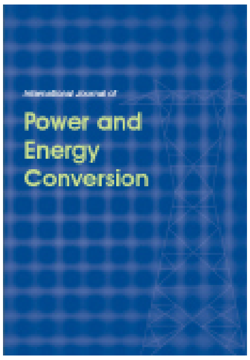

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A multivariate regression model of solar photovoltaic and its validation through ANN

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Abstract: The rapid integration of solar photovoltaic (PV) systems into the global energy landscape necessitates the development of accurate predictive models for PV system performance. A solar photovoltaic (PV) system is modelled either by its equivalent single-diode, double-diode or multiple-diode model. The model equations of these models need to be solved through iterative process which sometimes may not suitable for analysis. One cannot analyse a system using modal analysis, state-space analysis, linearisation, etc., when an iterative process is involved. Therefore, this paper suggests a multivariate regression based novel function of solar PV which replicates the actual PV system model. The model incorporates key factors such as solar irradiance, temperature, and system configuration to provide a comprehensive understanding of PV system behaviour. The proposed regressed model of the solar PV has been tested under various operating conditions and realistic solar data. To validate the accuracy and robustness of our multivariate regression model function, a feedforward back-propagation neural network has been used considering the data generated by the proposed regression model. It was also observed that the proposed model is good enough for the mathematical analysis of the PV integrated systems.

Keywords: feedforward neural network; maximum power point tracking control; MPPTC; multivariate regression; solar PV system.

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1 Introduction

The integration of the solar photovoltaic (PV) systems into the grid has been increased much in recent past. This is due to its clean form, abundant availability in the nature and support provided by the government agencies to set up such systems. Therefore, it is being discussed much among the researchers and policy-makers. Various issues related to the integration of PV in to the grid and its standalone operation have been discussed by many of the researchers (Jean and Brown, 2020; Jamil et al., 2017; Nwaigwe et al., 2019; Amery et al., 2017; Sharaf and Gandoman, 2015). It has been concluded by the researchers that the perfect model of the PV is required during simulation for the exact analysis of the PV integrated system.

During computer-based investigation, the PV system is equivalently modelled by its various models consisting number of diodes and resistances in series and parallel (Araújo et al., 2020). The single-diode and double-diode model are mostly used models for the power system analysis (El Ainaoui et al., 2023; Tavakoli et al., 2020; Nwaigwe et al., 2019; Villalva et al., 2009; Chan and Phang, 1987). These simplified models are sufficient when its voltage-current and voltage-power characteristics are taken into consideration for further investigation (Batzelis et al., 2019). However, in some of the advanced PV modelling theory, the Lambert W function is also used to formulate the model equations in simplified manner (Batzelis et al., 2018, 2019; Petrone et al., 2007) but the single-diode model is sufficient when variable irradiance and temperature variation are being accommodated (Batzelis, 2017; Lun et al., 2013). The equivalent circuit model equations of the multiple-diode and multiple-resistance PV need to be solved by the iterative process during simulation which may not be suitable for the investigation when the linearisation and associated analysis are done. Therefore, a straight forward model of solar PV is required which depends on all the associated dependent variables and reflects the actual characteristics of it. This has motivated the authors of this paper to develop its equivalent model which may further be used for the power system studies. This paper concentrates on the single-diode model and derivation of its multivariate regression model for its inclusion into the power system during linearisation, modal analysis and small signal stability analysis. The novelty of a learning algorithm for a multivariate regression model of solar PV systems lies in its ability to accurately predict the outputs of the solar PV by taking into account multiple variables and factors simultaneously.

The regression model of a linear system can be easily obtained using its input-output values but it is more difficult when the considered system has nonlinear characteristics (Specht, 1991). The regression model helps to ease the dynamics and that is why much popular in designing a model for nonlinear systems (Specht, 1991; Zazoum, 2022; Park et al., 2020; Khandakar et al., 2019; Yadav and Chandel, 2017; Prajapat et al., 2017). The solar PV system has nonlinear characteristics with umber of input variables and hence require a multivariate model. Although, the machine learning models based on support vector machine (SVM) and Gaussian process regression (GPR) (Zazoum, 2022), univariate linear regression (Park et al., 2020), linear regression model, M5P decision tree and GPR model (Khandakar et al., 2019) has been reported in the literature for the different applications. A multivariate regression model (Alexopoulos, 2010) is best suited for nonlinear dynamics as it helps us to understand the relationships among variables present in the dataset and can incorporates multiple independent variables. It can also define the correlation between independent variables and dependent variables.

