# Proactive Identification of Optimal Operating Points in Photovoltaic Power Systems

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*Abstract-* We can use specific control algorithms for generating the maximum possible power in photovoltaic power systems. Several methods to determine the optimum working point have been introduced in recent decades. In Maximum Power Point Tracking (MPPT) methods, the ideal operation is to determine the maximum power point (MPP) of the photovoltaic (PV) array directly rather than track it by using the active operation of trial and error, which causes undesirable oscillation around the MPP. Since the output characteristics of a PV cell with environmental changes such as radiation and temperature levels can change from moment to moment, Therefore, in order to identify the optimum operating point tracking of PV power systems are used in real time. In this paper, several methods are introduced to identify the optimum operating point and because of measurement power is usually associated with noise, Kalman filter and the position error are used to estimate the optimum operating point.

Keywords- Method of Least Squares; the Position Error; Parameter Estimation; Real- Time System and the Kalman Filter

## I. INTRODUCTION

In Photovoltaic power systems, Maximum power point tracking is essential for optimal use of solar energy. Two main methods of tracking the optimal operating point can be measured including observation and anxiety and the incremental conductance method. These two methods are based on the PV array voltage to track the optimum set point, indicating the optimum working point (Figure 1).



Fig. 1 Block diagram of MPPT technology observation and anxiety and the incremental conductance method

Local optimum point continuously tracked and updated by a detector such as MPP that the relation  $\frac{dP}{dV} = 0$  is always

established, in this equation *P* is the output power of PV array and *V* is the voltage of PV array. Continuous oscillation around the optimal operating point of observation and anxiety is an inherent feature that will cause power dissipation and system instability. Incremental conductance method is designed to overcome this disadvantage. Experiments show that under stable conditions yet to be discrete maximum as  $\frac{dI}{dV} = \frac{-I}{V}$  that equivalent with  $\frac{dP}{dV} = 0$ , there are some fluctuations [1]. Another disadvantage of these two methods is that the anxiety level of the PV voltage transient and steady states is complex so that a compromise is made between. In [2] a general method to identify the real MPP is based on recursive least squares method and Newton's method and PV curve with a polynomial approximation expressed. Since power is commonly measured with noise, in addition, the convergence of the Newton-Raphson's method is dependent on the initial value, in this article for immediate identification of MPP Kalman filter and the position error is used. Therefore, it is desirable to determine the VOOP directly during the real-time operation, instead of tracking it simply through trial and error. In part II various modeling techniques of PV cells will be discussed. Proactive identification methods are discussed in Part III. Proactive identification in Part IV for the case with noise measurements and conclusions are given in section V.

### II. MODELING

One of the most important parts of Proactive identification is the model structure. So it is essential, a mathematical model that can accurately show the PV array electrical characteristics easily be solved with analytical methods we have. Since PV

model identification is performed during system operation, so a complete understanding of all aspects of the various models of real-time identification is required.

2-1 models used in this paper are as follows:

$$i = i_{ph} - i_{sat} [e^{\frac{(v+iR_s)}{v_t}} - 1]$$
(1)

$$v_t(T) = \frac{AkT}{q} \tag{2}$$

Which  $i_{ph}$  is Photocurrent, v is the cell voltage,  $v_t$  represents the thermal voltage,  $R_s$  Series resistance and  $i_{sat}$  is the diode saturation current. Thermal voltage  $v_t$  is a function of temperature T. A is Diode factor idealistic, k is Boltzmann constant and q is an electron(Fig. 2).



