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IMPACT OF PHOTOVOLTAIC SYSTEMS ON DISTRIBUTION NETWORKS WITH ADVANCES OF CLOUD, GRID AND CLUSTER COMPUTING

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Abstract. The impact of photovoltaic (PV) systems on distribution networks in advances of cloud, grid, and cluster computing was annoying in the study. Additional PV systems are explained with their working principles. Furthermore, A clustering-based model was developed to reduce the error in the calculation. The weather conditions were classified into different synoptic types. Prediction-based models were introduced after classifying the weather conditions in different optic types. For the movie, it was noted that conditions play a Vital role in predicting the output produced by a PV system. Moreover, a coherent discussion about the key elements regarding the impact of PV systems on Distribution Networks for Cloud, Grid, and Cluster Computing is done. Thus, through the discussion, an empirical knowledge-based analysis was presented.

Key words: cluster computing, PV system, solar grid, distribution networks. Secondary data

1. Introduction. The energy landscape is transforming with the global concern over depleting conventional energy sources and the pressing need for sustainable alternatives. Photovoltaic systems (PV) have emerged as a promising solution, harnessing solar energy to generate electricity. As societies strive to minimize their carbon footprint and embrace greener technologies, PV systems have gained prominence due to their renewable nature and potential for widespread deployment [1]. This transition to cleaner energy sources aligns with the broader global objective of mitigating climate change and achieving sustainable development.

Amidst this context, there is a growing recognition of the interplay between advancements in information technology and the energy sector. With its exponential growth and increasing computational demands, cloud computing stands out as a prime example of technology's burgeoning appetite for energy. This confluence of factors underscores the significance of exploring how PV systems can effectively power advanced technologies like cloud computing with their renewable energy generation capacity.

Research Scope: The scope of this study encompasses an in-depth investigation into the integration of PV systems with advanced technologies, focusing mainly on their potential to power cloud computing infrastructure. The research delves into the intricate web of factors, challenges, and opportunities associated with this integration. By examining the technological, environmental, and economic dimensions, the study provides a comprehensive understanding of the feasibility and implications of using PV-generated energy to sustain energy-intensive technologies like cloud computing.

Motivation: The motivation behind this research stems from the urgent need to address the energy challenges posed by the escalating adoption of advanced technologies. Cloud computing offers unprecedented scalability and efficiency but demands substantial energy resources. By leveraging renewable energy sources like PV systems to power cloud infrastructure, we can explore a pathway to more sustainable technology deployment. This study aims to contribute to the ongoing discourse on sustainable energy solutions and their role in supporting digital transformation.

Contribution: This research contributes to the existing body of knowledge by bridging the gap between renewable energy systems and advanced technology requirements. By explicitly focusing on PV systems and their potential to power cloud computing, this study offers insights into the feasibility, benefits, and challenges of such integration. The findings aim to inform policymakers, energy experts, and technology stakeholders about

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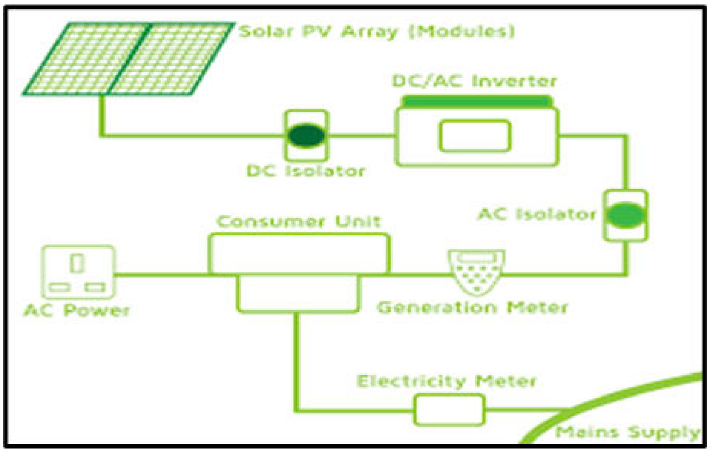


Fig. 2.1: PV system grid

the opportunities for reducing carbon emissions while meeting the energy needs of emerging digital landscapes. Through an empirical analysis of relevant secondary data and a systematic discussion of key factors, this study provides valuable insights into an evolving area at the intersection of energy and technology.

In the subsequent sections, we delve deeper into the factors that underscore the integration of PV systems with advanced technologies, particularly cloud computing. This study seeks to illuminate the path toward a greener and more sustainable technological future by examining technological considerations and a comprehensive analysis of associated factors.

