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Dynamic and Adaptive Maximum Power Point Tracking Using Sequential Monte Carlo Algorithm for Photovoltaic System

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Abstract

To produce maximum output power in a solar collector system, a maximum power point tracker (MPPT) is considered a vital component in system design. Though, due to partial shading effect initiated by dynamic weather conditions, the tracking process becomes more complex when locating the global maximum power point (GMPP). To solve this issue, an innovative and adaptive MPPT based on sequential Monte Carlo is suggested to accurately and efficiently predict the global peak under rapid changing weather conditions. The proposed method adaptively predicts the next best duty cycle value that will generate the maximum output power. The capability of the technique has been tested strongly under standard test conditions (STC) and dynamic weather conditions including random partial shading and changing irradiance and temperature input values. The new recommended technique is compared to the classical perturb and observe algorithm, in addition to the particle swarm optimization, and flower pollination tracking techniques. The simulated results illustrated dominance in accuracy and efficiency under varying environment conditions. The efficiency calculated was found to be as high as 99.89% at STC and as low as 98.58% at dynamic and random partial shading conditions. In addition, the results displayed high tracking speed in predicting the GMPP while maintaining no oscillations at the output power.

Keywords Maximum power point tracker · Photovoltaic system MPPT · Duty cycle optimization · Sequential Monte Carlo

1 Introduction

Ever since the first invention of the photovoltaic technology in 1954 by Fuller et al., researchers and scientists have been committing time and effort into determining the best maximum power point technique (MPPT) for producing the maximum power from photovoltaic systems [1]. However, despite the ability of harvesting decent results under constant weather conditions, many of these techniques failed extremely when encountering varying environmental condition (i.e., varying irradiance, temperature, and partial shading), because of having high divergence, incorrect pre-

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diction and selection of global peaks, or by presenting high power oscillations around selected MPPs [2]. Partial-shading arises when PV modules are faced with different solar irradiation than other modules in a PV system. This phenomenon produces multiple peaks displayed by power voltage characteristic (P–V) curves adding complexity to the tracking process [2, 4]. A well-designed MPPT intends to solve these issue accurately and effectively.

MPPTs are categorized into off-line techniques, for instance, fractionally short circuit current (FSCC) and opencircuit voltage (FOCV); on-line techniques similar to perturb and observe (P&O), or incremental conductance (InCond), and artificial intelligence (AI) techniques that hold a variety of algorithms such as fuzzy logic control (FLC), particleswarm optimization (PSO), artificial neural network (ANN) techniques, genetic algorithms (AG), and flower pollination algorithms (FPA)) [1].

Numerous studies have been proposed by many researchers to accurately locate the MPP in PV systems. For instance, Radjai et al. [5] and Chiu et al. [6] modified the InCond algorithm based on fuzzy duty cycle change, but the technique did not eliminate the oscillation around the MPP, or



improve the tracking speed significantly. Sundareswaran et al. [7] and Daraban et al. [8] suggested to unite the classical P&O with an AI technique (PSO or GA), but neither approach showed significant improvement in tracking speed or power oscillation, yet introduced high complexity designs. In addition, this approach degraded dramatically when the system encountered severe weather conditions, or when affected by partial shading due to the two known major issues of the P&O technique (i.e., drifting and local maximum power point (LMPP)). Furthermore, additional attempts were presented by Punitha et al. [9] and Syafaruddin et al. [10] and they applied ANN and FLC techniques to locate the GMPP, respectively. Besides the noticeable efficiency compensations, ANN process requires an additional sensor to acquire the temperature variation, while composite design of fuzzy instructions in FLC technique requires system data to locate the next GMPP. Moreover, interesting and distinctive techniques known as PSO and FPA (inspired and derived from *nature*) have been applied to locate the GMPP [11, 14]. Both techniques start with random searches to evade convergence to a local minimum and continue searching until the GMPP is located. Convincingly, these approaches provided an excellent performance solving a key issue of the steady-state fluctuations, but lately, converge to a local minimum once impulsiveness is reduced [11, 14]. In addition, parameter initialization is a complicated process for both techniques. Babu et al [12] and Ishaque [13] attempted to solve this issue, but both did not show their evaluations under varying irradiance and temperature conditions. Moreover, Prasanth et al [14] applied FPA to locate the GMPP and his approach showed significant improvement in terms of efficiency; however, the results did not consider a varying irradiance, temperature, or dynamic partial shading effect on the system, and only included a constant irradiance input values under specific partial shading patterns. Furthermore, their results show an obvious power oscillation, slower tracking speed, and in addition to some error in calculating the efficiency highlighted in Table 2.

This article proposes a stand-alone AI maximum power point tracker that is capable of handling severe and dynamic weather conditions while maintaining high accuracy, fast responding time, and a power-output that is oscillation-free. The proposed technique is based on applying the theory of sequential Monte Carlo algorithm for Bayesian computation to predict the most likely location of the MPP on a PV curve.

The remnant of this article is prepared in this manner. Section 2 will introduce the proposed methodology including the system description, solar P–V characterization, and the proposed DC–DC boost converter for a PV system. A brief description of recursive Bayesian estimation and sequential Monte Carlo techniques is explained in Sect. 3. Designed Simulink model and input data are discussed in Sect. 4, trailed by simulation and results in Sect. 5. Finally, conclusion is signified in Sect. 6.

2 Methodology

The methodology scheme of the design is broken into a PV system description including the booster configuration, the Matlab/Simulink designed model, and the mathematical model of SMC algorithm.

2.1 Proposed System Description

A diagram representation for a full photovoltaic design is represented in Fig. 1. The two-stage representation consists of a PV generator, a booster converter, an MPPT control algorithm, a DC link, an inverter, and a filter that is coupled to the main grid [15]. The MPPT control algorithm is considered an essential part to providing the best duty-cycle value that boosts the converter to produce maximum power output at every instance of time. Considering the second stage as a load, the focus will be on modeling the PV generator and power converter circuits as an accurate nonlinear state-space model that will be tracked by the recursive Bayesian estimate in the means of the SMC algorithm to predict the next suitable duty cycle value.

