EXPERIMENTAL ANALYSIS ON DIFFERENT EFFECTS OF PV MODULE WITH RESPECT TO PANEL ANGLE USING MACHINE LEARNING ALGORITHMS

S.Sandhiya[1], Prabha Umapathy[2], Abinaya Inbamani[3]

[1]*PG scholar, Department of Electrical and Electronics Engineering, Sri Ramakrishna Engineering College, Coimbatore*

[2]*Professor &Head, Department of Electrical and Electronics Engineering, Sri Ramakrishna Engineering College, Coimbatore*

[3]*Assistant Professor, Department of Electrical and Electronics Engineering, Sri Ramakrishna Engineering College, Coimbatore,.*

Abstract: Finding the optimum panel tilt angle for a photovoltaic device is crucial because it will efficiently convert the solar radiance into electricity. A variety of testing methods were used to determine the tilt angle so as to maximise the amount of radiation received by the solar panel. Recent research, however, has discovered that conversion efficiency is not exclusively determined by the amount of radiation received and it is also dependent on the tilt angle of the solar panel. Solar panel tilt angle optimization model based on machine learning algorithms is proposed in this paper. Concentration on tilt angle is done, that maximises photovoltaic (PV) device radiance into electricity. Five forecasting models were developed using linear regression (LR), Ensemble, random forest (RF), support vector machine (SVM), and Gaussian Process Regression (GPR), all of which took into account various factors such as weather and dust level. Our model showed an increase in PV yield as compared to ideal point models when we used the best model..

***Keywords*: solar panel, machine learning, tilt angle**

1. Introduction

The increase in demand for non-conventional energy sources such as solar energy, geothermal energy, and wind energy is due to rising energy costs, depletion of fossil fuel reservoirs, and global warming, among other factors. Solar energy is found to be the most applicable source of energy among them due to advantages such as pollution-free operation and the absence of any rotating parts, maintenance costs are lower, and so on[1]. A solar photovoltaic (PV) device is needed for direct conversion of solar energy into electrical energy in order to use this type of energy. Primary and secondary oil, commercial and non-commercial energy, renewable and non-renewable energy, traditional and non-conventional energy, and so on are all forms of energy. While, this work focuses primarily on renewable energy sources because they can be a cost-effective alternative to fossil fuels. Because of the abundance of renewable energy sources and the fact that they do not pollute the atmosphere, more research is being conducted on them these days. Solar energy is one of the most important renewable energy sources, and this research focuses on it. Despite the fact that solar energy is abundant, efficient solar energy use is critical in order to satisfy the rising demand. Photovoltaic modules are responsible for the generation and distribution of solar energy for commercial and domestic use. The PV cells are linked together to create a PV panel[2].

A solar PV array is made up of several solar panels connected together. The solar PV module is made up of solar cells that are connected in series and parallel. Due to the generation of photons, the photoelectric current flows through the load as light falls evenly in the solar cell. If the isolation in a series connected PV system is not standardised, generation occurs. As the atmospheric conditions change, the characteristics of solar cells become more complex. In India, only a few studies with real-time data on panel tilt angle determination have been performed. As a result, a pilot study was conducted to determine the optimum tilt angle at the chosen location using real-time data obtained from the rooftop PV panel. To evaluate the optimum tilt angle, a comprehensive theoretical and practical study was conducted[3]. Furthermore, the experimental findings have been confirmed. The study's main goal is to conduct a statistical analysis of real-time power output data from solar panels installed at various angles. Assessing the best tilt angles for panels mounted at 0°, 5°, 10°,15°, 20°, 25°, 30°, and 35° is also made. Analysis to determine the optimum angles is done. To incorporate the above study, AlokP solar panel is preferred. The specifications of the solar panel is mentioned in the table 1.

