Acta Scientific COMPUTER SCIENCES

Volume 3 Issue 11 November 2021

Research Article

An Application of Artificial Intelligence Models for Predicting and Controlling Solar Cell Output Power

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Received: September 14, 2021

Published: October 12, 2021

Abstract

The study describes the application and comparison of five artificial intelligence methods for PV system output power prediction. General Regression Neural Network (GRNN), Radial Basis Function network (RBF), Group Method of Data Handling (GMDH) network, Multilayer Perceptron neural network (MLP) and Linear Regression (LR). Measured values of temperature (T°C) and irradiance E (kWh/m^2) were used as inputs (independent variables) and PV output power P (Kw) was used as output (dependent variable). Predictive performances have been evaluated using statistical metrics. Comparison of the results provided by the five models has been conducted and commented. It was observed that predictive accuracy depend of the nature of data set used and the optimization parameters of each model. Response surfaces that represent the combined impact of simultaneous variation in temperature and irradiance on PV output power have been illustrated. Curves that showed how close were validation predicted values and actual values have been plotted. Relationship between output power and the two parameters have been illustrated and it was found to be nonlinear. Importance of each ambient parameter contribution to the PV output power has been demonstrated.

Keywords: GMDH; GRNN; MLP; PV Output Power; RBF

Introduction

To date, the interest in the use of photovoltaic (PV) energy conversion has increased worldwide. In fact, solar energy is a clean, abundant and easily available renewable energy, friendly source of energy, etc. Solar cell technology has become attractive for its potential in reducing greenhouse gas emission, consuming less fossil fuel, and providing higher penetration of renewable energy source. Also, due to its availability everywhere in the word, solar cell energy has opened up a wide range of potential applications like solar water heating, solar heating of buildings, solar distillation, solar pumping, solar drying of agricultural and power production, solar green houses, etc. [1,2]. Other advantages of the solar cells are high reliability, minimum of cost of maintenance, long lifetime, portability, modularity, no expenditure on fuel, pollution free working, etc. However, the performance of PV systems is constantly affected by various parameters such as irradiance (E), ambient temperature (T), etc. The main difficulty of a PV controller is to predict the PV output power in order to estimate the reserve capacity. There is very little published studies available in literature regard to the modeling and prediction of solar cell output power. Also the interaction impacts of different ambient parameters on the solar cell output power and its efficiency have not been discussed enough. A study of the impact of ambient parameters can help provide insight into how to control and estimate the solar cell energy. The range of values of the ambient parameters necessary for the optimization of the solar cell output power could be estimated. More recently, few studies using artificial intelligence approaches have been used to predict and model the PV power production [3-6]. However, their prediction accuracy is still a controversial issue and more attention is still needed in order to achieve acceptable predictable accuracy. The aim of this study is to apply artificial intelligence techniques for based ambient parameters modeling and prediction of solar cell output power. Five artificial intelligence models: General regression neural network (GRNN), radial basis function network (RBF), Group Method of Data Handling (GMDH) network, multilayer perceptron neural network (MLP) and linear regression (LR) will be explored and the results will be compared and commented. These methods have not yet widely explored in controlling solar cell output energy despite the main advantages that they offer.

PV system localisation and data collection

Data used in this study were collected from the PV system of the Hospital of the University of Burundi. Figure 1 shows the configuration of the system.

Figure 1: PV system configuration.

The PV site has latitude of 3°24' and longitude of 29°21'. 1920 PV panels are installed on the area of 6300 m^2. Its power capacity is of 400kW. Table 1 represents the specifications of the PV system. Hourly raw data including solar irradiation E (kWh/m^2), temperature T(^{o}C) and output power P (kW)were collected for a period of two months in rainy season(February and March) and two months in sunny season(July and August) 2017. Table 2 shows the attributes and statistical properties of the collected data sets.

Implementation of the methods

DTREG software [7] was used for implementation. Description of all the models can be found in details in [7]. DTREG can accept a dataset that contains a number of rows with a column for each variable. One off the variable is the target variable whose value is to be modeled and predicted as a function of the input variables. It analyses the data and generates a model that shows how best to predict the values of the target variable based on values of the predictor variables.

Table 4 shows the optimization parameters for each model. From the table, one can see that optimization parameters are dif-

Number of Panels	1920
Output power: P (kW):	400 kW
Open circuit voltage: V_{OC} (V)	407.2
Short circuit current: I_{CC} (A)	1336.8
Current at maximum power: I_{pm} (A)	1221.6
Voltage at maximum power: V_{pm} (V)	330.4
Conversion efficiency: η (%)	17.2
Area (m^2)	6300

Table 1: Specifications of the PV system.

