Enhanced Bayesian Based MPPT Controller for PV Systems

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This work was supported by the National Council for Scientific Research through the Grant Research Program.

ABSTRACT We tackle the problem of a photovoltaic (PV) controller for maximum power point tracking (MPPT) under varying insolation and shading conditions. A general-purpose adaptive maximum power controller is tailored to maintain operation of the PV system at the maximum power point while constantly avoiding local maxima for changing environmental conditions. While a variety of conventional MPPT algorithms have been designed for ideal operating situations, very few were able to deliver true maximum power under abrupt changes in sun shading. Under these dynamic changes, most MPPT techniques fail to rapidly locate the global maximum power point and are stuck at global maxima, leading therefore to inconsistent power generation and low system efficiency. In this paper, we apply Bayesian fusion, a machine learning technique otherwise used for unsupervised classification, curve detection, and image segmentation, in order to achieve global MPPT in record time. Simulation results validated with real-life experimental studies demonstrated the ameliorations of the proposed technique compared to state-of-the-art methods. Using this algorithm, the total output power of the solar system is maximized while minimizing the steady-state oscillations and the tracking time.

INDEX TERMS Solar power generation, photovoltaic systems, maximum power point trackers, power generation control, pulse width modulation inverters, proportional control, DC-DC power converters, Bayes methods.

I. INTRODUCTION

PHOTOVOLTAIC cell research is edging closer to the limits of sunlight-to-electricity conversion efficiency, and as new manufacturing processes are making PV solar panels more reliable and cost effective, solar power is increasingly becoming more able to compete with traditional methods for generating energy based on fossil-fuel. In fact, renewable energy sources could even terminate the global growth in demand for oil and coal by the end of this decade [1]. This scenario takes into account not only the latest cost reduction projections for the manufacturing of green technologies, but also the countries’ pledges to cut polluting emissions, which promotes solar power and electric vehicles as clean alternatives that could leave fossil fuels far behind.

Hence, the demand of PV generation systems is expected to increase dramatically in the coming years for both standalone and grid-connected PV systems. With this increase in demand comes a steady urge to develop techniques capable of generating power consistently and efficiently by constantly extracting maximum power from the PV system. To maximize the power generation efficiency of PV systems, a maximum power point (MPP) tracker is essential to trace the global maximum power at all environmental conditions and to force the PV system to operate at that global point.

Maximum power tracking starts by measuring the current and voltage of the PV array. Then the instantaneous output power is calculated and an MPPT algorithm is deployed to control the duty cycle or reference voltage for a DC-DC controller in order to match the instantaneous power to the MPP. Several MPPT techniques together with their implementation have been introduced in literature. A comprehensive study illustrating the differences between major techniques and classifying them based on control variables involved, types of circuitry, complexity of algorithms, complexity level of hardware implementations, and types of scientific and commercial application can be found in [2]. One class of these trackers is based on measuring the PV voltage and current and then calculating the corresponding output power and updating the PV output voltage, via a DC-DC controller, towards reaching the maximum power point. These techniques encompass Perturbation and Observation (P&O), Hill-Climbing, and Incremental Conductance
and less computational power, an intelligent MPPT algorithm
particles needed for covering the entire region. A large random search, and additional computational burden
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direct updating techniques like P&O, for instance, the conver-
ence to reach the global MPP was difficult to find, resulting
proposed PSO-based MPPT (PSO-MPPT) technique [13]. In the initially
shading conditions. It is the Particle Swarm Optimization-
in the PV characteristics of an array structure under partial
no overshoot, and show less fluctuations in the steady
state for rapid temperature and irradiance variations. This
improved performance comes at the expense of excessive
processing power and high computational and storage bur-
den. Fuzzy logic based MPPT is one example of intelligence
tics that do not require the knowledge of an exact PV model [11]. The artificial neural network (ANN)-
ased MPPT is another intelligent method that operates like a black box model, requiring no detail information about the
PV system [12]. However, for a proper performance, ANN and fuzzy logic necessitate a huge amount of data while training their networks and while running their fuzzification
processes, respectively. This raises the burden on data storage considerably. Nevertheless, one intelligent evolution-
dary algorithm exists which doesn’t require huge amounts of training data and is used when multiple maxima are found in the PV characteristics of an array structure under partial
shading conditions. It is the Particle Swarm Optimization-
based MPPT (PSO-MPPT) technique [13]. In the initially
proposed PSO-based MPPT, the optimum number of iteration
needed to reach the global MPP was difficult to find, resulting
more often than not in convergence problems and power loss. In modified PSO, and in PSO algorithms combined with
direct updating techniques like P&O, for instance, the converge-
gen problems were resolved by providing separate search
spacess to all particles. However, oscillations emerge due to
large random search, and additional computational burden
on the processor was added due to the enormous numbers of
particles needed for covering the entire region.