ISSN (Print): 2204-0595
ISSN (Online): 2203-1731

Table 1: Model of Specification

Operator	**AlokP**
Product ID	01040221116005618
Current temp. coeff. (mA)	3.0000
Voltage temp. coeff. (mV)	3.0000
Model area (cm2)	3158.75
Irradiance (mW/cm2)	99.9
Isc (A)	2.3893
Voc (V)	22.1528
Pmp (W)	43.8655
Imp (A)	2.3148
Vmp (V)	18.9500
F.F.	82.88
Module eff.(%)	13.90
Est. Shunt resistance	254.3624
Est. Series resistance	0.2179

2. Study Site and Data

99.9 mW/cm^2 is the maximum solar irradiance from the AlokP solar panel. The experiment was carried out on a solar panel made of Polycrystalline silicon content. The solar panels' measurements were 660 x 460 mm for two insight solar panels with halogen lamps as light sources. For the result analysis, the logger plotter is connected to the solar module production

[4]. For accurate data on PV and IV characteristics, the logger plotter is also connected to the device. The experiment was carried out with varying load resistances in the solar panel.

The load resistances were varied by keeping the constant tilt angle and the consecutive module temperature, voltage and current is measured. The module temperature is measured with PT100 sensor. The procedure is repeated with varying tilt angles and varying radiation from the halogen lamp. The power was calculated from the observed values of Current and Voltage. The formula used to calculate power was

$$P = I * V$$

P represents power in watts, I represents current in amperes, and V represents voltage in volts. To achieve the desired performance, solar panels can be connected in two ways: series and parallel. The voltage and current in the series and parallel connections of the solar panel were measured in steps as the radiation was changed[5]. The shading effect was applied to solar panels in both series and parallel connections. The obtained voltage and current values in the effect of shading were used to determine the PV panel's output power.

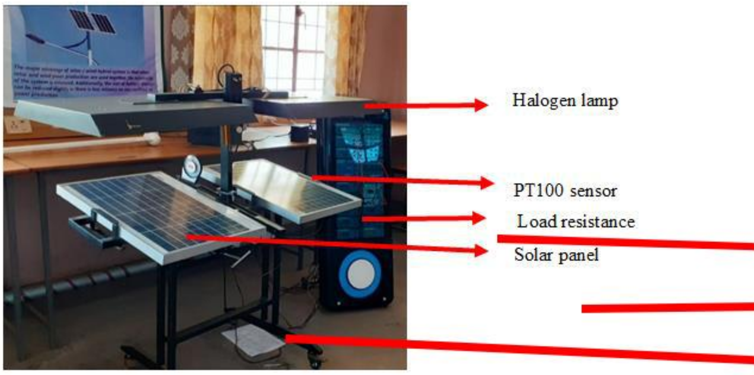

Figure 1:Site set up

Load resistance values are kept at 0 ohm with varying tilt angle and with various value of voltage, current and module temperature. The output power is calculated. The load resistance is changed to 20 ohm with varying tilt angle and the process is repeated. The load resistance is changed over 40 to 200 ohm and all the values are estimated[6].Machine learning algorithms is applied on the dataset obtained from the solar panel and the model is estimated and predicted with future values.

3. Methodology

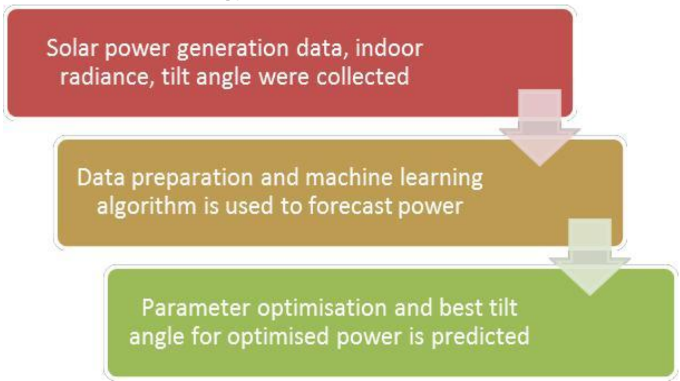

Figure 2 : Procedure of the proposed methodology.

Obtaining Data

The PV module data, meteorological data, and sun position data were all necessary for this report, as discussed in the previous section [7]. Sun location data were gathered for the entire period because each PV module's selection varied within the range of load resistance.

