Research Article

A Bayesian fusion technique for maximum power point tracking under partial shading condition

Ramesh Gugulothu[1] · Bhookya Nagu[1]

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Abstract

In this paper, a Bayesian fusion technique (BFT) based on maximum power point tracking (MPPT) is developed for the photovoltaic (PV) system that can exhibit faster and accurate tracking under partially shaded conditions (PSCs). Although the conventional hill-climbing algorithms have fast tracking capabilities, they are prone to steady-state oscillations and may not guarantee global peak under partially shaded conditions. Contrarily, the meta-heuristic-based techniques may promise a global peak solution, but they are computationally inefficient and take significant time for tracking. To address this problem, a BFT is proposed which combines the solutions obtained from conventional incremental conductance algorithm and Jaya optimization algorithm to produce better responses under various PSCs. The effectiveness of the proposed BFT-based MPPT is evaluated by comparing it with various MPPT methods, viz. incremental conductance, particle swarm optimization (PSO), and Jaya optimization algorithms in MATLAB/Simulink environment. From the various case studies carried, the overall average tracking speed with more than 99% accuracy is less than 0.25 s and having minimum steady-state oscillations. Even under the wide range of partially shaded conditions, the proposed method exhibited superior MPPT compared to the existing methods with tracking speed less than 0.1 s to achieve 99.8% tracking efficiency. A detailed comparison table is provided by comparing with other popular existing MPPT methodologies.

Highlights

- A Bayesian fusion technique (BFT)-based MPPT technique is proposed for PV system
- The BFT technique takes the best tracking solution by proper decision making on input data uncertainties
- The proposed technique is tested under different irradiance and shaded conditions of the PV system

Keywords Bayesian fusion method · Maximum power point tracking · Partially shaded condition · Photovoltaics

✉ Ramesh Gugulothu, rameshphd@student.nitw.ac.in; Bhookya Nagu, nagubhukya@nitw.ac.in | [1]Department of Electrical Engineering, National Institute of Technology Warangal, Warangal, Telangana, India.

1 Introduction

Photovoltaic (PV)-based power generation has gained immense attention over the past few decades. With advancements in PV technology, the PV cells have shown improved efficiency with reduced manufacturing costs [1]; also, PV systems have nonlinear characteristics dependent on various parameters such as irradiance, temperature, series, and parallel resistance. The power extracted from the PV panel is dependent on its output voltage for a given irradiance and temperature. This output voltage of the PV panel is usually varied using a power electronic converter that interfaces with load or grid. For full utilization of the installed PV panel, a proper maximum power point tracking (MPPT) technique that extracts maximum possible power from PV systems for a particular irradiance and temperature is needed. Conventionally, the MPPT technique such as perturb and observe (P&O) [2], incremental conductance [3] is used for PV power plants as appropriate for single peak characteristics to get MPPT and its improved strategies [4]. The main drawback of conventional methods is steady-state oscillations. Typically, the PV power plants are extended over a wide area by series and parallel combinations of multiple PV panels to increase the operating voltages and the capacity of the PV system. Due to the presence of multiple PV panels, there is a possibility of partial shading [5] where few PV panels get full irradiance and whereas others may be shaded due to passing clouds, shading effect of trees and buildings which in turn can lead to partial shading conditions (PSCs). The PV power plant under partially shaded conditions may exhibit multiple local peaks (MLPs) characteristics which include a global peak (GP) [6]. The conventional MPPT techniques based on the "hill-climbing" algorithm may not guarantee a global peak under these conditions and may be stuck at the local MPP. The multiple global maximum power point tracking (GMPPT) algorithms available in literature can be broadly categorized as (*a*). Two-stage algorithms for GMPPT and (*b*). Soft computing optimization algorithms.

A two-stage algorithm for GMPPT is explained in [7], in which the phenomena of PSC are detected in PV array using respective MLP voltage levels; the algorithm compares the power level of every MLPs to locate the GMPP. This method, however, requires more voltage sensors across every bypass diode thereby increasing the overall cost of the system. A modified hill-climbing technique is proposed in [8], where the currents at multiples of 80% of the open-circuit voltage of each panel are measured and used to estimate the *P*–*V* curve with MLPs. The modified hill-climbing technique identifies all the MLPs and compares their respective peak-power to get GMPP. Although this method can achieve GMPP, PVs are operated at a wide range of voltage levels for obtaining at MLPs before reaching GMPP.

A meta-heuristic particle swarm optimization (PSO)-based MPPT is used for the PSCs to guarantee convergence of the GMPP [9], but tuning of parameters such as initial weight factor and cognitive parameters plays a key role in successful tracking of the GMPP. Improper tuning of optimization parameters may either lead to sub-optimal MLP tracking or may lead to slow tracking speed along with steady-state oscillatory behaviour in the PV output power.

Many other meta-heuristic algorithms [10], such as genetic algorithm [11], artificial bee colony [12], grey wolf optimization (GWO) [13], ant colony optimization [14], flower pollination algorithm [15], overall distribution of PSO[16], Leader Particle Swarm Optimization [17], Fibonacci search (FS) [18], extremum seeking control (ESC) [19], Artificial Neural network (ANN) [20] and improved cuckoo search [21], hybrid adaptive P&O and PSO [22], the Hybrid Enhanced Leader PSO-P&O [23], are proposed to track GMPP for a PV system that has MLPs during partially shaded conditions. But all these algorithms optimize tuning parameters that need to be properly selected; otherwise the optimization algorithm may increase the tracking time or may be stuck at any local peak point. In [24], Jaya algorithms are proposed which do not require any parameter tuning for tracking the GMPP. This method is proved to track speed faster and exhibits less oscillatory behaviour steady-state at GMPP compared to PSO. Nevertheless, this method may still take significant time compared to the conventional methods and highly dependent on the initial candidate. Meta-heuristic-based modified butterfly algorithm (MBOA) [25] and a radial movement optimization (ARMO) [26] MPPT tracking algorithm were proposed optimal tracking under partial shading conditions and fast varying loads. But the tracking speed and accuracy of these methods are highly sensitive for the optimization parameter which should be properly selected for best results.

Under soft computing, optimization algorithms are used to implement the GMPP [27]. All these soft computing GMPPT techniques are favourable in finding the GMPPT for most PSCs, but they are computationally inefficient [28]. Consequently, these methods are executed at a predetermined time that may lead to inefficient tracking performance under fast irradiance variation.

In addition to this, machine learning-based approaches are developed for the accurate tracking of MPPT. A neural network is designed to track MPP for the PV system [29]. The main drawback of this method is that it needs exact data to give the optimal values, but the Bayesian fusion technique [30] mainly quantifies the uncertainty of the parameters (maximum values); this gives the distribution of parameter values (uncertainty), whereas neural network gives only optimal value with respect data, that is when the data is available, both neural network and BFT give accurate results, whereas, in the region where the data is insufficient or unavailable, BFT gives its confidence interval. A technique, which has not been considered for MPPT already, yet which is more popular in the section of machine learning, is the Bayesian fusion technique. This technique can detect global optimum as an insignificant function in very few evaluations. One well-known method is to design the undefined consequence as a Gaussian process (GP) [31]. The GP designs provide an expected estimate and uncertainty information, it is used as feature vectors function assessments to the position that are instructive regarding the maximum [32].

