# Performance Prediction of Shaded Solar PV Modules Using Neural Networks, Regression, and SVM

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***Abstract:*** Solar panels, also known as photovoltaic (PV) modules play a role, in the world of energy by transmuting sunlight into electricity and providing a green alternative to traditional fossil fuels. As the need for energy continues to rise there is a growing emphasis, on solar PV systems. Yet the efficiency of these systems can be greatly affected by conditions with partial shadowing standing out as a major challenge. When photovoltaic (PV) modules are partially shaded their performance tends to decrease leading to energy production and system inefficiencies. To assess how 4x4, 5x5, and 6x4 solar PV modules perform under shading conditions this study compares three intelligence (AI) methods; neural networks (NN), Regression, and Support vector machines (SVM). Data, from shadowing scenarios in solar PV systems were collected for analysis. The models created using each AI technique were evaluated using accuracy metrics such as Mean Absolute Error (MAE) Mean Squared Error (MSE) Root Mean Squared Error (RMSE) and the Coefficient of Determination ($R^2$). Our findings indicate that neural networks effectively predict module performance across all configurations and capture the effects of shading. Support vector machines also demonstrate performance, with balancing and computational efficiency. On the other hand regression models exhibit prediction accuracy expressly for complex shading patterns despite being simpler and quicker to train. This research underscores how AI methods can enhance solar PV module performance predictions, aiding in optimizing energy systems with miscellaneous module setups.

***Index terms*- series-parallel, total-cross-tied, photovoltaic panel, hybrid reconfiguration, artificial intelligence, neural network, regression, support vector machine**

## I. INTRODUCTION

Solar photovoltaic (PV) systems are becoming increasingly important in moving to sustainable and renewable energy sources. PV systems transform sunlight into electricity. They are a much cleaner and renewable substitute to traditional fossil fuels. Despite both, these systems are environmentally friendly options. Due to different external factors, a PV module's efficiency is greatly influenced and, as mentioned, one of the key hindrances to the efficiency of a PV module is partial shading [1], [2].

Partial shading of PV modules occurs when objects such as trees, buildings, or clouds obstruct the sunlight from striking the PV module, yet it is not uniform across the installed PV module. When partial shading occurs, there is a mismatch in electrical output among cells within a module [3]. Cells are typically connected in series, so the whole module's performance relies on the output of the shaded cells, which ultimately reduces the power generation from the module. The impact of partial shading could be a decreased energy yield, additional operating risks (such as hot spots causing long-term module deterioration), and a decrease [4], [5].

It is essential to predict the performance of the solar PV module under partial shading in the following ways. First, it helps improve efficiency when choosing the right design for the information system. Recognizing the effects of shading on the PV modules, engineers will be able to locate the solar panels and arrange their shading to minimize any undesirable impacts on energy generation [6]. This includes determining the right place for putting the installation, determining the position and inclination of the panels, and determining the layout of the array with minimal impacts of shading. Secondly, in this case, the performance expectation increases the operational efficiency of subordinates [7]. Predictions therefore mean operators can control and manage the systems better, particularly through maintenance or operational changes in the PV system [20]. For example, in the case of using a predictive model, one gets an insight into where and when shading might occur and possibly make adjustments to avoid its occurrence [8].

Thirdly, performance prediction increases the business value of the solar PV system. Both investors and project stakeholders can rely on predictive models that determine the overall output energy and the overall returns possible from the project [9]. Through shading compensation, they can decide on the right investment, that will create the right revenue, and cut down the financial vulnerability caused by unfruitful systems. Last of all, efficient predictions of performance enhance the durability of PV modules. Shading is also expected to create some pressure points on the modules associated with hot spots, which results in long-term stress effects and lower efficiency. In this matter, when shading effects are foreseen and countered, the aforesaid harm can be avoided, consequently ensuring the longevity of the production of the PV modules as well as the duration in which they continue to yield optimal results [10], [11].