Preprocessing of Data

All of the information gathered was written down on a table. As predicted by our model, the collected data from each PV module was aggregated to fit the device [8].Using the equations in the previous section, we determined average daily beam radiation (Rb) and average daily diffuse radiation (Rd) for each PV site for all possible panel tilt angles ranging from

ISSN (Print): 2204-0595
ISSN (Online): 2203-1731

0 to 35 degrees. Originally, data from 77 PV sites was obtained from a panel.

Analyzing Correlation

We used correlation analysis on PV sites and measured the correlation between input features and PV output to select appropriate features for our forecasting model during the data preprocessing stage[9].

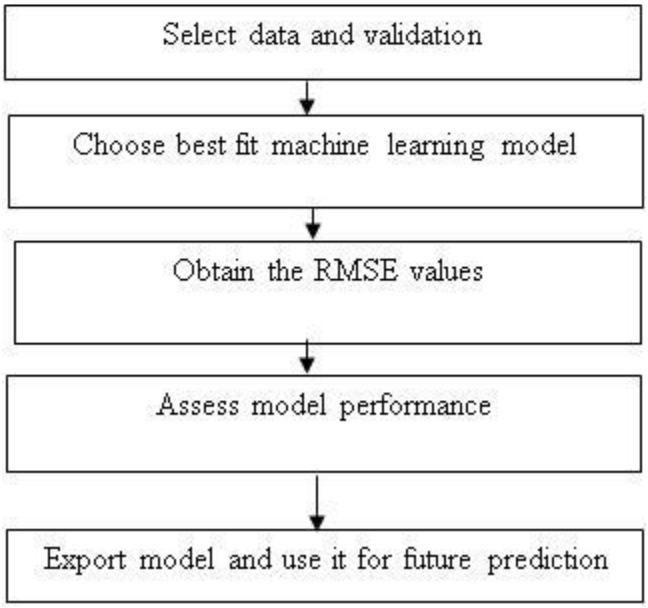

Figure 3: Proposed method

All of the data gathered in above PV module first to select the data and then we are validate that to choose the best fit machine learning model. After finding that we get obtained RMSE values to assess the model performance. After which, we are exporting model and using it for future prediction[10]

4. Modeling

Predictive approaches in machine learning serve various purposes depending on the type of prediction problem a researcher is working on Regression learners were considered as predictive method candidates because our aim is to create a model that can successfully learn from data to predict the PV output, which is a continuous variable[11].In this work, linear regression was used as our model's base algorithm. You can compare regression models based on model statistics, visualise outcomes in a response plot or by plotting real versus expected response, and test models using the residual plot after training regression models in Regression Learner. When you use k-fold cross-validation, the software computes the model statistics and reports the average values using the observations from the k validation folds. It makes predictions based on the validation folds' observations, and the plots display these predictions. It also calculates the residuals for the validation folds' observations. When you use holdout validation, the software computes the model statistics and makes predictions based on the observations in the validation fold[12]. These predictions are used in the graphs, and the residuals are calculated based on the predictions. The scores are re-substitution models statistics based on all the training data, and the predictions are re-substitution predictions if you use re-substitution validation. Check the Models pane after training a model in Regression Learner to see which model has the best overall performance. In a box, the best RMSE (Validation) is highlighted. The root mean square error (RMSE) on the validation set is used to measure this score. The score estimates the trained model's performance on new data. Using the score to assist you in choosing the best one. The score for cross-validation is the RMSE on all findings, counting observations while they were in a held-out (validation) fold. The RMSE on the held-out findings is used to calculate the score for holdout validation. The re-substitution RMSE on all the training data is used to measure the score for re-substitution validation. The model with the highest overall score might not be the best fit for your target. A model with a slightly lower overall score may be the better model for your target in some cases.