Fig. 2 Equivalent circuit SSDM

Mentioned methods, there are four parameters that need to experiment with short circuit tests, Open circuit and MPP are calculated. In short circuit condition, Photocurrent  $i_{ph}$  can be approximated as follow:

$$\hat{i}_{ph} = \hat{I}_{SC} \tag{3}$$

Which  $\hat{i}_{ph}$  estimation of Photocurrent  $i_{ph}$  and  $\hat{I}_{SC}$  is the short circuit current measured with a radiation level and constant temperature. For open circuit condition,  $i_{sat}$  the diode saturation current is:

$$\hat{i}_{sat} = \frac{\hat{i}_{ph}}{e^{(\frac{\hat{V}OC}{v_t})} - 1}$$
(4)

The variable  $\hat{i}_{sat}$  is the estimation of saturation current  $i_{sat}$  and  $\hat{V}_{OC}$  is the open circuit voltage measured in the similar conditions with short circuit. Thermal voltage  $v_t$  is a function of temperature T must be calculated. We have:

$$i_{mpp} = i_{ph} - i_{sat} \left[ e^{\frac{v_{mpp} + i_{mpp} R_s}{v_t}} - 1 \right]$$
(5)

By combining Relations (3), (4) and (5) we have:

$$\dot{i}_{mpp} = \hat{I}_{SC} - \left[\frac{\frac{v_{mpp} + i_{mpp}R_s}{v_t} - 1}{e^{\left(\frac{\hat{V}OC}{v_t}\right)} - 1}\right]\hat{I}_{SC}$$
(6)

From Equation (6) result that

$$R_{s} = \frac{v_{t} \ln \left[ \left( 1 - \frac{i_{mpp}}{I_{SC}} \right) e^{\left( \frac{\hat{V}_{oc}}{v_{t}} \right)} + \frac{i_{mpp}}{\hat{I}_{SC}} \right] - v_{mpp}}{i_{mpp}}$$
(7)

MPP, which occurs when  $\frac{dP}{dV} = 0$  where *P* is the module power output of *PV* and *v* represents the *PV* voltage. This equation can be written as follows:

$$\left. \frac{di}{dv} \right|_{v=v_{mpp}} + \frac{i_{mpp}}{v_{mpp}} = 0 \tag{8}$$

From Equations (1), we have:

$$\frac{di}{dv} = -i_{sat} \left\{ e^{\frac{v+iR_s}{v_t}} \left[ \frac{1}{v_t} + \left( \frac{R_s}{v_t} \right) \frac{di}{dv} \right] \right\}$$
(9)

That result:

updated as follows:

$$\frac{di}{dv}\Big|_{v=vmpp} = -\frac{\frac{\hat{i}_{sat}}{v_t}e^{\left(\frac{v_{mpp}+i_{mpp}R_s}{v_t}\right)}}{1+\frac{\hat{i}_{sat}R_s}{v_t}e^{\left(\frac{v_{mpp}+i_{mpp}R_s}{v_t}\right)}}$$
(10)

The parameters in Equations (1) with the numerical solution of Equation (8) are obtained. Newton-Raphson's method is one of the methods that are used for this purpose.

#### III. PROACTIVE IDENTIFICATION OF MPP

Solar power system parameters are changing continuously with temperature and environmental conditions. Therefore, it is necessary to reduce the time, parameters are calculated recursively. Using recursive least squares estimation of model parameters to minimize the error between the values measured with the system and views obtained. Parameter vector  $\hat{\Theta}$  is

$$\hat{\Theta}(k) = \hat{\Theta}(k-1) + M(k) [y(k) - \hat{y}(k)]$$
(11)

 $\hat{\Theta}(k-1)$  Previous estimates, M(k) weighted factors that calculated the correction amount are, y(k) and  $\hat{y}(k)$  are measured and estimated respectively. To determine the MPP, the P-V curve is more appropriate than V-I. Therefore, the output power stipulates as follows in terms of voltage.

$$p(k) = b_1(k)v(k) + b_2(k)v^2(k) + b_3(k)v^3(k) + b_4(k)v^4(k)$$
(12)

Where  $b_i$  is the model's parameter that changes in environmental conditions are changing and v(k) is the outputvoltage. We define

$$\Theta(k) = \begin{bmatrix} b_1(k) \\ b_2(k) \\ b_3(k) \\ b_4(k) \end{bmatrix} \qquad \varphi(k) = \begin{bmatrix} v(k) \\ v^2(k) \\ v^3(k) \\ v^4(k) \end{bmatrix}$$
(13)

