Model Development and Validation of a Dual-Axis PV Tracking System: A Case of South Africa

Percy Andrew Hohne[1], Kanzumba Kusakana[1], and Bubele Papy Numbi[2]
[1] Dept. of Electrical, Electronic and Computer Engineering, Central Univ. of Technology, Bloemfontein, South Africa
[2] Dept. of Electrical Engineering, Mangosuthu University of Technology, Durban 4031, South Africa
Email: phohne@cut.ac.za; kkusakana@cut.ac.za; numbib@mut.ac.za

Abstract—**Dual axis photovoltaic (PV) tracking system is considered in general to be a poor investment. This is mainly due to the substantial initial investment costs that these systems carry. However, in recent years, solar panels and accompanying component costs have decreased significantly. Additionally, electricity price hikes in South Africa have compelled most of the country's citizens to reconsider their sources of electrical energy. A popular alternative to grid energy in South Africa is the use of photovoltaic systems. Careful consideration is required when choosing from the various systems available on the market. The main method for maximizing the output power of these systems is to introduce solar tracking systems. Therefore, in this paper, a model of a dual axis tracking system is developed and validated against a real-world plant in the Bloemfontein region in South Africa. The presented model was observed to be accurate to within an error rate of 6.39%. Additionally, the performance of the inverters of the PV tracking systems were evaluated and discussed. The validated model may prove to be an excellent tool for energy managers to determine the feasibility of such systems, compared to conventional photovoltaic setups.**

Index Terms—**Dual axis PV tracking system, model development, model validation, PV performance analysis**

I. Introduction

In South Africa, the prevalence of renewable energy systems for power generation has increased tremendously in the last decade [1]. This is mainly due to the significant rise in electricity prices and the electricity supplier's inability to meet the energy demand of consumers [2]. As a result, the electricity supplier, Eskom, has introduced load shedding or curtailment in order to mitigate a total grid shutdown or blackout. Additional strategies to reduce the strain on the national grid are the implementation of time-based energy pricing and maximum demand penalties [3]. Time based energy pricing serves as an incentive to consumers to exercise demand side management, while maximum demand penalties are enforced when an upper demand limit is reached.

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Corresponding author: P. A. Hohne (email: phohne@cut.ac.za).

In hindsight, the rise in electricity prices along with time-based pricing and maximum demand penalties has resulted in exceedingly high grid energy costs. The rise in grid energy costs combined with reduced implementation costs of renewable energy systems has improved the feasibility of these systems [4].

Solar energy systems in particular, have been a proven and widely used method of alternative energy generation in most areas in South Africa, as opposed to wind energy harnessing technologies [5]. Various methods and technologies have emerged to increase the photovoltaic energy yield of photovoltaic (PV) modules. These include; enhancements in inverter technologies for maximum power point tracking (MPPT), cooling of PV modules to increase the efficiency of the modules and solar tracking systems to absorb maximum energy from the solar resource [6]. Substantial research has been conducted on improving the MPPT capability of inverters and cooling PV modules for increased efficiency as in [7], [8], which resulted in significant advances for PV power production. Similarly, solar tracking systems have been subjected to extensive experimentation. In most cases, a single axis tracking system offered sufficient performance given the price bracket for installing such a system [9]. Dual axis system, on the other hand, is often too costly in terms of the initial investment required for implementation. However, in recent years, with the decline in PV module costs and rise in electricity prices, these systems have become increasingly competitive with conventional stationary PV and single axis PV tracking systems. Additionally, it may be necessary in some cases to implement Dual axis tracking systems where the physical installation space is limited. Other benefits of these systems include PV power production during the costly regions of time-based pricing schemes [10].

In retrospect, it may seem difficult to compare these systems without accurate models to predict their performance under certain weather conditions in various regions. Several studies have been conducted on the model development of small-scale PV tracking systems as in [11]-[13]. However, for the specific case of South Africa, few studies have focused on large scale PV tracking system performance, particularly in the central

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region of the country. Therefore, in this paper, a model is developed and validated against the operation of a large-scale solar tracking plant, consisting of multiple standalone tracking units, in the Bloemfontein region in South Africa. The aim is to provide an accurate model to forecast the PV power production of these systems in order to compare the feasibility as opposed to conventional PV systems.