2.2 Solar PV Characterization

A comprehensive circuit illustration of a single cell generator is represented in Fig.2. The figure shows four main component blocks: PV panels, DC to DC converter, an MPPT algorithm, and a system load. A photovoltaic panel is a collection of multiple cells connected together to form a complete panel [16]. Each photovoltaic cell in the panel is described as a semiconductor component that transforms light energy into electricity [16]. The figure illustrates a PV module that consists of an independent current generator connected to a shunt resistor R_{sh} , a diode, and a series resistor R_s . A shunt resistor $R_{\rm sh}$ is needed because the diode is not an ideal diode, and the R_s is needed to represent the ohmic resistance of the materials [3]. Usually, the value of the series resistor is very small when compared to the value of the parallel shunt resistor $(R_{\rm sh} >> R_s)$ [3]. When light is supplied to the PV cell, an output (I_{ph}) current is generated. Using nodal analysis, $I_{\rm ph}$ can be expressed as [15, 16]:

$$I_{\rm pv} = I_{\rm ph} - I_d - I_r \tag{1}$$

 $I_{\rm pv}$ is the panel's current, and $I_{\rm ph}$ is the current produced from the light, and defined as [15, 16]:

$$I_{\rm ph} = Q_e (I_{\rm SC} [1 + b(T - T_{\rm STC})])$$
(2)





Fig. 1 A block diagram representation of a full photovoltaic system

Fig. 2 A circuit diagram representation of photovoltaic system



where Q_e is irradiance value, I_{SC} is the cell's short circuit current, *b* is a temperature constant, *T* is effective temperature, T_{STC} is the cell's temperature at STC In addition, I_d is the diode current and described as [15, 16]:

$$I_{\rm d} = I_{\rm s}(e^{(qV_d/(nkT))} - 1)$$
(3)

*I*_s is saturation/reverse current of the diode, *V*_d is diode voltage, *q* represent the charge value (1.602 * 10^{-19} C), *k* is Boltzmann's constant (1.38 * 10^{-23} J/K), and *n* is the diode optimist dynamic. Substituting Eqs. 2 and 3 into Eq. 1 yields a universal equation for the representative of the I–V curve of a PV cell [15, 16]:

$$I_{\rm pv} = I_{\rm ph} - I_s \left[e^{\frac{q V_{\rm pv} + I_{\rm pv} R_s}{nkT}} - 1 \right] - \left[\frac{V_{\rm pv} + I_{\rm pv} R_s}{R_{\rm sh}} \right]$$
(4)

where V_{pv} is the cell's voltage output, and it is modeled as [15]:

$$V_{\rm pv} = v_c + R_c (I_{\rm pv} - i_L) \tag{5}$$

where v_c is the voltage across R_c and C and i_L is the current through the inductor labeled in Fig. 2. The process of

extracting these parameters by using Lambert W {} function at STC (1000 W/m²-25 °C) is specified by [15, 16]. In general, the current and voltage produced by a single cell is very small [15, 16]. To harvest a worthy current and voltage values from a solar system, cells are coupled in parallel and in series combinations to attain a usable output values [4].

The output of a panel is a nonlinear power signal, and it is variably dependent on the irradiance and temperature input values [16]. As the irradiance increases, the generation of power increases; however, when the temperature is increased, the generation of power is decreased [3]. The relationship is shown in Fig. 3. From Fig. 3, it is clear that the maximum power generated is located at a single point (*without partial shading*), and locating that point is the interest of all MPPT techniques.

2.3 DC–DC Boost Converter Characterization

Power conversion in a grid-connected PV system is needed to maximize and improve the stability, reliability and quality of the power output for that given PV model [7]. A power converter is a two part system. The first part is a booster, and it is used to boost the direct current signal from one level to another (DC–DC) and maximizes its MPP voltage to





Fig. 3 P–V characteristics of an array while a varying irradiance at a temperature of 25 °C, b varying temperature at an irradiance of 1000 W/m²

generate at most quantity of power. The second section is an inverter that inverts the DC power value into a high quality AC power value and then it passes it to be used by the PV grid. The inverter section will not be taken into consideration when modeling the power system, since it does not contribute to the irradiance-driven dynamics [17].

The DC–DC boost converter is preferred and widely used in PV generated systems because of its high efficiency and controllability as an MPPT controller [7]. Figure 1 shows the circuit diagram of a DC–DC boost converter. As seen from the figure, a MOSFET transistor is used to help in regulating and amplifying the input voltage signal. With a simple mathematical arithmetic, a voltage gain can be calculated from the diagram as displayed in the equation below [18].

$$G_{\rm o} = \frac{V_{\rm o}}{V_{\rm i}} = \frac{1}{1-D} \tag{6}$$

where V_0 is the output voltage and V_i is the input voltage. *D* is the duty cycle. *D* is the fraction of time for one period in which the signal is active. Now, the average power output of the circuit model can be derived by recalculating the voltage and current over the switching period [15].

The model of the boost converter is described as a two differential equations and two state variables:

$$v_{c}' = \frac{I_{pv} - i_{L}}{C},$$

$$i_{L}' = \frac{V_{pv} - (R_{L} + DR_{D})i_{L} - (1 - D)[Vdc + \Delta V_{d} + (R_{c} + R_{dc})i_{L}}{L}$$
(8)

where $C, L, R_c, R_L, R_D, R_d, R_{dc}, and \Delta V_d$ are shown in Fig. 2.



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Fig. 4 Flowchart of MPPT-SMC controlled DC-DC boost converter

Furthermore, Fig. 4 provides a clear insight of the complete model behavior. The flowchart in Fig. 4 starts by reading out the current I_{pv} and voltage V_{pv} for each instance of time using sensors, then providing these data to the proposed MPPT-SMC algorithm to predict the suitable duty cycle that convey the MPP. This duty cycle is transposed as a PWM signal to control the DC–DC boost converter to adjust the PV panel' current and voltage output. The rest of the circuit is used to invert the output from DC to AC (Fig. 5).