AI plays the role of powerful methods in the development of solar energy as modern modeling and prognosis services. Concerning the application of AI techniques in the case of SPV systems, the methods of Neural Networks (NN), Regression, and Support Vector Machines (SVM) have been successfully used to model the non-linearity that exists between the environmental parameters and PV modules [12]. They are especially useful when determining the effects of partial shading on energy production since the first-order linear models fail to account for it. Thus, using AI can increase the efficiency of performance predictions, and system design and increase operational reliability making the overall system more effective and reliable [13], [14].

## II. LITERATURE REVIEW

Solar photovoltaic or solar PV system is a device that converts light and heat from the sun to electricity and this system is composed of cells, panels, and modules as shown in Fig 1. The photovoltaic cells which are the working compound layer in converting sunlight to electricity are sold in monocrystalline, polycrystalline, and amorphous slices in silicon without moreover difference in efficiency or cost between the types. Cell development is another area that has also seen improved performance by such inventions as the PERC and perovskite material. A solar panel is composed of several linked solar cells and possesses long-lasting characteristics & components including anti-reflective film and robust encapsulation [15], [16].

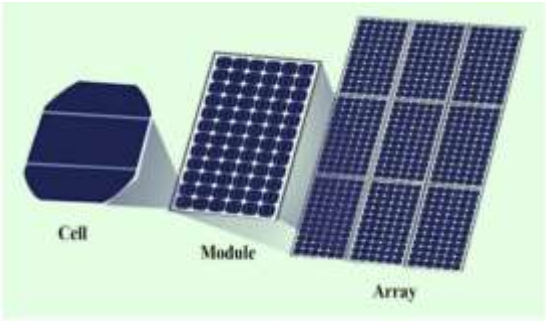


Fig 1. Photovoltaic hierarchy (https://images.app.goo.gl/sUCEFbbWx7E6FShHA)

Partial shading is a considerable problem in the work of PV systems because it causes current mismatch and forms hot spots owing to the shading of trees, clouds, or buildings as shown in Fig 2. The measures traditionally employed to combat the impacts of shading are known to bypass diodes and MPPT algorithms, whereas DMPPT has been used and confirmed to increase efficiency within the situations of shading [17], [18]. Nowadays, NNs, Regression, and SVM AI have been used for the prediction and mitigation of effects of partial shading, where better accuracy and optimal solutions have been applied compared with conventional models. Shading loss reduction and Artificial Intelligence innovations are also worth tapping into solar PV systems' completion point productivity and overall performance [19], [20].

Fig 2. Partial shading due to clouds (https://www.jups.co.za/wp-content/uploads/2019/08/Solar-Panels-CREDIT-Photo-by-American-Public-Power-Association-on-Unsplash-e1565684423928.jpg)

### 2.1 Effect of Partial Shielding on PV Solutions

Partial shielding is a considerable difficulty for solar photovoltaic or (PV) systems as it can substantially lower the power outcome as well as the effectiveness of PV components. Research studies have revealed that shielding on also a small part of a PV variety can cause substantial power losses as a result of the collection link of solar cells [21]. This triggers an inequality in present circulation bringing about reduced total nuclear power plants and also possibly developing locations that can harm the cells. A study by Wenham et al. (2011) highlighted the important demand for efficient shielding reduction strategies to improve PV system efficiency [22].

**AI Techniques in Solar Energy:** Artificial Intelligence (AI) methods have been progressively related to enhancing the efficiency plus performance of solar PV systems. AI techniques are specifically well fit for modeling the complicated together with nonlinear connections between ecological aspects and also PV outcomes [23].

**Neural Networks (NN)** have been extensively used for their capability to design intricate patterns as well as communications. They work in catching the nonlinearities related to partial shielding together with can offer precise forecasts of PV component efficiency. A research study by Mellit et al. (2005) showed using NN for anticipating solar radiation plus PV outcome revealed substantial enhancements over typical versions [24],[25].