If data collection is costly or complicated[13], you will want to remove certain predictors to prevent overfitting. In the Current Model Overview window, you can see model statistics and use them to analyse and compare models. The validation collection is used to measure the Training Results statistics. If shown, the Test Results statistics are based on an imported test set. The square root of the mean of the square of all errors is the RMSE Root Mean Square Error. Since it is scale-dependent, RMSE is a reasonable measure of accuracy, but it can only be used to compare prediction errors of different model configurations for a single variable, not between variables. Determination coefficient The coefficient of determination, abbreviated R2 and pronounced R Squared in statistics, is the proportion of the variance in the dependent variable that can be predicted from the independent variable. Mean Square normalised Error is a metric that measures how well a network performs.

The mean of squared errors is used to determine the network's efficiency. For regression tasks, the half mean squared error loss between network predictions and target values is computed using the half mean squared error operation [14]. MAE Mean Absolute Error is network output feature is performance. It assesses network performance as a whole. Linear Regression Model has linear predictors in the model parameters, is simple to understand, and makes predictions quickly. Because of these features, linear regression models are often used as a starting point. However, since these models are highly constrained, their predictive accuracy is frequently poor. Try developing more versatile models, such as regression trees, after fitting a linear regression model and compare the results. Regression trees are simple to understand, easy to suit and forecast, and use little memory.

ISSN (Print): 2204-0595
ISSN (Online): 2203-1731

To avoid overfitting, grow smaller trees with fewer larger leaves. With the minimum leaf size environment, you can control the size of the leaves. Fine trees are simple to interpret, with a large number of small leaves that allow for a very versatile response feature. It has a four-leaf minimum scale. Medium trees are simple to read and have medium-sized leaves that allow for a versatile response feature. It has a leaf size minimum of twelve. Coarse Trees are simple to understand, with a low number of broad leaves and a coarse response feature.

It has a minimum leaf size of 36 leaves[15]. Vector Support Machines (SVMs) Support-vector machines (SVMs, also known as support-vector networks) are supervised learning models that analyse data for classification and regression analysis in machine learning. The nonparametric, Bayesian approach to regression known as Gaussian process regression (GPR) is making waves in the field of machine learning. GPR has many advantages, including the ability to work with small datasets and have uncertainty measurements on predictions.

5. Result and discussion

The tilt angle of the module an be changed by rotating the lever. The halogen lamp is lilt and changes in the tilt of the module is obtained. The controller connections are given and the tilt is evaluated. For various tilt angle, the voltage, current and temperature are noted. From voltage and current and the power is calculated for various values of load resistance of 0, 20,40,60,80,100,120,140,160,180 ohm respectively.

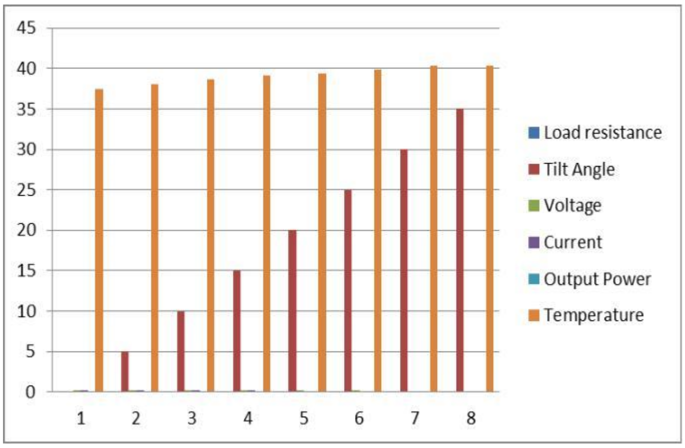

Figure 4. Voltage, current , output power, temperature at load resistance 0 ohm.