3 Recursive Bayesian Estimation

Recursive Bayesian estimation (or Bayes filter) is a method used for approximating an unidentified likelihood of concentration gathering iteratively in time by means of received quantities and a mathematical progression model [19]. Figure 6 shows the process of the recursive Bayesian prediction.

The derivation of the mathematical model consists of the following equation [20]:

$$p(S^{k} | M^{k}) = \frac{p(M^{k} | S^{k})p(S^{k})}{p(M^{k})},$$

$$= \frac{p(M^{k}, M^{k-1} | S^{k})p(S^{k})}{p(M^{k}, M^{k-1})},$$

$$= \frac{p(M^{k} | M^{k-1}, S^{k})p(M^{k-1} | S^{k})p(S^{k})}{p(M^{k} | M^{k-1})p(M^{k-1})},$$

$$= \frac{p(M^{k} | M^{k-1}, S^{k})p(S^{k} | M^{k-1})p(M^{k-1})p(S^{k})}{p(M^{k} | M^{k-1})p(M^{k-1})p(S^{k})},$$

$$= \frac{p(M^{k} | S^{k})p(S^{k} | M^{k-1})}{p(M^{k} | M^{k-1})}$$
(9)

where $p(M^k | S^k)$, $p(S^k | M^{k-1})$, and $p(M^k | M^{k-1})$ are likelihood, prior, and evidence, respectively. The likelihood $p(M^k | D^k)$ fundamentally controls the dimension noise model in the output equation. The prior $p(S^k | M^{k-1})$ describes the knowledge of the model, and calculated as [19]

$$p(S^{k} \mid M^{k-1}) = \int p(S^{k} \mid S^{k-1}) p(S^{k-1} \mid M^{k-1}) dx^{k-1}$$
(10)

defining $p(S^k | S^{k-1})$ is the alteration density of the state. Furthermore, the evidence also known as the standardizing constant hinge for $p(M^k | S^k)$, where it is distinct by means of measurement function and its noise, while being described by [20]

$$p(M^{k} \mid M^{k-1}) = \int p(M^{k} \mid S^{k}) p(S^{k} \mid M^{k-1}) dx^{k}$$
(11)

Calculating or calculating these three components is the essence of recursive Bayesian estimate. Additionally, based on the recursive Bayesian technique, stochastic filtering can be categorized into three main categories [20]:

Prediction: a priori arrangement of approximation. It aims to originate information regarding the magnitude of interest which will be at time $t + \tau$ in the upcoming ($\tau > 0$) by means of information measured up to time t. The prediction foresees the compactness gathering of the state onward from a measurement time to the next. The state is exposed to unidentified instabilities exhibited as arbitrary noise, and generally decodes, distorts, and ranges the state concentration [19]. Explicitly, provided the value of $p(S^{k-1} | M^{1:k-1})$ is accessible for t_{k-1} , this time comprises $p(S^k | M^{1:k-1})$.

Filtering: The extraction of desired information in time t by means of data distinguished up to time t.

Smoothing: Capturing the important patterns in the data by removing the noise. This step involves updating the prediction density from Eq. 10 constructed by the newest



Fig. 5 Flow diagram of suggested MPPT-SMC

measurement received, specifically specified by the measurement M^k [20].

3.1 Sequential Monte Carlo Technique

In general, the fundamental nature of SMC is to approximate the posterior density function by evaluating the weight of each sample [19, 20]. Specifically, using a sequential importance resampling (SIR) predictor, the proposed method will aim to estimate the most likelihood of the next best duty cycle x^{k+1} based on all previous duty cycle estimations. Now to achieve this, a state-space model representation of the PV system is required. A full nonlinear time invariant state-space







Fig. 6 Flow diagram of recursive Bayesian estimation

 Table 1
 Simulation specifications of model, PV arrays, and boost converter used in the design

Parameter	Value		
PV-array type	SPR-305E-WHT-D		
P _{max}	305.23 W		
$V_{ m mpp}\&I_{ m mpp}$	54.710 V, 5.580 A		
$V_{\rm oc}\&I_{\rm sc}$	64.2 V, 5.96 A		
Sampling time	50 µ s		
P&O D step size	300 µ		
Resistance (<i>R</i>)	$5\mathrm{m}\Omega$		
Inductor (L)	5 mH		
Irradiance (<i>Ir</i>)	100 Variable		
Temperature (T)	100 Variable		
Partial shading	100 Variable		

model is represented by [20]:

$$x^{k} = f(u^{k-1}), (12)$$

$$y^k = D(x^k). (13)$$

where x is the state vector, $u = [V_{pv}I_{pv}]^T$ is the input vector for the MPPT-SMC algorithm, and y is measurement vector that includes the predicted duty cycle, and they are represented as

$$x^{k} = \mathbf{A}u^{k-1} + n^{k-1},\tag{14}$$

$$y^k = \mathbf{B}x^k + v^k = D^k.$$
(15)

where $\mathbf{A} = \begin{pmatrix} -1/v_o & 1/I_{pv}^{k-1} \\ 0 & 1 \end{pmatrix}$, and is defined as the state transition matrix. $\mathbf{B} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$, and its defined as the measurement transition matrix. v_o is the priori estimation of the DC–DC boost converter output voltage estimated from the proposed distribution. n^{k-1} is a 2 × 1 matrix representing the state noise processes, and v^k is a 2 × 1 matrix representing the measurement noise process, and both are modeled as Gaussian with zero mean and covariance matrices of \mathbf{Q} and \mathbf{R} .

