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Solar Prediction Strategy for Managing Virtual Power Stations

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ABSTRACT

Indonesia is located on the equator, so it has the potential for solar power to be available and with good sunlight throughout the year. The Indonesian government finally has the consequence to develop a solar power plant and continue to protect the surrounding environment so that it is not polluted and global climate change occurs. Indonesia, which has direct sunlight exposure which is quite promising for predictions of solar power plants in the future. Solar energy generation in the last decade has continued to improve and develop in solar power predictions in a short time. Integration of solar power sources without accurate power predictions can hinder network operations and use of renewable generation sources. To solve this problem, virtual power plant modeling can solve as one of the successful solutions to minimize errors in predicting it. This research studies methods that can efficiently generate significant daily photovoltaic predictions at study sites using data available from the Meteorology, Climatology, and Geophysics Agency (MCGA). The second approach to the model based on RMSE and MAE, can be done virtual modeling of power plants to solve problems and as a management solution to minimize prediction errors. The performance of a verified prediction strategy on the PV module power output and a set based on geographical meteorological station data has been used to simulate a Virtual Power Plant (VPP). The power forecasting prediction refers to the LSTM (Long Short-Term Memory) network and gives an error close to other learning methods, based on the RMS characteristics of 4.19 W/m^2 under lead time with different launch times. Applying the VPP model using RMSE can reduce global errors by about 12.37%, and shows great potential.

Keywords: Solar Power Predictions, Virtual Power Plants, Photovoltaic, Solar Management
JEL Classifications: C13, C22, C36, C39, L94, Q42

1. INTRODUCTION

Indonesia is one of the countries in the Asia Pacific region whose energy contribution comes from hydro and geothermal power plants, reaching 8% and 5% respectively. Based on (Zambak et al., 2023), that one of the renewable energy potentials (Wind) in Medan has moderate potential to be used as a power plant with PJU lighting capacity. Indonesia currently plans to continue developing renewable energy with a policy of around 23% of its energy being supplied by modern renewable energy such as solar radiation in 2025, at least 31% will come from modern renewable energy sources in 2050. However, IRENA predicts Indonesia can target it within two decades previously. In his research (Pasaribu et al., 2023) has conducted an analysis of economic growth does not have a significant effect on energy consumption, consumption of sustainable renewable energy affects energy consumption in Indonesia, while economic growth, population, energy subsidies, and consumption of fossil fuel energy have a significant effect on sustainable energy consumption in Indonesia.

The developments followed by the rapid advancement of solar energy technology can be seen from the many researchers who focus on finding renewable energy sources. The renewable energy potential of solar energy is owned by Indonesia which is relatively large, namely 4.80 kWh/m^2/day and only uses 10 MWp in 2024 (Pambudi et al., 2023). Indonesia has relatively large solar energy of around 0.87 GW in 2025 (US Department of Commerce International Trade Administration, 2012). Indonesia also produces electricity from solar energy with a potential of around 640,000 Terrawatt-hours per year. The use of PV which is a renewable energy due to global warming from sunlight, results in the new and renewable energy industry growing rapidly in Indonesia and results in achieving the energy mix target to reduce greenhouse gas emissions through the development of renewable energy (Resources and Indonesia, 2012).

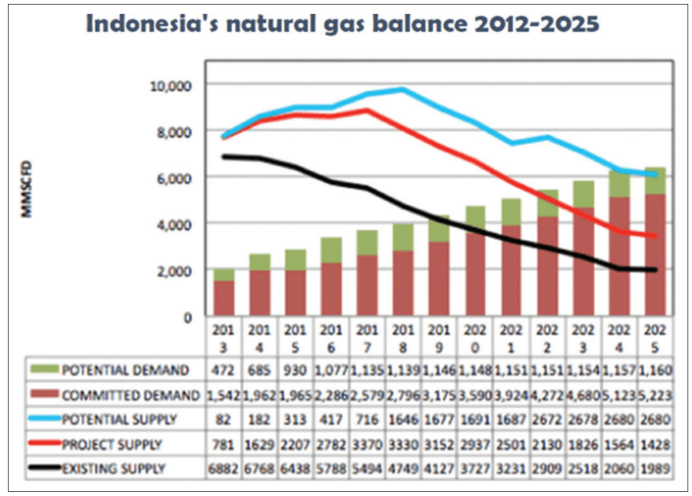
Energy is a basic need in daily activities and has an impact on economic growth and human welfare. According to the IEA, that the need for energy continues to increase and is expected to continue to increase by 30% in 2040 (McKinsey's, 2022). Indonesia's consumption of fossil energy until 2025 is shown in Figure 1, which is still dominated by oil, coal and natural gas until 2025, but new renewable energy is very low compared to current energy consumption and is expected to use up to 23% renewable energy in 2020. the same as providing convenience in its investment to make Indonesia green. The participation of academics in encouraging the development of renewable energy is urgently needed, where PT PLN (State Power Plant Limited Company) seeks to minimize global temperature rise by stopping steam power plants until 2056, and initial participation in 2030-2035 by stopping the operation of several power plants. Fossil fuel electricity and concentrate on renewable energy (Handayani, 2019).

