A Simple Method for Predicting the Output of Dual-Axis Tracking Systems from Fixed-Tilt System Outputs

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Abstract—**This paper begins by summarising a piece of work by the author which conducts a comparative analysis on the variability of fixed-tilt (FT) system and dual-axis tracking (DT) system. The results of this work revealed a relationship between the variability of the two systems associated with sun position. Consequently, a simple method for predicting the output of DT from FT output data was developed. The method is applied to the prediction of both magnitude and variability; the performance results of the method are presented and show it to be acceptable as an easily implemented prediction technique in the case where irradiance measurements at the sun's elevation angle are not available**

Keywords-photovoltaics, solar tracking, power generation, intermittent generation

I. INTRODUCTION

The work presented in this paper extends a study conducted by the authors comparing the output variability of four types of photovoltaic (PV) systems: Fixed orientation and tilt (FT), Double-Axis Tracking (DT), Single-axis tracking (ST) and concentrator [1]. The systems are located at the Desert Knowledge Centre in Alice Springs, Australia. This previous study assesses the difference in variability between these different PV technologies, primarily between FT and DT systems from actual performance data. The data set used for the analysis is sourced from the Desert Knowledge Centre website and consists of 3 years' worth of time synchronized, 5-min average power (kW) samples. There are 16 FT systems, 1 ST system, 3 DT systems and 1 concentrator system located on the one site. Most studies utilising such data focus on the expected (and perhaps expected distribution) of system output over a day and how this changes over the year. However, another potentially important issue is the variability associated with this output. This is particularly relevant when considering integration challenges for high penetrations of PV into electricity networks because secure power system operation requires that supply equal demand at all times and locations within the network. Large changes in PV output therefore need to be managed through other system resources.

The study results include the average hourly output yet also variability of the different technologies over a year and differences in this variability for different technologies. The results illustrate how the variability of all systems will vary throughout the year due to the changing Alice Springs desert climate (which moves between a wet and dry season) and changing path of the sun, as shown in "Figure 1" for the example of the ST system. There are clearly greater levels of variability from November to February than for the middle of the year. This period of higher variability coincides with the wet season and greater cloud activity. By comparison, the dry season occurs during the middle of the year with very little cloud activity as reflected in the reduced level of variability.

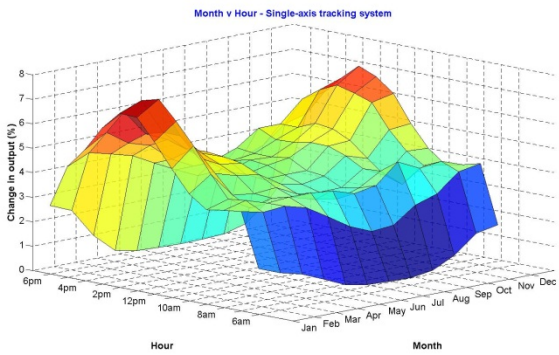

Figure 1 Month v hour surface plot for the ST system. That is actually absolute average change in output right

"Figure 2" takes a "slice" of the surface plot along the 2pm axis with the range of variability values for each week presented as a scatter plot. The negative and positive mean are also plotted

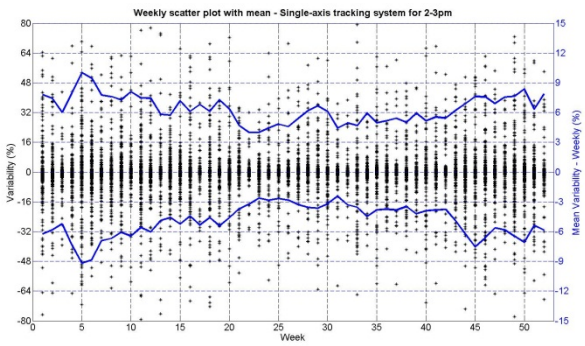

Figure 2 Weekly scatter plot with mean - ST system for 2-3pm

The lead author is a recipient of an Australian Solar Institute (ASI) postgraduate scholarship

"Figure 2" shows the range of actual experienced variability over five minute intervals over the range of ±80% of all experienced variability. Via the mean we can see more clearly how the variability changes throughout the year with peaks of around ±9% during week 5 (first week of February) down to around ±3% in week 23 (second week of June). The next plot "Figure 3" takes variability and magnitude data for a particular month and hour, a "data point" from the surface plot of "Figure 1", and generates a probability distribution function (PDF).

