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APPLICATION OF MACHINE LEARNING/ARTIFICIAL INTELLIGENT (AI) TECHNIQUE TO PREDICT THE PERFORMANCE OF SOLAR PV PLANTS

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ABSTRACT

The widespread use of solar energy in the global power grid has facilitated the urgent need for accurate solar energy prediction models to minimise the negative impacts of photovoltaics (PV) on electricity and energy systems. In this paper, the proposed prediction is based on real meteorological data series of Monash University for the year 2019. The data consists of previously measured weather data and PV power generation data that are used as inputs to predict the future PV power generation. The proposed model was a simplified or vanilla Long Short-Term Memory (LSTM) network. Additionally, an Artificial Neural Network (ANN) was also developed to act as a benchmark model for comparison purposes. Solar irradiation and module temperature have been used as input features to both models. Only four months' worth of data were studied, and a set of the proposed and benchmark model were created for each of the four months. Through various optimisation processes such as data processing, model fitting, hyperparameters tuning and metric evaluation, the results show that the proposed simplified LSTM model outperforms the ANN model. The simplified LSTM model for each of the months studied displays a better ability to respond to fluctuations and follows the trend of the actual power generation signal more closely. The average nRMSE, nMAE and R^2 of the proposed LSTM for the four months are 0.0980, 0.0041 and 0.8546 respectively. Overall, the proposed method is expected to contribute to stable power system operation.

1. INTRODUCTION

In the last two decades, power production from renewable energy sources has spread around the world due to the ever-growing demand for electricity and the necessity to progressively phase out from conventional power generation methods, mainly involving natural gas and coal. It is estimated that renewable power capacity globally will expand by 50% between 2019 and 2024, led by solar PV. Solar PV alone accounts for about 60% of the anticipated growth [1]. On average the solar radiation intensity on the Earth's surface is 1367 W/m^2 and the total global absorption of this electromagnetic energy is roughly 1.8 x 10^{11} MW [2]. In simple terms, this is sufficient to meet all power requirements worldwide and the main advantage is that it is considered to be limitless in nature.

Despite it being a competitive and viable alternative to fossil fuels, there remains strong barriers for integration of solar PV with the grid due to the high level of uncertainty and variability associated with it. PV output greatly depends on weather conditions that are by nature highly uncertain and dynamic. The weather parameters include solar irradiance, air temperature, cloud variation, wind speed, relative humidity, etc [3]. To this day no model has been able to precisely predict their time evolution since their dynamics have not been modelled exhaustively yet. There is therefore a significant demand for reliable and accurate forecasting methods.

A forecasting model that is relatively accurate has various advantages such as planning and set-up of solar plant, managing distribution networks and power reserve, and ensuring grid stability [4]. Major factors that significantly affect the forecast model's performance in determining the solar PV power are time-horizon and time resolution, geographic location, weather conditions, availability and quality of the data [5]. It has been determined that the errors for most models developed are significant, reaching average values between 15 to 20 % [6]. Despite this, of the possible methods, artificial intelligence (AI) has been shown to outperform other methods and is the best available option out there.

The problem with AI methods, including machine learning (ML) and deep learning (DL), is that they are relatively new and despite all its advantages there are numerous shortcomings that have yet to be solved completely. So far from the literature review done, there is no one single generic prediction method or model that can accurately forecast for all cases. Each system is unique and forecasting models must be optimised based on the available data. A main problem primarily consists of the possible configuration and architecture of the model. Of the various models created by various researchers, most use only a select few techniques which have proven to be popular.

The objective of this research is to develop and apply two AI models, an ANN and LSTM network, to accurately predict the performance of solar PV plants. These models are then validated and tested. The performances of the developed models are compared and analysed. Three popular performance evaluation metrics which are mean absolute error (MAE), root mean square error (RMSE) and the coefficient of determination (R^2) are used to determine the accuracy of each model's prediction. Furthermore, the scope of this project is limited to only grid-connected solar PV systems.

