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Research Article

INVESTIGATION OF THE MOST SUITABLE POWER OUTPUT PREDICTION METHODS WITH ARTIFICIAL INTELLIGENCE IN A ROOFTOP PHOTOVOLTAIC POWER PLANT

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Abstract: *Installing photovoltaic (PV) systems in buildings effectively achieves sustainable energy targets and reduces carbon emissions. Energy demand is increasing day by day. Accessing solar energy is preferred, especially in urban areas, because it is easier and more economical than other renewable energy sources. It is important to calculate the losses that occur in the integration of PV systems into the interconnected system and to select the appropriate material for the system. In the feasibility reports prepared before the system is installed, the selection of appropriate materials for the system, system cost, energy production and consumption, and amortization periods are calculated by considering the environmental and physical conditions. The dataset used in this study was obtained from two rooftop PV systems (each 200 kW) installed on separate buildings of Yüksek İhtisas Hospital in Bursa, Turkey, with production and ambient temperature data collected at 15-minute intervals throughout 2024. This study investigates the use of artificial intelligence techniques—Decision Tree, Random Forest, LSTM, and Linear Regression—for predicting photovoltaic (PV) power output using real data from two 200 kW rooftop PV power plants located at Yüksek İhtisas Hospital in Bursa, Turkey. One-year production, irradiance, and ambient temperature data recorded at 15-minute intervals were used. The aim was to forecast the expected power output of a 440 kW PV system to be installed on the BTU G Block under similar environmental and technical conditions. The effects of environmental and physical conditions on one-year production data were examined using various artificial intelligence methods such as Random Forest, Decision Tree, Linear Regression, and LSTM. The aim was to predict the production data that would arise when a power plant with similar environmental and physical conditions is established. According to the analysis results, the Decision Tree method was determined to be the highest-performing technique, providing a 99.6% R^2 accuracy value.*

Keywords: *Photovoltaics, Power Prediction, Artificial Intelligence, Decision Tree, LSTM*

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1. Introduction

The growing interest in zero-emission management systems in many countries has strengthened the position of solar energy among renewable energy sources, leading to an increase in both the number and capacity of solar power plants in order to reduce carbon emissions and greenhouse gas emissions [1-4]. With the increase in the number of solar power plants, energy production forecasts, material selection, economic return calculations, and meteorological and geographical factors affecting the plant's output have made accurate production forecasting more critical [23-25]. Reliable and timely forecasts of solar irradiance enable the anticipation of sudden changes between energy production and consumption, contributing to the sustainable planning of energy infrastructure, the maintenance of system stability, and the enhancement of supply security. Additionally, these forecasting models make it possible to integrate with smart grids, thereby reducing energy waste and facilitating more efficient use of production capacity [5-9]. The electrical grid has been significantly impacted by recent technological advancements in both electricity production and the transmission and distribution processes, benefiting from these developments [10]. According to projections by the International Energy Agency, global electricity demand—driven by industrial and service sector growth—is expected to increase by 50% by 2050, while CO_2 emissions may double in the same period. As a response, investments in electricity grid infrastructure are anticipated to reach 6 billion dollars by 2030 [11-12]. To overcome these challenges, the use of next-generation information and communication technologies that integrate renewable energy sources with real-time management approaches and enable fundamental changes in electricity consumption is of great importance [13]. The processing and evaluation of this data is regarded not only as a new challenge but also as a significant opportunity for the 21st century [14]. The efficiency of electrical energy generated from photovoltaic panels varies depending on the geographical characteristics, climate conditions, and installation parameters of the location. Therefore, it is essential to predict power outputs that are both safe and economically suitable for panel placement and to identify the factors that affect performance. As photovoltaic systems find increasing applications, forecasting power production based on environmental variables and analyzing the factors influencing panel efficiency are becoming increasingly critical [15].

This study aims to predict the production data of two power plants, located in the same location and utilizing identical conditions and materials, using artificial intelligence methods. The objective is to identify the most effective prediction method and subsequently apply it to forecast the production of a new power plant that is planned to be established

2. Materials and Methods

An alternative method can be employed to determine the irradiance level (G) reaching a specific area, without relying on a specially designed radiation sensor known as a pyranometer. This approach involves monitoring the short-circuit current ($\boldsymbol{I_{scREF}}$) and the temperature ($\boldsymbol{T_{REF}}$)of a photovoltaic module. The short-circuit current is directly related to the solar irradiance received by the panel and its operating temperature, and this relationship is defined through Equation (1) [16].