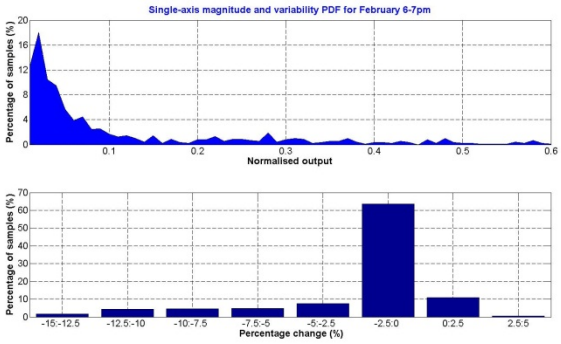

Figure 3 Magnitude and variability PDF for ST system for February 6-7pm

This PDF gives the percentage chance of the occurrence for both magnitude and change in output. The possible values are "Binned", with a bin width of 2.5% for variability and 0.01 for magnitude. The magnitude is normalized so values range from 0 to 1. The magnitude PDF shows that for most of the time the output sits beneath 0.15 and that the majority of the samples show a variability of between -2.5 to 0%. The magnitude PDF is weighted to relatively low output while the variability PDF is heavily weighted towards negative changes in output which is as expected considering the time; 6-7pm when the output of the system is ramping down. The final section of work in [1] looked into the variability relationship between FT and DT systems. Using the data for the month v hour surface plot (see "Figure 1") for FT and DT, a surface plot was generated presenting the percentage difference in variability between the two systems. "Figure 4" taken from [1] is this plot. One would conclude from "Figure 4" that the variability relationship between the two systems is reasonably independent of month and heavily dependent upon the time of day. At 4pm for example, the difference in variability sits at around 25% for all months. A key issue here is the greater output of a DT system at earlier and later hours during the day. As the results of "Figure 4" looked very much like an inverted path of the sun, this has prompted further work, presented in this paper, to establish the nature of the relationship between the variability of FT and DT systems is due to sun position, and the potential to forecast DT system performance from FT system performance. This is a potentially valuable capability as the decision to use tracking systems involves weighing the additional complexity and cost of tracking against the improved performance that will be achieved. Models of DT performance generally require actual or estimated direct as well as diffuse irradiance.

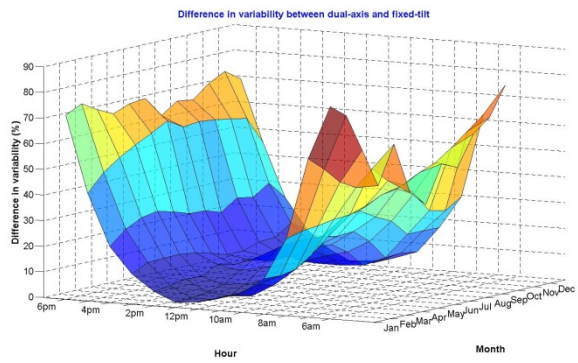

Figure 4 Month v hour surface plot - FT and DT percentage difference in variability

Direct irradiance measurements are expensive and consequently not available at many existing sites. For example, according to the Australian Bureau of Meteorology (BOM) website, there is only 10 weather stations currently measuring irradiance (global, diffuse and direct) across Australia. By contrast, there are a growing number of FT systems across Australia which, if appropriate methods exist, might be used to predict DT performance.

Only limited work to date has been published on this issue. Reference [2] predicts the output for a DT system based on irradiance measured at a fixed tilt as input into a PV power model. The prediction is made through knowing the path of the sun and an estimation of diffuse irradiance. The work undertaken in our study effectively replicates much of what has been done in [2] but adds some extensions. In [2] the model is tested using irradiance data for what appears to be a sunny day with very little variability. As our study is attempting to establish a robust relationship between the variability of FT and DT systems, highly variable days are used for testing. It should be noted that a full year validation is conducted in [2] using data from the PVGIS atlas which would take into account highly variable days. However, this approach only gives the irradiance for a typical day for each month and therefore has insufficient resolution to draw strong conclusions on how well the model performs for highly variable days. Another difference is the data used to generate the prediction and for validating our method is actual generation data as opposed to modelled. Our study therefore extends the work of [2] by testing the methodology more thoroughly and could be said to provide further validation of the approach.