2. Objectives. The objective of the study provided an outline for the overall analysis. In addition, the overall analysis is based on the following objectives:

1. To observe the different components of PV systems
2. To discuss the working principle of the PV system
3. To discuss different models to predict the output of Systems
4. To analyze the best prediction algorithms for PV system output
5. To analyze the problem of the PV system in cluster computing

3. Methodology. The methodology of n research looks into different factors and methods implemented to develop an empirical analysis. Moreover, different research strata and other factors aided the process of creating the study based on the objectives and justified through an appropriate methodology [3]. To comprehend different aspects of PV systems and the impact of the same on cluster computing, the method of secondary qualitative analysis was employed. To collect data for the study, secondary data sources such as past research, articles, news, and other authentic external resources were collected. At the same time method of qualitative analysis was used to analyze the collected data for the study [5]. The secondary quantitative method calls for authentic data and factor-based analysis for the study, therefore. The method of secondary research is beneficial to develop a knowledge-based result that has tangible implications in real life. Therefore, a secondary quantitative method of analysis was used to create the overall analysis in a systematic manner [2].

4. Working process of a photovoltaic (PV) system. For understanding the process of a photovoltaic (PV) system in a comprehensive manner it is essential to understand the components associated with the same. Additionally, it is essential to understand the basic working process of a PV system. Thorough knowledge of such systems provides the premises to understand the impact of the PV system in cluster computing [6].

A photovoltaic (PV) system converts the packets of energy of sunlight into eclectic energy. The basic working principle is that solar light which contains packets of energy or photons falls on the solar panel and through a process called the photovoltaic effect, it is converted into electric current. Each of the panels converts photons into electricity and produces a small amount of electric energy. Thus, small panels are interconnected

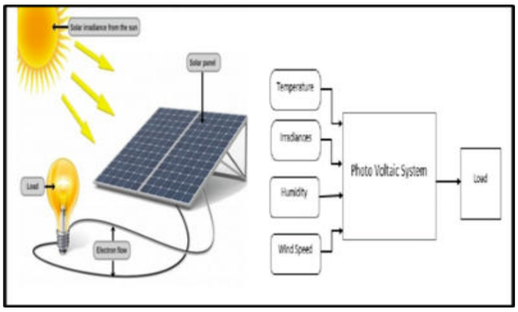


Fig. 3.1: PV system unit

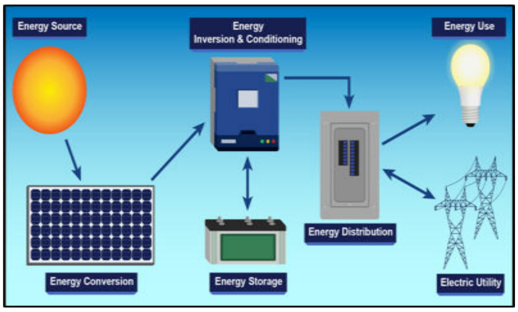


Fig. 4.1: Gride design

in a solar array in order to produce a large amount of energy.

Figure 2.1 of the analysis is related to the grid design of a solar panel. A dollar panel produces DC current as a result. However, most cluster computing technology uses AC current for its functioning [7]. Therefore, an electrical unit grid and inverters are connected with the panels in order to produce concert DC current in AC current.

At the same time, there are different other components that are associated with the main system in order to produce electricity. Following is a brief discussion about the different components:

a) Solar Panel

The solar panel of a PV system consists of solar cells having semiconductor properties in the material. Additionally, the semiconductor material works as a shield that protects the panel from the environment. After the conversion of solar photons into usable electricity through the photovoltaic effect the conducting material collects the electricity. The semiconductor is presented on either of the panel [9, 4]. Additionally, there is a layer of antireflection coating in order to prevent reflection and minimize the loss of energy. The primary component of the solar panel is crystalline silicon which has a 33% capacity of energy producing capacity from sunlight [24, 8]. However, there are other semiconductor materials that have the same functionality however the price for them is higher.

b) Inverters

Inverters of solar units are the components that intake DC electricity and convert that to AC flow. The current produced by a solar panel is DC current, however, in cluster computing AC current is required [11]. Therefore, an inverter unit of the PV system converges DC to AC current. Hence, the inverter is the most important and expensive component after solar panels [10].

