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Interval-based Solar PV Power Forecasting using MLP-NSGA II in Niroo *Research Institute of Iran*

M. Khademi*
Assistant Professor

A. Nikookar†
PhD Student

P. Khodabakhsh‡
M.Sc.

M. Moadel
PhD Student

This research aims to predict PV output power by using different neuro-evolutionary methods. The proposed approach was evaluated by a data set, which was collected at 5-minute intervals in the photovoltaic laboratory of Niroo Research Institute of Iran (Tehran). The data has been divided into three intervals based on the amount of solar irradiation, and different neural networks were used for predicting each interval. NSGA II, a multi-objective optimization algorithm, has been applied to search an appropriate set of weights, which optimized the neural network with two or more conflicting objectives. The MLP-NSGA II algorithm provides better results with the Mean Square Error (MSE) and correlation coefficient (R^2) of 0.01 and 0.98, respectively, in comparison with Linear Regression, MLP, and MLP-GA. By the way, obtained results show that the precision of prediction models would be improved by reducing input parameters' time intervals.

Keywords: PV output Power Predication, Multi-Objective Optimization Algorithms, Neural Network, NSGA II.

1 Introduction

Solar cells operate as quantum energy conversion devices and are therefore subject to the thermodynamic efficiency limit. The thermodynamic efficiency limit is the absolute maximum theoretically possible conversion efficiency of sunlight to electricity, which is about 86%, based on the temperature of the photons emitted by the Sun's surface [1].
Consequently, the performance of a PV module depends on the solar irradiance's intensity at the location and the PV-module temperature. Thus, reliable knowledge and understanding of the PV module performance under different operating conditions is of great importance for correct product selection and accurate energy supply and demand planning.

*Corresponding Author, Assistant Professor, Department of Applied Mathematics, Islamic azad university South Tehran Branch, khademi@azad.ac.ir
* PhD Student, Department of Computer Engineering, Islamic azad University South Tehran Branch, A_Nikookar@azad.ac.ir
† M.Sc., Department of Computer Engineering, Islamic azad University South Tehran Branch, st_p_khodabakhsh@azad.ac.ir
‡ PhD Student, Department of Energy Engineering, Islamic azad University Science and Research, st_m_moadel@azad.ac.ir

Efficiency is a great importance in such systems regarding both output power and cost of generation, where more efficiency results in more power and less expenditure. It is determined by performing various tests in different conditions; however, the tests require advanced equipment and large facilities' costs which are not simply accessible in all situations and locations. With regards to these restrictions, the researchers have tried to facilitate this process by determining the efficiency of PV solar systems through modeling them. Many systematic formulations have been proposed, but their accuracy was not acceptable according to their complexity. In recent years, numerous studies have been conducted for predicting PV solar system's efficiency and optimize the useful parameters by using computational intelligence techniques [2]. Among many of CI methods employed for finding the efficiency of PV panels, artificial neural network (ANN) gained the most [3-11]. Regardless of the network type, different factors of PV modules through a specific duration were given as input parameters to an ANN to create a model based on the behavior of the panels.

In 2010, a method based on an artificial neural network was proposed which predicted si-crystalline and CIS PV modules electrical behavior. One of the significant advantages of this model was the capability of providing the V–I curve for any value of irradiance and module cell temperature without having to do the whole process [3]. In (2011), a model based on a neural network was proposed to approximate the maximum power generation from a PV module. The model used the environmental information and was able to predict the next day's generation from the PV systems [4]. In (2013), Karamirad et al. used an artificial neural network to predict Photovoltaic panel behavior based on the Meteorological condition of the PV module location [5]. In this year, ANN was utilized to estimate the profile of the generated power of PV module. According to different weather conditions, two ANNs were developed. The networks' inputs were only the ambient temperature, solar irradiation, and clearness index [6]. In 2014, ANN was employed to forecast the delivered power which is generated by a large solar system. Simultaneously, the temperature level of the system which can be reached was predicted by the network [7]. Teo et al. employed the artificial neural network model based on extreme learning machine (ELM) to cut down the training time.

