PSO, MFFNN and FPWM Algorithms
For Grid-Connected PV System

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Abstract—This paper summarizes a whole work on grid-connected photovoltaic system based on shunt power active filter with a view to simultaneously compensate harmonic currents and reactive power, thus improving the quality of the energy supplied to consumer. The proposed MPPT is Particle Swarm Optimization (PSO) method and the shunt power active filter is built by Multilayer Feed-Forward Neural Network (MFFNN) and Fuzzy Pulse Width Modulation (FPWM). The simulation of the system under Simulink environment on Matlab software proves the robustness of the control used, which guarantees the elimination of harmonic currents and reactive power in addition to the injection of the maximum solar power to the power grid.

Keywords Particle Swarm Optimization; MPPT; Multilayer Feed-Forward Neural Network; Fuzzy Logic Pulse Width Modulation; Shunt Active Power filter.

1. Introduction

The need of the human being for energies appeared with the appearance of his species, starting with heating and cooking his food, this need exploded with the industrial revolution at the beginning of the XIX century. Since then, a race behind energy sources has been launched.

According to [1], Energy Information Administration (EIA) initiatives that the world energy use will develop by almost 56% between 2018 and 2040. When the fossil energy (oil, coal, gas) accounts for 80% of world energy production through 2040. This growth in demand will quickly lead to the depletion of energy resources, which have been the object of several economic conflicts.

Furthermore, humanity's use of considerable quantities of fossil fuels causes a significant imbalance in the carbon cycle, conductive to an increase in the condensation of greenhouse gases in the terrestrial atmosphere and, as a result, to destructive climate change. The energy security and prevention of the planet are ensured by the sources of renewable energy (26.2% of global electricity generation in 2018 [2]). Solar energy (photovoltaic solar, thermal solar), hydroelectricity, wind power, biomass, geothermal energy are inexhaustible energy flows. Several countries have fully understood this challenge and despite the natural and financial constraints, great efforts are devoted to the development of these resources, in particular photovoltaic energy, which is the focus of our work. According to [2] new annual installations in 2020 will reach 142 GW (gigawatts), seven times of the whole installation in the prior decade (which was 20 GW in 2010) and 14% rise over the previous year.

Solar energy is a very interesting alternative for a country as well sunny as Tunisia from 1800 kWh/m² to 2600 kWh/m² per year (from the north to the south) [3]. Photovoltaic energy is the results of the transformation of a portion of solar radiation into electricity. The photovoltaic cell is the relevant agency of this transformation by generating an electromotive force after exposing to light. The association of many PV cells in series and parallel creates a photovoltaic generator (PVG) that has a non-linear characteristic of the current-voltage (I-V) with a maximum power point MPP [4]. In addition, they depend on the light, luminous intensity and temperature degree. Or, with partially shading, the P-V and I-V curves of PV panel show many maximums and as a result the tracking of maximum power point (MPP) is becoming more complicated. To remedy this phenomenon, several maximum point tracking (MPPT) algorithms have been proposed such as the incremental of conduction (IncCond), perturb and observe (P&O), particle swarm optimization (PSO), fuzzy logic (FL) and many other techniques. Due to their ability to search the global power and their derivative-free advantage, meta-heuristics algorithms are the appropriate selection to solve this problem [5-7]. Thus, PSO is the suggested algorithm to maintain the MPP.

Besides, industrial and domestic equipment is increasingly using electronic circuits with non-linear behavior, which is the reason of drawing harmonic currents.
Classically, passive filters are widely used in power quality matters, then advanced filtering technologies are becoming the interest of many researches such as Shunt Power Active filter (SAPF) [8]. Many structures of SAPF are studied in recent researches such as the instantaneous active and reactive power (PQ), the PI or proportional-integral regulator, the synchronous reference frame and the greatest tendency is the use of smart techniques which demonstrated their relevance including fuzzy logic controllers and deep learning like GA, Swarm, ANN and Bee [9].

Multilayer Feed-Forward Neural Network, where it is not necessary to establish specific input-output relationships, is the proposed estimation method in the specific SAPF. Furthermore, in FPWM or Fuzzy Pulse Width Modulation (FPWM) is suggested to command the IGBTs and reduce the THD value. As thorough in [8-9], this technique is similar to the classical PWM method.

Therefore, the present paper is organized as follows, after presentation of the system in section 2, the proposed MPPT based on PSO is detailed in section 3. The SAPF is introduced in section 4, followed by simulation results in section 4. Finally, the paper is ended with a conclusion in section 5.

2. System Topology

The grid-connected photovoltaic system is depicted in Figure 1. The first part of the energy conversion chain contains a PV module, which is formed by connecting multiple modules in parallel and series, combined with a DC/DC converter (BOOST) in order to maintain the PV array producing continuously its maximum power into the electric grid, by using the PSO MPPT method. The second part interfaces the first part generated energy to the electric grid through a DC-AC inverter, which acts as a shunt power active filter to not only compensating harmonics at the AC main but also reducing the reactive power.