Most of the inverters come with a conversion efficiency of 90%. In addition, some of the solar panels can produce more power than that. The safety feature of an inverter is a significant feature that includes fault circuits. Additionally, a ground fault circuit is one of the most important features of a PV system that shuts

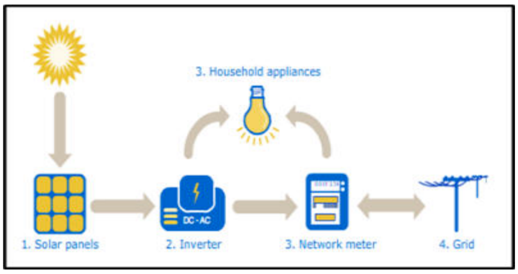


Fig. 4.2: Components of the PV system

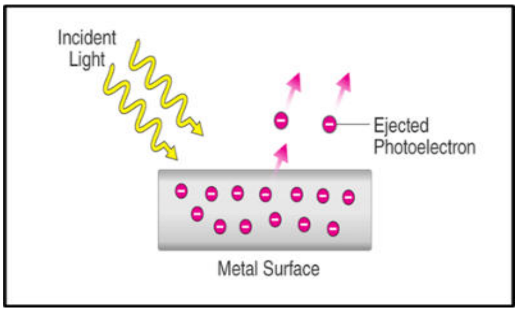


Fig. 4.3: Photovoltaic effect

down the system when there is a fault detected in the grid system.

c) Racking

The rack is the mount that is used to fix the solar array with a base. Usually, the construction of the rack is aluminum or steel. Additionally, one of the significant features of the solar array is of grounding of the overall grid system [12]. The Racking of a solar panel is mechanically grounded with the ground in order to prevent electrocution.

d) Other Important Components

There are other essential components of a PV system that are essential for the systematic functioning of the system. For instance, disconnects, combiners, meters, breakers, and wiring are important for the functioning of the system. The main function of a solar combiner is to connect two or more cables in a single unit [14].

Electrical systems are shielded from surges or overcurrent by circuit breakers or breakers. Breakers can also be manually actuated, serving as an extra disconnect, although they are designed to activate automatically when the current exceeds a certain value [13]. Electric meters track the quantity of energy flowing through a system moreover usage and energy consumption are calculated through the meters. Additionally, there are wirings that must be of the correct size to carry the current and convey electrical energy from and between each component.

5. Photovoltaic effect. The process of Photovoltaic effect is the process of generating electricity from solar energy. When sunlight is reflected off of it. This phenomenon, which results from the solar panel's cells converting sunlight into electrical energy, is what makes solar panels valuable. Types of semiconductors that are used for the PV effect are p-type and n-type. A p-n junction is created between the different types of conductors. The major principle that the Photovoltaic effect works on is the concept of the photoelectric effect [15].

Considering, light is a particle in nature, the photoelectric property can be explained. The photons of light are then converted into energy. Planck's equation connects the energy of a photon to the frequency of the light.

$$E = h\nu = h\frac{c}{\lambda}$$

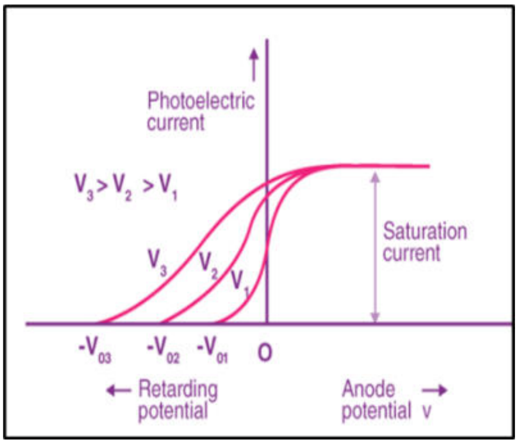


Fig. 5.1: Photovoltaic effect

In the above equation, E stands for the energy of the photon, which is the frequency of the light. In addition, h is Planck's constant, and c is the light speed (in a vacuum). Furthermore, λ is the wavelength of the light.

It can be comprehended that different frequencies of waves from different light sources consist of photons with different energies [12]. For instance, red light has more frequency than blue light. Hence the energy that a photon of blue light has is higher than that of a photon of red light.