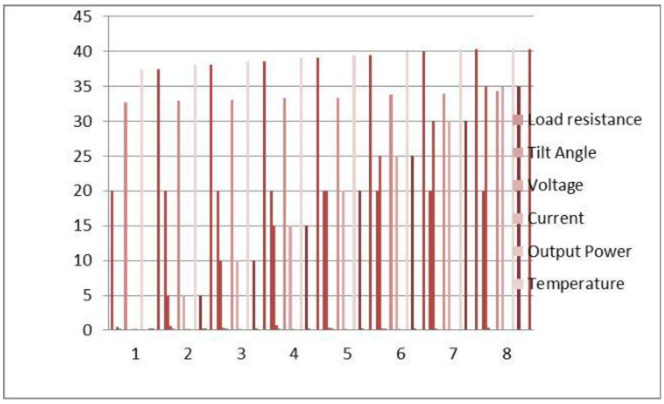

Figure 5. Voltage, current , output power, temperature at load resistance 20 ohm.

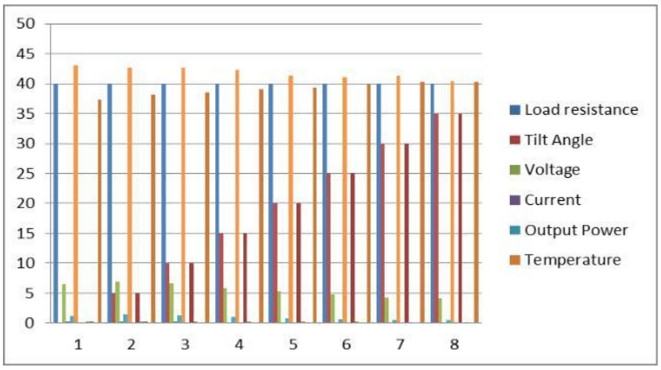

Figure 6. Voltage, current , output power, temperature at load resistance 40 ohm.

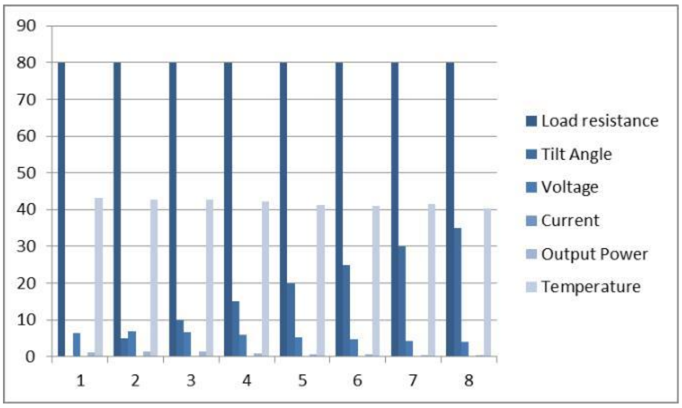

Figure 7. Voltage, current , output power, temperature at load resistance 60 ohm.

ISSN (Print): 2204-0595
ISSN (Online): 2203-1731

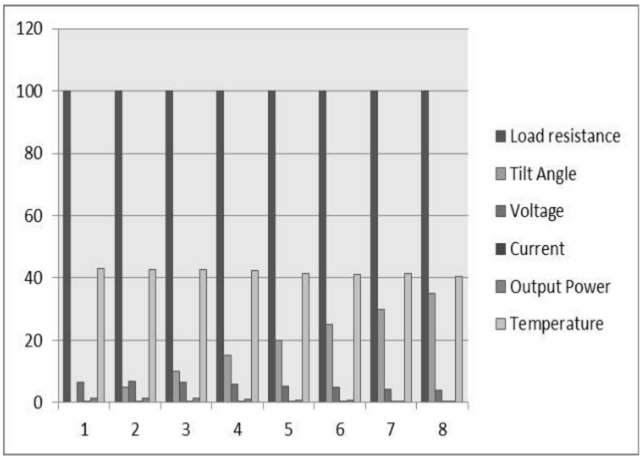

Figure 8. Voltage, current , output power, temperature at load resistance 80 ohm.