Section II presents the prediction methodology, the performance results of the prediction are given in Section III with the results discussed in Section IV.

II. METHODOLOGY

The time synchronized 5-min average kW data for all PV systems at the Alice Springs DKA PV testing site was downloaded from the DKA website [4] as a CSV file; the data was then cleaned and imported into Matlab with all data analysis executed using Matlab. The following sections describe the procedures followed to achieve the results presented in Section III.

A. Variability

The variability was determined using the normalized data sets, this simply involved shifting the data set forward by one time sample and then subtracting the shifted data set from the non-shifted – the absolute value of this shift is used. As the data set was already normalized against rated output this gave a percentage change in output compared to the peak value.

B. Prediction method

As mentioned in the paper Introduction, our prediction method effectively replicates the work done in [2] with the difference being that the actual output data from a FT system and a DT system, located close to each other, are used to test the method as opposed to the reconstitution of DT output using FT irradiance as input into a PV power model. The method is also performed in reverse where the FT output is predicted from DT. Also, as our work has a particular interest in the relationship between the variability of FT and DT systems; highly variable days are used to validate the effectiveness of the method. It is assumed that, if the output for a DT system can be accurately predicted from that of a FT system over 5 minute to one hour time periods for a highly variable day then the variability for the DT system can also be accurately predicted. The proof is based on the assumption that the incidence angle (representing the path of the sun) and the percentage of diffuse irradiance as a component of total irradiance are the factors which determines the difference in output, and therefore variability, between FT and DT systems.

1) Incidence angle

The incidence angle (θ_i) is the difference between the angle normal to a FT surface and the angle of the sun. The angle of all the FT systems at the DKA is 20° to the horizontal, facing due north (azimuth of 0°). For Alice Springs (Latitude 23° S, Longitude 133° E) the incidence angle was calculated for each 5-min time stamp in 2010, "(1)" gives the equation for the incidence angle θ_i.

$$\cos\theta_i = \cos\beta(\sin\delta\sin\emptyset + \cos\delta\cos\emptyset\cos\omega) - \cos\delta\sin\omega\sin\beta\sin\sigma + \sin\beta\cos\sigma(\sin\delta\cos\emptyset - \cos\sigma\cos\omega\sin\emptyset). \quad (1)$$

θ_i = Incidence angle
β = Fixed tilt angle of the system to the horizontal
δ = Declination angle
$\emptyset$= Latitude
ω = The hour angle
σ = Fixed tilt system azimuth angle

This value is then normalised, where an angle of 90° gives a value of 1. The incidence angle produced gave an hourly resolution which turned out to be too coarse and resulted in a poor prediction. This hourly resolution is due to the equation for hour angle (ω), see equation "(2)" below

$$\omega = 15(t_s - 12). \quad (2)$$

t_s = Solar time in hours

To improve prediction performance the resolution of solar time (t_s) was calculated at increments of 5 min instead of1 hour and then smoothed, using the mean of the previous and subsequent 5 values. In [2] the resolution for solar time is kept at 1 hour; the prediction results for a sunny day are fine under this resolution but would likely be less accurate for more variable days. "Figure 5" below shows the difference between the 5-min smoothed and 1 hour incidence angle with the hourly jumps clearly obvious.

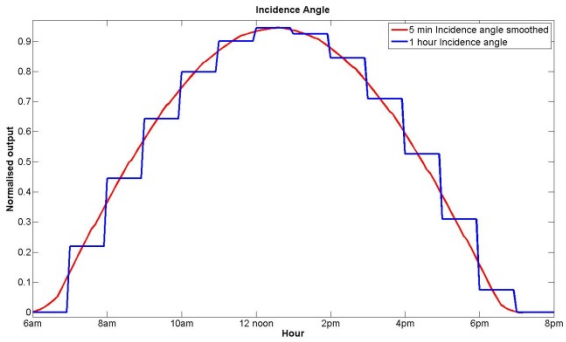

Figure 5 1 hour and 5 min smoothed incidence angle – average day

A thorough explanation of sun path geometry mainly concerned with declination and hour angle is given in [2].

