A Review on Employing Weather Forecasts for Microgrids to Predict Solar Energy Generation with IoT and Artificial Neural Networks

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***Abstract*—In this study, an artificial neural network (ANN) based approach is studied about the prediction of solar energy generation in a microgrid using weather forecasting. The ANN is trained using historical data of solar energy generation and weather forecast data. The input parameters for the ANN include weather variables such as temperature, humidity, wind speed, and solar irradiance. The output parameter is the solar energy generation in kilowatt-hour (kWh). The proposed approach is implemented and tested using real-world data from a microgrid. The results indicate that the ANN-based approach is effective in predicting the solar energy generation with high accuracy. The proposed approach can be used for optimizing the operation of microgrids and facilitating the integration of renewable energy sources into the power grid. This study proposes the use of an Artificial Neural Network (ANN) to predict the solar energy generation in a microgrid using weather forecast data. Weather forecasting has become more precise and dynamic with the integration of IoT data with advanced analytics and machine learning models. These models are quite accurate at predicting solar irradiance and analyzing patterns. The microgrid comprises of a photovoltaic (PV) system which generates solar energy and a battery storage system which stores and supplies the energy to the load. Accurate prediction of solar energy generation is crucial for optimizing management of the microgrid. The inputs to the ANN model include temperature, humidity, wind speed, cloud cover and solar irradiance, which are obtained from weather forecast data. The output of the model is the predicted solar energy generation. The performance of the ANN model is evaluated using various performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2). This study presents a practical approach for predicting solar energy generation in a microgrid using weather forecast data, which can be used for efficient management of the microgrid.**

Keywords*—Microgrid, Prediction, IoT, Solar Energy, Artificial Neural Network, Weather Forecasting, Renewable Energy

I. Introduction

Solar energy is one example of a renewable energy source that is gaining popularity due to its affordability and favorable environmental effects [1]. The intermittent nature of solar energy generation, however, makes it difficult to integrate solar energy into the electrical grid. Microgrids are compact, self-sufficient power systems that can run separately from or concurrently with the main grid [2]. They are good in controlling renewable energy sources, such solar energy, and making it easier for them to be integrated into the power system. For microgrid management to be effective, solar energy generation forecasting must be accurate. Accurate weather forecasting can help in predicting solar energy generation because weather conditions have a big impact on solar energy production [3]. Conventional techniques for predicting solar energy rely on statistical and meteorological models, which are frequently intricate and demand a lot of processing power. Due to its capacity to recognize intricate correlations between input and output data, ANNs represent a possible alternative.

Earlier studies looked into using ANNs to forecast solar energy production. In order to forecast solar energy production, these research have used a variety of input data, including temperature, humidity, wind speed, and sun irradiation [4]. Unfortunately, the majority of these research has relied on weather and solar energy production historical data, which might not be sufficient for precise prediction. The method put forward in this study makes use of both historical data and data from weather forecasts to increase the precision of solar energy forecasting. To cut carbon emissions and ensure energy sustainability, the power grid must incorporate renewable energy sources like solar energy. Solar energy production, however, is sporadic and varies with the weather. Accurate prediction of solar energy generation is essential for effective management of microgrids that incorporate solar energy sources. In this study, we suggest using weather forecast data to anticipate solar energy generation in a microgrid. The suggested method makes use of a backpropagation training algorithm with a feedforward neural network [5]. One of the most basic kinds of artificial neural networks is a feedforward neural network (FNN). There are several layers of neurons in it, and since there are no cycles in the connections between the neurons, information only flows from the input layer to the output layer via the hidden layers. Backpropagation, which is an acronym for "backward propagation of errors," is an essential method used in artificial neural network training. In order to reduce the error between the expected outputs and the actual targets, it is utilized to modify the network's weights. For neural networks to perform more accurately in tasks like forecasting, regression, and classification, this optimization process is essential. Weather factors like temperature, humidity, wind speed, and sun irradiation make up the input layer of the ANN. The anticipated solar energy generation, expressed in kWh, is what the ANN's output layer consists of. A microgrid's actual data is used to implement and test the suggested strategy. The proposed approach in this work has a number of advantages over more well-known methods for solar energy forecasting. Second, it uses both historical data and data from weather projections, which can make solar energy more predictable. Moreover, an ANN is used, which can learn intricate relationships between input and output data and produce precise predictions [6]. Finally, it has a high computational efficiency and is simple to integrate into existing microgrid management systems. For instance, it can be used to optimize the operation of microgrids by forecasting solar energy generation and controlling the power output of other energy sources appropriately. It can also be used to plan and schedule maintenance operations, like cleaning solar panels, to guarantee optimum solar energy generation.