$$I_{sc} = \frac{I_{scREF}}{G_{REF}}(1 + a(T_p - T_{REF}) \tag{1}$$

In this context, the reference panel temperature (25°C), GREF represents the reference irradiance value (1000 W/m²), α is the short-circuit current temperature coefficient as listed in the photovoltaic panel's catalog, and corresponds to the short-circuit current under reference conditions, as provided in the panel's catalog. By isolating the irradiance parameter in Equation (1) through appropriate mathematical manipulation, Equation (2) is derived, which expresses the irradiance incident on the photovoltaic panel as a function of the short-circuit current and the panel temperature [17].

$$G = \frac{G_{REF} I_{sc}}{I_{scREF}(1+a(T_p - T_{REF}))} \tag{2}$$

To determine the amount of irradiance falling on the photovoltaic panel, it is necessary to measure the panel's short-circuit current and temperature, as indicated by Equation (2) [15].

2.1. Artificial Intelligence Models

2.1.1 Random Forest Regression

Random Forest Regression is an algorithm commonly used in machine learning, providing high accuracy in both classification and regression problems. This model combines decision trees and minimizes the loss function by sequentially adding these models. In classification tasks, it is used to assign data to a specific class or to calculate the probability of each class. In regression problems, it serves as an effective tool for predicting numerical values [16].

2.1.2 Long Short-Term Memory

Long Short-Term Memory (LSTM) architectures are commonly used in time series forecasting and predictions. They are built upon Recurrent Neural Networks (RNN), which are frequently employed in natural language processing tasks such as speech recognition and text recognition [17].

2.1.3 Linear Regression

Linear Regression seeks to establish a linear connection between the dependent and independent variables to forecast future outcomes. The model assumes that the dependent variable can be represented as the sum of the products of the independent variables and their respective coefficients, with the coefficients indicating the impact of the independent variables on the dependent variable [16].

2.1.4 Decision Tree

It is a technique used to examine various decision points that arise in relation to sequentially dependent events, which can assist in defining preferences, risks, gains, and goals by business management, and can be applied in many key investment areas [18].

2.1.5 Confusion Matrix

The Confusion Matrix is a C x C dimensional matrix that visualizes and summarizes the performance of a classifier (C), where C represents the number of classes in the set [19].

2.2. Performance Evaluation Metrics

To assess the outcomes from the four distinct machine learning algorithms applied in the study, performance metrics including R^2, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were utilized. The formulas for calculating R^2, RMSE, MAE, and MAPE, which are used for performance evaluation in this study, are presented in Equations (3-6) [19].

$$R^2 = 1 - \frac{\Sigma(Y_i - \hat{Y}_i)^2}{\Sigma(Y_i - \bar{Y})^2} \tag{3}$$

$$RMSE = \sqrt{\frac{1}{m}\Sigma_{i=1}^{m}\left(Y_i - \hat{Y}_i\right)^2} \tag{4}$$

$$MAE = \frac{1}{m}\Sigma_{i=1}^{m}|Y_i - \hat{Y}_i| \tag{5}$$

$$MAPE = \frac{100}{m}\Sigma_i^m\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \tag{6}$$

2.3. Creation of Data Set and Estimation Method

Our dataset belongs to two separate power plants with a capacity of 200 kWe each, located approximately 800 meters from the Mimar Sinan Campus of Bursa Technical University, installed in the Women's and Obstetrics Building and the Main Building of the Yüksek İhtisas Hospital, which was commissioned in the last quarter of 2021 and connected to two separate grids. The dataset consists of 15-minute production data for the year 2024 from these power plants, along with the ambient temperature and solar irradiance values measured throughout the year. In this study, production forecasts for the Women's and Obstetrics Hospital building were made using the production data, ambient temperature, and irradiance data from the Main Building, and these predictions were compared with the actual data of the hospital to determine the most accurate prediction method.

In this study, since panels of the Alfa Solar brand were used, the panel datasheet [20] values were inserted into the formulas at the appropriate places to calculate the panel temperatures and current values.

The dataset used in this study comprises one-year production data, recorded at 15-minute intervals throughout 2024, from two separate 200 kWe photovoltaic power plants located at Bursa Yüksek İhtisas Hospital. These data, supplemented with corresponding ambient temperature and solar irradiance measurements, were utilized to develop and evaluate forecasting models. The general layout of the system is illustrated in Figure 1.