2) Prediction calculation and diffuse irradiance

We consider four possible approaches to making the performance prediction, with each approach varying according to how the diffuse irradiance is defined. The first prediction approach uses the diffuse irradiance at the horizontal (DKA provides diffuse and global irradiance data for the horizontal at 5-min intervals, time-synchronised with the PV output data). The second and third approaches use the diffuse irradiance at a 20° tilt and at the suns angle of elevation for every 5-min sample. These values are derived from the horizontal and global irradiance data using two different methods, Castro and Koronakis [4].These two methods for determining diffuse irradiance were chosen for their simplicity, both performed sufficiently well compared to the other methods presented in [4] and are considered by the authors to adequately serve the purpose of providing prediction results to which the final approach (which doesn't utilise any irradiance measures) can be compared.

Castro:

$$I_{D,\beta} = 1/3 \times I_D(2 + \cos\beta). \quad (3)$$

Koronakis:

$$I_{D,\beta} = 1/2 \times 0.1 \times I(1 + \cos\beta). \quad (4)$$

Where
β = Tilt angle
$I_{D,\beta}$ = Diffuse irradiance at tilt β
I_D = Diffuse irradiance at the horizontal
I = Global irradiance at the horizontal

The final approach is the simplest; the diffuse irradiance is considered to be 25% of the incidence angle, selected after a process of trial and error. This approach is included as it provides a way to predict DT variability from the output of a FT system (and vice-versa) without any need for irradiance measurements at all. Using the 25% of incidence angle approach, the method for predicting DT from FT is further explained. The first step requires that the non-diffuse output of the FT system be calculated. The non-diffuse output is considered to be all values greater than 25% of the incidence angle. This non-diffuse output is then divided by the incident angle matching the values' timestamp. The non-diffuse output alone is divided by the incident angle as the diffuse component for both systems should be more or less the same and shouldn't be impacted by the incidence angle. Referring to "Figure 6", the FT output (red line) above the 25% incidence angle (black area) is increased by dividing its output by the cosine of the incidence angle (black line) and then 25% of the incidence angle is added to the result to give something very similar to the dual-axis output (blue line).

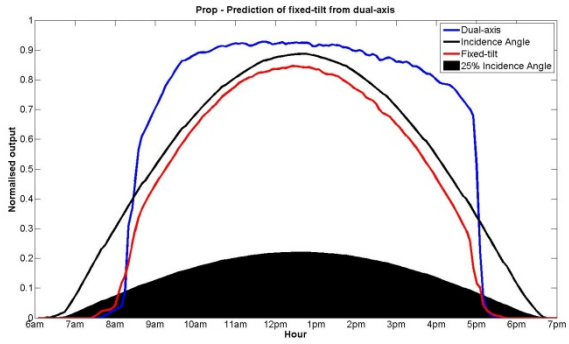

Figure 6 Figure to assist explanation of development of predicted DT output from FT

The method, incorporating all 4 approaches for determining diffuse irradiance, is used to predict both magnitude and variability.

III. RESULTS

All analysis and comparisons are performed on a 5.4 kW, polycrystalline, Kyocera DT system and a 5.4 kW, polycrystalline, Kyocera FT PV system. The first figure for the results, "Figure 7", is similar to "Figure 4" and shows the variability relationship between FT and DT systems. All lines are made up of the yearly average for that 5-min timeslot. The blue line is the incidence angle; the black is the horizontal diffuse irradiance and the green the difference in variability between FT and DT systems. The figure confirms the link between FT and DT variability is heavily dependent upon sun position by the inverse relationship between the variability difference and incident angle.

A. Magnitude prediction

Testing of the prediction method started with magnitude at the 5-min scale to clearly show how precise the prediction is. The results for predicting variability, in the next section, are calculated at larger scales (day and month).

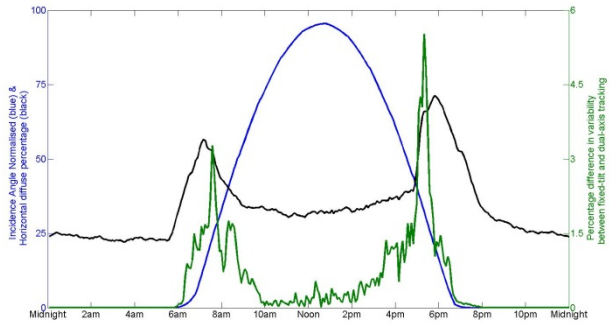

Figure 7 FT and DT variability difference plotted against incidence angle and horizontal diffuse irradiance, given as a percentage of global.

