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Intelligent solar photovoltaic power forecasting

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Abstract

This paper presents a day-ahead forecasting method for photovoltaic (PV) power plants in commercial sectors. The method is based on numerical weather prediction (NWP) models from open weather maps and power plant specifications. The output of the model is the predicted power output from the PV power plant, which is incorporated into an optimal control strategy of the PV plant using battery storage. The use of optimal algorithms assists in the PV power plant curtailment in cases of over-generation and reduces the dependence on conventional power sources such as generators in cases of under-generation by the PV plant. It was found that most forecasting methods do not incorporate PV power and storage systems for proper optimization and demand management. This can be seen as a gap for further research of forecasting models integrated with battery storage systems to improve PV power system performance. Results obtained show a good performance of the developed model. A root means square error (RMSE) of 425.79 W and 595.10 W and a mean absolute error (MAE) of 246.26 W and 238 W were achieved for a summer and winter day, respectively. Furthermore, an excellent positive correlation exists between the predicted output power and the observed results, with R^2 values over 90%.

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Keywords: Commercial sectors; Demand management; Forecasting; Optimization; PV power plants; System planning

1. Introduction & literature review

The introduction of solar photovoltaic (PV) power systems into the energy sector has increased due to the fall in solar PV module prices over recent years [1–3]. As solar PV systems have uncertainties in the power output due to changing weather patterns, there is an increasing importance of forecasting. Forecasting the PV power output helps in monitoring the relationship between the PV power supply and the conventional power supply [4]. Furthermore, accurate forecasting reduces the uncertainties of PV power output on the grid. This ensures that power quality is maintained and ultimately improves the reliability of the system. An increase in penetration levels for PV systems into the power grid can thus be achieved with improved reliability and quality [5].

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Forecasting solar PV output power is complex as the power supply fluctuates. Several methods have been researched and developed to improve PV power forecasting [6]. Of the many existing techniques, machine learning models are widely being used and stand as the most recently developed models [7]. Numerical weather prediction (NWP) methods are also being developed in conjunction with machine learning techniques. Due to the intermittent nature of solar energy resources, power from PV plants connected to the transmission and distribution system directly cannot be easily dispatched [8].

Solar PV power forecasts based on regression models have also been developed in recent studies of optimizing the PV power output. A study was conducted on the relationship between temperature and power output [9]. A piecewise quadratic function of temperature was included in the multiple linear regression model as an independent variable. This was done to improve the accuracy of the model. The model achieved an accuracy of 4.6%. The drawback of this proposed model was that it depended largely on historical data to forecast. This was identified as a research gap for proposing methods to forecast PV power output using real-time weather data. A polynomial regression method was used in another study to further improve the NWP models for renewable energy applications [10]. The model aimed at improving performance by using solar zenith angle and clear sky index data to perform bias removal of forecasting errors on the predicted output. It was also shown that Kalman filtering could be used to improve the NWP model as it was found that extensive data was required, as well as heavy computing for perfecting the proposed polynomial regression NWP method without using machine learning techniques.

In another research, a support vector machine (SVM) based model was developed to forecast PV power output [11]. The model classified the output power according to weather conditions. An SVM model was trained using the historical output power of the PV plant. A root means square error (RMSE) was used to measure how well the model performs. The RMSE was at an average of 8.64% when considering four weather conditions. According to industry requirements for short-term PV power forecasting, the RMSE of a model should be less than 20% [11,12]. This model seemed to work well as it met the criterion; however, the errors encountered were a significant issue as they were 39%–50%.

With several forecasting methods having been developed and still being widely researched, the accuracy of these methods is a concern. Inaccurate forecasts from models can cost utilities large sums of money [9,13]. Lonij et al. [14] showed that global horizontal irradiance (GHI) and direct normal irradiance (DNI) could be used in a numerical atmospheric model called weather research and forecasting (WRF). This model, however, requires 50 h in advance to forecast, an aspect which is not ideal for the day ahead forecasting. The week ahead and month-ahead forecasting cannot provide accurate forecasts for dramatic weather changes [15].

