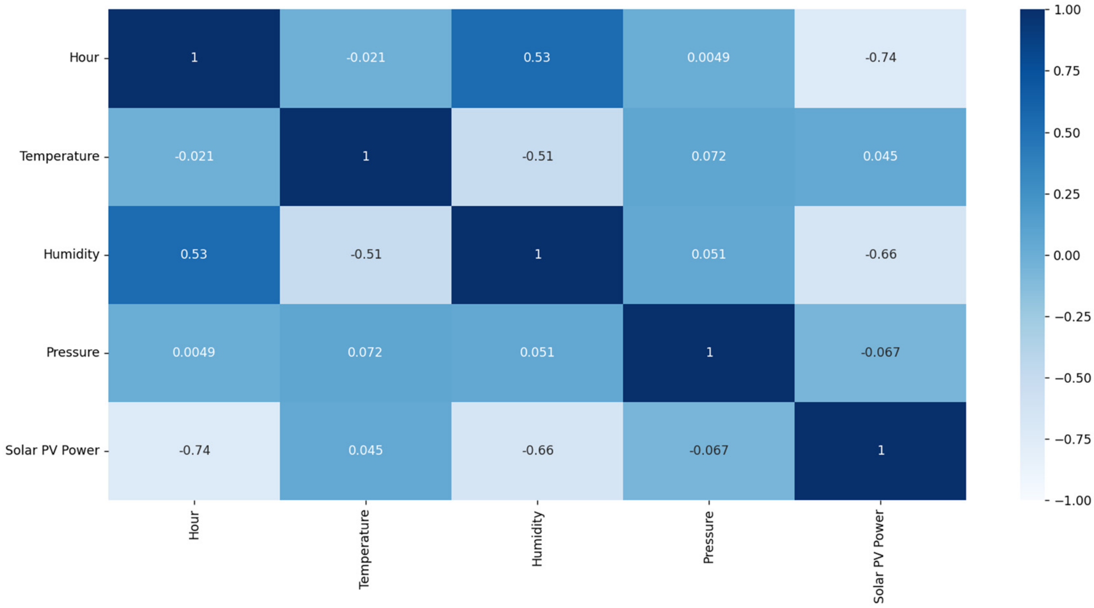

Figure 5. Correlation between current features and solar PV power output.

From the correlation graph, it can be observed that the features with the highest correlation to power output are hour and humidity. Additionally, a similar strong correlation between humidity and temperature is also evident. Following the identification of the relationship between meteorological data and solar PV power output, the dataset was subjected to machine learning models. The graph in Figure 6 presents the predicted values against the actual test data for solar PV power output estimations performed using linear regression, SVM, decision trees, random forest, and KNN algorithms.