High energy consumption causes fossil energy to run out and can cause an energy crisis. To overcome the energy crisis and the environmental impact arising from the fossil energy industry, countries in the world are committed to replacing fossil energy with clean and sustainable energy that is environmentally friendly, one of which is solar energy (Sharvini et al., 2018). Figure 1 shows that expressions of demand that are much greater than the potential supply of energy can result in energy scarcity and you have to look for alternative energy that is available in that place. Therefore, this paper is very important to be supported and encouraged so that energy supply in the future can be fulfilled.

Solar energy is radiant energy from the future sun as renewable energy, using various photovoltaic cell technologies. An effective form of solar energy and a renewable energy solution that can reduce the greenhouse effect and global warming. The growth of the solar energy market can reduce environmental pollution and can drive demand in the power generation sector (Hamed and Alshare, 2022). The demand for solar cells is currently gaining traction as they can be shaped to suit rooftop installations as well as increasing operations in the architectural sector, thereby centralizing the market. The main factors contributing to the growth of the global solar market due to rising prices of fossil fuels and the adverse effects of toxic gas emissions are driving the growth of the global solar market during the forecast period. Market demand for solar energy is driven by government incentives and tax breaks for installing solar panels and increasing environmental pollution (Campillo and Foster, 2008). Forecasting the demand for the solar power market until 2020 is shown in Figure 2, (https://www.precedenceresearch.com/solar-power-market).

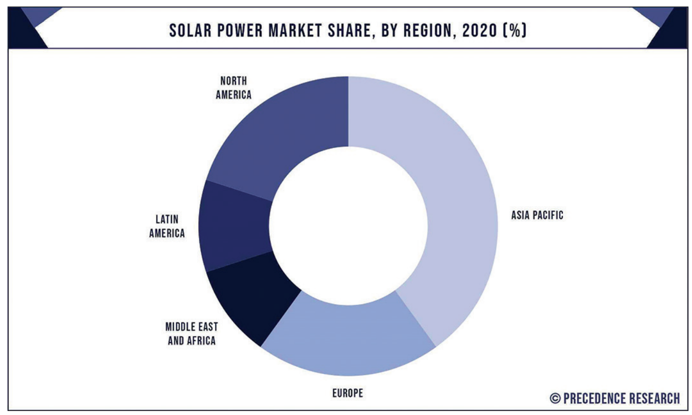
The need for solar energy in the global market is dominated by Asia Pacific, North America, Europe, Latin America, the Middle East and Africa. Indonesia in 2030 will use energy in the form of bioenergy according to the needs of the industrial market as liquid biofuel for transportation (Andrae and Edler, 2015). REmap has illustrated that the implementation of solar and thermal power in Indonesia has contributed around 15%, hydropower (14%), and geothermal power (9%), as shown in Figure 3 below.

Figure 1: Consumption of fossil energy in Indonesia until 2025



Reference: IRENA

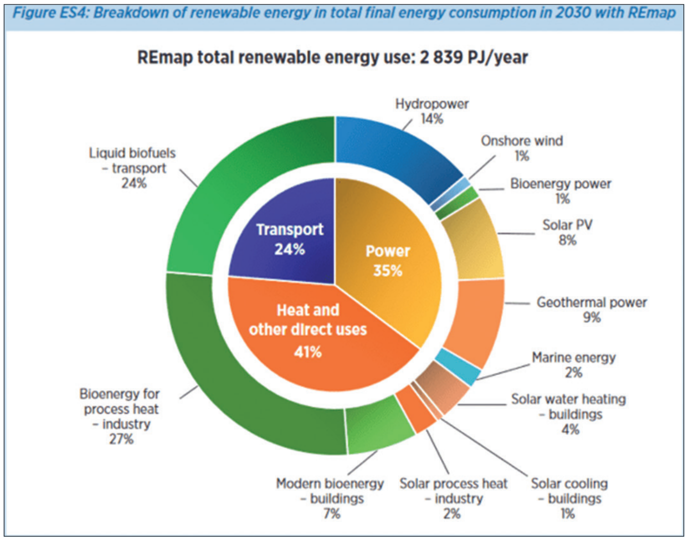
Figure 2: Solar market demand in 2020



The spread of solar energy includes the decline in the price of solar panels, and environmental, political, social, and cultural issues. Based on research according to (Goodstein and Lovins, 2019), global installed capacity is impacted by identified bottlenecks hindering the pace of achieving solar dominance, under-investment for efficiency, and regulations governing solar distribution. Coordination of PV installations with VPP models for global production prediction provides accurate value integrated into the network (Nosratabadi et al., 2017).

The power prediction at PV and the selected prediction interval for PV facilities in the VPP model can be replicated for real PV and can improve high accuracy with both MAE and RMSE models with values of 12.37% and 11.84% respectively (Moreno et al., 2021). Technology in the past has had an impact on the current electricity network, it is necessary to carry out a fundamental restructuring of fossil energy to serve the needs of renewable energy in the

Figure 3: Global energy consumption in 2030



future (Rangu et al., 2020). The integral part and participation of distributed and decentralized energy resources small-scale power generation units with traditional mass power generation have been passively constrained by existing distribution networks, driven by one-way energy flow mechanisms (Ullah and Mirjat, 2021a).

Combining renewable energy sources (RES) to overcome energy shortages when the RES output is low or to store energy when the RES generation is high. This combination gave rise to the idea of a VPP, which is described as a collection of various DERs functioning as one unit (Sarker et al., 2021). Overview of the VPP model has been discussed in real-life research (Ullah and Mirjat, 2021b). Power system design with a high proportion of RES is an important part of the renewable energy system change (Knopf and Nahmmacher, 2015), (Plebmann and Blechinger, 2017). Application of RES on a large scale can reduce GHG emissions and the current energy shortage problem, but can pose a new challenge in the safe and economical operation of modern electric power systems (Pasaribu et al., 2023).

