Hour-Ahead Bivariate and Multivariate Solar PV Power Forecasting for Effective Grid Integration

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Abstract

For an effective grid integration of large-scale solar PV plants and their market participation, accurate power forecasting is very crucial. System operators use power forecasting to maintain power system security and reliability with economic energy dispatch. Machine learning models like Support Vector regression (SVR) are popularly used in short-term forecasting for better accuracy than other artificial intelligence (AI) models. However, SVR models need large amounts of data and involve very complex computations to achieve better accuracy. To address these problems, this research aims to develop an SVR model improved by integrating the non-linear least square Gauss-Newton method (SVR+GN) for hour-ahead solar PV power forecasting with a five-minute resolution. The performance of this model was verified in bivariate and multivariate modes by comparing the forecasting results with SVR, non-linear and persistence models on sunny, partly sunny and overcast days. To further verify the accuracy of SVR+GN, SVR, persistence and non-linear models, error evaluation parameters like Mean Absolute Percentage Error (MAPE), Mean Relative Error (MRE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were used. The improved SVR model needed fewer data and simpler computations for training and it achieved better accuracy even on overcast days. This is extremely useful for efficient grid integration and market participation of solar PV plants.

Keywords: Bivariate, Hour-ahead Forecasting, Multivariate, Power Forecasting, Solar PV, Solar Power Forecasting, Support Vector Regression (SVR)

1. Introduction

For system operators, accurate forecasting is of utmost importance for economic dispatch, power system planning and management to ensure power system reliability and security ((AEMO); Forecasting). Accurate forecasting helps solar PV plants to bid in the electricity markets and provide electricity with minimum curtailment and financial penalties. Power system operators use day-ahead electricity markets for unit commitments and economic electricity dispatch decisions. Hour-ahead electricity markets are mainly used for market clearing, precise dispatch for power system security and reliability, ancillary services and reserves procurement (Das et al., 2018; Ross Gillett, 2018). For effective grid integration and market participation, renewables like solar PV need accurate power forecasting.

Abundant research has been conducted in direct i.e. solar power forecasting and indirect i.e. solar irradiance forecasting with different time horizons. In the last decade, machine learning techniques like Support Vector Regression (SVR) are popularly used in short-term forecasting because of their high accuracy and less computational complexity. Various error parameters are used for these forecasting models to validate their performance. Alfadda et al confirmed that for hour-ahead solar PV power forecasting, the SVR model performs 2.6% better than the Lasso regression and linear regression forecasting models. Root Mean Square Error (RMSE) method is used for comparing the performance of these models (Alfadda et al., 2017). Performance of SVR and Random Forest (RF) models are verified in (Yen et al., 2018) using Mean Absolute Error (MAE), RMSE, Mean Forecast Error (MFE) and Mean Absolute Scaled Error (MASE). Using these error parameters, the authors observed that RF achieves 37 to 40% better accuracy than the SVR model. It was concluded from the results that RF tends to overestimate while SVM tends to underestimate the hour-ahead solar PV forecasting. (Guermoui et al., 2021) investigated incorporating SVR with least square methods to build hybrid models for 1 to 12 hours ahead solar forecasting and evaluated their performance using RMSE, relative RMSE (rRMSE), Mean Absolute Bias Error (MABE) and correlation coefficient (r). Results showed that using Artificial Bee Colony optimisation

doi:10.18086/swc.2021.17.02 Available at http://proceedings.ises.org

to solve least square equations in SVR can improve the accuracy of solar forecasting.

However, all these SVR and hybrid SVR models use a very large amount of data for training to achieve better accuracy and are computationally very complex. (Yen et al., 2018) also recommended that if more data is used for processing and training the model, it will help to further improve the accuracy of the models. To address these issues, this research aims to develop an SVR model improved by integrating the non-linear least square Gauss-Newton (GN) method for hour-ahead solar PV power forecasting with a five-minute resolution. The performance of the presented model is verified using the similar error parameters used in above mentioned research.

The organization of the rest of the paper is as follows. A review of solar PV power forecasting methods is presented in section 2. Section 3 provides a methodology of the SVR+GN model, residual monitoring and error parameters used for analysis. Results and error analysis are discussed in section 4. And finally, in section 5, the conclusions are summarized.

2. Solar PV Power Forecasting Methods

There are numerous methods present in the literature for forecasting. Depending on the type of the technique used for forecasting, the forecasting methods are mainly categorized into four types i.e. Physical, Statistical, Artificial Intelligence (AI) and Hybrid (Antonanzas et al., 2016; Das et al., 2018; Voyant et al., 2017; Wan et al., 2015). Configuration of forecasting methods depending on these four techniques is shown in Fig. 1.

