An Adaptive Predictive Control Strategy for RMPPT under Partially Shaded Conditions

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Abstract: As one of key technologies in photovoltaic converter control, Maximum Power Point Tracking (MPPT) methods can keep the power conversion efficiency as high as nearly 99% under the uniform solar irradiance condition. However, these methods may fail when shading conditions occur and the power loss can over as much as 70% due to the multiple maxima in $I - P$ curve in shading conditions v.s. single maximum point in uniformly solar irradiance. In this paper, a Real Maximum Power Point Tracking (RMPPT) strategy under Partially Shaded Conditions (PSCs) is introduced to deal with this kind of problems. An optimization problem, based on a predictive model which will change adaptively with environment, is developed to tracking the global maxima and corresponding adaptive control strategy is presented. No additional circuits are required to obtain the environment uncertainties. Finally, simulations show the effectiveness of proposed method.

Keywords: Photovoltaic systems, RMPPT, Partial shading, Adaptive predictive control

1. INTRODUCTION

Photovoltaic (PV) energy has gained great popularity in electricity generation, due to its clean and sustainable nature. A number of achievements have been made in academia and industry (Ching et al. (2010), Ribrant et al. (2007), Sachin et al. (2008), Chen et al. (2011)), where many researchers put their efforts on maximization of power extracted from solar panel, which is commonly referred to as Maximum Power Point Tracking (MPPT). Conventional MPPT methods, like Perturbation and Observation (P&O) method, Incremental Conductance, and Ripple Correlation Control, are very useful when the PV receives uniform solar irradiation. However, solar irradiance applied on entire PV array cannot guarantee uniform density continuously. That’s because part of PV panel may be shielded by trees, clouds or buildings. In this case, the nonlinearity of the PV characteristic curve has been changed from a unique maximum to multiple local maxima, which make the traditional MPPT methods without considering PSCs cannot be applied directly. Therefore, a lot of researchers are interested in finding effective MPPT algorithms with stronger adaptability under PSCs.

Existing schemes working on this issue have been reported in the literature, for example, a new tracking method based on the combination of two loops for MPP at the PV array was presented (Mohammad et al. (2011)). The first loop was off-line set point calculation, which is fixed and cannot change with environment. The second loop was online tuning loop, which was used to tracking the derived fixed set point. Chin et al. (2011) introduced parallel off-line tracking function to assist an on-line fuzzy logic P&O method to enhance RMPPT performance, which can continuously search the absolute MPP beyond the trapped maxima. The information of operating voltage and the corresponding generation current is required to store in a database, which means an additional circuit for the measurement is needed. Patel et al. (2008) and Ishaque et al. (2012) discussed a modified P&O with global maxima tracking subroutine method, which was based on particle swarm optimization algorithm. However, many parameters are required to be adjusted, which is not easy to be applied in commercial PV systems. Methods mentioned above have some drawbacks with respect to fixed setting-point loop, additional circuit, and difficulties to apply in already installed systems, especially invalid when there is a large difference on solar irradiation level. Young-Hyok Ji et al. (2011) proposed a MPPT method with a simple linear function to moving the operating point toward the lower voltage level, by which the maxima can be tracked under PSCs without any additional circuits. Three special cases were discussed to illustrate the effectiveness of the linear function. However, whether the lower voltage level found by the designed linear function is close to the global maxima or not is not be discussed, which may result a local maxima be tracked instead.
In this paper, an adaptive predictive control principle is presented to overcome the environment uncertainties. No additional circuit is required to measure operating voltage. An RMPPT optimization problem with constraints is defined, where the change rate of duty cycle is also considered to prevent power switches damages and reduce unnecessary energy losses. Moreover, the corresponding adaptive control strategy is developed under PSCs, which can cope with the varying operating conditions and change model parameters according to temperate and radiation. The rest of this paper is organized as follows: Firstly, the characteristics of PV system under PSCs are analysed in Section 2. Secondly, a predictive output power model and the optimal problem are designed in Section 3. Then, simulations are presented in Section 4 to illustrate the effectiveness of the proposed control method. Finally, a conclusion is made in Section 5.

