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A Transfer Function Modelling Using System Identification for Air-cooling Photovoltaic System

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ABSTRACT

Mathematical modelling is essential in comprehending, optimising, and administering air-cooling photovoltaic (PV) systems by considering factors like temperature, irradiance, and module characteristics. Mathematical modelling allows for informed decision-making, optimisation, and risk management in designing, operating, and maintaining air-cooling PV systems. This study creates mathematical models to identify an air-cooling PV system and anticipate the PV module's output performance based on the solar irradiance received. The air-cooling PV system is modelled using the system identification toolbox, which relies on experiment data. The modelling process utilises a black-box approach, eliminating the necessity for internal parameter knowledge. The transfer function estimation method was selected as the best non-linear model due to its superior fit percentage. Prior to the installation of the air-cooling system, the data-driven analysis produced a continuous-time transfer function with an accuracy of 90% for the PV module model, whereas the air-cooling PV system model obtained an accuracy of 94.3%. The validity of the acquired models was assessed using Simulink by employing multiple levels of PSH. The model exhibits a failure rate of less than 10% in predicting inequality. The validation results for the PV module model were 90.1% and 90.8% for high, moderate, and low PSH, respectively. Similarly, the air-cooling PV system model got validation results of 91.7%, 93.2%, and 91.5%, while the mean output

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voltage increased by 10.8%, 17.5%, and 15.3%. Consequently, a continuous-time transfer function model is created, which will be utilised for developing and tuning controllers in future research.

Keywords: Air-cooling PV system model, mathematical model, modelling, system identification, transfer function model

INTRODUCTION

Cooling is required for a photovoltaic (PV) module because it can substantially boost the PV output performance. Without proper cooling, a substantial quantity of energy is lost as heat, as only 13-15% of solar radiation is converted into electricity (Mattei et al., 2006). Solar irradiance and operation temperature of the PV module (T_{cell}) were found to be impediments to reaching larger PV system outputs (Mustafa et al., 2023). A PV module's power output and electrical efficiency are determined by its T_{cell} and temperature coefficient (Dubey et al., 2013; Popovici et al., 2016). For each degree over 25°C, there is an average reduction in efficiency of around 0.45% (Haidar et al., 2018). The output voltage of the PV module can be calculated using Equation 1:

$$V_{pv_x} = V_{x\_stc}\ X\ [1 + \left(\frac{\gamma_{V_x}}{100}\right)\left(T_{cell} - 25^{\circ}C\right)] \quad [1]$$

where V_{pv_x} is the voltage for the PV module at x condition, V_{x_stc} is the voltage for x condition at Standard Test Condition (Volt), and γ_{v_x} is the temperature coefficient for the voltage at x condition.

There are two categories of cooling methods for PV modules: active cooling, which involves energy consumption, and passive cooling, which utilises conduction or natural convection to remove heat. Wind cooling can improve the performance of PV modules, but passive cooling is inefficient due to the limitations of natural heat transfer (Mustafa et al., 2024). Despite the fact that water cooling is more effective, air cooling is preferred due to its minimal construction and operating costs. PV module efficiency was better by 6.2% as a result of the cooling experiment (Erol et al., 2021). In addition to lowering the T_{cell} continuous cooling also increases the power of the PV module by 20% compared to the non-cooled one (Luboń et al., 2020). Cooling PV module is a key strategy for enhancing the efficiency of their output performance.

Mathematical models serve as the foundation for most analytical techniques used in engineering. These models can be derived by a theoretical method that relies on fundamental physical rules or through an experimental approach based on system measurements (Assani et al., 2022; Cheng & Lu, 2022). Generating models based on empirical data is commonly referred to as system identification (SI) (Bhuvaneswari, 2012) and numerical modelling can be enhanced with the use of an additional experimental-based approach (Al Hadad et al., 2018). An identification experiment aims to ascertain the dynamic properties of a certain process. One of the benefits of using models is that the step test employ is comprehensive, making it simple and cost-effective to apply. Step testing is often conducted on a system once the process has been identified or stabilised. Mathematics modelling is a systematic procedure that involves acquiring, structuring, processing, and identifying mathematical models derived from raw data from real-world systems. Modelling process control is of utmost significance since an effective control system is contingent upon the presence of a well-constructed model that precisely depicts the dynamics of the process (Tawerghi et al., 2021).

Modelling photovoltaic systems is challenging due to their non-linear characteristics, particularly when integrated with cooling structures (Adak et al., 2022). Several studies have previously focused on mathematical models for PV modules, but none of them have specifically addressed air-cooling PV systems. An air-cooling PV system requires a mathematical model to facilitate engineering analyses involving PV modules and air-cooling systems (Adak et al., 2021). Mathematical modelling plays an important role in optimising the efficiency of air-cooling PV systems, both in terms of PV module performance and the effectiveness of the air-cooling mechanism. Algorithms for air-cooling PV systems provide notable advantages by enabling cost reduction through the simulation and evaluation of the cooling system prior to its physical implementation. For existing air-cooling PV systems, having a data-based model is essential. The quality of a model is contingent upon the calibre of the input data, which is acquired through experimental methodologies. Therefore, the experiment must be conducted according to the appropriate standard procedures, and all factors that might impact the outcome must be considered to ensure the accuracy of the data. This model enables the analysis of the system's impact and facilitates research on enhancing the performance of the air-cooling system and PV module under different irradiance levels without the need for additional devices, resulting in a cost reduction. This air-cooling PV system model allows for accurate prediction of the performance of PV modules and the air-cooling PV system without the need for conducting experiments.

Therefore, the aim of this paper is to develop mathematical models using real data experiments to predict the output voltage of the PV module and prove that the recommended air-cooling PV system successfully increased its output performance. One of the greatest challenges in this study was to make sure the obtained models were appropriate and met the high, medium and low levels of solar irradiance in a day according to the solar irradiance and expected output PV based on the mathematical relationship. This study uses black-box methods for non-linear systems to investigate a data-based model for PV module output and air-cooling PV systems. Different black-box model structures are used for precise models. Data collection for this study involves solar irradiance, T_{cell} output voltage, and PV module power.