2. RELATED WORK

There have been numerous approaches taken to successfully forecast the future solar PV power of various PV sites around the world. Jebli et al. studied the efficiencies of three DL models suitable for forecasting time series data, namely RNN, LSTM and GRU. Prior research has found that Adam optimiser is the best optimiser and Tanh activation function shows good fitting capabilities. Results show that the RNN and LSTM both have similar performance in terms of accuracy and can be considered as reliable models for time-series regression problems [7]. Bao et al. research results agree on the suitability of LSTM for time series prediction but disagree with the use of RNN for such problems [8]. Huang et al. compared MLP and LSTM prediction models. The study showed that increasing the input sample size leads to complex hyperparameters of the neural networks. Up to a certain point, the prediction accuracy improves as the model complexity increases. It was concluded that the LSTM model is slightly better than the MLP due to its better memory in training historical data [9].

A simplified LSTM algorithm in [10] for the forecast of one day-ahead solar power generation uses a moving window technique to read the past observations. The model uses RMSE as loss calculation in addition to a dropout layer to prevent overfitting. It is observed from the dataset that the signal variations are cyclic and has a strong correlation with the sun activity. The LSTM model produces the best results achieved for sunny and low light weather profiles which have smoother lines. Park et al. also proposes a LSTM model. Fine tuning of parameters was done by varying the number of hidden layers and hidden neurons whilst keeping the initial learning rate constant. The study demonstrated that the use of multiple layers can further deepen the learning as compared to a single-layer model. The graphs plotted indicate that the single-LSTM model and multi-LSTM model both trend in almost the same pattern. However, the results also infer that the larger the amount of solar PV power generation, the lower the accuracy of the single-LSTM model while the opposite relationship is true for multi-layer LSTM model [11].

The paper by Konstantinou et al. proposed a stacked LSTM network that predicts the PV power output for 1.5 hours ahead or six timesteps. The model only uses endogenous data which is split in such a way that the first 80% of observations were used for training and the rest for testing. To make predictions the previous 3.2 days' worth of data or 192 timesteps before the target is used. Results indicate that the actual power output of at least the previous day affects the trend of the predicted power for any given day. To better evaluate the prediction accuracy k-fold cross-validation is introduced [12]. Hossain and Mahmood created two forecasting algorithms each consisting of two stacked LSTM hidden layers. The first model forecast a single step ahead PV power whereas the second is capable of forecasting intraday rolling horizons. The optimal input sequence length is found to be 12-time steps. Increasing the input sequence length any further will have a detrimental effect on the accuracy. Both models' accuracy changes by the season and the results indicate a strong correlation to the solar irradiance. The second model developed proves that adding more predictors can effectively improve the performance and that the error is significantly lower for smaller forecast horizons [13].

3. METHODOLOGY

3.1 Dataset

The dataset used in this research project is provided by Monash University Malaysia for its newly installed rooftop solar PV power plant as shown in Figure 1. Data is available for the entire calendar year of 2019 and has a resolution of five minutes. The data consists of past observations of measured weather data and PV power generation data. This is real-world data that will be used as historical data in the ANN and LSTM forecast models to predict the future solar energy that will be produced by the PV system. Two key observations are immediately evident upon plotting the graph of output power against time. Each day the signal varies in a manner that can be characterised with a bell curve, where the peak power is produced around noon. There is an obvious correlation of output power with the sun activity. Furthermore, the signal variations are periodic, repeating every single day [14].

Figure 1: Monash University Malaysia solar PV plant located on the roof of the building

The colossal size of the dataset which would require extensive amounts of computational memory and time for training, validation and testing of the model. Hence, the study has been limited to just four months for which an individual model would be designed for each month. The months of interest are February, June, August and November. These months have been chosen specifically to provide a comprehensive study on the models' performances in different weather conditions. The month of February had the most sunshine and least rainfall recorded while November had the most rainfall and least sunshine recorded. June was slightly sunny while August was slightly raining. These information was found from the data and validated from an online source [15].

