Maximum Power Point Tracking of Photovoltaic Generation Based on Forecasting Model

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***Abstract*—In order to make full utilization of photovoltaic (PV) array output power, which depends on solar irradiation and ambient temperature, maximum power point tracking (MPPT) techniques are employed. Among all the MPPT strategies, the Perturb and Observe (P&O) algorithm is more attractive due to its simple control structure. Nevertheless, steady-state oscillations always appear due to the perturbation. In this paper, forecasting model of maximum power point (MPP) based on Support Vector Machine (SVM) is established, and a new MPPT algorithm composed of the forecasting model and small step P&O is presented. Experimental results show that SVM model could predict the MPP exactly, and the effectiveness of the proposed MPPT algorithm is validated using hardware platform based on single-chip microcomputer.**

***Index Terms*—maximum power point tracking, Perturb and Observe, support vector machine, forecasting model**

I. Introduction

As a renewable source, photovoltaic (PV) generation is becoming increasingly important since it has many merits such as cleanness, little maintenance and no noise. The output power of PV arrays is always changing with solar irradiance and ambient temperature, and exhibits a power-voltage characteristic with a unique maximum power point (MPP) under uniform condition. Therefore, the maximum power point tracking (MPPT) which extracts maximum power from the PV arrays at real time is of great importance in PV generation systems.

In recent years, a great number of techniques have been proposed for tracking the MPP, Ref.[1-4] present a comprehensive comparative review, including Constant Voltage Tracker(CVT), Perturb and Observe (P&O), Incremental Conductance(INC), Fuzzy Logic, Neural Network, and so on. CVT method has the merits of simplify and high reliability, but the PV array works with a fixed voltage, which is usually not the MPP as the solar irradiance or ambient temperature changes, enhance power loss is great relatively. P&O algorithm is easy to implement for the simple control structure, nevertheless, steady-state oscillations always appear due to the perturbation. In addition, the precision and rapidity of tracking are influenced by initial value and perturb step, sometimes tracking failure may occur. The INC algorithm is relatively more accurate, but needs high precision instruments. Neural Network algorithm is adopted to establish the forecasting model of MPP, but there is error between the real MPP and the forecasted MPP due to the finite samples, so power loss is unavoidable. Other complex algorithms like Fuzzy Logic and Sliding Model are also adopted in some papers [5-8].

This paper proposes a new MPPT algorithm based on SVM model and P&O. At first, SVM model forecasts the reference point which is close to MPP, then the work point is adjusted to the reference point by PI controller, and small step P&O is performed to track the MPP. Experiments are performed on hardware platform based on single-chip microcomputer, and the results indicate that the proposed algorithm is effective.

II. MPPT Principle of PV Array

A. P-V Characteristics Curves

The typical characteristics of PV array are represented as following Equation:

$$P = I_s V - I_o V\{\exp[\frac{q}{AKT}V]-1\} \tag{1}$$

Where I_s is short-circuit current, which is decided by solar irradiance, I_o is reverse-saturation current, T is absolute temperature, A is p-n junction constant, K is Boltzmann's constant, q is charge constant, and P,V are the output power and output voltage respectively of the PV array. P-V characteristics curve could be get by (1), as Fig.1 shows.

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The *P-V* characteristics curve changes dramatically as the solar irradiation or ambient temperature changes, and there exists a unique MPP on uniform condition. The output power increases as the output voltage increases when output voltage is smaller than MPP voltage V_{max}, and it decreases as the output voltage increases when output voltage is bigger than MPP voltage V_{max}. The process of MPPT could be realized by controlling the output voltage V always at the V_{max} as the solar irradiation or ambient temperature changes.

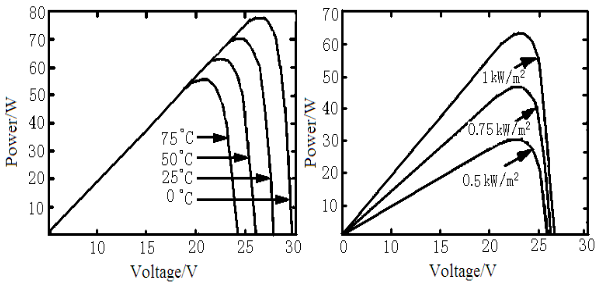


Figure.1 P-V characteristics curves.