II. Model Development

The output power of the PV array may be modelled as [14]:

$$P_{\mathrm{PV}} = P_{\mathrm{PV,STC}} N_{\mathrm{PV}_P} N_{\mathrm{PV}_S} \frac{I_{\mathrm{total}}}{1000}\left[1-\alpha(T_{\mathrm{cell}}-25)\right] \tag{1}$$

where P_{PV} is the output power generated by the PV at maximum power point while subjected to standard test conditions (STC). N_{PV_P} and N_{PV_S} are the number of PV panels connected in parallel and series, respectively. I_{total} denotes the total solar irradiance on a tilted surface, measured in Wh. α represents the temperature coefficient of power. T_{cell} is the temperature of the PV cell in ℃. The cell temperature [15] may further be calculated as

$$T_{\mathrm{cell}} = T_{\mathrm{amb}} + \frac{I_{\mathrm{total}}}{800}(T_{\mathrm{NOC}}-20) \tag{2}$$

where T_{amb} and T_{NOC} are the ambient air temperature and nominal operating cell temperature in ℃, respectively.

The total irradiance I_{total} received by the PV cell may be calculated with respect to the three components of solar irradiance. These components are direct normal irradiance (DNI), diffuse horizontal irradiance (DHI) and global horizontal irradiance (GHI) noted as I_{DNI}, I_{DHI} and I_{GHI}, respectively. Eq. (3) denotes how these components of solar irradiance may be incorporated to determine the total irradiance on a tilted surface [16]:

$$I_{\mathrm{DNI}}\cos\theta_{\beta} + I_{\mathrm{DHI}}\left(\frac{1-\cos\beta}{2}\right) + \rho I_{\mathrm{GHI}}\left(\frac{1-\cos\beta}{2}\right) \tag{3}$$

where θ_{β} is the angle of incidence of the solar irradiance on a tilted surface in degrees (°); β is the tilted angle in degrees (°); and ρ is the reflectance factor of the surrounding area.

III. Model Validation and Results

Multiple variables are taken into consideration in the developed model to represent the accurate operation of a dual axis PV tracking system. To this end, model validation is a necessity to ensure that this representation is verified against the operation of a real-world system. Therefore, historical data was obtained from dual axis tracking systems previously installed on the Central University of Technology's (CUT) premises. A total of 12 PV Tracking units were installed on the premises each rated at 12.6kWp. Each tracking unit consists of 42 panels rated at 300W each. The output of all the tracking units combined may deliver a total power of 151.2kWp. Each of the tracking units are fitted with a 15KVA inverter with MPPT capability. Five of these tracking units are shown in Fig. 1. In Fig. 2, the weather station, located near the PV tracking plant is shown. The data from the weather station may be used for model validation purposed, more details of the station are provided further in this section.

On average, the tracking units yield approximately the same amount of energy throughout the day with slight variances (<5% deviation from the average production) due to shading from trees, high mast flood lights and buildings close to the PV tracking arrays among others. This occurs during the early mornings and late afternoons.

Other factors influencing the output power generated from PV modules and by extension the whole PV tracking array include; type of PV material, temperature of the module, parasitic resistances, inverter efficiency, dust and bird droppings and PV array orientation [18]. Although these PV tracking units are identical in terms of the manufacturer, slight variances in the type of PV material, parasitic resistances and inverter efficiencies may be experienced which combined result in a significant PV output power deviation from the average. The variances not dependent on the manufacturer include; temperature of the module, dust and bird droppings. The temperature of the module and PV output power may differ from other modules due to hot spots formed as a result of shading, bird droppings or excessive dust.

Fig. 1. Dual axis PV tracking systems installed on CUT premises.

Fig. 2. Weather station (SAURAN) on CUT rooftop [17].

TABLE I: MONTHLY PV OUTPUT POWER YIELDS FOR 2019 [MWH]