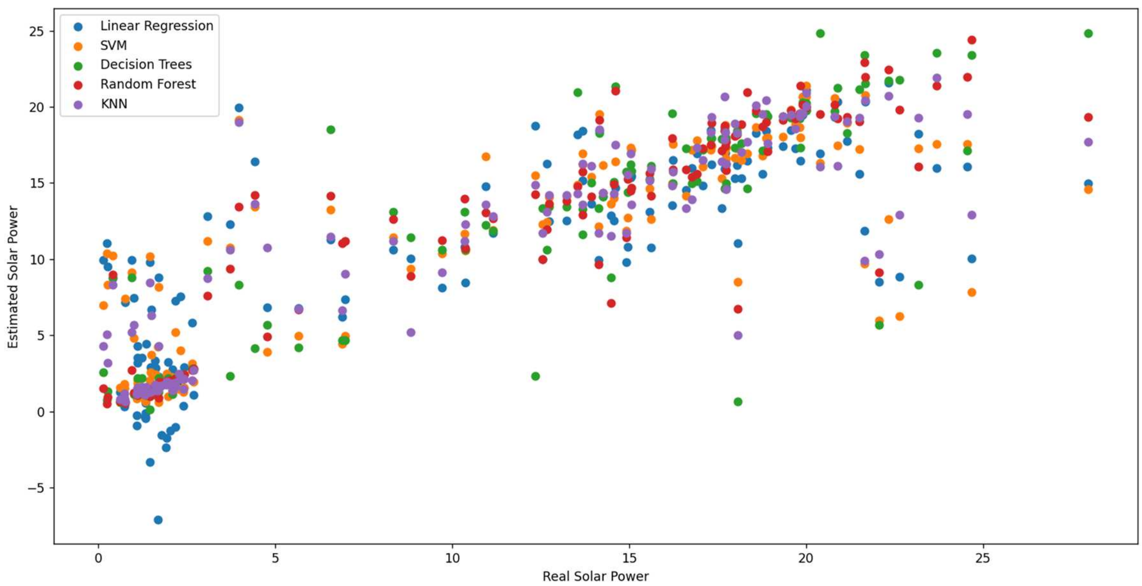

Figure 6. Predicted values against real test data.

After obtaining the graph depicting predicted values corresponding to real test data, the performance of the models was quantified numerically. At this stage, metrics such as MAE, MSE, RMSE, and R^2 were employed as performance evaluation criteria. The comparison of model performances based on these evaluation criteria is presented in Table 2.

Table 2. Comparison of prediction models based on MAE, MSE, RMSE, and R^2 evaluation criteria.

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Model	MAE	MSE	RMSE	R^2
Linear Regression	3,41	23,53	4,85	0,64
SVM	2,76	21,25	4,60	0,67
Decision Trees	1,72	12,48	3,53	0,81
Random Forest	1,52	8,57	2,92	0,87
KNN	2,15	13,48	3,67	0,79

According to the performance evaluation criteria presented in Table 2, it can be deduced that the most successful prediction model across all domains is the Random Forest, while the least performing prediction model is linear regression. Based on the MAE evaluation criterion, the random forest algorithm exhibits approximately 13% less error than the decision trees algorithm, which provides the closest result. The error difference between the KNN, SVM, linear regression algorithms, and the random forest algorithm is 41%, 81%, and 124%, respectively. In terms of the MSE evaluation criterion, the random forest algorithm outperforms the decision trees algorithm, which provides the closest result, by approximately 45%. The error difference between the KNN, SVM, linear regression algorithms, and the random forest algorithm is 57%, 147%, and 174%, respectively. Considering the RMSE evaluation criterion, the random forest algorithm possesses about 20% less error than the decision trees algorithm, which provides the closest result. The error difference between the KNN, SVM, linear regression algorithms, and the random forest algorithm is 25%, 57%, and 66%, respectively. With regards to the R^2 evaluation criterion, the random forest algorithm performs about 7% better than the decision trees algorithm, which provides the closest result. The difference in performance between the KNN, SVM, linear regression algorithms, and the random forest algorithm is 10%, 29%, and 35%, respectively. The percentage representation of accuracy performances of the prediction models on test data is illustrated in Figure 7.