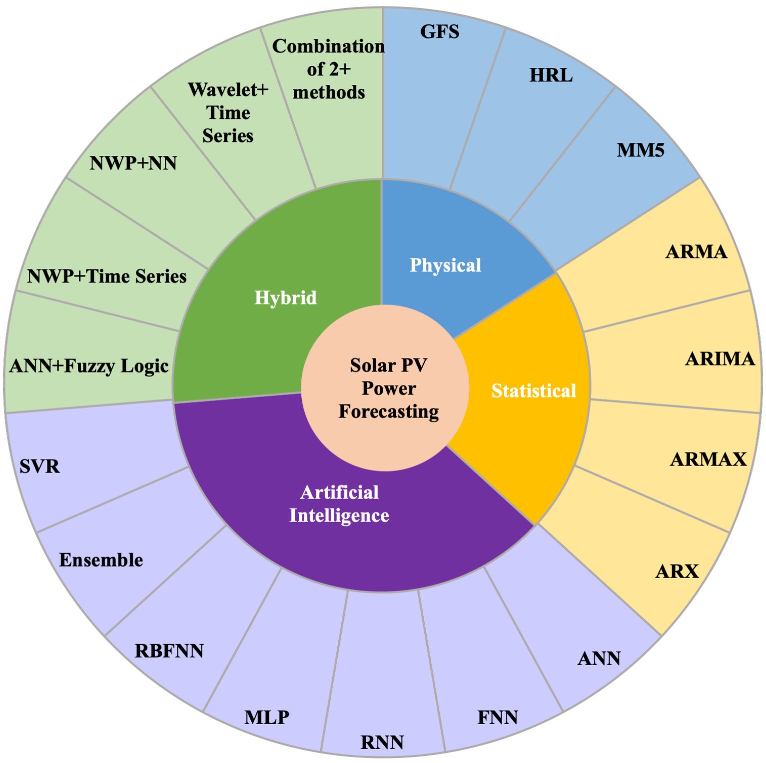


Fig. 1: Solar PV Power Forecasting Methods

Physical methods use numerical weather prediction (NWP) data along with PV plant characteristics like the location of the plant and orientation data to forecast solar irradiance and this forecast is then used to calculate solar PV power output. Physical methods may not need historical data for solar irradiance and power output of the PV plant but their accuracy is highly dependent on the quality of NWP data. Models like Global Forecast System (GFS), MM5 fall under this category and are used for forecasting solar irradiance to further calculate solar PV power.

Statistical methods use historical data of solar irradiance, NWP and power output to calculate the relation between these data to train the model and this model is then used with future NWP data to forecast PV output power. These methods are complex mathematical methods and to achieve higher forecasting accuracy, one has to compromise on pre-processing of large training data and complexity of these models. Methods based on time series analysis and regression analysis e.g. Auto-Regressive Moving Average (ARMA), Auto-Regressive Integrated Moving Average (ARIMA), Auto-Regressive Integrated Moving Average with Exogenous variable (ARMAX) and Auto-Regressive with Extra input (ARX) are the statistical methods.

AI methods like SVR, Artificial Neural Networks (ANN) are commonly used in solar forecasting. SVR is mostly popular because of its better accuracy than other AI methods (Antonanzas et al., 2016). Forecasting models using AI methods do not need PV plant characteristics data like physical methods and are easy to model.

In hybrid methods, either two or more statistical methods, statistical methods with physical methods, pre or post data processing with statistical or physical methods are used to improve the accuracy of the forecasting. However, all this complex processing results in higher computational cost, data processing time and requires a large amount of training data.

For hour-ahead forecasting, there is a need for a solar PV power forecasting model which requires less amount of data for training, has less computational complexity while providing better accuracy than the models using the above explained forecasting methods. To suffice this need, the SVR+GN model is proposed in this research. The methodology of this proposed model is described in detail in the section below.

3. Methodology of SVR+GN

The SVR+GN model was developed by integrating the non-linear least square Gauss-Newton (GN) method with a simple SVR method for hour-ahead solar PV power forecasting with a five-minute resolution. This model is roughly based on the previous work (Pawar et al., 2020). The SVR+GN model was further improved for hour-ahead power forecasting. Also, the training of the model was monitored to improve the accuracy. The SVR+GN model can be used to operate in both bivariate and multivariate modes. In bivariate form, only solar insolation and solar PV power output data were used to train and test the model. In multivariate mode along with solar insolation and solar PV power output, temperature and humidity data were also provided.