The above graph is related to the photovoltaic effect and a threshold of electricity generation is shown in the above graph. The positive potential is steadily increased while the light's intensity and frequency remain constant [10]. When the potential between the metal plate and the collector rises to a certain level and is positive, the photoelectric current increases. In addition, When the potential is raised above the typical value for any rise in the accelerating voltage, the photoelectric current remains unchanged [16]. The current's maximal value is referred to as the saturation current.

The XG-Boost self-organizing map (TS-SOM) represents a sophisticated technique that combines the power of two distinct methodologies: the XG-Boost algorithm and the self-organizing map (SOM). The SOM is a neural network-based approach for clustering and visualizing high-dimensional data, while XG-Boost is an ensemble learning algorithm that excels in predictive modeling.

1. Self-Organizing Map (SOM) Component: At its core, the SOM is an unsupervised learning technique that organizes data points into a grid-like structure based on similarity. Neurons within the grid (also called nodes) compete to represent input data, and the competition results in a topological mapping of the data. SOMs are well-known for their ability to reveal underlying patterns and relationships within complex datasets.
2. XG-Boost Component: XG-Boost, on the other hand, is a boosting algorithm that constructs a strong predictive model by iteratively adding weak learners (usually decision trees) to the ensemble. It addresses issues of bias, variance, and overfitting by combining the predictions of multiple weak models. XG-Boost is widely recognized for its high performance in various machine learning tasks, including classification and regression.

Integration of XG-Boost and SOM: Data Tree Structure In this study, the innovative concept of the "data tree structure of the XG-Boost self-organizing map (TS-SOM)" is introduced. This hybrid structure combines the SOM's grid-like organization of data and the predictive power of XG-Boost. Here's how the integration works:

1. The data tree structure represents a hierarchical arrangement of nodes that captures both the topological relationships derived from SOM and the predictive capabilities of XG-Boost. Each node in the tree corresponds to a cluster identified by SOM, and it contains an XG-Boost model trained on the data points belonging to that cluster.

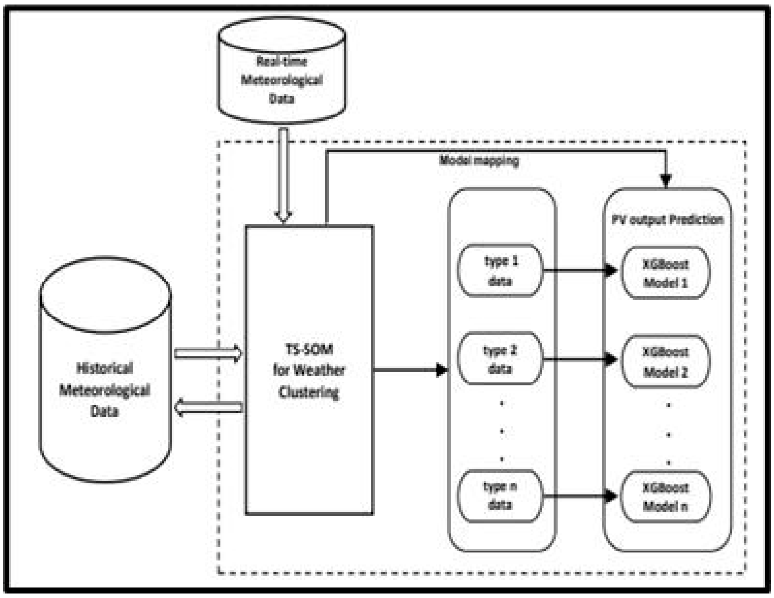


Fig. 6.1: Algorithms used in the study

2. When a new data point is introduced to the TS-SOM, it traverses the data tree structure from the root to a leaf node. At each node, the XG-Boost model provides predictions based on the learned patterns of the data points in that cluster. The prediction is propagated down the tree until the data point reaches a leaf node, and the final prediction is the aggregated result of predictions from multiple nodes.

6. Output calculation of PV system for cluster computing . The data tree structure of the XGBoost self-organizing map (TS-SOM) is used in order to calculate the output of a PV. Based on the machine learning model the output is calculated in different sections [19]. Additionally, with the implication of the aforementioned training models, low computational overhead allows for the precise PV power output forecast, which makes a variety of edge devices appropriate for its usage can be done. The PV output in different circumstances is essential to calculate, Furthermore, an overall output production of the PV system aids the functioning of the cluster computing. Additionally, the grid system and the power output depend on the field of energy [17]. In addition, the performance of output is calculated based on broadly used. Moreover, a Generalised Regression Neural Network (GRNN) was used for prediction accuracy. Additionally, a fair comparison of the system's Long Short-Term Memory (LSTM) was used. Furthermore, SVR is trained with a similar training model to GRNN. Moreover, an identical training approach was used XGBoost approach [18].