ELM training speed caused a considerable reduction in training time compared to gradient descent based training algorithm. In this research, initialization training parameters such as learning rate and stopping criterion can be overlooked. The model proved tuning the input variables do not cause the best performance [8]. Due to a complex relation of PV output power to climatic parameters, the results were not precise. From last decade, some new studies which were based on ANNs have better results [9,10,12]. Recently the PV power forecast has been widely addressed by adopting several methods, and they could be mainly grouped in physical, stochastic and hybrid methods [13, 14] . Hybrid methods, which are proved to be the most efficient ones [15-20], combine different models with unique features to overcome the single negative performance and finally improve the estimation. Khademi and et. al. in their study predict the daily PV output power using MLP-ABC algorithm considering cloudy weather condition and financial analysis. Ambient temperature, solar irradiation, and humidity as input parameters were measured in Tehran climatic condition.The network output parameter was PV output power. Evaluation parameters as MAPE, MBE and R^2 were 3.7, 3.1 and 94% [21].

2 Materials and Methods

In this study, a neuro-evolutionary model, a neural network optimized by a multi-objective optimization algorithm is proposed to predict a PV output power. The weather condition of PV module location, including ambient temperature, solar radiation, and wind speed were used as network inputs. Figure (1) illustrates the main components which were used to predict the PV module output.

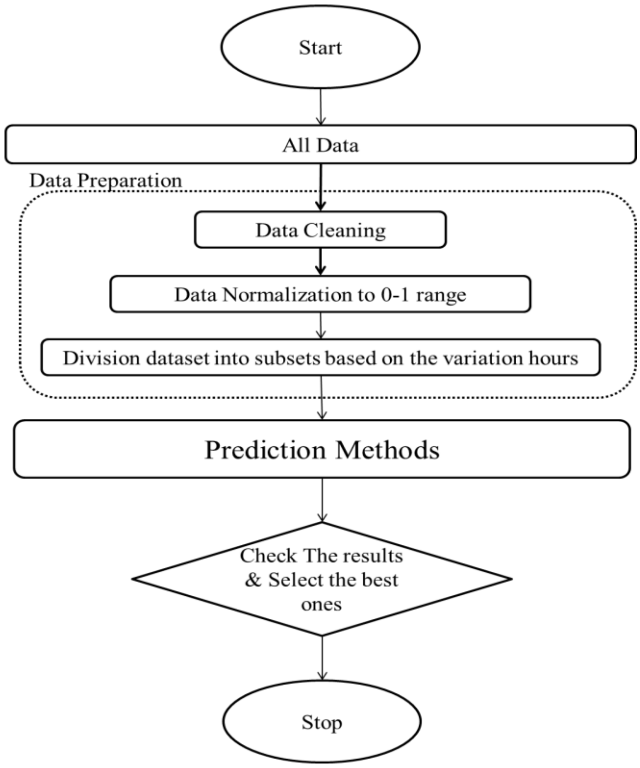

Figure 1 The main components of Prediction model

As the figure has shown, the proposed model is composed of three stages: data preparation, prediction model, and evaluation. In general, data is aquired from a source and prepared for building the models. The prepraition step includes removing null data and outliers, clean the unwanted data and normalize them as well as diving them into three parts to improve the final results. At last, three sub-models are built to predict the output for each duration.

2.1. Data Preparation

To build and evaluate our proposed model, we provide a dataset that was measured every five minutes in the photovoltaic laboratory of Niroo Research Institute of Iran (Tehran) from April 4, 2016, to May 28, 2016, at a longitude of N° 37.51, a latitude of E° 47.35, and an altitude of 1548 meters.

It contains the meteorological conditions of PV module including ambient temperature, solar radiation, and wind speed as well as PV module output. These conditions play key roles in the PV module performance.

The dataset contains the 8503 records, divided into three sets: train, test, and validation with 70%, 15%, and 15% proportion respectively. To enhance the accuracy of the prediction, a filtration has been employed to modify the data source and omit the data that measured incorrectly. Afterward, normalization was applied, and the dataset was scaled to a smaller range between 0 and 1.