3.2 Simulation Environment

In this experiment, the hardware environment includes Windows 10, 8GB RAM memory, and Intel Core i7-7500U CPU processor. The software environment used was MATLAB which is ideal for iterative analysis and design processes. In MATLAB the Deep Learning Toolbox and Statistics and Machine Learning Toolbox were used.

3.3 Data Pre-Processing

The data in Excel is first imported into MATLAB. Since the dataset provides the output power measured by five separate inverters, it is necessary to create a new column that consist of the total AC power produced. The historical data recorded has a variety of features but not all of them are useful for the prediction. By only selecting the most appropriate features that can positively impact the learning, the number of variables is reduced, thus minimising the complexity of the training data and enhancing the efficiency and accuracy of the model. Pearson correlations, which is a popular statistical method shown in Eq. (1), is used to identify the features that have the highest degree of correlation to the solar PV power output. The higher the correlation coefficient is, the stronger the correlation between the two variables [16].

$$r_{x,y} = \frac{\sum(x-\mu_x)(y-\mu_y)}{\sum(x-\mu_x)^2 \times \sum(y-\mu_y)^2} \tag{1}$$

where x is the meteorological data, y is the PV power generation and μ is the average value.

The important features selected from the dataset are of different scales. Training the model with data that has not been scaled could potentially lead to a false prioritisation of some of the variables [17]. To avoid this, the features are scaled by normalising all the data so that each variable is within a range of 0 to 1. Literature has proven that this pre-processing method can have a significant, beneficial influence on the predicted output as it ensures the quality of the input data is less dispersed. Normalisation can be done with the formula given by Eq. (2) below.

$$x_{normalised} = \frac{x - x_{minimum}}{x_{maximum} - x_{minimum}} \tag{2}$$

where x is the real data of the features and the target power output, $x_{minimum}$ and $x_{maximum}$ is the minimum and maximum value respectively of the feature being normalised.

The dataset consists of observations recorded throughout the entire day by data loggers. As a result, many observations are found with a PV power output of zero. These readings correspond to night-time values when no solar PV power is produced due to an absence of sunlight. The inclusion of all these night-time observations which provide no significant value would affect the performance of the model and lead to a poorly trained model. To circumvent this issue, only the observations for the time period of 07:00 to 19:55 are kept while the rest are discarded. This selection is made by inspecting the data to identify the earliest and latest time for which solar PV power is generated in any given month at the site's location. Additionally, the selected timeframe was also made so that each day has at least one zero value.

3.4 Training, Validation and Testing Datasets

Instead of splitting the data randomly which is usually the case, in this work the data is split sequentially or in order due to it being a time-series regression problem. Firstly, the data belonging to the last day of the dataset is removed and stored as the testing dataset to be used at the end. From the remaining data the training dataset consists of the first 85% data while the validation dataset occupies the last 15%. Since the validation dataset is not seen by the model during the training phase, it is used to tune the hyperparameters. This split ratio is done in order to avoid over fitting. Finally, the test dataset mentioned earlier is used to fairly test the model.

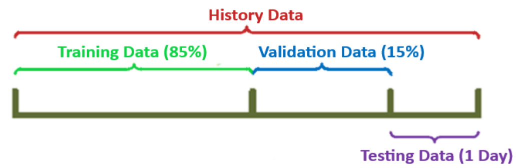

Figure 2: The specific division of the history data

3.5 Development of ANN Predictive Model

An ANN is a machine learning technique that replicates the information processing mechanism of the human brain and its neurons. It has a unique capability to learn and approximate nonlinear functions with high fidelity and accuracy. The advantage of ANN lies in its self-training mechanism which compares the predicted and actual results and its self-learning ability to adjust its weights to minimize the error. This has made ANNs suitable for many diverse applications, especially in forecasting of future trends or events [18]. These models are becoming increasingly popular and are treated by many researchers as a benchmark [19].