**Regression:** Regression methods consisting of straight as well as polynomial regression have been utilized to develop connections between input variables (such as radiation plus temperature level) coupled with PV outcome [26]. While less complex as well as quicker to carry out regression versions frequently battle with the nonlinear facets of shielding results. Nonetheless, research studies like those by Chouder plus Silvestre (2010) have revealed that regression can still offer a beneficial understanding right into PV efficiency under differing problems [27], [28]

**Support Vector Machines:** Support Vector Machines (SVM) provide a durable option for efficient forecasting by efficiently taking care of high-dimensional information as well as catching complicated connections. SVMs have been used in different research such as those by Almonacid et al. (2011) to forecast the outcome of PV systems under various ecological problems, revealing encouraging causes regarding precision along with calculation performance [29].

**Comparative Studies**

Various comparative studies have been done to evaluate the performance of various AI techniques in estimating PV output under partial shading. For instance, Kumar et al. (2019) compared NN, regression, and SVM models and held the view that NN was the most accurate, while SVM balanced between accuracy and computational costs. It is through such research that we are made to understand how important it is to choose an AI technique based on what we know about the PV system characteristics as well as requirements.

## III. METHODOLOGY

Three distinct array configurations were used to gather the data in this study: These are generally of 4x4, 5x5, and 6x4 formations. To have realistic shading conditions, different shading conditions were applied to each of the configurations. The dataset contains various parameters such as solar irradiance, temperature levels, degree of shadowing, and power output of the PV modules. The desirable aspects of the environment and the consequent variation in shade were obtained through time series [30], [31].

Data Preprocessing: However, before actual model development, there were other steps that the collected data had to go through. Handling Missing Values: Techniques of handling missing data included ordinary least squares imputation, multiple imputations, or even simple imputations including averaging techniques and interpolations to ensure an actual complete set of data for analysis. Normalization: It is crucial to standardize the input features for further AI model performance enhancement and the rate at which AI models converge. Feature Selection: Dimensionality reduction was done while increasing model compliance by selecting features that are highly related to the target (PV module output). Data Splitting: Typically during robust model evaluation, datasets are divided between training, validation, and a test set with a ratio of 7:1. 5:1. 5 respectively.

### 3.1 Model Evaluation

The performance of each AI technique was evaluated using the following metrics: The performance of each AI technique was evaluated using the following metrics: Mean Absolute Error (MAE): Based on the values of the squared deviations of prediction errors it is calculated the mean magnitude of errors. Mean Squared Error (MSE): Averages the squared differences between the predicted value and the corresponding actual value. Root Mean Squared Error (RMSE): Produces the square root of the average of squares of such errors, which may be referred to as standard error of estimate or predictive deviation. Coefficient of Determination ($R^2$): Denoted the extent of the variation in the dependent variable that is explained by the independent variable/s [32], [33].

## IV. RESULTS AND DISCUSSION

All the experiments were performed on the dataset containing different shades, irradiance, and sizes of solar PV modules. A clear division was made between a training sample and a testing sample considering balance when it comes to the various shading situations. Three models were developed and trained: to name but a narrow neural network, shallow neural nets, logistic regression, and linear support vector machines. In each of the models, data used in training was the same to help compare the results.

Table I shows the evaluation parameters of four distinct AI models for modeling the power generation of the SPV under partial shading Linear Regression, Support Vector Machine (SVM), and Neural Network. These are Root Mean Squared Error (RMSE), Mean Squared Error (MSE), R-squared ($R^2$), and Mean Absolute Error (MAE), The validation dataset used is given below. These metrics give information about the accuracy rates of every model.