This paper proposes a Bayesian fusion technique (BFT) for tracking GMPP under PSCs. In this method, the Bayes' theorem is applied to obtain a proper GMPP solution by combining the information obtained from two methods [33–35], i.e., incremental conductance and Jaya algorithm for different partially shaded conditions. As the solutions from both conventional method and meta-heuristic algorithms are used, based on previous probabilities, the BFT technique can reduce the overall convergence time, increase tracking accuracy, and reduce steady-state oscillation. For this reason, the BFT method is more satisfactory than the distribution-based techniques. The BFT adopts its solution based on the inputs obtained from incremental conductance and Jaya algorithm-based tracking information and is a step towards the best solution in the search domain.

The article is organized as follows. Section 2 explains the basics of solar PV modelling and its characteristics under PSCs, Sect. 3 briefs about incremental conductance, and Jaya MPPT techniques. The mathematics for basic Bayesian fusion and the proposed BFT-based MPPT tracking and the proposed method is evaluated in Sect. 4, various simulation case studies are outlined in Sect. 5, results of comparative studies are reported in Sect. 6, and 7 concludes the paper.

Table 1 Rating of the PV module

P_{max}	V_{oc}	I_{sc}	V_{max}	I_{max}
60 W	21 V	3.8 A	17.1 V	3.5 A

2 Modelling of solar PV and its characteristics

PV module takes part in assembling by the number of solar PV cells. Accordingly, single diode model representation and its characteristics of the solar PV cell have been shown in Fig. 1, the mathematical outline equations for the [36] modelling of PV module have been given below, and the parameters are shown in Table 1. The solar PV module connected to the boost converter to gain the output power is shown in Fig. 2a.

$$I_{pv} = I_{ph} - I_O - \frac{\left(V_{pv} + I_{pv}R_S\right)}{R_{sh}} \tag{1}$$

$$I_{ph} = \left\{I_{SC-STC} + K_i\left(T - T_r\right)\right\} \frac{G}{G_{STC}} \tag{2}$$

$$I_o = I_{o1}\left(\exp\left(\frac{q\left(V_{pv} + I_{pv}R_s\right)}{Ak_bT}\right) - 1\right) \tag{3}$$

where V_{pv},I_{pv} are the output voltage, the current of the PV cell, q is the electron charge 1.602×10^{-19}C, I_{ph} is the solar photocurrent generated, R_S, R_{sh} are series and shunt resistance, A is diode ideality factor,I_O flows through diode it depends on the PV cell reverse saturation current I_{o1} that mainly depends on the temperature, K is the Boltzmann's constant, i.e., $1.38 \times e^{-23}$, I_{SC-STC} is the short circuit current

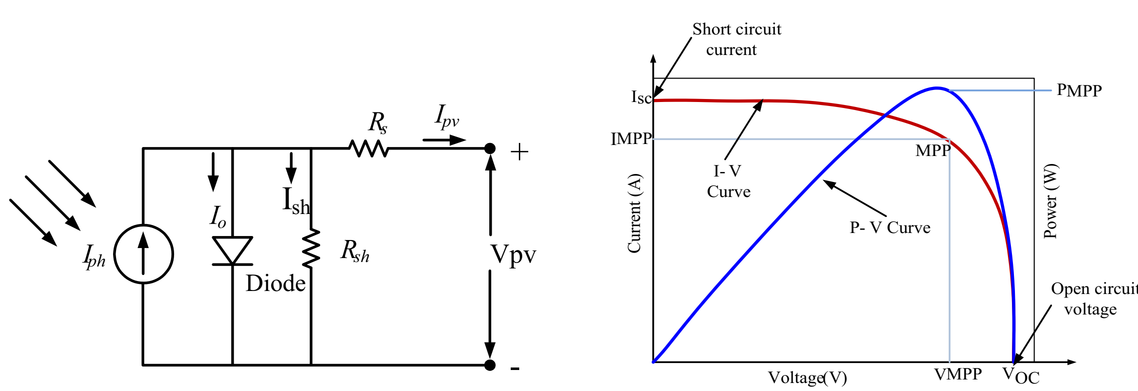

Fig. 1 Single diode model for solar PV and its characteristics

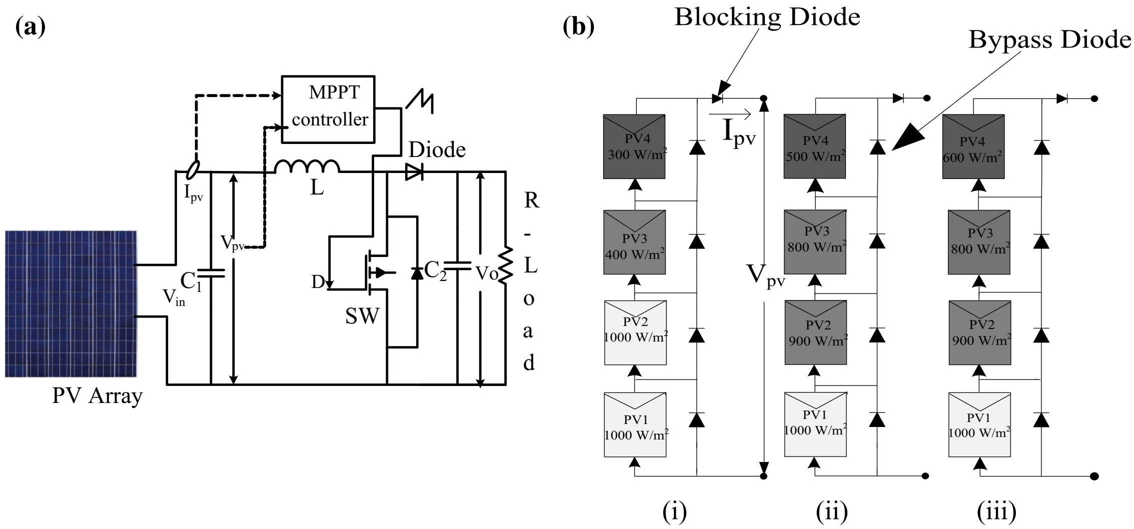

Fig. 2 **a** Schematic diagram of PV with boost converter. **b** Three different arrangement of array configuration exposed to different levels of partially shaded condition (i) pattern-1 (GMPP on the left side of the PV curve) (ii) Pattern-2 (middle global peak of the PV curve) (iii) pattern-3 (GMPP at right side of the PV curve)

Table 2 different patterns of the Irradiance (w/m^2) value

Module (PV)	Pattern-1 (W/m^2)	Pattern-2 (W/m^2)	Pattern-3 (W/m^2)
PV1	1000	1000	1000
PV2	1000	900	900
PV3	400	800	800
PV4	300	500	600

at STC. G_{STC} is the standard solar irradiation quantity on a solar PV cell (i.e.,1000 W/m^2),V_t is the thermal voltage of the diode, G is the solar irradiation quantity (W/m^2), T is the ambient temperature and T_r is the reference temperature.

