Comparing ANN frameworks for solar PV power estimation

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Abstract:

The escalating demand for renewable energy sources necessitates robust methods for predicting solar photovoltaic (PV) power output. This prediction is crucial for maintaining grid stability as solar power integration increases. This study investigates the efficacy of various artificial neural network (ANN) architectures in estimating and forecasting the total output power of PV systems. Three distinct ANN models - Multilayer Feedforward Neural Networks (MLFFNNs), Recurrent Neural Networks (RNNs), and Nonlinear Autoregressive Exogenous (NARX) models - are employed. Historical data from four PV substations is utilized for training, with solar radiation and surface temperature as input variables and total output power as the target variable. To address the challenge of limited monitored plant data, an upscaling technique is implemented to estimate regional solar PV output. The trained ANN models are rigorously validated, and their performance is comparatively assessed. This comparative analysis aims to identify the ANN architecture that delivers the most accurate solar PV power predictions, ultimately facilitating the seamless integration of renewable energy sources into the grid.

1. Introduction:

Over the past few decades, the extensive use of fossil fuels has led to global warming, an energy crisis, and significant impacts on government economic policies, climate conditions, and energy security. As a response, there has been a growing emphasis on developing and utilizing alternative, sustainable, and clean energy sources to replace current energy production methods. This shift towards renewable energy resources, particularly solar and wind power, has become crucial to avoid power failures, reduce CO2 emissions, and mitigate pollution.

However, transitioning to these energy sources presents challenges, particularly in terms of infrastructure. As a result, full reliance on renewable energy generation for national power systems is not yet feasible. Photovoltaic (PV) power forecasting emerges as a crucial aspect in integrating renewable energy into conventional electricity grids, offering reliability and cost-effectiveness.

PV power forecasting plays a vital role in various aspects such as the establishment of large PV generating stations, power system stabilization, green power initiatives, and providing warnings for power disturbances. It aids in optimizing power system utility, reducing the need for reserve capacity in generating stations, and consequently lowering electricity production costs while enhancing system reliability.

Forecasting PV power generation for the next day is a daily practice for PV power stations, but inaccuracies in forecasting can significantly impact economic operations and overall power system productivity. Due to the influence of atmospheric parameters like temperature, cloud cover, and dust, achieving accurate PV power predictions can be challenging.

Several forecasting techniques have been developed over the years, broadly categorized into hybrid, artificial intelligence, statistical, and physical approaches. Statistical approaches rely on historical data to forecast solar time series, while artificial intelligence techniques like artificial neural networks are integrated into statistical methods. Physical models, on the other hand, predict solar irradiance and generation based on numerical weather predictions or satellite imagery.

Hybrid approaches, combining various methods, have emerged as promising solutions. Depending on the prediction horizons, different forecasting approaches are considered to meet decision-making requirements. Statistical forecasting techniques, including time series and regression analysis, play a crucial role in power generation systems, but they require mathematical relationships and calibration processes, which can be time-consuming.

This paper provides an overview of PV power forecasting techniques developed in recent years and compares them to proposed forecasting techniques. Notably, the extreme learning machine (ELM) model is utilized for short-term PV power prediction and compared with existing algorithms like backpropagation (BP). Challenges in the study include selecting proper weights for the forecasting model, which various modified particle swarm optimization (PSO) techniques aim to address. Among these, the ELM optimized with accelerated PSO (APSO) shows promising performance improvements over other optimization algorithm.

2. PV model:

PV forecasting for sunlight or photovoltaic energy. The Characteristics of solar electricity generation such as system flexibility and forecast horizons are important for predicting PV capacity and energy consumption. Standardized performance assessment indices help develop predictive models for new solar forecasts. There are different types of PV models, ranging from simple analytical models to complex numerical models. These models are used for a variety of purposes, including system design, performance analysis, and solar PV installation optimization.