The method suggested in this article makes use of ANNs to forecast solar energy production in a microgrid utilizing data from weather forecasts. The method can increase the precision of solar energy predictions and is computationally efficient. It has a number of potential uses in microgrid management, including as enhancing the performance of microgrids and scheduling maintenance procedures. The outcomes of the experiments demonstrate how well the suggested method predicts solar energy generation. In order to increase the precision of solar energy prediction, more study can investigate the usage of additional machine learning algorithms and input factors [7]. The proposed approach has several potential benefits for microgrid management. Accurate prediction of solar energy generation can improve the management and optimization of microgrids, allowing for efficient integration of renewable energy sources into the power grid. The approach can also be used to plan and schedule maintenance activities, such as cleaning solar panels, to ensure maximum solar energy generation. To collect real-time, high-resolution meteorological data, including solar irradiance, temperature, humidity, wind speed, and cloud cover, the article highlights the integration of IoT devices. In comparison to conventional methods that rely on sparse weather station data, the inclusion of a dense network of IoT sensors allows for more granular and localized weather data, boosting the accuracy of solar energy forecasts.

II. Internet of Things

The Internet of Things, or IoT, is transforming how we use technology by integrating sensors, software, and connection into commonplace things to gather and share data. This network of linked gadgets includes anything from industrial machines and medical wearables to security cameras and smart thermostats for the home. By providing remote control and real-time data analysis, IoT improves efficiency, convenience, and cost savings while fostering smarter decision-making. But it also comes with drawbacks, such privacy issues, security flaws, and the requirement for device compatibility. IoT holds great potential to alter industries and improve daily life as long as AI, machine learning, and 5G continue to grow. This suggests a future where devices seamlessly interact and communicate to optimize many elements of our existence. With a large network of connected devices, the Internet of Things (IoT) seamlessly integrates the digital and physical worlds, marking a revolutionary leap in technology.

These gadgets, which are equipped with sensors, software, and communication features, range from sophisticated industrial gear and medical equipment to commonplace home appliances like smart lighting and refrigerators. IoT makes it possible for these things to gather and share data, which improves efficiency, allows for remote monitoring and control, and offers deeper insights through real-time analytics. Fig. 1 shows the infrastructure of the IoT-based digitalization and control of the MG system IoT devices in smart homes automate security, heating, and lighting depending on user preferences and behaviors, saving energy and providing unmatched ease.

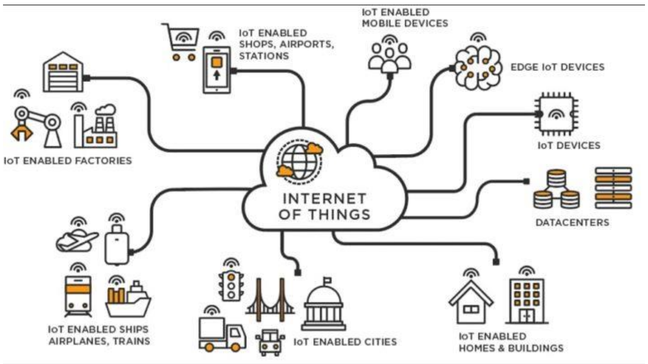

Fig. 1. Operation and control of microgrids using IoT

Vital signs and chronic illnesses are tracked by wearables and remote monitoring systems in the healthcare industry. This continuous health data is sent to patients and physicians, improving patient outcomes and enabling proactive therapy. Predictive maintenance, in which sensors on machinery identify problems before they happen and cut downtime and maintenance costs, is one way that the industrial sector gains from IoT. Additionally, IoT in agriculture maximizes crop management through weather patterns, crop health, and soil conditions monitoring, which raises yield and resource efficiency. Adoption of IoT is fraught with difficulties notwithstanding these advantages. Given the growing number of connected devices and the increased risk of cyberattacks and data breaches, security is of utmost importance. The massive volumes of personal information that these devices gather also give rise to privacy concerns. Furthermore, smooth integration and communication may be hampered by a lack of standards and interoperability among various IoT platforms and devices.

III. Artificial Neural Networks

The computerization of human abilities serves as the foundation for ANNs, a type of artificial intelligence.