Provided with the state-space model, the process begins by initiating a proposal distribution based on calculating the MPP voltage V_{mp} and current I_{mp} at standard test conditions (STC) provided by the PV array specification given in Table 1 and presented by the following equation,

$$q(x^{k} | x_{i}^{k-1}, y^{k}) = \mathbf{M}G^{k-1} + n^{k-1}$$
(16)

where $G = [V_{\text{mp}}^{k-1} I_{\text{mp}}^{k-1}]^T$, and $\mathbf{M} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$. Then, the proposed SMC method is expected to predict the next best duty

cycle D^k based on the previous duty cycle D^{k-1} and existing input PV current and voltage V_{pv} , I_{pv} values. Once D^k is predicated, the value is compared to the previous duty cycle D^{k-1} to obtain $\Delta D^k = D^k - D^{k-1}$. Where ΔD^k is the adaptive step size, D^{k-1} needs to be adjusted by either incrementing or decrementing it. Mathematically, the posterior density function can be expressed as [19, 20],

$$\hat{p}(x^{k} \mid y^{1:k}) = \sum_{i=1}^{N} w_{i}^{k} \delta(x^{k} - X_{i}^{k}),$$
(17)

where *N* represent the amount of resampling performed on each data "i.e., N = 10 was used", the Dirac delta distribution is represented by δ , and w_i^k is the normalized importance weight associated with particle x_i^k . To assess the above equation, an alternative illustration of the state space equations is presented as

$$x^k \sim p(x^k \mid x^{k-1}),$$
 (18)

$$y^k \sim p(y^k \mid x^k), \tag{19}$$

where $p(x^k \mid D^{k-1})andp(y^k \mid x^k)$ denote the probability of the state and measurement distribution. Following the derivations from [19], the normalized importance weight can be calculated by

$$w_i^k = \frac{p(y^k \mid x_i^k)p(x_i^k \mid x^{k-1})}{q(x_i^k \mid x_i^{k-1}, y^k)} w_i^{k-1},$$
(20)

where $p(x_i^k \mid x^{k-1})$ is the prior of x^k . $q(x^k \mid x_i^{k-1}, y^k)$ is a proposal distribution. For SIR, choosing the right proposal distribution is a very crucial step since there are an infinite number of choices. The prime proposal distribution is the one that shrinks the variance of the significance weights conditional to $x^{0:k-1}$ and $y^{1:k}$ [20].

$$w_i^k = p(y^k \mid x_i^k) w_i^{k-1}.$$
 (21)

Assuming the initial density function $p(x_i^0)$ is known and x_i^0 is the initial state, then initialization of particles and their weights can be performed by

$$x_i^0 \sim p(x_i^0), \qquad i = 1, \dots, N.$$
 (22)

$$w_i^0 = \frac{1}{N},$$
 $i = 1, \dots, N.$ (23)

Substituting equations (22) and (22) into equation (17) produce,

$$\hat{p}(x^0) = \sum_{i=1}^{N} \frac{1}{N} \delta(x^k - x_i^0).$$
(24)

For all $k \ge 1$, we assume that the following estimation is available.

$$\hat{p}(x^{k-1} \mid y^{1:k-1}) = \sum_{i=1}^{N} w_i^{k-1} \delta(x^{k-1} - x_i^{k-1}).$$
(25)

The flowchart in Fig. 5 summarizes the sequence of the SMC algorithm predicting the next best duty cycle that will be passed to the boost converter [20]. As the algorithm starts by initializing a set of duty cycle values and calculates their initial weights based on the priori distribution, the algorithm then moves to perform measurement updates based on the state space model. Furthermore, the density function estimation and new weight calculations are assigned to the particles. Then, resampling is performed if the weight particles are below certain level of threshold. Finally, the best duty cycle is predicted according to the proposal distribution. Figure 19 shows some examples of random partial shading patterns and their weight calculations along different location of the IV curves, in addition to the associated duty cycle values found on the PV curves. The figure displays the difference between duty cycle values and the LMPP in comparison with the GMPP points.

4 Designed Simulink Model and Input Data

A complete Matlab/Simulink design model is illustrated in Fig. 12. The model consists of ramp-up/down input blocks that provide a random solar irradiation and temperature values that feeds into SPR-305E-WHT-D 3-PV array system. Each PV array is designed to provide a 305.226 W maximum power. The V_{mpp} and I_{mpp} are 54.7 V and 5.58 A, respectively. The V_{OC} is 64.2 V, while the I_{SC} is 5.96A. The dynamic partial shading input to the model was designed as a uniformly distributed random signal between 0.1-1. Any of the PV array might have different shading on one or more of the arrays. The PV block is connected to a DC-DC boost converter. The boost converter's duty cycle is controlled by the MPPT-SMC block where it provides a duty cycle value after its predictions. The rest of the system's blocks are required to connect to the main grid. The complete specifications for the PV arrays and boost converter are provided in Table 1. A high-level design of the complete level including the used input data (partial shading, temperature, and irradiance wave forms) is provided in Figs. 7, 8, 9, 10 and 11.





Fig. 8 Simple partial shading pattern at STC (Array1 = 0%, Array2 = 20%, Array3 = 30% shades)

4.1 High-Level Simulink Model

4.2 Mathematical Model of SMC Algorithm

In general, the fundamental nature of SMC is to approximate the posterior density function by evaluating the weight of each sample [19, 20]. Specifically, using a sequential importance resampling (SIR) predictor, the anticipated method will aim to estimate the most likelihood of the next best duty cycle S^{k+1} based on all previous duty cycles calculations. Now to reach this, a state-space typical representation of the solar system is required. A full nonlinear state space representation is given by [15]:

$$S^k = f(u^{k-1}),$$
 (26)

$$M^k = D(S^k). (27)$$

while *S* is the state function, $u = [V_{pv}I_{pv}]^T$ is input function for the MPPT-SMC algorithm, and *M* is measurement vector that includes the predicted duty cycle, and they are represented as [15]:

$$S^{k} = \mathbf{A}u^{k-1} + n^{k-1}, (28)$$

$$M^k = \mathbf{B}S^k + v^k = D^k.$$
⁽²⁹⁾

where $\mathbf{A} = \begin{pmatrix} -1/v_o & 1/I_{pv}^{k-1} \\ 0 & 1 \end{pmatrix}$, and it is defined as the state transition matrix. $\mathbf{B} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$, and its defined as the measurement transition matrix. v_o is the priori estimation of the DC–DC boost converter output voltage estimated from the proposed distribution. n^{k-1} is a 2 × 1 matrix representing the state noise processes, and v^k is a 2 × 1 matrix represent-





Fig. 9 Moderate partial shading pattern at STC (Array1 = 0%, Array2 = 60%, Array3 = 20% shades)



Fig. 10 Severe partial shading pattern at STC (Array1 = 30%, Array2 = 90%, Array3 = 70% shades)

ing the measurement noise process, and both are modeled as Gaussian with zero-mean and covariance matrices of \mathbf{Q} and \mathbf{R} .