System Identification

SI is the process of creating mathematical representations of dynamic systems using statistical techniques applied to collected data. The process of designing experiments to effectively collect data from the system to develop models and lower model complexity was part of the study of SI. In the process of SI, a mathematical model is constructed to represent a dynamic system by utilising a collection of measured stimulus and response samples. The present focus lies on the identification of parameters and attributes of dynamic systems through the utilisation of specialised identification methods (Valousek & Jalovecky, 2021). SI uses measured input and output data to construct a precise model to create a mathematical representation of the system (Schoukens et al., 2012). Input and output vectors are used to define these systems, but the majority of physical systems are non-linear, making their models difficult to linearise analytically (Dorf & Bishop, 2010). Constructing models that meet analytical criteria may require non-linear engineering models. The mathematical model accurately determines the effects and reactions on the constructed model (Tuhta, 2021).

The process of SI involves several key components, including experiment design, experiment implementation, data pre-processing, model structure selection, model fitting to data, and model validation, as shown in Figure 1 (Šajić et al., 2022). These components are essential for effectively identifying and understanding the various aspects of a given system. Continuous time transfer functions (TF) can be used to describe physical models more generally. In MATLAB, the SI toolbox is a series of procedures used to identify and analyse different system components, including their structure, properties, and measured data from the time domain (Ljung, 2012). It also simplifies SI using experimental data. The SI tool incorporates the transfer function (TF) models or process models' functionalities, which facilitate the use of distinct identification approaches. A dynamical mathematical model is a mathematical representation that explains the behaviour of a system or process dynamic, which can occur in either the time

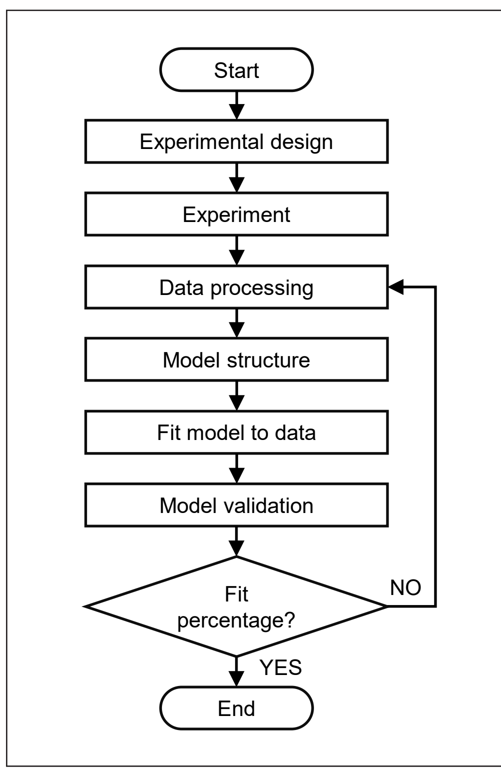


Figure 1. Cycle for system identification

or frequency domain (Åström & Eykhoff, 1971). The programme offers a dependable and near-accurate model structure. The proposed model underwent testing and simulation to demonstrate its effectiveness and reliability. This approach can also be used to estimate the model of an air-cooling PV system. Various modelling techniques, such as intelligent, linear, and non-linear models, can be applied.

METHODOLOGY

This study used the SI toolbox in MATLAB as an approach for the data-based model development. The research in this study includes the collecting and processing of all essential data, the selection and creation of the model structure, the estimate of model parameters, and the validation of the model. An experiment at an existing PV system in a tropical region, Kajang, Selangor, Malaysia, provided the data. All collected data was divided into training and testing sets. SI process and collected data were utilised in a black box for transfer function model development with different time delays and orders. Various models are investigated to determine the best structure yielding satisfactory accuracy based on the fit percentage. The selected model was tested using high, medium and low levels of solar irradiance generated data in a day from the experiment for optimisation, evaluation and validation for the most optimal model.

Data Collection and Pre-processing

A PV system was chosen at the German Malaysian Institute in Kajang, Selangor, Malaysia. The system consists of two 3kW PV sub-arrays of poly-crystalline PVs. Each sub-arrays grid-connected PV system utilised 12 pieces of 250 W poly-crystalline PV modules, installed by one string with 12 modules per string. An air-cooling system prototype was installed on a 250 W module of the PV system. Only one module was tested in the experiments. The irradiance metre was strategically placed near the PV module area to ensure the accuracy of the measured irradiance for analysis. A digital temperature sensor was attached to the back of the PV module to monitor temperature fluctuations on the T_{cell}. An energy meter was connected to the PV module to record voltage and current measurements. Small boxes are added to both ends of the cross-flow fan to elevate it away from the heated surface of the roof, as shown in Figure 2. This is done to guarantee that the temperature of the fan is not impacted by the surface temperature of

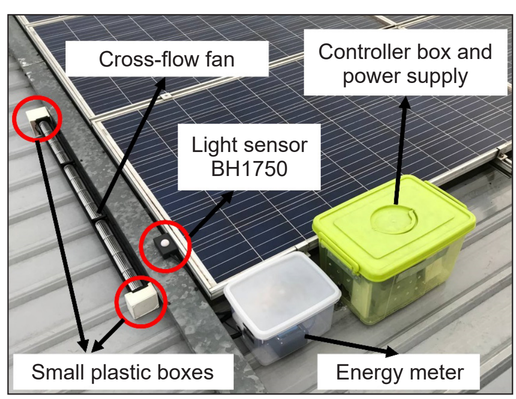


Figure 2. The placement of the fan, irradiance meter, energy meter, and controller box in the PV system

the roof and, therefore, the wind created by the fan is not affected by the roof's temperature. The experiment was conducted at the site for 12 consecutive hours, from 7.00 a.m. to 7.00 p.m., for several days before and after the installation of an air-cooling system. All data for solar irradiance, T_{cell} and electrical parameters data are trended at 3-second i ntervals.

The output voltage of the PV module, $V_{pv_{exp}}$, T_{cell}, and solar irradiance were measured and recorded during the experiment before and after applying the cooling system. Estimating the current output of a PV module or array under real-world operating circumstances is critical. This is because irradiance and temperature are instantaneous factors that directly influence the PV module's output. The concept of expected instantaneous output, where how much output of PV module per peak sun factor (PSF) at 1000 Wm^2, was implemented in this study using Equation 2 (Mustafa et al., 2024):

$$PSF = \frac{G_{array\_plane}}{1000\ Wm^2} \quad [2]$$

where G_{array_plane} is solar irradiance in array plane (Wm^2).