Standard computer processing takes place in a fundamentally different way from how the human brain works, which must be taken into account. The human brain can execute some tasks better than even the most sophisticated conventional computers, such as pattern recognition and vision, because of its complex, nonlinear, and parallel working [8]. Artificial intelligence has improved computer capabilities by modeling the biological information-processing system of humans. Since ANNs may imitate the biological neural network seen in the human brain, they are very adept at recognizing patterns and predicting future values.

An artificial neural network (ANN), a method for machine learning, is based on how the human brain functions and is organized. It is composed of a network of weighted nodes, also known as synthetic neurons, that are stacked in layers and connected. The input layer receives input data, processes it at the hidden levels, and then sends it to the output layer, which produces the output in the end. During training, the weights of the connections between the nodes are changed to enhance the performance of the network. ANNs are frequently used in applications such as audio and picture recognition, natural language processing, and predictive modeling [9]. Artificial neural network shown in Fig. 2.

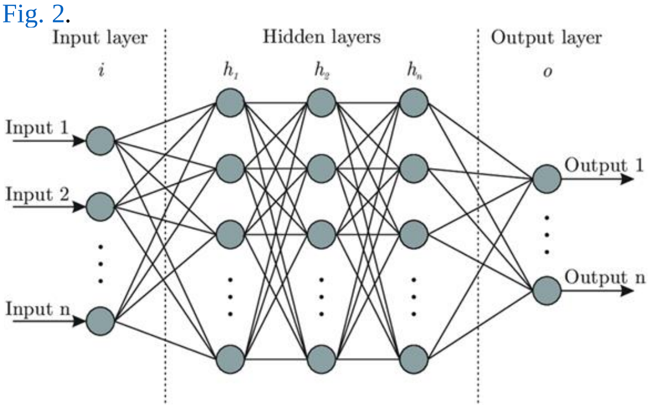

Fig. 2. Artificial neural network [10]

Among other techniques, they can be trained using supervised learning, unsupervised learning, and reinforcement learning. Convolutional neural networks, recurrent neural networks, and feedforward neural networks are only a few of the several types of ANNs. Each category is suitable for different tasks and data types. ANNs are a popular topic in the artificial intelligence community and have shown to be powerful solutions for solving challenging issues.

There are several advantages of artificial neural networks (ANNs), which include:

1. Non-linearity: ANNs are especially helpful in applications where the relationship between variables is difficult to quantify since they can simulate complicated non-linear interactions between inputs and outputs [11].
2. Robustness: Even with noisy or inadequate data, ANNs are capable of making accurate predictions or classifications [12].
3. Adaptability: Without making substantial modifications to the model structure or technique, ANNs can adjust to changes in the input data or the problem being solved [13].
4. Parallel processing: Due to their parallel computing capabilities, ANNs are ideal for applications needing real-time processing or extensive data analysis [14].
5. Fault tolerance: Even when part of the connections or nodes fail, ANNs may still make precise predictions [15].
6. Feature extraction: The requirement for human feature engineering is decreased by the ability of ANNs to automatically extract pertinent features from the input data.
7. Generalization: ANNs are effective in applications like pattern recognition, picture and speech processing, and natural language processing because they generalize well to new, unseen data.

Overall, ANNs are powerful machine learning tools that can be used to solve a wide range of problems in different fields, including finance, healthcare, engineering, and many others.

Artificial neural networks (ANNs) are able to forecast energy production by examining the relationship between input variables like the weather and the output variable, energy generation. The historical data that is utilized to train ANNs includes the input variables solar irradiance, temperature, humidity, wind speed, cloud cover, as well as the associated energy generation values.

During the training phase, ANNs adjust their weights and biases to minimize the discrepancy between the expected and actual output [17]. In this procedure, the input variables are processed through the layers of the neural network before computing the anticipated result. Following a comparison of the expected output and the actual output, the weights and biases of the neural network are modified using backpropagation. Artificial neural network (ANN) architecture of building prediction model shown in Fig. 3.