	Rainy season				Sunny season			
Variable	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**
E	1.64	7.08	4.80	1.37	2.28	6.72	5.63	0.69
T	21.47	26.42	24.24	1.25	22.22	26.66	24.95	0.81
P	140.86	550.35	373.92	100.22	142.05	469.46	368.58	51.28

Table 2: Statistical properties of the attributes of collected data.

ferent from each model. The type of analysis was regression for all of the models. The method of validation that has performed well was 10-folds cross-validation for four models and leave one out (LOO) for MLP model.

Results Analysis and Discussion

Prediction performances of the five models were evaluated using the well-known statistical criteria. Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error.

MAPE and RMSE are the measures of the deviation between the actual and predicted values. The smaller the values of RMSE and MAE, the closer are the predicted power values to the actual power values. They are defined by equations (1)-(3). Other statistical metrics usually used such as mean squared error (MSE), proportion of variance explained by model (R^2(%)) and correlation between actual and predicted (R), coefficient of variation (CV), normalized mean square error(NMSE) will be considered for comparison reasons.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - P_p)^2} \text{ ---(1)}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|P_i - P_p\right| \text{ ------(2)}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|P_i - Pp|}{|P_i|} \times 100\% \text{ -------(3)}$$

Where n is the number of pairs, $P_i$andP_p are the i-th actual and calculated outputs, respectively.

Using GDMH model has been used to generate the mathematical expressions as the models to represent the PV output power as a function of irradiance and temperature and are given by equations (4) and equation(5) for the rainy and sunny periods, respectively.

P(Er,Tr)=375.0492+9.303935*T+13.27597*T^2+82.29614*E+ 7.232871*E^2-26.61747*T* ---(4)

P (Es,Ts)=382.3321-19.11256*T-7.604631*T^2+32.27855*E- 4.793281*E^2-13.60399*T*E -----(5)

Table 5 shows the training and table 5 shows the validation results of the five models. From the table, it is observed that all of models provided similar training results for each period data.

The situation is different for validation results presented in table 6. The performance of each model is detailed in the following paragraph. Only the main statistical criteria (RMSE, MAE, MAPE, R^2, R) are discussed as they are mostly used for accuracy evaluation of many prediction models. Other criteria may be used for other comparison purposes.

For GRNN, RMSE=30.91, MAE=20.53, MAPE=6.80, R^2=63.66, R=0.84 for sunny period data while RMSE=42.87, MAE=25.12, MAPE=7.21, R^2=81.7, R=0.90 for rainy period data. One can see that GRNN RMSE, MAE, MAPE values are better for sunny season data than that of rainy season. But the reverse situation is observed for R^2 and R.

For RBF, RMSE=24.23, MAE=20.35, MAPE=5.57, R^2=77.66, R=0.88 for sunny period data while RMSE=42.95, MAE=25.90, MAPE=7.59, R^2=81.62, R=0.90 for rainy period data. One can see that RBF RMSE, MAE, MAPE values are better for sunny season data than that of rainy season. On the contrary, RBF provided better R^2 and R values for rainy period data.

For GMDH, RMSE=26.22, MAE=21.28, MAPE=6.36, R^2=73.85, R=0.86 for sunny period data while RMSE=42.51, MAE=24.91, MAPE=7.21, R^2=82, R=0.90 for rainy period data. One can see that GMDH RMSE, MAE and MAPE values are better for sunny season data than that of rainy season. But the situation is different for R^2 and R values.

For MLP, RMSE=24.88, MAE=19.90, MAPE=5.82, R^2=76.46, R=0.88 for sunny period data while RMSE=41.46, MAE=23.41, MAPE=6.39, R^2=82.88, R=0.91 for rainy period data. One can see that MPL RMSE, MAE and MAPE values are better for sunny season data than that of rainy season. But the reverse situation is observed for R^2 and R values.

For LR, RMSE=37.77, MAE=26.06, MAPE=7.80, R^2=54.03, R=0.73 for sunny period data while RMSE=40.28, MAE=22.25, MAPE=6.27, R^2=83.84, R=0.91 for rainy period data. One can see that MPL provided better, MAE, MAPE, R^2 and R values for rainy season data than that of sunny season.