Operational systems against renewables that cannot be delivered directly such as photovoltaic and wind under the high breakthrough renewable energy scenario and the internal potential of RES for the provision of Additional Services (AS) need to be tapped. Although RES is currently banned from the world market due to the uncertainty of location and time dimensionless data modeling resulting in the trend of electricity demand liberalization which allows VPPs based on RES to participate in the energy market and ancillary services market simultaneously. There have been many relevant studies showing that both wind and PV energy are technically capable and suitable for supplying the US (El Mokadem et al., 2009), (Camal et al., 2018), (Banshwar et al., 2017). The prospecting and assessment of PV Generation possibilities to provide density support services has been investigated in several countries and the methodology is based on QRF modeling to obtain the optimal supply of automatic frequency recovery reserves provided by renewable power aggregators (Camal et al., 2018). Overview of the provision of various Additional Services from alternative energy in various electricity markets around the world (Banshwar et al., 2017).

Shifting to renewable energy use can help reduce greenhouse gas emissions by limiting the impact of weather and climate extremes while supplying reliable, timely and cost-effective energy. As a result, increased PV breakthroughs can be attributed to increased integration of PV systems into virtual generation modeling, which makes this energy sales model difficult to implement due to current regulatory constraints. The virtual generation model is one of the main solutions for reducing the carbon footprint of conventional power grids and the integration of PV and wind generation. However, the source of this new and renewable energy generation to the VPP is still being determined due to the resulting uncertainty (Liu et al., 2021). VPP to address sudden climate change due to output of PV generators, as well as management of other energy needs under the same VPP (Mahmud et al., 2020). The main divisions of uncertainty that need to be managed by the VPP (Yu et al., 2019).

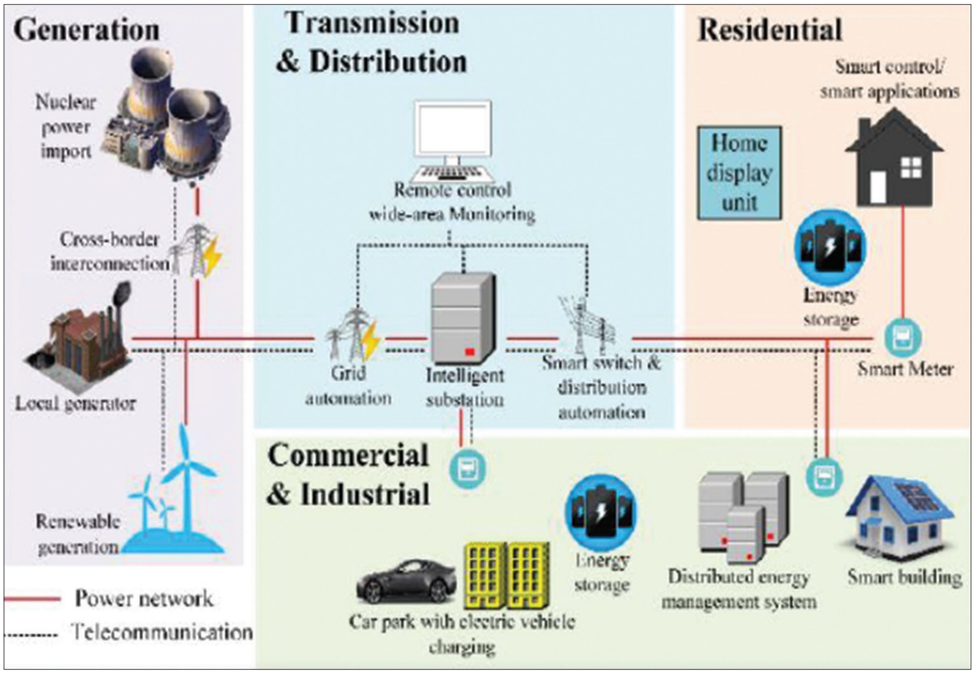
A common solution for managing the uncertainty of PV generation is to invest in energy storage capabilities in batteries (Liu et al., 2019), however, the ongoing investment in the source can be reduced by predicting the best from the PV generator. The VPP generator model is expected to have real-time operational capacity to match the design that has been designed previously based on forecasts of other PV generators (Fan et al., 2020). Adjustments are made to get market offers from before by implementing a second-order VPP model on real market trading (Qiu et al., 2017).

Modeling of VPP generators is based on collecting scattered data and managing scattered energy sources to meet certain optimizations (Naval and Yusta, 2021). VPP discovery and modeling involves complex information techniques related to modeling and energy flow, predicting local energy demand and energy generation, optimizing operations to meet defined goals using simple and efficient rules, and managing paperwork and follow-up to close rounds (Park and Son, 2020). The concept of smart grid in general VPP generator modeling is shown in Figure 4.

Forecasting overall energy capability as a provider of electric power from a variety of widely distributed energy sources such as solar, wind and hybrid electric vehicles using automated technology for supply chain monitoring, control and analysis. Whereas the direct model predicts PV through a dataset of past data from PV and climate conditions. Indirect forecasting is the prediction of solar radiation and solar energy that can be calculated using a solar generator performance model (Colman et al., 2020).