The predicted output of PV power is affected by many factors like the measurement of solar irradiance, reflectivity, estimation of PV cell temperatures etc [24]. The maximum power output is modeled by

$$P_v=gAI[1-0.05(t-25)]$$

Where g represents the conversion efficiency (%) of the PV array, A is the array area (m2), 'I' is the solar Irradiance (kW/m2), and't' is the outside air temperature. The parameters of the simulink model under study are mentioned as maximum power Pmax = 105 W, voltage at maximum power Vmax = 18.46 V, current at maximum power IMAX = 5.74A, short circuit current Isc = 6.11A, open-circuit voltage Voc = 21.6 V, shunt resistance Rsh = 1000O, series resistance Rs = 0.0001O, number of series cells Ns = 36, number of parallel cell NP = 1

This method can be implemented by addition of a PI controller which can improve the incremental conductance (IC) MPPT performance by reducing the error between the actual conductance and the incremental conductance so that the required adjustment can be done and the system can be gradually updated according to necessity. Moreover, this PI controller overcomes the drawbacks of perturb and observe (P&O) MPPT technique like its oscillation around the MPP under fast varying atmospheric condition shown in Figs. 1 and 2. Whether MPPT has reached the MPP or not, it is determined by the increment conductance of PV module and also it determines the stopping criteria for perturbation at the operating point [27,28]. In this MPPT technique, the MPP can be derived from the relation between dI/dV and I/V. The slope dP/dV is negative when the maximum power point is right side of the P-V curve and it is negative for right side position of MPP

2.2. Maximum power point tracking (MPPT):

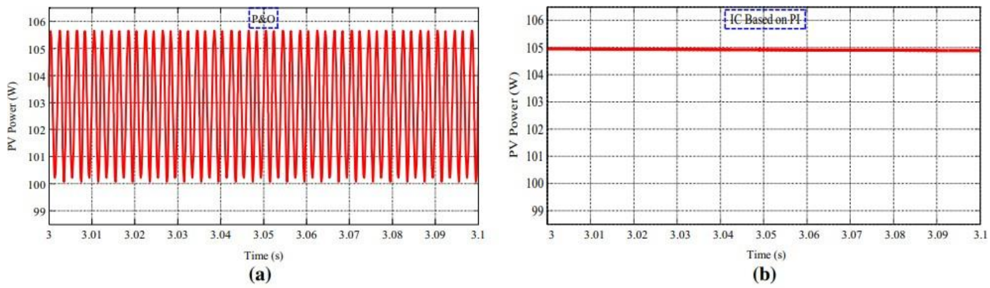

Fig. 2. Power ripples in steady state (approximately 105 W) (a) P&O MPPT and (b) IC MPPT Based on PI.

Figure. 2: Power ripples in steady (approximately 105 W) (a) P & O MPPT and (b) IC MPPT based on PI

2.3. Advantages of maximum power point tracking (mppt) techniques:

This section discusses the benefits of utilizing Maximum Power Point Tracking (MPPT) algorithms in solar photovoltaic (PV) systems. One key advantage of advanced MPPT techniques, compared to simpler methods like Perturb and Observe (P&O), lies in their superior precision in reaching the Maximum Power Point (MPP). This translates to higher efficiency, particularly during rapidly changing environmental conditions. Unlike P&O, advanced MPPT algorithms can determine the optimal direction to adjust the PV generator's operating point, ensuring a more direct approach towards the MPP. This reduces the risk of mistakenly moving away from the MPP under fluctuating weather patterns. Additionally, once the MPP is reached, these algorithms prevent the operating point from oscillating around it, leading to more stable power output.

Solar PV Power Forecasting with Neural Networks: The ability of Neural Networks (NNs) to generalize under varying circumstances makes them well-suited for solar PV power forecasting. Studies have demonstrated the effectiveness of NNs in this application. For instance, Kumar et al.explored the use of three different NN architectures (Elman NN, Feed-forward NN, and GRNN) to predict solar PV output power based on historical data encompassing weather variables and solar radiation. Their findings indicated promising results, with the Elman NN achieving a Root Mean Squared Error (RMSE) of 0.25, followed by the Feed-forward NN at 0.30, and the GRNN at 0.426. However, further research is needed to evaluate the generalizability of these NNs under significantly different operating conditions.