nverter	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.	Average
01	4,06	5,67	3,38	1,03	4,96	2,99	5,21	5,82	1,16	2,09	7,4	5,21	4,08
02	0,24	3,45	2,62	1,39	0,08	0,61	3,28	0,15	0,38	0,55	3,48	3,28	1,63
03	3,61	2,23	0,16	2,18	2,87	4,09	0,27	4,74	4,48	1,6	1,14	0,27	2,3
04	2,37	3,44	4,24	2,33	1,5	2,48	2,13	1,41	0,15	2,58	1,86	2,13	2,22
05	2,15	2,26	2,14	0,59	0,28	2,15	2,15	1,61	1,38	0,15	2,39	2,15	1,62
06	2,83	0,23	0,87	0,94	3,08	3,52	0,92	5,31	2,07	0,96	1,2	0,92	1,9
07	8,91	0	1,73	2,14	7,15	11,32	1,34	10,71	0,39	1,18	1,85	1,34	4,01
08	0,91	3,35	1,82	0,51	1,27	0,14	2,84	3,13	1,84	0,68	3,76	2,84	1,92
09	2,92	5,36	4,25	2,95	2,65	1,49	2,34	5,15	3,46	4,3	4,04	2,34	3,44
10	4,23	1,19	3	3,24	1,75	4,85	2,85	2,97	1,65	2,74	1,53	2,85	2,74
11	4,84	3,58	2,15	0,33	1,48	3,54	1,69	3,75	0	3,97	1,69	1,69	2,39
12	2,65	1,4	4,78	1,5	0,88	1,58	3,68	0,81	0,29	2,55	2,11	3,68	2,16

TABLE II: PV OUTPUT POWER DEVIATION FROM AVERAGE [%]

nverter	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.	Average
1	2,518	2,62	2,806	2,3	2,613	2,503	2,482	2,851	2,876	3,209	3,015	2,482	2,69
2	2,421	2,859	2,869	2,256	2,486	2,381	2,845	2,768	2,919	3,463	3,433	2,845	2,8
3	2,521	2,75	2,867	2,3	2,573	2,487	2,729	2,875	2,968	3,386	3,291	2,729	2,79
4	2,487	2,855	2,914	2,277	2,531	2,461	2,815	2,102	2,926	3,448	3,363	2,815	2,75
5	2,489	2,831	2,842	2,235	2,509	2,439	2,807	2,766	2,873	3,442	3,39	2,807	2,79
6	2,494	2,795	2,852	2,286	2,572	2,463	2,768	2,856	2,918	3,431	3,351	2,768	2,8
7	2,203	2,815	2,877	2,204	2,23	2,165	2,795	2,623	2,939	3,446	3,377	2,795	2,71
8	2,411	2,84	2,837	2,217	2,476	2,381	2,836	2,729	2,895	3,46	3,418	2,836	2,78
9	2,372	2,66	2,698	2,169	2,432	2,333	2,692	2,665	2,782	3,265	3,188	2,692	2,66
10	2,307	2,699	2,728	2,179	2,412	2,308	2,677	2,645	2,816	3,299	3,251	2,677	2,67
11	2,511	2,798	2,854	2,232	2,56	2,507	2,809	2,738	2,927	3,461	3,367	2,809	2,8
12	2,329	2,654	2,729	2,203	2,464	2,377	2,587	2,661	2,853	3,254	3,204	2,587	2,66

It may be argued that the PV array orientation is dependent both on the manufacturer and environmental conditions. The solar tracking sensor and tracking actuators may have certain tolerances of operation from the manufacturer in which the orientation of each array can vary with respect to each other. In addition, considering environmental conditions, accumulation of dust and dirt on the sensors and actuators along with scattered cloud conditions may similarly affect the performance of each tracking array.

In Table I, the monthly PV output power yields are shown. The PV arrays with the highest output power is highlighted in green in groups of two, while the lowest output power for each array is highlighted in red. From the table, it may be observed that inverters 1 to 6 had the highest concentration in maximum power output throughout the year, while inverters 7 to 12 showed poor performance in comparison.

In hindsight, the highest annual average in power production was observed to be Inverter 6 and Inverter 11, while Inverter 9 and Inverter 12 had the lowest power yield for the year.

In Table II, the deviation in PV output power from the overall average power produced is shown on a monthly basis. In this Table, the lowest deviation is highlighted in green, while the highest is shown in red.

From the table, it may be observed that Inverter 1 and Inverter 7, deviated substantially from the average with Inverter 2 and Inverter 5 showing the lowest deviation.

Comparing the maximum power output with the deviation reveals that the inverters that produced the highest power have relatively low deviation from the average power produced. However, on the lower performing units, a mixed result is observed, where inverter 9 shows a high deviation from the average, while inverter 11 shows a comparatively low deviation.

In hindsight, the deviation shows little correlation with the PV tracking array's performance. However, the deviation may be used to determine the accuracy of the model given the average power produced from all the tracking arrays.

