

# Application of Artificial Neural Networks for Maximum Power Point Tracking of Photovoltaic Panels

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**Abstract**—Maximum power point tracking technique for PV panels with support of online learning artificial neural network is offered. Mathematical model of the system is implemented in Matlab/Simulink environment. Maximum power point tracking is performed using *IncCond* algorithm and radial basis function artificial neural network. Several criteria for estimation of system performance were derived. It is shown that ANN can increase overall system efficiency by 10%.

**Index Terms**— Photovoltaic cells, artificial neural networks, adaptive algorithm, sensitivity.

## I. INTRODUCTION

Maximum power point tracking (MPPT) enables to increase efficiency of electricity production of photovoltaic (PV) module [1]. To reach the maximum instantaneous power the controller must adjust the load of PV module according MPPT algorithm depending on varying cloudiness and temperature of the module. The controller must quickly respond to the mentioned and similar factors, and to assess their impact on the solar module, and adjust battery charging modes. The power generated by PV module depends on speed and accuracy of load matching.

Tracking of maximum power point (MPP) is provided by electronic system used to exploit maximum power from PV modules, which these modules are capable to produce. Controller with MPPT algorithm follows the maximum voltage and current intersection point of the module and guarantees the highest received power [2].

When solar energy flux (SEF) is changing rapidly, most of the controllers fail to keep tracking the MPP. This reduces the efficiency of PV module. This problem can be solved using artificial neural networks (ANN) [3], [4], which in case of rapid change in SEF, predict the current situation of MPP and determines the necessary system parameters.

This paper presents analysis of *IncCond* MPPT algorithm and comparison of operation with and without ANN. Mathematical models used for simulation are described in [5].

## II. MAXIMUM POWER POINT

In Fig. 1 current-voltage characteristics of the solar module at different SEF and module temperatures are shown. In each curve an intersection point of maximum current  $I_{max}$  and voltage  $U_{max}$  can be found at witch solar module generates the maximum power  $P_{max} = U_{max} \cdot I_{max}$ . The current-voltage characteristic is unique for each set of SEF and temperature values, so as the  $I_{max}$  and  $U_{max}$ .

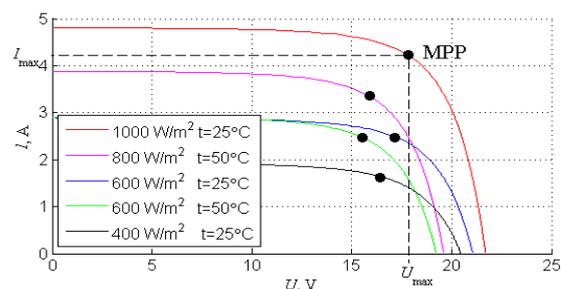


Fig. 1. MPP at different SEF and temperatures.

Maximum power  $P_{max}$  is reached when the solar module is loaded by a characteristic resistance  $R_m$  (Hussein K. *et. al.* 1995), which is calculated as follows

$$R_l = R_m = \frac{U_{max}}{I_{max}}. \quad (1)$$

So, the solar module generates a maximum power only when the load resistance is equal to the characteristic resistance of the module  $R_l = R_m$ . This point correspond the current and voltage intersection in voltage-current characteristic and is called the maximum power point. Solar module characteristic resistance  $R_m$  is not fixed – it depends on the type of solar module, its temperature, SEF and even the life-time of the module [6], [7]. There is no possibility to calculate  $R_m$  from parameters of PV module. Because of that different convergence algorithms are used, which control the size of the load resistance  $R_l$ , while monitoring voltage and current at output of the PV module in order to keep load resistance closer to the instantaneous value  $R_m$  – follows the maximum power point.

One of the most popular MPPT algorithms is Perturb and Observe (*P&O*) [2]. This algorithm perturbs  $R_l$  in each operating cycle, and observes the variation of PV modules output power. According to the results  $R_l$  is perturbed again. This means that even at the MPP the system will not remain in it, and change  $R_l$  around  $R_m$ . For this reason power is lost and the output of PV module is not stable.

The Incremental Conductance algorithm (*IncCond*) is analysed in the paper. The algorithm is based on simple mathematical expressions, and it avoids most of the *P&O* drawbacks [6].