The expected output voltage for the PV module at the maximum power point, V_{pv_roc}, corresponding to the T_{cell}, can be calculated from Equation 1. Technically, peak sun hour (PSH) is the number of hours in a day with an irradiance intensity of 1000 Wm^2. An estimation of solar irradiance magnitude using total solar irradiance (TSI) was used in order to differentiate between levels of solar irradiance received (Egorova et al., 2018; Seleznyov et al., 2011). Total PSH in a day was used as TSI to classify the level of solar irradiance received per day. Solar irradiation levels are classified as high when the number of PSH exceeds 5.5, moderate when the range is between 3.5 and 5.4, and low when the level is below 3.5. Figure 3 shows a graph for the high, moderate and low levels of PSH used in this study to develop the desired models.

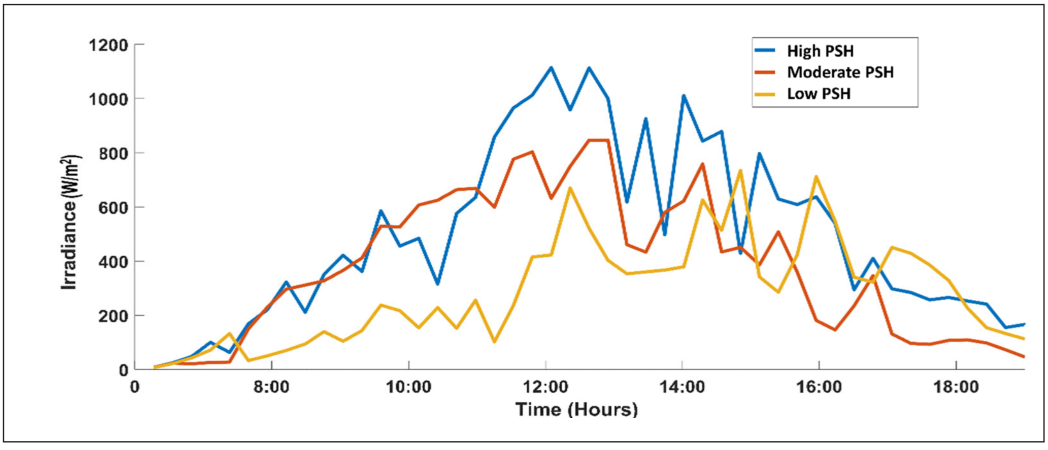


Figure 3. High, moderate and low PSH received in a day

T_{cell} and $V_{pv_{exp}}$ data were used to develop a data-based model using SI. These models will then be used as model-based control for further work on controller design and investigation to improve the efficiency of the proposed air-cooling system. This air-cooling PV system model refers to a PV module using an air-cooling system. PV module output and air-cooling PV system model was developed using SI. The strategies of SI might use all acquired data as input and output data or solely the output data. As shown in Figure 4, the PV module model input is T_{cell} while the model output was the output voltage of PV before applying an air-cooling system. This output voltage of PV data will be an input to the air-cooling PV system model, while the output voltage after applying the cooling system data will be the output for the air-cooling PV system model. During the development of the data-based model, the following assumptions were considered.

(i) Due to the tiny airspace between the PV module and the roof and the restriction of natural heat transmission, the wind does not affect the T_{cell}.

(ii) Solar irradiance and T_{cell} were evaluated in this study as the determining factor for PV module output.

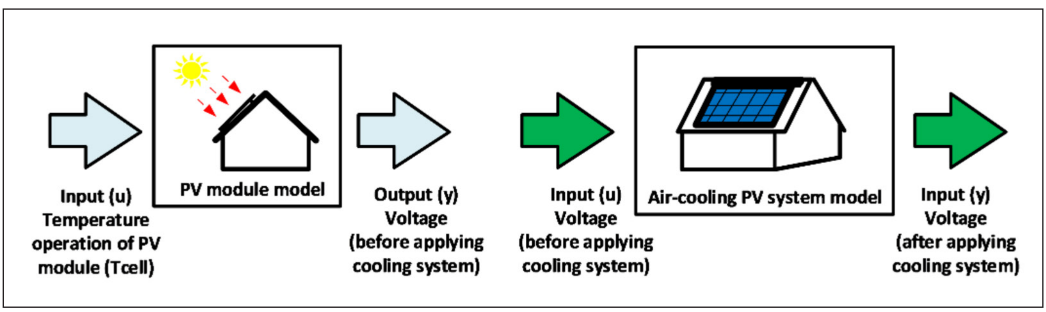


Figure 4. Input and output for PV module and air-cooling PV system model

Model Estimation and Optimisation

The developed models rely significantly on data. The available data set allowed us to evaluate a non-linear model of a PV module's output in the context of solar irradiance, voltage and T_{cell}. Experimentation on the PV module before and after installation of the air-cooling PV system provides the data used for the model estimate. For every 3 seconds from 7.00 a.m. to 7.00 p.m., 14 400 data points were sampled at the German Malaysian Institute. Prior to testing, the analysis of input and output signal processing is conducted, and the TF of the system is determined using MATLAB's SI Toolbox. Parametric models are employed to identify, wherein a mathematical model is derived from empirical data (Rachad et al., 2014; Sumalatha & Rao, 2016). It is imperative for the model to possess the ability to quantify the output of the system. In order to optimise the transfer function estimation system and achieve precise output (Donjaroennon et al., 2021) of the photovoltaic (PV) module, it is imperative to design the Pole and Zero of the system in a manner that maximises the fit of the graph. Various models were found with the aim of determining the most optimum solution. The transfer function was employed in these structures to establish the most effective model, whereby the order of the polynomial functions of the numerator $Nu_i(s)$ and denominator $De_j(s)$ was manipulated (Equation 3).