Therefore, for model validation purposes, two tracking systems are identified for each month that produced the highest output power. This would minimize the uncertainties in the model, such as all the factors that affect PV output performance as discussed previously in this section.

The power yield readings from the energy monitoring dashboard of these existing (real world) systems, logged at 5-minute intervals were used as historical data to validate the PV tracking model.

Exogenous data obtained from a weather station located approximately 250 m from the solar tracking arrays at the Central University of Technology (CUT) were fed into the developed PV tracking model to determine the output power for comparison with the existing system [17]. The weather station at the CUT forming part of the South African Universities Radiometric Network (SAURAN) is shown in Fig. 2.

The data acquired from the weather station are noted in (1) to (3). These include; solar irradiance (global horizontal, direct normal, diffuse horizontal irradiance), ambient air temperature, azimuth angle, tilt angle of the irradiance sensor.

In order to simulate the operation of the dual axis tracking PV array, the tilt angle noted by (β) in Eq. (3) was equated to the calculated tilt angle of the solar irradiance measurement system of the weather station.

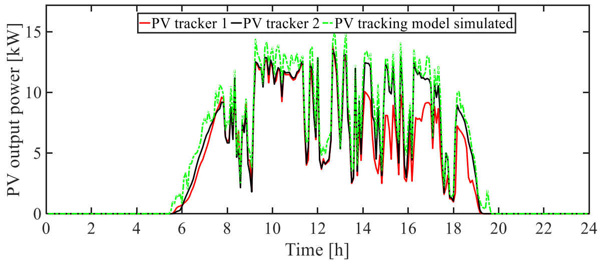

Fig. 3. Actual tracking system vs. model for a selected day in Jan.

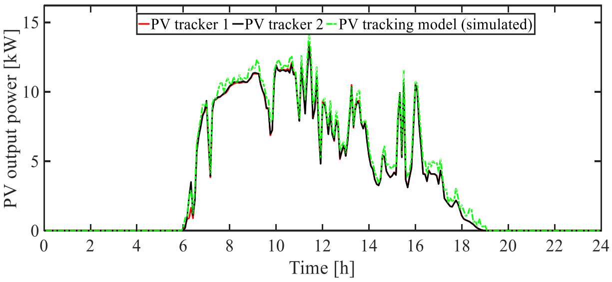

Fig. 4. Actual tracking system vs. model for a selected day in Feb.

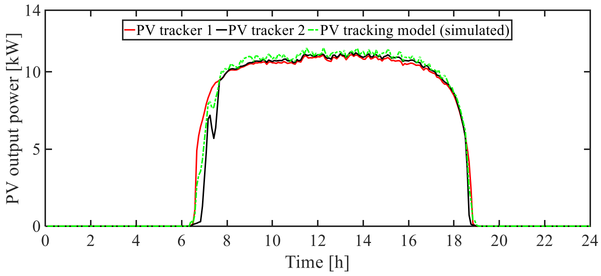

Fig. 5. Actual tracking system vs. model for a selected day in Mar.

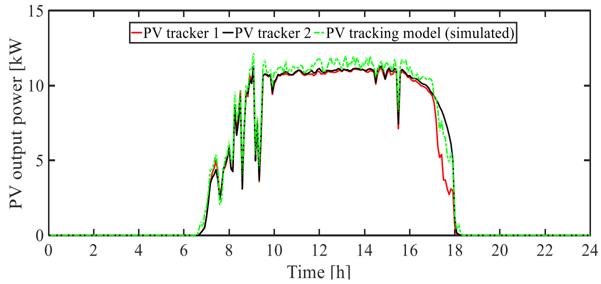

Fig. 6. Actual tracking system vs. model for a selected day in Apr.

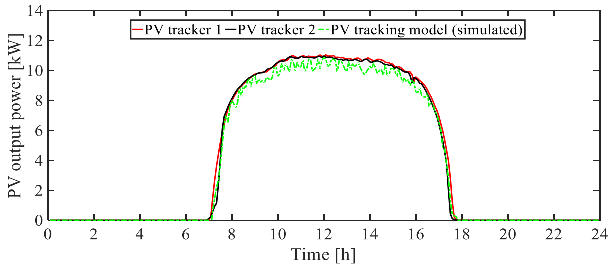

Fig. 7. Actual tracking system vs. model for a selected day in May.