2.4. Exploration of learning algorithms for NN- based forecasting:

Several studies have investigated the impact of different learning algorithms on the performance of NN-based solar PV power forecasting models. In [40], a multi-layer perception-based ANN was proposed for short- term power prediction. Another study by [41] compared the performance of Levenberg- Marquardt (LM) and Bayesian Regularization (BR) learning algorithms for various weather variables, concluding that BR outperformed LM (RMSE of 0.0706 compared to 0.0753). Furthermore, research by [42] explored the effectiveness of combining different learning algorithms with various training datasets, demonstrating the potential of such combinations to significantly improve prediction accuracy. Additional research on NNs for solar PV power forecasting has been conducted in [41], [43], and [44]. However, a more comprehensive understanding of how these NNs perform under diverse real-world conditions remains an area for further investigation.

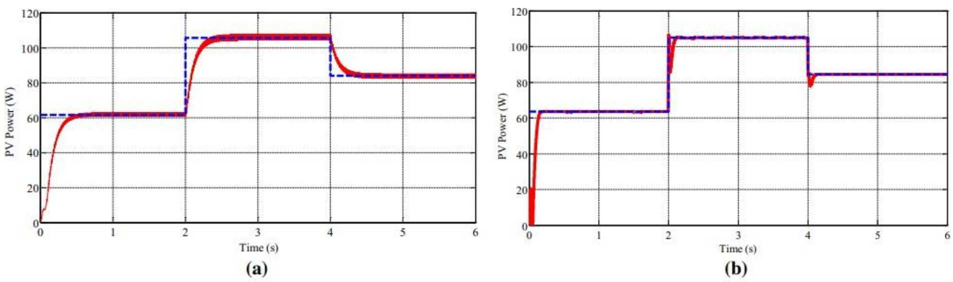

Fig. 1. Power extracted from PV module with MPPT techniques (a) P&O and (b) IC Based on PI.

Figure. 1: Power extracted from PV module with techniques (a) P & O and (b) IC based on PI

3. Analysis of solar PV output power calculation:

Traditional methods for calculating the electrical power generated by a solar photovoltaic (PV) module rely on complex equations with numerous parameters, as referenced. These parameters include:

$P = \eta_S \tau_g \alpha_S [1 - \mu_S (T_S - T_r)]$

- η_S : Reference efficiency of the PV cells
- τ_g : Glass transmissivity (how much light passes through the glass)
- α_S : Solar cell absorptivity (amount of light absorbed by the cell)

- R : Solar radiation (W/m^2)
- A :Total area of the solar cell (m^2)
- μ_S :Thermal coefficient of PV cell efficiency (% change per degree Celsius)
- Ts : Solar cell temperature (°C)
- Tr :Reference temperature (°C)

Accurately determining all these parameters can be challenging. Proposed Approach: Utilizing ANNs for Simplified Power Calculation This study proposes a novel approach for calculating solar PV power output that is both easier and more efficient. Our method aims to rely solely on two readily measurable parameters: surface temperature and solar radiation. To achieve this, we explore the implementation of three different artificial neural network (ANN) architectures. The effectiveness of this approach will be demonstrated through the results presented later in the paper. The main aim of our proposed work is to calculate the electrical power easier, efficiently, and depending only on two parameters which are the surface temperature and the solar radiation. Therefore, the three ANNs types are proposed and implemented for this purpose. The results that are presented later in this paper prove this issue. The main elements effecting the performance of solar PV systems are identified by this investigation. It's critical to assuring efficient operation and optimizing system architecture. Learning about the computation of solar PV output power helps system performance as well as efficiency. Significance of Understanding Solar PV Output By identifying the key factors influencing the performance of solar PV systems, this research contributes to ensuring efficient operation and optimized system design. Understanding the calculation of solar PV output power is crucial for optimizing system performance and maximizing its efficiency.The main features of this study are: Solar radiation: Managing how much sunlight reaches the location of a PV system is crucial. Data on solar radiation helps us understand how much energy the system can generate under different weather conditions and at different times of the day. Panel features, it is important to understand the features and operation of a PV panel. Factors such as rated capacity, temperature profiles, and degradation over time affect overall system performance. Shadow Effects are used for Analysing potential shadows from nearby objects or buildings helps identify areas where solar panel performance may be compromised by reducing shadows and ensuring optimum energy efficiency. Temperature Considerations is important to understand the effect of temperature on track performance. PV panels are less efficient at higher temperatures, so this must be included in the calculation. System design is used for Consideration of the layout, orientation, and layout of PV system components (e.g., panels, inverters, and wiring) helps to optimize energy production and reduce losses Inverter efficiency which is required to convert DC electricity from r which is required to convert DC electricity from the panels into usable AC.