In any of the energy system, its design criteria always talk about the maximum extraction of energy out of it. Therefore, the maximum power point tracking control (MPPTC) of the PV system is one of the essential controls which should be provided for the extraction of maximum power (Esram and Chapman, 2007; Sridhar et al., 2015). The MPPTC of the solar PV can be achieved by the existing single-diode or multi-diode model of PV through iterative process (Hohm and Ropp, 2003) using voltage-power characteristics. However, it can be inferred from the literature (Salhi, 2009; Salas et al., 2006; Enany, 2017) that the single-diode PV model is acceptable when MPPTC is concerned. The proposed regression model based on single-diode PV is tested for the maximum power capture under the different irradiance and temperature levels.

Recently, the control of PV system through machine leaning techniques are quite popular, especially, the artificial neural network (ANN) is employed in many of cases (Kumar et al., 2019; Sun et al., 2017; Rezvani et al., 2015; Khanam and Foo, 2018; Kumar, 2023). The ANN control based on approximate dynamic programming (ADP) for optimal control of PV is reported in Sun et al. (2017) which performs well even in the presence of noise. Other control like MPPTC through perturb and observe (PAO) can also be obtained using ANN as reported in Rezvani et al. (2015), Khanam and Foo (2018) and Sridhar et al. (2015). Similar reported works on ANN for the control applications shows its superiority method of forecasting in almost all cases. Thus, a feedforward backpropagation ANN has been used to validate the proposed multivariate model of the PV model.

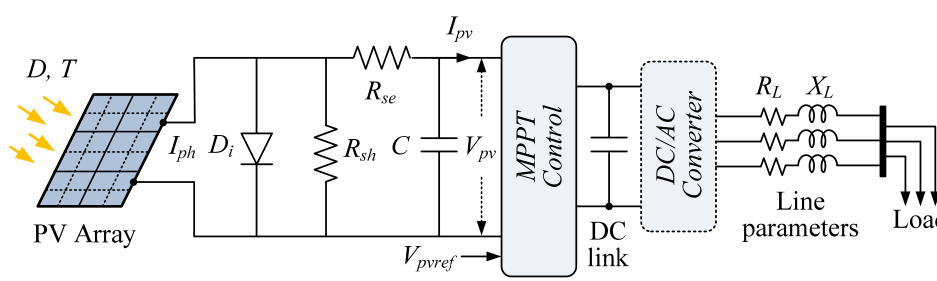
The major contribution of this paper includes the development of a multivariate regression model of solar PV system. The proposed model has been tested under the variable irradiance and temperature condition, especially with maximum power extraction. It model has been validated through a neural network. The proposed model is tested and compared with the benchmarked multi-diode models and found well fitted under various disturbance conditions together with real data of irradiance.

The rest of the paper is organised as follows. The studied solar PV system with its detailed model equations of an equivalent single-diode model is presented in Section 2. Thereafter, the formulation of the PV model through proposed multivariate regression model is explained in Section 3. In Section 4, the ANN model, its training and testing from the data generated from the proposed model is presented. Further, the verification of the proposed regression model and its validation has been analysed by performing the simulation in steady-state and time-domain data in Section 5 followed by the conclusion in Section 6.

2 Model description of solar PV system

The equivalent single-diode model of solar PV system with its classical control for MPPTC and DC/AC converter and supplying to the load is shown in Figure 1. Its simplified model is equivalently expressed by an anti-parallel diode to the PV array composed of several PV cells and two resistances, one in series resistance R_{se} and one in parallel resistance R_{sh}. The incidence of the photons, in terms of temperature, T and irrdiance, D on the solar array develops a photon current, i_{ph} as shown in figure. The equivalent model of the solar PV gives the output current, I_{pv} corresponding to the output voltage V_{pv} and can be expressed by the following set of generalised equation (Araújo et al., 2020; Villalva et al., 2009).

Figure 1 Solar PV system with its control (see online version for colours)



$$I_{pv} = i_{ph} - i_0\left(e^{\left(\frac{V_{pv}+I_{pv}R_{se}}{aV_{th}}\right)} - 1\right) - \frac{V_{pv}+I_{pv}R_{se}}{R_{sh}} \tag{1}$$

where i_0 is the diode saturation current and a is the ideality factor of the diode while the thermal voltage of the array V_{th} is expressed as follows.

$$V_{th} = \frac{kT}{q}N_s \tag{2}$$

where $k = 1.38 \times 10^{-23}$ Joules/ Kelvin is the Boltzmann constant, T is temperature of the $p–n$ junction in Fahrenheit, $q = 1.602 \times 10^{-19}$ C is the electron charge and N_s is the number of PV cells connected in series. The photon current i_{ph} directly depends on the solar irradiance D and temperature T and represented as follows (Chan and Phang, 1987; Villalva et al., 2009).