### III. INCCOND ALGORITHM

According the algorithm, PV modules output power derivative with respect to voltage  $dP/dU$  is calculated (Figure 2). The result describes the position of systems operation point in the power characteristic in relation with MPP.

Power derivative can be expressed in terms of voltage and current

$$\frac{dP}{dU} = \frac{d(IU)}{dU} = I + U \frac{dI}{dU}. \quad (2)$$

This allows to calculate the derivative in voltage-current characteristics and to determine the direction of change in load resistance. According to (2) the load resistance change can be described by these conditions:

$$\begin{cases} \frac{dI}{dU} > -\frac{I}{U}, & R_l = R_l + \Delta R, \\ \frac{dI}{dU} < -\frac{I}{U}, & R_l = R_l - \Delta R, \\ \frac{dI}{dU} = -\frac{I}{U}, & R_l = R_l = R_m, \end{cases} \quad (3)$$

where  $\Delta R$  – step of load resistance change.

The model uses time step of 1 second, so derivatives defined in (2) are calculated approximately [7]

$$\frac{dI}{dU} \approx \frac{\Delta I}{\Delta U} \pm \zeta, \quad (4)$$

where  $\Delta I$  and  $\Delta U$  current and voltage change in 1 s,  $t$  – time in seconds and  $\zeta$  – marginal error.

Marginal  $\zeta$  is necessary because  $\Delta I / \Delta U$  does not exactly correspond to actual derivative. Allowing small marginal error  $\zeta$  stabilizes the algorithm.

According to (2), (3) and (4) the load resistance is changed as follows:

$$\begin{cases} \frac{\Delta I}{\Delta U} + \frac{I}{U} > \zeta, & R_l = R_l + \Delta R, \\ \frac{\Delta I}{\Delta U} + \frac{I}{U} < -\zeta, & R_l = R_l - \Delta R, \\ -\zeta \leq \frac{\Delta I}{\Delta U} + \frac{I}{U} \leq \zeta, & R_l = R_l = R_m. \end{cases} \quad (5)$$

Mathematical algorithm corresponding to (5) is used for MPPT analysis and implemented in Matlab / Simulink environment and used with the SEF and PV module mathematical models described in this paper [8].

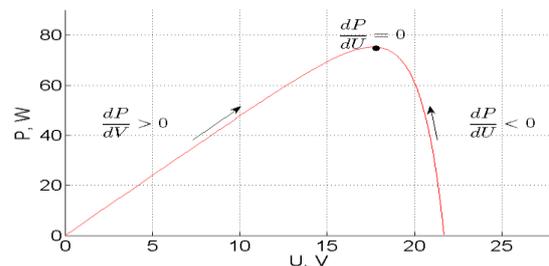


Fig. 2. MPP tracking with *IncCond* algorithm.

### IV. VERIFICATION OF THE MODEL

To analyse the operation of mathematical model and MPPT algorithm it is necessary to define numerical criteria, which define the performance of MPPT. These criteria will be used to compare various modes of operation of *IncCond* algorithm and evaluation of ANN effect on system performance.

In Fig. 2 it is shown, that power dependency on voltage is not linear. So according to (1) can be concluded that  $dP(R_l) / dR_l$  is not linear function also. For this reason, it is not enough to evaluate  $R_l$  error of the algorithm. At this stage, it is also important to determine the optimal load changing step  $\Delta R$ .

For this purpose *Simulink* model is formed implementing the following expression

$$\frac{dP(R_l, E_T)}{dR_l} \approx \frac{\Delta P(R_l, E_T)}{\Delta R}, \quad (5)$$

where  $E_T$  – total SEF falling the surface of PV module.

According to (6), system sensitivity diagram at different load resistance and SEF values is calculated (Fig. 3). The black curve denotes the case when

$$\frac{dP(R_l, E_T)}{dR_l} = 0. \quad (6)$$

This curve is obtained by modelling the system with very small load resistance step  $\Delta R$  values. In Fig. 3 the black curve describes the dependence of characteristic resistance  $R_m$  on SEF. So, it can be regarded as reference curve  $R_{me}(E_T)$ .