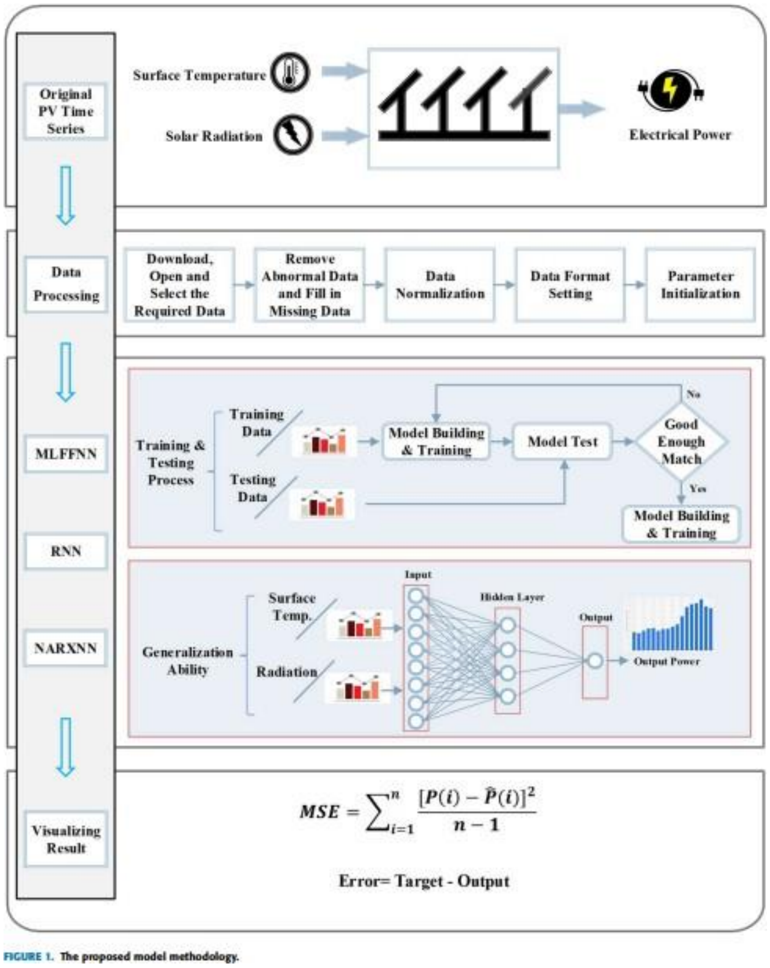

Figure. 2: The proposed model methodology

4. The proposed model methodology:

This section details the proposed method for predicting the power output of a solar photovoltaic (PV) subsystem using artificial neural networks (ANNs). ANNs are known for their ability to approximate complex functions, both linear and nonlinear .Additionally, they possess the valuable capability of generalizing their learned patterns to new situations. This study employs three specifically designed and trained ANN architectures: Multilayer Feedforward Neural Networks (MLFFNNs), Recurrent Neural Networks (RNNs), and Nonlinear Autoregressive with Exogenous Inputs (NARXNNs). These architectures form the core of the proposed model, which follows a four-step process:

4.1. Data acquisition:

Historical time series data from four solar PV substations located in Egypt is collected. This data includes surface temperature (or solar cell temperature) and solar radiation measurements.

4.2. Data preprocessing:

The collected data undergoes preprocessing to ensure its quality and consistency. This may involve handling missing values or outliers.

4.3. ANN training and testing:

Each of the three ANN algorithms (MLFFNN, RNN, and NARXNN) is trained and tested on the preprocessed data. This training process involves feeding the network historical data and allowing it to learn the underlying relationships between input parameters (temperature and radiation) and the target variable (solar PV power output).