Here, the output voltage of a Boost converter depends upon the duty cycle for balanced utilization of the MPPT procedure [37]. The interconnection for that input and output voltage as the results of the duty cycle can be communicated as (4)

$$\frac{V_O}{V_{in}} = \frac{1}{1 - D} \tag{4}$$

where V_O = Output Voltage, V_{in} = Input Voltage and D = Duty cycle.

This paragraph discusses the Solar PV under partially shaded condition (PSC) and discusses a PV array which accommodates the various PV modules that are associated in series and parallel [38]. The combination of every module generates power, which implies the PV array power. Out of the PV module, any single PV module is shaded instead of inadequate solar irradiation to achieve output power, assume as the shaded module in different levels are shown in Table 2 and shaded modules are shown in Fig. 2b, In every PSC combination, the number of PV modules is associated with a series arrangement called the patterns. The remaining modules generate the power and dissipate power to the load. The PV array works like a current I_a, but shaded modules are forced to operate the reverse-biased operating region, and the PV array behaves as a load rather than the power source [39]. This indicates more localized power loss and the hotspot will appear on an object with irreversible damage of the shaded PV module. Hence to avoid the hotspot by bypass diode is added into the PV modules under the PSC condition [40]. Bypass diode has been added in the configuration as shown in Fig. 2b, to protect from hotspot during PSC [41], under uniform irradiation plane, the bypass diodes are in forwarding biased as well as the current flow the diode in place of the module. Because of the bypass diodes, the multiple local peaks of the *P*–*V* curve appear under the PSC. For the simulation studied, three partially shaded patterns are considered, i.e., GMPP at the left side of the PV curve, the middle global peak of the PV curve, and GMPP at the right side of the PV curve. For the partially shaded condition, 4 series PV modules configuration are used as shown in Fig. 3.

Under normal conditions, conventional MPPT methods, which are P&O, incremental conductance methods [2, 42] track the maximum power. But under the PSC it is difficult to differentiate in the middle of local maximum power point and global maximum power point (GMPP). Hence, in this paper, some modifications are made to eminent tracking about the GMPP under PSCs.

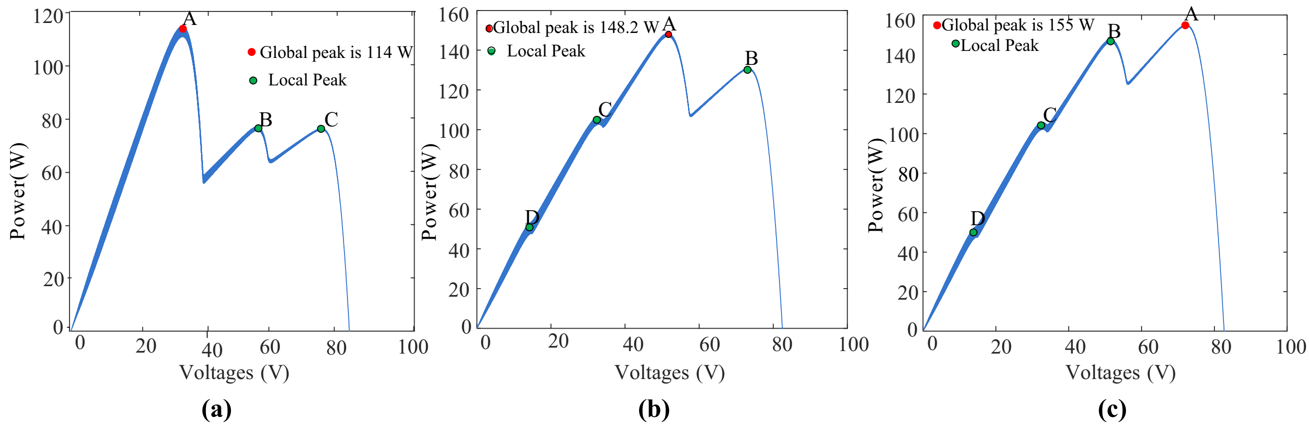

Fig. 3 *P–V* curves of the partially shaded patterns; **a** GMPP on the left side of the PV curve; **b** Middle global peak of the PV curve; **c** GMPP at right side of the PV curve

3 GMPPT methods

3.1 Incremental conductance method

The incremental conductance MPPT method is the most frequently utilized method because its performance has precise regulation with less steady-state oscillation under sudden change in weather conditions. In this method, the incremental conductance $\left(\frac{dI}{dV}\right)$ is compared to instantaneous conductance $\left(\frac{I}{V}\right)$ [4]. The operating point at which the difference between incremental conductance and instantaneous conductance will be zero is considered to be MPP are shown in Fig. 4. [42]. The detailed expressions that govern the incremental conductance MPPT are given by (5)–(9).

$$\frac{dP}{dV} = \frac{d(IV)}{dV} = I + V \cdot \frac{dI}{dV} = 0 \tag{5}$$

The above equation can be changed into the subsequent equation

$$-\frac{I}{V} = \frac{dI}{dV} = \frac{\Delta I}{\Delta V} \tag{6}$$

$$\frac{dI}{dV} = -\frac{I}{V}, \text{ at MPP} \tag{7}$$

$$\frac{dI}{dV} > -\frac{I}{V}, \text{ left of MPP} \tag{8}$$

$$\frac{dI}{dV} < -\frac{I}{V}, \text{ right of MPP} \tag{9}$$

A system to track the MPP by using an incremental conductance with a Cuk converter is presented [43].

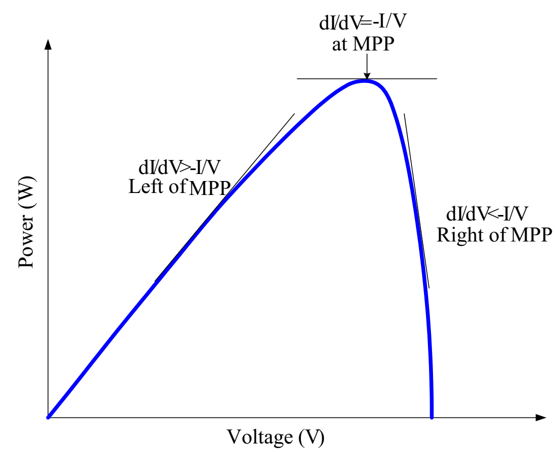

Fig. 4 basic *P–V* characteristics of incremental conductance method

The solar PV system operates under different environmental changes and is implemented by using simulation [44]. With a variable step, incremental conductance is implemented [45]. The effect of the IC parameter on the output is estimated, and the difference between the other algorithms is presented in [46]. A differentiation between IC and P&O is introduced [47]. The significant disadvantage of the above conventional technique has deviated from the maximum power point if there should be an occurrence of quickly changing weather conditions. More slow assembly, complex control hardware, and steady-state tracking oscillations around MPP are because of fixed step size. Anyway, these disadvantages are dispensed with if there is an occurrence of the Jaya method.

3.2 Jaya algorithm

Jaya algorithm is latterly developed as the meta-heuristic technique for solving optimization under constrained and unconstrained problems [48]. This method differs in algorithmic specific parameters compared to other heuristic techniques in that it has only two common parameters such as iteration and population size, and these parametric values are easily initialized. This critical improvement makes the utilization of the Jaya algorithm simple and proficient.

