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Empirical modeling of combined factors and their impact on solar power generation in Eastern Uganda

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Abstract

The growth of solar energy infrastructure in Eastern Uganda has not consistently produced optimal levels of solar power because of a complex interplay of environmental and physical factors. In order to quantify the combined effects of crucial factors on solar power generation performance, ambient temperature, cell temperature, wind speed, and solar irradiance, this study presents an empirical model. Experimental data was collected from four operational solar power plants of Busitema, Soroti, Mayuge, and Tororo over a 215-day period by recording key parameters at 15-minute intervals. An empirical model with combined physical factors was developed and evaluated using two solar photovoltaic panels and digital technology for accurate monitoring. Available Model 1 utilizes the use of uncoupled physical factors, as compared to the developed Model 2, which combines coupled physical factors. Due to excellent wind conditions (up to 3.43 m/s), the Mayuge plant produced the most power, demonstrating that Model 2 drastically reduced the gap between design capacity (10 MW) and actual generation. The combined-factor model's higher accuracy was confirmed by Root Mean Square Error (RMSE) findings. This study demonstrates that regionally coupled empirical modeling is essential for precise forecasts, optimal plant design, and increased solar photovoltaic (PV) system operational efficiency. The suggested approach can direct the development of solar energy infrastructure and policies in Eastern Uganda and other comparable areas across the world.

Keywords Solar power generation, Combined factors, Empirical model, Solar energy systems, Renewable energy, Energy efficiency

1 Introduction

Utilizing solar energy has tremendous potential to promote sustainable development in Eastern Uganda and around the world, where a lot of sunshine is still wasted. The real output of solar power systems frequently falls short of expectations despite increased demand because of a complex interaction of technical, socioeconomic, and environmental factors. This study presents an empirical model that measures the combined effect of these factors on the performance of solar power generation in the area.



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Globally, Cuello-Polo & O'Neill-Carrillo [1] presented models of platform electrical power for different aircraft designs using solar irradiance models, calculated energy generation efficiency, and discussed parameter changes and model fidelity. Yue et al. [2] examines solar radiation measurement errors and proposes a model for effective radiation in photovoltaic systems. It reveals that 8 h after sunrise is optimal for power generation. The corrected annual average effective efficiency is 28.66% higher than the existing study, providing a theoretical basis for photovoltaic technology development and full-spectrum solar energy use. Premalatha & Valan Arasu [3] developed an Artificial Neural Network model for accurately predicting solar radiation using meteorological data from five Indian locations, achieving low mean absolute percentage error for solar energy installations. AlKandari & Ahmad [4] presented a hybrid model combining machine learning and Theta statistical methods for accurate solar power forecasting, utilizing long short-term memory (LSTM), gate recurrent unit (GRU), Auto-LSTM, and Auto-GRU models, and proving superior to traditional models. Suanpang & Jamjuntr [5] compared Light Gradient Boosting Machine (LGBM) and K Nearest Neighbors (KNN) machine learning models for solar power generation forecasting in microgrid applications, finding LGBM has superior accuracy but requires longer training times and higher memory usage. Kumar & Singh [6] provided a detailed simulation of a solar PV module using a single diode equivalent circuit model in Matlab/Simulink ambience, providing comprehensive understanding for researchers, manufacturers, and social communities and also Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS)-based forecast models for predicting PV generation in India, addressing natural fluctuations in renewable energy sources. Olojede & OO [7] analyzed rotational and static power models using mathematical models based on time, current, and voltage. The models showed high accuracy in predicting and compensating for energy deficits, with MABE and RMSE values of 1.3030 and 0.7431, respectively. Farooq et al. [8] presented a comparison of machine learning methods for accurately projecting solar power generation in half-hourly cycles, revealing improved accuracy in the first plant and potential for sustainable energy sources. Uddin et al. [9] presented a machine learning model for estimating solar power generated using the k-NN algorithm. The model, applied to a solar power plant data set, achieved an accuracy of 69.6% in simulation tests, making it useful for estimating solar power potential in regions. Balal et al. [10] used machine learning models to predict solar PV power generation in Lubbock, Texas. Random Forest Regression and Long Short-Term Memory models outperform others, capturing intricate patterns and complex relationships. These models can help investors streamline processes and improve solar energy planning. Chakraborty et al. [11] estimated the impact of weather parameters on solar PV power generation using Ensemble Machine learning (ML) models like Bagging, Boosting, Stacking, and Voting. The performance is validated using a 10 kWp power plant dataset in Eastern India. The results show 96% prediction accuracy for stacking and voting ensemble ML (EML) models. Salman et al. [12] revealed that the convolutional neural network (CNN)–long short-term memory (LSTM)–transformer (TF) hybrid model outperforms other models in capturing complex patterns in solar power data, emphasizing the need for accurate forecasting. This paper presents an Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS)-based forecast model for predicting PV generation in India, addressing natural fluctuations in renewable energy sources. Bhutta et al. [13] utilized