Previous researchers have done a lot of research, but there are methods that have been used that may have errors in forecasting solar power plants, so that it becomes a challenge to optimize the operation of PV generators, but there are small errors that do not affect the operation of solar power plants. Operational differences can hinder performance to assess variables with certainty in the scheduling and operation of PV plants, so one of the quantification of forecast uncertainty becomes very important. Some consideration of intervals for predictions also

Figure 4: Concept of energy and technology used for VPP



takes into account expected uncertainties which can provide additional information in making judgments that are expected to provide a reasonable number of values and assigned probabilities of those values (Talagala et al., 2019), (Wang et al., 2023). To overcome this problem, researchers present an approach to predict PV power by using a program tool for the locations studied. The results of this research show that the reduced error of the RMSE is influenced by several important factors that affect the accuracy and strategy used (Chai and Draxler, 2014). The PV generation system is one of the easiest and most cost-effective Renewable Energy Sources (RES) that can be utilized in households and it is possible to convert PV modules into VPP nodes that can be adapted to such needs (Khandelwal et. al, 2021).

Indirect forecasting results for PV system performance models are needed to obtain predictions of solar power plants, however a strategy used to predict performance under radiation and temperature conditions should be adopted (Kim and Byun, 2022). If the operational location of the PV panels is determined, alternative methods can be obtained (Al Shahri et al., 2021) and can improve accuracy, whereas other studies that use whole population models are calculated to simplify the process (Kalkan et al., 2018).

The forecasting strategy proposed in this paper uses the Rayleigh model with the main contributions being (a) the PV forecasting model obtained at VPP to minimize forecasting errors by modeling a two-parameter function; (b) the prediction interval time to model the prediction uncertainty is a function that depends on the hold time and launch time with the CCF; (c) forecasting and data input strategy for this prediction comes from data sources that have open access and are free in cost savings in VPP model generators.

2. DAILY ELECTRICITY STRENGTH PREDICTION MODEL

The proposed daily electricity forecasting strategy is depicted in Figure 5. It shows the proposed daily power prediction consisting of data input and pre-processing power prediction, and the VPP model generator. Steps for preprocessing input data as used in training and prediction models. The expected output from the prediction algorithm is the EMS input from the VPP observed and analyzed.

2.1. Enter Research Data

Input data consists of various classifications that are adjusted to the source and information needed. Initial input data consists of turbidity and temperature from prediction maps at a scale obtained from the Meteorology, Climatology and Geophysics Agency, as well as turbidity data intended to determine CCF (Cloud Cover Factor), to indicate cloud area on a shadow NWP-based turbidity map at a power plant PV. Some of these parameters determine the type of: brightness, overcast, and overcast. These parameters can be obtained from datasets that can be assigned to different groups in terms of creating prediction intervals. The temperature data is used to estimate the temperature of the solar panel cells at the time of prediction (Aoun, 2022), (Ciulla et al., 2013). Based on the climate map for the NWP it is very interesting due to some useful weather changes that may not be available in a solar power installation.

Forecasting modeling using the MAE model is implemented for temperatures related to the NWP map of around 2.13^{o}C with a power gain of around 46.96 W/m^2, for measurements throughout the year. Modeling the forecasting data set for training purposes consists of two parameters, namely for the position of the sun, used in calculating the CCF in determining daily data, while spatial radiation is used for prediction and radiation on an inclined plane from the location of the solar generator module.