$$i_{ph} = \frac{D}{D_n}\left(i_{phn} + K_i \Delta T\right) \tag{3}$$

$$\Delta T = T - T_n \tag{4}$$

$$i_{phn} = I_{scn} \tag{5}$$

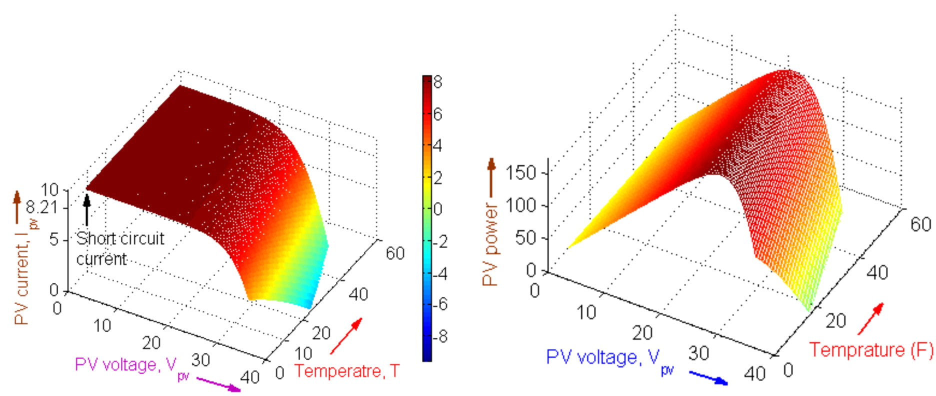
where D_n and T_n are nominal solar irradiance and temperature respectively, K_i is short-circuit current-temperature coefficient. The photon current of every cell i_{phn} is assumed to be equal to the short-circuit current I_{scn} which is the maximum current available at the terminals of the practical device. Further, the saturation current i_0 can be expressed by the improved model reported in Villalva et al. (2009) to accommodate the open-circuit voltages of the model for a very large range of temperatures.

$$i_0 = \frac{\left(I_{scn} - K_i \Delta T\right)}{e^{\frac{V_{ocn} + K_v \Delta T}{a V_{th}}} - 1} \tag{6}$$

where K_v is the open-circuit voltage-temperature coefficient. The saturation current i_0 strongly depends on the temperature and it simplifies the model and cancels the model error at the vicinities of the open-circuit voltages. Once the PV current, I_{pv} corresponding to the PV voltage V_{pv} is obtained, the output PV power, P_{pv} of the solar PV can be calculated as follows.

$$P_{pv} = V_{pv} I_{pv} \tag{7}$$

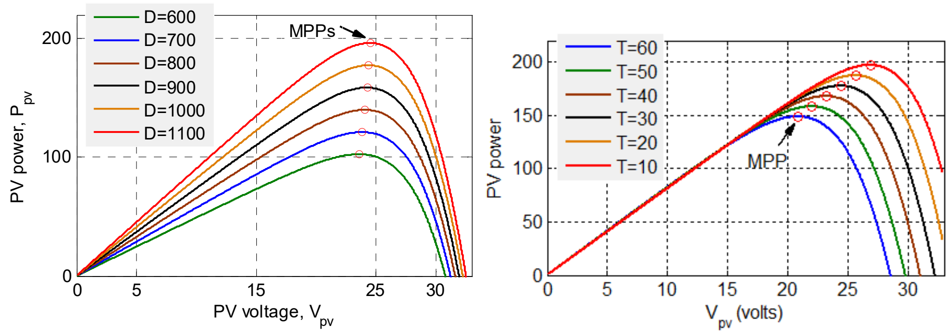
Figure 2 (a) $I_{pv} - V_{pv}$ characteristics and (b) $P_{pv} - V_{pv}$ characteristics at different temperature (see online version for colours)



(a) (b)

The single-diode model of the solar PV has been simulated through iterative process using (1)–(7) and its characteristics have been drawn. The $V_{pv} - I_{pv}$ and $V_{pv} - P_{pv}$ characteristics under different temperature are shown in Figures 2(a) and 2(b) respectively. The PV power at the different level of irradiance and temperature are also drawn as shown in Figure 3. It can be observed from the curves that its current and power are nonlinearly dependent on the temperature and irradiance. Therefore, it requires a multivariate regression model of it for further use for power system analysis problem.

Figure 3 PV power, P_{pv} at different irradiance level (see online version for colours)



Further, it can be experienced from Figure 3 that the output PV power is higher when the solar irradiance is higher and vice-versa while the power is higher at lower level of temperature and vice-versa. The characteristics also shows that the output power is maximum at an specific value of PV voltage as mentioned by the maxim power points (MPPs) in figure. The tracking of the maximum power is performed by the observing voltage in this paper.