Provided the state-space model, the process begins by proposing a proposal distribution based on calculating the MPP voltage V_{mp} and current I_{mp} at STC provided by the PV array specification given in Table 1 and presented by the following equation [19]:,

$$q(S^{k} \mid S_{i}^{k-1}, M^{k}) = \mathbf{Y}G^{k-1} + n^{k-1}$$
(30)

where $G = [V_{mp}^{k-1}I_{mp}^{k-1}]^T$, and $\mathbf{Y} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$. Then, the proposed SMC method is expected to predict the next best duty cycle D^k based on the previous duty cycle D^{k-1} and existing input PV current and voltage V_{pv} , I_{pv} values. Once D^k is predicated, the value is compared to the previous duty cycle D^{k-1} to obtain $\Delta D^k = D^k - D^{k-1}$, where ΔD^k is the adaptive step size that D^{k-1} need to be adjusted by either incrementing or decrementing it. Mathematically, the poste-





Fig. 11 Dynamic partial shading patterns at STC (shading is random)

rior density function can be expressed as [19, 20],

$$\hat{p}(S^k \mid M^{1:k}) = \sum_{i=1}^N w_i^k \delta(S^k - S_i^k),$$
(31)

where *N* represent the amount of resampling performed on each data "i.e., N = 10 was used", the Dirac delta distribution is represented by δ , and w_i^k is the standardized importance weight related to a particle x_i^k . To assess the above equation, an alternative illustration of the state equations is presented as [19, 20]

$$S^k \sim p(S^k \mid S^{k-1}), \tag{32}$$

$$M^k \sim p(M^k \mid S^k), \tag{33}$$

where $p(S^k | D^{k-1})$ and $p(M^k | S^k)$ symbolize likelihood of the state to measurement scattering. Following the process from [19], the standardized weight can be calculated by [20]

$$w_i^k = \frac{p(M^k \mid S_i^k) p(S_i^k \mid S^{k-1})}{q(S_i^k \mid S_i^{k-1}, M^k)} w_i^{k-1},$$
(34)

where $p(S_i^k | S^{k-1})$ is the subsequent of S^k . $q(S^k | S_i^{k-1}, M^k)$ is the proposed distribution. For the algorithm, selecting the accurate proposal distribution is a critical key to enhance the performance. The prime proposal distribution is the one that shrinks the change of the consequence weights conditioning on $S^{0:k-1}$ and $M^{1:k}$ [20].

$$w_i^k = p(M^k \mid S_i^k) w_i^{k-1}.$$
 (35)

Presumptuous the initial compactness function $p(S_i^0)$ is provided and S_i^0 is the preliminary state, then initialization can be performed by [20]

$$S_i^0 \sim p(S_i^0), \qquad i = 1, \dots, N.$$
 (36)

$$w_i^0 = \frac{1}{N},$$
 $i = 1, \dots, N.$ (37)

Fill in for equations (14) and (15) into equation (11) yield,

$$\hat{p}(S^0) = \sum_{i=1}^{N} \frac{1}{N} \delta(S^k - S_i^0).$$
(38)

Provided for all $k \ge 1$ the subsequent approximation is accessible [19].

$$\hat{p}(S^{k-1} \mid M^{1:k-1}) = \sum_{i=1}^{N} w_i^{k-1} \delta(S^{k-1} - S_i^{k-1}).$$
(39)

The flowchart in Figs. 5 and 6 recapitulates the sequence of the SMC algorithm predicting the next best duty cycle to be provided to as an input to the converter [20]. As the algorithm starts by initializing a set of duty cycle values and calculate their initial weights based on the priori distribution, the algorithm then moves to perform measurement updates based on the state space model. Further, the density function estimation and new weight calculations are assigned to the particles. Then, resampling is performed if the weight particles are below certain level of threshold. Finally, the best duty cycle is predicted according to the proposal distribution.





Fig. 12 A circuit diagram representation of photovoltaic system



Shading Pattern	Comparison @ STC/slow changing weather conditions			No/simple shadin	No/simple shading patterns		
	Algorithm	MPPT power (kW)	Rated power	Tracking speed	Efficiency	Oscillation	
No shading	P&O	300.74	303.17	0.73 s	99.20%	Low	
(STC)	PSO	148.61 (W)	148.9 (W)	1.05 s	99.81%	Zero	
	FPA	148.64 (W)	148.9 (W)	0.45 s	99.85 %	Zero	
	MPPT-SMC	302.85	303.17	0.18	99.89 %	Zero	
No shading	P&O	ave(275.95)	ave(285.69)	ave(0.73 s)	96.59%	Moderate	
(Varying Irradiance)	PSO	NP	NP	NP	NP	NP	
(Varying Temp.)	FPA	NP	NP	NP	NP	NP	
	MPPT-SMC	ave(285.32)	ave(285.69)	ave(0.19 s)	99.87%	Zero	
Simple shading	P&O	69.07 (W)	69.68 (W)	0.75 s	99.12%	Strong	
(Constant Irradiance)	PSO	68.81* (W)	69.68 (W)	1.2 s	99.90%*	Zero	
(Constant Temp.)	FPA	69.91* (W)	69.68 (W)	0.45 s	99.90%	Zero	
	MPPT-SMC	NP	NP	NP	NP	NP	
Simple shading	P&O	ave(178.90)	ave(198.31)	ave(0.89 s)	90.21%	Moderate	
(Varying irradiance)	PSO	NP	NP	NP	NP	NP	
(Varying temp.)	FPA	NP	NP	NP	NP	NP	
	MPPT-SMC	ave(197.18)	ave(198.31)	ave(0.21 s)	99.43%	Zero	

