Maximum Power Point Tracking for a PV System using Support Vector Machine

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***Abstract*—Since the maximum power point (MPP) of a photovoltaic system changes with the changes in irradiation and temperature, an appropriate maximum power point tracking (MPPT) controller must be applied in the photovoltaic system.**

In this article, one of the powerful machine learning, support vector machine (SVM) is used as a predictive model, combining two traditional MPPT methods and the most commonly used: perturb and observation and incremental conductance to force photovoltaic systems to operate more efficiently In different weather conditions. The effectiveness of the proposed method is verified by Mathlab/Simulink simulation.

***Keywords*—PV system, maximum power point tracking (MPPT), support vector machine (SVM), Perturb and Observe (P&O), Incremental Conductance (INC).**

I. Introduction

Energy production has become a crucial issue, as the need for energy has been increasing in recent years. Knowing that a large part of the world's energy consumption is covered by fossil sources (oil, natural gas, coal) that increase pollution [1-3].

Since then, renewable energies have become a hot topic. In this context, photovoltaic energy is one of the most important alternative energy sources. For this purpose, several methods called maximum power point tracking techniques (MPPT) have been developed and improved to obtain the maximum power and improve the efficiency of photovoltaic systems under varying atmospheric conditions (light and temperature) [4].

MPPT techniques are basically divided into three categories [5]:

Online MPPT: as perturbation and observation (P&O) and Incremental conductance (INC), which are widely used for their ease of implementation. These methods require instantaneous measurements of PV current, voltage, and power.

Off-line MPPT: which are machine learning techniques such as fuzzy logic control (FLC), artificial neuro-fuzzy inference systems (ANFIS) [6] and neural networks (ANN), these methods need existing data on the PV system. Offline methods have better efficiency than online methods. Nevertheless, offline MPPT techniques have some drawbacks such as high memory consumption.

Hybrid MPPT: which is the combination of online techniques and offline techniques, to have a better performance, like the cascade combination of ANN-P&O [7,8].

In this paper, one of the powerful machine learning techniques, which is SVM combined with online methods perturbation and observation (SVM-P&O) and Incremental of conductance, (SVM-INC) in order to ensure the continuation of the maximum power delivered by the photovoltaic array under the variation of the climatic conditions.

Our paper is organized as follows : The second section introduces the modeling of the solar panel and its characteristics as a function of temperature and irradiation. In the third section, we will explain the MPPT methods used, including P&O, INC, and SVM. The fourth part includes the use of Matlab/Simulink simulation tools to simulate the model. The fifth section shows the results and discussion, followed by a brief conclusion.

II. Solar Cell Model

In solar conversion, the equivalent electrical diagram of a photovoltaic PV cell shown in Fig.1 is the most used [9-14]. Where Iph is the photocurrent, assembled in parallel with a diode D, and Id is the current of the diode in the dark. Rp is the parallel resistance and Rs is the series resistance.

The following equation describes the current-voltage characteristics of the PV module [14,16]

$$I = Ipv - I0\left[\exp\left(\frac{V+RsI}{NsVtA}\right) - 1\right] - \frac{V+RsI}{Rp} \quad (1)$$

With $$Vt = KT/q \quad (2)$$

The generated photocurrent associated to the solar irradiation can be written by the next equation

$$Ipv = (Ipv,n + Ki\Delta T)\frac{G}{Gn} \quad (3)$$

Moreover, the diode saturation current I0 is strongly dependent to on the temperature by the following equation

$$I_0 = \frac{Isc,n+Ki\Delta T}{\exp\left(\frac{Voc,n+Kv\Delta T}{NsVtA}\right)-1} \quad (4)$$

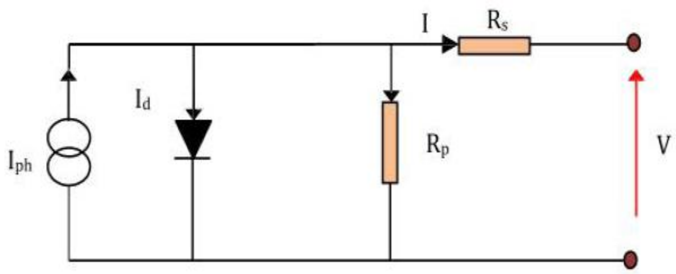

Fig. 1. Single diode equivalent model [17]