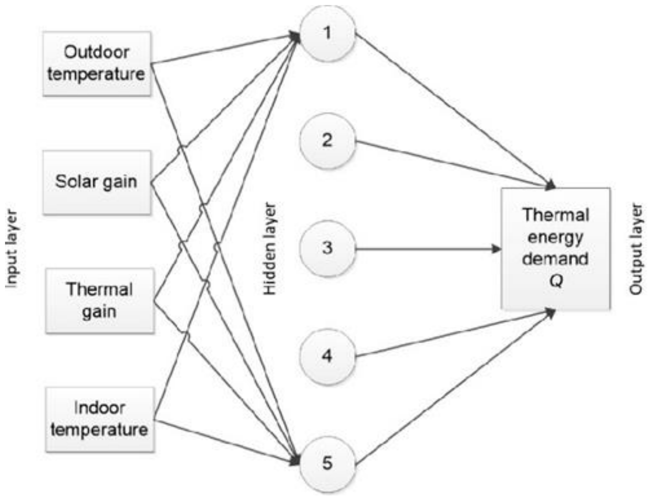

Fig. 3. Artificial neural network (ANN) architecture of building prediction model [16]

The neural network can be used to forecast energy generation for new input variables, such as upcoming weather conditions, after it has been trained. The trained neural network receives the input variables as input and processes them to calculate the anticipated output of energy generation.

How correctly the neural network predicts energy generation depends on a number of factors, including the quality of the training data, the complexity of the neural network design, and the accessibility and accuracy of the input variables [18]. Yet, in order to increase energy output and reduce costs, ANNs are commonly used in renewable energy systems. They have shown promising outcomes when predicting energy production.

IV. Artificial Neural Networks (ANNs) Model

To predict solar energy generation using artificial neural networks, we can follow these general steps:

1. Data collection: Collect data related to solar energy production, such as historical solar irradiance data, temperature data, humidity data, and historical solar energy production data [19].
2. Data preprocessing: Clean and preprocess the collected data. This includes handling missing data, scaling the data, and splitting it into training, validation, and testing sets [20].
3. Model selection: Choose the appropriate type of artificial neural network that best fits the problem. For solar energy generation prediction, a feedforward neural network or a recurrent neural network might be appropriate.
4. Model architecture design: Determine the number of input features, hidden layers, and number of neurons per layer for the selected neural network model [21].
5. Model training: Train the neural network model using the preprocessed training data. This involves adjusting the weights and biases of the neural network to minimize the prediction error.
6. Model validation: Use the preprocessed validation data to evaluate the performance of the trained neural network model. This helps to identify if the model is overfitting or under fitting the data.
7. Model testing: Use the preprocessed testing data to evaluate the final performance of the neural network model.
8. Model deployment: Deploy the trained neural network model to predict solar energy generation for future periods. This involves using the trained model to predict solar energy generation based on new data, such as solar irradiance, temperature, and humidity data.
9. Model monitoring and improvement: Continuously monitor the performance of the deployed neural network model and update the model as necessary to improve its accuracy and reliability [22].

V. Methodology

The following is a methodology for solar energy generation through artificial neural network using weather forecast for microgrid:

1. Collect weather data: Get weather information from a variety of places, such as the meteorological office or weather websites. Climate-related factors including precipitation, wind speed, humidity, and sun irradiance should all be included in the data.
2. Gather solar data: Assemble solar data from the microgrid's solar panels. Variables like solar panel capacity, efficiency, and orientation should be included in the data.
3. Develop artificial neural network: Create an artificial neural network (ANN) model that uses weather data to forecast the production of solar energy. For the ANN to successfully forecast future solar energy generation, historical weather and solar data should be used as training data.
4. Test and validate ANN model: Using current meteorological information and data on solar energy production, test and validate the ANN model. Based on the weather forecast, the model ought to be able to estimate solar power generation with accuracy.
5. Integrate the ANN model into the microgrid: By incorporating the ANN model into the microgrid system, solar power generation may be adjusted automatically based on the weather forecast. By doing this, the microgrid will be able to optimize the amount of solar electricity it generates while minimizing any unnecessary energy output.
6. Monitor and optimize the microgrid: To make sure the microgrid system is running well, monitor and improve it. The ANN model can be regularly updated to reflect the most recent information on the weather and solar power generation.

Ultimately, this technology makes it possible for a microgrid system to deploy solar power generation more effectively and efficiently by making use of the capabilities of artificial neural networks and weather forecast data. With the aid of weather forecast data and artificial neural networks (ANNs), solar energy generation in a microgrid can be predicted [23]. In order to identify patterns and relationships in big datasets, ANNs are a form of machine learning technique that is well suited for forecasting complex systems like solar energy generation.