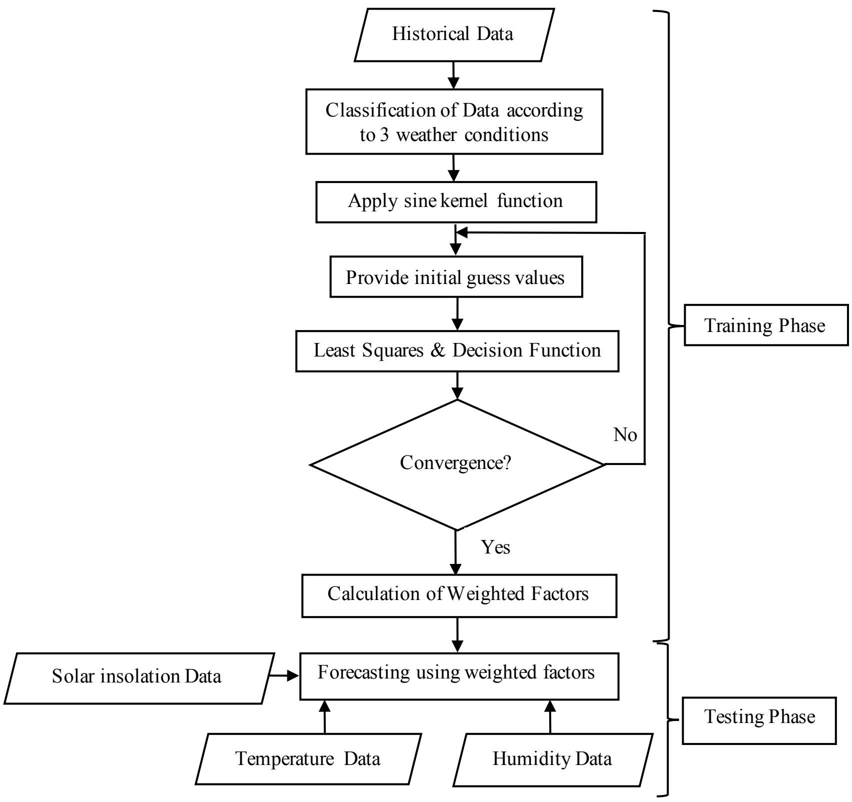


Fig. 2: Flowchart for Forecasting using the SVR+GN Method

As shown in the flowchart of the SVR+GN in Fig. 2, historical data of solar insolation, temperature, humidity and solar PV power output were provided to this proposed model during the training phase depending on its mode of operation. These data were then classified according to three different weather conditions i.e. sunny, partly cloudy and overcast using standard deviation calculated for daily solar insolation data using eq. 1.

$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}} \qquad \text{(eq. 1)}$$

σ is the standard deviation value, x_i denotes the data points, μ is the mean of the data and the total number of the data points on the day is denoted by N.

The standard deviation of the data provides the amount of variation in the data. The solar insolation tends to be steady on a sunny day while it varies with few peaks and troughs on a partly cloudy day. On an overcast day, the solar insolation data varies greatly with more peaks and troughs. Hence, according to the value of standard deviation for the solar insolation, the data were classified in three different weather conditions. For sunny weather, the standard deviation was in the lowest range from 1 to 9. The standard deviation ranging from 9 to 70 was considered for partly cloudy weather whereas, for overcast conditions, the standard deviation of 70 and above was used for classification as shown in Tab. 1.

Tab. 1: Classification of Data in Three Different Weather Conditions

Standard Deviation Value Range	**Weather Condition**
1 to 9	Sunny Day
9 to 70	Partly Cloudy Day
70 and above	Overcast Day

Next, the sine kernel function given in eq. 2 was used in the SVR+GN model instead of the radial basis function which is generally used in a simple SVR model.

$$f(x,t) = x_1 * \sin(x_2 * t + x_3) + x_4 \qquad \text{(eq. 2)}$$

Initial guess values for x_1, x_2, x_3 and x_4 in eq. 2 were provided to train the model using solar insolation, power output, temperature and humidity data. To solve the non-linear least squares problem, the Gauss-Newton method was used (Hartley, 1961; Heath, 2018). This method is known to find convergence in fewer than 12 steps. Once the solution was found the weighted factors for each data were calculated. These calculated weighted factors were then used in the testing phase to determine the solar PV power output using the data of solar insolation, temperature and humidity depending on the bivariate or multivariate mode of operation.

