System-Independent Irradiance Sensorless ANN-Based MPPT for Photovoltaic Systems in Electric Vehicles

Baldwin Cortés *, Roberto Tapia and Juan J. Flores

Facultad de Ingeniería Eléctrica, Universidad Michocana de San Nicolás de Hidalgo, Morelia 58030, Mexico; roberto_ts@hotmail.com (R.T.); juan.flores@umich.mx (J.J.F.)
* Correspondence: baldwin.cortes@umich.mx

Abstract: The integration of photovoltaic systems (PVS) in electric vehicles (EV) increases the vehicle’s autonomy by providing an additional energy source other than the battery. However, current solar cell technology generates around 200 W for a 1.4 m² panel (to be installed on the roof of the EV) at stable irradiance conditions. This limitation in production and the sudden changes in irradiance produced by shadows of clouds, buildings, and other structures make developing a fast and efficient maximum power point tracking (MPPT) technique in this area necessary. This article proposes an artificial neural network (ANN)-based MPPT, called DS-ANN, that uses manufacturer datasheet parameters as inputs to the network to address this problem. The Bayesian backpropagation-regularization performs the training, ensuring that the MPPT technique operates satisfactorily on different PVS without retraining. We simulated the response of 20 commercial modules against actual irradiance data to validate the proposed method. The results show that our method achieves an average tracking efficiency of 99.66%, improving by 1.21% over an enhanced P&O method.

Keywords: maximum power point tracking; artificial neural networks; photovoltaic; electric vehicles; Bayesian regularization

1. Introduction

Solar energy is a promising and freely available energy source for countering carbon dioxide emissions (CO₂) produced by burning fossil fuels. The massive releases of CO₂ contribute strongly to global warming and affect ecological communities through multiple processes, including temperature elevation, extreme weather events, and rising air pollution [1–3].

In recent years, PVS has become a popular form of electrical generation due to its advantages, such as the absence of fuel cost, infrequent maintenance, and noiseless operation. This growth is supported by extensive research, with more than 48,000 studies published on solar energy since 1900. Half of those publications appeared between 2015 and 2020. This work has allowed a significant reduction in costs by introducing new materials and better technology [4]. As a result, the broad integration of photovoltaic (PV) generation in the residential, commercial, and industrial sectors drastically decreased their CO₂ emissions [5].

Nevertheless, the transportation sector has not shown much improvement in lowering its emissions since it depends almost exclusively on internal combustion engine vehicles. From 2001 to 2011, CO₂ emissions increased by 13%, 25% of which is attributed to vehicles [6]. To reduce CO₂ emissions, many countries are making strategic plans to replace conventional vehicles with electric vehicles (EV) [7]. Furthermore, the integration of PV panels on their rooftops and hoods as an additional power source would increase the driving distance and decrease the amount of fossil fuel burnt to provide electricity for battery charging [8,9]. Some car manufacturers such as Mercedes Benz (E-Class, 1987) and Audi (A8, 1994; A4, 2001) introduced photovoltaic panels in some of their vehicles as an added value. In 2011, the Fisker Karma became the first mass-produced vehicle with
a sunroof; however, the project did not work out. Other manufacturers such as Toyota (Prius, since 2010) and Hyundai (Sonata, 2020) offer special editions of their hybrid vehicles that include a sunroof; nevertheless, both manufacturers offer this characteristic as an added value [10]. In June 2021, the Lightyear One solar car set a new autonomy record, achieving a distance of 725 km on a single charge, an improvement close to 20% over purely electric vehicles [11]. Lightyear One’s body design provides the least air resistance, and the inclusion of PV panels shows promising results [12].

The low conversion efficiency of solar cells is the main difficulty that prevents their widespread use in the transportation sector. Improving the conversion efficiency of PV cells is not easy, as it depends on the currently available technology [13]. Consequently, how to generate the maximum amount of energy is one problem that must be solved.

In a PVS, solar irradiance and temperature are two key factors that directly affect the amount of produced energy [14]. There is a unique operating point under certain atmospheric conditions at which its power output is the maximum [15]. Thus, the PVS should always operate at the maximum power point (MPP). The control action that maintains the PVS operating at its MPP is known as MPP tracking (MPPT).