Figure 5: Proposed forecasting framework

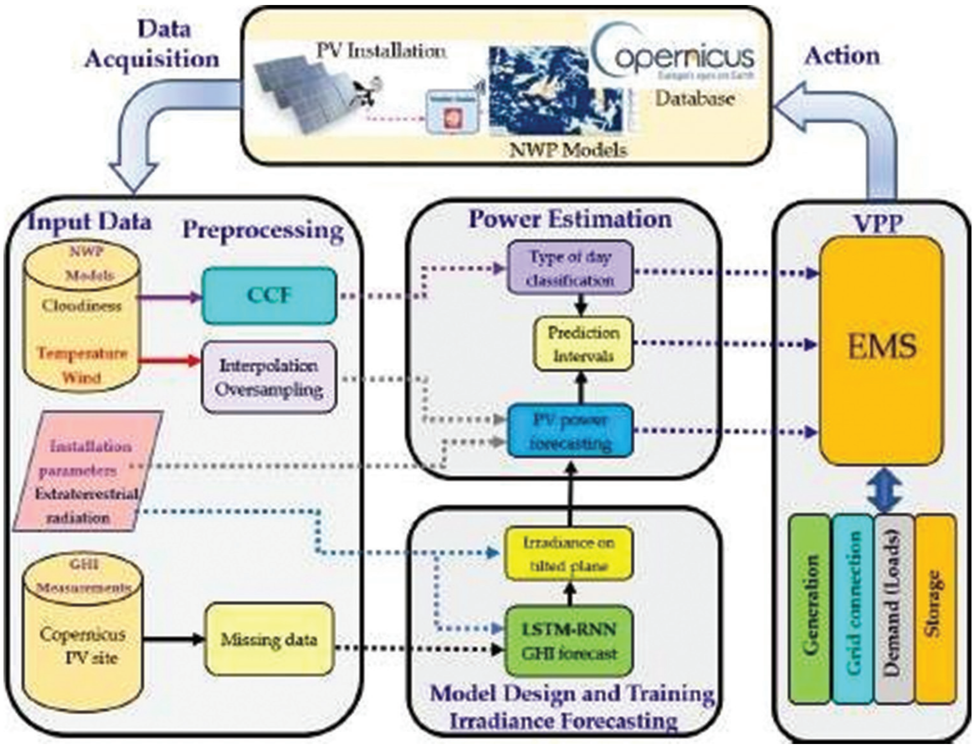


Table 1: Daily solar radiation data for one year

Month	Air temperature (0C)	Relative humidity (%)	Precipitation (mm)	Daily solar radiation-horizontal (kWh/m²/d)
January	26.7	85.5	309.69	3.67
February	26.7	83.5	269.92	4.00
March	27.2	83.0	209.56	3.97
April	27.8	82.5	181.20	4.22
May	27.8	81.5	142.29	3.81
June	27.8	79.5	89.10	3.61
July	27.2	76.5	72.85	4.03
August	27.2	76.0	65.10	4.33
September	27.8	74.5	73.80	4.31
October	28.3	76.0	125.55	4.17
Nopember	27.8	79.0	186.00	3.78
December	27.2	81.5	229.47	3.89
Annual	27.5	79.9	1,953.53	3.98
Source	Ground	Ground	NASA	Ground

2.2. EB. Research Data Pre-Processing

Forecasting power on PV modules consisting of cell temperature and radiation on an inclined plane, quadratic interpolation is required to predict NWP. Changes in temperature around the study can be assumed for NWP maps as proposed by (Cho et al., 2022). Proper proof with a 1-year approach model is shown in Table 1 which gives an illustration that the ambient temperature is obtained from the predicted value measured from the MCGC station located in the PV module. These parameters allow the daily radiation to influence the identification of certain periods to change the PV in the period of the presence of clouds to change the PV generation in the region by preventing solar radiation (Peratikou and Charalambides, 2022), which provides an accurate description of the detected parameter calculations. Table 1 provides information about data reconstruction that is affected by conditions of air temperature and relative humidity to daily sunlight for 1 year.

2.3. EC. Modeling and Forecasting Research Irradiation

Forecasting from solar radiation based on Rayleigh modeling with the aim of (i) getting the average power of the PV model every day for 30 min on the PV generator module (ii) seeing the possibility of uncertainty in the forecast results (Zsiborács et al., 2022). The data information in Table 1 above shows the main input for EMS at the VPP node.

Figure 6 shows the prediction and prediction results of the modeling, by minimizing the error of the training process by calculating the RMSE and considering the incongruence of the corresponding system but also taking into account the computation time. Forecasting the effective solar radiation on the inclined plane of the PV generator module, to calculate the effective irradiation using data from two irradiation elements on a flat plane, either direct or diffuse. In this problem, the albedo is zero and is estimated as a function of the clarity index (kth) and calculating the mass transfer fraction (kdh) (Hofmann and Seckmeyer, 2017). On this information, the conversion to an inclined plane is estimated by diffuse radiation and albedo (Padovan and Del Col, 2010), (Bugler, 1977):

$$albedo = r_0 ghm_0 (1 - cos\beta)/2 \tag{1}$$

where r_o is the albedo coefficient, with a value of 0.2 ghm0 as the GHI and β as the angle of inclination of the panel. The effective radiation is determined taking into account the angular loss (Barman et al., 2021) and spectral (Martin and Ruiz, 2001) with p-Si module and moderate dust level at DT 0.97 for installation.

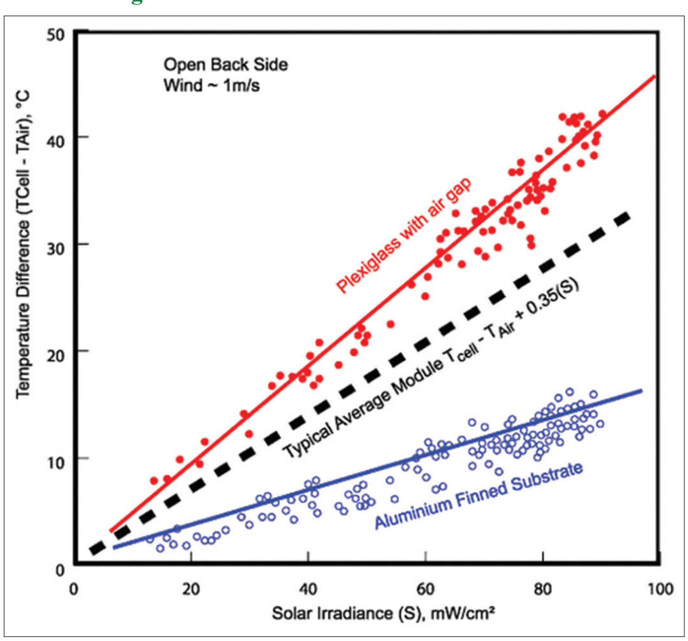
Osterwald model (Osterwalder and Pigneur, 2010) change the PV power of its effective solar radiation.

$$P_{DC} = SF\eta_{DC} P_{peak} \frac{G_{panel}}{G_{STC}} \left(1 + \delta P_m (T_{cell} - T_{cell,STC})\right) \tag{2}$$

where P_{DC} is the PV approximation, SF serves to represent the shade loss due to the environment, for this particular case, η_{DC} = 0.928 including cable loss, with module tolerances and mismatch losses; Ppeak = 2.98 kW is the peak power of the installation, Gpanel serves as the useful solar radiation from the panel is calculated, GSTC is 1 kW/m^2 which is the solar radiation under standard test conditions with (STC), δP_m is 0.4%/^{o}C which is the change in temperature of the PV panel installation, T_{cell} as a function of cell temperature, and $T_{cell,STC}$ is the cell temperature below STC.