I , Ipv PV output current and Photovoltaic current
I0 Saturation current
V PV output voltage
Vt Thermal voltage
ΔT $\Delta T = T - T_n$ with T and T_n the actual and nominal temperature,K
G Irradiation, W/m^2
Gn Irradiation level for standard test condition

A Diode ideality factor, $1 \leq A \leq 1.5$
K Boltzman's constant, 1.380658×10^{-23} J/K
Rs Serial resistor
Rp Parallel resistor
Ns Cells connected in series
q Electron charge, $1.60217733 \times 10^{-19}$ **C**
Ki Current temperature coefficient
Kv Voltage temperature coefficient
Ipv,n Current generated in the conditions STC
Isc,n Nominal short-circuit current
Voc,n Nominal open circuit voltage

III. MPPT METHOD

A. *Support vector machine SVM*

Support vector machines (SVM)[18,19] is a classification and regression prediction tool [20] using supervised learning to maximize predictive accuracy [21].

SVMs have several promising features such as better empirical performance, which have made it gain popularity [22]. The goal of SVM is to find a classifier that can classify the data and separate them. This classifier is known as the hyperplane Fig. 2 [23]. The classification model predicts the outputs (responses) for the inputs that have not yet been seen from the existing inputs (predictors) and previous responses.

The separating hyperplane has the equation

$$w.X + b = 0 \quad (5)$$

Where w represents the normal vector of the hyperplane and X is the input vector.

The distance from a point to the plane is given by :

$$d(x) = \frac{|w.X + b|}{|w|} \quad (6)$$

The objective of SVMs is to find an optimal hyperplane that separates two classes with a maximum distance called the margin.

Let X1 and X2 be two points of different classes f(X1)= +1 and f(X2)= -1

Hence (w.X1)+b= +1 and (w.X2)+b= -1

Then (w.(X1-X2))+b=2

The margin is given by the following equation

$$M = \frac{(X1 - X2).w}{|w|} \quad (7)$$

The maximizing is represented by the equation

$$maximum \qquad M = \frac{2}{|w|} \quad (8)$$

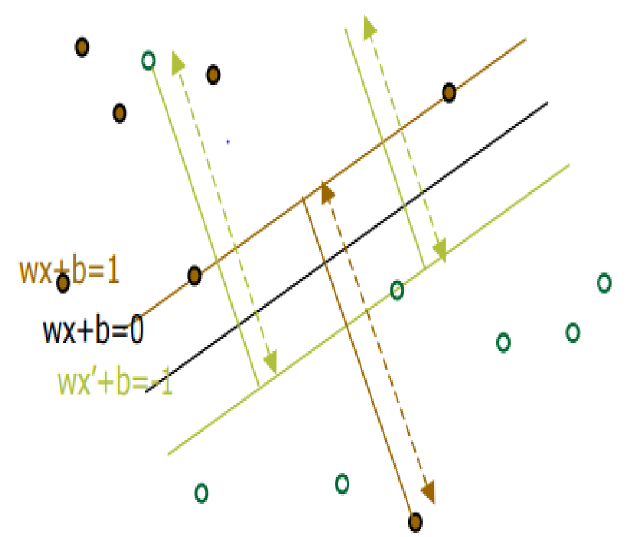

Fig. 2. Representation of Hyper planes [21]

The kernel is a set of mathematical functions that SVMs use, these functions take input data and transform it into the required form. There are different forms of kernel function that generate different SVM algorithms, and among the most used kernel functions are : Plynomial, linear, sigmoid, radial basis function (RBF), and exponential radial basis function (ERBF),...etc.

In this article we will test types of kernel function: RBF and ERBF, because they are perfectly suitable for modeling nonlinear systems [24], which are represented by the following mathematical equations:

$$RBF: \qquad K(u,v) = \exp\frac{-\|u-v\|^2}{2\sigma^2} \qquad (9)$$

$$ERBF: \qquad K(u,v) = \exp\frac{-\|u-v\|}{2\sigma^2} \qquad (10)$$

Where σ^2 is the variance and our hyper-parameter, because it is important to choose the right value of to get occurate results.