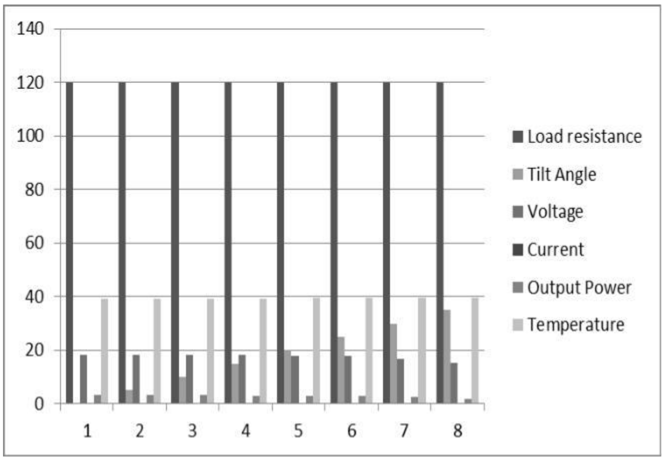

Figure 9. Voltage, current , output power, temperature at load resistance 100 ohm.

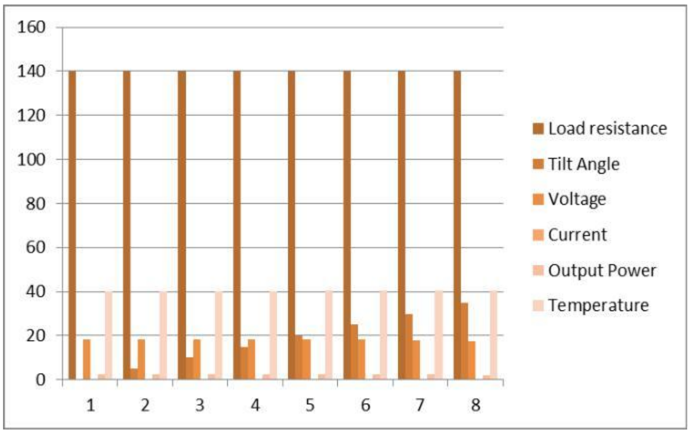

Figure 10. Voltage, current , output power, temperature at load resistance 120 ohm.

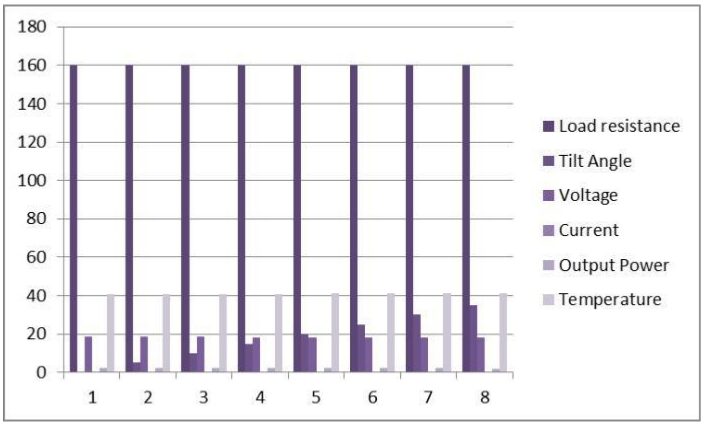

Figure 11. Voltage, current , output power, temperature at load resistance 140 ohm.

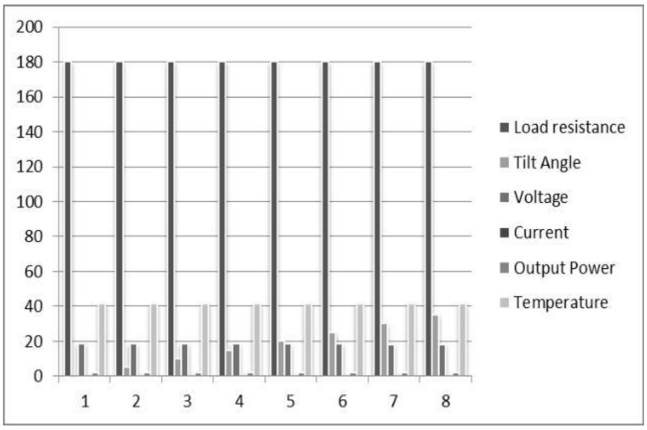

Figure 12. Voltage, current , output power, temperature at load resistance 160 ohm.