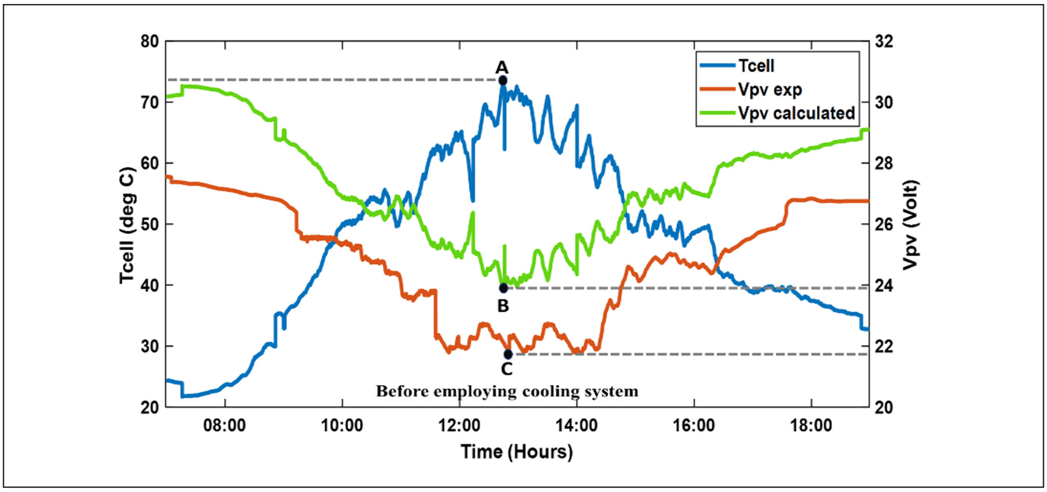
$$G(S) = \frac{Nu_i(s)}{De_j(s)} \qquad [3]$$

The identification procedure entails iteratively choosing model structures, identifying the optimal model inside the structure, and assessing the features of this model to determine their adequacy. The models that demonstrated the highest performance were chosen for validation based on the assessment measure employed. After successfully completing the model validation procedure, the model's acceptability may be determined by comparing the output of the measurement with the model's simulation output, which leads to the creation of the model's outcome curve. The acquired models were utilised in Simulink to verify their performance under varying levels of irradiance, including high, moderate, and low levels.

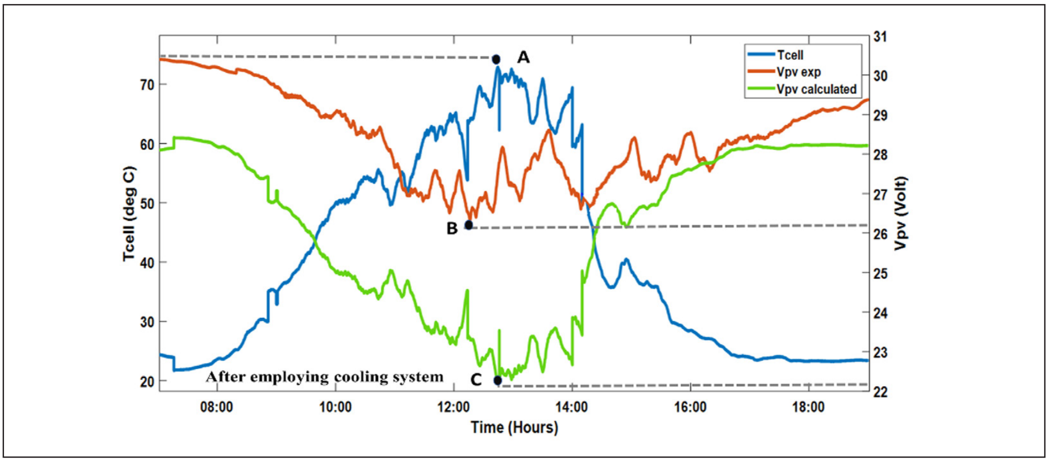
RESULTS AND DISCUSSION

Figure 5(a) depicts the graph for V_{pv_exp} that was influenced by T_{cell}, compared to the calculated data, $V_{pv\_calculated}$, before installing the air-cooling PV system. The highest T_{cell} (point A) was 74.3°C. It is essential to ensure that the backside of the PV module is cooled to reduce the T_{cell}. An initial rise in irradiance led to an increase in the V_{pv_exp} and T_{cell}. However, based on the experimental data depicted in the graph, the V_{pv_exp} started to lower due to the rising temperature and irradiance. The increase in T_{cell} resulted in a significant decrease in V_{pv_exp} compared to $V_{mp\_calculated}$ before implementing an air-cooling system. The lowest $V_{pv\_calculated}$ (point B) was 23.9 V, while the lowest V_{pv_exp} (point C) was 21.8 V. The measured value of V_{pv_exp} remains lower than the calculated value of $V_{pv\_calculated}$. After 3.00 p.m. both V_{pv_exp} and $V_{pv\_calculated}$ exhibit an upward trend, whereas T_{cell} experiences a decline. This is caused by a decrease in irradiance at this particular time. Consequently, the decline in T_{cell} no longer results in a rise in V_{pv_exp} and $V_{pv\_calculated}$ at this juncture as a result of the diminishing irradiance. Figure 5(b) depicts the graph after employing an air-cooling system. As the irradiance increased, an increase in T_{cell} led to a decrease in both V_{pv_exp} and $V_{pv\_calculated}$, with V_{pv_exp} remaining higher than the calculated value. The lowest V_{pv_exp} (point B) was 26.2 V, while the lowest $V_{pv\_calculated}$ (point C) was 22.2 V. Figure 5 satisfies Equation 1, which states that the voltage will decrease when the T_{cell} exceeds the standard test condition (STC) temperature, 25°C. This happened because of the thermal effect on the PV module due to the negative value of the temperature coefficient for voltage and power, γ.

The input and output signals for the PV module model are shown in Figure 6. The input is the value of T_{cell}, and the output is the output voltage of the *PV* module. For the air-cooling PV system model, the input and output signals are shown in Figure 7. The input is the output voltage of the PV module without the air-cooling system, $V_{pve_{xp\_uncool}}$, while the output signal is the output voltage of the PV module with the air-cooling system, $V_{pve_{xp\_cool}}$. The model was constructed using the PV module's output voltage at maximum power point, corresponding to the current irradiance. The data was separated into two sections for model estimation. The initial section of data is used to determine the system's model, while the other part is used to validate the model. SI toolbox in MATLAB was utilised to perform all estimation processes.



