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A Case Study of Using Long Short-Term Memory (LSTM) Algorithm in Solar Photovoltaic Power Forecasting

L.C. Kho[1*], S.S. Ngu[1], J. Annie[1], S.K. Sahari[1], K. Kipli[1] and R. Rulaningtyas[2]

[1]*Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak, Malaysia.*

[2]*Physics Department, Faculty of Science and Technology, Universitas Airlangga, Jawa Timur, 60115 Indonesia*

Solar photovoltaic power plays an important role in distributed energy resources. The number of solar-powered electricity generation has increased steadily in recent years all over the world. This happens because it produces clean energy, and solar photovoltaic technology is continuously developing. One of the challenges in solar photovoltaic is that power generation is highly dependent on the dynamic changes of environmental parameters and asset operating conditions. Solar power forecasting can be a possible solution to maximise the electricity generation capability of the solar photovoltaic system. This study implements the deep learning method, long short-term memory (LSTM) models for time series forecasting in solar photovoltaic power generation forecasting. The data set collected by The Ravina Project from 2010 to 2014 is used as the training data in the simulations. The root mean square value is used in this study to measure the forecasting error. The results show that the deep learning algorithm provides reliable forecasting results.

Keywords: renewable energy; solar power forecasting; deep learning algorithm; time series prediction

I. INTRODUCTION

The global trend of energy sources has shifted towards renewable energy in the last few decades. It has driven the development of solar photovoltaic technology. The production cost of electricity from solar photovoltaic dropped significantly while the energy conversion efficiency has increased. This makes solar photovoltaic energy an alternative energy source in many countries. However, the solar photovoltaic system poses a significant limitation, which is the uncertainty of power generation. It depends heavily on weather conditions such as solar irradiance, cloud cover, wind velocity, etc (Rana *et al.*, 2016). This affects the quality of the connected electrical system. Thus, solar power forecasting plays a vital role in solar photovoltaic plant installation, process, and reliability of solar power transfer. To accomplish a high penetration of commercial solar power into the grid, practical power forecasting approaches should be developed for the electric grid by integrating solar power. The current research on the electrical grid mainly focuses on the safety and reliability of distributing power from generation sources by advanced monitoring and control of transmission lines to the distribution lines. This encouraged the performance monitoring and control of the photovoltaic system processes.

Solar power generation reliability, stability, and planning strongly depend on the accuracy of power forecasting. It provides essential information to the electricity providers and independent system operators to reduce the uncertainty of solar power generation. To achieve the high accuracy of power forecast in solar power generation, information such as weather records, solar irradiance, and solar power generation monitoring data must be provided by the forecasting system (Fan *et al.*, 2021). The dynamic change of

*Corresponding author's e-mail: lckho@unimas.my

weather parameters and cloud cover are the critical factors of forecasting accuracy for the day-ahead forecast. Another issue that affects solar power forecasting accuracy is the irradiance values.

The mathematical approach has been used widely to forecast solar power generation. The techniques can be classified into two: persistence models and statistical methods. Unluckily, these techniques have low forecasting accuracy and do not work correctly when non-linear data is applied. To reduce the limitation, machine learning and metaheuristic techniques have been applied in forecasting. Machine learning can handle problems that are unsolvable by an explicit algorithm. It can develop a relationship between inputs and outputs without concerning their representation (Akhter *et al.*, 2019). This makes it suitable to be used for forecasting. The machine learning techniques commonly used in solar power forecasting can be classified into three; numerical/statistical, physical, and hybrid. Machine learning, such as artificial neural networks, extreme learning machines, and support vector machines, are classified under statistical techniques. It extracts information from historical data to forecast time series. Meanwhile, physical techniques like numerical weather prediction, satellite/remote sensing, and sky model depend on the physical state and dynamic motion. The hybrid techniques involve a combination of both statistical and physical.

There is another subset of machine learning techniques called deep learning. It is the next evolution of machine learning. Deep learning algorithms are eventually inspired by the pattern of information processing found in the human brain. It works like our brain to classify different types of information and identify the pattern of the information. Deep learning uses the training loop to learn and accomplish the same tasks. It also deciphers the information received, just like the human brain, by transferring and classifying the items into various groups. Deep learning has shown the strengths of representation learning and time series in forecasting research lately. It delivers good results for real-time prediction, particularly for learning from the dynamic changes in environmental conditions. It provides better accuracy forecasting results. Thus, it motivates the researchers to study the deep learning algorithm, especially in solar power forecasting. This paper aims to investigate the performance of a deep learning algorithm, the LSTM when applied in solar power generation.

