ISBN: 978-1-7281-4590-7
IEEE Catalog Number: CFP20F42-ART

Proceedings
2020 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM)

Sochi, Russia

May 18-22, 2020

2020 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM)

IEEE Catalog Number: CFP20F42-ART

ISBN: 978-1-7281-4590-7

Features of Precedents Space of Artificial Neural Networks for the Solar PV Station Controlling

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Abstract*—In the partial shading conditions, when photovoltaic modules in different parts of the vast area of the solar station are under different insolation, many local maxima appear on the energy characteristic, among which only one provides the maximum power generated by the power station. Standard methods for search and maintaining the maximum power point, designed to work under uniform insolation conditions, lose the ability to detect the maximum power point with partial shading and bring the photovoltaic station mode to a local peak point with significantly less power generation. Since the configuration of insolation can change relatively quickly, special algorithms are used to control the efficiency of the photovoltaic station, providing a quick determination of the vicinity of the global maximum power point. In this paper, a new algorithm implementing a high-speed output of a photovoltaic station mode in the vicinity of a point with maximum power generation with subsequent pass of control to standard methods of maintaining a working point. The basis of the algorithm is a neural network using four nonlinear classifiers, tuned with the use of support vector method. The space of precedents of the training sample of the neural network has a dimension equal to 3, although the measurement vector includes power values at 4 points of the energy characteristic. To make the algorithm universal, it is proposed to present the characteristics of the photovoltaic modules of the power station in the form of normalized dependencies. The process of tuning the neural network is illustrated by images of dividing surfaces in the use-case space of the training sample. A tuned neural network transfers the photovoltaic station mode to maximum energy production mode in a maximum of four stages of voltage change at the output of the photovoltaic modules.

Keywords: photovoltaic station, maximum power point, maximum power point tracking, non-uniform insolation, partial shading, machine learning, support vector machine

I. INTRODUCTION

If the insolation of photovoltaic (PV) modules is uniform, their energy characteristic has a single maximum, so maintaining the energy efficiency of a PV station is not particularly difficult. Well-known maximum power point (MPP) search algorithms make it possible to meet this challenge [1–4]. One of the methods, commonly used in uniform insolation mode, is the "Perturbation and Observation" (P&O) method. The advantage of this method is visual clarity and simplicity. According to this method, the operating point is maintained near the MPP on the energy characteristic due to the continuous scanning of the MPP position by changing the voltage at the output of the PV module in the vicinity of the

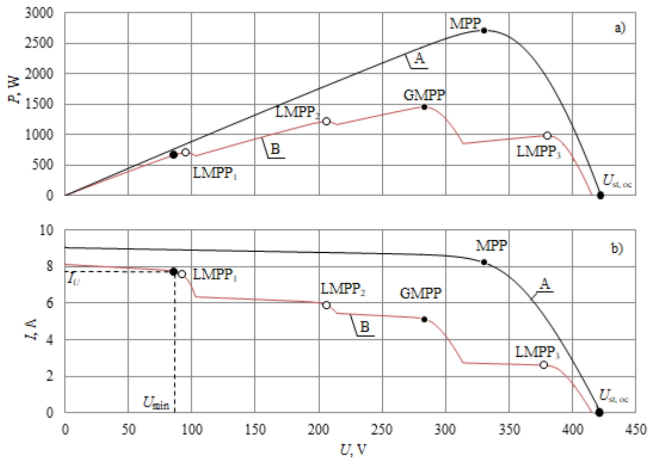

Fig. 1. Energy $P(U)$ (a) and volt-ampere $I(U)$ (b) characteristics of the PV module under uniform insolation (A) and partial shading (B). The dark circles indicate the GMPP (MPP) points, the light circles indicate LMPP

MPP point. If an increase in power is observed with increasing voltage, then it is assumed that the MPP is located on the right, otherwise it is on the left. In the first case, the voltage is increased, and in the second, it is reduced

However, in partial shading conditions, when the PV modules are under different insolation conditions, many local peaks (Local Maximum Power Point) LMPP appear on the energy characteristic (Fig. 1, a). Under these conditions, the P&O method loses the ability to identify the point of real maximum generated power GMPP (Global Maximum Power Point), bringing the PV station to a working point with less power generation (in the figure). To ensure the efficiency of the PV station under partial shading conditions, it will be required to use special methods for searching the maximum power point GMPP [5-13].

The report provides a new algorithm for a PV station mode control under a rapidly changing insolation configuration conditions, based on machine learning methods, and the peculiarities of creating a training case precedent space for a PV station control neural network are considered.