The spectral distribution (spectrum) of sunlight as one of the input parameters can influence the PV module output, and it varies during the day. Therefore, to gain more accurate results, the dataset was divided into sub-sets according to the amount of sunlight radiation in different hours of a day. The time intervals for different parts of the day were 11:00-15:00, 15:00-18:00 and 18:00-21:00, respectively. Dividing data into 3 parts can improve the performance of model up to 50 percent in terms of MSE criteria.

2.2. Prediction Model

2.2.1. Model structure

After preparing the data for creating our models (acquiring and performing preprocessing tasks), we built for models including Linear regression, MLP, MLP-GA and MLP-NSGA II. While our proposed model was MLP-NSGA II, others were chosen according to previous studies in the literature. The best model was then validated by the comparison between the predicted results and actual measured outputs.

2.2.2. Artificial Neural Network & Multi-Layer Perceptron

Artificial neural network (ANN) is one of the techniques which can find the hidden relationship among data. It mimics the structure and functionalities of a human brain and nervous system. Neurons are the constitutive units of every ANN. The network is divided into three functions: multiplication, summation, and activation. First of all, the inputs are multiplied by a connection weight (multiplication Function). In summation function, these products are simply summed, then, to generate the results and output, the sum of products fed through an activation function [22]. By far the multilayered perceptron (MLP) is recognized as the most popular architecture which can be trained by several training methods such as back-error propagation or optimization algorithms. The MLP is organized into interconnected layers of artificial neurons. After emerging of the MLP and its applying in different fields, mathematicians confirmed that any arbitrary function could be approximated by the MLP. Since prediction and classification problems can be solved by approximation problems, it has been applied in a wide range of domains [23]. In this research, the meteorological conditions and PV module output were considered as the network's inputs and the output, respectively.

2.2.3. Multi-Objective Optimization Algorithm

To maximize the precision of the neural network, an optimization algorithm was employed as a training algorithm, which generates population and calculates the objective function for each individual to achieve appropriate weights for the network. To satisfy the objectives, there are usually conflicting objectives. Optimizations of the one objective performance decrease the performance of one or more of the other objectives.
Classical methods restated multi-objective problems into single objective problems, and then they were solved as single-objective problems; therefore, they worked with a single solution in each iteration. On the other hand, another way to solve MOPs, which find the approximation of the whole Pareto front in one run, is Evolutionary Multi-objective Optimization (EMO) [24].

2.2.3.1. Non-dominated Sorting Genetic Algorithm (NSGA II)

The Genetic algorithm is a population-based which is inspired by the evolutionist theory [25]. It is considered as a search and optimization tool. To solve the problem, it simulates the evolution process in nature. The single objective GA can be improved to solve multi-objective [26]. Many GA based models have been introduced for solving multi-objective problems [27-31]. In (1995), Srinivas and Deb introduced NSGA (Non-dominated Sorting Genetic Algorithm) [32] and the improved algorithm put forward in 2000 which is called NSGA II.

Step 1: Generate the random population

Step 2: Mutation and Crossover

Step 3: Aggregate the Parents and offspring

Step 4: Evaluate by the objective functions and allocate ranks to each individuals

Step 5: Perform non-dominated sorting

Assign rates according to Pareto dominance Sort

Solution x_1 is called the dominated solution to the other solution x_2, if:

- The solution is no worse than the other in all objectives

$$f_j(x_1) \nprec f_j(x_2) \qquad for\ \ j = 1, \ldots.., M\ objectives$$

- The solution is better than in at least one objective

$$f_j(x_1) \nprec f_j(x_2) \qquad for\ \ j = 1, \ldots.., M\ objectives$$

Step 6: Compute the Crowding distance

Step 7: Select points which are on the lower front and outside a crowding distance.

Figure 2 NSGA II Semi Code

2.2.4. MLP-NSGA II

There are various factors which affect the neural network performance. As the training process in ANN is done by determining the weights, in this research, an optimization algorithm has been performed to optimize the neural network weights and biases, improve the network topology and consequently achieve better performance.