For system output magnitude, the prediction (for all four approaches) gave reasonably consistent errors throughout the year but increases around the more variable months of December and January. "Figure 8" gives an example of an occasion in early January where the prediction error is quite large while "Figure 9" gives an example of a good prediction taken from around the middle of the year. Both predictions are made using horizontal diffuse irradiance

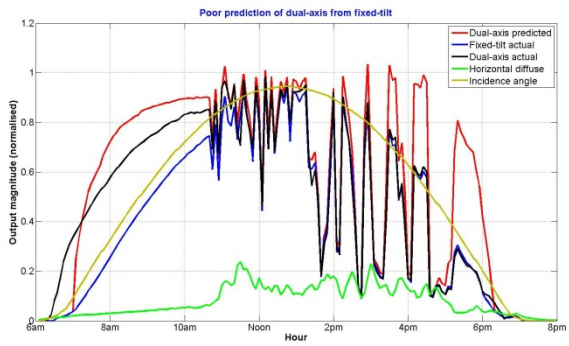

Figure 8 Poor prediction of DT from FT using horizontal diffuse irradiance

Looking at "Figure 8" it is evident that the prediction has failed where the FT output (blue) is well above the horizontal diffuse irradiance (green) at a low incidence angle (yellow). As a result the FT output is then divided by the incidence angle (~ 0.3) giving a prediction of almost triple the FT output. The behaviour of the DT system is hard to explain, with its output effectively the same as the FT system from around midday onwards. This normally only occurs when all generation (for both systems) is due to diffuse or when the tilts of both systems are the same. The DT system seems to be behaving more like a FT system instead and may not have been tracking correctly at these times. Note that these bad prediction days are rare; see analysis associated with "Figure 11" for further discussion. "Figure 9" by comparison a relatively good predictive capability. For this to be the case the diffuse irradiance at 20° and at the elevation of the sun must have been similar to that on the horizontal. It was, therefore, thought that using the diffuse irradiance at 20° tilt and at the suns elevation (through Castro and Koronakis) for the

prediction might resolve the issue but this was not the case; no real improvement was observed. “Figure 10” plots the prediction performance for each of the approaches with little difference between them. Of note is that the simple “25% of incidence angle” approach performs as well as the other three. For all approaches aside from Castro the prediction error sits below 4% for around 300 days, only breaking above this during December and January when the most cloud activity occurs.