machine learning hybrid models like HCLN and HGRN to enhance solar power generation efficiency in smart grid contexts, demonstrating superior accuracy in predicting power production and performance ratios. Das et al. [14] discussed direct forecasting of PV power generation, analyzing input-output data correlation, model preprocessing, strengths, weaknesses, hybrid models, performance matrices, and optimization benefits. Petrosian & Zhang [15] used explainable artificial intelligence (XAI) techniques to enhance the interpretability of black-box models in solar power generation, identifying Light GBM as the model needing explanation. Aouidad & Bouhelal [16] compared regression and classification machine learning approaches for solar energy production prediction, finding regression outperforms in accuracy but not peak power values. Son et al. [17] revealed that airborne particles significantly reduce solar PV power generation at Yeongam and Eunpyeong-gu power plants in Korea, under normal and bad air quality conditions. Çelik & McInnes [18] presented an analytical model for calculating total energy delivered to a stationary ground target, demonstrating its significance and scalability for testing at various solar system objects. Islam et al. [19] evaluated utility-connected PV power generation in Khulna, Mymensingh, and Sylhet districts, demonstrating potential for 135.33 GWh annual energy production at USD 0.098/kWh. In Uganda, Sareen et al. [20] analyzed Uganda's energy policy, utilizing a 'scales of accountability' framework, to identify challenges in achieving solar mini-grids and multi-scalar solar energy transitions for universal clean energy access. Aarakit et al. [21] revealed that flexible payment mechanisms positively influence solar PV system adoption in Uganda, with rural residence, income, and house type being significant drivers, while education attainment is positive but insignificant. Mugagga et al. [22] examined Uganda's Solar Photovoltaics (PV) growth since the 1980s, highlighting market segments, opportunities for development, and financial, environmental, institutional, and socio-economic factors. Kavuma et al. [23] assessed Uganda's grid-connected solar PV's performance, revealing a projected 6.1% solar penetration by 2021, generating 69.52 GWh of annual energy. Alinaitwe [24] examined factors influencing Ugandan solar PV adoption, revealing savings, income, education, and household size as major drivers, with urban, grid-connected, reliable, and female-headed households less likely to adopt. Mundu et al. [25] explored the potential of integrating solar energy into healthcare in rural Uganda, highlighting cost savings, operational efficiency, and environmental benefits, and calling for collaboration and funding. Nnamchi et al. [26] explored solar power generation above ground level using modeling, simulations, and experimentation. Results show 1000 m yields 2.5%, while 8100 m yields 23%, applicable to areas near 1100 m. Atwongyeire et al. [27] used the fuzzy analytic hierarchy process to evaluate smart grid areas for solar and small hydro energy generation in Western Uganda, focusing on economic, environmental, and technical aspects, providing initial insights. Akankunda et al. [28] evaluated Uganda's power plants' techno-economic performance from 2010 to 2021, revealing average capacity factors of 19.8%, 22.9%, 18.4%, and 58.6%, with lower levelized electricity costs compared to retail prices. Cartland et al. [29] indicated that hybrid hydro-power systems can decrease customer enrollment, energy sales, and system shutdowns, potentially enhancing fuel efficiency, system reliability, and livelihoods. Nansamba & Harb [30] proposed a fault prediction tool for a Ugandan solar plant, using neural networks for power prediction and a statistical process control tool for final fault prediction, achieving 4.2% and 6.9% mean absolute errors respectively.

While several studies have used machine learning and simulation techniques to improve solar power forecasting and efficiency modeling worldwide, few studies have placed these advancements in the context of Eastern Uganda's particular environmental factors. The majority of current models ignore the impact of combined physical factor such cell temperature, ambient temperature, wind speed, and irradiance. By creating an empirical model specifically suited to Eastern Uganda, this work fills that crucial gap by capturing the combined physical factor effects of regionally on the performance of solar power generation.

2 Materials and methods

2.1 Study area

This study was carried out in Uganda. Uganda has a latitude of 1.3733° N and a longitude of 32.2903° E. Uganda is situated at the equator, which is suitable for optimum solar power generation. Uganda borders Kenya to the east, Sudan to the north, the Democratic Republic of the Congo to the west, Rwanda to the southwest, and Tanzania to the south. This study focused on the eastern (1.2692° N, 33.4384° E) region of Uganda, and the four solar power plants were considered, namely Busitema, Mayuge, Tororo, and Soroti solar power plants. Due to the installation of the majority of the solar power plants, as shown in Fig. 1.

The annual solar power generation from four major solar power facilities in Uganda's Eastern Region from 2021 to 2024 is shown in Table 1. The plants are located at different geographic coordinates and include Busitema, Mayuge, Soroti, and Tororo Solar North. With figures often falling between roughly 6.7 GWh and 17.2 GWh, the data demonstrates year-to-year variability in power generation. Busitema generates the least amount of energy, averaging roughly 7 GWh per year, while Mayuge and Soroti contribute the most, generally exceeding 15 GWh.