4.4. Visualization and evaluation:

The final stage involves analyzing the results obtained from each ANN model. This may include visualization techniques to understand the model's behavior and performance metrics to evaluate its accuracy in predicting solar PV power output.

The implementation of the latter three stages (data preprocessing, training/testing, and visualization) is carried out using MATLAB software on an Intel Core i5-8250U processor. A flowchart summarizing the proposed methodology and the key contributions of this article are presented in Fig. 2 for better understanding.

5. NN design for PV output power prediction:

Optimizing Neural Network Design for Solar PV Power Prediction: This section focuses on designing the artificial neural networks (ANNs) for effective solar PV power prediction. The primary objective is to achieve high performance, characterized by minimal Mean Squared Error (MSE) and Tracking Error (TE) values, ideally close to zero. This efficiency is achieved by utilizing only the surface temperature (Ts) and solar radiation (Si) data as the main inputs from the four PV substations. These two key parameters, along with the number of substations (four), contribute to the total of eight input elements (2 parameters/substation * 4 substations = 8). Fig. 3 illustrates the collected input data. Network Architecture and Training:

Each of the three proposed ANN types (MLFFNN, RNN, and NARXNN) consists of three layers: input, hidden, and output layers. Table 3 provides a comparison of the specific designs for these three network architectures, while Figure 4 visually depicts their structures.The training process involves comparing the actual total power output (P) measured from the four real PV plants with the estimated total power output ($\hat{P}$) predicted by the designed ANNs. This comparison allows the networks to learn the underlying relationships between the input parameters and the target variable (solar PV power output).

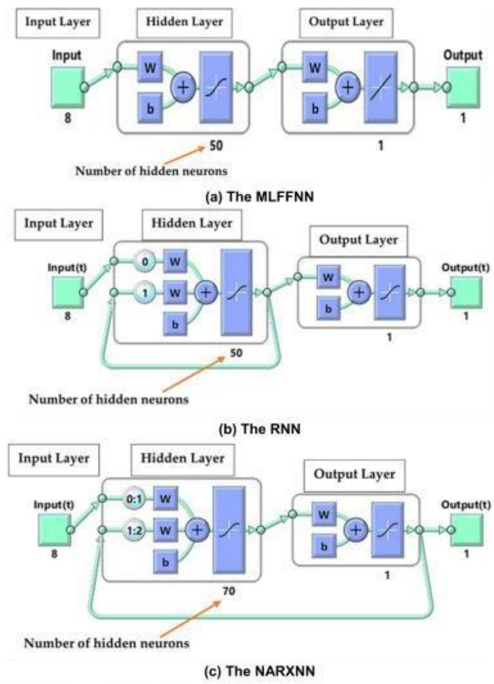

FIGURE 4. The structure of the designed NNs.

Figure. 4: The structure of the designed NNs

6. NN training and testing for pv output power prediction:

Training the Artificial Neural Networks (ANNs), this section details the training process for the three constructed neural networks (MLFFNN, RNN, and NARXNN). The Levenberg-Marquardt (LM) algorithm is chosen for its efficiency and convergence properties:

- Fast Data Processing: LM is known for its ability to handle large datasets efficiently, as referenced in.
- Rapid Convergence: It is a second- order optimization method inspired by Newton's method, offering a strong theoretical foundation and fast convergence.
- Balanced Learning: LM strikes a balance between the guaranteed convergence of gradient descent and the faster learning speed of traditional Newton's method, making it suitable for complex problems with large datasets.