According to the recursive least squares method estimated parameter vector  $\hat{\Theta}$  using the following recursive equations is obtained:

$$\hat{\Theta}(k) = \hat{\Theta}(k-1) + M(k) \left[ p(k) - \varphi^T(k) \hat{\Theta}(k-1) \right]$$
(14)

$$M(k) = W(k)\varphi(k) = \frac{W(k-1)\varphi(k)}{\lambda + \varphi^{T}(k)W(k-1)\varphi(k)}$$
(15)

$$W(k) = \frac{\left[I - M(k)\varphi^{T}(k)\right]W(k-1)}{\lambda}$$
(16)

p(k) measured power, M(k) weighting factor. In order to calculate the correction, W(k) A non-specific matrix and  $\lambda$  is forgetting factor that is variation between 0 to 1. Due to changes of temperature and environment, model parameters are time-varying. Recursive equations with initial conditions W(0) and  $\hat{\Theta}(0)$  are necessary.

## A. Calculate the Voltage of the Optimum Working Point

To determine the optimum working point voltage must be have:

$$\left. \frac{dp}{dv} = \right|_{v=V_{OOP}} = 0 \tag{17}$$

In this equation p output power and v is PV voltage. For simplicity we define:

$$f(v) = \frac{dp}{dv} \tag{18}$$

So,  $V_{OOP}$  is obtained from the equation f(v) = 0. This equation can be solved by using Newton-Raphson's method. In this numerical method we needed to determine f'(v). In FSSDM we have

$$f(v) = \frac{dp}{dv} = i_{ph} + i_{sat} \left[ 1 - \left( \frac{v}{v_t} + 1 \right) e^{\left( \frac{v}{v_t} \right)} \right]$$
(19)  
$$f'(v) = \frac{d^2 p}{d^2 v} = -i_{sat} e^{\left( \frac{v}{v_t} \right)} \frac{1}{v_t} \left( \frac{v}{v_t} + 2 \right)$$
$$f(v) = \frac{dp}{dv} = \dot{b_1} + 2\dot{b_2} v + 2\dot{b_3} v^2 + 4\dot{b_4} v^3 = 0$$
(20)

To calculate the derivative of function f(v) we have Fig. 3:



Fig. 3 Flowchart Raphson Newton algorithm

## B. Convergence Analysis

The most important requirement is the convergence of numerical algorithms and system identification. If the minimum squares recursive algorithm, forgetting factor  $\lambda$  is chosen small constant, Algorithm speed increases. However, a small selection of forgetting factor  $\lambda$ , causes enlargement of the matrix W and instability is detected. Usually, the forgetting factor had chosen Compatible with Changes Dynamic System. In this paper, the prediction error to select appropriate forgetting factor Are:

$$\lambda(n) = 1 - k\varepsilon^2(n) \qquad 0 \le k \le \frac{1}{10\varepsilon_{\max}^2}$$
(21)

$$\varepsilon(n) = y(n) - \hat{y}(n) \tag{22}$$

The factor k chose Proportional to System Dynamics.  $\varepsilon$  is the error between measured and predicted output power y(n) and  $\varepsilon_{\max}$  is the maximum error. In MPPT system changing in cell temperature causes changes in  $V_{OOP}$ . Generally, cell temperature changes have a slow dynamics in PV power system and sudden increase or decrease in temperature rarely happens. Forgetting factor to why it is necessary, is adjusted to suit the dynamics caused by temperature changes. In [2] we assume that k = 0.005. Fig. 4 shows coefficients of variation b,  $b_2$ ,  $b_3$  and  $b_4$  that determine as recursive method of minimum squares and also variation of  $V_{OOP}$  to Newton-Raphson's method with initial value v(0) = 15V.