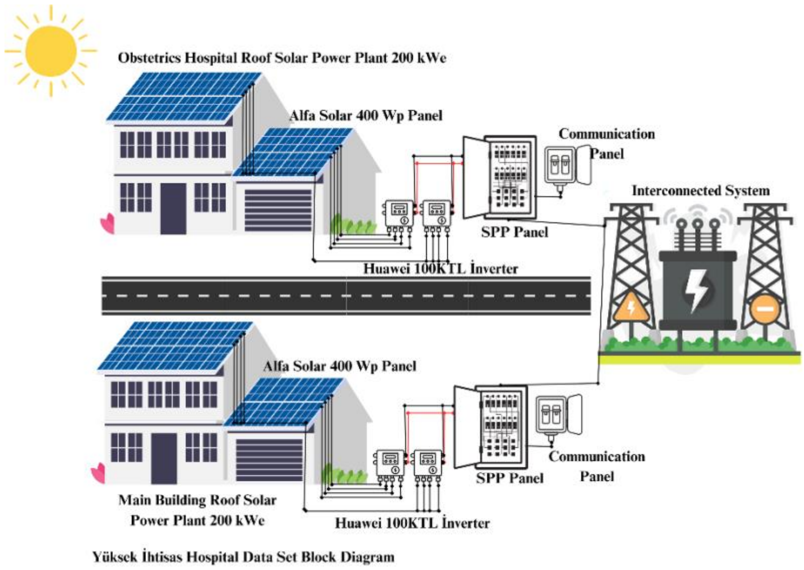

Figure 1: Connection Diagram of PV Power Plants

Additionally, the 1-year temperature data collected at 15-minute intervals from the existing ambient temperature sensor in the system were used to prepare the methods developed using Artificial Neural Networks (ANN) in the MATLAB environment. To generate forecast data, 1-year average irradiance data for the power plant area were obtained from the Global Solar Atlas [21]. The irradiance value tables are provided in Figures 2 and 3.

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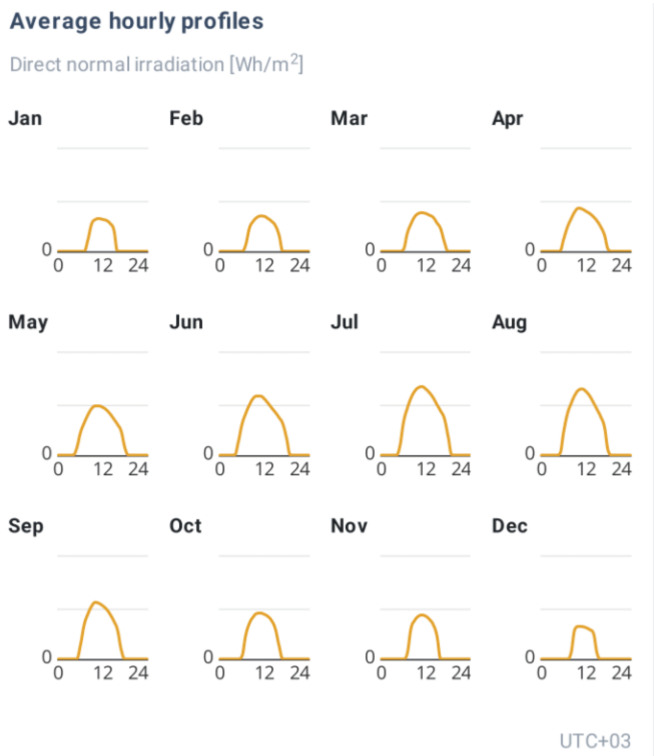

Figure 2: Bursa Yüksek İhtisas Hospital Main Building Regional Radiation Profile

Average hourly profiles

Direct normal irradiation [Wh/m²]

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0 - 1												
1 - 2												
2 - 3												
3 - 4												
4 - 5												
5 - 6				4	68	127	87	17				
6 - 7			20	119	220	301	324	231	136	28		
7 - 8		63	175	237	314	407	457	404	334	232	55	
8 - 9	110	227	268	317	394	491	559	505	440	349	297	62
9 - 10	266	293	338	387	455	555	625	586	516	411	378	289
10 - 11	310	331	370	422	481	578	661	636	554	445	419	319
11 - 12	320	345	377	413	481	578	670	647	544	449	430	317
12 - 13	312	342	370	392	468	551	647	623	521	437	419	307
13 - 14	302	321	353	370	443	509	610	579	488	416	387	288
14 - 15	273	293	332	338	403	462	561	516	437	374	336	254
15 - 16	210	251	278	297	353	418	494	447	371	293	226	55
16 - 17		156	220	238	301	367	431	374	282	127		
17 - 18			90	158	232	306	358	274	89			
18 - 19				18	69	168	184	41				
19 - 20						3	3					
20 - 21												
21 - 22												
22 - 23												
23 - 24												
Sum	2,102	2,622	3,190	3,711	4,682	5,820	6,671	5,881	4,712	3,562	2,946	1,891

Figure 3: Bursa Yüksek İhtisas Hospital Main Building Annual Average Radiation Values

Two separate datasets for the main building and the obstetrics hospital were preprocessed and organized, followed by the creation of the preprocessing graphs for the data. Subsequently, model predictions were made using Random Forest (RF), Long Short-Term Memory (LSTM), Linear Regression, and Decision Tree methods. The performance of the models was assessed using statistical evaluation metrics, and the most successful method was determined.