Let us consider $P = F(X)$ as the objective function, to maximize the P, $F(X)$best and $F(X)$worst is the description of the best values and worst values of the $F(X)$ out of all candidate solutions during every iteration [49, 50]. First the n number of candidate solutions are initialized and the next iteration of the Jaya algorithm is updated. Let k is the candidate solution under the ith iteration, the modified value of k^{i+1} is calculated by using the Jaya algorithm given below in Eq. (10)

$$x_i^{k+1} = x_i^k + r_1\left(X_{\text{best}} - X_i^k\right) - r_2\left(X_{\text{worst}} - X_i^k\right) \tag{10}$$

where x_i^k and x_i^{k+1} are the present and updated values, X_{best} and X_{worst} are the best and worst solution among all the candidates, r_1 and r_2 are the arbitrary numbers in between $U[0, 1]$, the term $r_1\left(X_{\text{best}} - X_i^k\right)$ is the solution of closer to the best, and $r_2\left(X_{\text{worst}} - X_i^k\right)$ is the avoid the worst solution. This method also observes fewer oscillations while tracking the GMPP, and it takes more iteration to reach the GMPP. This proposed technique combined the recent meta-heuristic Jaya algorithm and incremental conductance to improve the maximum power point tracking with less oscillation and less iteration.

4 Proposed Bayesian fusion technique for MPPT

This proposed work is based on the concept of Bayesian decision theory [35], to grow a mathematical fusion structure. This conceptualization enhances the integration of two or more MPPT tracking methods based on feature vector construction. Because of its probabilistic approach this proposed, approach can easily handle the uncertainties in irradiance and temperature [51].

4.1 Bayesian fusion formulation

The Bayesian technique has the provision of a reverse probability that models uncertainty based on available observations (likelihood and prior knowledge). There are two different interpretations of probability theory, in which one is a frequentist interpretation that provides the probability about the frequencies of events or trials. The other one is Bayesian interpretation that provides the probability to quantify the uncertainty about some parameters [52].

The most commonly used statistical interpretation method is the frequentist (or classical) method. In this interpretation, the unknown parameters are assumed as constant, and they define probability based on relative frequencies of event occurrence. This limits the decision-making capabilities on uncertain parametric conditions.

Bayesian fusion optimization techniques offer an alternative strategy; they treat as random parameters, and they define probability as "degrees of belief" has regard from these proposes that probabilities are instinctive and that can make probability explanations about parameters utilizing Bayes' theorem. Using Bayes' theorem. The Bayes theorem is intended to solve the problem after collecting the observed data events by using inverse probability.

Suppose an unknown state "S" which needs to be identified from the data set $a = \left\{a_{1,\ldots,}a_n\right\}$ by utilizing a statistical model characterized by a probability $P(a|S)$. Bayesian philosophy is used where uncertainty concerning the parameter limitation is expressed during the probability evidence and distributions. The following steps illustrate the essential fundamentals of Bayesian inference:

1. For the probability distribution "S" is a construct as $P(S)$ which is named as the prior distribution. This distribution communicates the probabilities (for example, on the mean, the skewness, the spread, etc.) about the given parameter before examining the given information.
2. For the given particular data a, the statistical model is represented as $P(a|S)$ is obtained to describe the distribution of S in given data.
3. The probabilities about S are updated by combining data information from the given prior distribution, and calculation the data through posterior distribution $P(S|a)$.

Simply, Bayes' theorem updates existing knowledge with new information. In the concept of Bayesian fusion, methods provide simple alternatives for the statistical inference all the inferences muster against the posterior probability distribution $p(S|a)$.

Practically, the posterior probability distribution can be obtained with simple analytical solutions for most rudimentary problems. Sophisticated computations with the inclusion of simulation methods are a part of most Bayesian analyses. The posterior distribution from the given sample data is defined as (11)

$$P(S|a) = \frac{P(a|S)P(S)}{P(a)} \tag{11}$$

For n number of independent random variables, vary from $n = 1$ to 2 N

$$P(S|a_n) = \frac{P(a_n|S)P(S)}{\sum_{n=1}^{2N} P(a_n|S)} \tag{12}$$

This Eq. (12) can be written as the product of the conditional probabilities

$$= \frac{1}{\sum_{n=1}^{2N} P(a_n|S)} [P(a_n|S)P(S)] \tag{13}$$

$$\frac{1}{Z} = \frac{1}{\sum_{n=1}^{2N} P(a_n|S)} \tag{14}$$

For n number of independent random variables, the posterior probability is given by

$$P(S|a_n) = \frac{1}{Z} \prod_{n=1}^{2N} P(a_n|S)P(S), \tag{15}$$

where $\frac{1}{Z} = \frac{1}{\sum_{n=1}^{3N} P(a_n|S)}$, $P(a_n|S)$ is the likelihood, $P(S)$ is the marginal distribution, and $P(S|a_n)$ is the conditional probability.

4.2 Maximum power point tracking using Bayes fusion technique

The BFT-based MPP tracking technique is designed using a Bayesian network [34]. A Bayesian network is a high-powered tool derived from the Bayes theorem that is used for the joint probability distribution of statistics fusion. In Bayes theorem, the posterior probabilities depend on prior probability distribution. The prior probability distribution is obtained from the statistical inference collected using a set of available prior information. Using current system information, a best rational assessment is applied to obtain the posterior probability. The prior probabilities are continuously updated based on the previous information available and thereby estimate the new posterior probabilities using Bayes' theorem. These posterior probabilities will help in identifying if the set of information passed is either new event-information or existing event information. This complete BFT process can be segmented into two parts.

(1) Feature vector production
(2) Decision making

4.2.1 Feature vector production

For multiple random variables, a Bayesian network is used to move in the direction of obtaining GMPP under the PSCs for PV array. The proposed work was done based on the joint probability distribution of statistics fusion of incremental conductance and Jaya algorithm. For better understanding, consider a PV system with four modules connected in series with each module having an input combination of voltages and currents pairs at 1000 W/m^2, and the total open-circuit voltage of the PV system will be $V_{oc} = nV_{OCM}$. Now, a Bayesian network is designed and observations input nodes, i.e.$\mathcal{L} = \{a_1, \dots a_n\}$, are equally divided into two parts named, left nodes $\{a_1, \dots, a_n\}$ and right nodes $\mathcal{R} = \{a_{n+1}, \dots, a_{2n}\}$, respectively. The left nodes $\mathcal{L} = \{a_1, ..., a_n\}$ are assigned with the voltage information of individual panels when operated at MPP obtained by incremental conductance under a partially shaded condition. Similarly, the right nodes $\mathcal{R} = \{a_{n+1}, \dots, a_{2n}\}$ are assigned with input voltages obtained across individual panels when the PV system operates using the Jaya MPP algorithm for similar partially shaded conditions. The network arrangement for the Bayesian network is shown in Fig. 5, in this network the output node is defined as "S". After assigning values to all observation nodes, the individual nodes of the left nodes are compared with the all right node to identify the matching nodes. Then the feature vector a is formulated using (16)

$$a(i) = a(j) = \begin{cases} 1 \text{ if } \mathcal{L}_i = \mathcal{R}_j \\ 0 \text{ if } \mathcal{L}_i \neq \mathcal{R}_j \end{cases} \forall i = 1, 2, ..\frac{n}{2}; j = 1, 2, \dots .\frac{n}{2} \tag{16}$$

If any two nodes on the left and right nodes are matched, then condition that "1" placed in the feature vector otherwise "0" placed. Such that feature a vector is signified by $a(t) = \{a_1(t), \dots ..a_n(t)\}$, where $a_i(t)$ represents to the condition of ith node at time t.