B. MPPT Control Circuit

The commonly used control circuit in MPPT is DC-DC converter, which has many types as Buck, Boost, Buck-Boost, Cuk, and so on. Considering the general load type is series of voltage source and resistor, and steady-state of DC-DC converter in current continuous mode can be equivalent to transformer of which the ratio is adjustable, so the maximum power point tracking control principle can be expressed by Fig.2. Adjust the duty cycle of PWM in DC-DC converter, the equivalent load of PV array is changed, and MPP could be captured.

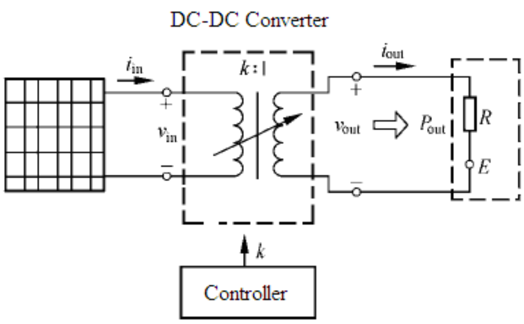


Figure.2 MPPT control circuit.

III. MPPT Control Algorithm Based on SVM Forecasting Model

A.Perturb and Observe (P&O)

Perturb and Observe algorithm is currently one of the most commonly used algorithms to realize MPPT for advantages of clear principles, simple to implement, less measured parameters, and the PV array characteristic curve is not needed. The principle of P&O is to perturb solar array working voltage value ($V+\Delta V$) periodically and then observe the power change before and after the disturbance. If output power increases, it means that the original perturb direction is the right direction, and continue to perturb in the same direction ($+\Delta V$); If output power decreases, it means the original perturb direction the error direction, and continue to perturb in the contrary direction (-ΔV). The program flowchart of the algorithm is shown in Fig.3.

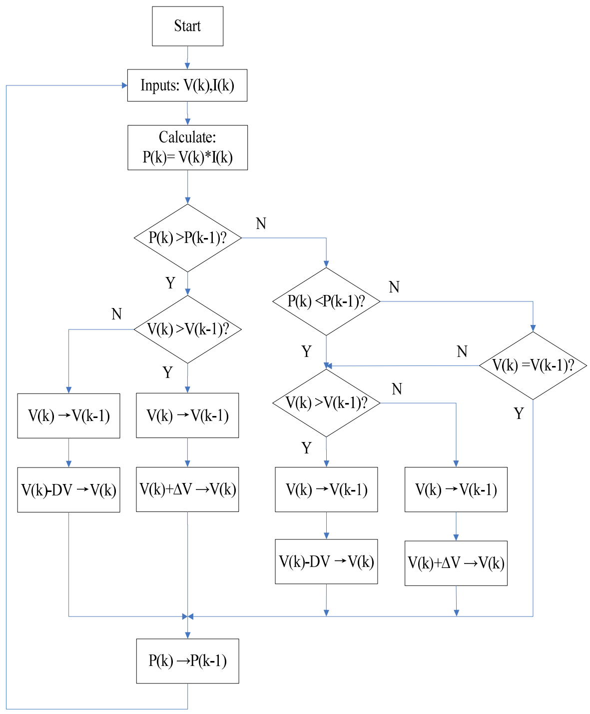


Figure.3 Program flowchart of P&O

There are some defects about the P&O algorithm. Firstly, power loss is unavoidable, because perturbs never stop for a while even at the MPP. Secondly, the perturb step is difficult to select, tracking speed would be quite slow if perturb step is too small, and steady-state oscillations would be drastic if perturb step is too big. What is more serious, it is incidental to choose the wrong perturb direction when the solar irradiation or ambient temperature changes, which would cause greater power loss.

B.SVM Forecasting Model

Support vector machine is a new machine learning method presented by Vapnik, etc [9]. Based on statistical learning theory of VC dimension and principle of minimal structure risk, it could effectively solve practical problems like few samples, nonlinearity, high dimension and local minimizing. At present, the support vector machine has been successfully applied to the load forecasting of power grid, natural gas and other fields [10-13].