Some of the visualized data obtained from the dataset are presented in Figure 4.

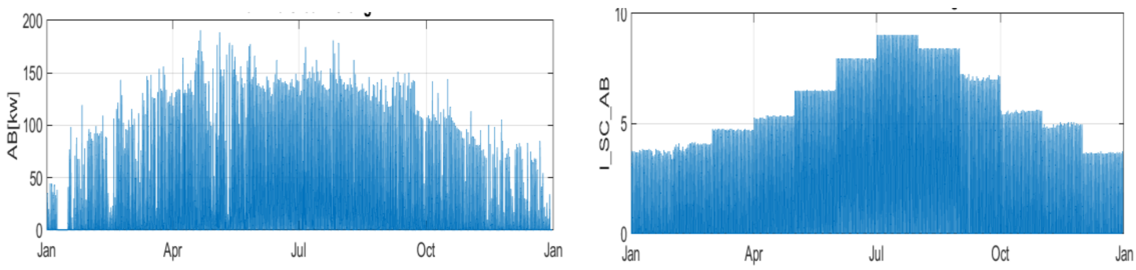

Figure 4: a) Main Building Output Power, b) Output Current Graph

The visualized data, as shown in the flowchart in Figure 5, were processed using different artificial intelligence methods, and the method with the most reliable performance in PV power prediction was determined.

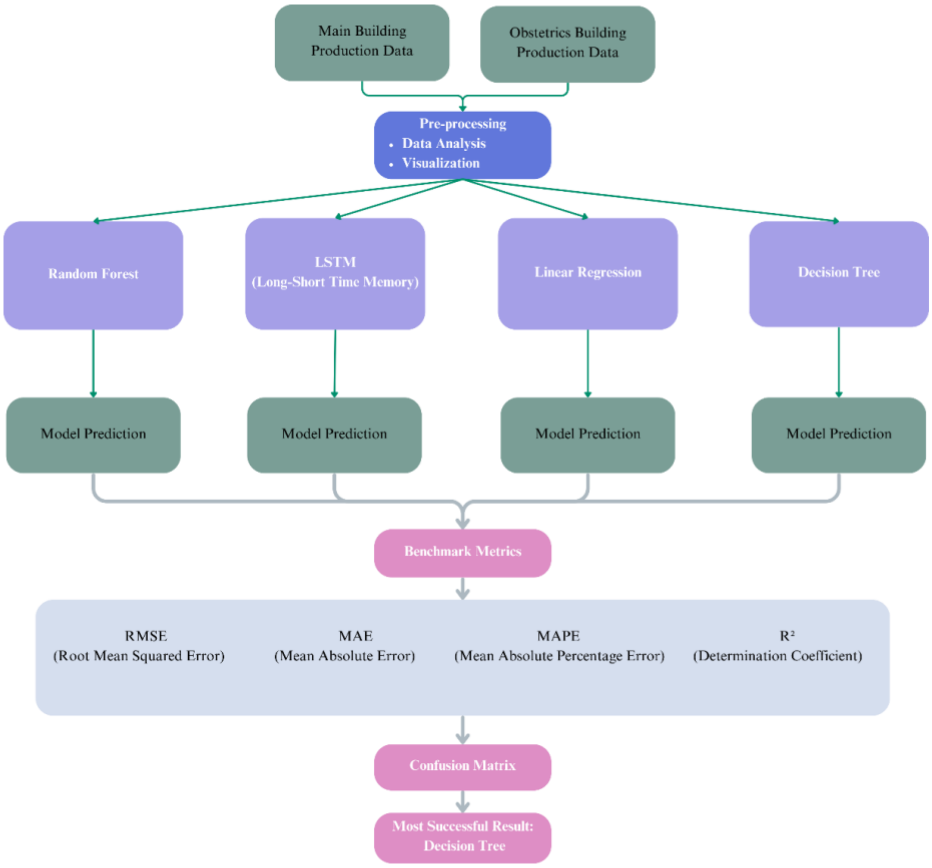

Figure 5: PV System Production Data Analysis And Identification of the Best Prediction Method Flowchart

This model has distinguished itself by successfully learning the relationships between the variables in the dataset, with low error rates and high generalization capacity. The preliminary study shows that the Decision Tree method performed the power prediction with the highest accuracy, achieving an R^2 value of 99.9%.