The paper is organised as follows: Section II reviews the literature containing solar power forecasting methods that use machine learning and deep learning. Section III discusses the methodology for this research. LSTM is adapted for solar photovoltaic power forecasting, and the simulations are performed using MATLAB. The data set from the Ravina Project is used for this study. Section IV presents the result and discussion. The conclusion is written in the final sections.

II. RELATED WORK

Solar power forecasting is not a new research topic. A good survey of solar power forecasting paper can be found in (Inman *et al.*, 2013). Ferrero Bermejo *et al.* (2019), Foley *et al.* (2012), Giebel *et al.* (2011), and Lei *et al.* (2009) wrote review papers that cover other types of renewable energy power forecasting. Various forecasting techniques have been introduced. They can be grouped into short-term techniques, which are covered by Costa *et al.* (2008), mid-term techniques by Mirasgedis *et al.* (2006), and long-term techniques by Hong *et al.* (2014).

Machine learning is a popular technique for forecasting tasks. It was integrated with other mathematical prediction models for solar power forecasting. For example, the numerical weather prediction (NWP) technique was used together with machine learning by Li *et al.* (2016) to forecast the cumulative sum of solar power generation for the places separated by the geographic cluster. The results showed an improvement in the accuracy of forecasting compared with the existing technique. The fuzzy inference method was used by Yang *et al.* (2014) to select an adequately trained model; meanwhile, machine learning techniques such as self-organising map, learning vector quantisation, and support vector regression (SVR) were used for data classification, learning, and training, respectively. These works presented better results than artificial neural networks and simple SVR techniques. The genetic algorithm was used for bulk and threshold optimised by Luo *et al.* (2017) to overcome an over-appropriate scene of extreme learning machine (ELM) due to the random generation. The forecasting results were acquired from the training of neural networks on local meteorological data. The forecasting structure design here was simple and solves inherent defects in the artificial neural network. Besides, Malvoni *et al.* (2017) examined the data process skills by a hybrid prediction model called group least-square support-vector machine (GLSSVM). This model was integrated by the group method of data handling and the least-square support-vector machine technique. The results showed that the data-driven prediction technique combined with the pre-processing data methods could increase the prediction level.

Several studies on applications of deep learning in power forecasting were done. The convolution neural network (CNN) and LSTM were used by Lee *et al.* (2018) to develop the time series data in deep learning. CNN was applied to extract short-time local features, while the LSTM was used for the long-time feature. The deep belief network (DBN) and non-linear kernel-based parallel evolutional approach are proposed by (Jiang *et al.*, 2016) to forecast the evolution of the compound system in a grouping way. The DBN can routinely study and snap effective non-linear features for system evolutions without past knowledge. The proposed approach provides better performance than a support vector machine (SVM) and can provide intelligent choice support tools for accurate prediction. Lastly, Chang and Lu (2020) integrated the DBN with the grey theory-based data preprocessor. Five forecasting methods have been used here to obtain the test results, which are autoregressive integrated moving average model (ARIMA), back propagation neural network, radial function neural network, SVR and DBN. These models showed that forecasting accuracy is suitable for a day solar power output prediction.

Many machine learning and deep learning techniques for solar power forecasting have been discussed in this paper. Tables 1 and 2 show the commonly used machine learning and deep learning in solar power forecasting.

Tables 1 and 2 clearly show that machine learning is used mainly for short-term forecasting; meanwhile, deep learning can be applied to achieve long-term forecasting. Deep learning is proposed to overcome the problem that machine learning faces, which is the long-term dependency problem. A bigger dataset can be trained in deep learning to achieve long-term forecasting. This also helps to reduce the forecasting error rate.