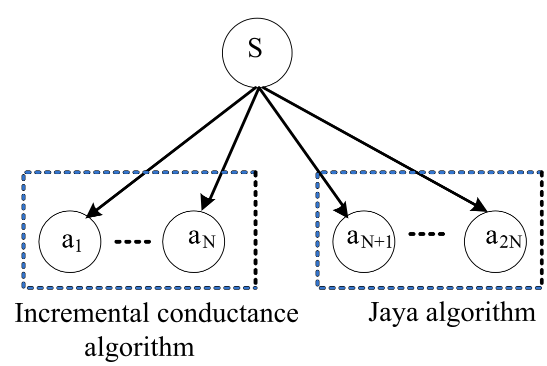

Fig. 5 Bayesian fusion structure for MPPT information

4.2.2 Decision making

The sample training data sets, i.e., input combination of voltages and currents pairs (V, I) of solar cell module with different irradiance and temperature, are noted and the output at each training data sets the GMPP (output) for both Jaya and incremental conductance method noted. This input data set (voltage, current, and corresponding output (GMPP)) serves as data set, 80% of samples are randomly picked as training data set, and 20% samples are picked as the testing set. The training data set (input, output) is utilized to train the BFT.

As mentioned above input nodes to be stated as {0 or 1}, and "S" has output nodes, i.e. $N_S + 1 = 527 + 1$ states, states: $S = \{s_1, \ldots \ldots S_{NS}$, No Event}. Every state $\{s_1, \ldots s_{Ns}\}$ compares to an expected point on the I-V curve. The location of the output point "S" (maximum power point) is estimated from the feature vector by appropriately tuned by the BFT.

When values of "S" are given, then the values of a_i are conditionally independent on "S". Hence conditional probability distribution based on the Bayes rule, $P(S|a_1, \ldots, a_N P(S|a_{N+1,\ldots}a_{2N})$, this distribution can be written as the product of the conditional probabilities $P(a_n/S)$ by using Eq. (17)

$$P(S/a_1, \ldots \ldots, a_{2N}) = \frac{1}{Z} P(S) \prod_{n=1}^{2N} P(a_n/S). \quad (17)$$

By using BFT is trained to estimate the prior and likelihood distribution and the constant value "Z" is calculated from the training data set. These distributions are used to predict the output "S" from the trained BFT.

Where $\frac{1}{Z} = \frac{1}{\sum_{n=1}^{2N} P(a_n|S)}$, $P(a_n|S)$ the likelihood, $P(S)$ is the marginal distribution, and $P(S/a_1, \ldots \ldots, a_{2N})$ is the conditional probability approximate from the training data sets. For every feature vector, the output "S" is given as a tag. The calculated conditional probability data saved in a particular table is called the conditional probability table (CPT). In this method, I-V curve points are stored under different irradiation, the temperature under partially shaded conditions. Hence, these are used as training sets. Irradiation values were changed from 1000 W/m^2 to 200 W/m^2 with a difference of 50W/m^2, with temperature changed from − 10 to 50 °C with a range of 2 °C in each combination in between these groups was considered for PV modules, the MPP values of voltages and current combinations are taken. These samples are used to deploy as a governor to the CPT training. The block diagram of the Bayesian fusion optimized proposed controller is shown in Fig. 6. As well as in the flowchart shown in Fig. 7.

At this point, once the PV array system is under operating conditions, the feature vectors were determined each time as evidence. By using evidence obtaining the conditional probability as above (17), conditional probability determined to the most credible state of "S" was acquired, i.e. the most probable maximum output power with less steady-state oscillation, more tracking speed, with less iteration with more efficiency is observed by combining the incremental conductance and Jaya algorithm compared to individual meta-heuristics techniques.

5 Simulations and discussion

A PV system with 4 PV modules configured in series is connected to the standalone loads using a boost converter shown in Fig. 2a which is considered for simulation studies. The parameters of the boost converter and algorithms data values have to be shown in Table 3. The simulation outcome is executed by applying the proposed Bayesian fusion optimization technique (BFT) to get the global maximum power point (GMPP) in MATLAB/SIMULINK for three possible patterns shown in Table 1 under the PSCs.