Fig. 4 Estimation of parameters and the minimum squares method and the recursive Raphson-Newton's method

Newton-Raphson's method is a rapid method to determine the roots of the equation f(v) = 0. Convergence of this algorithm is dependent on the choice of initial value of v(0). In cases where  $\frac{df}{dv} = 0$ , the problem has no answer. The following table (Table 1) shows the values of  $V_{OOP}$  for each different values of v(0).

TABLE 1 AMOUNT OF  $V_{OOP}$  per different amounts o v(0)

Interval changes $v(0)$	value V <sub>OOP</sub>
v(0) < 9 IF	Don't exist
v(0) = 10	670 volt
v(0) = 15	Volt 17/7323

### IV. PROACTIVE IDENTIFICATION OF MPP FOR THE CASE POWER MEASURED WITH NOISE

Measurement power is usually associated with noise. In this paper we estimate the parameters of the Kalman filter used and consider the convergence of Newton-Raphson's method is dependent initial value, error position method is used for estimating the optimum operating point.

Consider the following linear state space model

$$x_{t+1} = F_t x_t + G_t u_t$$
  

$$y_t = H_t x_t + e_t$$
(23)

Where:

$$E\begin{bmatrix}u_{t}\\e_{t}\\x_{0}\end{bmatrix}\begin{bmatrix}u_{t}^{T} & e_{t}^{T} & x_{0}^{T} & 1\end{bmatrix} = \begin{bmatrix}Q_{t} & 0 & 0 & 0\\0 & R_{t} & 0 & 0\\0 & 0 & P_{t} & 0\end{bmatrix}$$

$$E\begin{bmatrix}u_{t}\\e_{t}\end{bmatrix}\begin{bmatrix}u_{t+k}^{T} & e_{t+k}^{T}\end{bmatrix} = \begin{bmatrix}Q_{t} & 0\\0 & R_{t}\end{bmatrix}\delta_{k} \quad ; \quad \delta_{k} = \begin{cases}1 & k=0\\0 & otherwise\end{cases}$$
(24)

If  $u_t$ ,  $e_t$  and  $x_t$  have a Gaussian distribution, i.e.:

$$u_t \approx \mathcal{N}(0, Q_t)$$
,  $e_t \approx \mathcal{N}(0, R_t)$ ,  $x_0 \approx \mathcal{N}(0, P_0)$  (25)

It is proved that the Kalman filter, is optimized [6]. The linear state space model (23) processes equivalent noise characteristics (24) and (25) are assumed. In addition

$$\begin{bmatrix} Q_t & 0 & 0 \\ 0 & R_t & 0 \\ 0 & 0 & P_0 \end{bmatrix} > 0$$
(26)

For each time of  $t \ge 0$  we have:

$$p(x_t | Y_t) = N(\hat{x}_{t|t}, P_{t|t})$$

$$p(x_{t+1} | Y_t) = N(\hat{x}_{t+1|t}, P_{t+1|t})$$
(27)

Where the average values and state covariance change as follow

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + P_{t|t-1} H_t^T S_t^{-1} (y_t - H_t \hat{x}_{t|t-1})$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1} H_t^T S_t^{-1} H_t^T P_{t|t-1}$$

$$S_t = R_t + H_t P_{t|t-1} H_t^T$$

$$\hat{x}_{t+1|t} = F_t \hat{x}_{t|t}$$

$$P_{t+1|t} = F_t P_{t|t} F_t^T + G_t Q_t G_t^T$$
(28)

With the initial value  $P_{0|-1} = P_0$  and  $\hat{x}_{0|-1} = 0$ 

For estimating parameters Photovoltaic power system equation of state and observation is assumed as follows.

$$\Theta_{t+1} = I\Theta_t$$

$$p(t) = \varphi^T(t)\Phi_t + e(t)$$
(29)

Wherein I is unique matrix unit, p(t) measured power,  $\varphi(t)$  Regression vector,  $\Theta_t$  Vector of parameters that are defined as