3 Formulation of multivariate regression function

A regression model signifies a function between the correlated variables. It is a statistical technique that relates dependent variables to one or more independent variables, called predictors. It is widely used to predict the behaviour of the response variables associated with the changes in the predictor variables. The multivariate regression model is best suited when a system consists two or more independent variables. A generalised model of a multivariate regression can be represented as follows.

$$\begin{bmatrix} y_1 \\ y_2 \\ . \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & x_{12} & . & x_{1m} \\ 1 & x_{21} & x_{22} & . & x_{2m} \\ . & . & . & . & . \\ 1 & x_{n1} & x_{n2} & . & x_{nm} \end{bmatrix} \begin{bmatrix} \varphi_{01} & \varphi_{02} & \varphi_{03} & . & \varphi_{0n} \\ \varphi_{11} & \varphi_{12} & \varphi_{13} & . & \varphi_{1n} \\ . & . & . & . & . \\ \varphi_{m1} & \varphi_{m2} & \varphi_{m3} & . & \varphi_{nm} \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ . \\ \zeta_n \end{bmatrix} \tag{8}$$

$$\boldsymbol{Y} = \boldsymbol{X\varphi} + \boldsymbol{\zeta} \tag{9}$$

where $\boldsymbol{Y}$ are responses, $\boldsymbol{X}$ are predictors, $\boldsymbol{\varphi}$ and $\boldsymbol{\zeta}$ are associated with the cost functional. The solution of a multivariate regression problem starts from the selection of the predictors, responses and cost functional which further needs to be minimised (Snedecor, 1956; Alexopoulos, 2010). In this paper the squared error is taken as the cost functional. In the studied solar PV model, it has temperature, irradiance and PV voltage features as predictors and PV current and power are responses. The designed solar PV model can be expressed in its summarised form as follows.

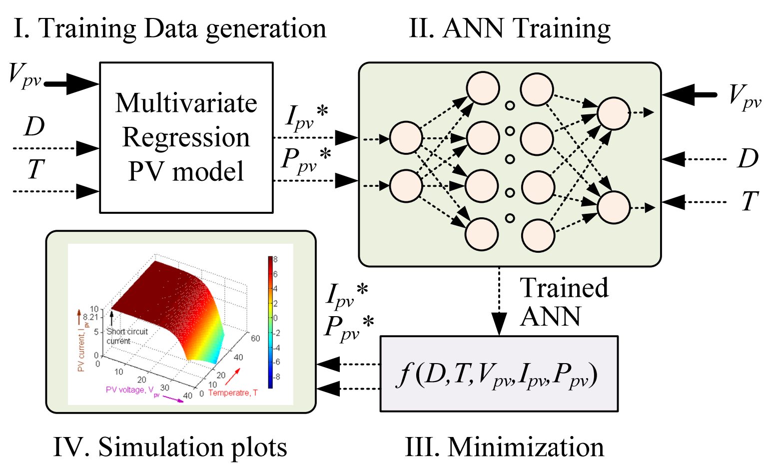
$$\left[I_{pv} P_{pv}\right]^T = f_{pv}\left(D, T, V_{pv}\right) \tag{10}$$

The input-output data are extracted using nonlinear simulation through iterative process considering (1)–(7) which further used to form the f_{pv}. The novelty of a learning algorithm for a multivariate regression model of solar photovoltaic (PV) systems lies in its ability to accurately predict and optimise the performance of solar PV installations by taking into account multiple variables and factors simultaneously. A multivariate regression model for solar photovoltaic systems has its ability to leverage advanced techniques, handle multiple variables and integrate diverse data sources.

4 ANN model of solar PV system

An ANN processes the information in parallel and can be used to develop a nonlinear and complex relationships through input-output training models. It takes the input-output data sets provides nonlinear mapping between inputs and outputs. The architecture of a generalised ANN consists connection between nodes, activation function and connection weights which need to be updated during its learning process. In this paper, the feedforward back-propagation neural network is used to validate the solar PV function made by the multivariate regression. The implementation process of the ANN for the present problem is shown in Figure 4. The input-output data sets have been generated from the proposed regression model and trained the network minimising the errors.

Figure 4 ANN architecture and training-testing process (see online version for colours)



The feedforward back-propagation neural network was trained using the data extracted from the regression model considering solar irradiance, temperature and PV voltage as inputs and the PV current and power (I_{pv}^*, P_{pv}^*) as outputs. The hyper parameters settings or configurations used in the ANN are set prior to the training process. They control the behaviour of the model and can significantly impact its performance. The number of hidden layers in the considered model were 10 and the learning rate considered was 0.01. A tangent sigmoid function was used as an activation function and the network training function was based on resilient back-propagation algorithm.