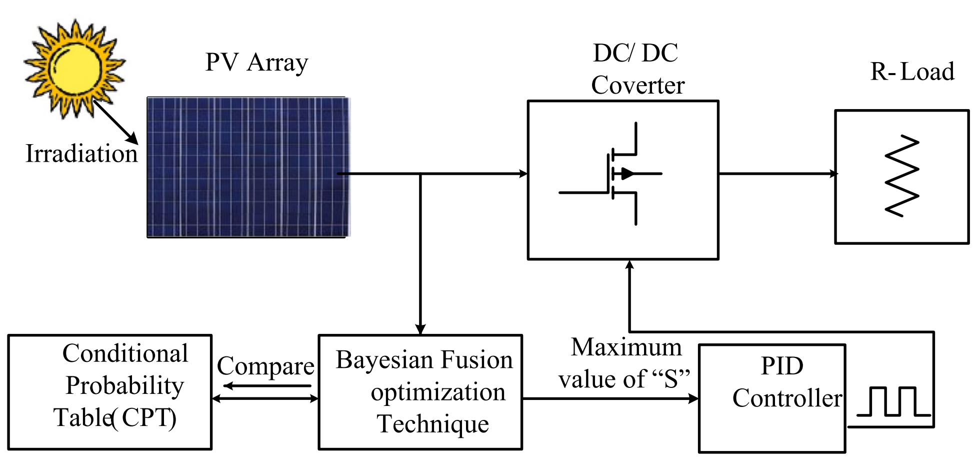

Fig. 6 Block diagram of proposed Bayesian fusion optimized controller

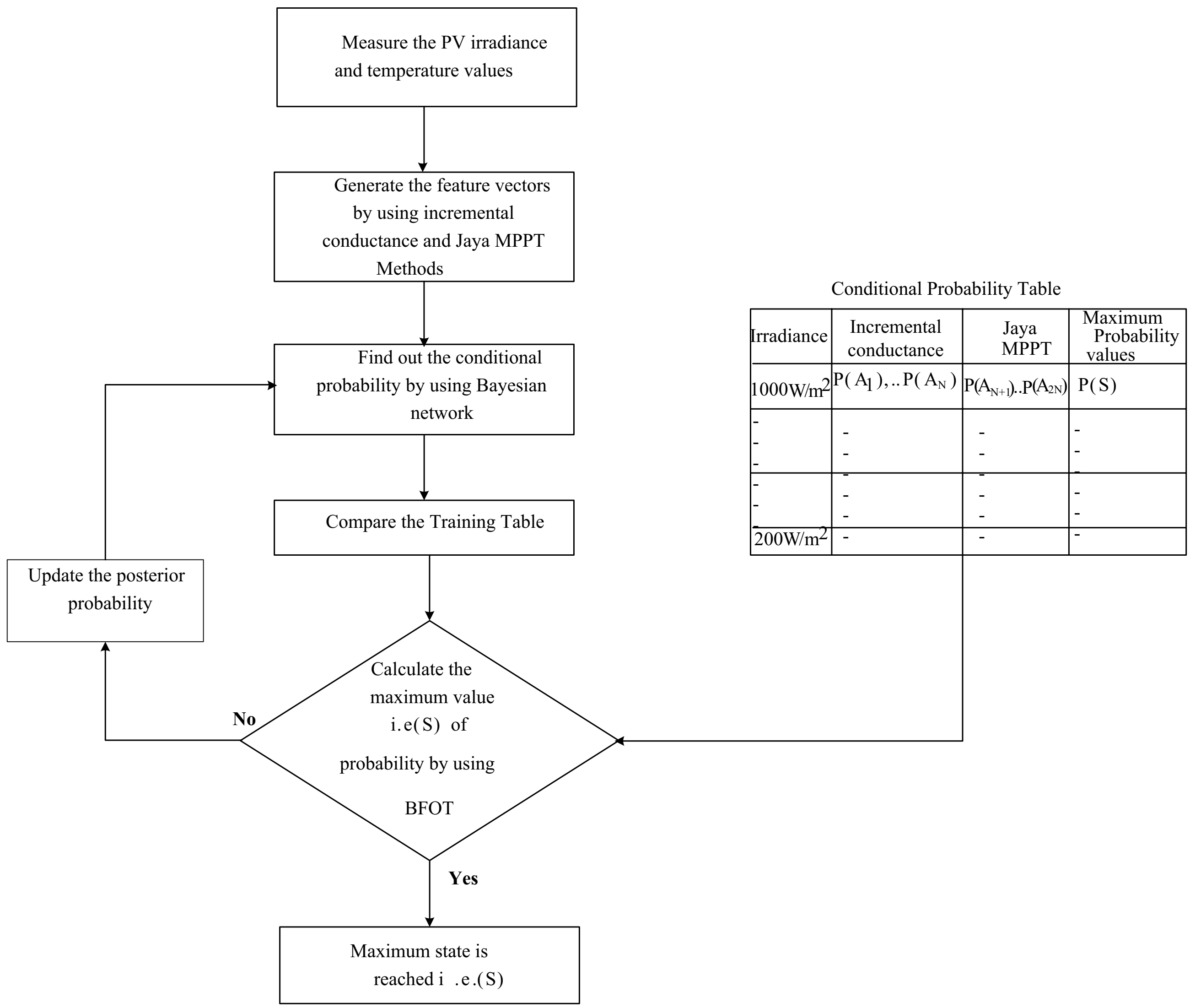

Fig. 7 Flow chart of the proposed Bayesian fusion method

Table 3 Utilized algorithm and boost converter parameters are given below

Particulars	Specifications
Bayesian Fusion	Total set of data = 527, training data = 80% of 527(421), testing data = 20% of 527 (106)
Jaya	Maximum iteration = 100, population size = 3
Incremental conductance	Dinitial = 0.15, Delta D = 0.0051
Boost converter	$L = 5.20$ mH, $C1 = C2 = 10\ \mu F = 10$ kHz, Switch (MOSFET)
Sampling period (T_s)	For simulation T_s=0.0023 Sec

The performance of the proposed method is evaluated by comparing it with the existing methods such as the incremental conductance method, PSO method, and Jaya method. Three different case studies are performed with three different partially shaded conditions of the PV system as detailed below.

1. Simulation results with GMPP at the left side of the PV curve.
2. Simulation results with the middle global peak of the PV curve.
3. Simulation results with GMPP at the right side of the PV curve.

5.1 Case. 1: simulation results with GMPP at left side of the PV curve

In this scenario, the irradiance on each PV module is shown in Table 2. Here, PV module—1 and PV module—2 are considered to have the same irradiance values thus leading to three different characteristics that are generated from that PV module, and the complete *pv*—characteristics of the PV system are shown in Fig. 3a. It can be observed that the maximum global peak lies on the left side of the PV curve with the maximum power being 114.1 W, while the other peaks—middle and right peak—are local peaks (LPs) of the PV array for the considered PV configuration. The time response of the PV output while reaching maximum peak point using incremental conductance, PSO, Jaya, and the proposed method is shown in Fig. 8a. The incremental conductance algorithm was able to track a maximum power of 110.5 W with the tracking time being 0.39 s. Moreover, a significant steady-state oscillation and power loss while tracking MPP were observed while using incremental conductance. The PSO-based MPPT method was able to extract a maximum power of 111 W in 63 iterations with a tracking time of 0.43 s. With PSO, the steady-state oscillations are significantly reduced compared to incremental conductance, but there were increased oscillations during the tracking period. The power extracted by the Jaya algorithm was 111 W and took around 28 iterations with a tracking time of 0.19 s and there were fewer oscillations.

The proposed method was also able to extract 113 W with a tracking time of 0.3 s global peak of the left side peak. In the proposed technique, the tracking time, steady-state power oscillations are fewer compared to other methods as observed in Fig. 8. There is almost no oscillatory behaviour observed while tracking MPP as compared to incremental conductance, PSO, and Jaya technique indicating the superior performance of the proposed Bayesian fusion technique. The relative waveforms of the voltage and current are shown in Fig. 8b, c, and analytic comparison is provided in Table 4

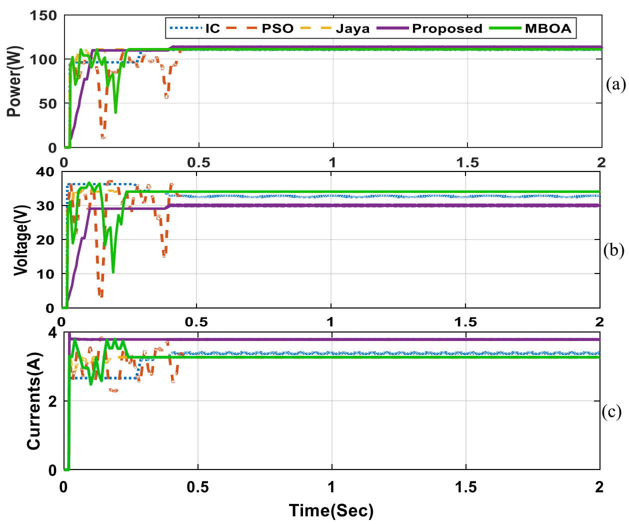

Fig. 8 Simulation performance with GMPP at left side of the PV curve

Table 4 Simulation analysis of proposed Bayesian fusion along with incremental conductance, PSO and Jaya algorithms as for PV array system of 4 series configurations