The NSGA II was applied to optimize the neural network weights through simultaneously minimize the MSE and maximize the R-square. For the neural network weight optimization, the following process has been carried out: According to the Figure (2), NSGA II process began with generating the population. Each chromosome was considered as a solution which coded the total number of parameters in the neural network of interest. Therefore, each chromosome indicated a neural network, including weights and Biases. Once the NSGA II has been run, Mutation and Crossover operators were employed to create a new offspring and then, the parents and offspring were aggregated. Having the new population assigned to weights and biases, the neural network was run over the training, and objective functions (MSE and R-Squared) were calculated.

2.3. Proposed Model

In this research, a model based on MLP architecture has been considered training by NSGA-II Multi-objective optimization algorithm. The given neural networks have three inputs including Solar irradiation, Ambient Temperature, and Wind speed. During the training phase, ranks were allocated to each individual (representing a neural network) based on the objective functions. Subsequently, the population was sorted by non-dominating sorting. Furthermore, a new score was computed for each member of the population which entitled crowding.

This measure referred to the distance between every two neighbors and was used in the final sorting and selection process. In the end, the solution which satisfied all objective functions was selected. It was vitally necessary to compute both crowding distance and rank. Table(1) shows that the parameters of optimization algorithm which is obtained by trial and error.

Table 1 Optimization Algorithm Parameters

Parameters	Values
Population	150
Max Iteration	100
CrossOver Rate	0.8
Mutation Rate	0.3

Table 2 Architecture of 3 MLP-based Models

Models	Number of Layer	Number of Neurons
MLP	1,2,1	3,18,12,1
MLP-GA	1,2,1	3, 21, 14,1
MLP-NSGA II	1,2,1	3,18,12,1

The proposed network had two hidden layers which contain 18 and 12 neurons, respectively and finally the output of the PV Module is considered as the networks' outputs. Table (2) illustrated the architectures of three MLP-based models.

3 Evaluation Parameters

To evaluate the models, we employed the mean square error (MSE) which is defined by equation (1):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\widehat{Y_i} - Y_i\right)^2 \quad (1)$$

Where Y_i is the observed values corresponding to the inputs to the model, and $\widehat{Y_i}$ is the vector of n predictions [21].
Moreover, in [21], to show how well solar PV power predicted by our model, we used the coefficient of determination, is also known R-squared or correlation coefficient as follows.

$$R^2 = 1 - \frac{\sum_i(\hat{y}_i - \bar{y})^2}{\sum_i(y_i - \bar{y})^2} \quad (2)$$

where the $\bar{y}$ is computed by $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$.

4 Results and Discussion

In this research, the power generated by PV panels was separately predicted by four different models based on MLP, MLP-GA, MLP-NSGA II and Linear Regression). Error calculation and the evaluation of results showed that our proposed model (MLP-NSGA II) could reduce errors for different conditions (Table 3).
As mentioned before, a more accurate output energy prediction of PV panels could improve the precision of energy supply planning and the design accuracy of control systems. Following data validation, with the mean square error (MSE) and correlation coefficient (R^2), of 0.01 and 96%, respectively, our proposed model provides better results than others (in R^2 the same as MLP and slightly better than MLP-GA). It seems that NSGA II could help the netwrok to adopt better to the function of the prediction by choosing better weights and bias.

Table 3 Comparison of the MLP-NSGA II results with other approaches

Methods	MSE	R^2
Linear Regression	0.190	0.83
MLP	0.0594	0.96
MLP-GA	0.0201	0.95
MLP-NSGA II	0.01	0.96

Although the various models have employed to predict the output of PV module over the years, the results and performance of the models remained the same (Table 3). Also, as mentioned before, the environmental conditions have a crucial effect on the output performance, but the variation of solar irradiation and temperature makes total PV module output prediction indeterministic. However, during the smaller intervals, the rate variability will be less, and the prediction can be more accurate. Therefor, in this research, the dataset has divided 1-hour intervals. On Table (3), a noticeable change was observed, in particular between 12:00 and 12:55 which the module receives the most solar irradiation rate and generate the most power output (Figure 3).