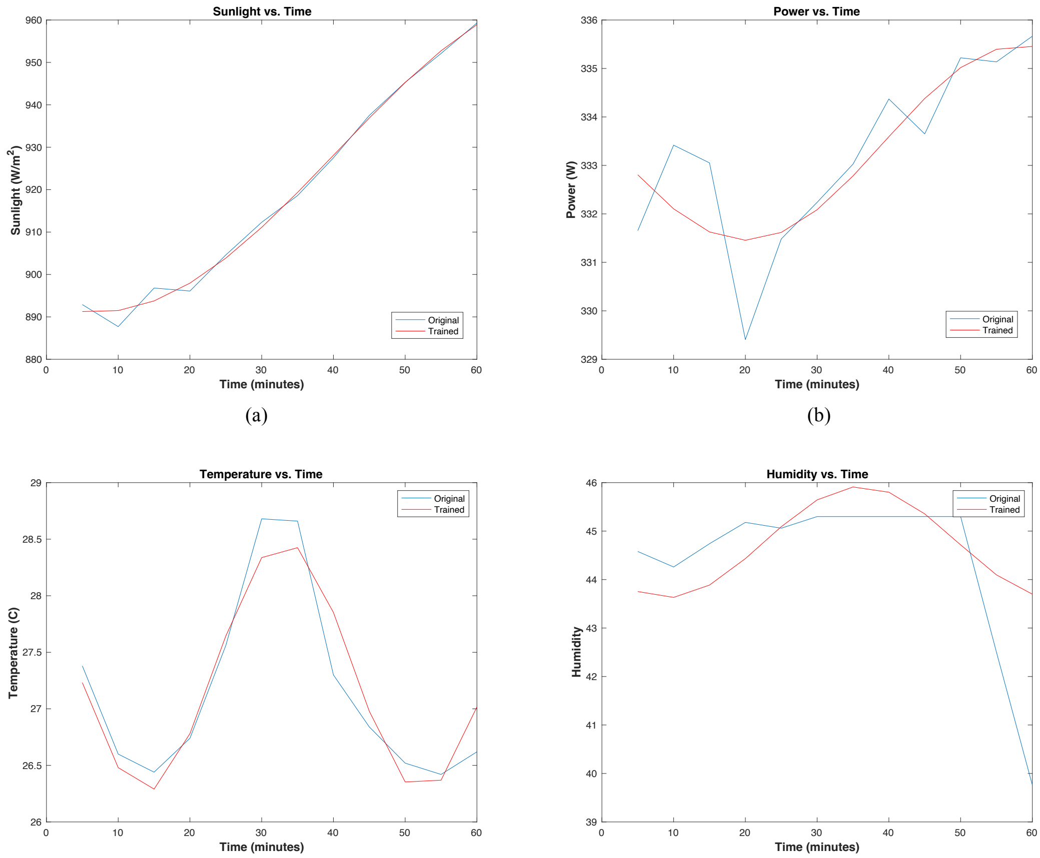
3.1. Residual Monitoring

Over-fitting and under-fitting of the data lead to lower accuracy. However, this was monitored in the training phase in the SVR+GN model using the residual function. The equation for the residual function is given in eq. 3 below.

$$r_i(x) = y_i - f(t_i, x) \qquad \text{(eq. 3)}$$

Where $i = 1, \ldots, m$; $r(x)$ is the residual values for data y i.e. the data provided to the model and $f(t,x)$ are the trained data values. To easily interpret the residual or how well the model was trained for given data, graphs of the input data and trained data were plotted. Random samples of these graphs are shown in Fig. 3. Blue curves in the graph represent original input data provided to the model during the training phase whereas red curves represent the trained values of that data.

As seen in the graphs below, if the data for sunlight, solar PV power, temperature and humidity are fluctuating over the period, data fitting in the training phase is also affected giving high residuals. This is mostly observed here in samples Fig. 3(b) and Fig. 3(d). This eventually adds up to the forecasting errors and the accuracy of the forecasting is greatly affected.



(a) (b) (c) (d)

Fig. 3: Graphs of Trained vs Original Input Data for (a) Sunlight, (b) Power, (c) Temperature and (d) Humidity

3.2. Forecasting Error Analysis

As the SVR+GN model used both SVR and the non-linear GN method, the forecasting results for the SVR+GN model were compared with simple SVR and non-linear models to verify whether the proposed model can improve the accuracy of these individual models. In short-term forecasting, generally, persistence forecast is used to compare the performance of forecasting methods, therefore, the persistence model was also used for comparison in this research.

The simple SVR model was developed using radial basis function kernel as shown below in eq. 4 where x_1, x_2 are the data points, $\| x_1 - x_2 \|$ is the Euclidean distance between data points x_1, x_2 and σ is the hyperparameter or the width of the kernel.

$$f(x_1, x_2) = e^{\frac{-||(x_1 - x_2)||^2}{2\sigma^2}} \quad \text{(eq. 4)}$$

For a non-linear model, a simple non-linear function shown in eq. 5 was used.

$$y = b_1 + b_2 * (x)^{b_3} \quad \text{(eq. 5)}$$

Where b_1, b_2, b_3 are coefficients whose values were provided in the algorithm, x is the matrix of the data set.