Different levels of insolation (G) and temperature (T) with the previous PV current and voltage can be represented as input variables to build a model able to predict Vref and Iref.

B. Perturb and observe

It is a power feedback method and has become the most commonly used MPPT method due to its simplicity and ease of implementation [25]. As the name suggests, this method is based on the perturbation (increase or decrease) of the voltage Vref and the observation of its influence on the power, directly acting on the duty cycle of the DC/DC converter.

The observation of the power then allows a decision to be made about the next disturbance to be introduced, if the power increases, the disturbance will continue in the same direction, otherwise, the opposite [26].

The algorithm ensuring the P&O command is described in Fig.3 below :

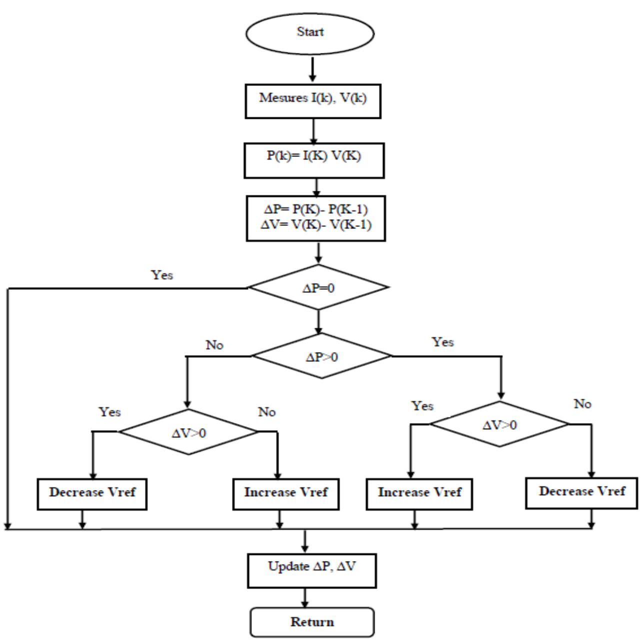

Fig. 3. The Flowchart of the P&O Method

C. Incremental Conductance

The Incremental Conductance method is based on the variation of power with voltage [27]. If the dp/dv derivative is zero it means that we are on MPP, if it is positive the operating point is to the left of the maximum, and when it is negative, we are on the right [28].

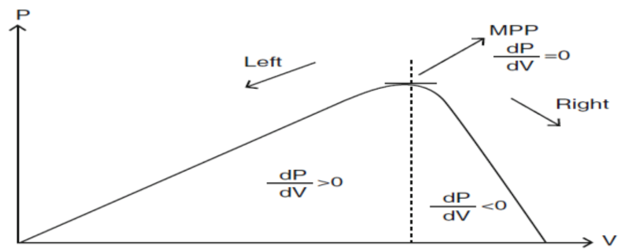

Fig. 4.Basic idea of incremental conductance method on a P-V curve of solar module

Knowing that $\qquad P=I.V \qquad (10)$

Hence, P is the PV power, I is the PV current, V is the PV voltage.

The derivation of the product with respect to the voltage V gives the following relation

$$\frac{dP}{dV} = \frac{d(IV)}{dV} = I + V\frac{dI}{dV} = I + V\frac{\Delta I}{\Delta V} \qquad (11)$$

Then the new conditions on the variation of conductance is as follows:

$$\frac{\Delta I}{\Delta V} = \frac{-I}{V} \qquad at\ MPP \qquad (12)$$

$$\frac{\Delta I}{\Delta V} > \frac{-I}{V} \qquad left\ to\ MPP \qquad (13)$$

$$\frac{\Delta I}{\Delta V} < \frac{-I}{V} \qquad right\ to\ MPP \qquad (14)$$

If the relation (12) is verified, then the MPP is reached no change of the voltage is necessary. If the relation (12) is false, the voltage is adjusted according to whether V is greater or less than Vmp.

Where Vmp is the maximum power point voltage.