Table 1. Machine Learning Forecasting Technique

No.	Machine Learning Technique	Forecasting Range
1	NWP	2 days (Li *et al.*, 2016)
2	Fuzzy Inference	1 day (Yang *et al.*, 2014)
3	GLSSVM	1 day (Malvoni *et al.*,2017)
4	Genetic Algorithm	Daily (Luo *et al.*, 2017)
5	Weight Varying Ensemble	5 minutes (Luyao L. *et al*, 2019)
6	Probabilistic Forecasting	5 minutes (Zhang, W. *et al,* 2017)

Table 2. Deep Learning Forecasting Technique

No.	Deep Learning Technique	Forecasting Range
1	Multi-site PV forecasting	1 year (Lee J. I. *et al*., 2017)
2	Bayesian Approach	1 year (Obane H. *et al*., 2017)
3	Time Series Prediction	1 year (Jiang P. *et al*, 2016)
4	DBN	1 year (Jiang *et al*., 2016)
5	Deep Recurrent Neural Network	1 day or month (Alzahraniet A. *et al*, 2017)
6	Auto LSTM	Monthly forecast (Zaouali K. *et al*, 2018)

III. METHODOLOGY

In this study, the LSTM network is used for solar power forecasting. This technique is formed from the recurrent neural network. Unlike the usual multilayer perception in the artificial neural network, the recurrent neural network uses temporal information of input data via the recurrent connection between the neurons. An example of LSTM cell is shown in Figure 1, where F_t is the forget gate, $\overline{C_t}$ is the candidate layer, I_t is the input gate, O_t is the output gate, h_t is current cell output, h_{t-1} is the previous cell output, C_t is current cell memory, C_{t-1} is the previous cell memory, and X_t is the input vector.

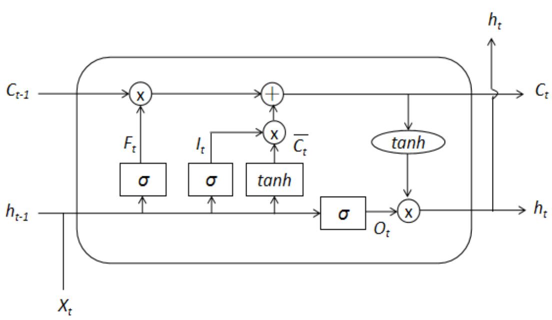

Figure 1. LSTM cell applied in PV forecasting.

The LSTM solar power forecasting will first decide the type of information to be removed from the cell state. This decision is made in the forget gate layer. For example, the previous data will be kept in the cell if an LSTM power forecasting wants to forecast the next solar power generation. However, the previous data will be forgotten when a new solar power forecasting result is viewed. The new information is usually stored in the cell state to be updated or added on. The decision is done by a sigmoid layer called the forget gate layer, F_t. With the current memory state, C_t, the new memory state will be calculated from the input state, I_t, and the candidate layer, $\overline{C}_t$. In this paper, new data on PV power is added to the cell state to remove and replace the forgotten data. The equation for C_t is shown below:

$$C_t = F_t \times C_{t-1} + I_t \times C_t \tag{1}$$

Lastly, the output will need to be decided by the LSTM cell. The sigmoid layer must first run and decide the parts of the cell state that are going to be the output. So, the data sent through the *tanh* layer needs to be multiplied with the output of gate O_t. The equation for cell output h_t can be found using the equation shown below:

$$h_t = O_t \times \tanh(C_t) \tag{2}$$

MATLAB is used to simulate the results. The time series prediction of the LSTM algorithm has been written in MATLAB code. The data set of solar power generation from The Ravina Project is used as a benchmark here. The Ravina Project is a privately funded green energy research project in Toronto, Canada, at 43.68 N and 79.34 W. The annual hourly PV data for this project is complete and available to the public.

The root mean square error (RMSE), is used to evaluate the performance of the time series LSTM.

$$RMSE = \sqrt{\frac{1}{N}\sum_{n-1}^{N}(x_n' - x_n)^2} \tag{3}$$

where x_n and x_n' is the forecasted and actual values respectively. The N is the size of the testing data set. Besides, the regression graph is used to measure how close the data is compared to the fitted regression line.

The schematic block of the proposed solar power forecasting model is shown in Figure 2.

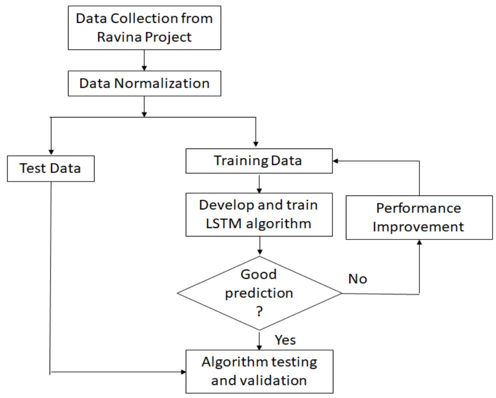

Figure 2. Schematic block of the proposed solar power forecasting model.