The control of PV systems is enabled through the power converter, which acts as an interface between the PV and the grid. For the two-stage PV system in Fig. 1, the dc/dc conversion stage is responsible for the PV power control, while the dc/ac conversion stage is in charge of grid interactive [10]. From the PV side, the dc/dc converter regulates the extracted power from the PV arrays by controlling the operating point of the PV array (e.g., PV voltage) according to the P-V characteristic of the PV array. This can be done by using a proportional-integral controller to regulate the PV voltage, whose reference is determined by the MPPT algorithm, to continuously track the MPP and maximize the energy yield during operation.

As the PV power is controlled by the dc/dc converter, the role of dc/ac conversion stage is to ensure that the extracted power is delivered to the ac grid. One possible way to do so is to regulate the dc-link voltage, as the dc-link voltage should be kept constant when the dc power and ac power is balanced. By doing so, the output of the dc-link voltage controller will give a required amplitude of the grid current, according to the difference between the reference and the measured dc-link voltage.

a) Modeling of the PV array

PV module topology is known as parallel-series connection of multiple cells and the its equivalent circuit is displayed in figure 2.
The output current of the PV module is mathematically modeled as the equation (1) [7]:

\[ I_{pv,\text{array}} = N_{mp}N_p I_{ph} - N_{mp}N_p I_0 \left( \frac{V_{pv} + I_{pp}R_s}{N_sAV_T} \right) - 1 \]  

(1)

\( I_{ph} \) is the module photocurrent and it linearly varies with the solar radiation and also influenced by the temperature as equation (2).

\[ I_{ph} = \left[ I_{scr} + K_i(T_K - T_{ref}) \right] \frac{\lambda}{1000} \]  

(1)

\( I_0 \) is the diode saturation current for series connected modules and is calculated using \( I_{rs} \) as given in equation (3).

\[ I_0 = I_{rs} \left( \frac{T}{T_R} \right)^3 e^{-\frac{qE_g0}{AK} \left( \frac{T}{T_R} - 1 \right)} \]  

(3)

\( I_{rs} \) is the reverse saturation current and is given in equation (4).

\[ I_{rs} = \frac{I_{scr}}{e^{\frac{qE_g0}{AK} \left( \frac{T}{T_R} - 1 \right)}} \]  

(4)

Equation (1) comprises four parameters \( I_{ph} \), \( I_0 \), \( A \) and \( R_s \). Figures 3a and 3b show, respectively, the resulting P-V curve of the PV array operating under uniform temperature and irradiation. Whereas, figures 3a and 3b depict one single MPP, Figures 3c and 3d present more local MPP and one global MPP while the PV system is operating under shading conditions.

MPP controller is necessary to track the new modified maximum power point in its interrelated curve once temperature and/or irradiation change appears. Therefore, different MPPT methodologies have been realized with the aim of extracting the MPP under varying atmospheric conditions. Nevertheless, the occurrence of multiple peaks decreases the performance of many MPPTs owing to their incapacity to differentiate between local and global MPP [11]. This problem is solved with intelligent techniques, like Particle Swarm Optimization or PSO [11-12].

b) Modeling of the DC/DC converter

In order to match the intrinsic impedance of the PV generator to that of the load, a boost type power converter must be inserted between the two elements. In this case, an optimal transfer of power between the PV system and the load is ensured. The adapting of impedance load is achieved by adjusting of the duty cycle of the converter, so that the photovoltaic generator can be operate at its maximum power point. The circuit diagram of the boost-type power converter is presented in Fig. 4.

Note that \( \alpha \) is the duty cycle, the average value output quantities \( (I_{dc}, V_{dc}) \) can then be expressed as a function of the input quantities \( (V_{pv}, I_{pv}) \) by (5):

\[ V_R = \frac{V_{dc}}{1 - \alpha} \text{ and } I_R = (1 - \alpha)I_{dc}. \]  

(5)
Then, the equivalent resistance seen by the noted GPV is then expressed by:

\[ R_e = \frac{V_{pv}}{I_{pv}} = \frac{R}{(1-\alpha)^2} \]  

(6)

So at fixed load resistance, we can therefore change the value of this resistance and the optimal point operation can be tracked by adopting the value of the duty cycle according to a boost converter.

![Fig 4. BOOST converter topology](image)

3. PSO MPPT technique

In PV systems, one main consideration is the efficiency of the power production of the system. It is desirable that the PV systems deliver the maximum available power to the grid all the time because of the fact that PV modules have relatively low conversion efficiency. Therefore, in most cases, it is required for PV systems to operate at the maximum power point. As shown in Fig. 3.c and fig 3.d, the MPP of the PV arrays varies with the environmental conditions.