When evaluating the production data from both the Main Building and the Obstetrics Hospital, the RF model produced more stable predictions compared to other methods and demonstrated a more robust structure against small data fluctuations. Its capacity to generalize well across different input conditions while maintaining low prediction errors constitutes a significant advantage.

3. Power Production Prediction with Decision Tree Method

After determining the Decision Tree method as the most suitable model, a new dataset for the G Block of Bursa Technical University (BTÜ) was created using the irradiation and temperature data of the Main Building, and the most accurate production prediction was performed on this dataset, as shown in Figure 6.

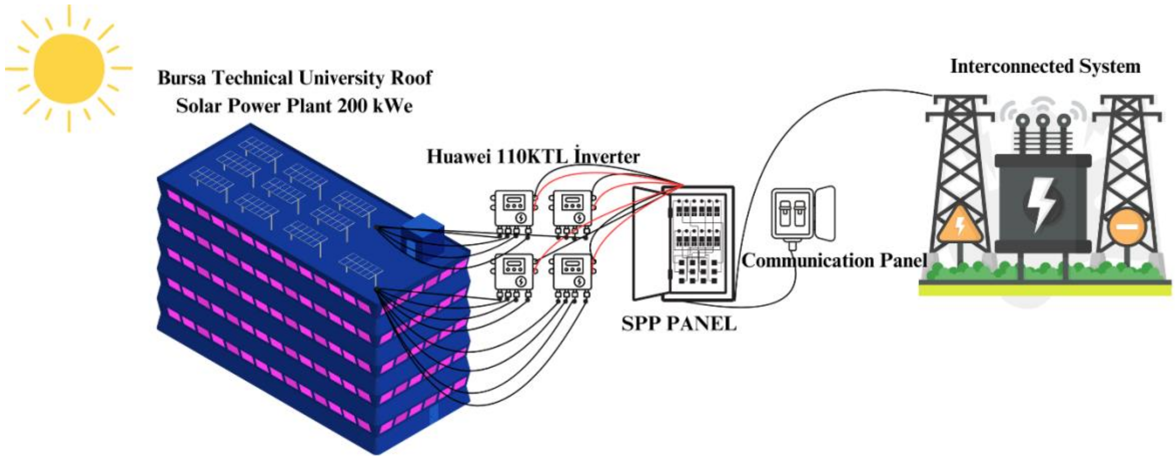

Figure 6: PV Power System Diagram of BTÜ G Block

After determining that the Decision Tree method is the most suitable model, a new dataset for the BTÜ G Block energy production plant was created using the irradiance and ambient temperature data and relevant parameters for the Main Building. In line with the previously designed electrical projects for the BTÜ G Block, the current panel selection was made, and solar power system electrical projects, panel layouts, and grounding projects were prepared. In this context, production values were estimated based on the technical specifications of the 545W ZES brand MBB HC BIFACIAL model panel [22] used in the electrical projects.

The created dataset was processed through a preprocessing phase, and meaningful insights were derived by applying data analysis and visualization methods. Model evaluation was conducted using quantitative metrics to determine prediction accuracy and consistency. Based on the analysis carried out according to the analysis workflow presented in Figure 7 facilitated the identification of the most accurate forecasting model and the most accurate production forecast for the BTÜ G Block were obtained.

Figure 7: BTU G Block Electric Power Generation Prediction Flowchart

4. Discussion

The results obtained were analyzed in detail using comparative performance metrics, and the predictive power of each model was compared. Figure 8 shows the main building decision tree prediction result, and Figure 9 shows the main building LSTM prediction result, respectively. Among the models evaluated, the Decision Tree algorithm emerged as the most successful prediction method. It consistently provided the highest R^2 scores and the lowest error rates, including MAE and MAPE, across datasets from both the Main Building and the Obstetrics Hospital. Its interpretability, ease of implementation, and fast training time further support its applicability for photovoltaic power prediction tasks.