Fast ramping in supply requires an optimal forecasting method which will respond fast to weather changes or any other changes in the power system [15]. Liu et al. [16] realized that there is a relationship between temperature and load by using a nonparametric regression model. The relationship was nonlinear from the gathered hourly data of a particular year. The influence of weather on load forecast was also examined by Black [17], who used a multiple linear regression model but mainly focused on summer weekdays. Temperature, humidity, and solar radiation were independent variables, and the model had an improved error of 2%–3%. A nonparametric forecasting model was used to forecast the output power of 5 PV plants vertical tracking in Spain Nonnenmacher and Coimbra [18]; the model used WRF methods. Cloud cover, GHI and temperature from WRF were used with random variation forests and quantile regression forests (QRF) to forecast the output power. A model which resulted in 6.4%–9.2% RMSE values was presented for Canada-based PV systems [19]. A year's worth of testing data for three small plants was used.

Commercial sectors prioritize energy security the most as this heavily affects production rates [5,20]. The integration of PV systems in most commercial buildings has thus been influenced by the need to improve or maintain production rates. With solar PV systems in place, efficiency and maximum power output utilization must be considered. PV energy storage is vital to ensure the commercial sector survives the peak demand hours [20]. PV-battery hybrid systems are recently being widely researched and developed. It was also shown that PV output power for a particular commercial building exceeds the load during weekends and early weekday mornings. This excess output can be stored and used on high-demand weekdays [5]. As restaurants and office buildings have peak demand during daylight hours, the number of battery storage systems needed for matching PV power output to peak demand is low. Mbungu et al. [21] presented an advanced energy management prediction model for an industrial load, which integrated the grid with a hybrid PV-wind battery for an industrial load.

The uncertainty of solar generation can be costly; any imbalances faced as a result of over or under-generation may require other conventional resources to be ramped up (in cases of under-generation) or PV plants to be curtailed (in instances of over-generation) [22–26]. In commercial sectors, costs incurred from imbalances of PV power generation need to be compensated by fuel costs for generator supply, as well as fast shutdown or start-up costs. Start-up and shutdown costs are directly proportional to the level of penetration of solar PV systems in an area [9].

Designs of power systems are engineered to accommodate load variability. Solar PV systems, however, add more variability and uncertainty to the supply side in utilities [27]. The addition of solar PV systems into the grid increases the challenges of power system stability. This creates a need for methods which provide balance to achieve high penetration levels of solar energy. Feasible methods need to be implemented for monitoring and controlling without expanding power systems at a high cost [28–31]. Solar energy depends mainly on weather conditions, so PV systems can generate energy when the demand is low [32]. However, when high generation is experienced during low load levels, energy can be wasted away. Therefore, energy storage facilities are essential when dealing with renewable energy [33,34].

The development of an integrated dispatchable photovoltaic system (DPV) for commercial buildings was supported by the Department of Energy in the United States [35]. With DPV systems, PV power plants are used together with battery storage systems to reduce and meet peak demand in commercial buildings. These systems have also been proposed as emergency power services to commercial sector buildings in grid power outages [35]. In a study on the DPV systems, the National Renewable Energy Laboratory (NREL) used variables such as customer demand characteristics, solar resources, system component efficiencies, and utility prices to develop a model which evaluates the economics of PV integration in commercial buildings [35]. The developed model was simulated with battery storage as well as without battery storage.

The problem to be addressed is to accurately forecast solar energy production to effectively manage solar power variability by integrating a battery storage system to improve the optimization and availability of solar PV energy during high demand levels in commercial sectors. This paper presents a day-ahead forecasting method for photovoltaic (PV) power plants in commercial sectors. The use of optimal algorithms allows for the proposed model to reduce the curtailing of PV plants and the need for conventional reserves such as generator to ramp up the required power of a commercial building in cases of over and under-generation, respectively. However, the use and dependence on historical data for forecasting models leave a gap for further research and development of models that can use real-time weather data to forecast. The contributions of the work presented are outlined as follows:

- Design a forecasting solar power output model from online open weather source predictions without dependence on historical data.
- Introduce the behaviour of forecasting models from a South African context to the research field using the data to test the forecasting model. However, very few studies have been conducted.
- Propose an optimal control strategy for demand management. The control strategy will switch between different power sources.
- Accurately forecast solar energy production to effectively manage solar power variability for commercial buildings using an optimal algorithm model integration. In addition, the model considers integrating a battery storage system to improve the optimization and availability of solar PV systems during high demand levels in commercial sectors.