(a)



(b)

Figure 5. Experimental and calculated values (a) before and (b) after employing an air-cooling PV system based on the corresponding T_{cell} for the respective testing day

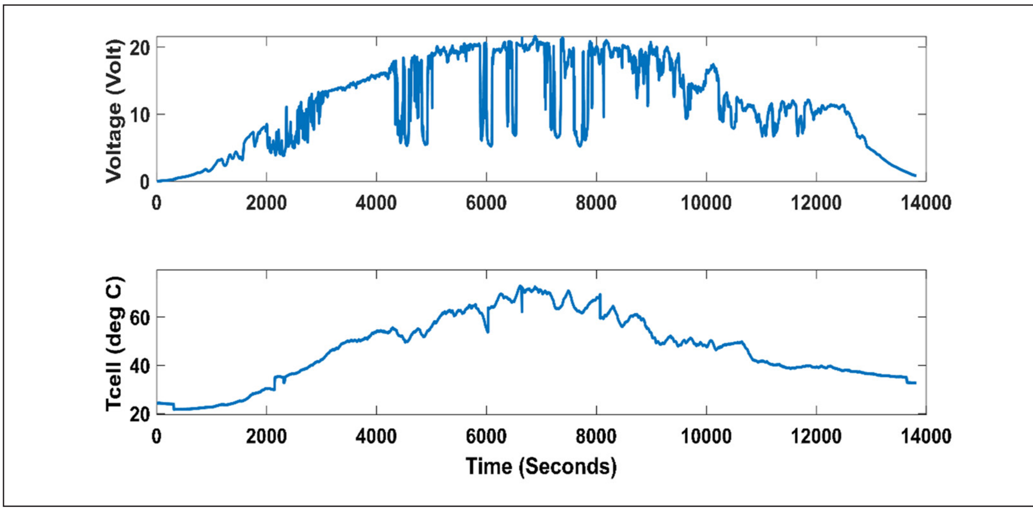


Figure 6. Input and output signals in system identification toolbox MATLAB for PV module model development

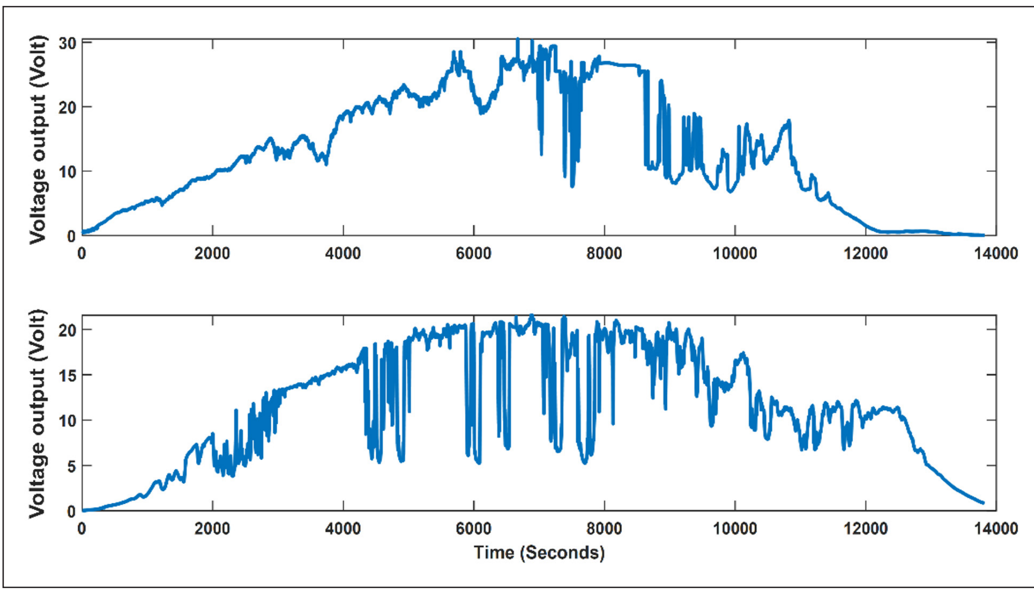


Figure 7. Input and output signals in system identification toolbox Matlab for air-cooling PV system model development

Validation

As a general rule, models can be accepted when the percentage of fit is at least 90%. Figures 8 and 9 depict the output model curve from which the TF model polynomials may be derived. The output models' curves reveal that the percentage of fit is 90% for the PV module model and 94.3% for the air-cooling PV system model. Figure 8 demonstrates