The basic architecture of an ANN consists of an input layer, one or more hidden layers and an output layer. Each of these layers comprises of artificial neurons, the basic processing elements of this network [20]. The chosen training procedure is feed forward back-propagation (BP) algorithm which is one of the most powerful supervised learning algorithms. The output of neurons in each layer are fed forward to their next level while the error rate obtained in the previous iteration is used for fine-tuning the weights of neurons. [21].

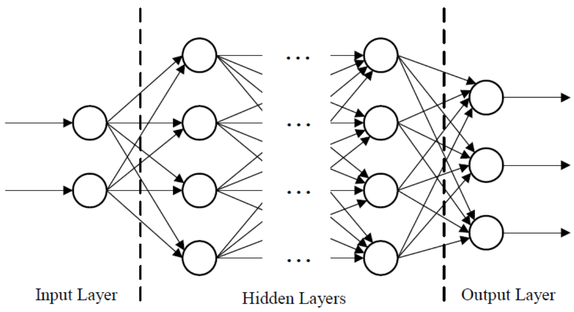

Figure 3: Schematic diagram of a multilayer ANN architecture [22]

3.6 Development of LSTM Predictive Model

LSTM is a special kind of RNN designed to resolve gradient disappearance and gradient explosion problems encountered in RNN models [23]. It has numerous memory blocks connected through a succession of layers. Within the block, the LSTM cells consists of three type of gates, namely input gate, forget gate and output gate. These gates oversee the information update procedure, maintenance and deletion present in cell status [24]. They also preserve weights propagated through time and layers. The presence of memory blocks gives LSTM networks an edge over other existing methods as it addresses the gradient issues due to its ability to memorise network parameters for long durations. This makes LSTM suited to model input data with time-series characteristics such as sequential data and exhibit excellent performance in dealing with nonlinear relationships in long-range dependencies problem [25] [26]. For the purposes of this research only simplified LSTM models will be developed which essentially means the LSTM consists of only one hidden layer. The motivation behind this is related to the findings by Jozefowicz et al. that state variations made to a simplified LSTM do not significantly improve the performance for sequential tasks [27] .

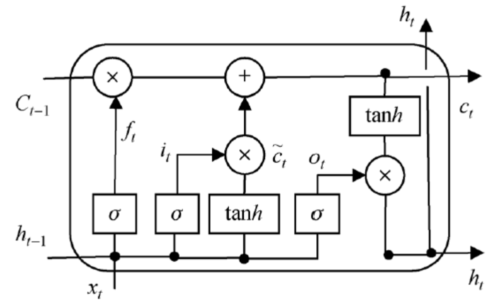

Figure 4: Architecture of a LSTM cell [28]

3.7 Performance Evaluation of Model Accuracy

Four commonly employed evaluation functions are used to verify the model performance. These are chosen as they have been found to be most suitable to the context of DL and regression problems. Each of the above performance metric provide different relevant information about the accuracy or error of the model. Hence, they are not comparable between them.

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}{\sum_{j=1}^{n}(y_j - \mu_{\hat{y}})^2} \tag{5}$$

where y_j is the actual output, $\hat{y}_j$ is the simulated output, $\mu_{\hat{y}}$ is the mean of the simulated output and n is the number of observations. It should be noted that nMAE and nRMSE are just normalised performance metric. The equations are the same with the only difference being the inputs to the equation are normalised.

4. RESULTS AND DISCUSSION

4.1 Optimisation of Predictive Modelling

It is found that PV power generation has the strongest correlation to solar irradiance. The Pearson's correlation coefficient of each variable is summarised in Table 1. Despite solar irradiance and module temperature having two of the highest correlations, the best possible combination of features to use as predictors to the model was found to be solar irradiance and ambient temperature. The summarised results are shown in Table 2. This shows that solar radiation and temperature have a monumental impact on the power production of photovoltaic systems

[29].