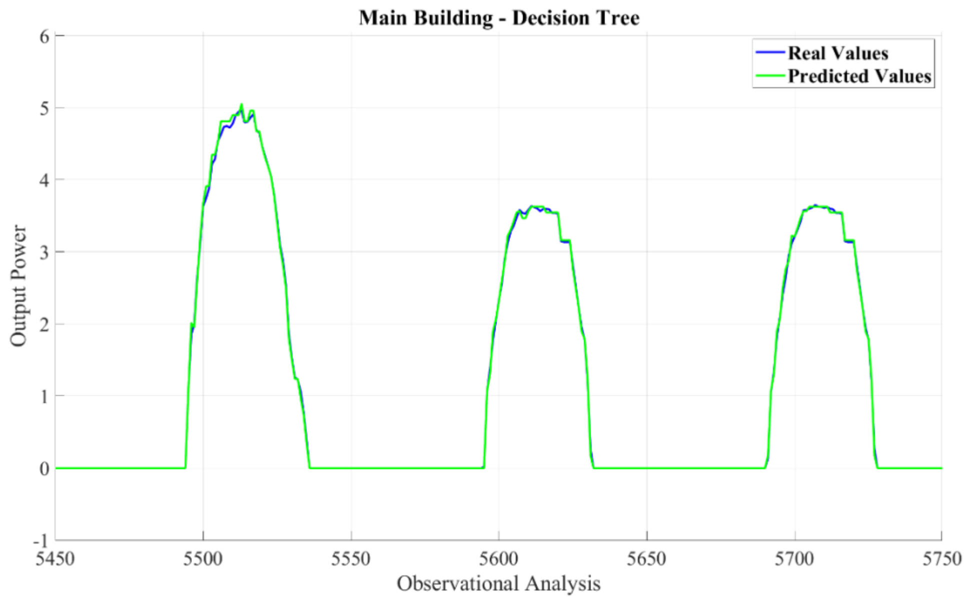

Figure 8: Main Building Decision Tree Prediction Result

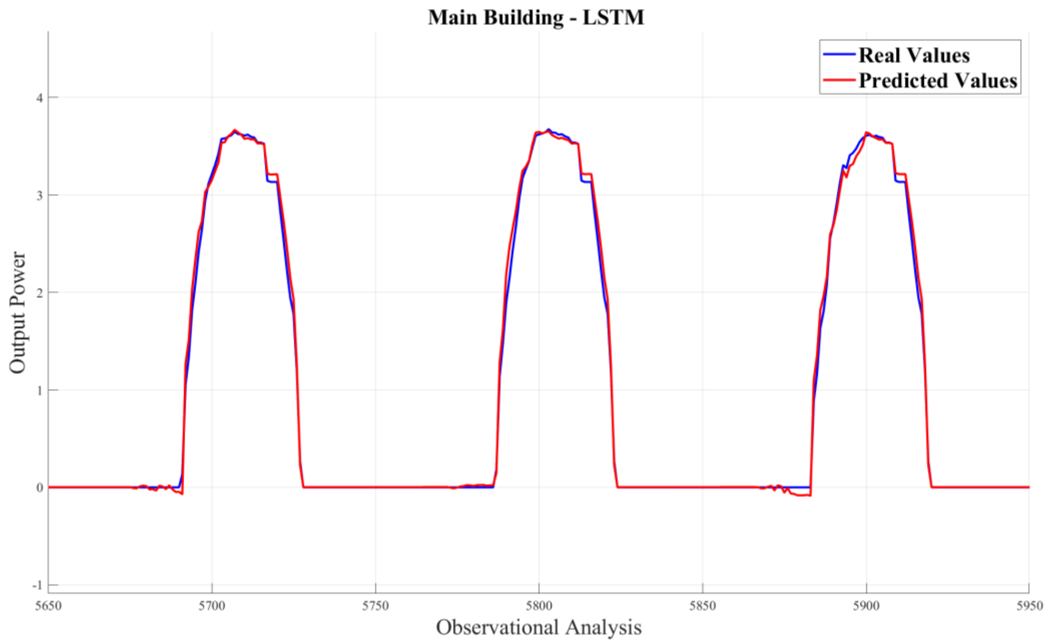

Figure 9: Main Building LSTM Prediction Result

Although the Decision Tree model had a high accuracy rate, it encountered difficulties in generalization due to its sensitivity to small data fluctuations. The Linear Regression model, on the other hand, yielded successful results under linear assumptions; however, due to the complexity of the data and the presence of non-linear relationships, it exhibited lower performance compared to other models. In particular, when examining the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values of the predictions, it was observed that the Linear Regression model had higher error rates than the other models.

Although the Long Short-Term Memory (LSTM) model has the capacity to process time series data, it did not demonstrate the expected performance. One of the main reasons for this is that the model exhibited large errors at certain data points during the learning process, thus posing a risk of overfitting. Although LSTM is well-suited for handling complex temporal data, its performance in this context was suboptimal due to the relatively limited data volume and variability.