As Figure (3) illustrates the comparison of the daily solar irradiation (3.a) and PV module output (3.b) from 11:00 AM to 14:55 PM during seven days are selected randomly. The PV module receives the most solar irradiation rate over the 6:35 AM through 07:15 PM, and during this period the solar irradiation rate fluctuates slightly. Some sharp fluctuations mainly are occurred by passing clouds which prevent the solar irradiance to be received by PV panel. It is expected that interval shortening has a considerable effect on the power prediction.

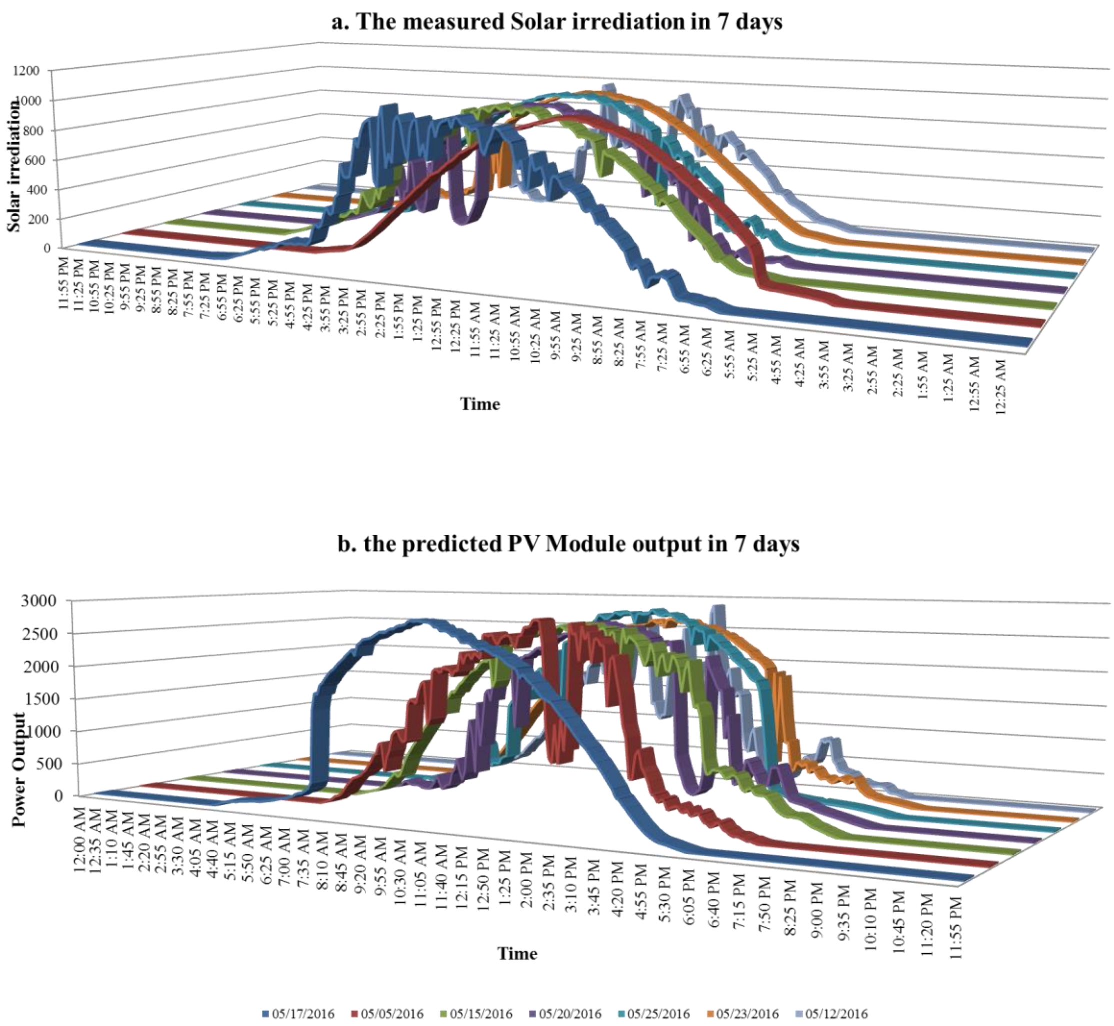

Figure 3 Comparison the Solar irradiation and PV module output in 5 days. a. The Solar irradiation b. PV module output.