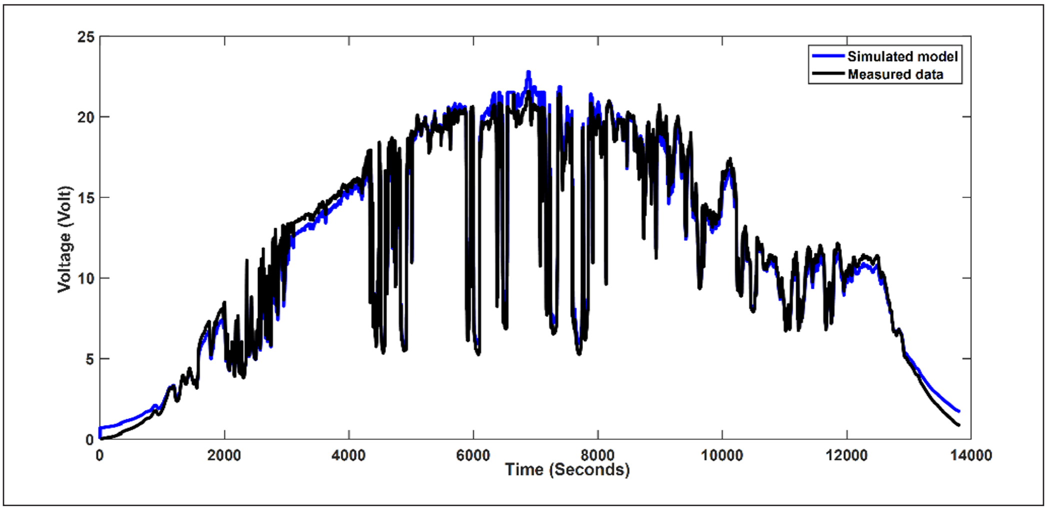


Figure 8. Estimated PV module model in *German Malaysian Institute*

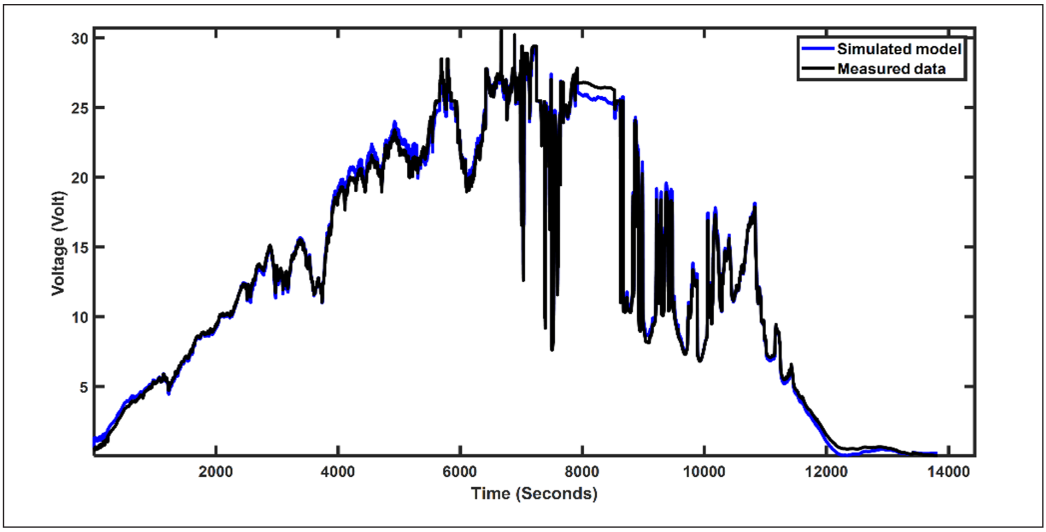


Figure 9. Estimated air-cooling PV system model in *German Malaysian Institute*

the output voltage for the PV module before implementing an air-cooling system, while Figure 9 demonstrates the output voltage for the PV module after implementing an air-cooling system.

The Simulink model of the air-cooling PV system is designed to represent parameter changes over time-based on solar irradiation. The model was developed as a transfer function, which is performed in the continuous-time domain, as stated in Equation 4.

$$G(S) = \frac{728.1s^2 + 0.121s + 0.0003856}{s^3 + 563.7s^2 + 0.09345s + 0.0002981} \qquad [4]$$

The transfer function model G(s) contains three poles and two zeros. It accurately represents the data from the German Malaysian Institute's system, with a fit of up to 94.3%. The transfer function associated with the third-order differential equation yields a linear model. Additionally, the controllability and observability of the developed mathematical models were evaluated. The Bode plot in Figure 10 displays the frequency response of the model. The pole and zero were plotted for each model and observed to narrow down the model. An optimal model will exhibit stability when all its poles and zeros are located within the unit circle. A model is considered the best when all its poles and zeros are located within the unit circle, indicating stability.

Figure 11 illustrates that each zero and pole is inside the unit circle. This is referred to as a minimal phase model. This model specifically focuses on the principles of causality and stability. It is intended to be utilised for in-depth research and to establish a relationship between both input and output variables. The model used to estimate the output of a PV module with an air-cooling system is noteworthy for its linearity and description by a transfer function. Additionally, it relates to a third-order differential equation. The model guaranteed stability, allowing for further examination of its controllability and observability aspects.

These mathematical models were used to achieve the highest output of the PV module when receiving solar irradiance by decreasing the influence of T_{cell}. A model estimate of solar irradiance and voltage was performed using a generic SI approach, including data analysis, model structure selection, parameter estimation, and model validation (Ljung, 2012). Data evaluation is done to acquire decent data. The model structure is selected to ascertain the desired model for generation. It may take linear, non-linear, or intelligent model form. Validation serves the objective of comparing the predicted output of the model with

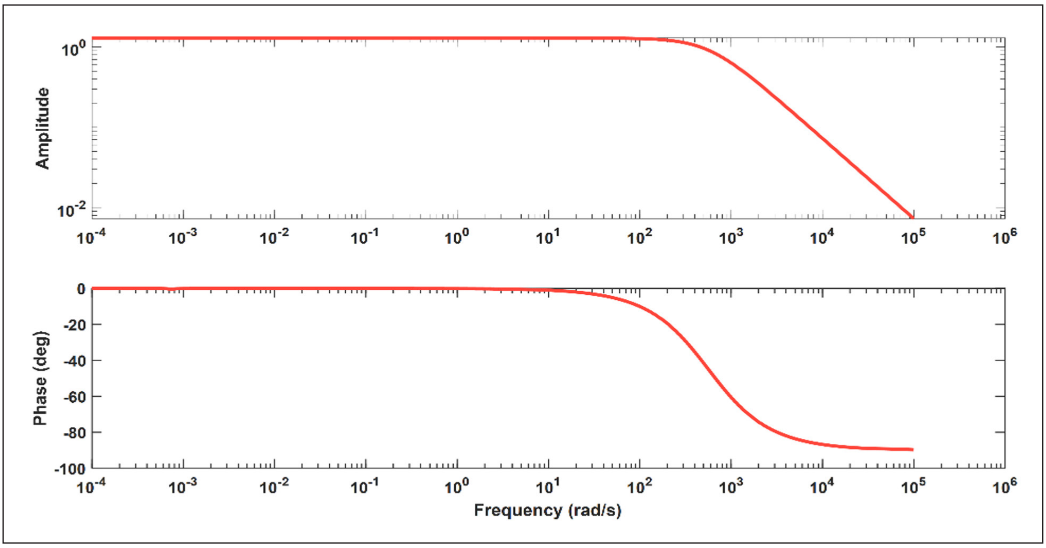


Figure 10. Frequency response for the air-cooling PV system development

the observed outcome of the experiments. It might be deemed acceptable if the model validation satisfies the required percentage of fit and other criteria (Ljung, 2012). In contrast to traditional approaches, this identification technique exhibits enhanced speed and accuracy. The highest percentage of fit was utilised to determine its selection and ascertain the transfer function that most accurately reflects the accuracy of the estimation output model with respect to the input data. It is necessary to compare the accuracy of the selected transfer function computation with the input data provided by MATLAB. Furthermore, MATLAB can generate graphical representations such as output response, impulse response, and Bode diagrams based on the transfer function. In Simulink implementation, the models obtained were used to observe the output performance of the PV module before and after implementing the proposed air-cooling system using different levels of solar irradiance data. This step is very important to ensure that the developed models are compatible with multiple levels of solar irradiance. Figure 12 shows the simulation block diagram in Simulink used for air-cooling PV system observation.