2. PV CHARACTERISTICS UNDER PSCs

A general Photovoltaic system consists of four parts, namely the photovoltaic array, power converter, controller with environment sensor, and grid, where its major technical issues include improving the energy conversion efficiency, enhancing stability of power grid, and reducing components cost. A suitable control technology for the power electronic devices is one of the keys to improve the efficiency of grid-connected PV systems, that is, how to keep the PV system working on its maximum power point to maximize the power conversion regardless of weather situation. However, unlike the uniform irradiation condition, the same string may be exposed to different irradiation. The bypass diode in PV array will divert the current from the module, showed in Fig.1, producing multiple peaks in P-V curve of the panel, which make the traditional MPPT methods not applicable.

To illustrate clearly, a 10×10 PV panel under PSCs is given as an example. Fig.2 (a) shows no shading in the panel when the whole panel exposure under 800W/M². The V–P curve is shown as solid grey line in Fig.3. Fig.2 (b) to Fig.2 (e) expresses different shading cases whose area extend from 20% to 80%. It means the shaded part of the panel receives a partial solar irradiation, say 600W/M², and the rest is under full irradiation, which makes the panel

\[
I = I_p - I_o \left[ \exp \left( \frac{q(V + IR_s)}{aBT} \right) - 1 \right] - \frac{V + IR_s}{R_{po}} \tag{1}
\]

Photovoltaic cells can be seen as photo-generated current sources which have the same basic characteristics as a diode. These cells are combined into a photovoltaic array in series and/or parallel connection. Mathematic model of output current of the photovoltaic cell can be expressed as follows (see Pandey et al. (2010) and Mutoh et al. (2006)).
where I and V are output current and voltage respectively; \( I_p \) is the photo-generated current; \( I_r \) indicates the reverse current of equivalent diode; \( a \) is idealized factor of the diode values; \( R_w \) and \( R_p \) are equivalent series resistance and equivalent parallel resistance; \( q \) is electron charge; \( B \) is Boltzmann constant; \( T \) is temperature. Photo-generated current \( I_p \) and reverse saturation current \( I_a \) can be expressed as:

\[
I_p = (I_w + \kappa \Delta T)G
\]

\[
I_a = \left( \frac{T}{T_n} \right)^{\frac{q}{\alpha}} \exp \left[ \frac{qV_s}{aB} \left( \frac{1}{T_n} - \frac{1}{T} \right) \right]
\]

in which \( G \) is an actual light intensity while \( G_n \) is a standard light intensity; \( \kappa \) is the temperature coefficient; \( \Delta T \) stands for temperature difference; \( T_n \) is the standard temperature; \( V_g \) is the band of energy gap of semiconductor material. \( N_s \) represents series modules, when part of the PV array, see \( N_s \) in \( xth \) string, is shaded, the bypass diode will divert current, leading the output current as:

\[
I_s = \sum_{s=1}^{N_s} I_s = \sum_{s=1}^{N_s} I_{w,s} \alpha
\]

in which \( N_p \) is the parallel modules; \( I_{w,s} \) is short circuit current in \( xth \) string; the adaptive factor \( \alpha \) which contains shading information \( N_{ds} \) \( (N_{ds} < N_s)\) can be expressed as:

\[
\alpha = 1 - \exp \left( \frac{q(V_s + RI_{w,s} - V_{osc})}{AKTN_s(N_s - N_{ds})} \right)
\]

where \( N_s \) is modules; \( V_s \) is parallel voltage of entire array; \( V_{osc} \) means open circuit voltage of shading modules in \( xth \) string. The existing of shading parameter \( N_{ds} \) leads string current \( I_s \) different, so the PV \( I - P \) curve will be multiple peaks.

**REMARK 1:** When shading modules \( N_{ds} \) values zero, then \( V_{osc} = 0 \) and the adaptive factor \( \alpha \) converts to:

\[
\alpha = 1 - \exp \left( \frac{q(V_s + RI_{w,s})}{AKTN_s^2} \right)
\]

which means uniform solar irradiance is applied on the entire PV array, then parameters of each string is the same, the output current can be represented as:

\[
I_s = N_p I_{w} (1 + \exp \left( \frac{qV_s}{NK} \right) \alpha)
\]

in this case, only one maxima will appear in \( I - P \) curve, same as \( N_{ds} = N_s \), which means the array is under another solar irradiance degree.