5 Simulation and validation

To confirm the effectiveness of the proposed method, the simulation of the proposed algorithm was performed in MATLAB environment. The proposed model was examined first under the step, ramp and realistic temperature and irradiance disturbances and then validated using ANN. The parameters of the studied system are given in Table 1.

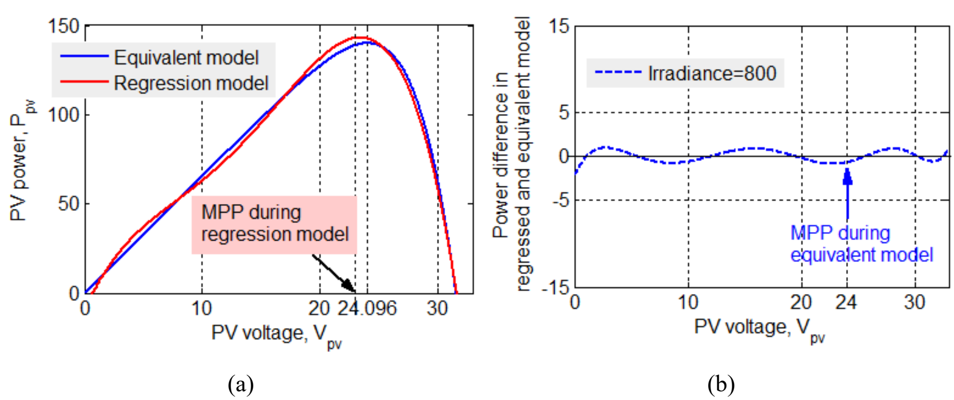
Table 1 Parameters of the examined solar PV

Parameters description	*Values*
Open circuit voltage, V_{ocn}	32.9 V
Short circuit current, I_{scn}	8.21 A
Nominal Temperature, T_n	25°C
Nominal Irradiance, D_n	1,000 W/m^2
Ideality factor, a	2.0
Model series resistance, R_{se}	0.221 Ω
Model parallel resistance, R_{sh}	415.405 Ω
Number of PV cells in series, N_s	54
Short-circuit current-temperature coefficient, K_i	0.0032
Open-circuit voltage-temperature coefficient, K_v	–0.123

5.1 *Equivalent PV models Vs regression model*

First the model mentioned in (1)–(7) have been simulated through iterative calculations in MATLAB and input-output variables has been recorded under different environmental conditions. Once the input-output variables have been generated, the solar PV system can be considered as a black-box with temperature, irradiance and voltage as input and solar PV current and power as output. Later, the multivariate regression model of the solar PV has been designed considering irradiance, temperature and voltage as predictors.

Figure 5 (a) PV power, P_{pv} during equivalent PV and regression model (b) Error (see online version for colours)



The PV power, P_{pv} of the solar system at D = 800 W/m^2 with the different models are drawn and shown in Figure 5. It can be observed from Figure 5(a) that the proposed multivariate regression model is matching with the equivalent PV model. Their maximum power points (MPP) have a negligible difference (24.096–24.000 ≈ 0.096 V) which allows its design. Also, the error in the power during equivalent and regression model is insignificant as shown in Figure 5(b).

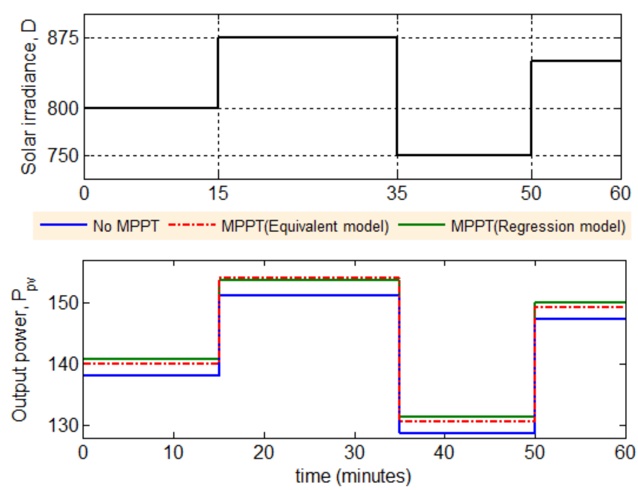
5.2 *Time response of proposed model*

To demonstrate the effectiveness of the proposed model under different temperature and irradiance penetration levels, its performance has been examined in step and ramp disturbances. The responses obtained are shown in Figure 6 and Figure 7.