An extensive amount of research has been conducted, and many MPPT methods have been proposed so far [16–20]. Among the numerous MPPT techniques described in the literature, P&O [21–26] is the most popular one, and it is widely installed in commercial PVS using low-cost microprocessors [27]. Despite the algorithm’s simplicity and reliability, it forces the PVS operating point to go back and forth around the MPP, resulting in continuous output power oscillations. As a result, the energy yield reduces, and hence the efficiency drops [28].

Many new MPPT methods based on fuzzy logic (FL) [29–32], evolutionary algorithms (EA) [33–35], hybrid methods [36–38], and other methods [39–42] have been applied to PVS. Considering the expected performance of the revised MPPT techniques in EV applications, they share one main problem: the tracking speed is not fast enough to follow sudden changes in irradiance. These changes are more common in vehicles than in fixed-location PVS due to the exposition to shadows from trees, buildings, and structures, caused mainly by the displacement of the vehicle [8].

Fortunately, artificial neural networks (ANNs) can quickly and precisely respond once the training concludes. Numerous studies demonstrate the capability of ANNs as MPPT techniques [43]. In this manner, the input signals to the ANN can be electrical (voltage and current) [13,44–46], non-electrical (temperature and irradiance) [47–50], or any combination of these [8,51–53]. Generally, electrical inputs are preferred to non-electrical inputs from cost and robustness points of view [8].

While ANNs can perform efficiently in real-time [54–56], they present two major drawbacks: long training times [57] and strong dependency on training data [58]. Although the training process is computationally intensive and often requires a large amount of time, modern parallel computing systems provide the capability to reduce it [59]. Also, cloud computing may provide an excellent way for processing large volumes of data without any hardware investment [60]. Once the training completes, the configuration (weights and activation functions) can be transferred to low-cost embedded systems based on FPGAs [61,62] or micro-controllers [63–65].

On the other hand, it is not possible to guarantee network performance when the inputs to the network are outside the range of the training set [66]. There is a significant flaw in most revised ANN-based MPPT methods: the network is trained with data collected from a single PVS (or with different PVS sharing the same characteristics) [49]. Thus, the ANN-based MPPT might not perform satisfactorily in a PVS with different characteristics without retraining the ANN.

To overcome this issue, Natsheh et al. [67] present an ANN-based MPPT whose inputs are the cell temperature, the solar irradiance, and the PVS reference open-circuit voltage ($V_{oc}$). This approach was able to estimate the MPPT of four different PVS. Nonetheless,
the irradiance sensor may not be available in an EV since this type of sensor is spacious and could interfere with the photovoltaic module’s space.

Our contribution: we propose an ANN-based MPPT technique that works for any PVS composed of polycrystalline PV cells without retraining. This ability is due to the information from the PVS (datasheet) being used as input to the neural network, in addition to measurements of ambient temperature and current and voltage of the PVS. We call this MPPT technique DS-ANN (datasheet-ANN).

The DS-ANN technique is compared against two P&O MPPT techniques, outperforming both of them. We use synthetically generated data to analyze the feasibility of the proposed technique.

Although we present an approach based on EVs, the same fundamental concepts apply to all PVS, so our algorithm is not limited to EVs, but it is suitable for any MPPT application.

The remainder of the paper is organized as follows: Section 2 presents the mathematical model of a PV cell, Section 3 gives a generalized model of an EV and explains the MPPT problem, Section 4 presents the ANN model and defines the Bayesian regularization-backpropagation algorithm used for the training process, and Section 5 presents the implementation of the DS-ANN MPPT technique. The results and comparison against two P&O MPPT techniques are presented in Section 6, and finally, Section 7 concludes the paper.

2. Photovoltaic Systems

The primary device of a PVS is the PV cell. For simplicity, we use the single-diode model of a PV cell in this article, whose equivalent circuit is shown in Figure 1. This model offers a good compromise between simplicity and accuracy [68]. Equation (1) describes the single-diode model.

\[
I = I_{ph} - I_0 \left[ \exp \left( \frac{V + IR_s}{nV_t} \right) - 1 \right] - \frac{V + IR_s}{R_p},
\]  

where \( I \) is the output current, \( V \) is the voltage at terminals, \( I_{ph} \) is the light-generated current (i.e., the component of cell current due to photons), \( I_0 \) is the reverse saturation current of the diode, \( n \) is the diode ideality constant, \( V_t = kT/q \) is the junction thermal voltage, \( R_s \) is the series resistance, \( R_p \) is the parallel resistance, \( T \) is the junction temperature (in Kelvin degrees), \( k \) is the Boltzmann constant (\( \approx 1.38064852 \times 10^{-23} \) J/K), and \( q \) is the electron charge (\( \approx 1.60217662 \times 10^{-19} \) C).