Data Acquisition and Preprocessing, The training data for the ANNs originates from four interconnected solar PV plants located in Egypt. This data represents the actual electrical output power calculated using Equation (1). A two-month period (58 days) of data is collected. We then divide this data into two sets:

- Training Set (44 days): This data is used to train the designed ANNs, allowing them to learn the relationships between input parameters (surface temperature and solar radiation) and the target variable (solar PV power output). This training set comprises 12672 input-output pairs.
- Testing and Validation Sets (14 days): This data, further divided into testing (10%) and validation (5%) sets, is used to evaluate the performance and generalizability of the trained ANNs. Network Optimization and Training, optimal parameters for each ANN (number of hidden neurons and weight initialization) are determined through a trial-and-error approach after exploring various configurations. Since training occurs offline, the duration is not a critical factor. The primary goal is to achieve well-trained neural networks capable of accurate and efficient solar PV power prediction. In Performance Evaluation Figure 5 presents the Mean Squared Error (MSE) obtained after training each ANN. As evident from the figure, the MLFFNN exhibits consistently lower MSE values compared to the other networks, indicating better convergence and approximation capabilities. Additionally, training time for the MLFFNN is shorter, suggesting faster convergence. Nevertheless, both the RNN and NARXNN achieve acceptable and low MSE results.

Following training, the three trained networks are tested using the same dataset employed for training. Figure 6 depicts the difference between the actual total power output from the real PV plants and the estimated power predicted by each ANN. The figure demonstrates minimal approximation errors for all three networks (MLFFNN, RNN, and NARXNN), reflecting their ability to accurately predict PV power after extensive training. However, the approximation error is demonstrably lower and more efficient when using the MLFFNN compared to the other network types. The NARXNN exhibits slightly higher approximation errors in Figure 6.

The next section will explore the generalization ability and effectiveness of the trained ANNs under different operating conditions.

7. NN Generalization and upscaling technique for PV output power

prediction:

This section presents the generalization capacity and efficacy of the three trained neural networks (NNs) utilizing non-training data. The remaining information that has been gathered which is the half-month's (15-day) worth of data is utilized in this way. Because the three NNs have received good training, they are capable of accurately and efficiently estimating the PV output power given a variety of data and circumstances. This demonstrates the efficiency and range of each trained neural network. Additionally, the data demonstrate that the trained MLFFNN performs better than the other trained NNs. When utilizing the trained MLFFNN instead of the trained RNN and NARXNN, the error is reduced and the performance is improved. In comparison to the other trained NNs, the trained NARXNN has the lowest performance and the biggest resulting error. The four PV models' distributed generation is estimated and predicted using the upscaling technique. In fact, scaling the data is the primary objective of the upscaling technique. To determine the output power of the entire set, use the subset's output power. There are two actions that should be taken in order to construct the upscaling technique. First and foremost, the subset needs to be selected so that its power output behaviour is indicative of the behaviour of the entire PV total station.

Next, MLFFNN-based models are designed to forecast the overall power production of the plant Using this method, a random subset of one of the four PV models is chosen. Consequently, the suggested MLFFNN predicts the total output power of the entire set using the inputs of this subset system. When compared to the prior value, the upscaling result demonstrates an improvement in the accuracy of regional power estimation and forecast. It results in a 4.2% reduction in the power estimation's MSE and a 20% reduction in the RMSE. The Multilayer Feedforward Neural Network (MLFFNN) demonstrates remarkable performance in upscaling the predicted power output for the entire PV system. The error between the predicted power and the actual output power is minimal, approaching zero. To quantify this performance, we calculated the following error statistics for the absolute error: Average: 0.0720, Maximum: 5.2702, Minimum: 0.0, Standard Deviation: 0.2299.

These values indicate excellent agreement between the MLFFNN-based upscaling prediction and the actual PV system output.

7.1. Generalizability of the upscaling method:

To verify the effectiveness and generalizability of the upscaling prediction method beyond the training data, we conducted an additional test. We used two weeks' worth of data from a subset of input parameters (solar radiation and surface temperature) for verification. This test confirms the low approximation error of the upscaling method even when applied to unseen data. The specific error statistics for the absolute value of the approximation error using upscaling are presented later in the paper.