The flow chart of incremental conductance MPPT is shown in Fig.5 :

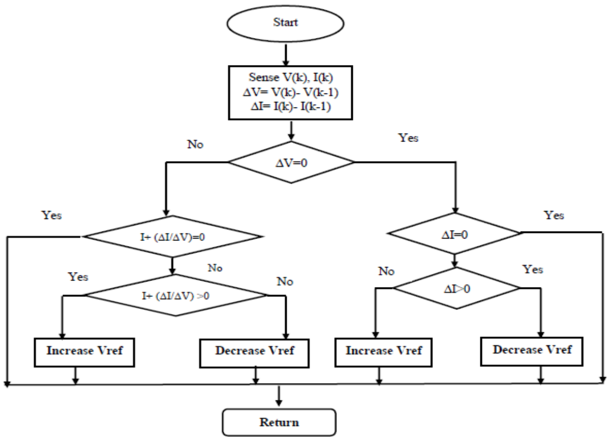

Fig. 5. The Flowchart of the INC Method

IV. Simulation Model

Matlab/Simulink software was used to verify and validate the effictivnesse of the proposed method SVM with P&O.

The system shown in Fig.6 consists of a PV model, MPPT technique, SVM predicting model using kernel function, PWM generator, Boost converter, and 50 Ohms load resistor. The switching frequency of the system is defined as 20KHZ.

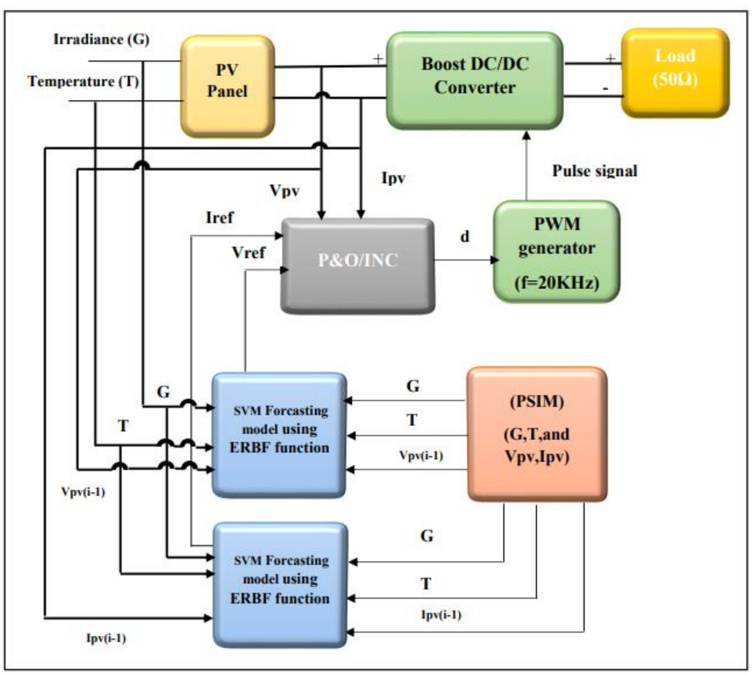

Fig. 6. Complete PV system designed using SVM with P&O and INC

A KYOCERA KV200GT PV module is adopted as PV power source whose specifications are quoted in Table I.

TABLE I. SPECIFICATION OF KC200GT PV PANEL [22]

Parameter	Value
Maximum current (Imp)	7.61A
Maximum voltage (Vmp)	26.3V
Maximum power (Pmax)	200.143W
Short circuit current (Isc)	8.21A
Open circuit voltage(Voc)	32.9V
Temperature coefficient of Isc (Ki)	3.18e-3A/K
Temperature coefficient of Voc (Kv)	-0.123V/K
Number of cells in series (Ns)	54
Diode ideality factor (A)	1.3
Series resistance (Rs)	0.221Ω
Shunt resistance (Rp)	415.405 Ω

Boost DC-DC converter shown in Fig.7. is utilized to step up the output voltage, compared to that delivered by the source [25], hence the name'boost'.it is used as a power conversion stage to mutch the source and load impedance.

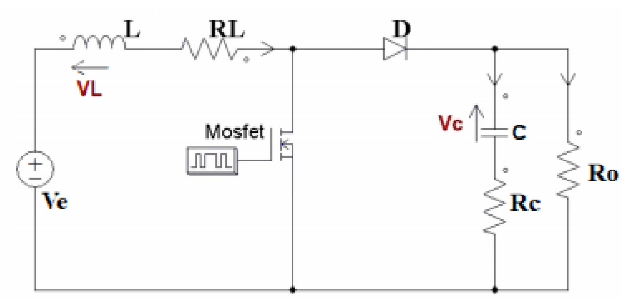

Fig. 7. Equivalent model of boost converter

Parameters used for the boost converter has the following specifications [16].