By analyzing the above results, it is observed that the performance of each model depends on the nature and structure of the data set used. For instance, RBF provided smallest RMSE value for sunny data and highest RMSE for rainy data. Smallest MAE was provided by MLP (sunny data) and highest MAE (sunny data) has been provided by LR. MAPE smallest value was provided by RBF and highest value by LR. Better value of R^2 (rainy data) as well the worse value (sunny data) were provided by LR. Better R value resulted from MLP and LR (rainy data) while the worse R value is from LR (sunny). From these results, it is not possible to determine which model that is more powerful than others but it is observed that RBF has performed well for sunny season data in comparison with other models while LR has done better for rainy period data.

Table 3 represents the computed importance of temperature and irradiance contribution on PV output power. From the table, one can see that irradiance is the main contributor on the PV output power. However, temperature importance is significant even if some models have provided small values.

Response surfaces that represent the combined impact of simultaneous variation in temperature and irradiance on PV output power have been plotted and are shown in figure 2 and figure 3. They represent in a compact way all the information in the ambient parameters controller. From the figures, it is revealed that the relationship between ambient parameters and output power is nonlinear. The curvatures of the response surfaces show that interactions between the two ambient parameters can be depicted. These interactions can be also depicted from equation (4) and equation (5).

Figures 4-8 show the 10-folds cross-validation process. Only figures representing the rainy dataset are shown. From figures, one can see how closer the mean validation predicted power values are to the mean actual input power values.

Sunny season data							**Rainy season data**				
Type of model		**GRNN**	**RBF**	**GMDH**	**MLP**	**LR**	**GRNN**	**RBF**	**GMDH**	**MLP**	**LR**
Importance (%)	E	100	100	100	100	100	100	100	100	100	100
	T	76.66	48.00	44.89	43.61	14..97	0.019	3.84	12.13	4.78	3.06

Table 3: Computed importance contribution of each parameters.

Optimization parameters	**GRNN**	**RBF**	**GMDH**	**MLP**	**LR**
Type of analysis	Regression	Regression	Regression	Regression	Regression
Validation method	Leave one out(LOO)	10-folds cross -validation	10-folds cross -validation	10-folds cross -validation	10-folds cross -validation
Number of neurons	-	7	-	-	-
Minimum radius	-	0.26561	-	-	-
Maximum radius	-	375.318	-	-	-
Minimum Lambda	-	0.9305	-	-	-
Maximum Lambda	-	5.87793	-	-	-
Number of layers	-	-	-	3 (1 hidden)	-
Hidden layer 1 neurons:	-	-	-	Search from 2 to 20	-
Hidden layer activation function	-	-	-	Logistic	-
Output layer activation function	-	-	-	Linear	-

Table 4: Optimization parameters.

Sunny period dada						Rainy period data				
Statistical parameter	**GRNN**	**RBF**	**GMDH**	**MLP**	**LR**	**GRNN**	**RBF**	**GMDH**	**MLP**	**LR**
MTVID	368.58	368.58	368.58	368.58	368.58	373.92	373.92	373.92	373.92	373.92
MTVP	368.68	368.58	369.23	368.65	368.58	374.02	373.92	374.73	374.71	373.92
CV	0.0327	0.0462	0.0594	0.0549	0.0837	0.1003	0.0999	0.1035	0.1032	0.1025
NMSE	0.0553	0.1104	0.1825	0.1561	0.3619	0.1401	0.1391	0.1491	0.1483	0.1464
MSE	145.55	290.43	480.23	410.85	952.04	1408.16	1397.39	1498.00	1489.82	1471.53
RMSE	12.06	17.04	21.91	20.26	30.85	37.52	37.38	38.70	38.59	38.36
MAE	8.70	14.09	18.26	16.57	24.17	21.41	21.60	21.96	22.35	20.89
MAPE	2.32	3.79	5.30	4.49	7.0558	5.7958	5.9240	6.0627	6.3176	5.8724
R^2	94.46	88.95	81.74	84.38	63.80	85.98	86.088	85.08	85.16	85.35
R	0.97	0.94	0.90	0.91	0.79	0.92	0.92	0.92	0.92	0.92

Table 5: Analysis of variance for training data.

MTVID: Mean Target Value of Input Data; MTVVPD: Mean Target Value of Predicted Data; CV: Coefficient of Variation; NMSE: Normalized Mean Square Error.