A persistence model is very simple and was developed as per eq. 6 given below. It considers that the value of forecasting at time t+1 will be equal to the value of the parameter at time t.

$$x_{t+1} = x_t \quad \text{(eq. 6)}$$

To further quantify and validate the performance of the SVR+GN model, error analysis of the forecasted power using SVR+GN, SVR, Non-linear and Persistence models was performed. Error parameters used in this research were Mean Absolute Percentage Error (MAPE), Mean Relative Error (MRE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Eq. 7 represents the formula for MAPE while formulae for MRE, RMSE and MAE are given in eq. 8, eq. 9 and eq. 10 respectively.

$$MAPE = \frac{1}{N}\sum_{I=1}^{N}\frac{|P_{estimated}-P_{actual}|}{P_{actual}} * 100\% \quad \text{(eq. 7)}$$

$$MRE = \frac{1}{N}\sum_{I=1}^{N}\frac{|P_{estimated}-P_{actual}|}{P_{installed}} * 100\% \quad \text{(eq. 8)}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_{estimated} - P_{actual})^2} \quad \text{(eq. 9)}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|P_{estimated} - P_{actual}| \quad \text{(eq. 10)}$$

Here, N is the number of measurements, P_{actual} is the original or actual power output of the solar PV plant, $P_{estimated}$ is the estimated power of solar PV plant using forecasting models and $P_{installed}$ is the total installed capacity of the solar PV plant.

3.3. Data for Forecasting

To verify the reliability and robustness of these models, the estimated power using all these models was compared with the actual output power of The University of Queensland, Australia (UQ)'s 2.3MW solar PV. A month-long data was used to train the SVR+GN model in the training phase. Whereas, three different weather days were used for model verification that was outside of the training phase data. Dataset used in this research comprised solar insolation, PV power output, temperature and humidity data for the UQ solar. The data were available for every minute of the day, however were averaged to five minutes for this research. Section 4 will present the results and discussion on the performance of the SVR+GN model using UQ solar PV data.

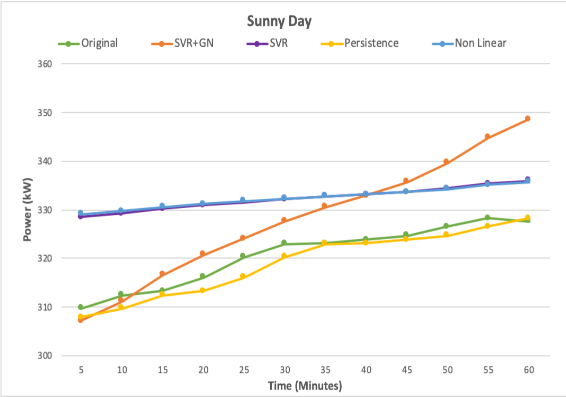
4. Results and Discussion

As discussed in section 3, an hour-ahead bivariate and multivariate solar PV power forecasting model (SVR+GN) was developed by integrating the SVR with Gauss-Newton (GN) method. Performance of SVR+GN, simple SVR, non-linear and persistence models was verified in three different weather conditions i.e. sunny, partly sunny and overcast days. This research focuses on solar PV power forecasting for the energy market participation of the solar plants. For the bidding purposes, every hour the solar plants need to provide an hour ahead forecast with five minutes resolution. Therefore, the solar PV power forecasting graphs are presented as a random sample of hourly forecasting with a five-minute resolution. Error analysis for the proposed model was performed using the formulae from section 3.2.

4.1. Bivariate Mode

In bivariate mode, the SVR+GN model was trained and tested using only solar irradiance and power output data. Fig. 4 shows hour ahead solar PV power forecasting using SVR+GN, SVR, persistence and non-linear models in a bivariate mode. From these graphs, it can be seen that the models perform differently in all three different weather conditions.

On a sunny day, the proposed SVR+GN model was able to perform better than the simple SVR and non-linear model. However, the persistence model performed better than the SVR+GN model in sunny weather. On the partly sunny day, the SVR+GN model did not seem to be performing up to the mark and the other three models in comparison seemed to perform better. However, on an overcast day, the SVR+GN model was able to perform better than SVR, non-linear as well as persistence model. It is clearly visible from the graph in Fig. 4(c) that the forecasted power of SVR+GN is closer to the original power while forecasted power using the non-linear model is the farthest and the forecasted power using persistence and SVR cannot keep up with the unpredictable cloudy weather.