Given the sample set $\{(X_i, Y_i)\}_{i=1}^{N}$ ($X_i \in R^n$ is input vector, $Y_i \in R$ is the corresponding output value, N is the number of samples, n is the dimension of input vector) , the linear regression function in SVM is:

$$y = f(X_i) = \sum_{i=1}^{N} W_i \phi_i + b \tag{2}$$

Where $\{(\phi(X_i), y_i)\}_{i=1}^{N}$ is nonlinear function mapping the samples from input space to feature space, and the coefficients W and b could be obtained by minimize

$$\frac{1}{2}\|W\|^2 + C\frac{1}{N}\sum_{i=1}^{N}(\xi_i + \xi_i^*)$$

$$\text{s.t.}\begin{cases} y_i - W_i\varphi(X_i) - b \leqslant \varepsilon + \xi_i \\ W_i\varphi(X_i) + b - y_i \leqslant \varepsilon + \xi_i^* \\ \xi_i \geqslant 0, \xi_i^* \geqslant 0 \end{cases} \tag{3}$$

where the first part $\frac{1}{2}\|W\|^2$ determines generalization ability of the regression function, and the second part is the empirical risk. Constant C(C>0) is penalty factor to the training error ε, and a bigger C means more empirical risk. ξ_i and ξ_i^* are slack variables.

Lagrange equation could be established according to (3), and the solution to linear regression equation is

$$f(X_i) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)K(X_i, X) + b \tag{4}$$

where α_i 、 α_i^* are dual parameters, $K(X_i,X)=\varphi(X_i)\varphi(X)$ is kernel function, which must satisfy the Mercer theorem.

Different support vector machines could be generated by choosing different forms of kernel function. Commonly used kernel functions include Polynomial function, Gaussian function, Sigmoid function etc. This paper selects the following Gaussian function for the kernel function:

$$K(X_i, X) = \exp\left(-\frac{\|X_i - X\|^2}{\delta^2}\right) \tag{5}$$

where δ^2 is the width parameter of Gaussian function, which impliedly defines the nonlinear mapping from input space to high dimension feature space.

Main environment parameters that influence the MPPT voltage V_{max} include solar irradiation E and ambient temperature T. The open-circuit voltage V_{oc} could reflect solar irradiation E well, and the measurement is easy to implement, so V_{oc} is chosen to construct the sample instead of E. Suppose certain environment parameters are $X(i)=[V_{oc}(i),T(i)]$, corresponding MPP voltage is $V_{max}(i)$, then one sample $(X(i),V_{max}(i))$ is constructed. A sample set $\{X(i),V_{max}(i)\}$ is obtained through collecting 3600 samples in various environments, then SVM is adopted to build a model which could forecast the V_{max} using V_{oc} and T.

Statistic average relative error Δ_{MRE} is selected to evaluate the performance of the forecasting model, the expression is:

$$\Delta_{MRE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y - \hat{Y}}{Y}\right| \times 100\% \tag{6}$$

Where $\hat{Y}$ is the forecasting value of Y.

In order to avoid the phenomenon of undertraining or overtraining during the training process, 1800 samples is randomly selected from the sample set to construct the training samples, and remain 1800 samples are used to construct the test samples. The minimum Δ_{MRE}=0.648% is achieved on test samples when set $C=10^2$, $\delta^2=1$, and the obtained SVM model includes 260 support vectors.

C.MPPT Algorithm based on SVM Forecasting Model and P&O

This paper combines the SVM forecasting model with P&O, and the flowchart of the algorithm is shown in Fig.4.

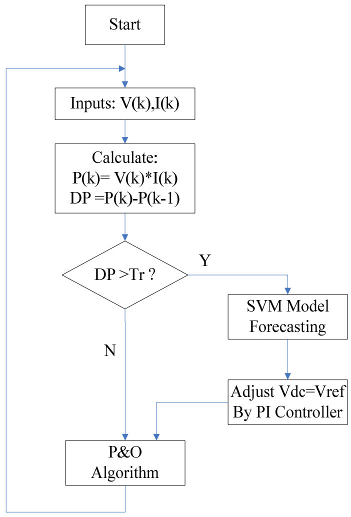


Figure.4 Program flowchart of the proposed algorithm.