The Random Forest (RF) model demonstrated the most successful prediction performance with the lowest MAPE values on both the Main Building and the Obstetrics Hospital production data. By aggregating predictions from multiple decision trees, the RF model effectively captured non-linear patterns in the dataset, leading to high robustness and reduced overfitting. Particularly on the Obstetrics Hospital data, it provided the lowest error rates, indicating that it is the most suitable model for this dataset. Figures 10 and 11 illustrate the model outputs for the Obstetrics Hospital, highlighting the comparative performance of the Decision Tree and LSTM methods.

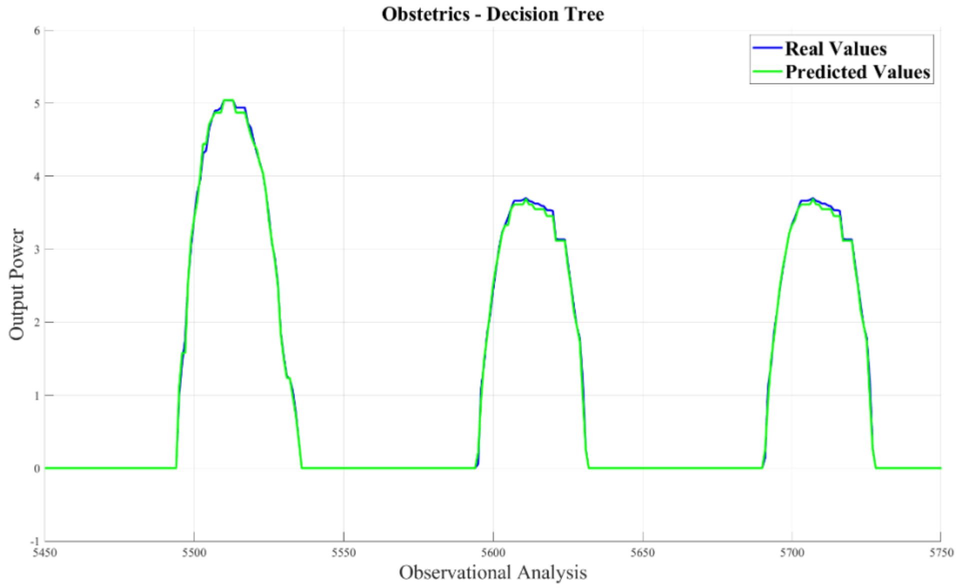

Figure 10: Obstetrics Building Decision Tree Prediction Result

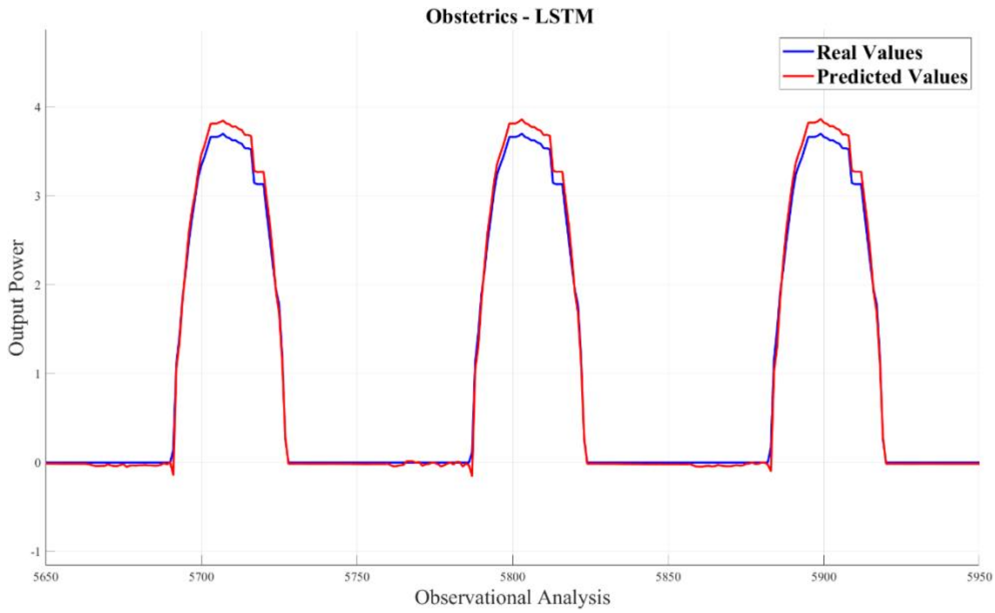

Figure 11: Obstetrics Building LSTM Prediction Result

In line with the analyses conducted within this scope, while the Decision Tree model emerged as a strong candidate in terms of overall accuracy, the Random Forest model provided the best result in terms of prediction accuracy by minimizing error rates. As a result, considering predictive power, error rates, and generalization capability, the Decision Tree model was identified as the most successful method, particularly for the Obstetrics Hospital dataset.