5.2.1 *System with step change in irradiance*

The step disturbance in any of the system is an extreme case wherein the performance of a controller can be observed. Therefore, such a step change in solar irradiance disturbance is introduced in the system shown the output power is observed. The output power at different level of irradiance in one hour duration is shown in Figure 6. As soon as the irradiance increases, the output power, P_{pv} is increasing instantly and vice-versa because of its static dynamics. Further, the proposed regression model is perfectly fit with the MPPT control since it is responding as same as the equivalent model while when there is no MPPT, the output power is lesser than the case of MPPT.

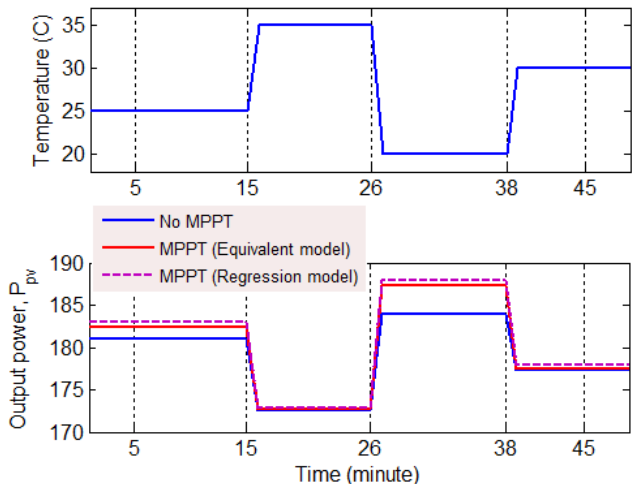
Figure 6 Variation in the PV power with irradiance in an hour (60 minutes) (see online version for colours)



5.2.2 *System with ramp change in temperature*

The system was also examined under the ramp change in the temperature and the recorded responses are drawn as shown in Figure 7. Similar to the case of change in irradiance, the power pattern varies similar to the change in the temperature. The slope of the ramp remains same to the temperature due the static dynamics of the solar PV system. Again, when there is no MPPT, the output power is lesser at all steps.

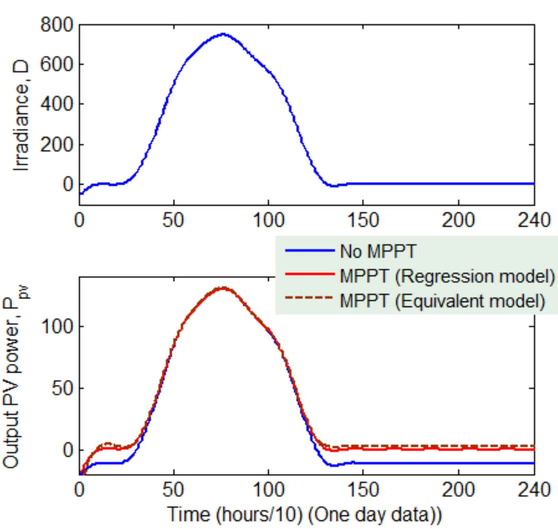
Figure 7 Variation in the PV power with respect to temperature (see online version for colours)



5.3 *Performance of the regression model under practical irradiance data*

The proposed multivariate regression model has also been examined under the real data obtained through the tool mentioned in Pfenningerand Staffell (2016). The irradiance data has been recorded online by an interactive web platform, www.renewables.ninja (2023) at location 28.0229°N, 73.3119°E near Bikaner, Rajasthan, India. The recorded irradiance has 10 samples in one hour. The proposed model has been tested for the irradiance data for one day as shown in Figure 8. It can be demonstrated from the power response that the proposed method performs satisfactory with the real solar data.

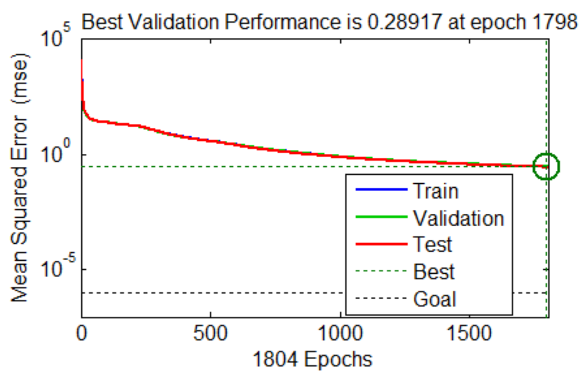
Figure 8 Output PV power for a day (see online version for colours)



5.4 Validation of the regression model using ANN

The proposed regression model has been validated through a feedforward back propagation ANN. The ANN model is developed using MATLAB. The number of hidden layers in the considered model were 10 and the learning rate considered was 0.01. A tangent sigmoid function has been used as an activation function. A tangent sigmoid function was used as an activation function and the network training function was based on resilient back-propagation algorithm. For training the ANN, 70% data points have been used while testing was done by 30% data points. The number of hidden layers considered was 10 and tangent sigmoid activation function was used. The input-output data points are obtained from the proposed regression model using simulation. The performance of the ANN model shows that mean square error (MSE) becomes minimum at 1,798 number of epochs as shown in Figure 9. The epochs are one complete sweep of training, validation and testing data set. The ANN model stops automatically when the error is minimum.