Cells may group to form panels or arrays. Cells connected in parallel increase the current, and cells connected in series provide greater output voltages. According to Gow & Manning [69], the equation for a system composed of several cells may be represented as in (2):

\[
I = N_p \left\{ I_{ph} - I_0 \left[ \exp \left( \frac{A}{nV_t} \right) - 1 \right] - \frac{A}{R_p} \right\},
\]  

where \( A := \frac{V}{nV_t} + \frac{IR_s}{nV_t} \), \( N_s \) is the number of series cells, and \( N_p \) is the number of parallel cells.

The I–V characteristic of a PVS depends on its internal characteristics (i.e., model parameters) and external influences such as irradiance and temperature.

The light-generated current of the PV cell depends linearly on the solar irradiance but is also influenced by the cell’s temperature as shown in (3) [70]:

\[
I_{ph} = \left[ I_{ph,ref} + \mu_i(T - T_{ref}) \right] \frac{G}{G_{ref}},
\]  

where \( G \) is the actual irradiance on the PVS surface, \( G_{ref} \) is the reference irradiance (1000 W/m²), \( I_{ph,ref} \) is the reference component of cell current due to photons, \( \mu_i \) is the short-circuit current/temperature coefficient, \( T \) is the cell temperature, and \( T_{ref} \) is the nominal temperature (298.15 K).
The diode saturation current \( I_0 \) and its dependence on the temperature may be expressed as in (4) [71]:

\[
I_0 = I_{0,\text{ref}} \left( \frac{T}{T_{\text{ref}}} \right)^3 \exp \left[ \frac{qE_g}{nk} \left( \frac{1}{T_{\text{ref}}} - \frac{1}{T} \right) \right],
\]

where \( I_{0,\text{ref}} \) is the nominal reverse saturation current of the diode, and \( E_g \) is the bandgap energy of the semiconductor.

As presented in Equations (2)–(4), the output current is highly nonlinear and depends, among other parameters, on the cell’s temperature. For simulations, the cell temperature can be estimated from the ambient temperature and irradiance as in (5) [72]:

\[
T = T_a + \left( \frac{\text{NOCT} - 293.15}{800} \right) G,
\]

where \( T_a \) is the ambient temperature (K), and NOCT is the nominal operating cell temperature (318.15 K, generally).

3. Generalized Electric Vehicle Model

This article aims to implement an MPPT based on artificial neural networks for any PVS composed of polycrystalline silicon cells allocated on an EV. Figure 2 presents the block diagram of a generalized electric vehicle with PV generation. The system consists of a PV module, a DC-DC boost converter, an AC-DC converter, a battery, and a generic load, which accounts for all the energy consumption within the EV, such as the electric motor, the lightning, and the air conditioner system.

The primary function of the battery is to store energy to satisfy the energy demand within the vehicle. Since it is not possible to meet the demand with the PV module alone, the battery needs to be recharged via the mains using the AC-DC converter [73]. Another function of the battery is to keep the DC bus voltage constant, which keeps the operating voltage of the PV module fixed [74].

The DC-DC converter function is to change the module operating voltage to ensure the operation at the MPP. If the load’s voltage remains constant, it is possible to model the converter and the load as a controlled voltage source. Thus, the relationship between the PV module voltage and the bus voltage is expressed as [75]:

\[
V_{\text{pv}} = (1 - D)V_{\text{bus}},
\]

where \( D \) is the converter duty cycle.

Directly from (6), the converter’s duty cycle can be determined if the optimum output voltage of the PV module is known, as follows:

\[
D = 1 - \frac{V_{\text{pv}}}{V_{\text{bus}}},
\]
The DC-DC converter design is out of the scope of this paper, but the reader can refer to five papers [76–80] for details.

The MPPT problem relies on finding the optimum operating voltage ($V_{mpp}$), which can be estimated using the ambient temperature and the module’s voltage and current measurements, $T_a$, $V_{pv}$, and $I_{pv}$, respectively [8].