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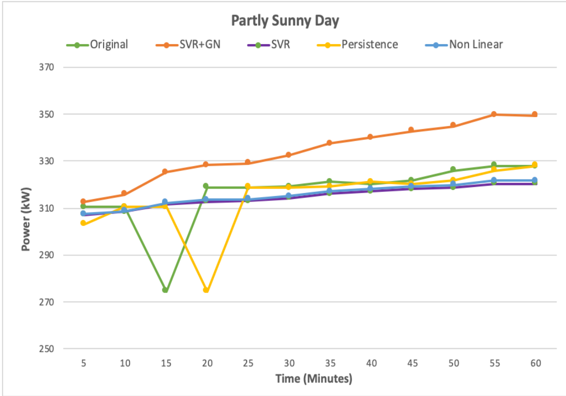

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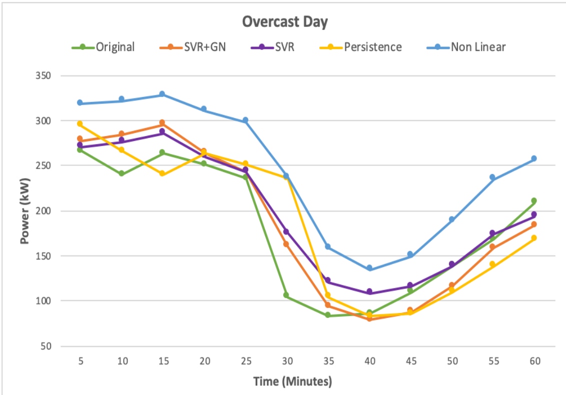

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Fig. 4: Bivariate Hour-ahead Solar PV Power Forecasting on (a) Sunny day, (b) Partly Sunny Day and (c) Overcast Day

To further verify the accuracy of SVR+GN, SVR, persistence and non-linear models, error evaluation parameters like MAPE, MRE, RMSE and MAE were used.

Tab. 2: Error Parameters for Bivariate Hour-ahead Solar PV Power Forecasting

Weather	Error Parameter	SVR+GN	SVR	Persistence	Non-Linear
Sunny Day	**MAPE**	2.52	3.64	0.55	3.68
	MRE	1.89	2.67	0.40	2.70
	RMSE	10.07	12.23	2.08	12.42
	MAE	8.19	11.59	1.75	11.71
Partly Sunny Day	**MAPE**	5.68	2.58	2.74	2.35
	MRE	4.05	1.79	1.90	1.62
	RMSE	21.16	11.92	16.65	11.73
	MAE	17.57	7.77	8.26	7.02
Overcast Day	**MAPE**	14.46	15.76	23.11	44.97
	MRE	5.07	4.59	7.40	15.04
	RMSE	26.57	27.87	44.82	69.36
	MAE	22.0	19.93	32.13	65.27

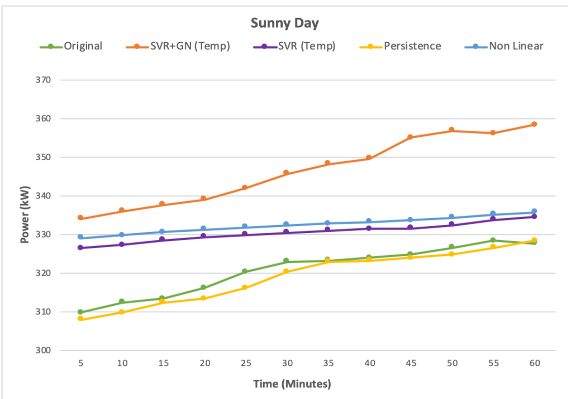
As shown in Tab. 2, the SVR+GN forecasted solar PV power output with higher accuracy on a sunny day than a partly cloudy and an overcast day in bivariate mode. In terms of MAPE, MRE and MAE, the values indicate that the SVR+GN model successfully achieved an accuracy of 97.48%, 98.11% and 91.81% respectively on a sunny day. The proposed SVR+GN model achieved better accuracy in comparison with SVR and non-linear models. However, the persistence model seemed to work better than the SVR+GN model on that day.

On a partly sunny day, the non-linear model was able to keep the error values at the lowest as compared to the SVR+GN, SVR and persistence models. In terms of MRE, the non-linear model achieved an accuracy of 98.38% whereas SVR+GN was able to forecast power output with 95.95% accuracy.

SVR+GN model achieved the best results on an overcast day. Generally, this type of weather makes it difficult for forecasting models to perform with higher accuracy. Nevertheless, the proposed model effectively achieved higher accuracy than the SVR, non-linear and persistence models. To calculate RMSE, the difference between original and forecasted solar PV power values is squared and hence, it has high values when the forecasted value is not in a near range of the original power output value. On an overcast day, SVR+GN was able to keep RMSE value half of that of the persistence model and one-third of that of the non-linear model. Therefore, it is proved that the SVR+GN model provides better forecasting than SVR and non-linear models on a sunny day. Additionally, the proposed model forecasts more accurately than the SVR, non-linear and persistence models on an overcast day in bivariate form.