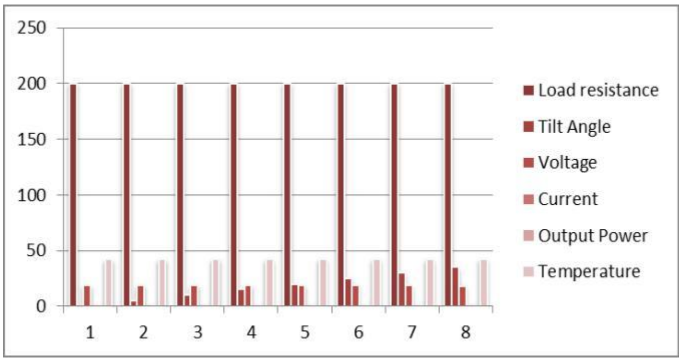

Figure 13. Voltage, current, output power, temperature at load resistance 180 ohm.

The dataset obtained after the experiment is fed into the MATLAB and RMSE values are estimated. The RMSE values gives the concentration of data around the line. Linear regression, fine tree, medium tree, coarse tree, robust linear, stepwise linear, fine tree, medium tree, coarse tree, linear SVM, Quadratic SVM, Cubic SVM, fine Gaussian SVM, medium gaussian SVM, ensemble boosted tree, GPR models are used and RMSE values are predicted. The dataset is split into trained and test data and model is trained and RMSE values are estimated. The 11 cross fold validation is used in the model and best fit algorithms is predicted.

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Model	RMSE
Linear regression	2.1868
Fine tree	0.8441
Medium tree	1.6363
Coarse tree	2.429
Interaction linear	0.86611
Robust linear	2.76
Stepwise linear	0.85335
Fine tree	0.8441
Medium tree	1.6363
Coarse tree	2.429
Linear SVM	0.7158
Quadratic SVM	0.37708
Cubic SVM	1.965
Fine Gaussian SVM	1.4519
Medium Gaussian SVM	2.4001
Coarse Gaussian SVM	2.4001
Ensemble boosted tree	2.0829
Ensemble bagged tree	1.6876
Squared Exponential GPR	0.23648
Matern 5/2 GPR	0.24775
Exponential GPR	0.4879
Rational Quadratic GPR	0.24753

Table 2. Estimated values for different models

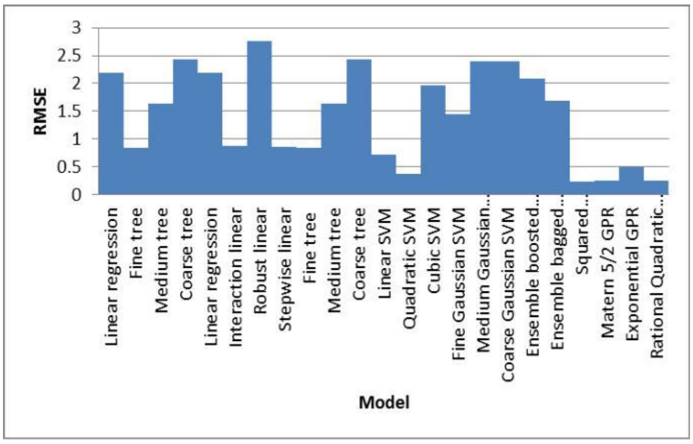

Fig 14: Models with RMSE

The assumptions of linear regression model is checked. This plot displays the response value on the y-axis and the voltage values on the x-axis.