To build an ANN model for solar energy prediction, several steps can be taken, including:

1. Collecting weather data: Accurate weather data, including temperature, humidity, wind speed, and cloud cover, is essential for predicting solar energy generation. This data can be collected from local weather stations or through weather forecasting services.
2. Collecting solar energy data: Historical solar energy generation data for the microgrid can be collected to use as training data for the ANN model.
3. Preparing the data: The weather and solar energy data can be preprocessed to ensure that it is suitable for use in the ANN model. This may include scaling the data, removing outliers, and transforming the data to make it easier for the ANN to learn from.
4. Training the ANN: The prepared data can then be used to train the ANN model. This involves feeding the ANN input data (weather forecast data) and corresponding output data (historical solar energy generation data) and adjusting the weights of the model to minimize the difference between the predicted and actual output values.
5. Testing the ANN: After the ANN model has been trained, it may be put to the test by forecasting solar energy generation using fresh weather data. By contrasting the anticipated and actual solar energy outputs, one may gauge how accurate the model is.

Therefore, employing weather forecast data in a microgrid, an ANN model can be a beneficial tool for forecasting solar energy generation. The model's accuracy will be influenced by the caliber of the weather data as well as the quantity and caliber of the training dataset. The benefits and drawbacks of employing artificial neural networks (ANNs) to forecast solar energy generation in a microgrid are listed in the following comparative Table 1.

Table 1. The benefits and drawbacks of employing artificial neural networks (ANNs) to forecast solar energy generation in a microgrid

Advantages	Disadvantages
Can handle nonlinear relationships between input variables. Also Can be used for other tasks in a microgrid, such as predicting energy demand and optimizing energy storage	Accuracy depends on quality of input data, especially weather forecasts
Can adapt to changes in input data, making them suitable for dynamic systems	ANN model needs to be trained on large dataset, which can be time-consuming and computationally intensive
Can learn from past data and make accurate predictions, making them useful for optimizing the operation of the microgrid	May not be able to capture all complexities of the microgrid system, leading to some inaccuracies in predictions

To assess current techniques and tools for forecasting solar energy production in microgrids. Comparing emerging techniques incorporating IoT and ANNs with more established statistical methods, physical models, and fundamental machine learning methodologies. to investigate how IoT gadgets and sensors may improve the gathering of high-resolution, real-time meteorological data. The deployment of IoT-enabled weather stations, the types of data collected (e.g., solar irradiance, temperature, humidity, wind speed), and the benefits of having granular and localized data for precise predictions. Overall, ANNs provide a number of benefits when used to forecast solar energy generation in a microgrid, including the capacity to handle nonlinear relationships and adapt to changing input data. However, training the model on a big dataset can be time-consuming and computationally costly, and the model's accuracy greatly depends on the quality of the input data. Also, the ANN model might not be able to fully represent the complexity of the microgrid system [24], which could result in some unreliable predictions.

VI. Discussion

A possible strategy for improving the performance of the microgrid is to predict solar energy generation using Artificial Neural Networks (ANNs) and weather forecast data [25]. Because they may increase energy reliability, robustness, and efficiency, microgrids are growing in popularity. Yet managing the balance between supply and demand is one of the key difficulties in running a microgrid. As the power generation of solar-based microgrids is greatly influenced by the weather, this is particularly challenging. There are various benefits to using ANNs to forecast solar energy generation in a microgrid [26]. First of all, nonlinear interactions between the input variables can be handled by ANNs, which is crucial when working with complicated systems like solar energy production. Second, given that ANNs are capable of adapting to changes in the input data, they are well suited to handle the dynamic nature of weather data [27]. Finally, ANNs are helpful for optimizing the operation of the microgrid since they can learn from historical data and produce precise forecasts. It is imperative to verify the precision of ANN-based projections using real data in order to maintain transparency and foster trust in the dependability of the suggested approach. In order to validate the model, genuine historical and current data on solar energy generation are compared with its forecasts. The review can objectively show the accuracy of the ANN model by using a range of performance indicators, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-squared (R^2), and Mean Absolute Percentage Error (MAPE).