Methods to use produce maximum Power	Rated power (W)	Power at MPP, (W)	Voltage at MPP, (V)	Current at MPP, (A)	Tracking Time at MPP, (sec)	Maximum efficiency produce from PV %
Incremental conductance method	114.1 (pattern-1)	110.5	34.06	3.3367	0.39	96.84
PSO method		111	34.08	3.176	0.44	97.2
Jaya method		111	34.08	3.262	0.29	97.2
MBOA		111	33.99	3.27	0.24	97.2
Proposed method		**113**	**41.22**	**3.621**	**0.23**	**99.03**
Incremental conductance method	148.2 (Pattern-2)	147	50.59	2.889	0.24	99.19
PSO method		147.6	49.65	2.85	0.55	99.59
Jaya method		147.6	49.65	2.975	0.53	99.59
MBOA		147.6	49.75	2.98	0.53	99.59
Proposed method		**147.5**	**38.16**	**3.628**	**0.27**	**99.52**
Incremental conductance method	155 (Pattern-3)	153.8	72.5	2.13	0.19	99.22
PSO method		154.4	74.18	1.957	0.18	99.61
Jaya method		154.4	74.18	2.084	0.17	99.61
MBOA		144.6	53.47	2.71	0.89	93.29
Proposed method		**154.7**	**45.7**	**3.43**	**0.07**	**99.80**

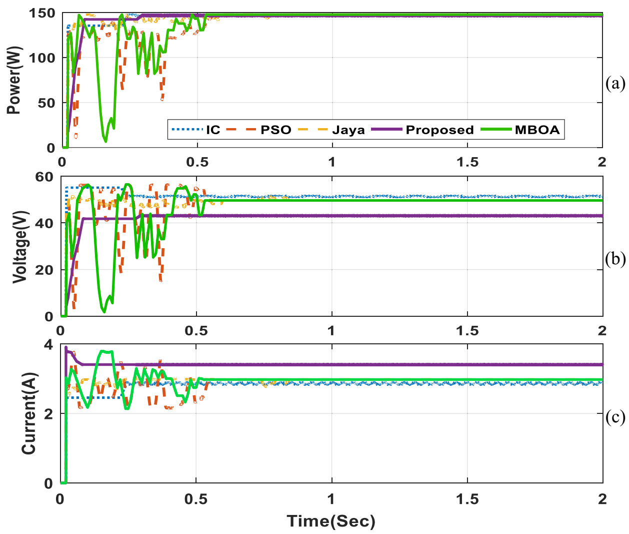

Fig. 9 Simulation performance with middle global peak of the PV curve

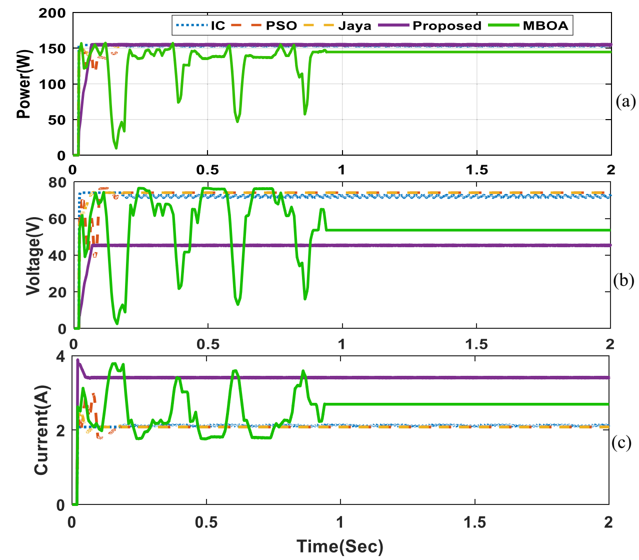

Fig. 10 Simulation performance with GMPP at right side of the PV curve

5.2 Case.2: simulation results with middle global peak of the PV curve

In this scenario, the irradiance on each PV module is shown in Table 2. While the four peaks are available in the *P*–*V* curve, as shown in Fig. 3b, it can be observed that a global peak exists in the middle of the PV curve, whereas the rest of the peaks lift the side of the PV curve and the right side of the PV curve has been considered as local peaks, maximum power is being 148.2 W. The time response of the PV output while reaching maximum peak point using incremental conductance, PSO, Jaya, and the proposed method is shown in Fig. 9a. The incremental conductance was able to track the maximum power of 147 W, with tracking time being 0.24 s. Moreover, a significant steady-state oscillation and power loss while tracking MPP were observed while using incremental conductance. The PSO-based MPPT method was able to extract a maximum power of 147.6 W, in 79 iterations with tracking time being 0.55 s. With PSO, the steady-state oscillations are significantly reduced compared to incremental conductance, but there were increased oscillations during the tracking period. The power extracted by the Jaya algorithm was 147.6 W and took around 28 iterations with a tracking time of 0.58 s and there were fewer oscillations. The proposed method was able to extract 147.5 W with a tracking time of 0.27 s global peak of the left side peak. In the proposed technique, the tracking time, steady-state power oscillations are fewer compared to other methods as observed in Fig. 9. There is almost no oscillatory behaviour observed while tracking MPP as compared to incremental conductance, PSO, and Jaya technique indicating the superior performance of the proposed Bayesian fusion technique. The relative waveforms of the voltage and current are shown in Fig. 9b, c, and analytic comparison is provided in Table 4.

5.3 Case. 3: simulation results with GMPP at right side of the PV curve.

In this scenario, the irradiance on each PV module is shown in Table 2. While the four peaks are available in the *P*–*V* curve, as shown in Fig. 3c, it can be observed that a global peak exists at the middle of the PV curve, whereas the rest of the peaks lift side of the PV curve and right side of the PV curve has been considered as local peaks, maximum power is being 155 W. The time response of the PV output while reaching to maximum peak point using incremental conductance, PSO, Jaya, and the proposed method is shown in Fig. 10a. The incremental conductance was able to track the maximum power of 153.8 W, with tracking time being 0.19 s. Moreover, a significant steady-state oscillation and power loss while tracking MPP were observed while using incremental conductance. The PSO-based MPPT method was able to extract a maximum power of 154.4 W, in 26 iterations with tracking time being 0.17 s. With PSO, the steady-state oscillations are significantly reduced compared to incremental conductance, but there were increased oscillations during the tracking period. The power extracted by the Jaya algorithm was 154.4 W and took around 26 iterations with a tracking time of 0.18 s and there were fewer oscillations. The proposed method was able to extract 154.7 W with a tracking time of 0.07 s global peak of the left side peak. In the proposed technique, the tracking time, steady-state