IV. RESULT AND DISCUSSION

In the simulation, 5 data sets are used. The first data set consists of the daily power output of the year 2010. The second data set consists of 720 days of power output from 2010 and 2011. The 3rd, 4th, and 5th data sets are the accumulative daily power output from 2010 to 2012, 2010 to 2013, and 2010 to 2014 respectively. The model is trained using the training set, and their training errors are calculated after each training iteration.

The results of trained data and test data for the data sets 1 to 5 are shown in Figures 3, 4, 5, 6, and 7 respectively. The results are shown in Table 3.

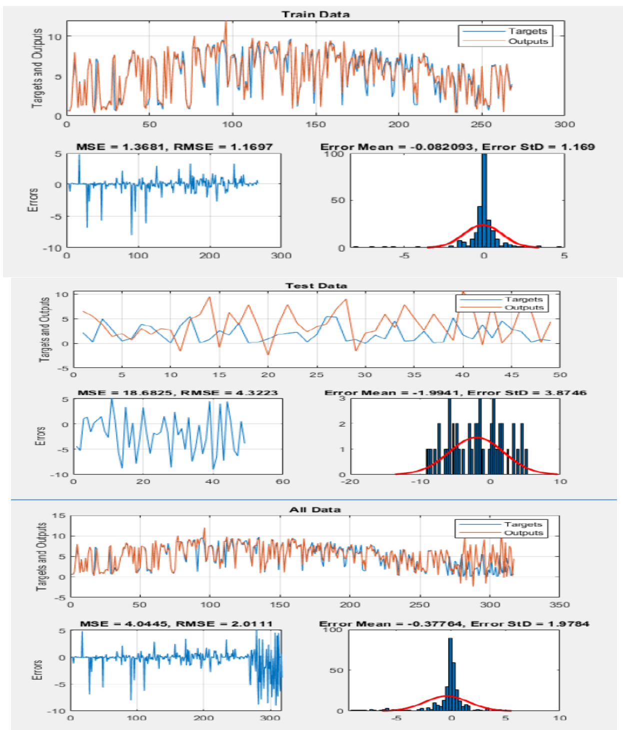

Figure 3. Results of trained data, test data, and all data for data set 1.

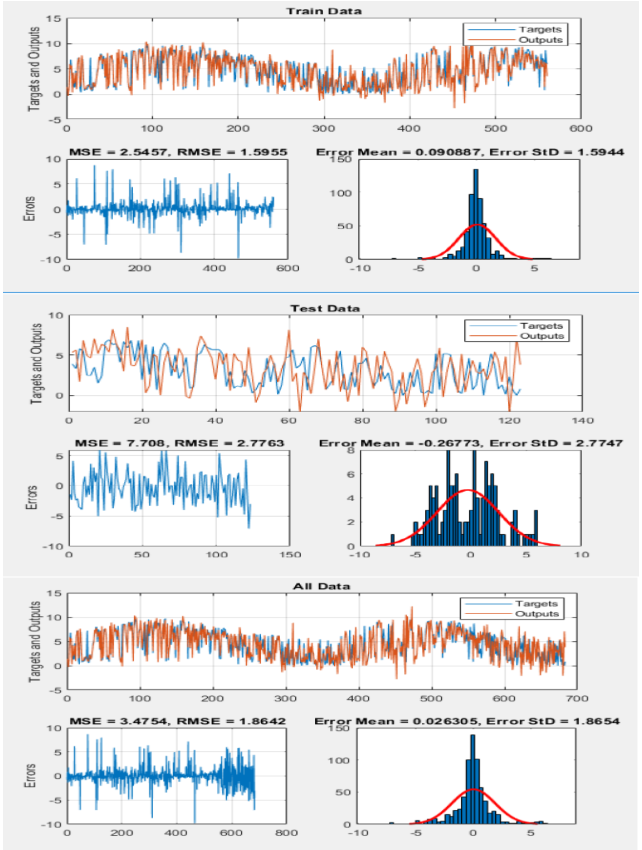

Figure 4. Results of trained data, test data, and all data for data set 2.