Determination of cell temperature is expressed by equation (3), ignoring wind speed which is a complex effect that is not significant to the model and does not affect panel facilities evenly (Ross, 1980):

Figure 6: Illustration of solar radiation at NOCT



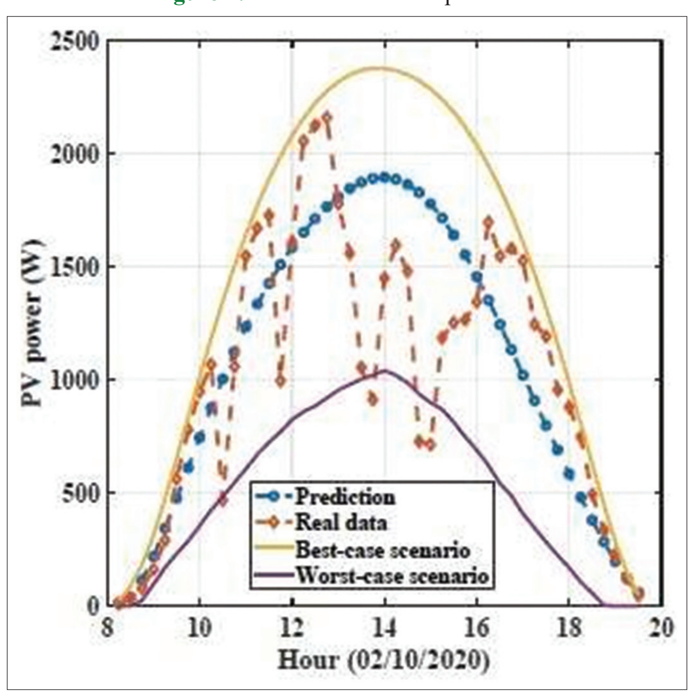
$$T_{Cell} = \frac{T_{Cell,NOCT} - T_{amb,NOCT}}{G_{NOCT}} G_{panel} + T_{amb} \tag{3}$$

with T_{cell}, NOCT= 45^{o}C which represents the cell temperature as a function of the Normal Operating Cell Temperature (NOCT); T_{amb}, NOCT = 20^{o}C is the ambient temperature in NOCT conditions; G_{NOCT} of 800 W/m^2 which is solar radiation in NOCT conditions; and T is the ambient temperature resulting from the NWP prediction. Once all data sets are related to PV predictions, it is possible to calculate prediction intervals to predict new ones. Prediction interval is a prediction interval with a random variable to assess in the future of unknown magnitude (Shrestha and Solomatine, 2006). In this paper, tabulated prediction intervals are used based on the work presented considering the Laplacian distribution model for errors as a function of waiting time, launch time, and day type (Butler and Rothman, 1980).

Solar radiation with changes in temperature between the module and the air results in heat transfer losses and faster heat transfer that occurs in damage to solar insulation for certain wind speeds with thermal resistance and heat transfer coefficients that do not vary too much with changes in temperature. NOCT for some best cases, worst cases, and average PV modules is shown in Figure 6, which for the best cases resembles aluminum fins on the back of the module for cooling which reduces thermal resistance and increases surface area for heat transfer in other media.

Figure 7 shows the time intervals for the 90% dailies which has provided valuable additional information from the predictions. The generation of PV modules is highly dependent on weather conditions and changes according to the seasons, due to the ability of forecasting algorithms to make appropriate predictions and can provide several levels of uncertainty that must be evaluated.

Figure 7: PV module interval prediction



3. RESEARCH RESULTS

The research results obtained from the proposed daily forecasting strategy for the VPP generator module are divided into: (1) PV module power estimation from forecast output; (2) quantitative scoring prediction interval; (3) VPP module schedule. The results of this study consist of two things: First, the research results are validated against the PV module installation which acts as a VPP model node. Second, a strategy was developed to replicate the VPP generator module, using data-driven meteorological stations. The proposed model was evaluated for its effectiveness and compared its performance to find out the accuracy related to the method proposed in the literature related to other studies.

3.1. EA. Forecasting for VPP Nodes

Forecasting for real VPP nodes was performed using irradiation measurements taken at the existing PV facility at MCGA. GHI Forecasting can provide launch and wait functions with specified future times and parameters to calculate forecasting intervals.

For error assessment will depend on two model metrics namely:

(1) metric dependence on the MAE and RMSE scales; (2) the percentage error of the rMAE and rRMSE metrics. The two metrics above provide an overview of the absolute value of the average forecasting information, but the squared value is more sensitive to data that deviates from the average of the data and is an analysis of both that allows us to study the prediction results as a whole.

A comparison value against error which also gives an understanding of what was done about the error i.e. a fair comparison for dependability, but since this value is close to zero, where a scale dependent metric is the preferred choice. Table 2 is a performance matrix for the value of Y_t, which is data measured from time t, $\hat{Y}_t$ is the forecast value for time t, and T is the length of the sequential time that can be used to provide the accuracy value of the algorithm.