Table 4 Prediction results according to shortened hour intervals

Methods	11:00-14:55		15:00-17:55		18:00-21:00	
	MSE	R-Squared	MSE	R-Squared	MSE	R-Squared
Linear Regression	0.005	0.95	0.008	0.93	0.02	0.98
MLP	0.05	0.97	0.05	0.96	0.05	0.97
MLP-GA	0.008	0.93	0.006	0.94	0.004	0.96
MLP-NSGA II	0.007	0.93	0.004	0.95	0.005	0.96

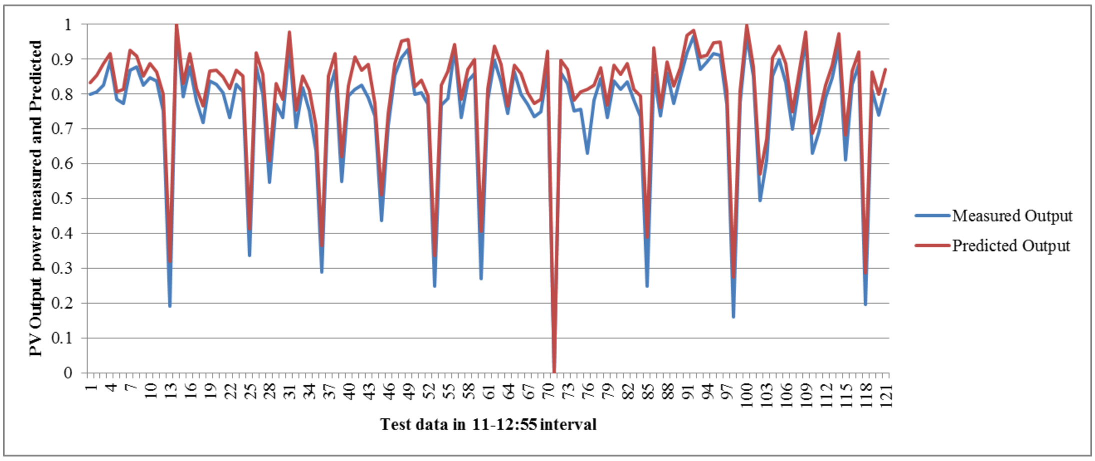

Figure 4 PV Output power measured and Predicted by ANN-NSGA II model

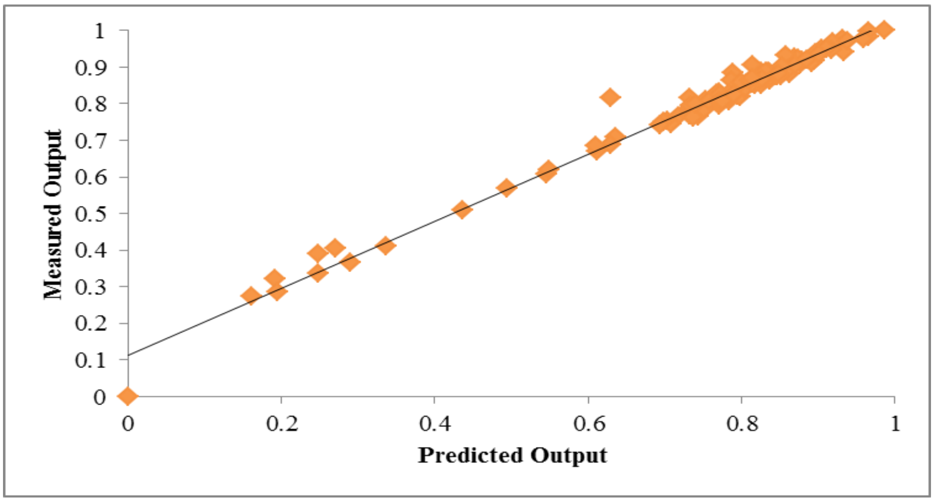

Figure 5 PV Output power measured and Predicted by ANN-NSGA II model

From the information supplied by Table (4), the results of dividing the dataset into short intervals and employing on three neural networks trained differently for each interval caused a general improvement. As in each shortened interval, there was constant solar irradiance; it seems the networks have been trained effectively to predict the output.

However, due to shortening the intervals, there was a general improvement in outputs, MLP-NSGA II's output resulted in better improvement. NSGA II searched an appropriate set of weights, which optimized the neural network with two or more conflicting objectives. Considering two different evaluation parameters, MLP outperformed the rest of the methods in R-Squared, and MLP-NSGA II did the same in MSE.

By examining each interval separately and comparing them together, all methods predicted the output in the third interval better than the second, and second better that first one. According to figures (4) and (5), the PV output power proposed by a model which is employed to predict the output power is compared with the measured power. As shown, the model has desired precision, and there are slight differences between measured and forecasted values. Limiting the dataset not only removes the fluctuation tracks in the dataset, but also enhance the forecasting precision.

5 Conclusions