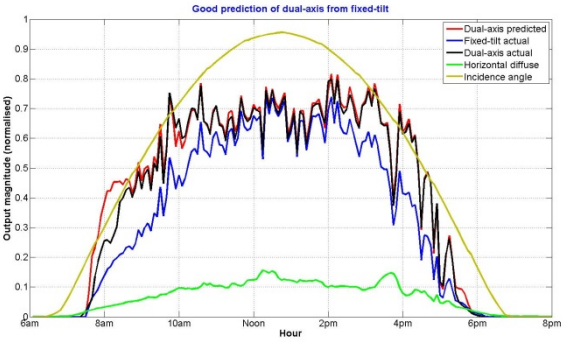

Figure 9 Good prediction of DT from FT

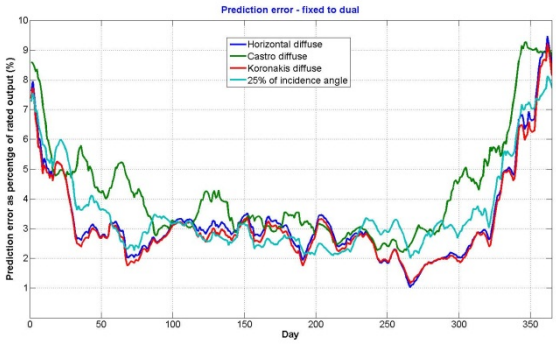

Figure 10 Prediction error of DT from FT

A matrix was developed to assist in identifying when this prediction error was occurring. The matrix consisted of 168 time-slots (5am-7pm) on the x-axis, 5% bins for the difference in dual and fixed output on the y-axis and the number of samples where the prediction error is greater than 30% for each timeslot and bin on the z-axis. “Figure 11” shows this matrix. The matrix reveals that the majority of the prediction error occurs around 5pm and also when there is very little difference between the dual-axis and FT magnitude. The samples where the error is greater than 30% and the difference in magnitude between FT and DT is less than 5% (clearly shown by coloured peak in “Figure 11”) were removed from the prediction method to see how it would impact on performance; “Figure 12” shows the result. The impact is significant considering that only 460 samples were removed from a total of 52560, approximately 0.9%. The insight provided by “Figure 11” is important in highlighting that the majority of the error in the prediction method occurs when the DT and FT output are similar. If the error is indeed not due to the DT system failing to track correctly, this ensures that for periods of high prediction error the actual variability for a DT system will be similar to that of the FT and not at extreme, unexpected levels. “Figure 13” shows that the method works equally well, indeed better, for predicting FT from DT. This can likely be attributed to the fact that the prediction target, a FT system, has a lower output profile than the DT system. Note that “Figure 13” should be compared with “Figure 10” and demonstrates that the prediction is approximately twice as accurate.

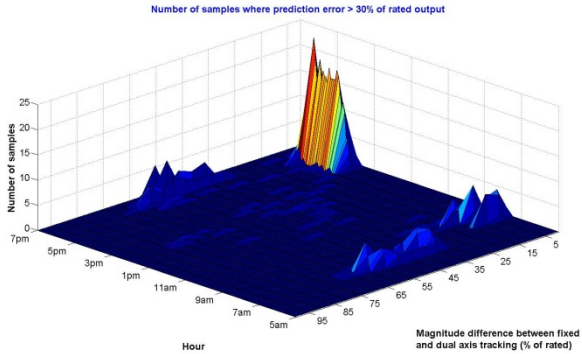

Figure 11 Number of samples where prediction error > 30% plotted against timeslot and dual-axis fixed-tilt magnitude difference

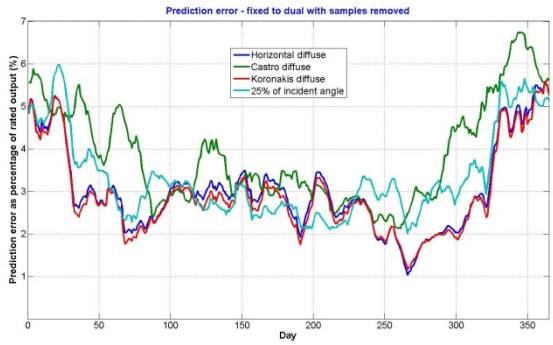

Figure 12 Prediction error DT from FT with matrix samples removed

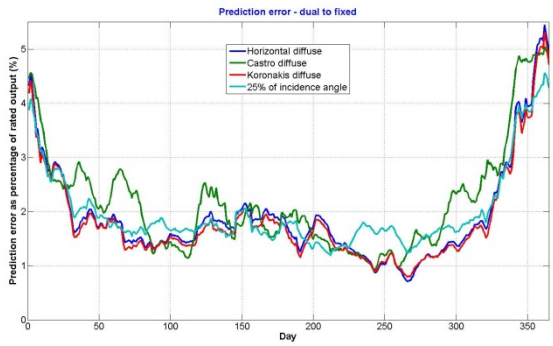

Figure 13 Prediction error of FT from DT

B. *Variability prediction for 25% approach*

This section considers the prediction of variability at larger time scales beyond five minutes, presenting an assessment of how well the 25% method performs at predicting the variability mean and standard deviation. Each prediction is presented in the same format; the hourly measure for each month. For example, the January 6am data point for the mean

variability, “Figure 14”, is the mean of all values between 6-7am for each day in January. All predictions are made using the 25% of incidence angle approach. This format, hour by month, as well as these measures is intended to allow for easy integration of these variability results into models examining the impact of high penetration PV variability on the electricity grid. “Figure 14” below gives a comparison of the dual-axis actual and prediction hourly variability by month, the top graph shows that the prediction closely follows that of the actual performance. The error is generally below 1% of rated output with a few spikes giving a mean prediction error of 0.5%. The error is measured as a percentage of rated output instead of a percentage difference between the actual and predicted to avoid the large (and misleading) error which occurs during periods of low output at dawn and dusk. As the variability increases towards the ends of the year so does the error. The larger spikes coincide with the “bad” magnitude prediction days (see “Figure 8”) according to both time of year and time of day. “Figure 15” presents the performance of the method for predicting standard deviation. The prediction error is again generally below 1% with the occasional spike higher and has a mean of around 0.5%. The error remains relatively flat throughout the year, unlike “Figure 14”, indicating that the predicted variation around the mean remains consistent with the actual despite the increase in mean variability prediction error. For this study, we did not feel it necessary to calculate and present the variability prediction performance of deriving FT from DT. As “Figure 13”, FT from DT, exhibits similar characteristics to that of “Figure 10”, DT from FT, but with reduced error, it is assumed that the variability performance would also be similar to DT from FT but reduced error.