The values of $Y_{t,t'}$ and $Y_{t0,t}$ are predictions of Y_t at t_0 and t_0 is the predetermined starting time for each day which is equivalent to sunrise. With the error assessment of the two parameters, it is necessary to determine the amount of waiting time and launch time. The exact lead time at (t'-t) gives the difference between the time when it was predicted and when the prediction was launched. The launch time is indicated by (t'-to) and is the difference between the current time and sunrise. The launch time and waiting time for the prediction of a certain day are described in Figure 9, with the launch time set and the waiting time used as a parameter, the prediction vector is obtained, but when both parameters are set to a certain value.

Figure 9 provides an illustration of the timeout and launch time errors leading to the following conclusions. First, for scaling errors, high error rates are observed for short launch times with medium timeouts. It is expected that the scale of the error will be mostly

Figure 8: The results of measurement and forecasting of the virtual generator module

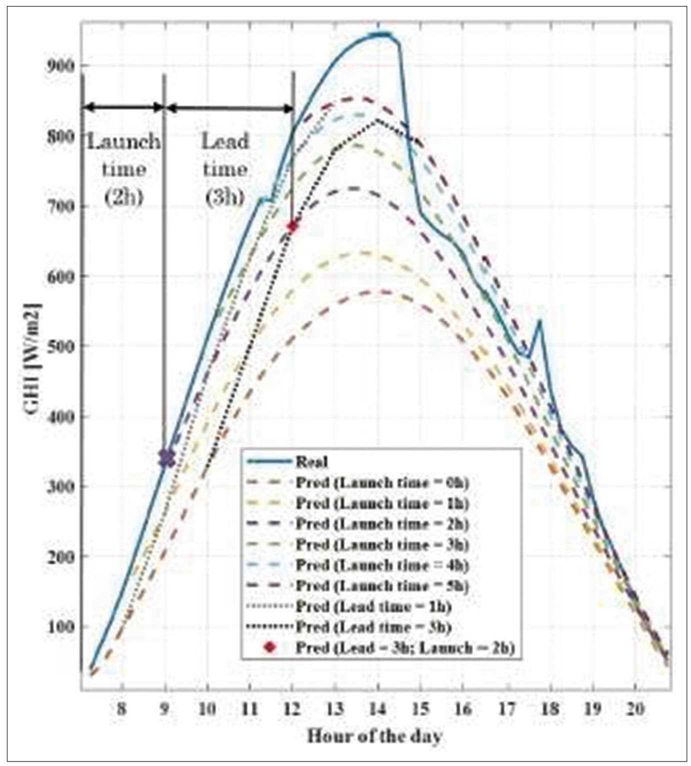


Table 2: Performance model matrix

Metric	Scale (W/m²)	Percentage
Absolute	$MAE = \frac{1}{T}\sum_{t=1}^{T}\left\|Y_t - \hat{Y}_t\right\|$	$rMAE = \frac{\frac{1}{T}\sum_{t=1}^{T}\left\|Y_t = \hat{Y}_t\right\|}{\frac{1}{T}\sum_{t=1}^{T}Y_t}x100\%$
Square	$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t - \hat{Y}\right)^2}$	$rRMSE = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t - \hat{Y}\right)^2}}{\frac{1}{T}\sum_{t=1}^{T}Y_t}x100\%$

under the previous setting with high solar irradiance, but as the launch time increases, this error decreases significantly. Second, the lower the solar irradiance, the smaller the error scale, and for the percentage error the opposite will occur; when the launch time is small (smaller than 1 h), a high percentage of errors will be regardless of the timeout (Lorenz et al., 2009). Finally, the forecasting interval is derived from the MAE, suggesting that a given distribution by dividing the predictions is a function of waiting time, launch time, and type of day which would be very useful at the high level of accuracy required for predictions. The predictions obtained with forecasting errors in this work are much smaller with short waiting times. A comparison strategy that has been presented in this paper regarding estimation can be concluded, that a small lead time will produce a better estimate compared to traditional methods.

3.2. Forecasting the PV Model from the GHI Forecast

In predicting the PV model from the GHI forecast, the following steps are carried out: (1) direct time prediction; (2) surveying the location from altitude, latitude, and longitude; (3) installation performance covered by panel orientation and inclination, PV model identifying parameters available in the data sheet and losses associated with each part of the installation; and (4) from NWP maps at ambient temperature. Analysis techniques are carried out to allow measuring errors made in solving problems. The results of the two different approaches consist of: First, making a comparison between the actual PV measurements at the location and the estimated PV values from the GHI measurements. Second, the PV module is predicted from estimated GHI values and evaluates the errors associated with all those processes.

Figure 9 is the result of a comparison between the measured value of the PV module at that location and the estimated PV obtained from GHI measurements at that location. Choose from three types of days namely; cloudy days, overcast days, and sunny days. The x axis is a function of solar time and the Y axis is the GHI to be searched for. For the experimental setup at the site under study which has buildings near PV panels providing partial shade until sunset. Modeling under these conditions is stated in equation (2), assuming that the change in this effect is linear with time as shown in Figure 8 with an SF of 0.95 at 16:36, decreasing to an SF of 0.4 at sunset, and also varies depending on the season of the year (Barlow, 2005), obtained an rMAE of 2.55% for sunny days, rMAE = 3.05% for partly cloudy days, and an increase in rMAE value of 4.04% for cloudy days. Observations are based on squared error, where the rRMSE value is 3.44% on sunny days and the rRMSE is 3.89% on partly cloudy days, up to 5.96% rRMSE on cloudy days. The switching characteristic of the MPPT inverter control in the presence of passing clouds causes the inverter operational point to become unstable. This increases the daily error but does not cause problems in the forecasting process with a time difference of about 15 min which can reduce negative effects.