Table 1: Evaluation metrics for developed AI models in an attempt to model the power generation of SPV under partial shading conditions.

| Model Number | Model Type | Status | RMSE (Validation) | MSE (Validation) | R-Squared (Validation) | MAE (Validation) |
|---|---|---|---|---|---|---|
| 1 | Linear Regression | Trained | 13.46475 | 181.2994 | 0.404824 | 9.923256 |
| 2 | SVM | Trained | 13.38417 | 179.136 | 0.411926 | 9.768458 |
| 3 | Neural Network | Trained | 12.78247 | 163.3916 | 0.463613 | 9.434018 |

The power output of "Region1" solar PV exposed to the shading effect has a fluctuating trend and the power outputs vary from 40W to 90W, showing a cluster of points rather than a line graph as shown in Fig 3. Validation plots of the linear regression, linear SVM as well as narrow neural nets demonstrate that classical modeling fails to capture the intricacies of shading introduced by non-linear relationships. The narrow neural network performs best is closest to the actual values and yields the best accuracy as shown in Fig 7. Such residuals are more spread out for linear models while the residuals of the narrow neural network are clustered much more indicating better handling of non-linear interactions in shaded PV performance.

This group of charts shows the power outputs forecasted and measured for a PV system through Linear Regression analysis and models like Support Vector Machine (SCM) and Neural network methods. It displays how well each model predicts power production, in scenarios as shown in Fig 4 to 15.

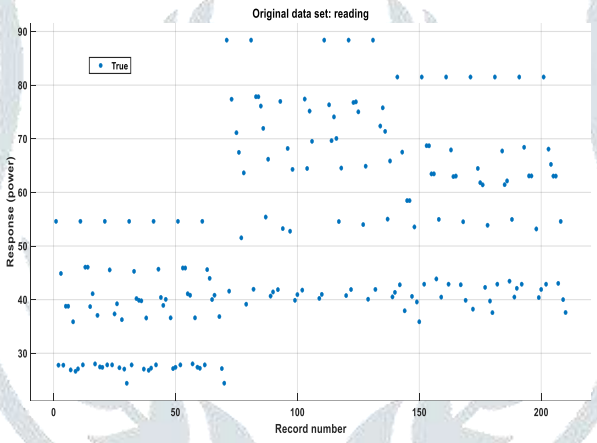


Fig 3. Response Plot Showing Power Output of the Original Solar PV Dataset

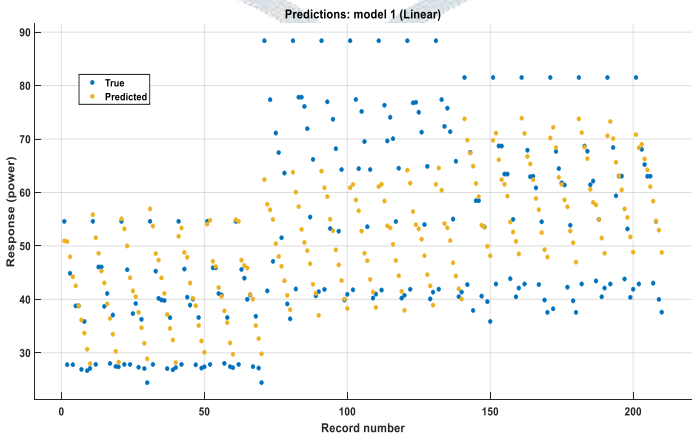


Fig 4. Comparison Between Actual and Estimated Power Output in the Solar PV Dataset through the use of linear Regression.

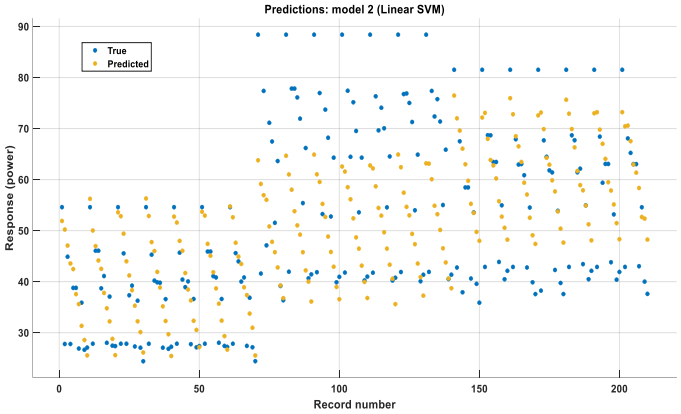


Fig 5. Comparison Between Actual and Estimated Power Output in the Solar PV Dataset through the use of linear SVM