TABLE II. BOOST CONVERTER AND RESISTIVE LOAD PARAMETERS

Parameters	Value
Input Capacitor (Cin)	1×10-6 F
Inductor (L)	0.011 H
Output capacitor (Cout)	6×10 F
Load	50 Ω

To train and validate the SVM algorithm, we used 130 data set from PSIM which consists of three input solar irradiance (G), temperature (T), and previous PV voltage (previous PV current) as predictors and voltage reference Vref (current reference Iref) as the output response.

As we have mentioned before for the forecasting SVM model we have tested two types of kernel function the RBF kernel and the ERBF kernel, the test results are summarized in Table III which compares kernels with performance measures, including support vector (SV) and its % (SV%).

The result shows that the ERBF kernel is the most suitable for our datasets, as it has the minimum number of support vectors, the minimum percentage of support vectors compared to the RBF kernel.

Fig.8. illustrate predicted values (Vref, Iref) with RBF and ERBF kernel with datasets (Vpv(i-1), Ipv(i-1)), we can see that the optimum kernel is ERBF kernel, whose values are closer to the datasets.

TABLE III. COMPARING KERNELS WITH PERFORMANCE MEASURES FOR PV VOLTAGE AND PV CURRENT

Kernel Function	Voltage SV	Voltage SV%	Current SV	Current SV%
RBF	50	38.8	79	61.2
ERBF	28	21.7	71	55.0

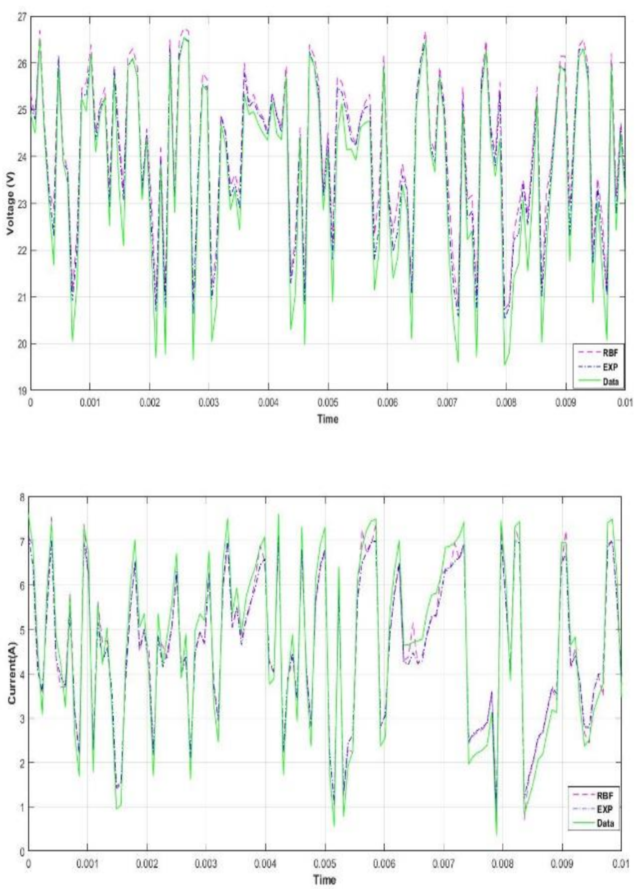

Fig. 8. Comparing predicted values (Vref, Iref) with RBF and ERBF kernel with datasets (Vpv, Ipv)

In order to obtain the optimal duty cycle d, we used two blocs of SVM with ERBF to build a model which can predict Iref and Vref and then passed to the P&O/ INC method, and finally processed to the boost DC-DC converter.

V. RESULTS AND DISCUSSION

TABLE IV and Fig (9-11) exemplify the tabularized and graphical results from the Matlab/Simulink simulation. The SVM-P&O and SVM-INC are compared to each other using PV and load efficiency under the different weather conditions (STC, PTC, and NOTC).

For the STC condition, results show that the SVM-INC had the best result with 99.50% PV efficiency and 96.65% load efficiency.