Figure 9 illustrates the error of the estimation resulting from the difference between the measured and estimated PV modules as a function of waiting time and launch time, so that it has a similar picture to the previous one, with almost the same percentage of error. It can be concluded that it is almost the same as that achieved in Figure 8, so that it can be stated that: (1) short launch times and medium waiting times result in high scale, but decrease significantly as launch time increases; (2) a launch time of less than an hour results in a high error rate that appears to be independent of the timeout; and (3) high error ratio at lead times higher than about 7 h.

3.3. Predicted PV Power Forecasting Intervals

As additional information for prediction intervals on reasonable PV power ranges generated at the site and a certain confidence level selected by the user. Taking forecasting intervals can increase the uncertainty of the point estimate and can avoid unexpected energy shortages or conversely less critical energy excesses because the inverter can change its operating point to produce the required energy, even if it is a waste of time. Usable energy source, excessive. In this paper, the prediction interval is obtained based on the operations performed to produce the best forecast (Qin et al., 2022). The results from the facts used aim to divide the forecast data set and create groups, assuming that a certain distribution is built on the MAE. The division of this group was determined at the time of choosing the launch time and waiting time where approximately 365 samples per group were obtained in one full year.

Figure 8 shows the different error distributions for launch time values of 2, 4, and 6 h, with timeout values of 1, 2, and 3 h. In the assumed Laplacian distribution, similar to the work done by the CCF function. The prediction interval for each subset can be determined by MAE assuming that it is for a Laplacian distribution (Berger and Kiefer, 2021).

A more detailed division can be determined with the selected groups as a function of CCF, but must take into account the number of groups as previously presented with a sample of each group is not enough to make a proper error distribution (Berger and Kiefer, 2021). Mitigate this drawback by reducing the number of CCF groups to three and using the type of day classification described above. Study measurements with CCF have an hourly verdict with a value of zero when the sun is not obscured by clouds and one when the sun is completely obscured. The k-nearest neighbor method is usually used to form groups which allows the datasets to be separated simply and offers independent solutions for each object in the VPP. Assume that for the Laplacian distribution, each new subset selected carries an error that needs to be measured. Coverage Probability Interval Prediction (Nagshima et al., 2019), and shows the division of the predicted values that fall within the selected interval and approximate the confidence level. The confidence level chosen in this study is 80%, although this number can be modified depending on the operational risk so that it can be handled by high-risk objects so that the benefits of the device are higher.

4. DISCUSSION AND CONCLUSION

The technical development of the VPP generator module must be supported by the current EMS technology with the PV module being a very important part. The energy produced by each VPP node which refers to renewable sources makes it possible to optimize the benefits expected from energy exchange with network operators. It is difficult to predict PV modules when it is necessary to collect information from multiple nodes spread over a large area and especially when the input data required to predict is expensive. This paper proposes a way to achieve this goal using a strategy based on the LSTM-RNN by carrying out GHI forecasting using a data set of solar radiation values obtained from direct satellite data and solar energy used by the PV module installation.

This paper first provides results related to GHI estimates for installs based on lead time and launch time, which allows regions of lower error and high levels of confidence to be generated in the form of day-type-dependent prediction intervals. The GHI error is a function of hold time and launch time, which shows low behavior when the launch time is lower than 1.5 h, based on sunrise. To avoid this, the forecasting process can start 1.5 h after sunrise. This proposed research can rely on predictions of days ahead made to derive solar radiation forecasts (Husein and Chung, 2019). The assessments of the accuracy and rigor of safety predictions and their results were compared with the literature, with results similar to those obtained from deep learning algorithms and outperforming existing traditional techniques. The difference between lead time and launch time allows for comparison which is better related to the literature, but it is difficult to summarize if the study is conducted with only one value, where MAE is related to each other without considering the leads. Time and launch time with a value of 44.18 W/m^2 which has similarities with previous studies.

After solar radiation has been estimated, the PV is then converted and calculated analytically by minimizing errors, namely 2.55-4.04% for rMAE values and 3.45-5.95% for rRMSE. The error matrix model shows results similar to those presented above, so it can be concluded that the general MAE and commitment in this case is 137.22 W which is facilitated by a PV of 2.97 kWp. The prediction interval is selected after an estimate of the available PV power can be obtained within a reasonably acceptable range of point prediction values. This method considers the Laplacian error distribution and distinguishes between the waiting time, the launch time, and the type of day, which is selected using instructions from k-NN as a function of CCF.

The significance level can be maintained by verification related to the calculated PICP and obtained a value of 80%. These results provide a clear difference between PICP and the level of confidence on cloudy days before sunset, but for predictions at these hours it is not too important, so it can be concluded that the chosen prediction interval is very relevant.

It is at the end that a PV power estimate is made and a prediction interval is selected for the PV module facility. It can be concluded that the VPP environment and PV facilities at the weather station can be simulated with an accuracy of 12.36% and 11.85% against MAE and RMSE, respectively.

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