Figure 9 MSE during training and testing of ANN (see online version for colours)



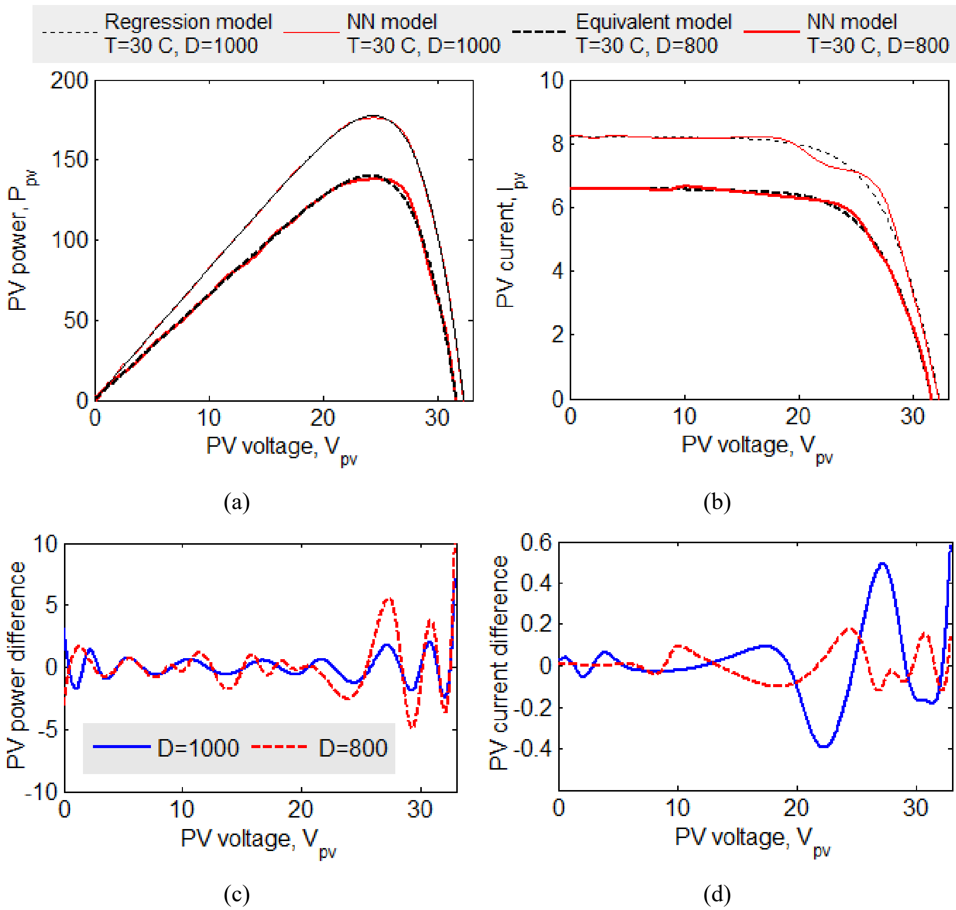
Once the ANN has been trained, it is ready to deliver the output corresponding to the set of inputs. The trained ANN has been examined under the different operating conditions and responses drawn are shown in Figures 10(a)–10(d). It can be seen from Figures 10(a) and 10(b) that the PV characteristics of the proposed regressed model is following the responses of equivalent model and the ANN model. The difference in the power and current shown in Figures 10(c) and 10(d) are allowable. Ultimately, it validates that the proposed model is good enough and can be further used for the mathematical analysis of the solar PV integrated systems.

5.5 Comparison with benchmarked multi-diode models

The single or double-diode model of PV are considered as benchmarked or reference model when solar PV system is considered into the system. Therefore, the proposed developed model have also been compared with single-diode and double-diode model (El Ainaoui et al., 2023). The comparison of these models with the novel regression models for solar PV systems can help us understand their respective advantages.

The models have been compared by considering the real data of the solar irradiance obtained at location 28.0229°N, 73.3119°E near Bikaner, Rajasthan, India. The recorded irradiance are of one week (7 days) and has ten samples in one hour as shown in Figure 12. It can be observed from the responses with the different models in Figure 11 that the proposed model is well fitted with the benchmarked and hence can be used as an equivalent numerical model of solar PV.