This research has been utilized to forecast the output power of a 3.2kW PV solar panel using an artificial neural network. The data were acquired from photovoltaic laboratory of Niroo Research Institute of Iran for duration of nearly two months and interval of 5 minutes. To improve the accuracy of the neural network, an optimization algorithm was employed as a training method. The neural network weights was optimized by NSGA II while simultaneously the MSE was minimized and the R-square was maximized. Network evaluation parameters, including the correlation coefficient (R2) and Mean Square Error (MSE), were 0.96 and 0.01, respectively. Employing NSGA II help the network to fit the prediction function better by finding the better wieghts and bias than others Furthermore, as solar irradiance varies during the day, to improve the accuracy of the prediction, the dataset was divided into smaller intervals and three models were developed for each interval.

The information supplied from the results indicated that reducing the size of dataset not only removes the fluctuation tracks in the dataset but also enhance the forecasting precision by putting the network focus on the behavior of a specific interval. The evaluation parameters in the case of dividing the dataset into intervals saw up to 50% improvement in MSE parameters. However, the R2 in some intervals decreased slightly. Employing Fuzzy models or Deep Learning techniques as well as diving the the day period into more parts and adding more parameters to the model as input may result in better output. The proposed model in this paper could aid researchers to perform the solar electrical energy supply planning in every climatic condition by assessing the output power of the desired PV panel for an energy system.

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چکیده

این تحقیق سعی دارد تا با استفاده از ترکیب روش‌های شبکه عصبی و الگوریتم‌های تکاملی، توان خروجی پنل‌های فتوولتائیک را پیش‌بینی کند. روش پیشنهادی با مجموعه داده‌هایی که در بازه‌های ۵ دقیقه‌ای، در آزمایشگاه فتوولتائیک موسسه تحقیقاتی نیرو ایران (تهران) ثبت شده بود، ارزیابی شد. داده‌ها بر اساس میزان شدت اشعه خورشید، به سه بازه زمانی مختلف تقسیم شدند. NSGA II، یک الگوریتم بهینه‌سازی چند هدفه، با انتخاب مجموعه وزن‌های مناسب، شبکه عصبی را از دو جهت بهینه نمود. روش ترکیبی MLP-NSGA II نسبت به روش‌های رگرسیون، MLP وMLP-GA به نتایج بهتری دست یافت و توانست MSE و R-Square را به‌ترتیب تا ۰,۰۱ و ۰,۹۸ بهبود بخشد. نتایج به‌دست آمده نشان می‌دهد با کوتاه کردن بازه زمانی ورودی، نتایج مدل پیشنهادی بهبود خواهد یافت.