2.2 Model formulation

As illustrated in Fig. 2, modeling and experiments are crucial to this study of solar energy. Experiments indicate that the thermophysical properties of the surrounding air, such temperature and wind speed, as well as external factors like sun irradiation, affect the production of solar power. The empirical generation of solar energy is also influenced by the temperature of the solar cells. Setting up the experiment close to the four solar power facilities that are now operating in eastern Uganda produced the experimental results.

Where H (W/m^2) is the solar irradiance, U (m/s) is the wind speed, P_{gen} (W) is the solar power generated, P_{stc} (W) is the solar power at standard test condition, T_a (K) is the ambient temperature, β_c ($1/K$) is the temperature coefficient of the solar cell, β_U ($1/ms^{-1}$) is the Wind speed coefficient, β_H ($1/Wm^{-2}$) is the irradiance coefficient η (%) is the efficiency of solar cell, N_p (–) is the number of solar panels and, T_c (K) is the solar cell temperature.

2.3 Empirical solar power generation model with combined factors

2.3.1 Previous developed models on solar power generation

Araneo et al., [32] Presented temperature model defined in Eq. (1)

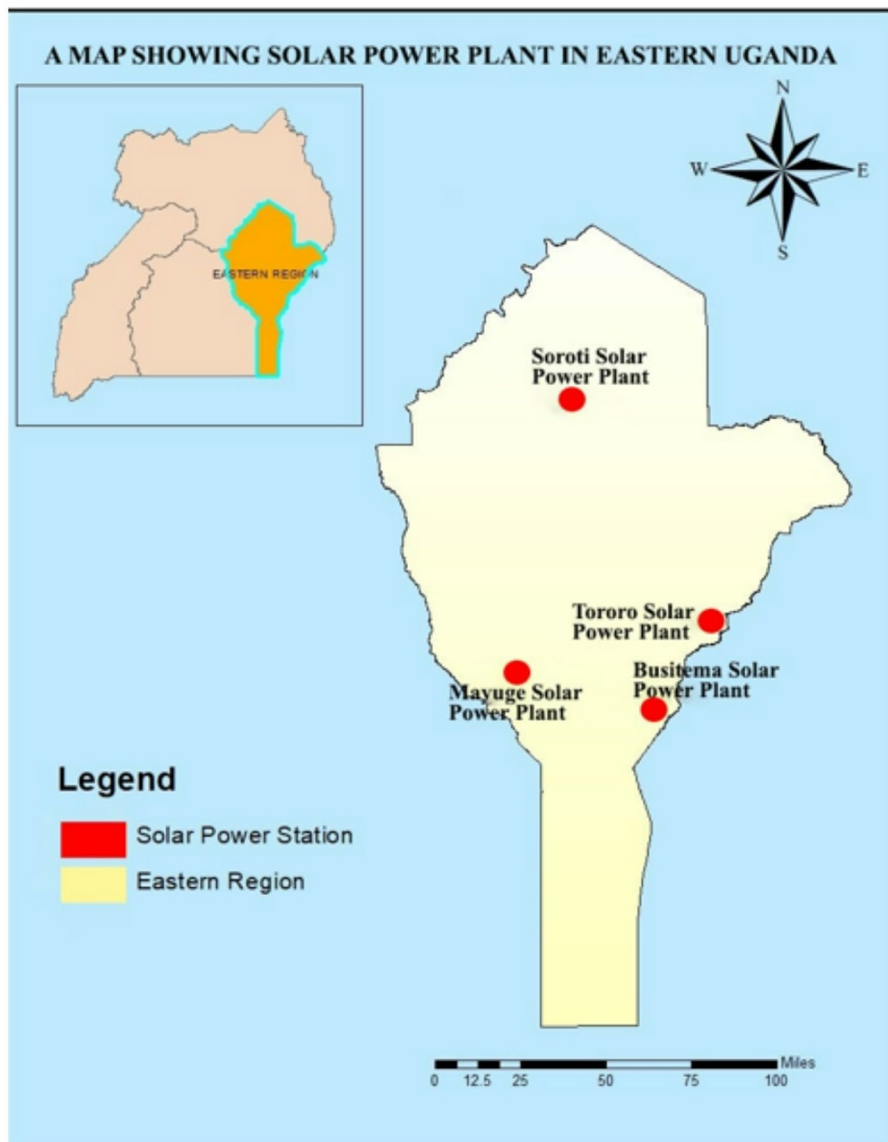


Fig. 1 Eastern Region

Table 1 Annual solar power generation from solar plants in Eastern region of Uganda

S#	Power Plant	Lat*	Long*	Annual Solar Power generation (GWh)					Source
				2021	2022	2023	2024	Average	
1	Busitema Solar power station (upgraded)	0.54722	34.0236	6.74	6.13	6.24	7.17	7.33	UETCL, [31]
2	Mayuge Solar Power Station (Emerging Power–Bifulubi)	0.495	33.4075	14.81	14.92	14.19	17.23	16.98	UETCL, [31]
3	Soroti Solar Power Station	1.685	33.6581	16.58	16.31	15.94	16.21	15.75	UETCL, [31]
4	Tororo Solar North	0.63889	34.1192	9.80	15.93	16.03	15.79	15.90	UETCL, [31]