The above image is related to the model that was used in the analysis. Moreover, historical data used in the model was output TS-SOM was gathered. It was found that meteorological factors have a huge impact on the system [25]. The PV output curves were seen to emit spikes and fall with abrupt changes in the weather. Thus, such unpredictability of meteorological influences creates hindrances in building a high-performing PV model. Therefore, Given prior understanding as historical data input about the weather changes over time. In addition, and in the meanwhile, is still capable of properly estimating PV power output for the electrical unit [19].

Additionally, the prediction-based model was completed with the capability of handling data loss. It was noted that the PV output system often faces data loss that leads to faulty prediction of the PV output system. moreover, it was noted that there is a hindrance in data transmission due to various reasons. hence handling Data loss is a major component of the PV system. In addition, it was found that there are various components that might be affecting the output results. Such as Global Horizontal Irradiance (GHI), Diffuse Horizontal Irradiance (DHI), and Direct Normal Irradiance (DNI) have a strong impact on the PV power output. All the

Table 6.1: Pearson Correlation

FIELD	PEARSON CORRELATION	DESCRIPTION
ghi	0.9767	Irradiance horizontal global for the centre value
ghi90	0.9744	Irradiance horizontal global at 90%
ghi10	0.9629	Irradiance horizontal global at 10%
dni90	0.8644	90% value direct normal irradiance
dni	0.9275	Centre value direct normal irradiance
dni10	0.9077	10% value direct normal irradiance
air temp	0.3350	Air temperature
cloud opacity	-0.2184	Cloud quantity
azimuth	0.0092	The azimuth angle of the sun. Range: -180∼180
dhi	0.9314	Diffuse irradiance (horizontal)

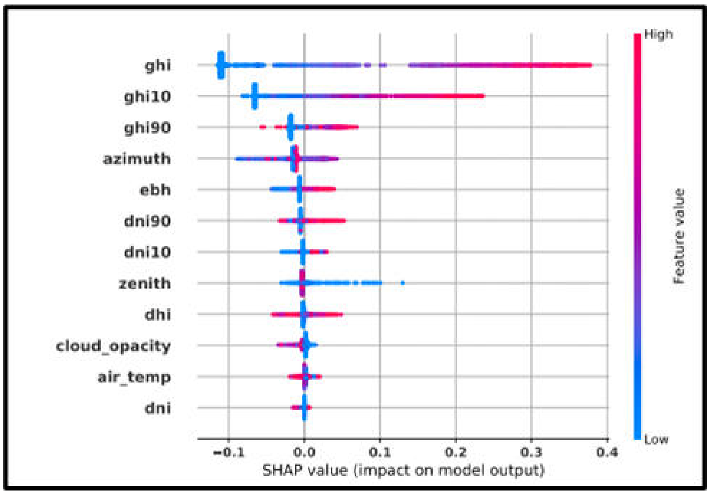


Fig. 6.2: SHAP Value

components are mentioned in Table 6.1 of the study [21].

For the first component, the roots are divided into two subsets of data considering response to the four different types of weather. Compared to the traditional SOM the implemented data tree structure is helped In the spring of the training process and provides faster results [20]. Additionally, parallel processors are employed in order to initiate the process of training which works as a catalyst for this prediction model.

The SHAP Value was calculated based on the four divisions of the data set which is shown in the above figure. Calculating the SHAP values was important in order to produce reliability in the training model Additionally interpretability of the training model is presented through the above figure. The features of the figure are present in a non-ascending order. Moreover, registration is based on the importance of different facts [22].

Additionally, figure 4.1 of the study contains localized Comprehension of the individual weather conditions and the values of contains are presented in the figure and the table. Clustering-based weather conditions were analyzed and compared with other models. In order to produce reliable data XGBoost Neural network was compared with Other regression methods such as super vector regulation (SVR) [25]. In addition, XGBoost was compared with GRNN and LSTN in order to produce comparable results for the prediction model. Furthermore, to produce a fair comparison all of the data sets were trained using a similar training model as XGBoost. The use of LSTM was considered due to its features of Analysing historical data and tackling information in specific