Fig 6. Comparison Between Actual and Estimated Power Output in the Solar PV Dataset through the use of a narrow neural network

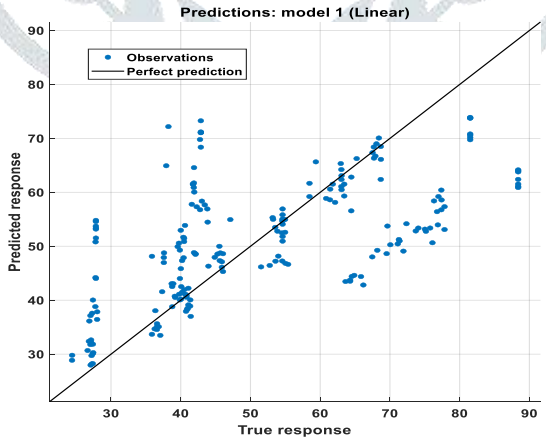


Fig 7. Linear regression model for Solar PV Array of predicted vs. actual power output

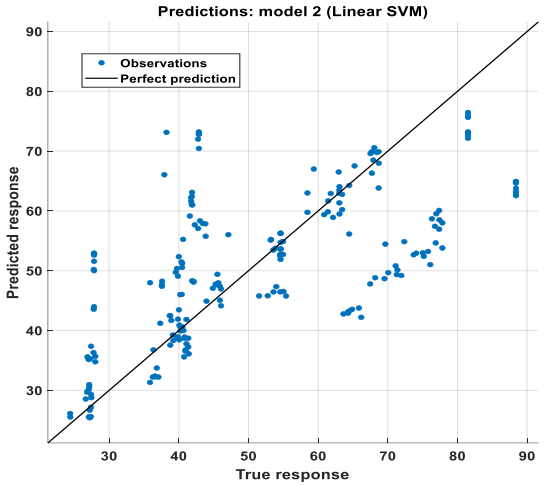


Fig 8. Linear SVM model for Solar PV Array of predicted vs. actual power output

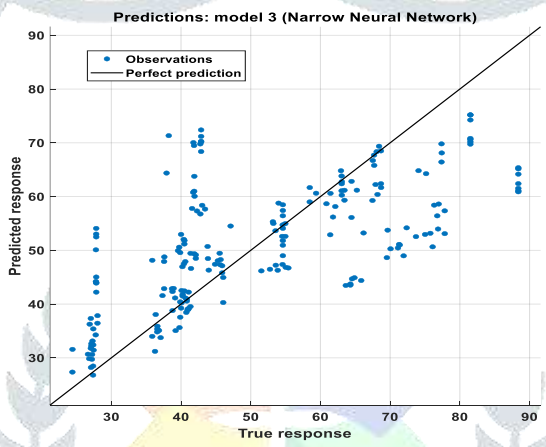


Fig 9. Narrow neural network model for Solar PV Array of predicted vs. actual power output