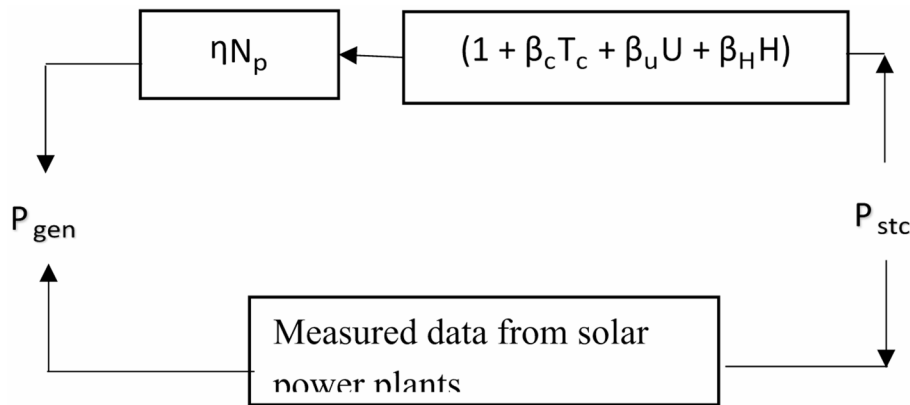


Fig. 2 Empirical modelling of solar power generation

$$T_c = T_a + \frac{I_{gt}}{I_{NOCT}} (T_{NOCT} - T_{a,NOCT}) \tag{1}$$

Where (T_{NOCT}) is nominal operating cell temperature, $T_{a,NOCT}$ is the ambient temperature at 20°C, I_{NOCT} is the Solar irradiance, I_{gt} is the intensity of the solar irradiance, T_a is ambient temperature.

Jadhav et al., [33] presented thermal power loss model defined in Eq. (2)

$$P = \epsilon \sigma A (T_R^4 - T_a^4) \tag{2}$$

Where ϵ is Receiver surface emissivity, σ is the Stefan Boltzman Constant in $W/m^2.K^4$, T_R is the Receiver surface temperature in K, T_a is the Ambient air temperature in K, A is aperture area for cavity receiver in m^2 .

Mundu et al., [34] presented actual solar power generation defined in Eq. (3)

$$P_{gen,actual} = \eta_{pv} \times \epsilon_{wind}^m \times SSP \times A_{pv} \tag{3}$$

Where ϵ_{wind}^m is the relative velocity or the effectiveness of wind flow, SSP is the solar power potential on horizontal surface for a specified location W/m^2 , η_{pv} is the solar photovoltaic module rated efficiency, A_{pv} is the catchment surface area of the module available for power generation in m^2

Asef et al., [35] Presented a model for generating power in the silicon layer defined in Eq. (4)

$$P_{C-si} = I_s \frac{V_s + 0.75}{m \times 60S} \tag{4}$$

Correa-Betanzo et al., [36] Presented photo voltaic electric efficiency defined in Eq. (5)

$$\eta_{PV} = \eta_{ref} \left(1 - \frac{\delta}{100} (T_{STC} - T_{cell}) \right) \tag{5}$$

Where η_{ref} is the cell efficiency, T_{STC} is the temperature at standard test conditions ($T_{STC} = 25^\circ C$)

Al-Bashir et al. [37] ; Scarabelot et al. [38]; Skoplaki et al. [39] presented empirical solar power model is defined in Eq. 6

$$P_{gen,1} = P_{STC} (1 + \beta_c (T_c - T_0)) \eta N_p \quad (6)$$

Previous models on solar power generation, such as temperature, thermal power loss, wind-influenced generation, silicon layer, and photovoltaic efficiency, focus on individual factors like temperature, irradiance, or wind speed. This study addresses this gap by developing a new empirical model that combines ambient temperature, cell temperature, wind speed, and solar irradiance, resulting in higher accuracy and reduced disparities.

Living et al., [40] presented empirical solar power generation model with uncombined parameters defined in Eq. (7)

$$P_{gen} = P_{STC} (1 + \beta_c (T_c - T_0) + \beta_u U + \beta_H H) \eta N_p \quad (7)$$

where P_{gen} (W) is the solar power generated, P_{STC} (W) is the solar power at the standard test condition, T_a (K) is the ambient temperature, T_0 (K) is the reference temperature, β_c (1/K) is the temperature coefficient of the solar cell, η (%) is the efficiency of solar cell, N_p (-) is the number of solar panels and, T_c (K) is the temperature of solar cell. However, the present work considers an combined physical factor of temperature, wind speed and irradiance, which improve the effectiveness of the combined empirical solar power generation model in Eq. (8) as.