Figure 10 (a) $P_{pv} - V_{pv}$ characteristics (b) $I_{pv} - V_{pv}$ characteristics (c) Power difference corresponding Figure 10(a) (d) Power difference corresponding to Figure 10(b) under different operating conditions (see online version for colours)



However, the single and multi-diode models have their own advantages. The choice of model depends on the specific objectives of the analysis or design and the available computational resources. Researchers and engineers often select the model that best balances the need for accuracy with practical considerations.

5.6 Energy capture through proposed model

It is expected that the suggested model should perform well with the controllers under different operating conditions. Thus, the proposed regression model has been tested under conventional MPPT controller. This controller has been appended in all the models one-by-one and responses observed under real solar data obtained in a week as shown in Figure 11.

Figure 11 Output power in real irradiance data of one week (see online version for colours)

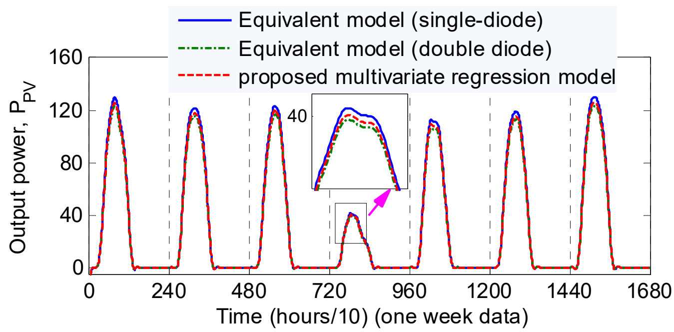
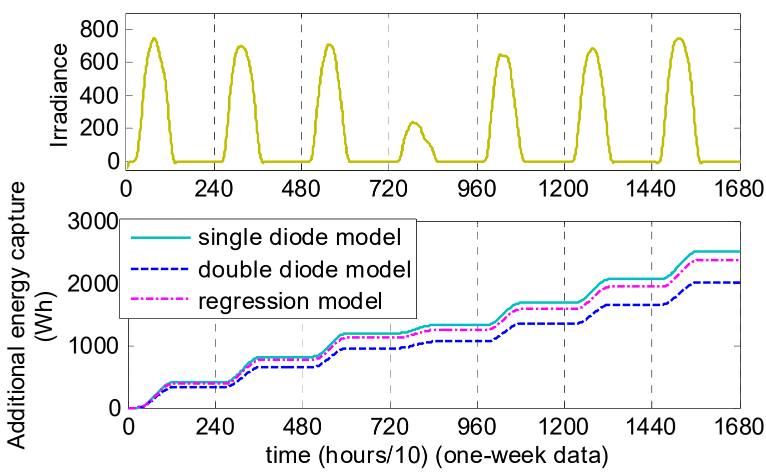


Figure 12 Energy capture as compared to off-MPPT operation with different model (see online version for colours)



The comparison has been made by looking onto the additional energy capture calculated by finding the difference between the output powers when the system is operating under MPPT and off-MPPT. It can be observed from the responses in Figure 12 that the proposed regression model captures additional energy up to the mark and matched with the reference models.

6 Conclusions

A multivariate regression novel model of solar PV has been proposed in this paper which replicates the actual PV system model. The purpose of proposing such a model is to avoid the solution of the conventional model through iterative process because the iterative function may not be suitable for some power system analysis. The designed model of the

PV system has been tested for MPPTC using look-up table in different operating conditions and found that it is performing perfectly. The control with the regressed function has also been tested under the realistic solar data. The proposed model has been validated through a feedforward back-propagation neural network and it was observed that it is good enough and can be further used for the mathematical analysis of the solar PV integrated systems. The developed regression model can further help to analyse the problem on the basis of modal analysis, state-space analysis, linearisation, etc. Also, the maximum power capture during the partial shading of the PV can be implemented through the minima-maxima of the proposed model. Multivariate regression model can be used in future for optimising the design and operation of solar PV systems taking care of optimal tilt angle, orientation, and the sising of the PV array for further assess the impact on the grid.

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Abbreviations

PV	photovoltaic
MPPTC	maximum power point tracking control
ANN	artificial neural network
SDM	single diode model
DDM	double diode model
PAO	perturb and observe
ADP	approximate dynamic programming
GPR	Gaussian process regression
SVM	support vector machine

Nomenclatures

k	Boltzmann constant (=1.38 × 10^{-23} Joules/ Kelvin)
T	temperature of the *p–n* junction (Fahrenheit)
q	electron charge (=1.602 × 10^{-19} C)
N_s	number of series connected PV cells
D_n	nominal solar irradiance

T_n	nominal solar temperature
K_i	short-circuit current-temperature coefficient
K_v	open-circuit voltage-temperature coefficient
α	ideality factor (= 2.0)
φ, ζ	cost functional associated with regression.