II. PV STATION MODE CONTROL ALGORITHM REQUIREMENTS

The applying of algorithms based on scanning the energy characteristic is limited by technological reasons: the PV station cannot be in the continuous MPP search mode with voltage changes over a wide range, since this affects the stability of the PV station and the energy efficiency of the PV station. Under partial shading conditions, the algorithm for detecting the point of the real maximum power for the current insolation configuration should provide a quick transfer of the PV station's operating point to the GMPP vicinity with subsequent transfer of control to standard methods of maintaining the operating point, for example, the P&O algorithm.

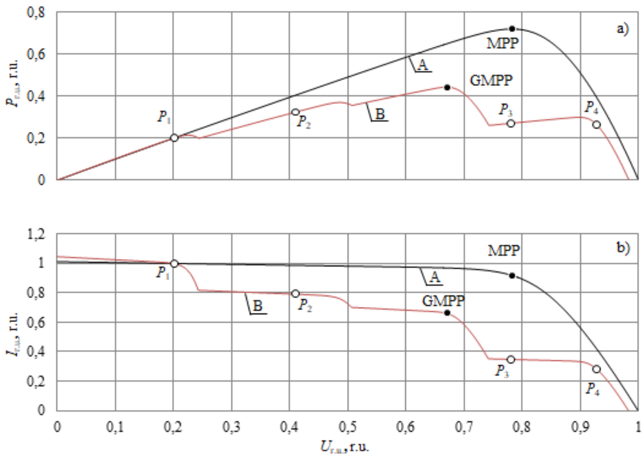

Fig. 2. Normalized energy (a) and volt-ampere (b) characteristics of a PV station under uniform insolation (A) and under partial shading conditions (B). Light circles show the control points used by the proposed algorithm. The remaining designations correspond to the designations of Fig. 1

At the same time, the algorithm should be universal and suitable for application in the control of solar stations with different numbers and types of PV modules. This property of the algorithm can be achieved if the energy and volt-ampere characteristics of a PV station are presented as normalized characteristics (Fig. 2).

The specifications are brought to a unified form by means of taking the rated value of the open-circuit voltage $U_{\text{st,oc}}$ and the current value I_U at the minimum permissible voltage as the base values, which guarantees the stable operation of the inverter, for example, $U_{\min} = 0,2U_{\text{st,oc}}$. Thus, measurements of electrical quantities in relative units will be as follows:

$$\begin{cases} U_{\text{r.u.}} = U / U_{\text{st, oc}}, \\ I_{\text{r.u.}} = I / I_U, \\ P_{\text{r.u.}} = U_{\text{r.u.}} I_{\text{r.u.}}. \end{cases}$$

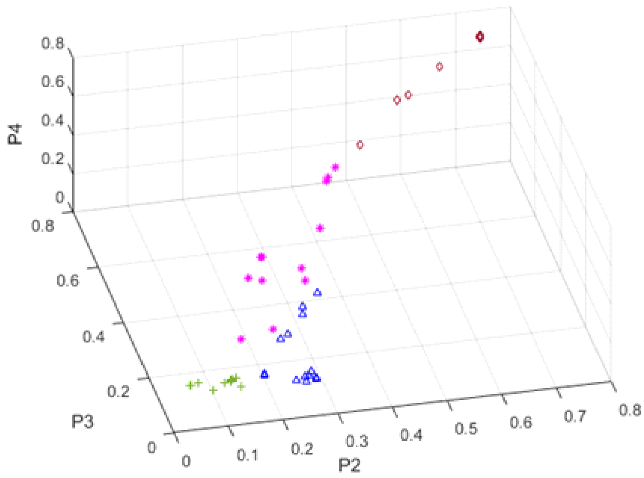

Fig. 3. The precedent space of the training sample. The angle selected in the figure shows that the use cases of different classes can be strictly separated. The following notation of precedents is adopted: “+” - first, “Δ” - second, “*” - third, “◊” - fourth class

III. FEATURES OF PRECEDENTS SPACE

The GMPP fast point search algorithm must be able to detect the GMPP vicinity for the minimum possible number of disturbances in the PV station operating mode. For this purpose, we use an algorithm based on measuring the power generated by the PV station at the four control points of the normalized energy characteristic. The power values P_1 and P_2 are determined at $U = U_{\min} = 0,2U_{\text{st,oc}}$ and $U = 0,85U_{\text{st,oc}}$, respectively, P_3 and P_4 are selected depending on the nature of the change in the curve of the energy characteristic for different configurations of the insolation of the PV modules (Fig. 2).