### 3. ADAPTIVE PREDICTIVE CONTROL FOR RMPPT

The main control objective of RMPPT in this paper is to operate the switch with a properly optimized duty cycle to make the PV output current track its reference accurately. The reference will change with the environment. So we design an adaptive controller to overcome this uncertainty and track the real reference with considering PSCs. Fig.4 shows control diagram with Support Vector Machine (SVM) as reference power producer. After training process in database and construct the fitting function ahead, output power and optimal current can be obtained by measuring the inputs parameters. Then the reference value of inductor current, together with the outputs of the predictive model will be inputted to the cost function. The optimal solution-duty cycle, will be inputted into converter to regulating the operating current and load voltage.

![Fig.4 Control diagram of proposed current control method](image-url)

**3.1 Adaptive Model for Output Power and Optimal Current**

We choose support vector machine as a useful tool for data classification and pattern recognition (Jiang et al. (2009), Yu et al. (2009), Ahemed et al. (2010)). This method can obtain estimated measurements by finding regression coefficients which can best fit with residual. Besides the solar intendency and temperature, the photo-generated current also has a mapping relationship with current at the real maximum power point. When the solar panel work under the shading condition, the photo-generated current reflects the shading information and can be measured in the confluence box. The shading percentage can be expressed as follows:

\[
I_p = \frac{(1 - S)G_{normal} - I_{p}}{G_s} = \frac{G_{shading}}{G_{normal}}
\]

\[
[P_{mp}, I_{mp}] = f(x) = f(g,t,I_p)
\]

\[
f(x) = \sum_{m=1}^{n}(a_m - a_n)k(x,x_m) + b
\]

where \( I_{mp} \) is photo-generated current under standard condition. Optimal current \( I_{mp} \) is corresponding with maximum power \( P_{mp} \), these parameters serve as output pair. SVM method is used to find the fit equation to observed variables and \( I_{mp} \) will be used as reference signal \( I^* \).

In order to construct the fitting function \( f(x) \) with residual less than \( e \), we have the following steps:
Step 1. Collecting input data: light intensity $g$, temperature $t$, and photo-generated current $I_p$ on $(n-1)_a$ and $n_a$ days, scoping fitting trade-off- C and insensitive loss function- $e$ to minimize the training error. The trade-off should be a small value to avoid over fitting phenomenon.

Step 2. Selecting a kernel function $k(x,x_a)$: using lagrangian multipler method and the selected kernel function $k(x,x_a)$ to work out the lagrangian multiplier- $\alpha, \alpha'$ and bias- $b$. Then the fitting function in Eq. (10) can be obtained.

Step 3. Finding the reference current: measuring $g, t$, and $I_p$ on $(n+1)_a$ day, substituting these three parameters to the fitting functions in Eq. (10), and by Eq. (9), the output power and optimal current can be calculated. The optimal current obtained is used as the reference input.

3.2 RMPPT Adaptive Predictive Control Algorithm

With the consideration of external parameter uncertainties, we design an adaptive controller based on mathematic model of boost converter (Giovanni et al. (2005)), which produce an optimized duty cycle to regulate the output current and then track its reference. The cost function we used is defined as follows:

$$
\min_{\delta,x} J = \sum_{j=0}^{M} \|i(j) - i^{*}(j)\|^2_2 + \sum_{j=0}^{M} \Delta d(k+j-1/k)\|^2_{\omega_m}$$

where $P$ is prediction horizon, $M$ is control horizon, $i(k+j/k)$ is the predicted output current at instant $k$, $i^*$ is reference current, $Q_{\omega}$ is a weighting coefficient to penalize output signal error and $Q_m$ is a weighting coefficient to penalize big changes in input signal. The cost function in Eq. (11) means that the derivation between output current and reference current will be minimized and that the fluctuation of duty cycle will be reduced, which can avoid the energy loss caused by frequent switching.