Towards an improved search with less oscillatory behavior and less computational power, an intelligent MPPT algorithm
called the whale optimization algorithm (WOA) [14] and
inspired by the bubble-net hunting strategy of humpback
whales was proposed in [15]. These whales hunt and encircle a school of fish by producing distinctive bubbles in a helical or spiral path with decreasing radius. This trajectory path is mathematically modeled by the WOA which initiates its prey search from the outer boundary of the search space and follows the trajectory path with decreased circling radius until it covers the total search space. The motion of the whale along the spiral trajectory is modelled in two parts: in a linear path and in circled spiral path. Since the algorithm runs over all the searching space, the probability of hitting a prey, or in case of MPPT, the likelihood of finding the global MPP depends on the number of searching whales and their spiral paths. When this number is low, the likelihood is high that the MPPT will be stagnating at a local maximum point. Only when this number is significantly high that finding the global MPP is guaranteed.

However, for the MPPT problem at hand where the environmental insolation, temperature and shading conditions are prone to change at every instant in time, a large number of searching whales is impractical. It increases the computational burden, delays the tracking, and leads to power loss. Hence, in an effort to mitigate these effects, a hybrid MPPT algorithm was very recently proposed which combines the WOA with differential evolution (DE) [16]. Studying this algorithm, one can appreciate how combining the fast searching ability of the original DE with the WOA is able to pull the solution out of stagnation and considerably reduce the number of needed iterations and searching whales. This combination is called WODE and is implemented in the following manner: Following every iteration of the WOA, only three best positions of the whale are taken as input to the DE method. Consequently, mutation, crossover and selection operators are applied to the input, and one single best position output is produced. This additional support to the WOA by the DE, after every iteration, considerably reduces the number of iterations, the convergence duration, the number of search agents, the output oscillation, and consequently the computational power.

In this paper, an intelligent Bayesian network technique is proposed for global MPP tracking of a PV array under partial shading conditions. The algorithm sweeps the output voltage of a DC-DC converter, measures the corresponding current, computes the resulting power, and uses the Bayes rule to compute an estimate of the MPP. A PID controller is used for more efficient real-time controller with minimum overshoot and minimum rise time in output power. The outstanding performance of this algorithm in terms of tracking efficiency, robustness, and speed is demonstrated through various simulated scenarios and validated via experimental setups, and is benchmarked to several intelligent state of the art MPPT techniques.

The rest of the paper is organized as follows: Section II describes several observations on the current versus voltage (I–V) curves and power versus voltage (P–V) curves of

(Volume 5, no. 1, March 2018)
partially shaded arrays. Section III describes the proposed control algorithm including the Bayesian network and PID controller. Section IV presents the simulation and experimental results, and the main conclusion is summarized in section V.

II. VARYING INSOLATION AND PARTIAL SHADING

The output power of a PV array depends on the array’s terminal operating voltage. The maximum power operating point varies considerably with variation insolation level and temperature. Practically, the MPPT should measure the PV array output current and adaptively drive the system to its maximum power point by varying the output voltage and hence the impedance seen by the array. As PV modules are DC systems, DC-DC converters are used to match the impedance of the array to that of the load. This is done by varying the duty cycle of the DC-DC converter. When the impedance is matched, the PV array will be operating at its maximum power transfer point.