Table 2 Simulation evaluation between rated power, classical P&O, PSO, FPA, and MPPT-SMC techniques

Refer to references [13, 14] for quantitative comparison values of FPA, PSO, and P&O

ave = The average of the rated power and actual power are changing since the irradiance and temperature input values are changing (see simulation figures)

NP not provided

*Error in provided data by reference [14], since it does not reflect the provided efficiency value

Figure 19 shows some examples of random partial shading patterns and their weight calculations along different location of the IV curves, in addition to the associated duty cycle values found on the PV curves. The figure displays the difference between duty cycle values and the LMPP in comparison with the GMPP points.

5 Simulation and Results

The evaluation of the MPPT-SMC presented in this article was executed using Matlab/Simulink software version 2019A. An average of a 100-kW grid connected PV array model has been used and modified to support the new proposed technique. The model consists of constant and ramp-up/down input irradiance and a temperature block, a block for the PV panels and a boost converter module with specifications listed in Table 1, an MPPT controller block, and a forced-commutated Voltage-Sourced Converter (VSC) that connected to a utility grid via a 100 kVA (260 V/25 kV) transformer. A total of 3 PV arrays were used in the simulation each having a 66-parallel string where each string is formed from 5 modules connected in series. Each module is designed from 96 PV cells [5].

The simulation results will consider six main patterns to assess the sturdiness and precision of the suggested

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algorithm. The first pattern will consider the standard test conditions where there are constant irradiance and temperature values with no partial shading affecting the system. The second pattern will move gradually to introduce changing irradiance and temperature values while having no partial shading. The third pattern will assess the system by stressing the system with simple partial shading while changing the irradiance and temperature input values. The fourth pattern will increase the partial shading to a moderate level. The fifth pattern will study the capability of the system while affecting it with a severe partial shading condition. The final assessment of the system will consider an approach that was not seen in the previous literature research and never was considered in the previous published algorithms and that is studying the system under dynamic partial shading environments.

The dynamic partial shading assessment is very crucial to evaluating any technique's accuracy and robustness, since it reflects the actual dynamic behavior of the environment where the system is placed by considering random changing irradiance and temperature values affecting the system while randomly changing the partial shading conditions. The random change in partial shading is a very likely condition, since partial shading depends on many factors, especially, random cloud movements, in addition to other random factors such as foreign objects and surrounding trees. So, evaluating the system with more realistic environment conditions will truly



Fig. 13 a Rated power versus generated power. b System generated current. c System generated voltage. d Predicted duty cycle for GMPP. Pattern-1: Simulated results comparison at STC: no partial shading, Irradiance = 1000 W/m^2 on each PV array, Temp = $25 \degree$ C)

give us an insight on the capability and sustainability of the MPPT algorithm. The results of the suggested technique will be paralleled to the conventional P&O, PSO, and FPA techniques. For reduction of cloudiness in all of the figures, the figures will only show the data of rated power (theoretically calculated), the suggested MPPT-SMC technique, and the classical P&O technique. PSO and FPA results data assessments will be listed in Table 2 referring to their references [11, 14], respectively.

5.1 Pattern 1: STC Constant Irradiance, Temperature, and No Partial Shading

As stated, the first pattern, considers a STC environment to evaluate the system at the best case scenario while having constant irradiance condition fixed at 1000 W/m², temperature fixed at 25°C and no partial shading affecting the

system. Figure 13 is divided into 4 subplots oriented top-left to bottom-right.

The first subplot shows the rated power vs. power output by means of the classical P&O technique, and the recommended MPPT-SMC technique. The second and third subplot give an insight view on locating the voltage and current values that produce the maximum power between the conventional P&O and the suggested MPPT-SMC techniques. The final subplot shows how the mentioned I–V points are predicted using the correct duty cycle.

From the results, the classical P&O technique shows a noticeable linger in its response when compared to the suggested MPPT-SMC. In addition, the outcomes illustrate that the anticipated MPPT-SMC technique has higher efficiency, better tracking speed, and almost no oscillation in contrast with the traditional P&O performance. I–V sub figures also show variation of locating the correct current and voltage





Fig. 14 a Rated power versus generated power. **b** System generated current. **c** System generated voltage. **d** Predicted duty cycle for GMPP. Pattern-2: simulated results comparison with no partial shading, Irradiance = $N(950, 100) \text{ W/m}^2$, f = 10 Hz, Temp = $N(46, 15) \circ \text{C}$, f = 3 Hz)

values using both techniques. The final efficiency, tracking speeds, and oscillation are listed and referenced in Table 2.

5.2 Pattern 2: Varying Irradiance and Temperature While No Partial Shading

In the second pattern assessment, a varying irradiance and temperature input waveforms were introduced to the system while the effect of partial shading on the system was kept out. The irradiance input waveform was selected as a random Gaussian distributed signal (ex. frequency of "f = 10 Hz", mean of " $\mu = 950$ ", and standard deviation of " $\sigma = 100$ "), while the temperature input waveform was selected, also, as a random Gaussian distributed signal (ex. f = 3 Hz, $\mu = 46$, and $\sigma = 15$), since the nominal cell temperature of the used PV panel is 46 °C and the variation of temperature in comparison with the irradiance is usually slower. Figure 7 exhibits an



example of the generated waveforms based on the described specifications. It is worth noting that many input waveforms were tried to ensure the robustness and the accuracy of the system and all provided the same results.