This paper is also an extension of the forecasting model [36]. The remaining part of this research study can be summarized as follows: Section 2 presents model development and a description of the proposed method. In Section 3, results, performance evaluation of the model and discussions are presented. Finally, Section 4 concludes the work and offers recommendations for future work.

2. Model development and description

The proposed solar power output forecasting model is shown in Fig. 1. In the model, irradiance and ambient temperature are used together with PV system data, such as PV panel specifications, to calculate cell temperature. The estimated cell temperature is then used to forecast the output power. The hourly output power forecast Y is expressed as follows [31,37]:

$$Y(t) = Y_{pv,stc}\frac{G(t)}{G_{stc}}\left[1 - \alpha(T_{cell}(t) - T_{cell,stc})\right] Z_{pv} \tag{1}$$

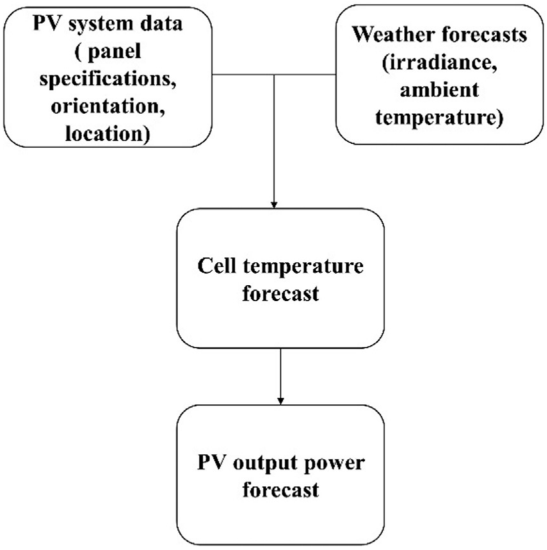

Fig. 1. Proposed solar PV power output forecasting model.

where $Y_{pv,stc}$, G, G_{stc}, α, T_{cell}, $T_{cell,stc}$, Z_{pv} describe the maximum rated PV power of the panels at standard testing conditions (STC), hourly irradiance, the irradiance at STC, power temperature coefficient, hourly cell temperature, cell temperature at STC, and configuration of the PV panels respectively.

The configuration of the PV panels is expressed as follows:

$$Z_{pv} = C_p C_s \eta_{pv} \tag{2}$$

where C_p and C_s express the number of PV panels in parallel and the number of PV panels in series, respectively. The efficiency of the solar panels is considered and described by η_{pv}. The output voltage of a solar panel is influenced by the cell temperature and is considered. The daily output power is thus expressed as:

$$Y_{day,forecast}(t) = \sum_{t=1}^{N} Y(t) = \sum_{t=1}^{N} Y_{pv,stc} \frac{G(t)}{G_{stc}} \left[1 - \alpha(T_{cell}(t) - T_{cell,stc})\right] Z_{pv} \tag{3}$$

Eq. (4) shows how the cell temperature is obtained.

$$Y_{cell}(t) = T_{amb} + \frac{G(t)}{G_{noct}} \left(T_{noct} - 20\ ^{\circ}\mathrm{C}\right) \tag{4}$$

The model is based on the ambient temperature T_{amb} at a particular hour t of the day to be forecasted. T_{noct} is the normal operating cell temperature (NOCT) of the PV panel, and G_{noct} is the irradiance level at NOCT. For this paper, ambient temperature and irradiance forecasts from an open weather source are used. The open weather source combines the WRF model for regions and global models. WRF is an NWP model common in the solar forecasting research space. The model is designed for applications such as operational forecasting and atmospheric research. The PV system needs to be integrated with battery storage to aid in the demand reduction of commercial buildings during peak. The demand reduction of the dispatchable photovoltaic systems (DPV), kW_{DPV}, is computed as [35]:

$$kW_{DPV} = kW_{pk} - (kW_{pv} + kW_{\ bat}) \tag{5}$$

The peak demand of the building is denoted as kW_{pk}, PV output at peak as kW_{pv}, and the output of the batter storage at peak as kW_{bat}. The optimal control strategy for demand management is shown in Fig. 2. The control strategy first checks the building demand and calculates whether this load can be supplied only from PV. The control strategy allows for this if the PV supply can meet the demand. If the demand exceeds the PV supply, it is supplied by battery storage plus PV power. If there is still a deficit in the power supply, grid power will meet the demand. Any excess energy from PV is stored.