A PV array is non-uniformly insolated when clouds, buildings, or trees cast their shadows on it. In such a case, some solar modules are non-uniformly insolated and therefore are partially shaded, while others are uniformly and fully insolated. Compared to the fully insolated modules, those partially shaded modules generate less current, and since all modules in the array are connected in series, the current flowing in the partially shaded modules’ parallel resistance causes a drop in voltage. This generates hotspots and lowers the overall output power of the system. To solve this problem, a bypass diode is connected in parallel to each module preventing it from acting as a resistive load in case of partial shading.

The plot in Fig. 1 shows typical I–V and P–V characteristic curves of a partially shaded PV array consisting of 5 modules connected in series each with different insolation levels.

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For a partially shaded PV array the power peaks are repartitioned at an integral multiple of 80% of the open circuit voltage of the used module ($V_{OCM}$) i.e. $V_{peaks} = n \times 0.8 \times V_{OCM}$, where “$n$” is an integer. The minimum displacement between any two consecutive peaks is also bound to 80% of $V_{OCM}$ [8]. The curves in Fig. 1 exhibit 5 peaks, one of which is the global MPP occurring at $n_3 \times 0.8 \times V_{OCM}$.

Fig. 2 illustrates another partial shading scenario where a PV array of 5 modules connected in series is shown. The left part of Fig. 2 also shows our experimental setup. Each module is shaded differently, but all are exposed to the same insolation. In this case as well, one can also observe 5 MPPs repartitioned at multiples of $0.8 \times V_{OCM}$, only one of which is the global MPP. A third important scenario is the combination of both scenarios of Fig. 1 and Fig. 2, in which the solar array is both partially shaded and non-uniformly insolated. This complex scenario will form the subject of our subsequent simulation and experimental studies.

The Bayesian network is a method of modeling a joint probability distribution of multiple random variables and is considered to be a powerful instrument for information fusion. In this work, a Bayesian network is used to detect the correct direction towards which the instantaneous output voltage of a certain PV array moves, in order to keep operating at the maximum power transfer point. The topology of the Bayesian network used in this paper is shown in Fig. 3. The network has any instant in time.
2N nodes $\{A_1, \ldots, A_{2N}\}$, divided in half. The first N nodes $\{A_1, \ldots, A_N\}$ correspond to those maximum power voltages (MPVs) on the P–V curve having a voltage around 80% of the multiples of $V_{OCM}$, i.e. $n \times 0.8 \times V_{OCM}$. The second N nodes $\{A_{N+1}, \ldots, A_{2N}\}$ correspond to the maximum power points obtained by the simple Inc-Cond algorithm.

For instance, if we consider 5 modules in series, each with a different irradiation and each with a $V_{OCM}$ of 43.5V at 1000 W/m$^2$, the array open circuit voltage would be 217.5V. In this example, the Bayesian network would have $N = 12$ nodes. The first 6 nodes $\{A_1, \ldots, A_6\}$ are obtained by considering all 80% multiples of $V_{OCM}$, i.e. $A_1 = 34.8V, A_2 = 69.6V, A_3 = 104.4V, A_4 = 139.2V, and A_5 = 174V, A_6 = 208.8V$. Since in our examples of Figures 2 and 3, five different insolation levels and 5 differently shaded groups are considered, respectively, only 5 of the Bayesian network nodes constitute MPVs.

It should be noted though, that one could lower the percentage of $V_{OCM}$ from 80% to 60%, which would undoubtedly increase the size of the conditional probability database when training the Bayesian network offline - and hence the time required to track the global MPP is increased, but the risk of missing the MPP is substantially minimized. The resulting point estimated after the Bayesian merging of all observation nodes is denoted by the symbol $S$.

After calculating all 2N observation points, the left and right sectors are then compared, node by node, to check for matching entries. If one node of the left set of nodes is found in the right set, a match is found and a state of “1” is inscribed into a feature vector, otherwise a “0” is inscribed. This extracted feature vector is denoted by $a(t) = [A_1(t), \ldots, A_N(t)]$, where $A_i(t)$ represents the state of the $i$th node at time $t$. For instance, a feature vector at one instant in time could be $a(t) = \{1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1\}$. The first 6 digits correspond to the left observation nodes and the remaining 6 digits correspond to the right nodes.