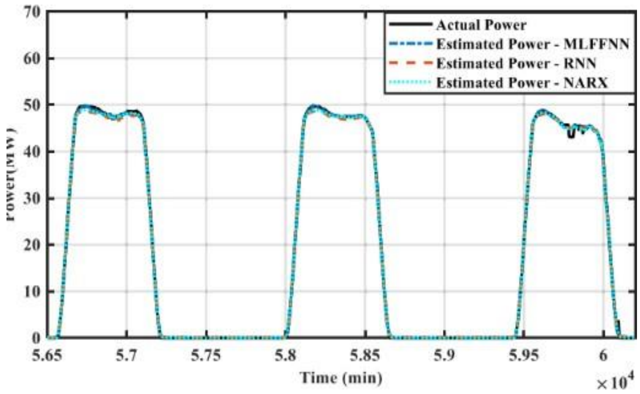

Figure. 7: The Approximation and the Convergence between the Actual Power PV and the Estimated Power by the Trained NN (MLFFNN, RNN, and NARXNN)

8. Comparative study:

This section analyzes the effectiveness of different solar PV power prediction methods. A key metric for evaluating these methods is the coefficient of determination (R-squared). Ideally, an R-squared value close to 1.0 indicates excellent convergence and agreement between the predicted and actual power outputs.

Our proposed approach, utilizing Multilayer Feedforward Neural Networks (MLFFNNs), achieves a superior R-squared value compared to other referenced methods, including those by Kazem et al., MFFNN-MVO, and Random Forest Regression. This signifies that the MLFFNN-based prediction exhibits higher accuracy in estimating solar PV output power. Furthermore, our proposed methods (MLFFNN, RNN, and NARXNN) demonstrate a significant advantage in terms of model complexity. They achieve high R-squared values while relying on only two input parameters (surface temperature and solar radiation).This contrasts with other approaches that often require a larger number of inputs, increasing their complexity. An additional strength of our proposed approach lies in its focus on generalizability. We evaluate the performance of our models under various operating conditions, demonstrating their ability to adapt and predict accurately across different scenarios. This aspect is not explicitly addressed in the referenced studies.