SVM forecasting model gives reference working voltage V_{ref} according to open-circuit voltage V_{oc} and ambient temperature T, then the work voltage is adjusted to V_{ref} directly using PI controller and start the P&O process with small perturb step. The critical value T_r is used to determine whether it is necessary to compute a new V_{ref}. If the power difference ΔP between $P(k)$ and $P(k$-1) is smaller than T_r, then continue the P&O process, else this means the environment has changed greatly, so SVM forecasting model is performed to give the new V_{ref}, and restart the P&O process.

This algorithm has following advantages:

1) Instead of adopting fixed step in P&O process, the process of adjusting the work voltage to V_{ref} is directly implemented by PI controller, which could ensure the rapidity of tracking.

2) Forecasted by SVM model, V_{ref} is very close to actual MPP. Therefore, take V_{ref} as initial value and choose small perturb step to perform the P&O process, the conventional steady-state oscillations could be effectively decreased, and power loss is greatly reduced.

IV. EXPERIMENTAL PLATFORM

A.Hardware Platform

In order to verify the correctness of the proposed MPPT algorithm, a set of experiment platform based on dsPIC microcomputer is established. the hardware structure diagram is shown in Fig.5，and the parameters of the experiment system is shown in Tab.I.

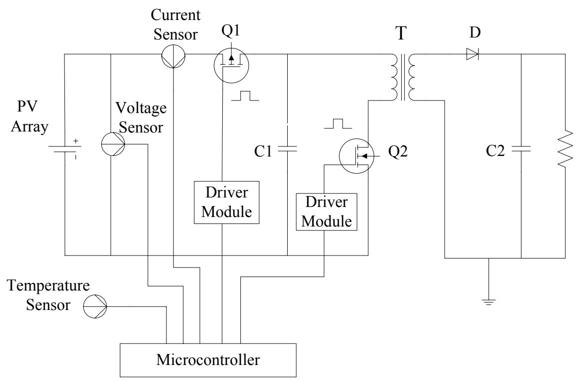


Figure.5 Hardware platform of experiment.

TABLE I.
PARAMETERS OF THE EXPERIMENT SYSTEM

PV array	
P=75W，V_{oc}=21.5V，I_{sc}=4.91A，V_m=17.5V，I_m=4.29A（standard test condition）	
chip type	
Microcontroller	dsPIC33FJ06GS202
Temperature sensor	Ds18b20
Current sensor	LA25-NP
Voltage sensor	LV28-P
T	KA4823-BL
Q1	IRF4905
Q2	IRF4321
D	C2D05120
Drive Module	MCP14E4
Circuit parameters	
C1=1800uF，C2=100uF，R=20Ω，f_s= 28.8 kHz	

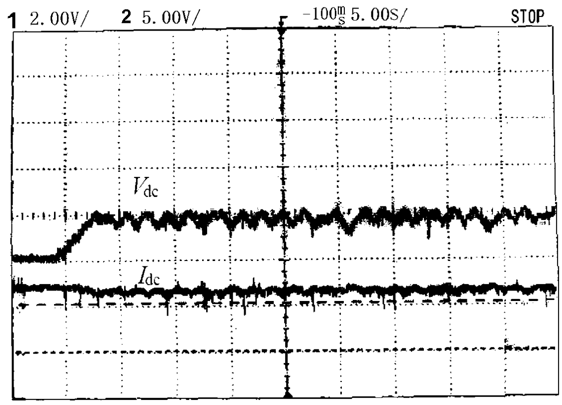
B.Sample Collecting

If MOSFET Q1 turns on, work voltage V of PV array could be measured by voltage sensor; If MOSFET Q1 turns off, open circuit voltage V_{oc} could be measured. Work current I and ambient temperature T of PV array are also measured by sensors. In order to eliminate the dithering caused by high frequency switches of MOSFET Q2, make AD module of microcomputer continue converting 16 times and take the mean as measured values of V and I.