IV. Discussion

From the results it can be concluded that with the prediction method presented here, for all four approaches modelling diffuse irradiance, it is possible to make reasonable estimates of the magnitude output profile as well as the variability of a DT system from the output data of a FT system.

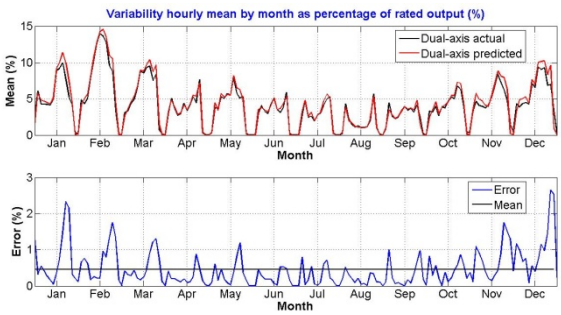

Figure 14 Prediction performance of mean hourly variability by month as percentage of rated output

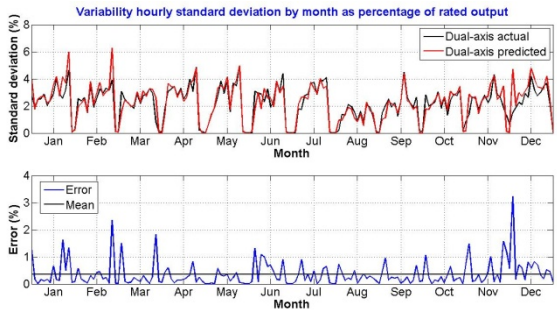

Figure 15 Prediction performance of the hourly standard deviation in variability by month as percentage of rated output

For both magnitude and variability, aside from the cases where the diffuse irradiance is significantly different from that on the horizontal, the prediction performed well considering its simplicity. For DT from FT, magnitude prediction error is around 3% for the majority of the year and mean estimations for variability mean and standard deviation produced an error of approximately 0.5%. It is argued that as the 25% per cent of incidence angle approach performed as well as the other three and that it is easily implemented, it could be considered acceptable for estimating dual-axis variability for locations with existing data for FT systems but no irradiance measurements. We would, however, caution that our results are based only on system performance data for one site. Furthermore, this site enjoys an inland desert climate. Still, this type of climate is likely to be targeted by large PV system projects due to the excellent solar resource that they offer. This finding would also seem to hold for estimating FT variability for locations with existing DT output data.

Acknowledgment

The authors gratefully acknowledge The Desert Knowledge Australia Solar Centre for providing the data used for the analysis presented in this paper.

References

[1] S. Heslop, I. MacGill, “Comparative analysis on the variability of fixed and tracking and photovoltaic systems,” unpublished.

[2] A. Coelho, R. Castro, “Modelling and validation of PV power output with solar tracking,” in *International Conference on Power Engineering, Energy and Electrical Drives*, 2011.

[3] A. M. Noorian, I. Moradi, G. A. Kamali, “Evalutaion of 12 models to estimate hourly diffuse irradiation on inclined surfaces,” *Renewable Energy,*33, 2008, pp. 1406–1412.

[4] G. Notton, C. Cristofari, M. Muselli, P. Poggi, N. Heraud, "Hourly Solar Irradiations Estimation: From Horizontal Measurements to Inclined Data," *Environment Identities and Mediterranean Area, 2006. ISEIMA '06. First international Symposium on*, 2006, pp.234-239.

[5] R. Perez, R. Stewart, R. Seals, T. Guertin, “The development and verification of the Perez Radiation Model,” Sandia National Laboratories, Contractor Report SAND88–7030, 1988