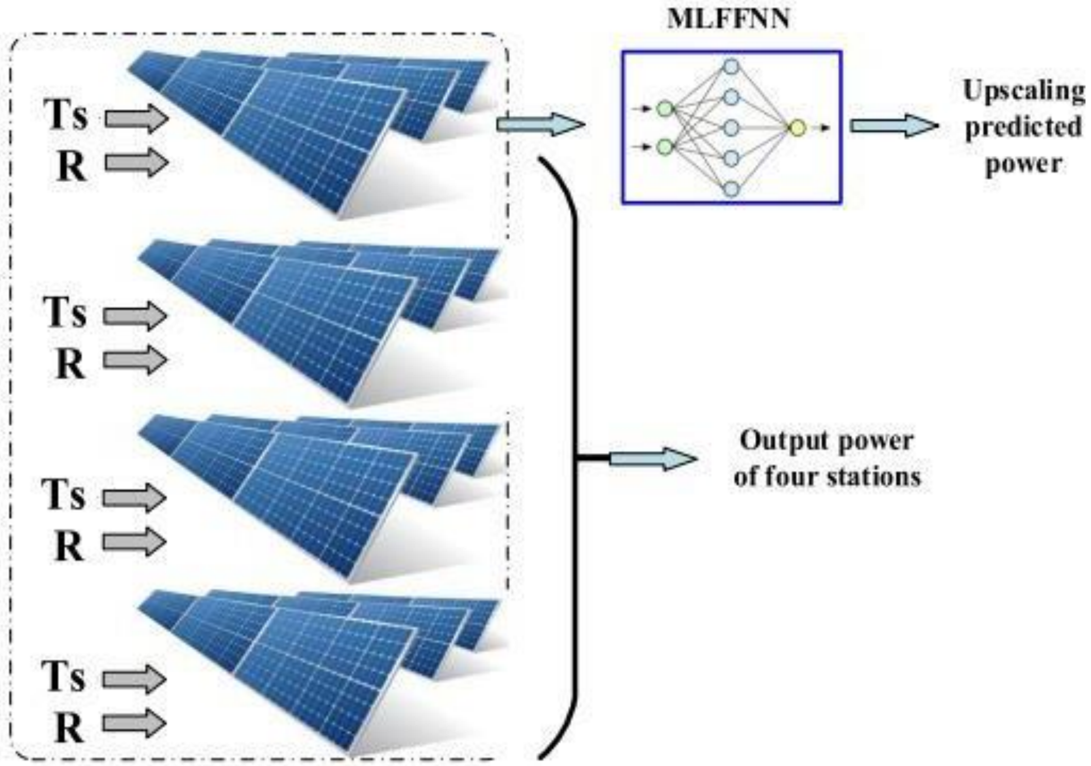

Figure. 8: The concept of upscaling technique

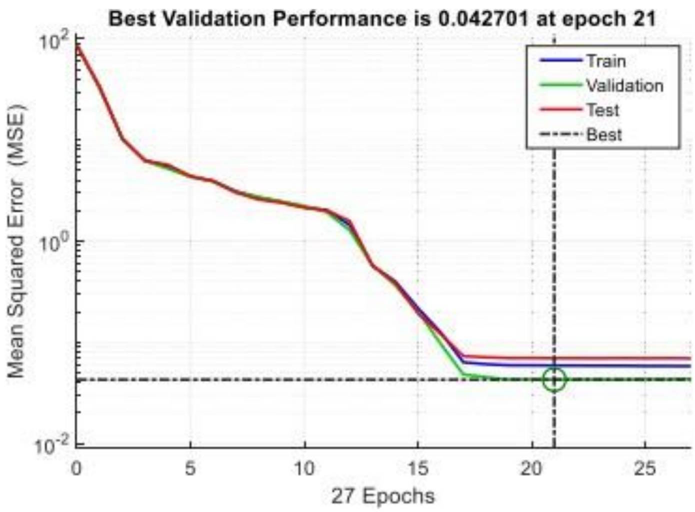

Figure. 9: The observed MSE of the upscaling technique

9. Conclusion and future work:

Improving the accuracy of neural networks (NNs) is essential for accurate prediction and forecasting of solar PV generation capacity. This helps reduce power outages and interruptions in the utility grid caused by environmental changes. In this study, three different trained networks (MLFFNN, RNN, and NARXNN) are proposed to estimate the total energy output of four small solar PV plants For these NNs, land surface temperature and sunlight serves as an input, while all PV power its output. Data for 60 days (2 months) were collected from four real small solar PV plants in Egypt. During these first 45 days, the LM was used to train the NN through the curriculum. The remaining 15 days of the semester are used to evaluate the performance and flexibility of the trained muscles in a new environment.

Moreover, these results reveal that MLFFNN outperforms RNN and NARXNN. The MSE and approximation error are largest when using the developed NARXNN compared to other neurons. Further investigation of the generalizability of the neural networks trained by different data from the training set confirms the results of the training phase Nevertheless, all trained neural networks show capability well under different conditions and with different data types.

Furthermore, MLFFNN, after training, showed better performance compared to other neurons, while NARXNN showed more inefficient performance after validation of the mathematical model project was used to monitor and predict regional solar PV power from four solar PV stations. Our method exhibited low mean square error (MSE) and robustness compared to others. In addition, only our proposed method investigated its generalizability. Future research will measure and compare deep learning algorithms. Additionally, data stored for longer periods of time, such as six months or one year, Will be used. In addition, other renewable energy sources such as wind energy will be explored through energy forecasting.

Accurate PV production forecasting is highly dependent on understanding the system behavior, which plays an important role in managing the operational network. An optimal forecasting model based on Extreme Learning Machine (ELM) adapted for PV systems has been developed using various particle swarm optimization (PSO) techniques to increase the forecasting accuracy the forecasting system is divided into several subcategories based on different time periods. From the results of the experimental study we can conclude that The ELM algorithm exhibits the best generalized forecasting performance compared to classical algorithms such as BP-ANN.

Among the proposed hybrid models, the APSO-ELM model performs better in short- term solar forecasting than other methods. The APSO algorithm adjusts the random weighting of the ELM quickly and accurately. Thus, the proposed optimization model based on the combination of PSO and ELM of feed-forward neural network at one layer effectively improves the accuracy of the prediction system. The combination increases the computational complexity of the proposed prediction model. Future work will focus on efforts to reduce computational complexity and improve predictive accuracy by collecting more data.

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