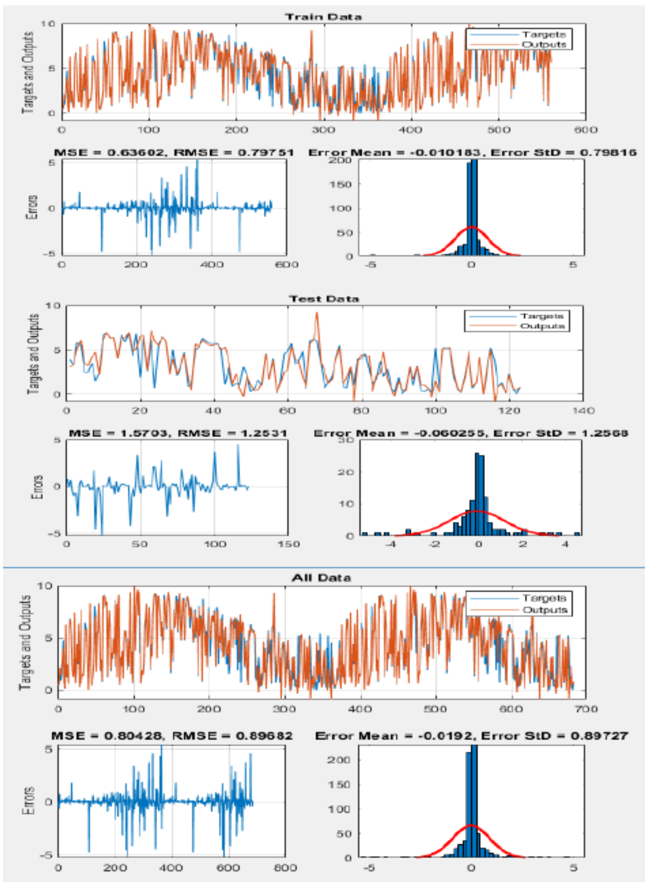

Figure 5. Results of trained data, test data, and all data for data set 3.

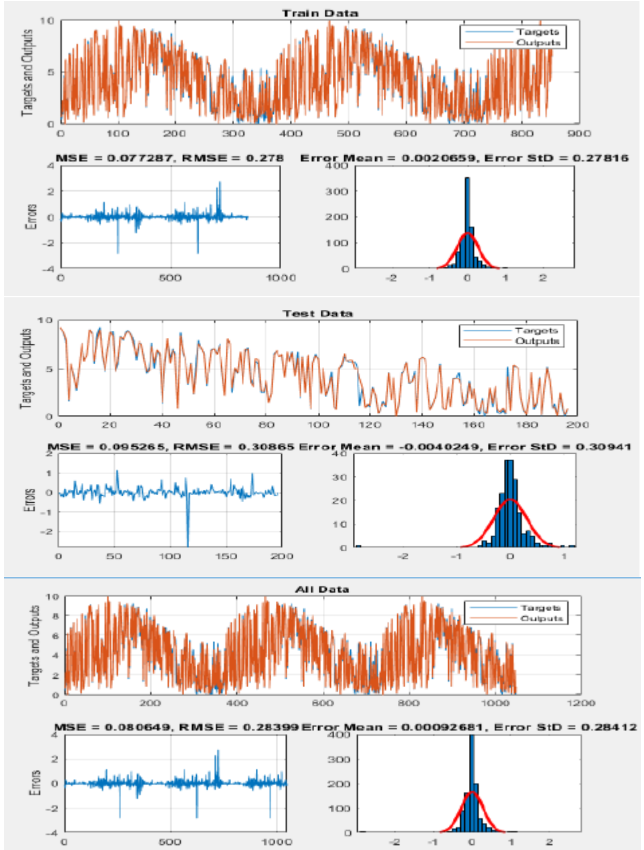

Figure 6. Results of trained data, test data, and all data for data set 4.