In the second pattern assessment, a varying irradiance and temperature input waveforms were introduced to the system while the effect of partial shading on the system was kept out. The irradiance input waveform was selected as a random Gaussian distributed signal (ex. frequency of "f = 10 Hz", mean of " $\mu = 950$ ", and standard deviation of " $\sigma = 100$ "), while the temperature input waveform was selected, also, as a random Gaussian distributed signal (ex. f = 3 Hz, $\mu = 46$, and $\sigma = 15$), since the nominal cell temperature of the used PV panel is 46 °C and the variation of temperature in comparison with the irradiance is usually slower. Figure 7 exhibits an example of the generated waveforms based on the described specifications. It is worth noting that many input waveforms





Fig. 15 a Rated power versus generated power. **b** System generated current. **c** System generated voltage. **d** Predicted duty cycle for GMPP. Pattern-3: simulated results comparison with simple partial shading, Irradiance = $N(950, 100) \text{ W/m}^2$, f = 10 Hz, Temp = $N(46, 15) \degree \text{C}$, f = 3 Hz)

were tried to ensure the robustness and the accuracy of the system, and all provided the same results.

Evaluating the system in this scenario by means of the suggested MPPT-SMC displays a noticeable advantage when correlated with the classical P&O technique and yields higher efficiency, higher tracking speed, and no oscillation about MPP as comprehended in Fig. 14. However, this scenario was not studied by the FPA and PSO techniques for comparison.

Refer to Table 2 for more detail comparison between all four technique. In addition, analyzing the subfigures of the current, voltage, and duty cycle from Fig. 14 shows the stability in finding all these measurement points that produce maximum power.

5.3 Pattern 3: Varying Irradiance, Temperature, and Simple Partial Shading

In the third pattern assessment, partial shading was introduced to the system. As before, the system had varying temperature and irradiance input waveforms, but simple partial shading conditions were presented to the system as an additional environmental effect reducing the amount of power generation. As stated earlier, partial shading adds complexity on locating the global maximum point due to the multiple or several peaks generated on the P–V curve. Locating the GMPP accurately and efficiently is the goal of the projected technique. The introduced partial shading





(a) Rated power vs. generated power.



(b) System generated current.



Fig. 16 a Rated power versus generated power. **b** System generated current. **c** System generated voltage. **d** Predicted duty cycle for GMPP. Pattern-4: simulated results comparison with moderate shading, Irradiance = N(950, 100) W/m², f = 10 Hz, Temp = N(46, 15) °C, f = 3 Hz

sequence was as follows: no shading affecting the first PV array, 20% shading on the middle PV array, and 30% shading on the last PV array.

Figure 8 displays the I–V and P–V curves of the simple partial condition at STC. The P–V curve figure displays three peaks, one of them is a global peak, while the other two peaks are local. Identifying the global peak quickly and efficiently was achieved using the proposed MPPT-SMC technique.

Figure 15 confirms that even with simple shading pattern affecting the PV system, the recommended technique successfully and quickly is able to identify and locate the GMPP to generate the max power available out of the design. From the figure, the variation is clearly seen between the classical P&O and the new suggested technique.

Table 2 shows the variation in efficiency and tracking speed between P&O, FPA, PSO, and MPPT-SMC suggested technique.

5.4 Pattern 4: Varying Irradiance and Temperature, and Moderate Partial Shading

For the moderate partial shading pattern assessment, the system input waveforms were kept as in the previous case; however, the partial shading effect was increased on the system. The moderate partial shading was as follows: no shading on the first PV array, 60% shading on the middle PV array, and 20% shading on the last PV array.

Figure 9 displays the I–V and P–V curve of the moderate shading condition at STC. The P–V curve in the figure clearly shows the increase in severity of partial shading condition by having more mature global and local maximum power points, and this adds complexity when attempting to locate the GMPP since any of the peaks can be mistaken to be a GMPP.



Shading pattern	Comparison @ dynamic weather conditions			Moderate/extreme shading patterns		
01	Algorithm	MPPT power (kW)	Rated power	Tracking speed	Efficiency	Oscillation
Moderate shading	P&O	ave(131.29)	ave(151.75)	ave(1.25 s)	86.52%	Strong
(Varying irradiance)	PSO	NP	NP	NP	NP	NP
(Varying temp.)	FPA	NP	NP	NP	NP	NP
	MPPT-SMC	ave(150.58)	ave(151.75)	ave(0.21 s)	99.23%	Zero
Severe shading	P&O	29.68 (W)	56.61(W)	1.36 s	51.52%	Strong
(Constant irradiance)	PSO	49.96 (W)	56.61 (W)	1.2 s	86.52%*	Zero
(Constant temp.)	FPA	55.71 (W)	56.61 (W)	0.60 s	99.21%	Zero
	MPPT-SMC	NP	NP	NP	NP	NP
Severe shading	P&O	ave(69.22)	ave(90.54)	ave(1.65 s)	76.45%	Strong
(Varying irradiance)	PSO	NP	NP	NP	NP	NP
(Varying temp.)	FPA	NP	NP	NP	NP	NP
	MPPT-SMC	ave(89.44)	ave(90.54)	ave (0.23s)	98.79%	Zero
Dynamic shading	P&O	ave(105.92)	ave(141.93)	ave(3.66 s)	74.63%	Strong
(Varying irradiance)	PSO	NP	NP	NP	NP	NP
(Varying temp.)	FPA	NP	NP	NP	NP	NP
-	MPPT-SMC	ave(139.91)	ave(141.93)	ave(0.35 s)	98.58%	Zero

Table 3 Simulation evaluation between rated power, classical P&O, PSO, FPA, and MPPT-SMC techniques continues

Refer to references [13, 14] for quantitative comparison values of FPA, PSO, and P&O

ave = The average of the rated power and actual power are changing since the irradiance and temperature input values are changing (see simulation figures)

NP not provided

*Error in provided data by reference [14], since it doesn't reflect the provided efficiency value

Figure 16 represents the maximum power produced by the system while under moderate shading circumstances. From the figure, it is obvious that the suggested MPPT-SMC quickly and precisely predicts the GMPP while varying the irradiance and temperature values. The figure indicated very high efficiency, high tracking speed, and no power oscillation. Additionally, the classical P&O technique lingers in finding the correct GMPP for the provided input waveforms, and once the point is found, the algorithm struggles on finding the next GMPP resulting in lower efficiency, slower tracking speed, and increased power oscillation. Table 3 has full comparison details to the remaining techniques.