Table 1: Pearson's correlation coefficient between meteorological data and PV power generation

Meteorological Parameters	Pearson's Correlation Coefficient
Irradiation	0.9861
Module Temperature	0.9229
Ambient Temperature	0.8425
Wind Velocity	0.0323
Insolation	-0.1079

Table 2: The impact of feature selection on estimation accuracy

Selected Input Features	nMAE	nRMSE	R^2
Irradiation	0.2318	0.3259	-0.6276
Irradiation & Module Temperature	0.0067	0.0912	0.8726
Irradiation & Ambient Temperature	0.0217	0.0954	0.8605
Irradiation & Module Temperature & Ambient Temperature	0.0089	0.0929	0.8677

4.1.1 ANN Model

In MATLAB using the Neural Network Time Series App, a nonlinear input-output type ANN is created which takes a specified number of past observations of inputs to forecast the current output. The two main factors that affect the accuracy of the prediction are the number of neurons in each hidden layer and number of hidden layers [30]. These two variables were varied one at a time using a trial-and-error method. The architecture that gives the lowest nRMSE is selected as the optimal model. As can be seen from Table 3 below, the optimal architecture for the models differs from a month-to-month basis. There is no one specific architecture that will yield the best performing model.

Table 3: ANN architecture

Month	Number of Neurons	Number of Hidden Layers
February	10	2
June	30	1
August	20	1
November	10	2

4.1.2 LSTM Model

The performance of an LSTM model is influenced by several learning variables. Hence, it is crucial to tune the hyperparameters of each of the four LSTM models created so that optimal results can be obtained. However, since the proposed model is a simplified LSTM, the number of layers will be kept fixed at the default of one hidden layer. With the combination of input features determined, a base model is created and one at a time each hyperparameter is varied while the others are kept fixed. The hyperparameters that will be tuned are sequence length, learning rate, mini batch size, dropout ratio, number of hidden units and dropout ratio. The optimiser chosen was Adam optimiser and was kept the same for all four modes. Past literature has shown that it is a computationally efficient algorithm capable of finding the optimal solution through the adjustment of the learning rate [31].

Table 4: Details of LSTM parameters for 4 months

Hyper-parameters	Feb	June	August	Nov
Hidden Units	150	200	150	150
Input Length	4	1	1	1
Mini Batch	8	16	16	8
Learning Rate	0.005	0.005	0.001	0.005
Max. Epochs	5	3	5	5
Dropout (%)	20	60	0	0

4.2 Comparison of Solar PV Power Prediction using ANN and LSTM model

In this section, the results of the models for each of the four months are presented and discussed. The experimental results are depicted graphically in Figure 5 to Figure 8 below to provide a qualitative assessment. It is evident that LSTM networks are superior to ANN models when it comes to dealing with time series data. It is apparent for all the months studied that the measured value and the predicted value of the LSTM models are basically fitted, and the error between them is relatively small. The graphs moved in a similar pattern and overall was able to capture the variations in the output power signal very well.

The same is not true for the ANN model where the predicted and measured graphs were contrastingly different. Whilst the overall general trend of the measured output power signal is replicated, the prediction graph is simply too erratic. For most of the months studied, the ANN prediction graph exhibited constant fluctuations, with there often being changes to the direction of the gradient despite there being no change in the slope of the measure graph. Only for the month of August was the prediction of the ANN very similar to that of the actual power signal. Besides the constant fluctuation and instability of the prediction, all the models created predict negative values of power at either the start of the day or towards the end of the day. This issue is less problematic for the months of June and August but still nonetheless present. This finding proves that the ANN is inferior to LSTM in regard to model fitting.

Despite the LSTM network proving to be the better and more accurate model, it too like the ANN model displayed a certain amount of error. From Figure 5 to Figure 8 it is observed that the accuracy of the LSTM deteriorates at extremely high PV power measurements, often predicting lower than the actual measured values. Research done by Park et al. also observed a similar trend in single layer LSTM models [11]. All the LSTM models also tends to not go back down to a PV power of zero at the end of the day as it should. The graphs indicates that while the LSTM prediction curve decreases as the end of the day approaches it still remains a little way off from the measured curve.