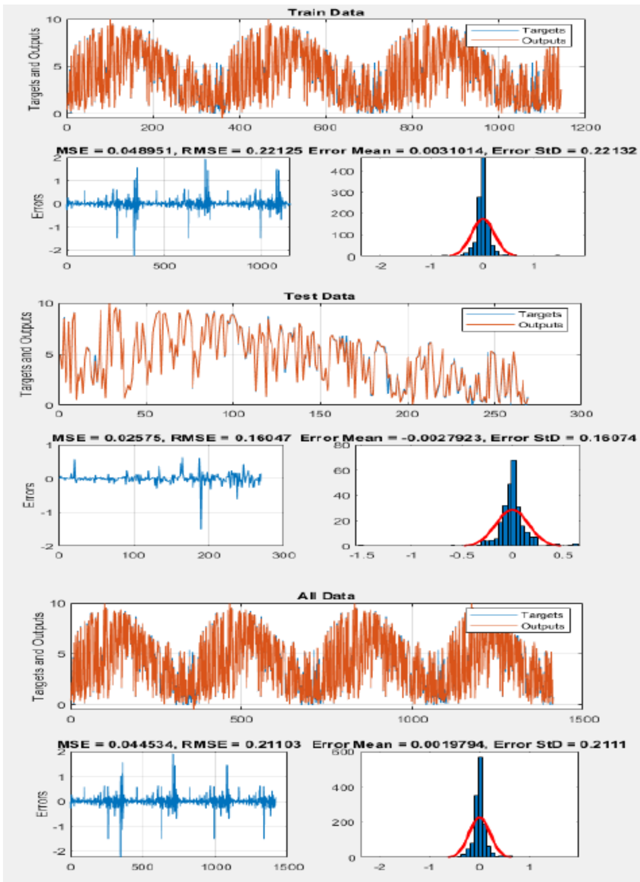

Figure 7. Results of trained data, test data, and all data for data set 5.

Table 3. Summarisation of the output training data

Data Set	Data Type	RMSE	Error Mean	Error Standard
1	Training	1.1697	-0.082093	1.169
	Test	4.3223	-1.9941	3.8746
	Overall	2.0111	-0.97764	1.9784
2	Training	1.5955	0.090887	1.5944
	Test	2.7763	-0.26773	2.774
	Overall	1.8642	-0.026305	1.8654
3	Training	0.79751	-0.010183	0.79816
	Test	1.2531	-0.060255	1.2568
	Overall	0.89682	-0.0192	0.89727
4	Training	0.278	0.0020659	0.27816
	Test	0.30865	-0.0040249	0.30941
	Overall	0.28399	0.00092681	0.28412
5	Training	0.22125	0.0031304	0.00132
	Test	0.16047	-0.0027923	0.16074
	Overall	0.21103	0.0019794	0.2111

The overall results show that the RMSE value drops when more information is provided in the model. This means LSTM can be trained for a long period with a large data set. It can store the previous information and give more accurate forecasting results. These results are comparable to the results by F. Harrou *et al.*, 2022 using a similar approach, which showed an approximate RMSE of 0.2 when the number of epochs is 60.

The linear regression graph for dataset 1 to 5 are shown in Figure 8 to Figure 12, respectively.

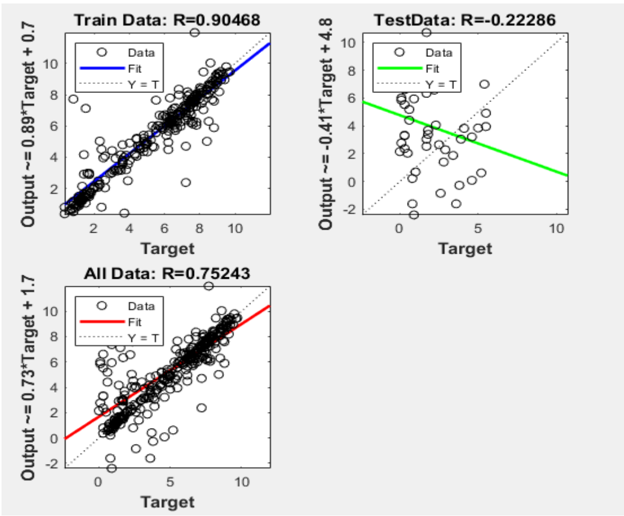

Figure 8. Linear regression graph for data set 1.

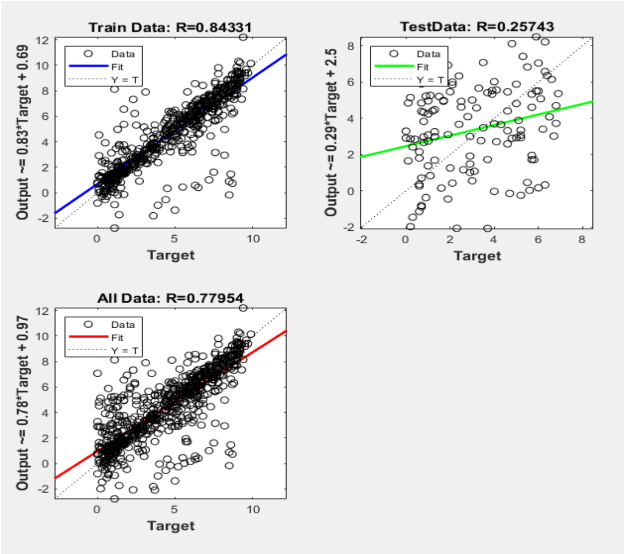

Figure 9. Linear regression graph for data set 2.