However, the electrical measurements depend on the system characteristics (i.e., datasheet information); therefore, it is necessary to use these as additional inputs to the ANN-based MPPT to differentiate between the measurements of different systems. Figure 3 shows the ANN-based MPPT diagram.

The proposed DS-ANN MPPT technique can be used for any polycrystalline PVS without requiring retraining. This is especially important in electric vehicles, as the microcontrollers used to measure and process electrical signals have limited processing capacity [81], so training a network in these devices would not be suitable.

In DS-ANN MPPT, a workstation (e.g., a laptop) performs the training process. Once completed, the microcontroller receives and stores the network parameters (i.e., the matrices) that control the duty cycle of the DC-DC converter.

Figure 2. Photovoltaic system with MPPT controller connected to a DC-bus in a electric vehicle.

Figure 3. ANN-based MPPT diagram.

4. Artificial Neural Networks

The MPPT problem can be seen as a function approximation: we need a function that maps from system characteristics and measurements to an estimation of the MPP. As the DS-ANN MPPT must perform well on PVS for which it was not trained, the ANN must have good generalization properties. Bayesian regularization is a training algorithm designed to train networks so that they generalize well in function approximation problems [66].

Artificial neural networks are biologically inspired computational models used in various engineering fields to solve various problems such as function approximation, pattern recognition, prediction, and optimization [8]. Each ANN comprises at least three layers: an
input layer, hidden layer(s), and output layer. Additionally, each layer is composed of several processors called neurons, which are interconnected by weighted links. Each neuron produces a single outgoing response by applying an activation function to the inputs’ weighted sum.

Mathematically, an artificial neural network composed of \( L \) layers (disregarding the input layer) is expressed as

\[
a^0 = p \\
a^l = f'(W^l a^{l-1} + b^l)
\]

where \( p \) is the input vector, \( W \) and \( b \) are the weights and biases, \( a \) is the output of the layer, \( f \) is the activation function, and \( j = 1, \ldots, L \) is the layer index. The input layer is numbered with a zero because it does not perform any processing.

During training, ANNs model the input-output relationship of a dataset by adjusting the weights to minimize the difference between the network outputs and the desired values. Once the training completes, the network can predict the output from a given input pattern.

The regularization algorithm introduces an additional term to the performance function, which restricts the weights in the network, thus avoiding overfitting [82]. This regularization algorithm is presented in Algorithm 1.

The default performance function for MLPs is mean square error (MSE), given by [66]:

\[
F_D(x) = \frac{1}{M} \sum_{i=1}^{M} \sum_{j=1}^{O} (e_{i,j})^2 = \frac{1}{M} \sum_{i=1}^{M} \sum_{j=1}^{O} (t_{i,j} - a_{i,j})^2, \quad (9)
\]

where \( x \) denotes the vector containing all the weights and biases of the network, \( t_{i,j} \) is the desired output \( j \) at input pattern \( i \), \( a_{i,j} \) is the corresponding network output \( j \) at input \( i \), \( M \) is the total number of input patterns, and \( O \) is the number of outputs.

The performance function (9) is modified by adding a penalty term \((\alpha / \beta) F_W\) as follows [83]:

\[
F = \beta F_D + \alpha F_W, \quad (10)
\]

where \( \alpha \) and \( \beta \) are the regularization parameters, and

\[
F_W = \frac{1}{Q} x^T x, \quad (11)
\]

represents the mean of the squared network weights, and \( Q \) is the total number of network parameters.

Note that if \( \alpha << \beta \), the minimization of the performance function (10) will be equivalent to that of (9); hence, no regularization is performed, and smaller errors are generated. On the other hand, if \( \alpha >> \beta \), the weights’ magnitudes are reduced at the cost of larger network errors.

The Bayesian regularization-backpropagation performs the task of finding the optimum values for the \( \alpha \) and \( \beta \) algorithm [83], which requires the computation of the Hessian matrix of \( F(x) \). This computation is costly, so the Marquardt backpropagation (MBP) algorithm is used to approximate the Hessian as

\[
H(x) \approx 2 \beta J^T J + 2 \alpha I_Q, \quad (12)
\]

where \( J \) is the Jacobian matrix of the errors, and \( I_Q \) the matrix identity.