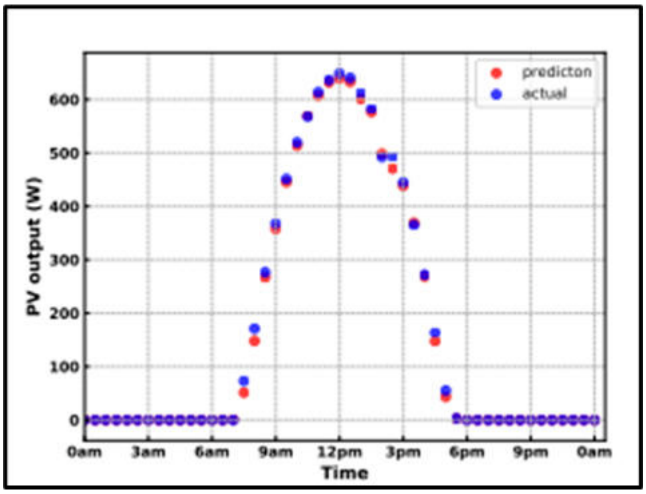


Fig. 6.3: XGBoost

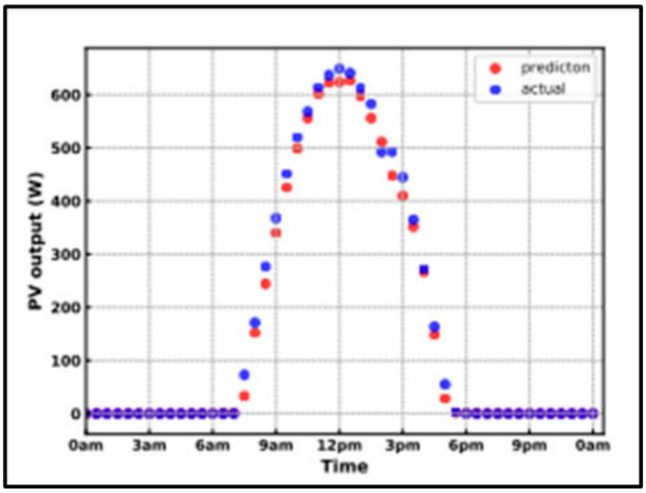


Fig. 6.4: SVR

time series. Additionally, meteorological features of different zones are fed into the model in order to active reliable statistics [22].

In order to produce the power output there are measurement metrics that aided in calculating the broader terms of the model. Measurement moduli such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and determination coefficient were used in the study (R square value)

In the above figure, the output data of the XGBoost is presented. It can be seen that there is similarity and comparatively less gap between the prediction and the actual output. Moreover, the outcome is calculated at 12 pm when the sun is at its peak. Additionally, the power output is maximum in the situation. On the other hand, it can be seen that at 9 pm the prediction is nearly too accurate, and similar results can be seen at the 3 pm mark [22].

The above figure is derived using the SVR and a similar training module. It can be seen that in the 12 pm mark, there is a difference between the actuarial output and the predicted output. Moreover, at the 9 am mark, a similar disparity is observed. At the same time for the 3 pm output, the prediction was close to the

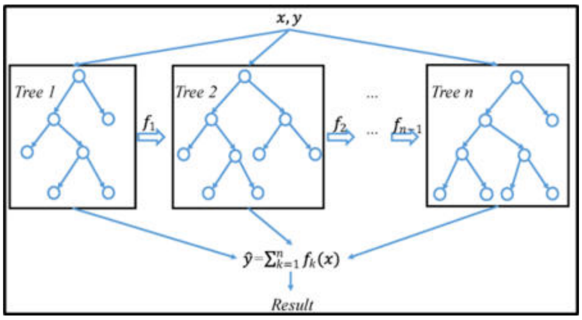


Fig. 6.5: XGboost working model

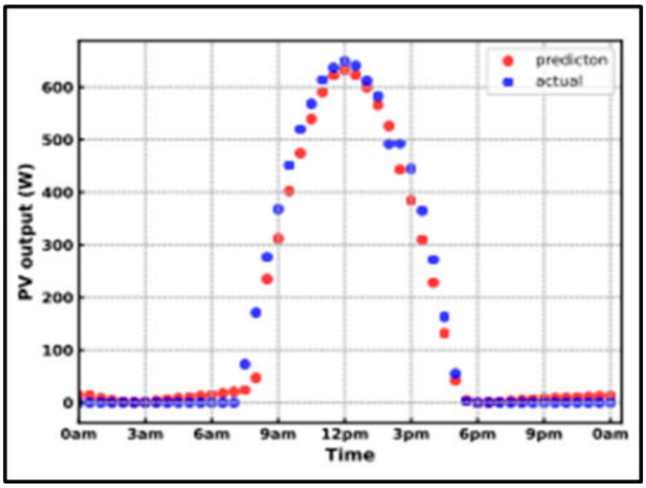


Fig. 6.6: GRNN

actual output. Therefore, it can be understood that. Hence, the disparity between the prediction and actual output is different with comparatively large values.