According to Fig. 3 the system sensitivity to the resistance step change is highly dependent on the SEF values incident upon the PV module surface at low SEF values, characteristic load resistance  $R_m$  increases exponentially. A small change in resistance  $\Delta R$  has a small influence on the system output power change  $\Delta P$ . When SEF values are high  $R_m$  decreases significantly and equals to 4.2  $\Omega$ . In this scope of SEF values the influence of  $\Delta R$  on the output power is much greater. So the following conclusions can be formed:

- 1) Because SEF is not stable, matching of the third condition in (5) is unlikely. Therefore, the system operation mode is always a little distant from the MPP;
- 2) To increase PV modules efficiency, load resistance change step  $\Delta R$  must be minimized at high values of SEF;
- 3) At low SEF values, system sensitivity is low and the small step  $\Delta R$  leads to slow approach to MPP and large energy losses;
- 4) Energy losses can be reduced throughout the range of SEF by selecting the optimum load resistance change step  $\Delta R_{opt}$ .

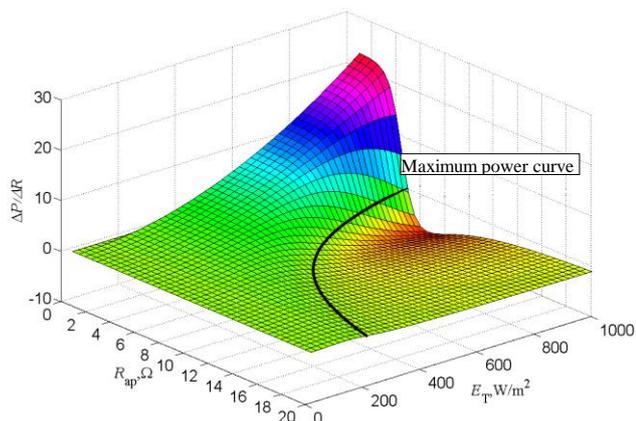


Fig. 3. Sensitivity diagram of the system.

Using the reference dependence  $R_{me}(E_T)$  and the mathematical model of the PV module it is possible to determine the dependence of  $P_c(E_T)$ . Power deviation errors can be derived:

$$\chi_p(t) = |P_c(E_T) - P(t)|, \quad (8)$$

$$\chi_{p\Sigma} = \int_{t_1}^{t_2} \chi_p(t) dt, \quad (9)$$

$$\overline{\chi_p} = \frac{\chi_{p\Sigma}}{t_2 - t_1}, \quad (10)$$

where  $\chi_p(t)$  – momentary output power  $P$  deviation from the reference value,  $\chi_{p\Sigma}$  – electrical energy lost during selected time interval,  $\overline{\chi_p}$  – average deviation of power during selected time interval.

Criteria  $\chi_{p\Sigma}$ ,  $\overline{\chi_p}$  are useful in different MPP tracking modes for comparison. They have several disadvantages: they are dependent on the law of variation of SEF (SEF waveform) and highest value of SEF obtained while measurements.

## V. MPP TRACKING PERFORMANCE ANALYSIS

To compare the performance of *IncCond* algorithm operating independently and with support of neural network, MATLAB/Simulink block for *IncCond* MPPT was created, compatible with solar power plant model described in [8]. Structure diagram of full model is presented in Fig. 4.

To test the operation of *IncCond* algorithm, ANN block is disconnected and a day with small rapidly moving clouds is simulated (Fig. 5). It is found experimentally, that for system

to remain in MPP when  $E=1000 \text{ W/m}^2$  load change step must be  $\Delta R \leq 0.3 \Omega$ . In Fig. 4 it can be seen, that system can't adapt to rapidly changing weather conditions fast enough and it often operates far from MPP. During simulations a weak point of the algorithm was found – if voltage and current change faster because of weather conditions than because of change in load, the second condition in (5) is evaluated incorrectly and load is increased instead of decreasing, especially when SEF is low. Sometimes this leads to outcome, that system constantly increases load to the point, from which it can't go back to normal operation. Repeatedly performing simulation the average efficiency of the system is calculated to be 89% in similar weather conditions.

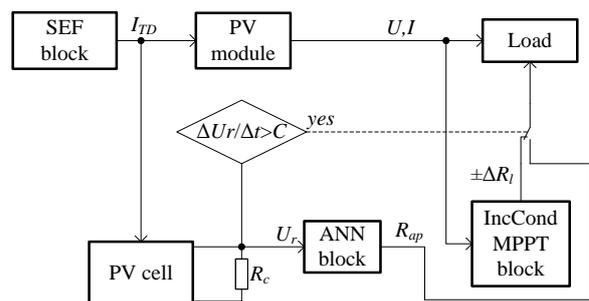


Fig. 4. Structure diagram of MPPT tracker with ANN.