Note that when choosing all control points, scanning of the characteristics of the station PV modules is not performed. Moreover, the power $P_1 = 0,2$ in all cases, since the current $I_1 = I_U$ at the point P_1 is taken as the base current, and therefore the normalized voltage and current are equal $U_{1,\text{r.u.}} = 0,2$ and $I_{U,\text{r.u.}} = 1$, respectively. Therefore, the power does not directly participate in the training of classifiers and only sets the position of the three-dimensional space of significant precedents of the training sample in multidimensional space. In other words, the training of a neural network is carried out in three-dimensional space with coordinates (P_2, P_3, P_4) (Fig. 3). In terms of machine learning, the task of searching for and tracking a real maximum point is formulated as creating a neural network that gives each input vector of measurements $\mathbf{x}_i^T = \left[P_{2,i}, P_{3,i}, P_{4,i}\right]$ of a sign of belonging to one of the classes.

Obviously, the vicinity of the GMPP point gravitates to the control point with maximum power. However, due to the small size of the vector of input measurements, this requirement is not met in many cases, which will require identification by the neural network trained of various patterns of energy characteristics created by many measurement vectors.

The power values at the control points are elements of the use case vectors $\mathbf{x}_j$ of the training sample $\mathbf{X} = \{(\mathbf{x}_j, y_j) \mid j = 1, \ldots, n\}$. Each of the vectors has a sign y_j of belonging to a particular class.

The training sample should be complete in the sense that the dimension of the space of its precedents should ensure the observability of the modes of the PV station, and have sufficient capacity so that many of its precedents are sufficient for the unconditional determination of the vicinity of GMPP. That is why many precedents of the training sample are divided into four classes, although the precedent space remains three-dimensional (Fig. 3):

$$\mathbf{X} = \{\mathbf{x}_1, \ldots, \mathbf{x}_j, \ldots, \mathbf{x}_n\} =$$
$$= \{(P_{2,1}, P_{3,1}, P_{4,1}), \ldots, (P_{2,j}, P_{3,j}, P_{4,j}), \ldots, (P_{2,n}, P_{3,n}, P_{4,n})\}.$$

IV. NEURAL NETWORK STRUCTURE

The search and tracking of GMPP are performed simultaneously with a change in the operating mode of the PV station, which in the conditions of a rapidly changing insolation configuration will require the high-speed output of the PV station mode to the vicinity of one of the considered control points close to GMPP. The control point number that defines the starting position when transferring control to the standard method of tracking the maximum power point, for example, the P&O method, will be set by the configured neural network by assigning the current measurement vector $\mathbf{x}_j$ to one of the classes.

Setting up a neural network requires training of classifiers, each of which will separate one class from the rest. The principle of "one against all" is used, according to which the classifiers are trained sequentially, dividing the training sample conventionally into two classes – on one's own and other's. Objects of the set $\mathbf{X}$ of their own class are provided with a sign $y_j = 1$, and the other's – $y_j = -1$.

Thus, the problem of finding the GMPP point is about a multiclass classification itself, and the idea of solving this problem assumes construction of four classifiers, each of which will separate one class from the other (Fig. 4)

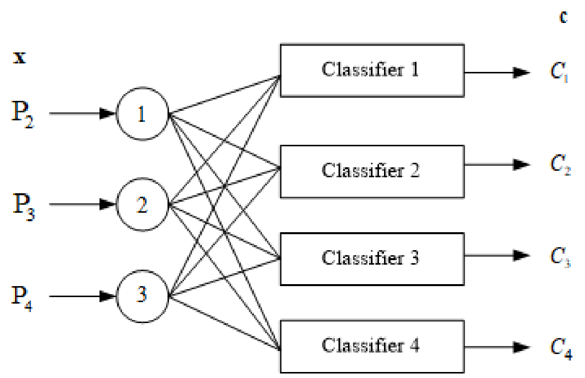

Fig. 4. Neural network for GMPP smart rapid search algorithm

The work uses one of the well-known machine learning methods, the so-called Support Vector Machine method – (SVM) [14–16]. The neural network is based on non-linear SVM classifiers that use special kernels $\mathbf{K}(\mathbf{x}_i, \mathbf{x}_j) = \langle \varphi(\mathbf{x}_i), \varphi(\mathbf{x}_j) \rangle$ to map use cases into a new rectifying space in which use cases become linearly separable [17]. We have chosen the radial basis core in the form of a Gaussian function