The above output was achieved with the GRNN model and the training was done through a similar data tree used for training other models. It can be seen that there is a noticeable difference between the actual output and the predicted output of a similar model. Moreover, the differentiation between the prediction and actual output can be noted from the 6 pm mark. Similarly, a major difference was noted at the 9 am mark where the output was nowhere near the actual output. Therefore, it can be said that GRNN showed a massive disparity in the actual and predicted output of the data [23].

In the end, the implementation of LSTM was considered for the prediction, it can be seen that there is a major differential between the prediction model and the actual output. At 3 pm March, there is an overlapping in the prediction and the actual output. However, the difference can be seen in other time marks [20].

From the above table, the related values of the algorithms can be seen. In addition, after a thorough analysis, it can be said that all of the values provided reliable statistics in order to prove liability.

7. Results. From the above analysis, it can be said that the fluctuation of power output needs to be managed in order to use a PV system, for cluster computing. Therefore, implementing an appropriate training model is essential for predicting stability.

It was found that implementing the XGBoost algorithm produces maximum reliability for the model. In addition, it was found that there are different components of a PV system that need to operate in a systematic

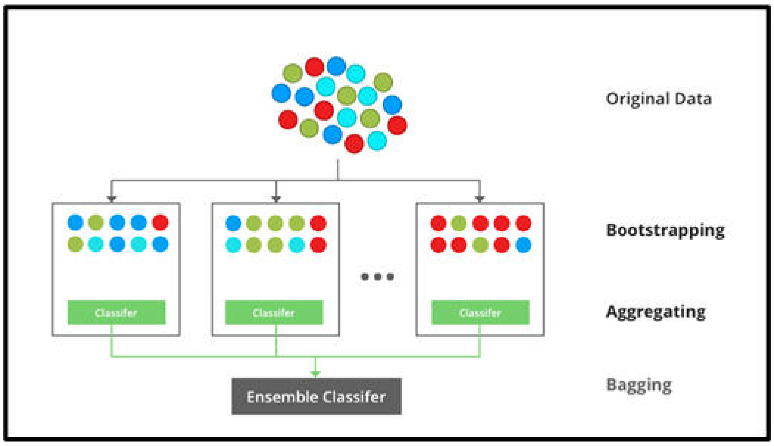


Fig. 6.7: XGboost clustering

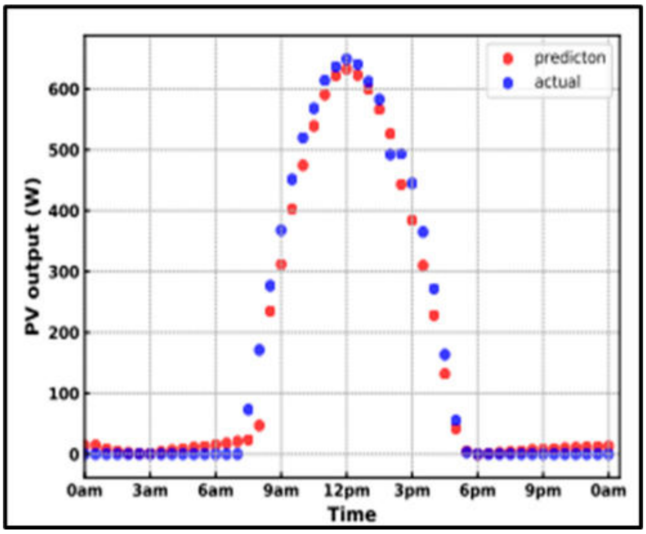


Fig. 6.8: LSTM

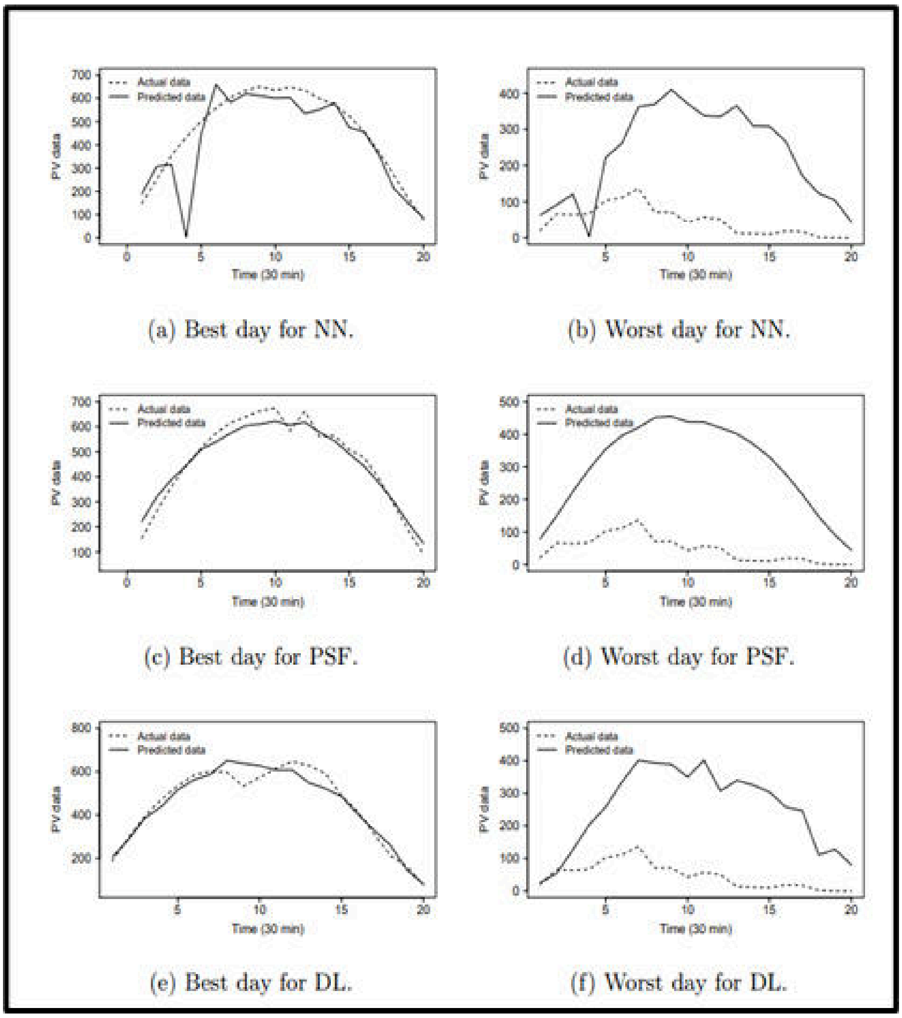