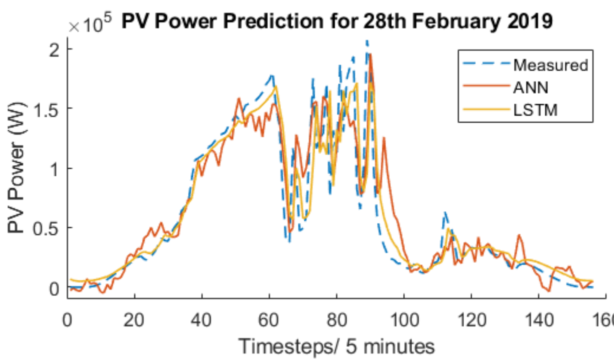

Figure 5: Comparison of ANN and LSTM predicted PV power output with the actual PV power output for test set in February

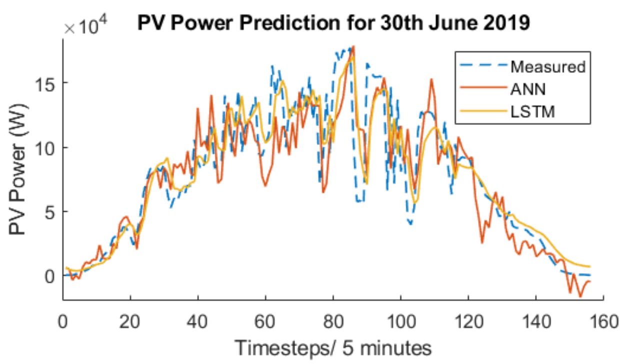

Figure 6: Comparison of ANN and LSTM predicted PV power output with the actual PV power output for test set in June

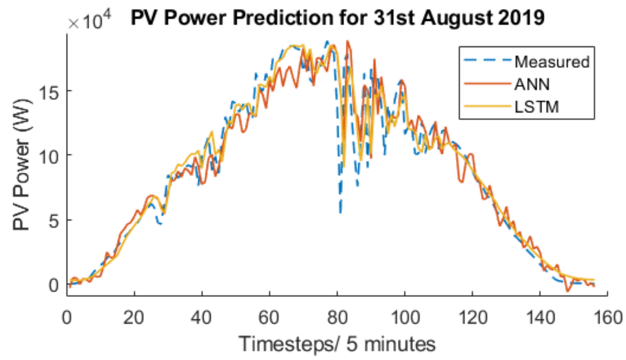

Figure 7: Comparison of ANN and LSTM predicted PV power output with the actual PV power output for test set in August

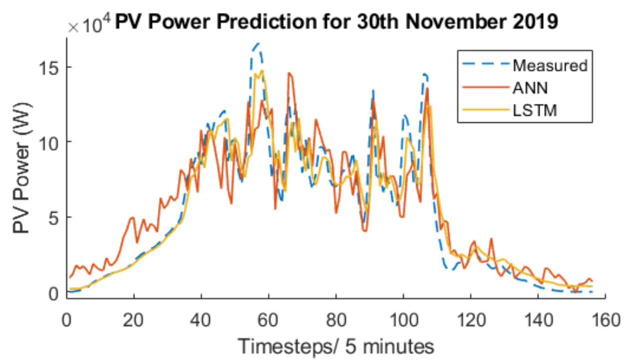

Figure 8: Comparison of ANN and LSTM predicted PV power output with the actual PV power output for test set in November

Although the graphical examination is essential, it does not permit quantitative assessment. To further validate the proposed simplified LSTM model three prediction performance metric are applied to the testing data of each of the four months. All the values presented here are on a normalised error metric scale. The normalised values are easier to interpret and provide a more meaningful representation of the results.