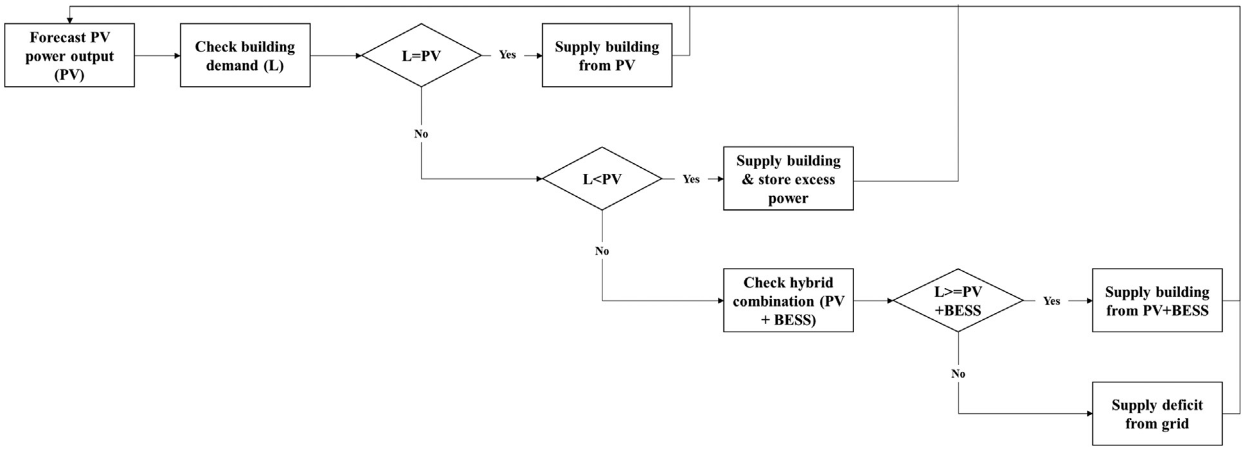

Fig. 2. Optimal control strategy for demand management.

3. Results and discussion

The proposed model is tested on a 16.8 kW PV power system with four strings, each with 14 modules. The AC inverter is simulated to be 15 kW $_p$. The system simulation is for a typical South African winter and summer day. Weather forecasts for a day in summer and winter are shown in Fig. 3. As can be seen in the figure, the winter daytime has relatively stable irradiance and lower ambient temperatures compared to summer. This is because the data used is from South Africa, which is in the Southern hemisphere and has high irradiance variability in summer due to cloudy weather conditions. The solar panel used is a 300Wp panel with a power temperature coefficient of −0.408%/K. The temperature coefficient is converted to °C as follows:

$$\alpha = -0.408\%/K = \frac{-0.408\%}{K} \times \frac{1K}{-272.15°\mathrm{C}} \times \frac{1}{100\%} = 1.4992 \times 10^{-5}/°\mathrm{C} \tag{6}$$