The predictive output is expressed as follows:

$$i(k+j/k) = \xi \cdot x(k) + \Omega \cdot \gamma(k+j/k)$$

where

$$\gamma(k+j/k) = (d(i), \delta(i), z(i))^T, \quad i \in \{k, K, k+M-1\},$$

$$\xi = c(A', A^2, K, A^M)^T, \quad \Omega = c(P_1, P_2, P_3),$$

$$P_1 = \begin{pmatrix} R & 0 & L & 0 \\ A'R & R & L & 0 \\ M & M & M & M \\ A^{p-1} & A^{p-2} & R & L & A^{p-M} & R \end{pmatrix},$$

$$P_2 = \begin{pmatrix} G & 0 & L & 0 \\ A'G & G & L & 0 \\ M & M & M & M \\ A^{p-1} & A^{p-2} & G & L & A^{p-M} & G \end{pmatrix},$$

$A', B', R$ and $G$ are matrices of state-space model of boost converter; $c = (1, 0)$; $\gamma(k)$ is the combination of $d(k)$, $\delta(k)$ and $z(k)$; $x(k)$ is the state variable at time $t_k$. By substituting $i(k+j/k)$ into the cost function $J$ in Eq. (11), a general form of the optimization problem is obtained:

$$\min_\gamma \gamma^T H \gamma + 2f^T \gamma$$

subject to: $F_i \gamma \leq F_i + F_i \cdot x_o$

where $H = \Omega^T Q_m + Q_m$, $f = 2 \cdot \xi^T Q_m \xi - 2 \cdot d^T Q_m \cdot x_o$; $\gamma$ is the solution sequence; $d$, is initial value of duty cycle in each computation period; $d(k)$ is valued between 0 and 1; $x_o$ is the initial state; $F_i$, $i=1,2,3$ are constraint matrices. Thus, the optimal control problem has been converted to solving a corresponding Mixed Integer Quadratic Programming (MIQP) problem, which can be solved by matlab function miqp.m.

Note that at step $k$, an optimal sequence $\gamma^*$ are obtained but only the first solution $d_i^*(k|k)$ from sequence $\gamma$ is applied.

4. SIMULATION RESULTS

To verify our proposed method, several simulations are carried out under different situations on the photovoltaic system, which is located at Shanghai Jiao Tong University as shown in Fig.5.
By Fig. 8, we can see the conventional method misses tracking the MPP during the partial shading period. The peak value of output power is around 13.2KW and the efficiency of the whole produce is 90.29%, while our proposed method can track the reference with peak value as 17.8KW and efficiency as 99.6%.

Moreover, the comparison of RMPPT performance between our proposed method and conventional P&O method is showed in Fig.8. By Fig. 8, we can see the conventional method miss tracking the MPP during the partial shading period. The peak value of output power is around 13.2KW and the efficiency of the whole produce is 90.29%, while our proposed method can track the reference with peak value as 17.8KW and efficiency as 99.6%.

To demonstrate effectiveness and fast response of the proposed method in a deeper perspective, the trajectory of operating points is compared with voltage-power and voltage-current curves to test whether the PV system is working at the true RMPPP. By Fig. 9 to Fig. 10, a detailed view of the RMPPT performance can be observed. When the shading appears, the working point follows the global optimum curve to jumping out of local optimum and the corresponding working voltage changes from 210V to 150V roughly. When the shading disappears, photovoltaic arrays receive uniform solar intensity again and the operating point move back to the theoretical optimal curve. These results show the feasibility of re-positioning and tracking the RMPPT among multiple local maxima exhibited.
Fig.10 Operating points versus PV V-I curves under shading

5. CONCLUSION

In this paper, an adaptive controller for RMPPT under PSCs was developed with the consideration of uncertainties of solar radiation and temperature. The RMPPT was achieved by solving an adaptive optimization problem which was formulated based on a SVM nonlinear system model. Simulations carried out shown the effectiveness of our proposed method.

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REFERENCES