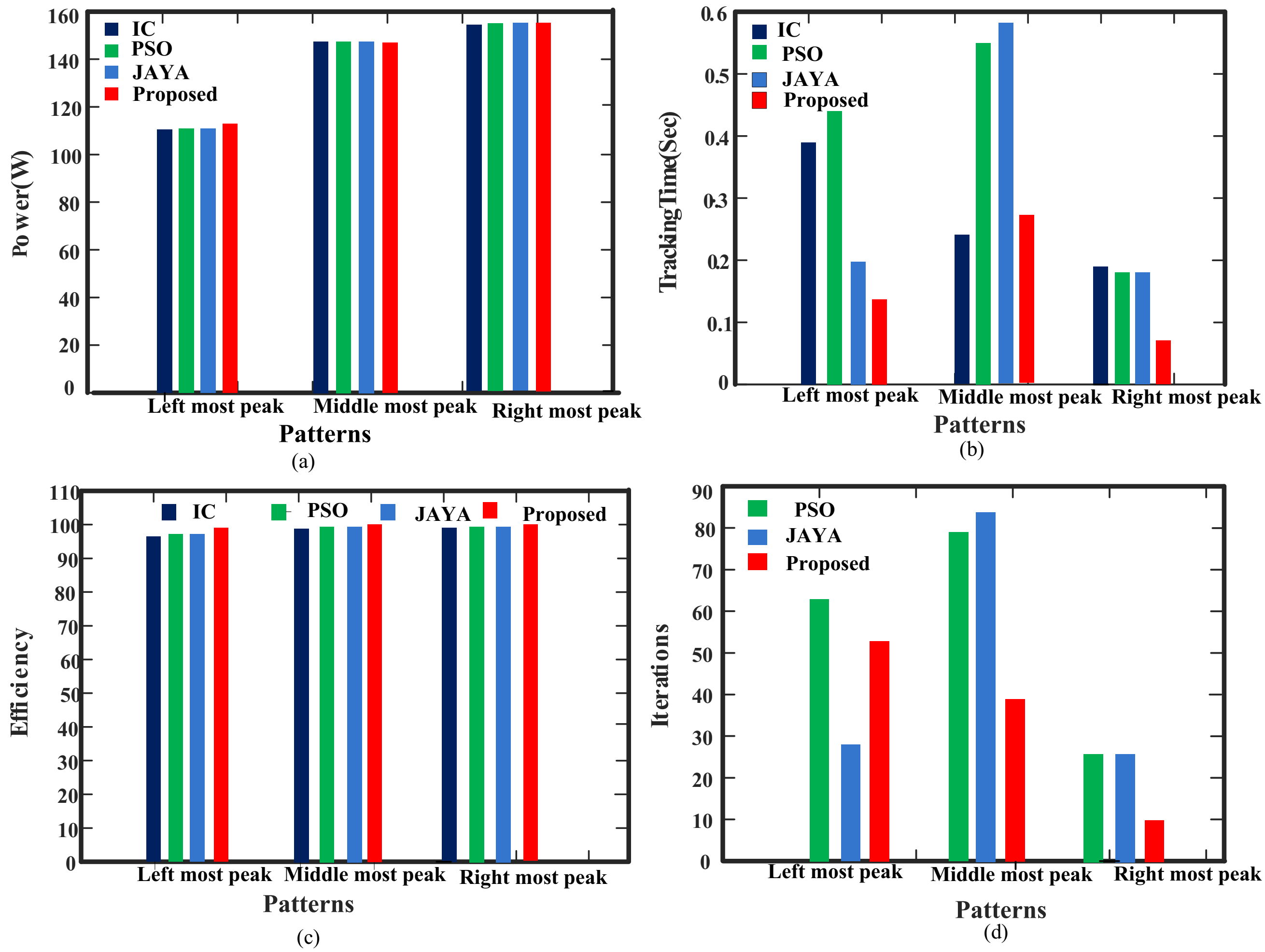

Fig. 11 Comparative results of, **a**. Power. **b**. Tracking time. **c**. Efficiency. **d**. Iterations

power oscillations are fewer compared to other methods as observed in Fig. 10. There is almost no oscillatory behaviour observed while tracking MPP as compared to incremental conductance, PSO, and Jaya technique indicating the superior performance of the proposed Bayesian fusion technique. The relative waveforms of the voltage and current are shown in Fig. 10b, c, and analytic comparison is provided in Table 4.

6 Comparative study

The proposed method portrayed and improved tracking accuracy and speed to achieve the GMPP under dynamic response, there are minimal oscillations tracking oscillations with almost negligible steady-state oscillation, and execution time is quicker compared to incremental conductance of [4], Jaya algorithm [23], and PSO [9] to achieve the global maximum power point tracking of the PV system. The problems in the incremental conductance algorithm are step size, and instability when there is a change in irradiance due to PSC. But PSO and Jaya algorithms show more oscillations during the tracking period and PSO needs comparatively larger time and more iterations to reach the GMPP. The proposed method compares with MBOA [25], as MBOA depends on one tunning parameter and one random number, whereas the proposed method does not require any tunning parameters and the random number, this makes the proposed algorithm more robust in implementation. Moreover, the average efficiency of the proposed method is almost near to that of MBOA, which is 99.45% and the response is fast to the sudden load variations. When compared with ARMO [26], the proposed method has GMPP tracking capability, simple with high efficiency, more tracking speed, and less steady-state oscillation with high reliability are shown in Table 5. The proposed BFT method is ideally suited to track the maximum power under PSC conditions. The performance of the proposed algorithm in terms of simulation results

Table 5 Qualitative presentation of the proposed Bayesian fusion with existing GMPPT algorithms

Type	IC [4]	PSO [17]	JAYA [49]	GWO [13]	MBOA [25]	ARMO [26]	Proposed
Number of tuning parameters	–	3	2	1	1	2	0
Number of random numbers	–	2	2	2	1	1	0
Average MPPT efficiency (%)	99.55	98.8	98.8	98.75	99.87	99.85	99.85
Response to load variation	Slow	Slow	Slow	Slow	Fast	Fast	Very fast
simplicity	Simple	Medium	Medium	Medium	Medium	Medium	Simple
Tracking speed	High	Medium	Medium	Medium	Medium	Simple	Simple
Steady state fluctuation	Yes	No	No	No	No	No	No
GMPPT tracking capability	No	Yes	Yes	Yes	Yes	Yes	Yes

of incremental conductance, PSO, and Jaya is explained clearly. Three patterns are reviewed for comparing the generation of current (*I*), voltage (*V*), and power (*P*) of all four algorithms on similar time measures, shown in Figs. 8, 9, and 10. Efficiency, tracking time, tracking power, and iterations against many patterns of the peak of the PV array of the entire four algorithms have to be shown in Fig. 11. In the Incremental conductance, tracking speed is very slow and tracking accuracy may track local MPP, where efficiency is very low and oscillation is very high compared to the proposed Bayesian fusion algorithm. When compared to PSO and Jaya algorithm, the iterations and dynamic oscillation are more compared to the proposed system, comparison of the proposed method with the existing method shown in Table 4.

7 Conclusion

In this paper, a Bayesian fusion technique-based controller for solar PV systems was designed for improved global maximum power point tracking under partially shaded conditions. The proposed method is simple to implement, highly cost-effective, and could achieve quicker and highly effective tracking performance compared to PSO, Jaya, and incremental conductance-based tracking methods. BFT is established to assist the controller in overcoming the stagnancy at the local peak position under a partially shaded condition. BFT has the provision of a reverse probability that models uncertainty based on available observations. To reach the GMPP, the proposed technique depicts enhanced tracking time, reduces the number of iterations, and is more efficient compared to many existing state-of-the-art techniques. This research could be expanded to cover different aspects within renewable energy areas, such as using machine learning to make a quick distinction in temperature difference(s), enabling efficient control of different hybrid renewable energy sources like solar energy, wind energy, etc.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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