5.5 Pattern 5: Varying Irradiance and Temperature, and Severe Partial Shading

Moving on with the analysis, the fifth pattern applied severe partial shading on the system. The system had 30% shading on the first PV array, 90% shading on the middle PV array, and 70% shading on the last array. Figure 10 expresses the I–V, and P–V curves of the severe partial condition at STC. From the figure, it is conspicuous that LMPPs and GMPP are very close to each other in values, and easily can be falsely interpreted of one another. Considering Fig. 17, the results display high performance efficiency using MPPT-SMC algorithm compared to the rated power and to the classical P&O technique. Moreover, the foreseen technique displays fast tracking speed, and no power oscillation around the MPP. The subfigures also displays the capability of the suggested MPPT-SMC algorithm to efficiently predict the duty cycle value that accurately locate the GMPP without producing any power oscillations.

5.6 Pattern 6: Varying Irradiance, Temperature, and Dynamic Partial Shading

In the final assessment, the anticipated MPPT-SMC technique was considered under dynamic partial shading while varying the input irradiance and temperature waveforms. Under dynamic partial shading conditions, the effect of partial shading changes dynamically and unpredictably representing actual and more realistic weather and environmental conditions such as movement of the clouds in the sky, or flying objects, birds, and soil/sand dust particles due to wind storm effects (i.e., common in desert areas, and specifically the middle east region). This study scenario was not seen nor considered by reviewed literature even though it is a





Fig. 17 a Rated power versus generated power. **b** System generated current. **c** System generated voltage. **d** Predicted duty cycle for GMPP. Pattern-5: simulated results comparison with severe partial shading, Irradiance = $N(950, 100) \text{ W/m}^2$, f = 10 Hz, Temp = $N(46, 15)^{\circ}$ C, f = 3 Hz)

very important case, because it usually cause a dramatic power degradation. Dynamic partial shading causes the system to keep jumping and relocating the GMPP randomly and dynamically to any place on the P–V curve, instigating intense complexity in localizing the GMPP correctly and efficiently. Considering this case, Fig. 11 demonstrates several possible partial shade conditions moving dynamically all over the P–V curve.

The figure shows how the suggested MPPT-SMC technique approaches this problem by focusing on the GMPP by assigning high importance weight to them and eliminating the LMPP by giving them lower weight values adapted from the nature of the algorithm. From the figure and with very few iterations ($N \le 10$), the algorithm was able to identify and assign weight to all MPP, then accurately identify and predict the most likelihood of the location of the global point on the I–V curve which then translated to a duty cycle using Eq. 6. The P-V curve in Fig. 11 shows the GMPP and LMPP with duty cycle values translated from the I-V curve. Examining Fig. 18 provides a clear insight on the accuracy and the fast tracking speed of the suggested technique to predict and locate the GMPP while dynamic shading is in effect. Furthermore, the recommended method displays no oscillation around the MPP, while keeping up with the dynamic partial shading condition. This case adds to the capability and sustainability of the proposed method when it comes to predicting and locating the GMPP to produce the highest power generation possible from the system. Refer to Table 3 for a complete measureable evaluation amongst the classical P&O, PSO, FPA, and the submitted MPPT-SMC techniques. Figure 19 is an illustration for several IV and PV curves demonstrating different and randomly selected partial shading weather conditions and the process of the SMC algorithm assigning weights for a variety of points on the IV curves.





Fig. 18 a Rated power versus generated power. b System generated current. c System generated voltage. d Predicted duty cycle for GMPP. Pattern-6: simulated results comparison with dynamic shading, Irradiance = N(950, 100) W/m², f = 10 Hz, Temp = N(46, 15) °C, f = 3 Hz)

Then, the model proceeds to calculate the duty cycle values for the points with the highest weights importance based on the designed state space model adaptively. From the figure, it is clear that the algorithm accurately and effectively locates the GMPP points while eliminating the LMPP points successfully. These duty cycles are then passed to a boost converter to adjust the load to manipulate certain PV panels power productions to allow the partially shaded PV panels to increase their production to optimize the overall system's power generation.

6 Conclusion

This article focuses on designing a new and highly power efficient maximum power point tracker technique based on the use of the sequential Monte Carlo technique that provides high power efficiency, fast tracking speed, while maintaining no power oscillation. From the different types of SMC algorithms, sequential importance resampling technique was used and modeled to predict the best duty cycle value that was provided for a boost converter to provide the highest power generation under all environmental conditions. The newly proposed technique was evaluated using Matlab/Simulink. The assessment considered several environmental conditions varying from simple partial shading to severe partial shading while having a varying input irradiance and temperature values. Finally, to further assess the capability and sustainability of the technique, dynamic partial shading patterns was considered in the evaluation. The importance of considering dynamic partial shading in the evaluation arises from the random behavior of the environment factors such as random cloud movements, irradiance, temperature, and shading objects present near the system. The results of the measure-





Fig. 19 Weight and duty cycle calculations using MPPT-SMC for several different partial shading patterns

ment were paralleled to the classical P&O, FPA, PSO, and to the rated power of the system. The results proved that the newly suggested MPPT-SMC technique showed an exceptional performance capability in regards to providing high efficiency, fast tracking speed, and no oscillation surrounding the MPP. The efficiency of the proposed MPPT-SMC technique ranged from as high as 99.89% under STC to 98.58% under severe and dynamic partial shading weather conditions while varying the temperature and the irradiance values. The tracking speed of the suggested MPPT-SMC techniques varied from 0.18 s under STC to 0.36 s when having dynamic and severe shading conditions. The overall evaluation of the model showed consistency on locating the MPP regardless of the present weather conditions.

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