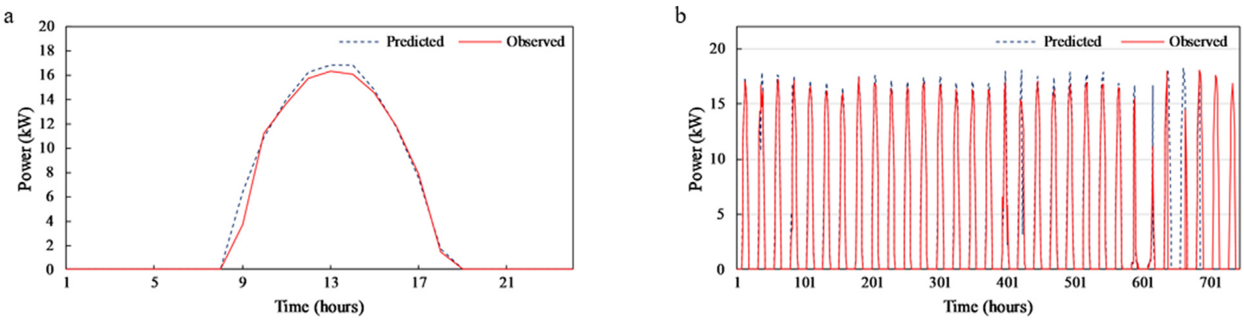

Fig. 3. Predicted and observed PV output power in summer: (a) over 24 h; (b) over 744 h.

3.1. Results

A 24-hour simulation horizon is considered for testing the model's performance. The hour simulation eventually assists in accurately modelling the day-ahead model to achieve the proposed aim. Fig. 4(a) and (b) depict the observed PV power output in a typical summer month over 24 and 744 h, respectively, with the forecasting model mapping out the prediction using the objective function in Eq. (1). It can be seen that the model can forecast the output power during a summer day accurately. However, missing data can also be noted in the figure, resulting in a significant mismatch between the predicted and observed output power between hours 100 and 199. Fig. 5(a) and (b) depict the observed PV power output in a specific winter month over 24 and 744 h, respectively. Winter days present a smoother shape in PV power output compared to the summer daytime. This can also be attributed to

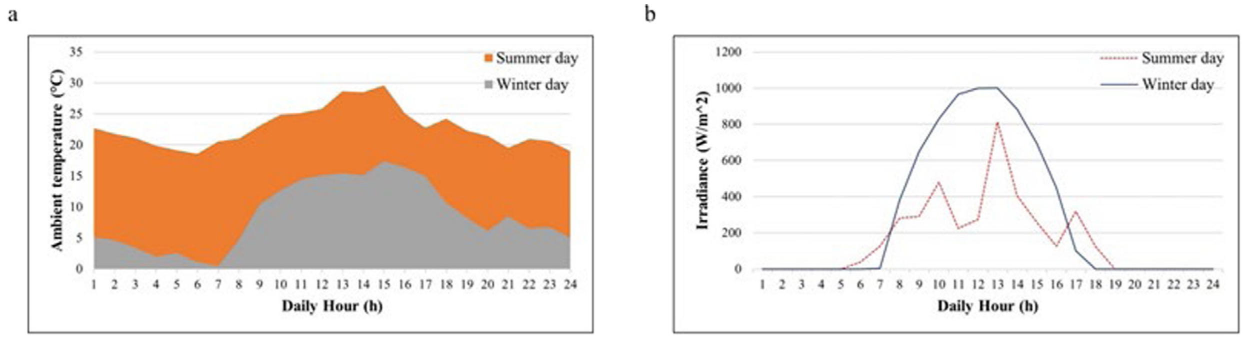

Fig. 4. Weather forecasts: (a) daily ambient temperature, (b) daily irradiance.

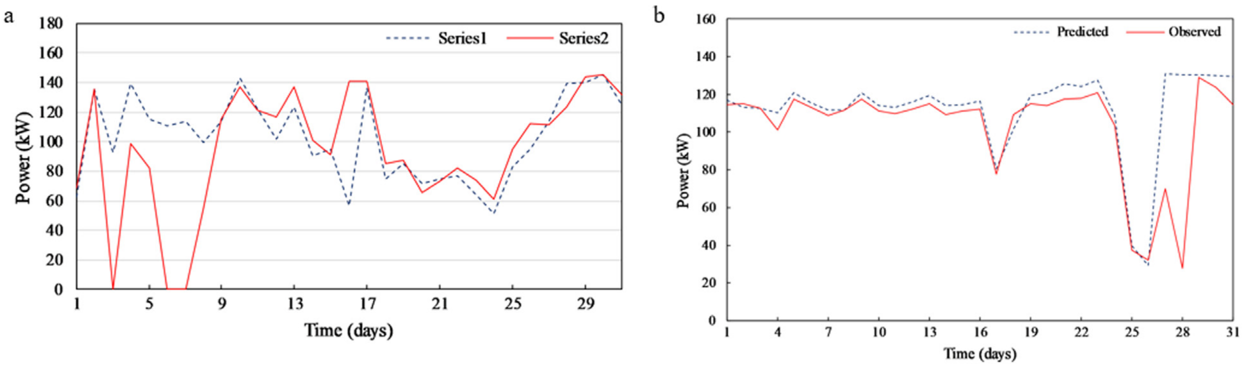

Fig. 5. Daily predicted and observed PV output power: (a) a summer month; (b) a winter month.