Seen equation without noise and considered  $e_t \approx N(0,5)$ ,  $\Theta_0 = [0\ 0\ 0\ 0]^T$ . After determining the parameters using the Kalman filter, to determine the optimum working point, we have

$$f(v) = \frac{dp}{dv} = \hat{b}_1 + 2\hat{b}_2v + 2\hat{b}_3v^2 + 4\hat{b}_4v^3 = 0$$
(31)

For solving this equation the position error method is used. The flowchart in Figure (5-1 a) is given. For b = 20 and all of the value  $0 \le v(0) \le 60$  except v(0) = 20 the optimum working point voltage be  $V_{OOP} = 17.7323V$ . Whereas, in accordance with Table 1 in Newton-Rawson's method  $V_{OOP}$  is dependent to the initial voltage v(0). Kalman filter algorithm in flowchart form, and position error (5 - a) is shown and Figure (5-b) shows algorithm flow chart of error position



Fig. 5 Algorithm flow chart of error position

Figure (6) shows coefficients of variation  $b_1 \cdot b_2 \cdot b_3$  and  $b_4$  Using the Kalman Filter and also changes of  $V_{OOP}$  with error position method.



Fig. 6 Coefficients of variation  $b_1 \cdot b_2 \cdot b_3$  and  $b_4$  and  $V_{OOP}$ 

#### V. CONCLUSION

In this paper, photovoltaic power system in real-time identification method is discussed. For the case measurements is with noise, the relationship between power and voltage with a polynomial approximation and the polynomial coefficients are determined using the Kalman Filter and to determine the optimum working point with respect to the convergence of Newton-Rawson's method the dependent on initial value and also in cases where the derivative is zero, it does not answer, error position method used.

#### REFERENCES

- K.H. Hussein, I. Muta, T. Hoshino and Osaka, "Maximum photovoltaic power tracking: An algorithm for rapidly changing atmospheric conditions", in Proc. IEE Generation, Transmiss, vol. 142, pp. 59-64, Jan. 1995.
- [2] Weidong. Xiao, Magnus G.J. Lind and William G. Dunford" Real-time identification of optimal operating points in photovoltaic power systems", in IEEE Transaction on industrial electonics, vol. 53, iss. 53, August 2006.
- [3] S. Liu and R.A. Dougal, "Dynamic multiphysics model for solar array", IEEE Trans, Enegy Convers., vol. 17. iss 2, pp. 285-294, Jun. 2002.
- [4] W. Xiao and W. G. Dunford, "A novel modeling method for photovoltaic cells", in proc. IEEE PESC, pp. 1177-1183, 2004.
- [5] A. Capel, L. M. Salamero, W. Xiao, and W.G. Dunford, "A novel approach to operate solar arrays at their MPP without tracking process", in Proc. Annu. Seminar Autom. Control, Ind. Electron. And Instrum., pp. 229-232, 2004.
- [6] GH. Mohammadadi , N. Pariz, "Particle filters in navigation", MS Thesis, Ferdowsi University, summer 2003.
- [7] M.E Salgado, G.C.Goodwin, and R. H. Middleleton, "Modified least square algorithm incorporation exponential resetting and forgetting," Int J.Control, vol. 47, iss. 2, pp. 447-491, Jan. 1988.
- [8] Giovanni Petrone, "Distributed Maximum Power Point Tracking: Challenges and Commercial Solutions" Atkaff, vol. 53, iss. 2, pp. 128-141, 2012.
- [9] Syafaruddin and Hiyama, Takashi "ANN based Optimal Operating Points of PV Array under Partially Shaded Condition" The International Conference on Electrical Engineering 2008.
- [10] Mohammad A. S. Masoum," Theoretical and Experimental Analyses of Photovoltaic Systems with Voltage- and Current-Based Maximum Power-Point Tracking" IEEE Transactions on Energy Conversion, vol. 17, iss. 4, December 2002.
- [11] Pawan D. Kale, "A Study of Efficient Maximum Power Point Tracking Controlling Methods for Photovoltaic System" ISSN: 2277 128X, vol. 3, iss. 3, March 2013.