New model

$$P_{gen} = P_{STC} \left(\frac{1 + \beta_c (T_c - T_0) + \beta_u U + \beta_H H + \beta_c \beta_u U (T_c - T_0) + \beta_c \beta_H H (T_c - T_0)}{+ \beta_c \beta_U \beta_H U H (T_c - T_0)} \right) \eta N_p \quad (8)$$

The coupling coefficients are Defined Eq. (3) as follows:

$$\beta_P = \frac{1}{P_{max}} ; \beta_H = \frac{1}{H_{max}} ; \beta_{T_a} = \frac{1}{T_{a,max}} ; \beta_U = \frac{1}{U_{max}} \quad (9)$$

Unlike Eq. (1), which analyzes temperature, wind speed, and irradiance separately, Eq. (8) takes into account the coupling of the parameters and coupling coefficients that account for the interactions between these variables as well as wind speed and explicit solar irradiation. By capturing cross-effects, such as how wind cooling mitigates the detrimental impacts of high cell temperature on efficiency or how temperature and irradiance jointly affect output, the coupling coefficients (specified in Eq. (9)) are meant to increase the predictive capacity of the model. The coefficients in Table 3 were computed by establishing the measured data, taking the parameters with the maximum recorded values of wind speed, temperature, power, and irradiance at each site, and then taking the reciprocal of these maxima (1 divided by the maximum value).

2.4 Experimental set up

The experimental setup depicted in Fig. 3 was set up adjacent to four solar power plants in the eastern region of Uganda: the Busitema, Mayuge, Soroti, and Tororo solar power plants. The experimental setup consisted of two ADH solar PV modules (ASO 15 W-18P), two digital solar power meters (SM206), a digital multimeter (DT9205A C€), two digital thermocouples (DM6802B K-type), and a digital anemometer (UNI-T UT363S). The following parameters were recorded: electric current, PV output voltage, wind speed, irradiance, cell temperature, and ambient temperature. On a daily basis, readings were taken every 15 min between 9:00 a.m. and 17:00 p.m. The study



Fig. 3 Experimental set up

was carried out in each study region for 215 days. The data collected was within 215 days, which is more than 7 months or half a year, and was sufficient to capture seasonal variations, environmental conditions, and solar energy performance trends in Uganda, and this could be enough for model development and solar plant optimization, Uganda has two consecutive rain and dry seasons in the first half of the year, the phenomenon observed in the first half of the year, repeats in the second half, which witnesses another rain and dry seasons. Thus, using seven months capture the rain and dry seasons.

A list of the equipment used in the study are provided in Table 1, encompassing solar PV modules, a digital anemometer, digital solar power meters, a digital multimeters, and a digital thermocouples. Each item is described along with its manufacturer and specifications.

3 Results and discussion

3.1 Results

The results in this study are made up of tables and figures presented in this sub-section.

where *MAD* implies mean absolute deviation and *SD* designates standard deviation.

The experimental data (ambient temperature, cell temperature, wind speed, irradiance, voltage, and current) was statistically analyzed in Excel to determine the minimum, average, maximum, standard deviation, and mean absolute deviation for each site, yielding the results shown in Table 4. The average produced powers $\bar{P}_{g,M1}$, $\bar{P}_{g,M2}$ in Table 5 were determined by applying Eqs. (1) and (2), respectively, and the errors $RM-E_1$ together with $RMSE_2$ were calculated using Eq. (4) in order to evaluate the correctness of the model. To verify the results on a site-specific basis, Google Maps was used to determine each solar plant’s latitude and longitude.

3.2 Error analysis and validation

The error analysis and validation of design capacity, *dc* and empirical solar power generation are given in Eq. (10)

$$RMSE = \sqrt{\sum \frac{(P_{gen,dc} - P_{gen,e})^2}{N}} \tag{10}$$

Table 2 Description of used equipment

Name	Specifications	Manufacturer details	Parameters measured
ADH solar PV modules (ASO 15 W-18P)	15Wp+0/6.49 Wp	CDB North FL.1924CIXICITY, NINGBO, China	Solar power output (current, voltage, power)
Digital solar power meters (SM206)	SM206, 0.1–1999.9 W/m ² , ±5%	Eujgoov ; ASIN, B095335QRQ, China	Solar irradiance (W/m ²)
Digital multimeter (DT9205A C€)	DT9205A C€, ±1% or less	Dongguan Xinghongwei Precision Measuring Instrument Technology Co., Ltd. Guangdong, China	Voltage and current
Digital thermocouples (DM6802B K-type)	DM6802B Ktype, ±2.2 °C or ±0.75%	NqQVsedLKcT/China	Ambient temperature and cell temperature
Digital anemometer (UNI-T UT363S)	UNI-T UT363S, 0.4–30 m/s, 10–50° C	China. Modified Item. No. UPC. 6,935,750,536,339	Wind speed and ambient temperature

Table 3 Experimental power generation coefficients

S#	Parameter	Coefficient	Busitema	Mayuge	Soroti	Tororo	Source
1.	Cell temperature	β_c (% °C ⁻¹)	-0.002969	-0.002974	-0.002952	-0.002958	Present study
2.	Wind speed	β_u (%sm ⁻¹)	0.2415460	0.291460	0.323625	0.181819	Present study
3.	Irradiance	β_H (%m ² w ⁻¹)	0.000800	0.000723	0.000751	0.000761	Present study

where N is the number of observations (215), P is the solar power generated (gen) and subscript, e is the empirical power generation.