the season having very minimal variability in cloud cover and, therefore, good irradiance throughout. In this case, there is no mismatch between predicted and observed output power. Finally, Fig. 6(a) and (b) show the daily output power forecast for a typical summer and winter month.

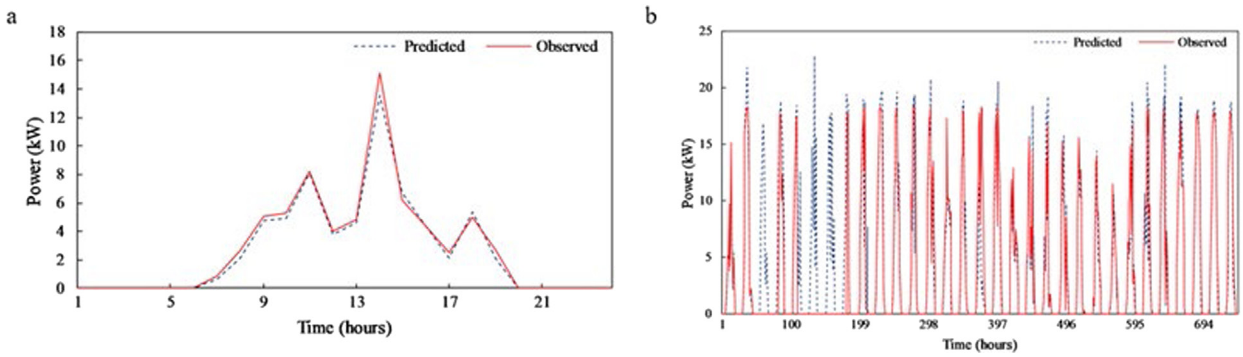

Fig. 6. Predicted and observed PV output power in winter: (a) over 24 h; (b) over 744 h.

3.2. Performance evaluation

To evaluate the performance of the model, standard error metrics such as RMSE, MAE were used. In addition, regression was computed to assess the closeness of the predicted values to the observed values. The equations used to calculate MAE and RMSE, respectively, are [4]:

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|\hat{P}(t) - p(t)\right| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\{\hat{P}(t) - p(t)\}^2} \tag{8}$$

where N is the number of forecasts, $\hat{p}\,(t)$ is a value of the predicted output power, and $p(t)$ is a value of the observed output power. Fig. 7(a) and (b) illustrate the relationship between the predicted output power and the observed output power from the PV plant on summer and winter days, respectively.

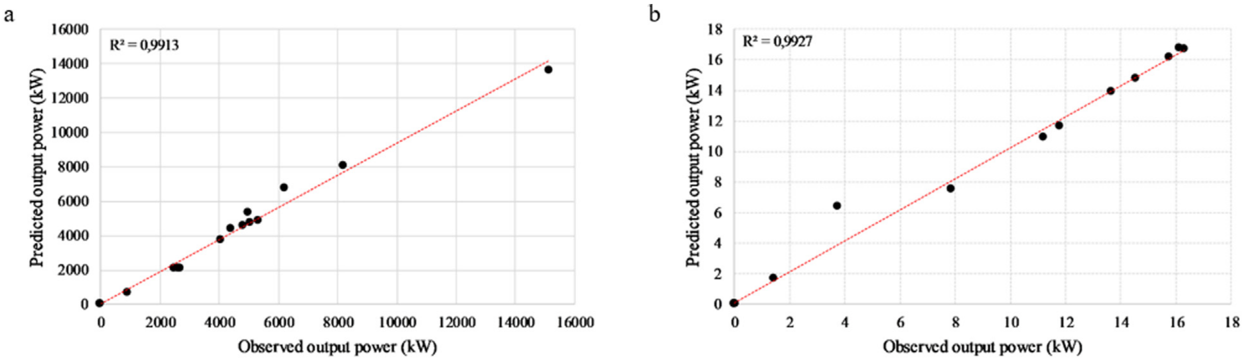

Fig. 7. The relationship between predicted output power and the observed output power from the PV plant: (a) a summer day; (b) a winter day.