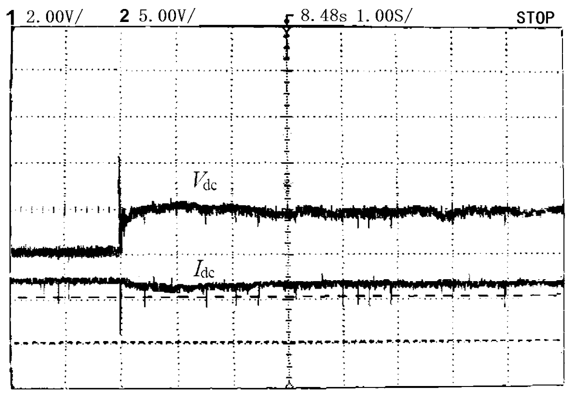
Sample set $\{(X(i),V_{\max}(i))\}$ is collected by comparison. For every sample collection, turn on the MOSFET Q1 first, initialize the duty cycle D of Q2 with a small value D_0, and increase D with a tiny fixed incremental ΔD every time. For the first k times, $D(k)=D_0+k*\Delta D$, then work voltage $V_{dc}(k)$ and work current of the photovoltaic array $I_{dc}(k)$ are measured, and the current output power $P(k)$ is calculated by $P(k)=V_{dc}(k)*I_{dc}(k)$. Compare $P(k)$ with the last output power $P(k\text{-}1)$, if there is $P(k)<P(k-1)$, considering the working point is close to the MPP at that time, make $D = D_0+(k\text{-}0.5)*\Delta D$, and V_{dc} is measured as maximum power point voltage V_{ref}. The next step is to turn off the MOSFET Q1, and measure the open circuit voltage V_{oc} and temperature T of the photovoltaic array, then one collection of $(X(i),V_{\max}(i))$ is completed.

V. EXPERIMENTAL RESULTS

In order to validate the correctness of the proposed MPPT algorithm, comparison of it and conventional P&O is performed on the platform. Given the same work condition, V_{oc}=20.5V, T=18℃, initial work voltage V_{dc}=10V, the tracking speed and the steady-state oscillations of two algorithms are observed respectively. The voltage curve and current curve recorded by digital oscilloscope are shown in Fig.6.



a. Conventional P&O algorithm



b. Proposed algorithm

Figure.6 Comparison of two algorithms.

Tracking process of conventional P&O algorithm (perturb ΔV=0.6V) is shown in Fig.6(a). After continuous positive perturbs for 8 times, work voltage V=14.8V, then evident oscillations appears near the MPP, which means it enters the process of steady-state, and the spent time is 2.80s. Tracking process of the proposed algorithm is shown in Fig.6(b), open circuit voltage V_{oc} and temperature T of the photovoltaic array are measured first, so the voltage as well as the current changes rapidly. The SVM forecasting model gives the forecasting MPP voltage V_{ref}=14.7V, and the work voltage is adjusted to V_{ref} using PI controller (K_p=0.35, K_i=0.08), then small step P&O process (ΔV=0.2V) is performed. Because V_{ref} is quite close to MPP voltage, it only spent 0.42s to enter the steady-state process, which is much faster than conventional P&O algorithm.

After entered the steady-state process, the oscillations of the proposed algorithm is apparently smaller than conventional P&O algorithm. Calculate the average output power in steady-state process for 40s, the proposed algorithm obtains 58.2W, and conventional P&O algorithm obtains 54.7W. This indicated that small step P&O could effectively reduce the power loss.

Power outputs of PV array with the MPPT and without the MPPT in different environments are compared in Table II. It is known that the output power changes small in different environments when PV array works without MPPT due to the work point is far away from the MPP. The power output of PV array changes dramatically in different environments when PV array works with MPPT, and it is obvious that more extra energy could be obtained especially in suitable environment for PV generation.

TABLE II.
COMPARISON OF POWER OUTPUT IN DIFFERENT CONDITIONS

Diffe-rent Cond-ition	V_{oc} (V)	T (℃)	Output Power Without MPPT (W)	Output Power With MPPT (W)	Increased Output Power (W)
1	19.2	13	6.23	18.09	11.86
2	19.4	17	17.83	25.2	7.29
3	19.8	23	19.35	35.7	16.42
4	20.1	20	22.54	43.62	21. 80
5	20.4	16	24.66	51.74	27.08

VI. CONCLUSION

This paper proposes a new MPPT algorithm which combines the SVM forecasting model with small step P&O. At first, SVM model forecasts the reference point which is close to MPP, then the work point is adjusted to the reference point by PI controller, and small step P&O is performed to track the MPP. Experiments are performed on hardware platform based on dsPIC microcomputer, and the results indicate that the proposed algorithm could track the MPP quite fast, and improve the ability of PV generation effectively.

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