**B. BAYES RULE-BASED DECISION MAKING**

As mentioned earlier, the input nodes are given the digital states 0 or 10, 1. The output node $S$ has $N_S + 1 = 1000 + 1$ states: $S = \{S_1, \ldots, S_{N_S}, NoEvent\}$. Each of the states $S_1, \ldots, S_{N_S}$ corresponds to an estimated point on the I–V plane. For instance, the state $S_i = \{7.25, 104.4\}$ corresponds to a current of 7.25 A and to a voltage of 104.4V. The state $S = NoEvent$ denotes the case when no change happens in the output voltage of the MPPT. The output node $S$ is estimated from the feature vectors using a properly tuned Bayesian network.

The values of the $A_i$s are assumed to be conditionally independent given the value of $S$. Therefore, based on the Bayes rule, the conditional probability distribution $P(S|A_1, \ldots, A_{2N}P(S|A_1, \ldots, A_N))$ can be written as the product of local conditional probabilities $P(A_i|S)$:

$$P(S|A_1, \ldots, A_{2N}) = \frac{1}{Z} \cdot P(S) \prod_{n=1}^{2N} P(A_n | S) \quad (1)$$

Where $Z = \int_S P(S) \prod_{n=1}^{2N} P(A_n | S) dS$. The conditional probabilities $P(A_i|S)$ are then calculated using training sets. For each feature vector, the value of $S$ is given as a label. The obtained conditional probability values are saved in a table called the conditional probability table (CPT).

In this study, I–V points taken under different irradiation and shading conditions and at multiples of $V_{OCM}$ were used as training samples. The irradiation was changed from 0 W/m$^2$ to 1000 W/m$^2$ in steps of 10 W/m$^2$. Shading patterns ranging from partially shaded modules in one group to fully shaded modules in all groups, and every combination in between were considered. Maximum power point voltages were taken at $n \times 0.8 \times V_{OCM}$. These samples were then deployed as a supervisor for the CPT training. When the PV system is in the operation mode, the feature vectors are calculated at every time block as evidence. Using the evidence and the conditional probabilities obtained above, the conditional probability (1) is calculated and the most likely state of $S$ is obtained. This state should avoid local MPPs and should correspond to the global MPP which maximizes the net output power of the PV system.

**C. PID CONTROLLER**

Despite the fact that numerous sophisticated control schemes exist for switching regulators of load voltages similar to the DC buck and boost converters used in PV systems, the majority of industrial processes today are still regulated by PID controllers mainly due to their flexible structure and optimizable performance. The PID conventional control expression used in this work is given by $G(s) = K_p \left(1 + \frac{1}{sT_i} + sT_d\right)$, where $T_i = \frac{K_p}{K_d}$ is the integral time constant, and $T_d = \frac{K_i}{K_d}$ is the derivative time constants. The terms $K_p$, $K_i$, and $K_d$ denote the proportional gain, integral gain and derivative gain, respectively.

From the standpoint of control performance, PID based MPPT does not allow sufficient and fast process control for dynamically changing environmental conditions, due to the various operational conditions, especially under partial shading. These changes drive the process in different operation points. Therefore, when dynamically fusing the observation points to update the state of the Bayesian network, updating the PID gains is necessary for a more efficient real-time controller with minimum overshoot and minimum rise time in output voltage.

Hence, for each maximum power point voltage which is an integer multiple of 80% of $V_{OCM}$, the Ziegler-Nichols method is applied in order to calculate the $K_p$, $K_i$ and $K_d$ gains. Towards that end, $K_i$ and $K_d$ are set to zero and the $K_p$ gain is increased until it reaches the final critical gain $K_{cr}$ at which the output of the control loop oscillates at constant amplitude. Then the critical oscillation period is computed $T_{cr}$. The gains are then calculated using the following equations: $K_p = K_{cr} \times 0.6, K_i = \frac{2K_p}{T_{cr}}$, and $K_d = \frac{K_p T_{cr}}{2}$. Using these PID tuned parameters the oscillation around the MPP is minimized. These parameters are computed and saved during the offline
training and then passed forward to the PID controller based on the state of the Bayesian network.