The Root Mean Square Error (RMSE) values for two datasets (RMSE1 and RMSE2) from four different study areas, Busitema, Mayuge, Soroti, and Tororo, are shown in Fig. 9. The RMSE1 (1.419) and RMSE2 (1.456) in Busitema are nearly equal, with RMSE2 being somewhat higher. A significant contrast is seen in Mayuge, where the disparity between RMSE1 (1.023) and RMSE2 (0.510) is almost double. The RMSE1 and RMSE2 values that Soroti recorded are rather close, at 1.151 and 0.991, respectively. Although RMSE1 is generally higher, Tororo has the highest total RMSE values, with RMSE1 at 1.683 and RMSE2 at 1.270.

3.3 Discussion of results

Table 2 gives a summary of experimental power generation coefficients used in the development of solar power generation models, whereas Table 3 provides a statistical description of the experimental data that was used in this study. The figures are as follows: Fig. 4 portrays the empirical solar power generation model at the Soroti solar power plant with combined factors, Fig. 5 shows the empirical solar power generation model at the Busitema solar power plant, Fig. 6 illustrates the empirical solar power generation model at the Mayuge solar power plant, Fig. 7 describes the empirical solar power generation model at the Tororo solar power plant, Fig. 8 demonstrates empirical solar power generation based on model 1 for the Soroti, Busitema, Mayuge, and Tororo solar power plants, and Fig. 9 depicts the empirical solar power generation based on model 2 for the Soroti, Busitema, Mayuge, and Tororo solar power plants.