The Marquardt backpropagation algorithm is presented in Algorithm 2 [84]. Note that network’s errors must be in vector form, given by

\[
e = [e_{1,1} \quad e_{2,1} \quad \ldots \quad e_{O,1} \quad e_{1,2} \quad \ldots \quad e_{O,M}]. \quad (13)
\]
Finally, the regularization parameters can be calculated as follows:

\[ \alpha = \frac{\gamma}{2F_D}, \]  
\[ \beta = \frac{s - \gamma}{2E_W}, \]  

where \( \gamma = Q - 2a \text{tr}(H)^{-1} \), and \( s = M \times O \).

**Algorithm 1:** Bayesian regularization [83].

1. Initialize \( a, \beta, x \) randomly;
2. while MBP does not converge do
3. Take one step of MBP algorithm;
4. Solve (12) to obtain \( H \);
5. Compute \( \alpha \) (14) and \( \beta \) (15);
6. end

**Algorithm 2:** Marquardt backpropagation (MBP) [84].

1. Initialize \( \mu, \Delta, F_{\text{min}}, \mu_{\text{max}} \);
2. Compute \( F_k \) (10);
3. while \( F_k > F_{\text{min}} \) or \( \mu_{\text{max}} > \mu \) do
4. Obtain network outputs \( a \) (8);
5. Compute \( e \) (13);
6. Compute the Jacobian matrix \( J \) of \( e \) w.r.t \( x_k \);
7. Solve \( x_{k+1} = x_k - (J^T J + \mu I)^{-1}J^T e; \)
8. Compute \( F_{k+1} \);
9. if \( F_{k+1} < F_k \) then
10. \( F_k = F_{k+1}; \)
11. \( x_k = x_{k+1}; \)
12. \( \mu = \mu \times 1/\Delta; \)
13. else
14. \( \mu = \mu \times \Delta, \) go to step 7;
15. end
16. end

5. Implementation of an ANN-Based MPPT

The training data must contain different I–V curves (determined by environmental conditions) for several PVS families (determined by the electrical characteristics) to improve the ANN generalization capabilities. This data collection task is not simple since it would involve acquiring several PVS, each with the necessary sensors to collect measurements. For this reason, we decided to generate synthetic data with the following assumptions:

- The diode ideality constant is set to \( n = 1.3 \) [85–87];
- The short-circuit current/temperature coefficient is set to \( \mu_I = 0.0006 \) [88];
- The bandgap energy of the semiconductor (silicon) is set to \( E_g = 1.12 \text{ eV} \) [71];
- The parallel resistance \( (R_p) \) is considered infinite [68];
- The number of parallel cells in the PVS is set to \( N_p = 1 \);
- The number of different weather conditions for each PV family is 10 (randomly selected);
- The number of measurements in each I–V curve is 10 (randomly selected).

Note that the data generation process would not be necessary if a PVS data repository with PVS characteristics and measurements were available (similar to ImageNet, used for image classification); we hope this will be possible soon.
5.1. Data Collection and Generation

The data generation process is based on [89] and may be summarized as the sweeping of a grid formed by four variables: three of them are found in the datasheet ($I_{sc}$, $V_{oc}$, and $N_s$), and the other is a model parameter ($R_s$).

Each set of variables represents a PVS family, whose dynamics are determined by Equations (2)–(5). Note that this set of equations requires irradiance and ambient temperature values as inputs in addition to the model parameters. In this manner, real irradiance and temperature time series were used to obtain appropriate dynamics, thus avoiding the unrealistic scenarios that synthetically generated data could present. The measurements range from 1 January 2017 to 31 December 2018 and provide readings of ambient temperature and solar irradiance every 5 min. These data were collected by a weather station located at the University of Michoacan, Mexico. Figure 4 presents a subset of the weather data.

The generated training data set comprises 300,000 observations (i.e., training examples). Table 1 shows a subset of the training data. The first 100 observations of the training set correspond to a single-family under different ambient temperature and solar irradiance conditions. Figure 5a shows the I–V curves obtained for these environmental conditions and the 10 points extracted (randomly) from each one. The MPP, obtained by sweeping the curve, is also indicated. Figure 5b shows the P–V curve for the same data set; the squares denote the maximum power points for each environmental condition.