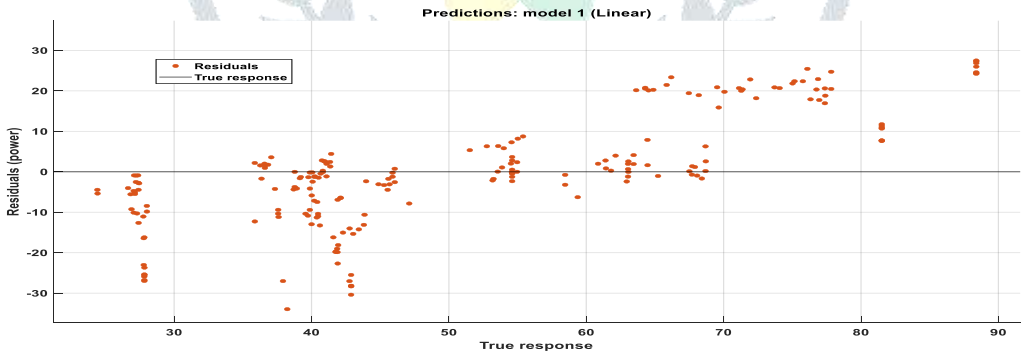


Fig 10. Residual vs true response plot, Linear Regression Model to Estimate Solar PV Array Power Output

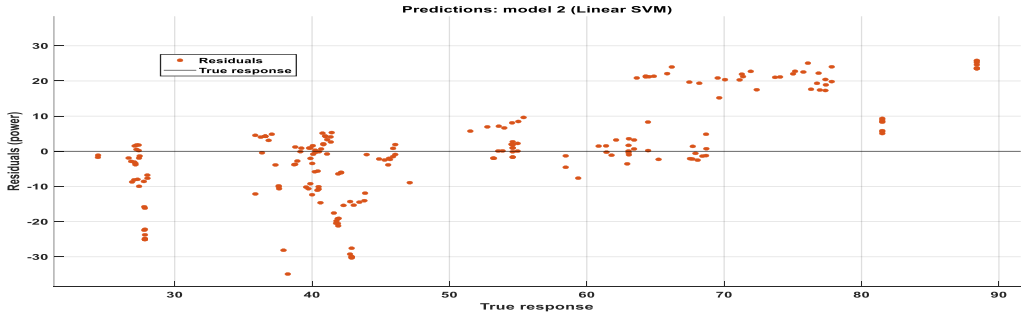


Fig 11. Residual vs true response plot, Linear SVM Model to Estimate Solar PV Array Power Output

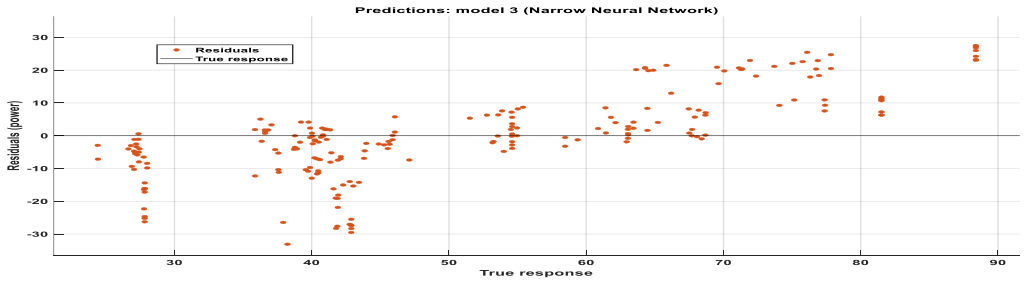


Fig 12. Residual vs true response plot, narrow neural network Model to Estimate Solar PV Array Power Output