From the results presented in Table 5, the LSTM models performs better in terms of all the performance metrics for all months tested. Lower values of nMAE and nRMSE indicate the difference in the prediction and the actual power is minimal. This is the case for all the LSTM models as seen in Table 5. In terms of the coefficient of determination, the higher values noticed for LSTM models is a positive sign as it implies a better fit and therefore higher prediction accuracy. The relatively low error of the proposed LSTM model can be attributed to the large number of timesteps used in the input sequence. The larger number of timesteps is useful for LSTM cells to remember longer-term trends in the data.

In terms of the improvements achieved by the LSTM network over the ANN model, the highest improvements are achieved for the months of February and November. These two months are on extreme ends of the spectrum in terms of weather conditions, with February having the highest amount of sunshine and November having the most rainfall, and hence least sunshine. The results infer that LSTM networks represents the overall trend in the data much better for extremely sunny weather conditions and extremely rainy weather conditions. For data that can be classified under one of these extremes, ANN models are simply incapable of accurately representing the data. For months that are slightly sunny and slightly rainy such as June and August respectively, both ANN and LSTM are adept at modelling the input data. However, LSTM is still the best possible choice as it still reduces the error and improves the fit of the model.

Table 5: Model's performance metrics

Month	Model	nMAE	nRMSE	R^2
February	ANN	0.0438	0.1237	0.8007
	LSTM	0.0055	0.1107	0.8404
June	ANN	0.0088	0.1198	0.7719
	LSTM	0.0035	0.1141	0.7892
August	ANN	0.0088	0.0975	0.9007
	LSTM	0.0068	0.0938	0.9066
November	ANN	0.0225	0.0975	0.7927
	LSTM	0.0005	0.0734	0.8821

Lastly, it should be noted that the time taken for training each individual model was recorded as is given in Table 6 below. ANNs require significantly less time to train compared to LSTMs. Nonetheless, it was found through the optimisation process that the selection of the optimal hyperparameters greatly reduces the training time and makes it practical for real-time forecasting. The LSTM models for all months besides February shows reasonably acceptable training time. For the month of February, the training time is much higher due to the model requiring an input sequence length amounting to four days' worth of data for each future prediction as compared to the one-day input sequence length for the rest of the models.

Table 6: The operating time of the different model in this paper in seconds

Model	February	June	August	November
ANN	75	84	108	30
LSTM	1361	166	260	382

5. CONCLUSIONS AND FUTURE WORKS

With the growing deployment of solar energy into modern grids, the need for SPV power generation forecasting has become increasingly important due to the intermittent nature of weather. An accurate and reliable forecast model would deal with the volatility and uncertainty associated with solar PV systems. This article proposed an ANN and LSTM network for short term SPV output power forecasting by considering solar irradiation and module temperature as input features. The study discussed in detail the various pre-processing steps undertaken to prepare the raw data such as normalisation and Pearson's correlation feature selection. In addition, both the ANN and LSTM were optimised before obtaining the results and comparisons were made. Three error metrics, MAE, RMSE and R^2 were used to test and measure the accuracy of each algorithm.

A visual examination of the results plotted suggest that the LSTM network reacts better to each fluctuation and follows the trend of the actual output power signal more closely as compared to the ANN model. The results also reflect that as the amount of solar irradiation changes, the amount of solar PV power generation changes in an identical pattern. However, the accuracy of both the ANN and LSTM suffer when the solar PV power generation is large. It was found that fine-tuning the predictive models enhanced the accuracy of the forecast tremendously. The RMSE was much lower for the LSTM regardless of the month tested. It can be concluded that LSTM showed very high accuracy and low errors. Overall, it is superior to ANN models in dealing with time series regression problems.

As for the future works that can be done to improve the LSTM forecasting model, different architectures of LSTM models could be utilised such as bidirectional LSTM and stacked LSTM. Besides that, significant improvements could be achieved by hybridisation with other optimisation methods such as PSO and ant-colony optimisation or with other DL methods such as convolutional neural networks and auto encoder. Lastly, the forecast model could be extended to longer term PV forecasting.

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