3.3. Discussions

The results show a good correlation between the actual observed power and predicted power output. Based on the inverter specifications, the observed power was converted to DC using the array-to-inverter ratio of 1.12. The model also shows a good forecasting ability using real-time weather forecasts. However, the sample data used for the summer and winter months has some missing points. This can be seen to affect the forecasting accuracy of the model. The impact of missing data points on the forecasting model accuracy can be observed in Fig. 6(a) and (b). At this point, it is important to note the importance of battery storage integration. While the model forecasts a good power output from the plant, as seen in Fig. 6(a), between day 6 and 7, the plant seemed to have been offline. Without the proposed optimal control strategy in place, commercial buildings would have to seek alternative conventional sources for supply urgently; the cost incurred from connecting to the grid during these times would also increase as they were not anticipated. The overall results in Figs. 4 to 6 show a following close trend of the forecasting model to the actual data. The irradiance and ambient temperature forecasts play a significant role in the accuracy of the model.

The weather source where forecasts were obtained uses a combination of regional and global models for forecasting. Thus, it is difficult to obtain highly accurate results for small plants when using regional models; this would imply that local forecasts should be used for each plant across the region to perform weather forecasts. However, local forecasts do not have a smoothing effect advantage as no other power plants are considered for error calculations of the forecasting model. Therefore, a combination of regional and local models is recommended to strengthen the model's accuracy.

Table 1 shows the error metrics and R^2 values for the model during summer and winter days, respectively. It can be observed that there is a good positive correlation between the model results and the observed data. The acceptable accuracy of the model can be seen from high R^2 values and a close relationship between the forecasted and observed output power for both months, as shown in Fig. 7(a) and (b). The RMSE for the selected summer and winter days is low, and it can be said that the model performs well for different seasons. Although the model results

Table 1. Performance of the model.

Season	R^2	RMSE (W)	MAE (W)
Summer	99.13	425.79	246.26
Winter	99.27	595.1	230.00

show accurate forecasting capability, it is important to note its shortcomings. Fig. 6(b) indicates a dramatic change in weather conditions at day 27, leading to an overestimation of the output power. Some of these dramatic weather changes are not concisely anticipated by WRF models for small local plants, which can impact forecasting accuracy. The results also highlight the importance of incorporating power plant schedules into the forecasting model. Power plant shutdowns and routine maintenance schedules can improve the forecasting accuracy of the model better as the inclusion of these schedules would reduce the over and under-estimation of the output power by the model.

The model presented contributes to the research on solar power forecasting for South African PV power plants. There have been complex and similar studies presented previously in other regions, and only very few in South Africa. It is, therefore, not easy to use other South African studies for comparison due to the different orientations and axis tracking ability of the power plants. However, the model can be tested against other noble ones developed from regions with similar or different climatic conditions to further validate the forecasting accuracy. Furthermore, to further support the demand management proposed in this paper, cost estimations for the energy used by commercial buildings should be researched. Finally, the advantage of solar power forecasting is that it can increase the flexibility of gridable electric vehicles [38].

4. Conclusion

This paper proposed an intelligent solar power forecasting model using the day ahead method. The forecasting model was designed and simulated from a 16.8 kW PV power plant. It can be observed that the model can accurately forecast PV power output and is suitable for integration with battery storage to aid in demand reduction during peak demand. Although the panel efficiency was considered, the inverter efficiency could have impacted the prediction accuracy of the model. Nevertheless, the model showed an ability to accurately forecast the output power of a PV plant using real-time weather data. Error metrics calculated for the model validate that the model is suitable to forecast for all seasons. It is recommended that the model should be tested against other previously developed models to validate accuracy. Shortcomings of the sources used in the forecasting model should be researched further, and the model improved after that. Future studies will focus on integrating the model with battery storage and analysing how it saves energy costs for a commercial building.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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