4.2. Multivariate Mode

The training and testing of the SVR+GN model were executed using temperature and humidity data along with solar irradiance and power output data in multivariate mode.



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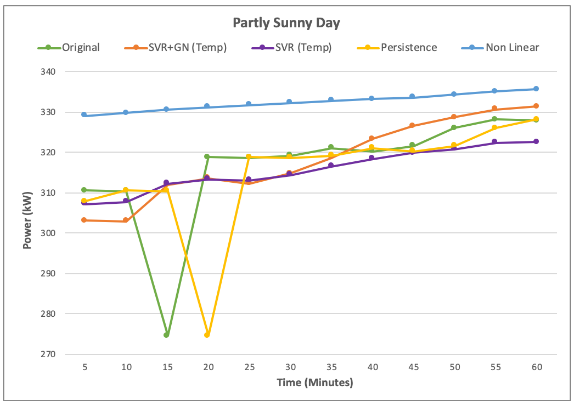

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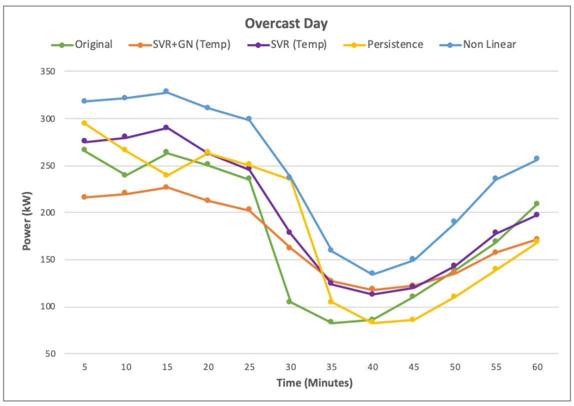

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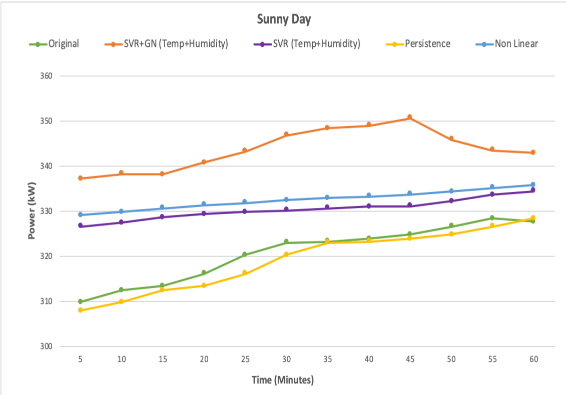
Fig. 5: Multivariate (with Temperature) Hour-ahead Solar PV Power Forecasting on (a) Sunny day, (b) Partly Sunny Day and (c) Overcast Day

Fig. 5 shows the solar PV power forecasting graphs in multivariate mode using temperature data. This introduction of new data in the training and testing phase had significantly affected the forecasting accuracy of the SVR+GN model. It can be seen that the performance of the SVR+GN model was lower than that of the other three models on a sunny day. However, the SVR+GN model was able to recover its performance on a partly sunny and overcast day. Graphs in Fig. 5(b) and Fig. 5(c) depict the forecasted power by the SVR+GN model was very close to the original power values as compared to the forecasted power by SVR, persistence and non-linear models.

Further, in the multivariate mode, the humidity data was also introduced along with solar insolation, power output and temperature data. The performance of all the models against the original power output of the UQ's solar PV plant is shown in Fig. 6.



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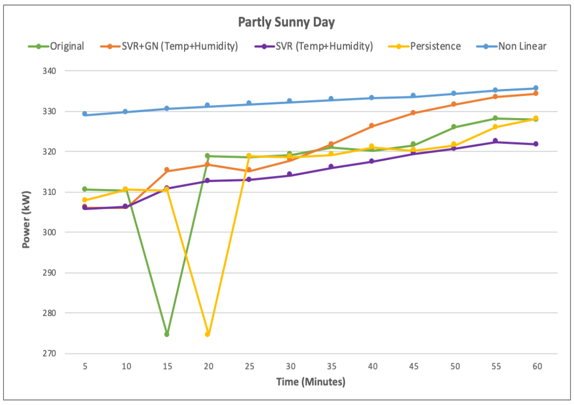