The block diagram of the PV system controlled by a single PID is shown in Fig. 4. In the proposed system the PID controller takes the Inc-Cond equality \( \left( \frac{1}{V} + \frac{dI}{dV} = 0 \right) \) as an error signal and tries to reduce it; in other words it tries to reduce the difference between the PV slope and an optimal reference value, and it controls the switching of a boost DC-DC converter through a PWM generator driven by duty cycles.

**IV. SIMULATION AND EXPERIMENTAL RESULTS**

The performance of the proposed MPPT control system is first simulated and then experimentally validated. The simulations used MATLAB 2013a software on Dell computer with Intel core i7, 3.5 GHz processor, 16 GB of RAM memory and windows 10 operating system. A PV array of 5 modules connected in series was considered. The modules are partially shaded as seen in Fig. 2 and in Fig. 4, i.e. the first module is 80% shaded and the last module is not shaded. Each module has the following characteristics: \( V_{OCM} = 43.5 \) V, \( I_{SC} = 7.25 \) A and \( P_{MPP} = 250 \) W under unshaded conditions. The array open circuit voltage under unshaded conditions and uniform insolation is \( V_{OC} = 217.5 \) V. The load consists of a battery bank of 217.5 V. A Bayesian network of 12 nodes was deployed. A simulation was run for 30s, during which the irradiation is made to change each 10s following the pattern of Fig. 5. The corresponding output power is illustrated in Fig. 6. As observed in this figure, 5 peaks emerge as maximum power peaks corresponding to the 5 times the 80% of module open circuit voltages, as discussed earlier. \( A_1 = 34.6V, A_2 = 69.1V, A_3 = 104.1V, A_4 = 138.8V, \) and \( A_5 = 173.7V. \)

A first crucial experiment in the context of performance analysis is to study the effect of the PID controller on the overall efficiency of the proposed system. Hence, the system was simulated for the same irradiation profile seen in Fig. 5, once with and once without the PID controller. The results are illustrated in Fig. 7. As shown in the figure and as expected, without the PID the output power suffers from wider transient oscillations and frequent steady-state oscillations, as illustrated by the crossed blue line. This is mainly due to the fact that the Inc-Cond technique, although simple and fast converging, yet its inherent mathematical division, and its conventional variable increment depending on the change of the array power with respect to the array voltage force the emergence of steady-state and transient oscillation especially under sudden changes in irradiation.

The performance of the proposed control system is further compared to state of the art methods as illustrated in Fig. 8. The proposed Bayesian based method shows a faster convergence towards the global maximum power point as compared to both WODE and GWO. Furthermore, the efficiency of the proposed control method was calculated as the ratio of the available output power to the maximum possible output power. Table 1. details the system tracking times and overall power efficiency.

For further validation of the results, 100 different irradiation patterns were simulated for the same 5 modules in...
series and the same Bayesian network. The results show an overall tracking average of 1.76s for the proposed method as compared to 2.57s to WODE and 4.28s to GWO. The overall efficiency was found to be 97.89% on average for the proposed technique as opposed to 95.84% for WODE and 91.24% for GWO.

The PV module and array characteristics used in simulations were taken from the real PV array used in experiments. These are illustrated in table 2. In the experimental setup, a total of 5 modules where connected in series. Each module was differently shaded as in Fig. 2 and as in the simulations. The array was then exposed to three different irradiation levels starting from 1000 W/m² for 10s, followed by 500 W/m² for another 10s and ending by 800 W/m² for the last 10s as illustrated by the irradiation pattern of Fig. 5. The results of the proposed tracking technique compared to state of the art techniques demonstrated that the proposed controller has an enhanced response time and efficiency compared to intelligent state of the art techniques.

This research can be extended to cover several venues in the renewable energy field. Rapid variations in temperature should be covered and efficient control of several hybrid renewable sources like solar, wind and fuel cells should be made more intelligent and more efficient.

**REFERENCES**


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