MPPT system is improved by introducing an ANN into control sequence. ANN's are ideally suited for rapid approximation of various nonlinear functions. Also online learning abilities allow constant adoption to a specified system.

According to the Fig. 5 ANN provides guess value or  $R_l$  only when SEF changes rapidly. All the other time *IncCond* algorithm operates as usual. When system is at MPP, learning samples are provided for ANN, so online learning is possible. For implementation of ANN it was decided to radial basis function (RBF) neural network, because this type of ANN is already implemented in hardware [9].

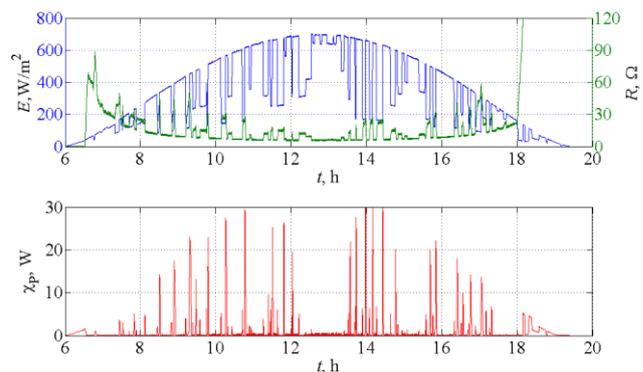


Fig. 5. SEF  $E$  reaching the PV module, load resistance  $R_l$  and the difference between maximum power and actual power  $\chi_p(t)$  during the cloudy day (independent *IncCond* MPPT operation).

Results of simulation of *IncCond* algorithm with ANN support are presented in Fig. 6. It is seen, that at the beginning of the simulation guess errors of  $R_l$  are high. During the time ANN is learning and errors are decreasing and closing to zero. High power deviation  $\chi_p(t)$  is available

during the first half of the day are present. But after noon, when SEF values start to decrease and ANN is already learned these,  $\chi_p(t)$  becomes very close to zero.

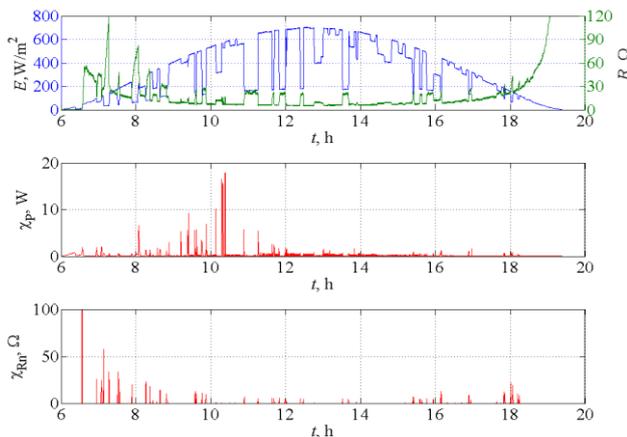


Fig. 6. SEF  $E$  reaching the PV module, load resistance  $R_l$ , the power deviation  $\chi_p(t)$  and the ANN guess error  $\chi_p(t)$  during the cloudy day (IncCond with ANN MPPT operation).

Repeating simulation many times showed, that average efficiency of system during the first day is 93% and during each following day  $\sim 99\%$ .

## VI. CONCLUSIONS

To test the performance of MPPT, reference dependency  $R_l(E_T)$  was derived and criteria  $\overline{\chi_R}$  and  $\overline{\chi_R}$  were defined.

Simulation of independent operation of *IncCond* algorithm revealed, that rapidly changing environmental conditions and low SEF can cause system instability and malfunction. Average efficiency of MPPT at such conditions is 89%

It is shown, that trained ANN allows usage of small  $\Delta R$  steps so avoiding oscillation of output power at high SEF values without losing the ability of fast MPPT at low SEF values

ANN significantly reduces power output deviation  $\chi_p(t)$  and increases the responsiveness and stability of MPPT. Using learned ANN the efficiency of MPPT can be as high as 99%.

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