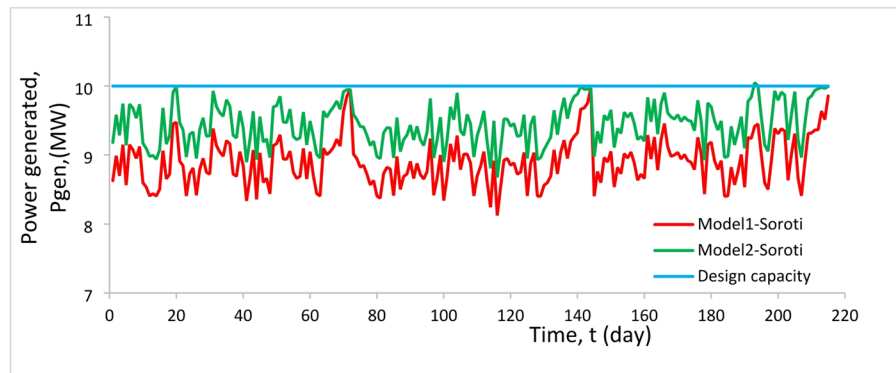


Fig. 4 Empirical solar power generation model at Soroti solar power plant

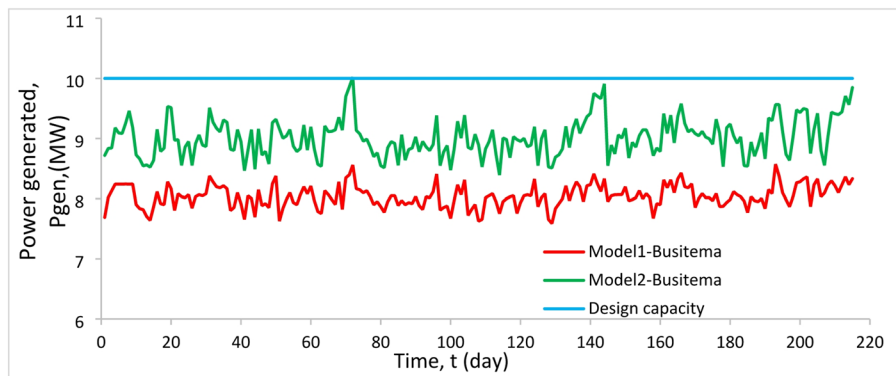


Fig. 5 Empirical solar power generation model at Busitema solar power plant

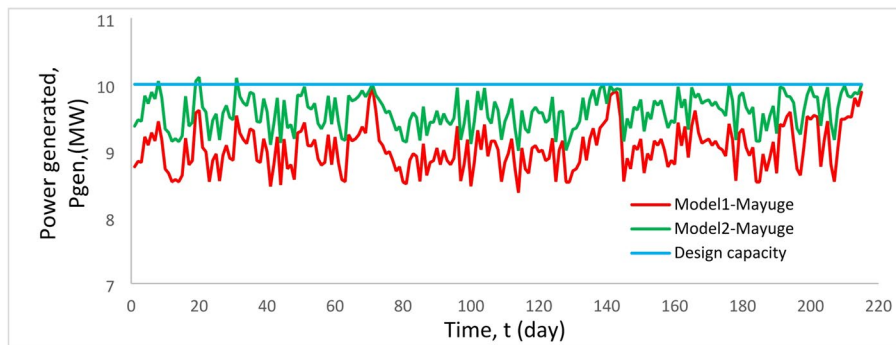


Fig. 6 Empirical solar power generation model at Mayuge solar power plant

3.4 Results of power generation coefficients

Table 4 presents the power generation coefficients of cell temperature, wind speed, and irradiance. Using the experimental data, these coefficients were determined using Eq. 3. These coefficients were used to calculate empirical solar power generation.

3.5 Development of empirical solar power generation models with combined factors

Considering the combined factors of cell temperature, wind speed, irradiance, The empirical models are vital in determining the cause of the significant differences between practical and design solar power plant generation capacity as displayed in Table 1 for

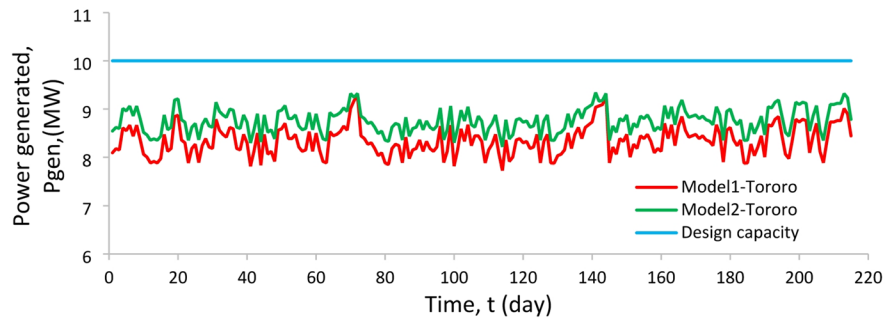


Fig. 7 Empirical solar power generation model at Tororo solar power plant

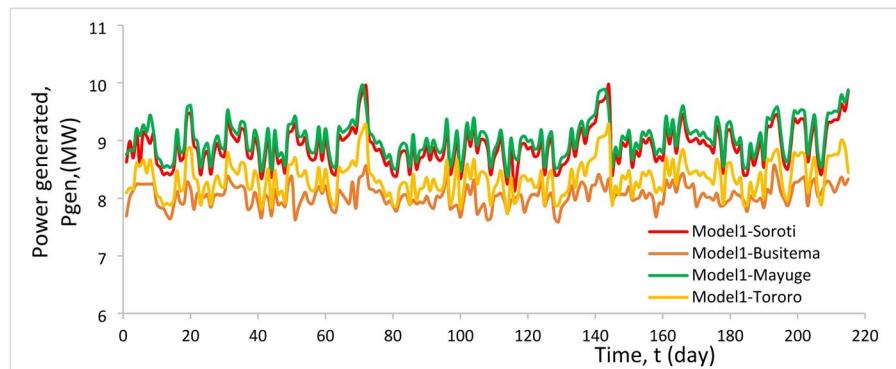


Fig. 8 Empirical solar power generation based on model1 for Soroti, Busitema, Mayuge, Tororo

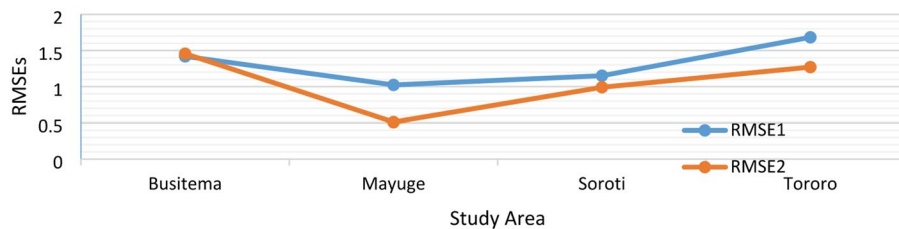


Fig. 9

the different areas in this study. The empirical model is categorized into two categories: model 1 as portrayed in Eq. 1 and model 2 as shown in Eq. 2. Model 1 is composed of wind speed, temperature, and irradiance, whereas model 2 comprises the combined factors of wind speed, temperature, and irradiance. Noticing Figs. (4, 5, 6, 7), model 1 is far from reaching the current design capacity of 10 MW. Model 2 minimizes the gap between the current design and operational solar power generation capacities of 10 MW; operational solar power generation data for model 2 is also much closer to the design and operational solar power plant capacities. The phenomena observed in these figures (4–7) show that the combined factor model/model 2 is much better for use in predicting the solar power generated in a given area. Rehman et al. [41], Yusuf et al. [42]

3.6 Empirical solar power generation based on the model 1 model 2

Taking into account Figs. 8 and 9, Mayuge generated the most solar energy based on models 1 and 2 when compared to the other study areas of Soroti, Busitema, and Tororo.