$$\mathbf{K}(\mathbf{x}_j, \mathbf{x}_i) = e^{\frac{-\|\mathbf{x}_j - \mathbf{x}_i\|^2}{2\sigma^2}} = e^{-\gamma\|\mathbf{x}_j - \mathbf{x}_i\|^2}, \#$$

known for its high performance. The nonlinear classifier in the general case will be as follows:

$$C_i = \operatorname{sign}\left(\sum_{j=1}^{s_i} \lambda_{j,i} y_{j,i} e^{-\|\mathbf{x}_{j,i} - \mathbf{x}\|^2} + w_{0,i}\right), \# \qquad \#$$

where $\mathbf{x}_{j,i}$ are the support vectors, s_i is the number of support vectors of the classifier C_i, $w_{0,i}$ is the displacement of the separating hypersurface in the use case space [18–20].

V. NEURAL NETWORK PARAMETERS

Setting up a neural network requires sequential training of four classifiers, each of which will separate one class from all the others. Fig. 6 shows the progress of the neural network setup.

The parameters of the classifiers are presented in Table 1, the relative position of the separating surfaces of the classifiers is shown in Fig. 7.

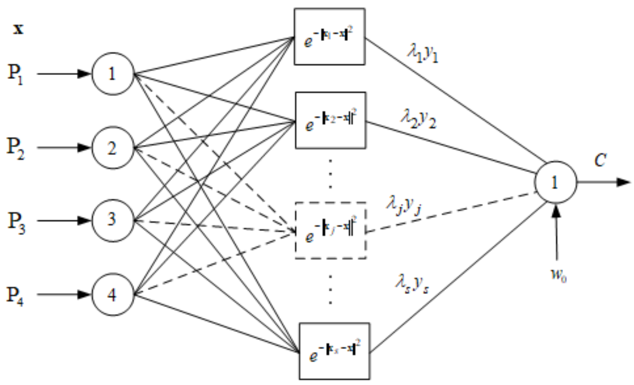

Fig. 5. The structural diagram of the classifier, where λ_j are the multipliers of the Lagrange function, w_0 is the scalar characterizing the displacement of the dividing line, s is the number of control points