![Figure 4. Subset of weather measurements used for the training phase.](attachment:image.png)
Table 1. Subset of the generated training data set.

| Ns | I_{sc,ref} (A) | V_{oc,ref} (V) | P_{max,ref} (W) | I_{mpp,ref} (A) | V_{mpp,ref} (V) | G (W/m²) | T_a (K) | V_{mpp} (V) | I (A) | V (V) |
|----|----------------|----------------|----------------|-----------------|-----------------|---------|---------|------------|------|------|
| 65 | 2.5996         | 42.4458        | 42.5783        | 1.8785          | 22.6661         | 531     | 292.9833| 24.4234    | 1.3901| 0.2066|
| 65 | 2.5996         | 42.4458        | 42.5783        | 1.8785          | 22.6661         | 84      | 293.8722| 29.7801    | 0.1041| 34.9496|
| 65 | 2.5996         | 42.4458        | 42.5783        | 1.8785          | 22.6661         | 531     | 292.9833| 24.4234    | 1.3901| 0.2293|
| 9  | 3.3776         | 5.3630         | 9.3137         | 2.8705          | 3.2446          | 889     | 299.7056| 2.8566     | 3.0553| 0.0863|

(a) Set of I–V curves produced by a 42-Watt PVS under 10 different weather conditions. 
(b) Set of P–V curves produced by a 42-Watt PVS under 10 different weather conditions. 
(c) Set of normalized I–V curves produced by 10 different PVS under different weather conditions.

Figure 5. Different characteristics presented in the training dataset.
Similarly, Figure 5c shows a set of I–V curves produced by the first 10 families in the database. Each family has a different voltage and current (depending on the number of series cells). Thus, the plots show normalized voltages and currents. Note that each family has a different series resistance, which produces different curve types.

5.2. Data Preprocessing

The primary purpose of the data preprocessing stage is to facilitate network training. In most cases, inputs must be scaled to adjust the different input values to a standard scale before applying them to the network. This process is of particular importance when dealing with heterogeneous inputs (i.e., inputs related to ambient temperature combined with inputs related to voltage). Furthermore, unscaled input variables can result in a slow or unstable learning process [90]. In this paper, we scale the training data in the range (−1, 1).

5.3. ANN Architecture

The most used ANN architecture for function approximation is an MLP. The typical MLP architecture for regression composes a hidden layer with sigmoid transfer functions and an output layer with linear transfer functions [66].

The most appropriate network architecture was chosen by trial and error, and it comprises two hidden layers with 30 neurons each. The number of neurons in the input and output layer is seven and one, respectively, as Figure 3 shows.

6. Results and Discussions

We present a case study to analyze the performance of the proposed DS-ANN MPPT technique, in which the original P&O and an improved P&O [91] MPPT techniques are used as the basis for comparison. The improved P&O algorithm allows toggling between two different step sizes (ΔV₁ and ΔV₂) based on the magnitude of detected power change (ΔP) to track sudden changes in irradiance quickly.

To compare the MPPT techniques’ performance, we use the tracking efficiency metric. The tracking efficiency is defined as (16) [92]:

\[
\eta = \frac{1}{M_s} \sum_{j=1}^{M_s} \left( \frac{P_{mppt,j}}{P_{max,j}} \right) \times 100, \tag{16}
\]

where \( P_{mppt} \) is the power output applying the MPPT technique, \( P_{max} \) is the maximum available power, and \( M_s \) the number of samples. The tracking efficiency indicates the percentage of power extracted by the MPPT algorithm from the maximum available power.

To obtain \( P_{max} \), we use the curve sweep method [93]. This method calculates the full I–V curve for each tuple of weather conditions and then locates the MPP by comparing each point in the curve. While this method is accurate, it is not useful in on-line applications because it forces the system to change its operating point along the curve for each environmental condition. Thus, once the weather changes, the entire process must be repeated, which yields energy losses.

All the equations and algorithms presented here were programmed using MATLAB®, while the Deep Learning Toolbox™ performed the networks’ training. The training processes were executed on a computer with two Intel Xeon E5-2650 v3 2.30 GHz processors and 32 GB RAM, using the 64-bit Windows Server 2016 Standard operating system.

Case Study

We use the Simulink™ environment to analyze the efficiency and generalization capability of the DS-ANN with different PV modules. Figure 6 presents the model block diagram utilized to perform the simulations. We used twenty distinct PV modules, listed in Table 2, whose datasheet and dynamics are available in Simulink. The boost converter uses the average model, and conduction and switching losses are not considered. The resistance
value in the load is 80 Ω. All simulations utilize the irradiance and ambient temperature measurements for 1 February 2019 (shown in Figure 7) to elaborate a fair comparison. Note that these measurements were not presented to the ANN during the training phase.