Table 4 Description of the experimental data

S#	Study area	Statistics	Ambient temperature (° C)	Cell temperature (° C)	Wind speed (m/s)	Irradiance (W/m ²)	Voltage (V)	Current (A)
1.	Busitema	Minimum	21.20	26.50	0.00	76.40	37.60	0.12
		Average	31.71	42.11	1.12	617.57	41.33	0.85
		Maximum	46.70	63.80	4.14	1249.50	43.10	1.94
		SD	4.14	7.65	0.75	335.48	0.80	0.44
		MAD	3.32	6.22	0.57	302.23	0.59	0.38
2.	Mayuge	Minimum	23.90	25.70	0.10	32.40	36.80	0.05
		Average	32.02	41.65	0.97	588.26	41.13	0.82
		Maximum	44.90	63.10	3.43	1382.50	43.40	1.94
		SD	3.70	9.15	0.57	353.13	0.87	0.48
		MAD	2.67	7.91	0.42	308.10	0.62	0.43
3.	Soroti	Minimum	21.00	32.00	0.02	207.60	38.70	0.31
		Average	28.55	44.46	0.99	717.74	41.47	1.01
		Maximum	43.70	65.60	3.09	1331.90	44.90	2.19
		SD	3.10	6.52	0.53	348.15	1.06	0.49
		MAD	2.38	4.99	0.39	313.91	0.83	0.43
4.	Tororo	Minimum	22.51	22.90	0.14	32.60	38.00	0.08
		Average	29.24	44.91	1.56	682.16	41.27	1.05
		Maximum	40.30	64.90	5.50	1314.00	43.40	2.29
		SD	3.24	10.28	0.98	343.08	1.06	0.49
		MAD	2.42	8.32	0.81	297.61	0.83	0.42

Table 5 Validation of solar power design capacity with the empirical solar power generation

S#	Study area	Coordinates		Solar power generation, P_{gen} (MW)			RSME ₁	RSME ₂
		Lat.	Long.	Design capacity, $P_{gen,dc}$	$\bar{P}_{g,M1}$	$\bar{P}_{g,M2}$		
1.	Busitema	0.547	34.023	10	8.676	9.585	1.419	1.456
2.	Mayuge	0.495	33.408	10	9.083	9.994	1.023	0.510
3.	Soroti	1.685	33.658	10	8.954	9.881	1.151	0.991
4.	Tororo	0.639	34.112	10	8.397	9.341	1.683	1.270

where RSME implies Root mean square error,

The RMSE analysis in Table 5 supports this finding. Additionally, Mayuge’s highest power generation may have been due to a favorable wind speed of up to 3.43 m.s^{-1} . Thus, Mayuge would be the site of the next solar power facility to improve solar power generation in eastern Uganda.

3.7 Applications of the developed empirical solar power generation models

The design of mega solar power plants in eastern Uganda and globally should use an empirical (combined factors) model because of its high sensitivity to solar power generation, which would help to minimize losses from solar power generation. Because the actual efficiency and output of solar power systems are determined by the combined impacts of wind speed, solar irradiation, cell temperature, and ambient temperature, it was very crucial to quantify these effects. More precise performance forecasts are produced by an integrated assessment, which directs the best possible site selection, plant design, and operational plans. This increases dependability, closes the discrepancy between anticipated and real generation, and encourages wise investment in solar energy that is sustainable. Using isolates crucial factor could be miss leading in forecasting of solar power generation, integration or combination of crucial factors would result

in realistic prediction of power generation, improved system design and optimization is achieved by integrating the crucial factors. Moreover, improved reliability and efficiency is guaranteed; the model results aid in robust economic and financial planning; the integrated model aids in policy making, grid integration and energy security.

4 Conclusions

This study successfully developed and validated an empirical model adapted to the distinct environmental and operational conditions of Eastern Uganda to evaluate the combined effects of key physical factors, such as wind speed, cell temperature, ambient temperature, and solar irradiance, on solar power generation. The study showed that models with multiple interacting parameters (Model 2) provide a significantly higher accuracy in predicting actual solar output than simpler models (Busitema, Mayuge, Soroti, and Tororo) through extensive experimentation and data collection from four major solar power plants. According to the results, Mayuge had the most potential for generation due to good wind conditions, and this makes it a great place for future solar projects. The empirical model developed here is a useful tool for improving solar PV system development, design, and efficiency optimization not just in Eastern Uganda, but also in other areas with comparable meteorological profiles. The broader objectives of sustainable energy development and well-informed investment in renewable energy infrastructure are supported by these insights, which help close the performance gap between design and actual outputs.

Author contributions

O. Living: Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. S.N. Nnamchi: Supervision. M.M. Mundu: Supervision. A. uzorka: Supervision. A.A Fashina Supervision. M. Bawa: Supervision.

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Data availability

The data used in this research will be made available on request.

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

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Competing interests

The authors declare no competing interests.

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