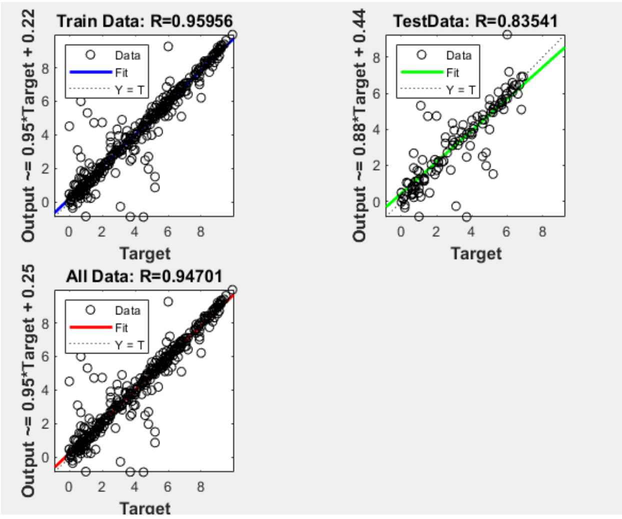

Figure 10. Linear regression graph for data set 3.

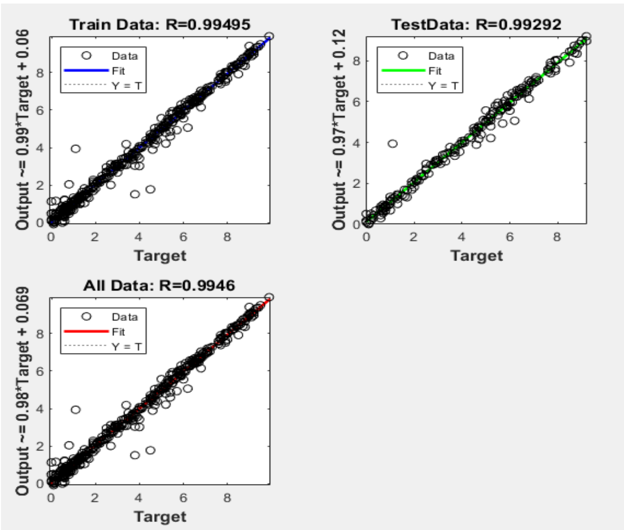

Figure 11. Linear regression graph for data set 4.

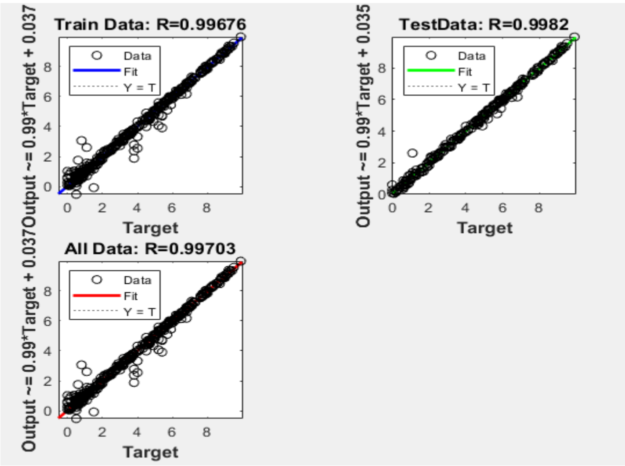

Figure 12. Linear regression graph for data set 5.

The R-value increased from data set 1 to 5. Thus, data set 5 provides the best forecasting model for solar power generation. Compared to data set 1, which only contains data obtained in 2010, data set 5 contains data accumulated from 2010 to 2015. It shows that when LSTM is trained with more data sets, R-value will be improved, thus providing a more accurate foresting result.

V. CONCLUSION

The results demonstrate that LSTM can be trained by providing a huge data set to provide better accuracy. This model can be used for long-term forecasting as well as for short-term forecasting for solar power generation. This information helps the energy provider in managing the electric supply generated by the solar power source to the grid system. The R-value, equivalent to 1 in the data set 5, shows that LSTM can provide reliable forecasting of solar photovoltaic power.

VI. ACKNOWLEDGEMENT

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