![Figure 6. Simulink model for testing the proposed DS-ANN MPPT technique.](image)

![Figure 7. Weather measurements station for the case study.](image)

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**(a)** Solar irradiance.

**(b)** Ambient temperature.
Table 2. Performance comparison of the different MPPT techniques for the case study.

| PV Module                | Tracking Efficiency (%) |
|-------------------------|-------------------------|
|                         | DS-ANN                  | Improved P&O [91] | Conventional P&O |
| Aavid Solar ASMS-185M   | 99.86                   | 98.17             | 97.92           |
| Advance Power API-P210  | 99.86                   | 98.60             | 98.08           |
| Canadian Solar CS6P-180P| 99.80                   | 98.49             | 97.99           |
| Celestica C60Q230       | 99.31                   | 98.61             | 98.10           |
| Centrosolar America D200| 99.80                   | 98.60             | 98.12           |
| Ecosol PV Tech ECS200P-54| 99.45                   | 98.60             | 98.25           |
| Foxconn FSM205-D3C0     | 99.26                   | 98.43             | 98.26           |
| Green Technology A10J-S72-175 | 99.86              | 98.36             | 97.92           |
| Innotech Solar x230     | 99.63                   | 98.61             | 98.11           |
| KD Solar KD-20012A2     | 99.63                   | 98.51             | 98.25           |
| Kyocera Solar KC200GT   | 99.62                   | 98.50             | 98.19           |
| LG Electronics LG210P1C-G2 | 99.80                 | 98.52             | 98.00           |
| Lumos LS200-72M-B       | 99.84                   | 98.17             | 97.84           |
| Nuvosun FL0927-240      | 99.73                   | 97.95             | 97.69           |
| Perlight Solar PLM-205P-60 | 99.80                 | 98.51             | 98.17           |
| Samsung SDI LPC235SM-02 | 99.29                   | 98.45             | 98.26           |
| Solar Liberty SLX215P6-30 | 99.45                  | 98.57             | 98.14           |
| Sun Earth TPB156x156-54-P 200W | 99.60              | 98.61             | 98.18           |
| Trina Solar TS1-180A    | 99.83                   | 98.34             | 97.98           |
| Westinghouse Solar ST-180-1 | 99.87                | 98.40             | 97.83           |
| Mean ± Std              | 99.66 ± 0.20            | 98.45 ± 0.17      | 98.06 ± 0.16    |

A P&O (with a fixed-step size determined by $\Delta V = 0.028V_{oc,ref}$) and a improved P&O [91] MPPT techniques (with parameters $\Delta V_1 = 0.028V_{oc,ref}$, $\Delta V_2 = 0.020V_{oc,ref}$, $\Delta P_{min} = 0.002P_{max,ref}$) are used as the basis for comparison.

To visualize the three compared methods’ tracking dynamics, we specifically used the Kyocera Solar KC200GT module, whose datasheet is shown in Table 3. However, the results obtained in the rest of the PV modules are similar, as shown in Table 2. Note that this datasheet and the other PV modules’ datasheets were not presented to the network during the training phase.

Table 3. Kyocera KC200GT datasheet characteristics and estimated model parameters [89].

| Datasheet Characteristic | Value      |
|-------------------------|------------|
| $I_{sc}$                | 8.21 A     |
| $V_{oc}$                | 32.9 V     |
| $P_{max}$               | 200 W      |
| $I_{mpp}$               | 7.61 A     |
| $V_{mpp}$               | 26.3 V     |
| $N_s$                   | 54         |

The performance results of the DS-ANN and the P&O MPPT techniques for the KC200GT module are shown in Figure 8. Figure 8a shows the P&O MPPT technique, where their oscillations in the power output and its slow tracking against sudden irradiance changes can be observed in the close-up views. The tracking efficiency is 98.19% due to power fluctuations and slow tracking speed.

Although the method proposed by Anya et al. [91] improves the tracking speed and reduces the amplitude of the oscillations in the generated power, it does not entirely solve the problem, as Figure 8b shows. This technique’s tracking efficiency throughout the day for the KC200GT module is 98.50%, which improves the conventional P&O approach.