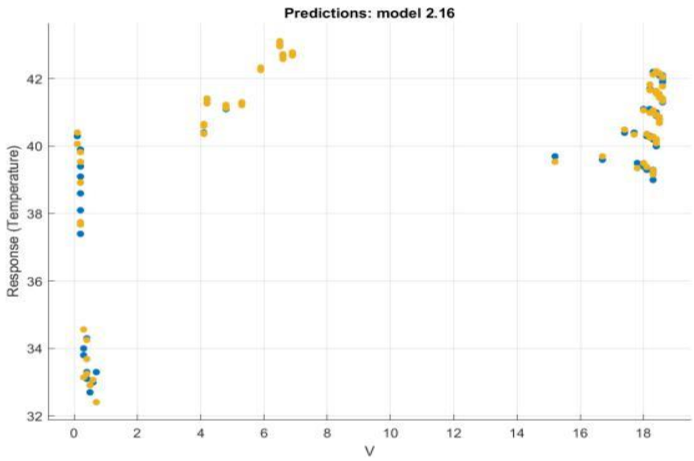

Figure 15: RESPONSE PLOT

A plot of residuals versus fits after a true response model was used on above said data. This plot of residuals versus fit shows the residual variance increases as the fitted values increases. This violates the assumption of constant variance.

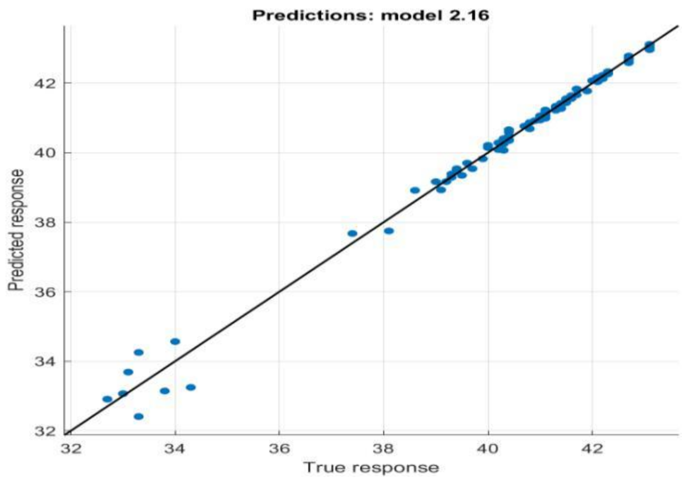

Figure16: PREDICTED PLOT

The plots below show how to validate the linear regression model's assumptions. This plot displays the residual value on the y-axis and the fitted values on the x-axis.

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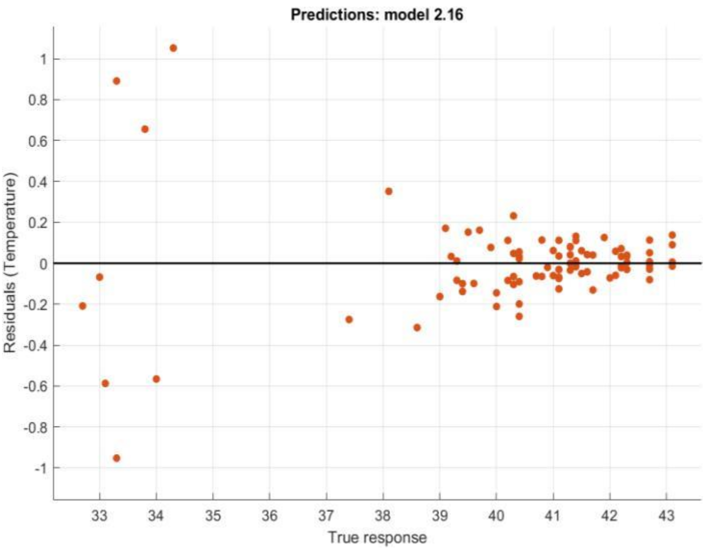

Figure17 :Residual Plot

6. Conclusion

A forecasting model based on the linear regression model algorithm was proposed to predict the amount of solar power produced by PV modules, after which the energy generation of PV modules was simulated to determine the optimal panel tilt angles. Each PV module's output changed, implying that the actual applied angles of these modules differed in efficiency. The total energy generation increased even further when the optimum angle of each PV module was measured and modified. Since the experiment was conducted on PV modules, we recognised the limitations of generalising our findings to different PV modules under various load conditions. In order to strengthen the generalisation of our approach, we expect to collect data on PV modules from various cities in the future. Furthermore, Incorporation on a variety of variables using a machine learning approach will be made.

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