The results obtained for the Main Building and the Obstetrics Building are presented in Table 1.

Table 1: Results of Prediction

Model	R^2	RMSE	MAE	MAPE	Training Time (sec)
Decision Tree- Main Building	0.9995	0.0423	0.0202	0.0295	0.6831
Decision Tree- Obstetrics	0.9996	0.0403	0.0197	0.0262	0.0339
Linear Regression- Main Building	0.9984	0.0970	0.0772	0.0810	0.8508
Linear Regression- Obstetrics	0.9976	0.1393	0.1002	0.0401	0.0429
LSTM- Main Building	0.9970	0.0112	0.0637	0.0646	84.7358
LSTM- Obstetrics	0.9962	0.0147	0.0805	0.0676	107.2715
Random Forest- Main Building	0.9672	0.3479	0.1306	0.0560	67.2440
Random Forest- Obstetrics	0.9853	0.2397	0.0611	0.0262	135.4271

While the Decision Tree model demonstrated high precision, it showed some sensitivity to minor data fluctuations, which can affect its generalization. The Linear Regression model, although performing reasonably well under assumptions of linearity, failed to capture non-linear patterns effectively, resulting in comparatively higher error rates. The LSTM model, known for its capacity to process temporal dependencies, did not perform as expected in this study. This is likely due to the relatively limited dataset, which made the model prone to overfitting and reduced its prediction stability.

Based on these evaluations, the Decision Tree model has proven to be a highly effective tool for forecasting power output in photovoltaic systems, particularly under consistent environmental and operational conditions. Its success reinforces the potential of simple yet powerful AI models in enhancing feasibility assessments and guiding strategic energy planning.

5. Conclusion

In this study, the effectiveness of artificial intelligence-based modeling techniques in feasibility analyses of power plants was evaluated; in particular, prediction models were developed for newly planned power plants using data obtained from existing plants by employing the decision tree algorithm. The accuracy of the model was assessed using the R^2 coefficient of determination, and the results demonstrated that the decision tree model is capable of making predictions with high accuracy.

The findings reveal that the accuracy performance of the model is closely related to the number, diversity, and quality of the input parameters. In artificial intelligence-based models, increasing the number of input parameters enhances the model's learning capacity and significantly improves its prediction performance. This provides considerable advantages, particularly in long-term investment planning and preventive risk analyses.

In the feasibility studies of new power plants to be built in the future, comprehensive data surveys at the regional level can be conducted by creating datasets related to many factors, such as the production data of previously established plants, horizontal irradiance amounts, ambient temperature, terrain elevation, wind speed, and types of materials used. The use of such diverse data as inputs in models makes it possible to successfully model many critical factors, such as correct material selection, healthy financial planning, optimization of maintenance periods, and the pre-estimation of the total operating cost of the plant.

Given that conventional modeling techniques typically rely on restricted input sets, the ability of artificial intelligence-based models to process multidimensional datasets creates a significant difference. Specifically, the decision tree algorithm used in this study has addressed the impact of production data and environmental variables in an explanatory structure; it has produced successful results in terms of predictability. Improved model accuracy plays a crucial role in minimizing uncertainty and enabling proactive risk assessment.

As a result, this study has shown that artificial intelligence-supported decision tree models can be an effective tool in reducing risks, increasing cost efficiency, and improving decision-making processes in energy projects. The inclusion of diverse and comprehensive input variables significantly enhances the predictive precision of the models; this opens the way for projects based on sustainable, reliable, and strategic planning in the energy sector.

Future studies can further improve prediction reliability by integrating additional environmental and operational parameters and exploring real-time deployment capabilities within smart grid infrastructures.

This study is structured as follows: Section 2 describes the materials and methods; Section 3 presents the model development and evaluation; Section 4 discusses the results and concludes the study.

Ethical statement

The author declare that this document does not require ethics committee approval or any special permission. This review does not cause any harm to the environment and does not involve the use of animal or human subjects.

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Authors' Contributions

Conceptualization and Methodology, R.B. and G.B.; Software, R.B. and O.C.; Validation, R.B., O.C. and G.B.; Formal analysis, Investigation, Data curation, Writing—original draft, R.B., O.C. and G.B.; Visualization, Supervision, and Project administration, G.B.

All authors have read and agreed to the published version of the manuscript.

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