The DS-ANN technique solves the oscillations problem and improves the tracking speed, as shown in Figure 8c, enhancing the tracking efficiency for the KC200GT module to 99.62%. Figure 8d shows a comparison of the three MPPT techniques for the KC200GT
module, where it is seen that the performance of the DS-ANN approach is better than that of the P&O methods.

Furthermore, Table 2 shows the comparison in the tracking efficiency for 20 different photovoltaic modules, where it is observed that our DS-ANN method has an average efficiency of 99.66 ± 0.20%. In contrast, the P&O methods have 98.45 ± 0.17% and 98.06 ± 0.16% efficiencies for the improved and the conventional P&O. These results highlight the great utility of the proposed DS-ANN technique for MPP tracking in EV applications, where reducing the energy loss by improving the tracking efficiency enhances the EV’s autonomy and hence lessens its CO₂ emissions.

![Graphs showing performance comparison](image)

Figure 8. MPPT techniques’ performance for the Kyocera Solar KC200GT module.

7. Conclusions

We discussed the application of an ANN as an MPPT technique (DS-ANN) whose required inputs are the ambient temperature, PV module’s voltage and current measurements, and its datasheet information. The latter allows the utilization of the MPPT technique on different PVS without the need for retraining.

The response of 20 different PV modules was simulated using irradiance and temperature measurements to verify the DS-ANN MPPT method’s performance. These modules’ information was not presented in the training set to demonstrate the ANN’s generalization capability.
The results of the simulations show the performance improvement of the proposed DS-ANN technique concerning two P&O MPPT techniques. The DS-ANN technique can track the sudden irradiance changes, which yields a better tracking efficiency and increases the generated energy, making it a reliable MPPT technique for any EV with integrated PV generation.

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**Abbreviations**

The following abbreviations are used in this manuscript:

- **ANN:** Artificial neural network
- **EV:** Electric vehicle
- **DS-ANN:** Datasheet ANN (proposed MPPT technique)
- **$E_g$:** Semiconductor bandgap energy (eV)
- **$G$:** Solar irradiance (W/m$^2$)
- **$G_{\text{ref}}$:** Solar irradiance at STC (W/m$^2$)
- **$I$:** PVS output current (A)
- **$I_0$:** Diode reverse saturation current (A)
- **$I_{0,\text{ref}}$:** Diode reverse saturation current at STC (A)
- **$I_{\text{mpp}}$:** Current value at the maximum power point (A)
- **$I_{\text{mpp,ref}}$:** Current value at the maximum power point at STC (A)
- **$I_{\text{ph}}$:** Light-generated current (A)
- **$I_{\text{ph,ref}}$:** Light-generated current at STC (A)
- **$I_{\text{sc}}$:** Short-circuit current (A)
- **$I_{\text{sc,ref}}$:** Short-circuit current at STC (A)
- **$k$:** Boltzmann constant ($\approx 1.38064852 \times 10^{-23}$ J/K)
- **MLP:** Multi-layer perceptron
- **MPP:** Maximum power point
- **MPPT:** Maximum power point tracking
- **$\mu_I$:** Short-circuit current/temperature coefficient (A/K)
- **$\eta$:** MPPT efficiency (%)
- **$n$:** Diode ideality constant
- **$N_p$:** Number of parallel PV cells in the PVS
- **$N_s$:** Number of series PV cells in the PVS
- **NOCT:** Nominal operating cell temperature (K)
- **$P$:** PVS output power (W)
- **$P_{\text{max}}$:** PVS maximum available output power (W)
- **$P_{\text{max,ref}}$:** PVS maximum output power at STC (W)
- **P&O:** Perturb and observe
- **PV:** Photovoltaic
- **PVS:** Photovoltaic system
- **$q$:** Electron charge ($\approx 1.60217662 \times 10^{-19}$ C)
- **$R_p$:** Parallel resistance (Ω)
$R_s$  Series resistance (Ω)

STC  Standard test conditions

$T$  PVS temperature (K)

$T_a$  Ambient temperature (K)

$T_{ref}$  PVS temperature at STC (K)

$V$  PVS output voltage (V)

$V_{mpp}$  Voltage value at the maximum power point (V)

$V_{mpp,ref}$  Voltage value at the maximum power point at STC (V)

$V_{oc}$  Open-circuit voltage (V)

$V_{oc,ref}$  Open-circuit voltage at STC (V)

$V_t$  Junction thermal voltage (V)

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