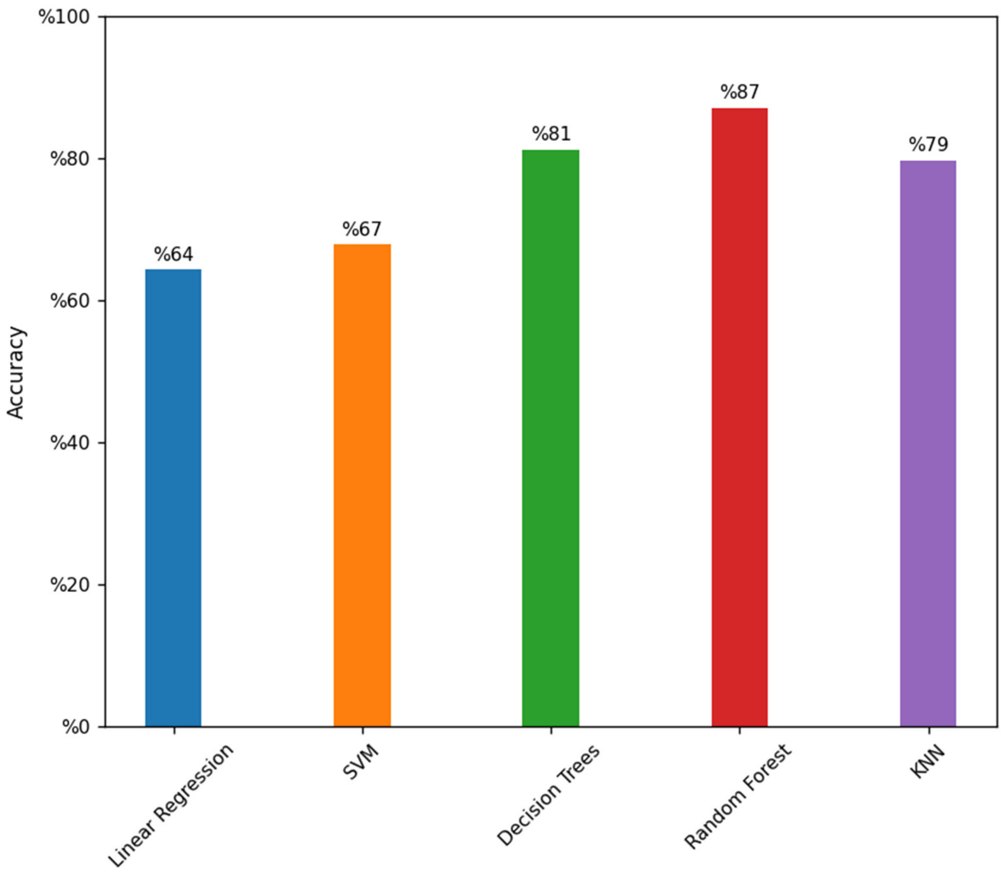

Figure 7. Accuracy performance of estimation models.

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According to the accuracy performance comparison of machine learning methods on test data, the prediction model utilizing the random forest algorithm has yielded the best result with an accuracy rate of 87%. When the prediction models using other algorithms are ranked in terms of success, decision trees have an accuracy rate of 81%, KNN has 79%, SVM has 67%, and linear regression has 64% accuracy rate.

5. Conclusions

In the first phase of this study, a reliable and cost-effective data monitoring system was developed to enable the remote and real-time monitoring of solar PV energy systems. The infrastructure of the IoT-based system consists of a data recording unit, a cloud system, a web interface, and a mobile application. Data from the solar PV system can be monitored independently of location through a mobile application that can be installed on smartphones or via the ThingSpeak platform. The distinctiveness of the proposed system at this point lies in making solar PV systems and the weather parameters affecting them accessible in a cost-effective manner through open-source software and mobile applications. In the second phase of the study, prediction models were developed to determine the expected data for comparison with the obtained real measurement data. This approach allows for the identification of potential system issues based on the difference between actual solar PV power and expected solar PV power derived from existing meteorological data. Machine learning methods including linear regression, SVM, decision trees, random forests, and KNN were employed to develop prediction models based on measurement data. The performance of these models was then numerically compared using performance metrics including MAE, MSE, RMSE, and R2. Through the comparison conducted using these performance metrics, the random forests algorithm emerged as the most successful model across all criteria. It exhibited superiority over other algorithms in the range of 13% to 124% for MAE, 45% to 174% for MSE, 25% to 66% for RMSE, and 7% to 35% for R2. In terms of accuracy performance on test data, the random forests algorithm achieved the highest accuracy rate of 87%. Other algorithms ranked in descending order of success were decision trees with 81%, KNN with 79%, SVM with 67%, and linear regression with 64% accuracy rates. In conclusion, this study successfully presents a cost-effective solar PV power monitoring system and a machine learning-based solar PV power predictor.

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Conflicts of Interest: The author declares no conflict of interest.

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