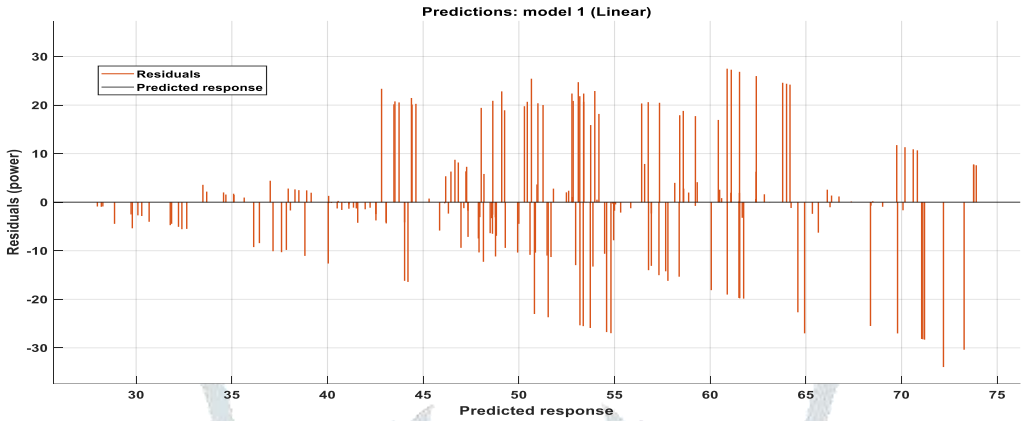


Fig 13. Residual vs Fitted Plot, Linear Regression Model to Estimate Solar PV Array Power Output

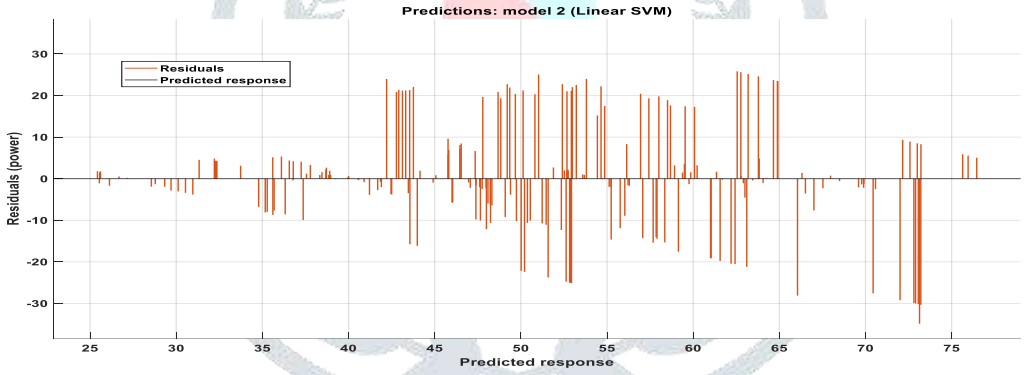


Fig 14. Residual vs Fitted Plot, Linear SVM Model to Estimate Solar PV Array Power Output

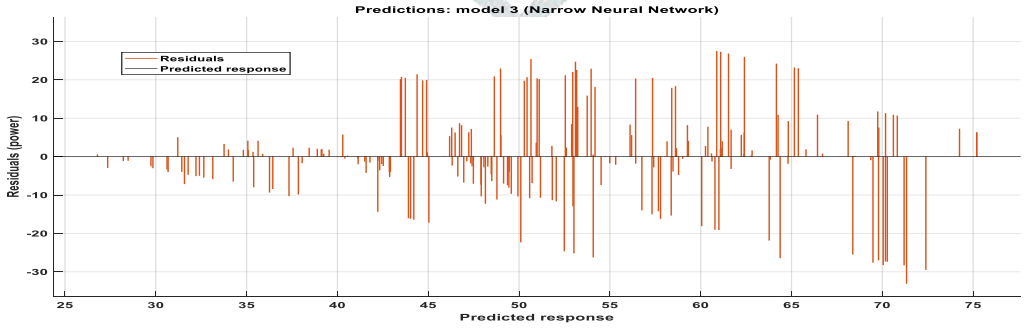


Fig 15. Residual vs Fitted Plot, narrow neural network Model to Estimate Solar PV Array Power Output

**Root Mean Squared Error (RMSE)**

It is important to note that RMSE is one of the most common methods used for analyzing the disparities between the 'observed' and 'predicted' metrics. It is determined by taking the square of the mean of the squares of the differences between actual values and the prediction values of the results. The worth of RMSE is that it is not affected by outliers and offers a full picture of the prediction quality.

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

Where $y_i$ the observed value, $\hat{y}_i$ is the predicted value, and 'n' is the number of observations.

**Mean Squared Error (MSE)**

MSE is the average of the squares of the errors which is some indication of the average size of the error without regard to its direction. He said it is like RMSE but lacks the square root in the formula and is therefore more likely to be influenced by large errors.