The use of ANNs for predicting solar energy does have some restrictions, though. Initially, the caliber of the input data affects how accurate the model is. Making effective predictions requires reliable weather data. The ANN model must also be trained on a sizable dataset, which might take a lot of time and computer power. Moreover, the ANN model might not be able to accurately represent all of the microgrid system's complexity [28], which could result in some inaccurate forecasts. Notwithstanding these drawbacks, using ANNs to forecast solar energy generation in a microgrid offers the potential to increase the system's effectiveness and dependability. The microgrid can better balance the supply and demand of energy by properly forecasting the solar energy output [29], which lowers the requirement for backup power sources and boosts overall energy efficiency. The quality of the meteorological data is one of the most important variables in effectively forecasting solar energy generation [30]. For accurate projections of solar energy output, precise meteorological data is crucial. Temperature, humidity, wind speed, and cloud cover forecasts can be obtained hourly, daily, or weekly through weather forecasting services. The ANN model can be used to predict solar energy production using this data.

Data on past solar energy generation and accompanying weather forecasts can be used to train the ANN model [31]. The model is made to spot trends in the data and forecast things based on those trends. By employing a larger training dataset and modifying the model's parameters, the accuracy of the model can be increased. Once the model has been trained, it can be used to make predictions of solar energy generation based on new weather forecast data. The accuracy of the predictions can be evaluated by comparing the predicted values to the actual solar energy generation data. In a microgrid, ANNs can be used to estimate energy demand, optimize energy storage, and predict grid stability in addition to forecasting solar energy generation. Energy efficiency can be raised and the system's overall reliability can be raised by utilizing ANNs to optimize the functioning of a microgrid. Furthermore, forecasting solar energy generation in a microgrid using weather forecast data has the potential to increase the system's effectiveness and dependability [32]. To make reliable forecasts, however, precise meteorological data is necessary, and the model's accuracy is based on the caliber of the training dataset and the model's parameters. ANNs have the potential to be an effectiv32e tool for improving the performance of a microgrid with appropriate training and parameter adjustment.

VII. Challenges

It is a challenging task to predict solar energy generation using an artificial neural network and weather forecast for a microgrid. Among the principal difficulties are:

1. Accuracy of weather forecasts: One of the biggest obstacles is weather prediction accuracy, which has a big impact on how accurately solar energy production is projected [33]. Several variables, including the quality of the weather data, the accuracy of the weather models, and data processing methods, affect how accurate the weather forecast is.

2. Microgrid Variability: Predicting the generation of solar energy might be difficult due to the microgrid's unpredictability [34]. This is due to the fact that microgrids' various layouts, parts, and load profiles may have a substantial impact on the solar energy generation.
3. Data Quality and Availability: These two factors can also be quite difficult to deal with. High-quality data that include the essential elements, such as sun radiation, temperature, humidity, and wind speed, among others, is crucial [35].
4. Another difficulty is the design of the neural network used to forecast solar energy production. This comprises, among other things, the choice of the appropriate architecture, the number of layers, the activation mechanisms, and the learning rate.
5. Training and Validation of the Model: Training and Validation of the Model can be a difficult task [36]. This include choosing the appropriate training and validation data, preventing overfitting, and assessing the model's performance.
6. Integration with Microgrid Control: Ultimately, it can be difficult to incorporate the anticipated solar energy generation into the microgrid control system [37]. This calls for a carefully thought-out control system that can account for the anticipated solar energy generation, the microgrid load, and additional limitations like battery storage capacity and grid connection limits.
7. A complete strategy that carefully considers data collecting and processing, neural network design and validation, as well as interaction with the microgrid control system, is needed to address these problems.

VIII. Conclusion

In conclusion, predicting solar energy generation through Artificial Neural Networks (ANNs) using weather forecast data in a microgrid is a promising approach for optimizing the operation of the microgrid. ANNs can recognize complex patterns and nonlinear relationships in the data, making them suitable for predicting solar energy output. IoT sensors supply high-resolution, real-time weather data, which increases the precision of weather forecasts utilized to anticipate solar energy. When compared to traditional models, Artificial Neural Networks (ANNs) can produce more accurate predictions of solar energy generation because they can represent intricate, non-linear correlations seen in weather data. Accurate weather data is essential for making accurate predictions, and the accuracy of the model depends on the quality of the training dataset and the parameters of the model. By accurately predicting solar energy output, the microgrid can better balance the supply and demand of energy, reducing the need for backup power sources and improving the overall energy efficiency. Additionally, ANNs can be used for other tasks in a microgrid, such as predicting energy demand, optimizing energy storage, and predicting grid stability. Overall, ANNs can be a powerful tool for optimizing the operation of a microgrid and improving its efficiency and reliability.

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