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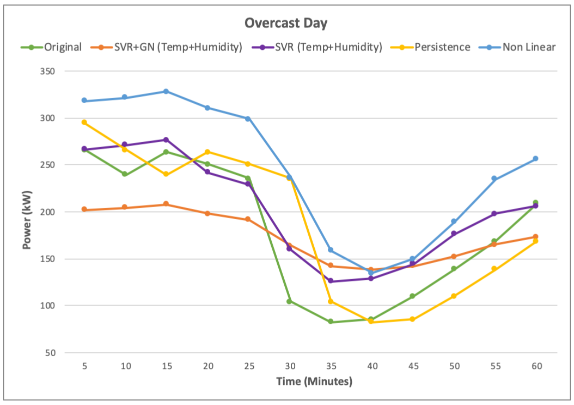

(c)

Fig. 6: Multivariate (with Temperature and Humidity) Hour-ahead Solar PV Power Forecasting on (a) Sunny day, (b) Partly Sunny Day and (c) Overcast Day

On a sunny day, the performance of the SVR+GN model was lower, however again it was able to perform better on a partly sunny and overcast day. Changes in the performance of SVR+GN and SVR models depending on the training data are evidently visible in Fig. 4, Fig. 5 and Fig. 6.

Generally, the solar PV power output is directly dependent on the solar insolation received by that PV. Though, temperature and humidity affect the solar PV power output; temperature and humidity does not affect the solar PV power output to a great extent. Solar insolation plays the main part in the solar PV power output. Interestingly, the performance of the SVR+GN model degraded as the data on which the solar PV output is less dependable like temperature and humidity data was added. However, the performance of the simple SVR model got better as the input data for the forecasting model were extended. Providing more data in the training phase for the SVR model did improve the accuracy of the forecasting. Whereas, the proposed SVR+GN model performed better and provided better accuracy in its bivariate form where no additional data or long data were needed in the training and testing phase.

Error Parameters for multivariate hour-ahead solar PV power forecasting are given in Tab. 3. The error parameters for SVR+GN and simple SVR models were calculated separately for temperature and temperature+humidity data. Notably, the values for MAPE on a sunny day for SVR+GN were increased by more than three times when the temperature data was added in training and testing the model. Whereas, MAPE for the SVR model with both temperature and temperature+humidity data were lowered than that in bivariate mode.

Tab. 3: Error Parameters for Multivariate Hour-ahead Solar PV Power Forecasting

Weather	Error Parameter	SVR+GN		SVR		Persistence	Non-Linear
		Temperature	Temperature +Humidity	Temperature	Temperature +Humidity		
Sunny Day	MAPE	8.03	7.17	3.07	3.02	0.55	3.68
	MRE	5.94	5.28	2.25	2.21	0.40	2.70
	RMSE	25.97	23.27	10.49	10.41	2.08	12.42
	MAE	25.78	22.93	9.76	9.59	1.75	11.71
Partly Sunny Day	MAPE	2.45	2.47	2.35	2.48	2.74	2.35
	MRE	1.68	1.71	1.62	1.71	1.90	1.62
	RMSE	11.80	12.60	11.69	11.50	16.65	11.73
	MAE	7.30	7.35	7.02	7.43	8.26	7.02
Overcast Day	MAPE	21.17	29.05	17.84	21.43	23.11	44.97
	MRE	7.22	9.76	5.28	5.87	7.40	15.04
	RMSE	35.11	46.13	29.98	31.02	44.82	69.36
	MAE	31.35	42.34	22.90	25.47	32.13	65.27

The SVR+GN model outperformed the persistence and non-linear model on a partly sunny day in terms of MAPE, MRE, RMSE and MAE. Moreover, if the proposed model is compared with the simple SVR model, their error values were mostly similar with a negligible difference.

On the erratic overcast day, all these models seemed to fail in the performance and their accuracy was highly affected as evident in their high values for all error parameters.

5. Conclusion

Accurate solar PV power forecasting is essential for the effective integration and participation of large-scale solar PV plants in the electricity markets. The hour-ahead forecasting is mainly used for market clearing and precise power dispatch. For this purpose, a robust forecasting model is required which can provide accurate solar PV power forecasting in different weather conditions which requires less training data, is quickly learning and computationally simple.

The SVR+GN model presented in this paper has proven to be computationally simple, quick learning and performs well even with less training data. The performance of this model was tested in both bivariate and multivariate modes. The proposed model was compared with simple SVR, non-linear and persistence models and the SVR+GN model outperformed simple SVR and non-linear models. In the multivariate mode, the SVR+GN model had higher accuracy than all other models it was compared with on a partly sunny day. This model proved its robustness with lower error parameters like MAPE, MAE, MRSE and MRE. Moreover, the SVR+GN model gave the best performance on the unreliable overcast day when all models failed to provide accurate forecasting.

To further improve the accuracy of power forecasting, the SVR and other machine learning models need more data to train. In contrast, the presented SVR+GN model performed much better in simple bivariate form. This model has even further potential to improve its forecasting accuracy by monitoring the residual between actual and trained data.

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