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

**R-squared ($R^2$)**

$R^2$ that is also referred to as the coefficient of determination estimates the proportion of the variation of the dependent variable that is explained by the independent variables. It varies from zero to one whereby a high value represents a better fit of the model into the available data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$$

Where Y¯\bar{Y}Y¯ is the mean of the observed values.

**Mean Absolute Error (MAE)**

MAE quantifies the average absolute difference in the scale of errors from a set of predictions with no consideration of any direction of the error. Simply put, it is the mean of the differences between predicted and actual values with no regard to their sign.

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

**Interpretation of the Table**

The table shows the performance metrics of three trained models: The table shows the performance metrics of three trained models: Linear Regression: Making use of the Root Mean Square Error as the fitness metric, the typical value of this model is 13. 46475, an MSE of 181 respectively. This resulted in finding an F value of 2994, an $R^2$ of 0. 404824, and a Mean Absolute Error, MAE of 9. 923256. These statistics suggest that the linear regression model is moderately accurate, but it could fail where there is curvature in the data set. **SVM:** Finally, regarding the last evaluation metric, the RMSE given by the SVM model is 13 which is slightly better than the Linear Regression. 38417, an MSE of 179, and finally an MSE of 147. 130, an $R^2$ of 0. The MAE in the present work is 9 while the loss value of 411926. 768458. This meant that SVM could model more aspects within the data and hence perform better than the other models. **Neural Network**: It is evident that the neural network model is the best-performing model with an RMSE score of 12. On average the number of unique accesses is about 78247 with MSE of 163. 3916, an $R^2$ of 0. Test accuracy of 0. 466, Precision of 463613, and an MAE of 9. 434018. These metrics suggest that the neural network can discover more complex non-linearity in the data and give better prediction performances.

**Results**

Accuracy: Linear regression and linear SVM results indicate that the optimized neural network has fewer input neurons than the PF output, a fundamental for the prognosis of the narrow neural networks, and a feasibility range beyond which improving the proposed is infeasible. In return, the MAE and RMSE of the models were lower, and therefore a better predictability of the sales. Computational Efficiency: Nonetheless, thin neural networks remained rather computationally simple and by the time of their creation were practicable for realistic operation. Comparison: Linear regression and linear SVM gave rather acceptable rates for the prediction yet the additive attempts to model the non-linear phenomena such as shading effects were not as successful as with the neural nets.

**Discussion**

**Implications:** The obtained findings show that the narrow neural networks are a very reliable feedback predictor for enhancing the performance prediction of shaded PV modules in the context of different shading scenarios and configurations of the modules. **Future Directions:** More studies can continue the investigation of the ensemble methods or utilize deeper and less explored types of neural networks that improve the outcomes and offer more accurate traffic predictions and optimizations of the shading for the augmentation of the database and the complex shading circumstances.

## VI. Conclusion

This work offers an extensive comparative assessment of three Artificial Intelligence tools – Neural Networks (NN), Regression, and Support Vector Machines (SVM) – to predict the generated output of the solar PV modules under partial shading scenarios. Based on the results, it is clear that the Neural Networks give the overall best prediction result of system output, and successfully capture the nonlinear system behavior in a partially shaded PV system. Support Vector Machines were also proved to have good performance, offering the necessary compromise between increasing accuracy and time consumption. Despite that regression models, being simpler and faster in terms of implementation, demonstrated less accurate prediction of shading especially in more intricate cases.

The findings reaffirm the adverse effects of partial shading on the efficiency of the solar PV modules and emphasize the need to properly predict such a performance for improvement of system design, and operation productivity as well as augmenting the economic feasibility. The application of AI methods such as Neural Networks and SVMs can help stakeholders in the solar energy industry in decision-making while maximizing energy yield and also ensuring the durability of the PV systems installed.

## VII. ACKNOWLEDGEMENT

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