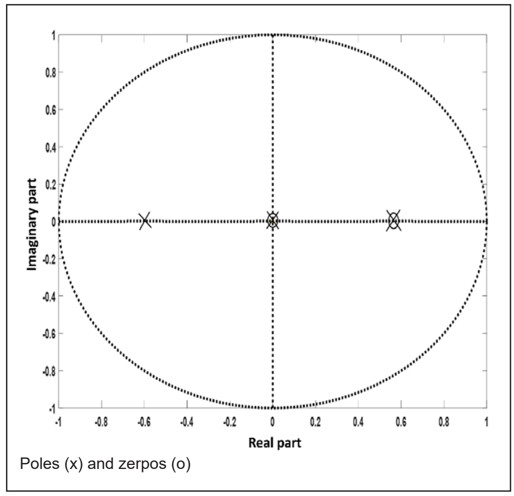


Figure 11. Pole zero plot for the air-cooling PV system model

The simulated data for multiple levels of PSH obtained from the model was then compared to measured data. Table 1 shows the percentage achieved for the validation models. From Table 1, the percentage of validation for high, moderate and low are above 90%. This means that the developed models are capable of anticipating a voltage output almost as accurately as the value when the experiment was carried out. The model's failure rate in predicting inequality is less than 10%. The results shown in Table 1 demonstrate the generated models' effectiveness in handling different PSH levels.

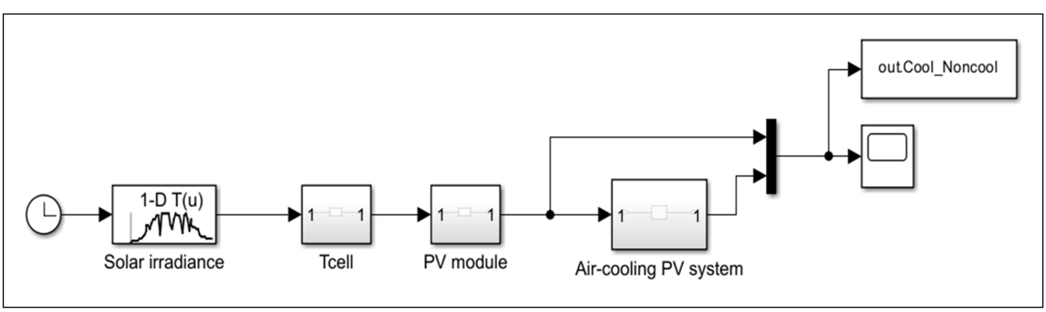


Figure 12. Simulation block diagram for air-cooling PV system

Strong evidence that the air-cooling PV system successfully boosted the output performance of the PV module was found when the output voltage after implementing the air-cooling PV system, $V_{pv_{exp\_cool}}$, was higher than before implementing the cooling system, $V_{pv_{exp\_uncool}}$. Using different levels of solar irradiance to represent multiple levels of PSH as an input to the model-based control developed, Figure 10 shows the output voltage, $V_{pv_{exp}}$, before and after applying the air-cooling PV system for high, moderate and low PSH. The results from Figure 13 indicate a 10.8% gain in mean output voltage after implementing the proposed air-cooling PV system for high PSH, 17.5% for moderate PSH and 15.3% for low PSH.

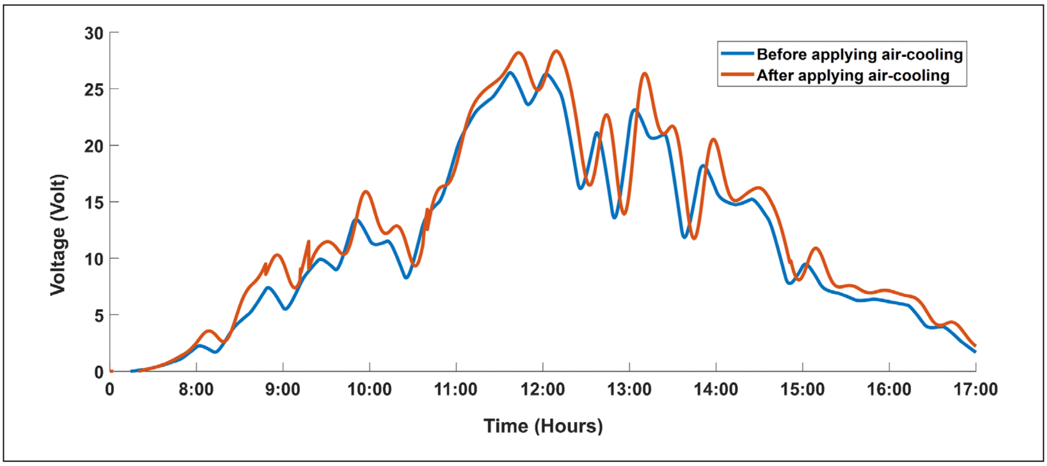
Table 1
Percentage of validation simulated model to measured data under high, moderate and low levels of solar irradiance

Model	**High PSH**	**Moderate PSH**	**Low PSH**
PV module	90.1%	92.4%	90.8%
air-cooling PV system	91.7%	93.2%	91.5%