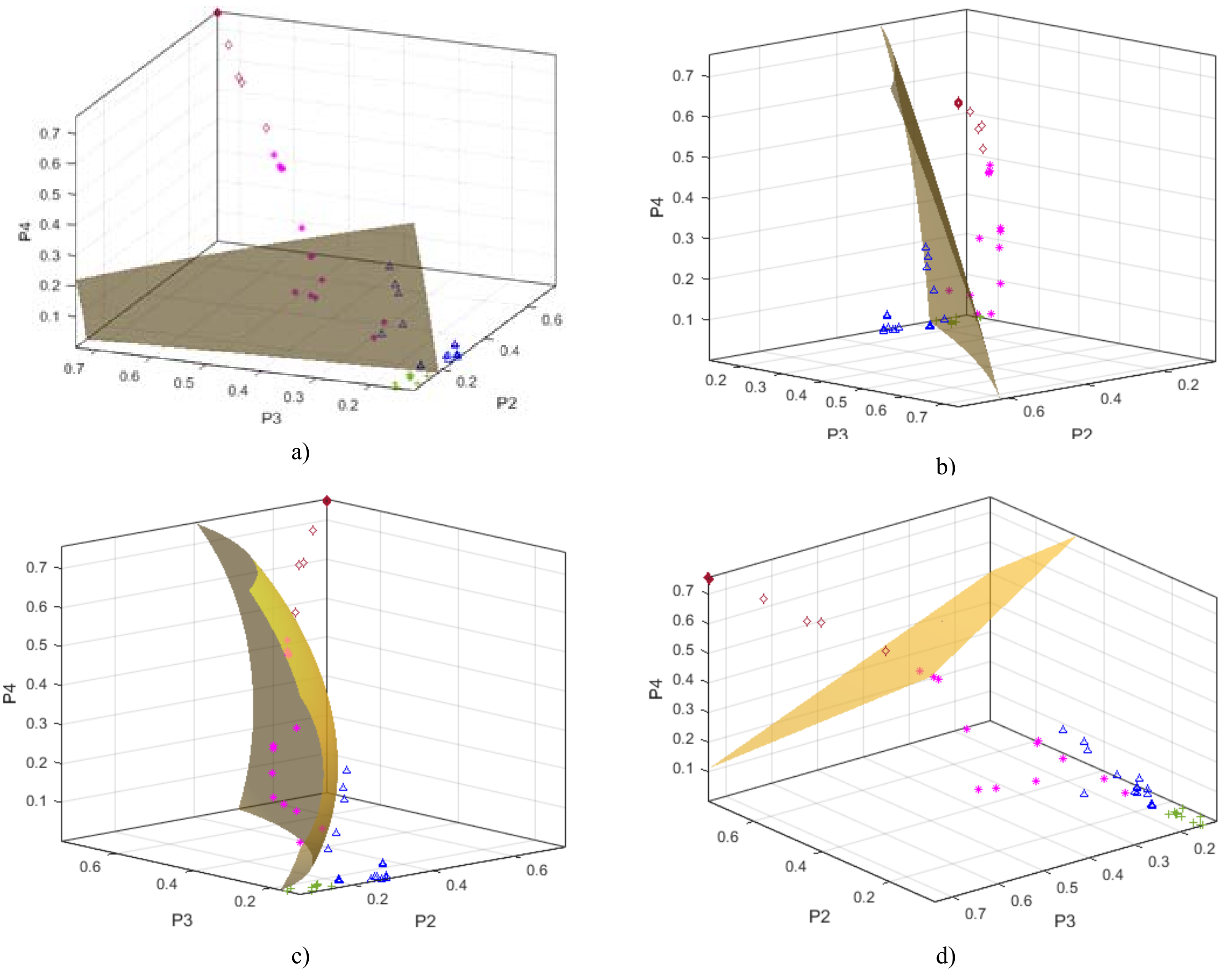

Fig. 6. The dividing surfaces of the first (a) – fourth (d) neural network classifiers. Designations correspond to the designations of Fig. 3.

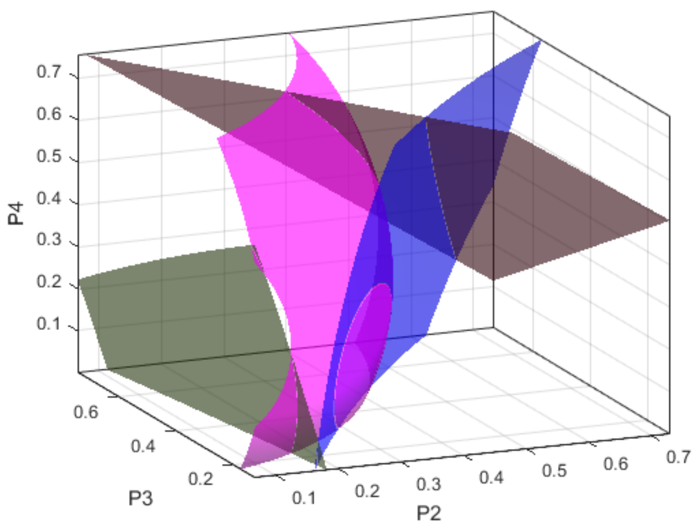

Fig. 7. The location of the dividing surfaces of the intelligent algorithm for finding the GMPP point in the use case space

TABLE I. NEURAL NETWORK PARAMETERS

Classifier Number (i)	Support Vector Number (j)	Support Vector coordinates ($x_{j,i}$)			Attributes of Support Vector ($y_{j,i}$)	Lagrange Coefficients for Support Vectors ($\lambda_{j,i}$)	Scalar ($w_{0,i}$)
		P_2	P_3	P_4			
1	1	0.151	0.164	0	1	389.4	-0.45
	2	0.203	0.162	0.002	-1	353.4	
	3	0.178	0.238	0.089		36.0	
2	1	0.242	0.21	0.106	1	1661	-4.26
	2	0.269	0.26	0.049		291.4	
	3	0.153	0.130	0.003	-1	214.9	
	4	0.237	0.242	0.111		1737	
3	1	0.237	0.242	0.111	1	3018	-28.7
	2	0.415	0.513	0.502		74.2	
	3	0.067	0.156	0.003	-1	498.3	
	4	0.293	0.244	0.205		1464	
	5	0.269	0.26	0.049		1130	
4	1	0.468	0.548	0.556	1	146.0	0
	2	0.415	0.513	0.502	-1	146.0	

CONCLUSIONS

1. Under conditions of a rapidly changing configuration of the station PV modules insolation, an algorithm is required for a rapidly changing PV station working point position, capable to move the working point to the vicinity of the global maximum power on the energy characteristic in just a few steps.

2. The use of a neural network with non-linear classifiers based on the radial basis core in the form of the Gaussian function, which is configured in the three-dimensional space of training case precedents, simplifies the control of the PV station mode. The universality and efficiency of the proposed principle of power station control are given by the use of normalized characteristics of station PV modules.

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