Sunny period data						Rainy period data				
Statistical parameter	**GRNN**	**RBF**	**GMDH**	**MLP**	**LR**	**GRNN**	**RBF**	**GMDH**	**MLP**	**LR**
MTVID	368.58	368.58	368.58	368.58	368.58	373.92	373.92	373.92	373.92	373.92
MTVP	368.00	368.94	370.60	367.48	369.77	375.23	375.00	371.31	371.72	372.97
CV	0.0838	0.0657	0.0711	0.0675	0.0943	0.1146	0.1148	0.1136	0.1108	0.1077
NMSE	0.3633	0.2233	0.2614	0.2354	0.4596	0.1829	0.1837	0.1799	0.1711	0.1616
MSE	955.86	587.47	687.77	619.19	1209.08	1838.16	0.1837	1807.10	1719.55	1623.22
RMSE	30.91	24.23	26.22	24.88	34.77	42.87	42.95	42.51	41.46	40.28
MAE	20.53	20.35	21.28	19.90	26.06	25.12	25.90	24.91	23.41	22.25
MAPE (%)	6.80	5.57	6.36	5.82	7.80	7.21	7.59	7.21	6.39	6.27
R^2(%)	63.66	77.66	73.85	76.46	54.03	81.7	81.62	82.00	82.88	83.84
R	0.84	0.88	0.86	0.88	0.73	0.90	0.90	0.90	0.91	0.91

Table 6: Analysis of variance for validation data.

Conclusion

In this study, the main objective was to apply and compare five artificial intelligence methods for PV system output power prediction. General regression neural network (GRNN), radial basis function network (RBF), GMDH network, multilayer perceptron neural network (MLP) and linear regression (LR) were considered. Using statistical metrics, their predictive performances have been evaluated. Comparison of the results provided by the fives models showed that predictive accuracy depend of the nature of data set used and the optimization parameters.The analysis of results comparison and the curves that illustrate how close were validation predicted values and actual values indicated that the five models

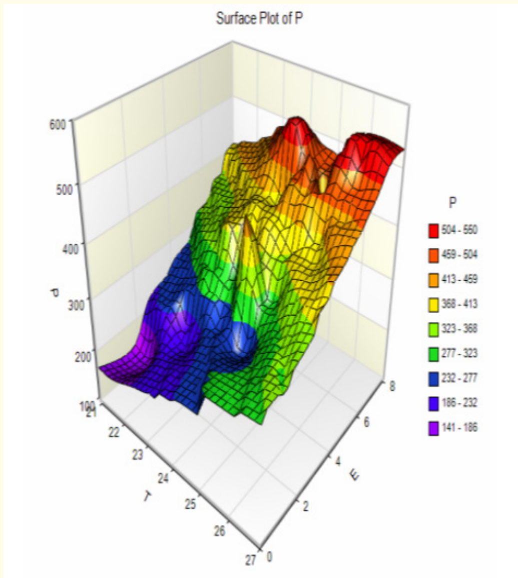

Figure 2: Response surface of PV output power (rainy period data).

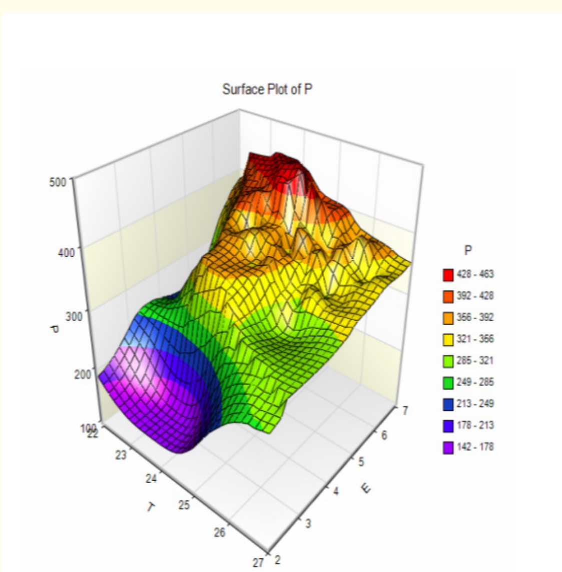

Figure 3: Response surface of PV output power (sunny period data).

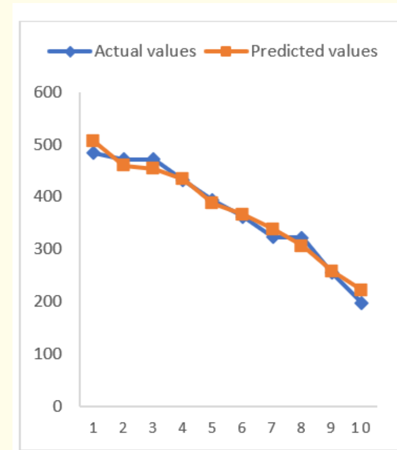

Figure 4: 10-folds cross validation for GRNN.