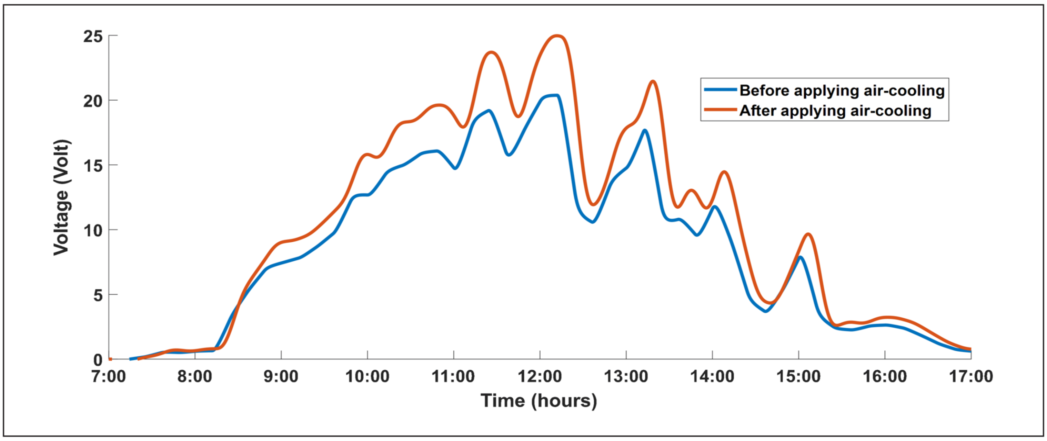
Since the PV module has the largest T_{cell}, it has the lowest percentage increase in output voltage under high solar irradiance. While it is probable that the fan in the cooling system has reached its maximum rotational speed, further time is required to decrease T_{cell} because, at the same time, the higher solar irradiance can keep T_{cell} high. Hence, while the PV module experiences a significant amount of solar irradiance at any one moment, the prolonged time of solar irradiance receipt also contributes to the time to decrease the T_{cell}. In moderate solar irradiance, the T_{cell} exhibits a lower magnitude compared to high solar irradiance. PV modules that receive moderate solar irradiance have a shorter time of high solar irradiance acceptance, resulting in a quicker temperature reduction compared to modules that receive high solar irradiance. This phenomenon results in a greater magnitude of voltage production compared to both high and low solar irradiance levels. While the T_{cell} experiences a decrease when exposed to low solar irradiance, the percentage output voltage rise is rather small compared to the moderate solar irradiance it receives. Despite the low temperature, it is important to acknowledge that a decrease in solar irradiation will result in a corresponding decrease in output voltage. The receipt of ample sun irradiance values in cold temperatures is highly advantageous for PV modules. This demonstrates the indispensability and significance of cooling in the restoration of the PV performance module, and the suggested air-cooling system is capable of effectively managing this task. The simulation results above demonstrate that the generated models effectively adjust to various amounts of solar irradiation, indicating their potential for further research.

CONCLUSION

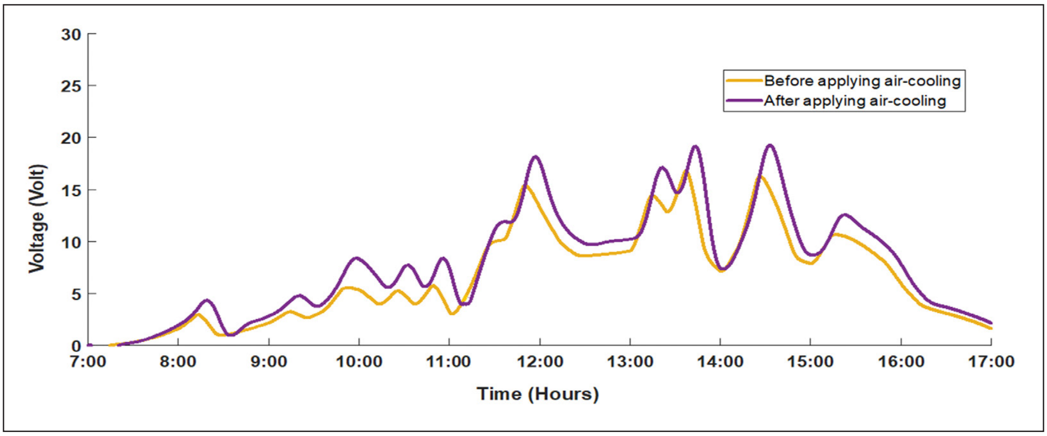
Before and after installing an air-cooling *PV* system, solar irradiance, T_{cell} and voltage output were measured to determine the actual *PV* output, $V_{pv_{exp}}$. Before installation of the proposed air-cooling *PV* system, the higher T_{cell} will cause the voltage and power output



(a)



(b)



(c)

Figure 13. The output voltage of the PV module before and after applying an air-cooling system using the SI model for (a) high-level irradiance, (b) moderate-level irradiance, and (c) low-level irradiance

of the *PV* system to decrease. The air-cooling *PV* system used to cool down the T_{cell} subsequently enhanced the output performance of the *PV* module. This paper develops and stimulates a data-driven mathematical model for PV modules and air-cooling PV systems. The experiment was conducted continuously for a duration of 12 hours, which is the longest period of uninterrupted data collection compared to prior studies. The data was taken at 3-second intervals, resulting in a total of twelve thousand data points, which is the highest number compared to the prior study. The use of extensive data in the development of a more precise model for air-cooling photovoltaic systems is a unique aspect of this work. A mathematical model has been constructed to optimise the performance of a PV module and air-cooling PV system under varying levels of solar irradiance. The lack of development in the prior air-cooling PV system model necessitated the development of this new model, which is a significant innovation in this study. The developed models could be utilised in future research endeavours aimed at enhancing the efficiency of the PV module and the proposed air-cooling PV system. The analysis shows that the TF model provides the greatest fit. The percentage of fitness for the PV module model is 90%, while it is 94.3% for the air-cooling PV system model. The simulation findings indicate minimal disparities in the average output voltage between the model system and the actual data across all levels of solar irradiation, with each discrepancy being less than 10%. The PV module model demonstrated validation values of 90.1%, 92.4% and 90.8% for high, moderate, and low PSH, respectively. The validation results for the air-cooling PV system model were 91.7%, 93.2%, and 91.5%. The output mean voltage exhibits a progressive increase, reaching 10.8% higher under conditions of high PSH, 17.5% higher under conditions of moderate PSH, and 15.3% higher under conditions of low PSH. Upon careful analysis of the data received from the validation of the models, as well as the findings from the simulation, it can be concluded that the produced model-based control has been effectively developed and may be utilised in future research, particularly in the field of controller design, to ensure optimal performance of the proposed cooling system.

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