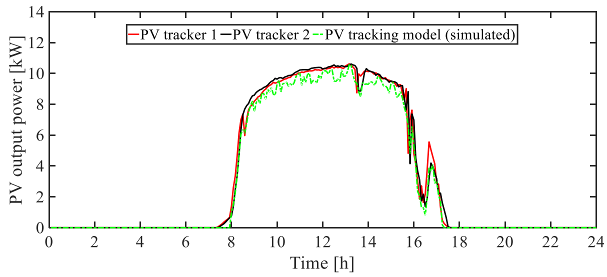

Fig. 8. Actual tracking system vs. model for a selected day in Jun.

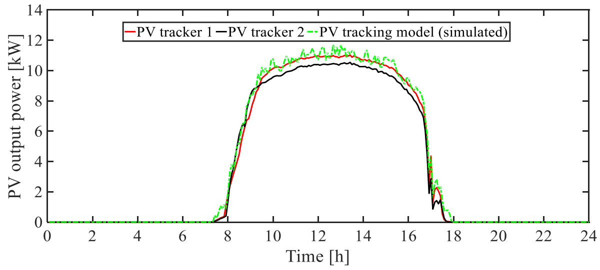

Fig. 9. Actual tracking system vs. model for a selected day in Jul.

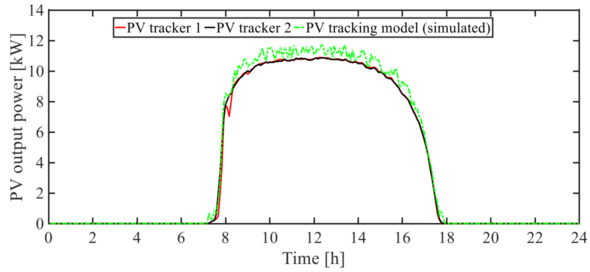

Fig. 10. Actual tracking system vs. model for a selected day in Aug.

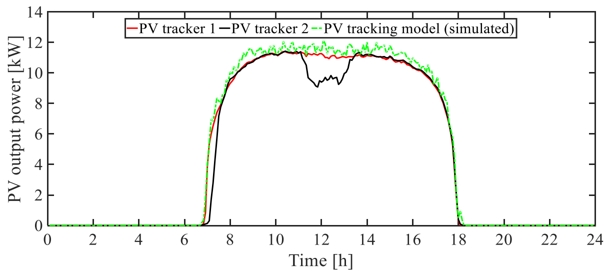

Fig. 11. Actual tracking system vs. model for a selected day in Sept.

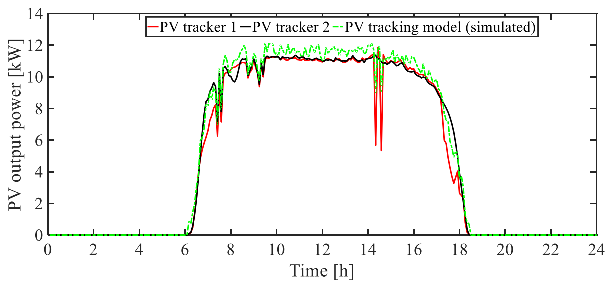

Fig. 12. Actual tracking system vs. model for a selected day in Oct.

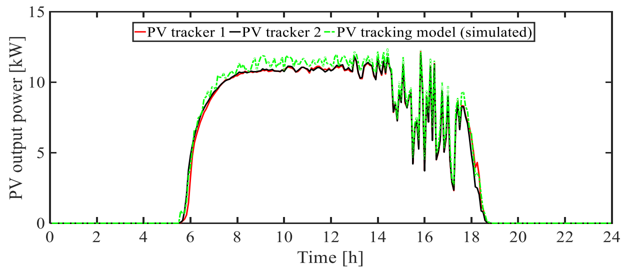

Fig. 13. Actual tracking system vs. model for a selected day in Nov.

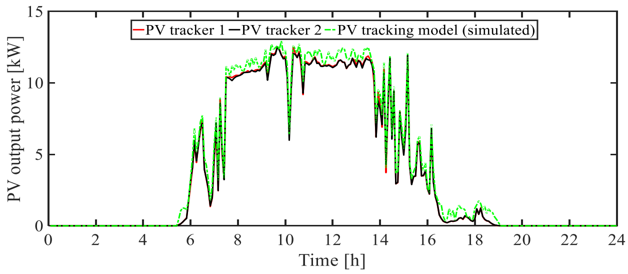

Fig. 14. Actual tracking system vs. model for a selected day in Dec.