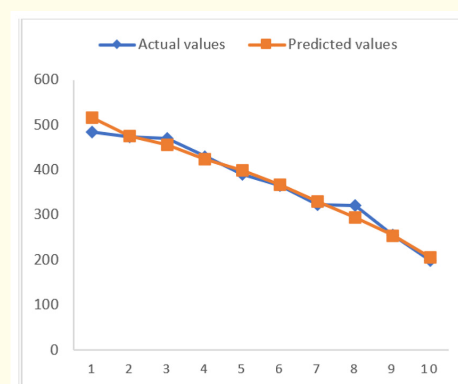

Figure 5: 10-folds cross validation for RBF.

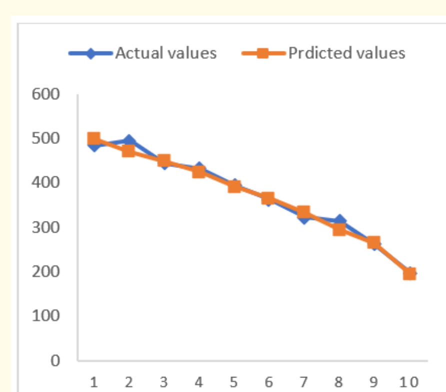

Figure 6: 10-folds cross-validation for MPL.

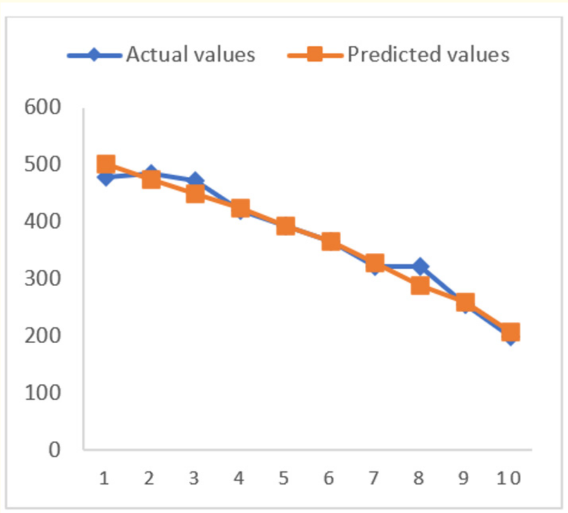

Figure 7: 10-folds cross-validation for GMDH.

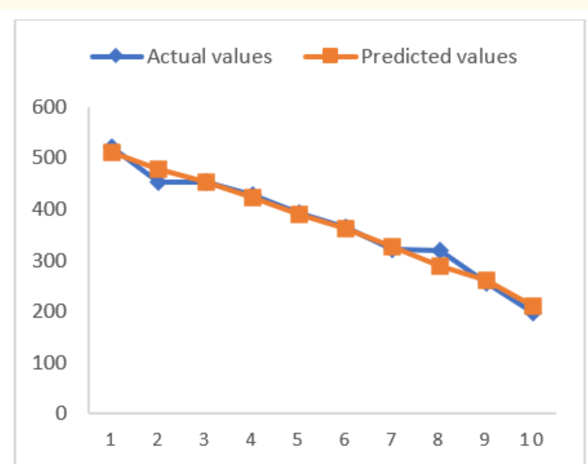

Figure 8: Folds cross-validation for LR.

cross-validation results were a little different. Results comparison also revealed that RBF and LR models provided better performance than other models. From the response surfaces, the combined impacts of simultaneous variation in temperature and irradiance on PV output power have been depicted. Relationship between output power and the two parameters was found to be nonlinear.The analysis of importance and of each parameter cntribution to the PV output power showed that outtputt power depends at less or great level on ambient parameters.The obtained results from the study could allow the PV system controler to predict and estimate the capacity of energy reserve.However, alternative artificial intelligence techniques should be explored andcompared in order to assess the expected predictive accuracy level.

Author

Deogratias NURWAHA holds a Ph.D. in Electrospinning Engineering from Dong Hua University, China. His current main research topics are Applicationof Artificial Intelligence Techniques in optimization of electrospinning process and in Solar Cell Energy. He is the author of many articles on application of Artificial Intelligence methods in electrospinning process and in solar energy. He is a reviewer of many scientific articles.

Conflict of Interest

Author declares no potential conflict of interest.

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