order for the sustainable development of the data [9]. Additionally, it was noted that the implication of the PV system depends on the fluctuation. Moreover, the fluctuation in the system can hinder the usability of PV systems in cluster computing. In the above image, fluctuation can be seen. Moreover, the differentiation indicates the use of a reliable model for sustainable and scalable clustering computing with a PV system

Conclusion

Thus, the PV system is analyzed based on different model models and algorithms. Moreover, an actual presentation of the clustering system is presented in the analysis. Additional PV system is explained with their different components. It was found that PV system is significant for cluster computing and influenced by weather conditions. Therefore, XGBoost is recommended for predicting the power generation of the PV system. Future research could delve deeper into the dynamic adaptation of PV systems to varying weather conditions. Developing algorithms and models that can dynamically adjust the PV system's behavior and output based on real-time weather data could significantly enhance its performance and efficiency. While XGBoost has shown promise in predicting power generation, exploring other advanced machine learning techniques, such as deep

Table 6.2: Regression analysis of algorithms

Algorithm	**R2**	**MAE**	**RMSE**	**Time cost(s)**
XGBoost	0.9863	12.21	27.49	0.047
SVR	0.9708	29.12	40.22	0.003
SVR	0.9649	23.22	45.38	0.29
GRNN	0.9824	15.29	31.19	0.090



(a) Best day for NN. (b) Worst day for NN.

(c) Best day for PSF. (d) Worst day for PSF.

(e) Best day for DL. (f) Worst day for DL.

Fig. 7.1: LSTM

learning or hybrid models, could lead to even more accurate predictions. These models could capture intricate relationships between weather patterns and PV output.

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