In Fig. 3 to Fig. 14, the comparisons between the simulated operation (model) and the actual data (real-world) of the system are illustrated for each month. This method follows historical data validation procedures to ensure accurate real-world representation of simulated results.

From Fig. 3, Fig. 4, Fig. 13 and Fig. 14, it may be observed that the PV output power trend varies substantially as oposed to the output power illustrated in Fig. 5 to Fig. 12. This is mainly attributed to the overcast/cloudy skies, frequently experienced during the summer months in South Africa. In hindsight, the error in PV output power increases for these scenarios where overcast skies are apparent. This increase in error is unavoidable as each tracking system receives different amounts of solar irradiance due to scattered cloud cover.

In retrospect, comparisons between the simulated results and the actual data of the PV tracking systems reveal that the model represents real-world operation of the system within a margin of error. In Table III, the observed error for each month is depicted.

The average error over the evaluated 12-month period was observed to be 7.56%. The average deviation of the inverter outputs compared to the average output power of the entire solar tracking plant was observed to be 2.53% from Table II. Combining the error rate of the model with the deviation rate of the inverters, to provide a worst case scenario deviation, may result in an overall error rate of < 9%. This may be considered as a large percentage, however, given the numerous factors that influence the PV output power of the tracking systems, these figures may fall within an acceptable range to predict the performance of a dual axis tracking system. The model may therofore be recommended for accurate performance and economic predictions of PV tracking systems in the Free-state region in South Africa and by extention the rest of the world.

TABLE III: PV OUTPUT POWER ERROR [%]

Month	Jan.	Feb.	Mar.	Apr.	May	Jun.
% Error	9.7	8.2	4.7	7.8	3.8	5.2
Month	Jul.	Aug.	Sept.	Oct.	Nov.	Dec.
% Error	3.6	3.7	4.8	7.9	9.1	8.2
Average			6.39			

IV. CONCLUSION

A mathematical model of a dual axis PV tracking system has been developed and validated against real world data. The real-world data was obtained from 12 identical dual axis tracking systems located in the Bloemfontein area in South Africa. The results showed that the model accurately represented the output power curve of an existing system within an error range of 6.39 %. In addition, the performance of the identical tracking systems was evaluated with respect to the monthly inverter power outputs of each tracking system. The highest deviation from the average power output of the tracking units were 4.08%, while the lowest deviation was noted to be 1.62%. An average deviation of 2.53% was observed.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Percy A. Hohne conducted the research and analyzed the data; Percy A. Hohne and Kanzumba Kusakana wrote the paper; Bubele P. Numbi assisted in the model development; all authors approved the final version.

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Percy A. Hohne obtained his B.Tech. degree in Electrical Engineering in 2016 and his M.Eng. degree in 2018 from the Central University of Technology. Since 2019 he has been working at the Central University of Technology as a lecturer and enrolled for the D.Eng. degree in Electrical Engineering. His area of interest is optimal energy management of hybrid renewable energy systems.

Kanzumba Kusakana is a professor in electrical engineering and the Head of the Electrical, Electronic and Computer Engineering Department at the Central University of Technology, Free State. He is well-received as a professional development short course instructor in South Africa based on his technical, consulting experience and academic qualifications. With over 150 publications in journal, conference proceedings and book chapters, his current research looks at small scale renewable power generation as well as optimal energy management; which support the UNESCO Sustainable Development Goals. He is currently an associate editor for the IET Renewable Power Generation Journal and has an H-index of 25. He is a senior member of the South African Institute of Electrical Engineers (SAIEE); a Professional Engineer (Pr Eng) registered with ECSA a NRF rated researcher.

He received his doctorate degree in electrical engineering in 2015 from the Central University of Technology, Free State, South Africa. He also holds a degree in electromechanical engineering from the University of Lubumbashi (2006); a degree in electrical power engineering from Tshwane University of Technology (2009), as well as an MBA in Energy Management (2019) from the Cyprus Institute of Marketing (BVI).

Bubele P. Numbi obtained his Ph.D degree in Elelctrial Engineeinrg, from the University of Pretoria (UP) in 2015. He is a NRF rated research. His research areas are power system dynamics and control, energy management, energy efficiency, and renewable energy. Dr Numbi is currently working as a senior lecturer in the Department of Electrical Engineering at the MUT.