At PTC condition, also SVM-INC whose product the best results with 99.31% PV efficiency and 96.28% load efficiency.

For the NOTC condition, the SVM-P&O technique had the best result this time with 98.30% PV efficiency however, it underperformed with 95.45% load efficiency.

TABLE IV. SIMULATED RESULTS OF SVM-P&O AND SVM-INC

Weather conditions	Measurment	SVM-P&O	SVM-INC
1000W/m^2, 25°C (STC)	PV efficiency	98.50%	99.50%
	Load efficiency	96.62%	96.65%
1000W/m^2, 20°C (PTC)	PV efficiency	98.41%	99.31%
	Load efficiency	96.65%	96.28%
800W/m^2, 47.4°C (NOTC)	PV efficiency	98.3%	98.16%
	Load efficiency	95.45%	95.72%

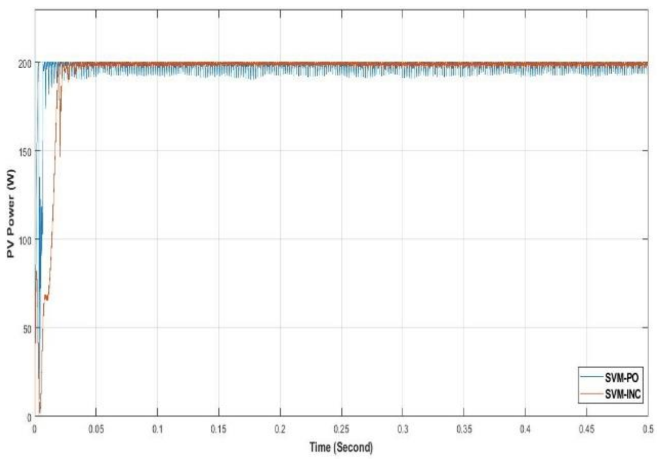

Fig. 9. KC200GT input power at STC

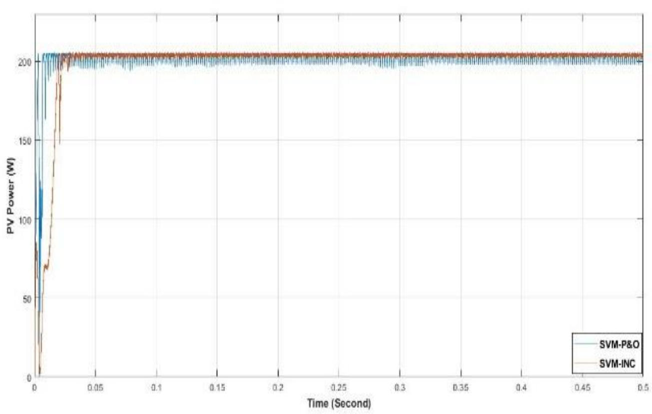

Fig. 10. KC200GT input power at PTC

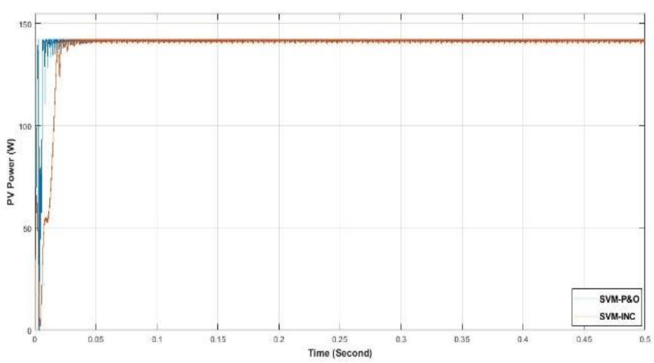

Fig. 11. KC200GT input power at NOTC

VI. Conclusion

This paper presents a combined SVM predicting model with conventional MPPT technique P&O and INC. First of all, we have tested two types of kernel function RBF and ERBF function for the SVM predicting model. Then after the selection of the optimal kernel function ERBF the SVM model predicts current and voltage reference using previous PV current and voltage to be after that the inputs of P&O and INC controller to track the maximum power point in the PV system. The obtained results indicate that the proposed technique can be used to extract the MPP under different weather conditions effectively.

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