To maximize the power production of PV systems, maximum power point tracking algorithm, which continuously tracks the MPP during operation, is essential. The most prevalent swarm intelligence-based optimization techniques being Particle Swarm Optimization (PSO) [12]. The standard PSO procedure was proposed in 1995 by Eberhart and Kennedy, and it is inspired from swarm behavior especially bird flocking [5]. Since then, other formulations of the conventional PSO algorithm have been developed [6].

To begin the procedure, PSO initializes a swarm of particles and distributes random positions to all particles. Then, in order to avoid abandoning particles from the search space throughout the first iteration, velocities are initialized with a small aleatory value or zero. Over the main loop of the algorithm, velocity and position of each particle are iteratively upgraded as equations (7) and (8) [10] [12-13].

\[
\begin{align*}
V_{i}^{k+1} & = \begin{cases} 
\frac{\text{Update velocity}}{\text{inertial component}} 
\text{c}_1 r_1 (P_{best,i} - x_i^k) 
\end{cases} + \frac{\text{c}_2 r_2 (G_{best,i} - x_i^k)}{\text{cognitive component}} \\
\frac{\text{social component}}{x_i^k} & = x_i^k + V_{i}^{k+1}
\end{align*}
\]

(7)

(8)

Where \(i\) is the variation of the optimization vector, the number of iterations is accounted by \(k\). The parameters \(v_i^k\) and \(x_i^k\) are the velocity and position, respectively, of the \(i\)th variable for \(k\) iterations, and the measure \(w\) is the inertia weight introduced by Shi and Eberhart [6-7]. The coefficients \(c_1\) and \(c_2\) are the acceleration parameters and their values are usually close to 2. \(r_1\) and \(r_2\) are two independent haphazard numbers regenerated for each velocity update (0 ≤ \(r_1\) ≤ 1 and 0 ≤ \(r_2\) ≤ 1).

The particle’s new location is identified by a velocity term \(V_{i}^{k+1}\). \(P_{best}\) is the best location that particle \(i\) has visited, that is the last value of \(x_i\), achieving the highest fitness value for that particle and the best fitness value attained by all candidates in the swarm, is named \(G_{best}\) (global best fitness) [7].

The variable \(P_{best,i}\) saves the best position reached by the \(i\)th particle up to the exact time of measurement only when the condition declared in equation (9) is satisfied.

\[ P_{best,i} = x_i^k \text{ if } f_i^k \geq f_i^{\text{fit}}(P_i) \]

(9)

To apply PSO as MPPT controller, the position of the particle \(x_i^k\) is chosen as the duty cycle of the DC-DC converter represented in (10). The velocity of each duty cycle \(V_{i}^{k}\) is altered as (11) and the PV system output power \(P_{pv}\) is selected as the fitness function. The procedure will discontinue and deliver the global best duty cycle when the condition (12) is satisfied.

\[ D_{i}^{k+1} = D_{i}^{k} + v_{i}^{k+1} \]

(10)

\[ v_{i}^{k+1} = w_{i}^{k} \times V_{i}^{k} + r_1 \times c_1 \times (D_{best,i} - D_{i}^{k}) + r_2 \times c_2 \times (G_{best,i} - D_{i}^{k}) \]

(11)

\[ P(D_{i}^{k}) > P(D_{i}^{k-1}) \]

(12)

With \(P, D, K\) and \(i\) are, respectively, the output power, the duty cycle, the number of iterations and the number of current particles.

The variable coefficients PSO, proposed by the authors of [13] and [14], are chosen as (13), (14) and (15).

\[ w = w_{\max} - \frac{k}{k_{\max}} (w_{\max} - w_{\min}) \]

(13)

Where \(k\) and \(k_{\max}\) are the iteration and maximum iteration numbers. Additionally, \(w_{\max}\) and \(w_{\min}\) are the maximum and minimum values of the coefficient and their values could be selected as \(w_{\max}=1\) and \(w_{\min}=0.1\) .

Also multidirectional laws and linear changes in \(c_1\) and \(c_2\) are proposed as (14) and (15).

\[ c_1 = c_{1\max} - \frac{k}{k_{\max}} (c_{1\max} - c_{1\min}) \]

(14)

\[ c_2 = c_{2\min} + \frac{k}{k_{\max}} (c_{2\max} - c_{2\min}) \]

(15)
The upper and lower bounds of change $c_M$ and $c_z$ are defined as the following range: $c_M^{\text{er}} = c_z^{\text{er}} = 1.0$ and $c_M^{\%\hat{}} = c_z^{\%\hat{}} = 2.0$. The experimental results in [13] and [15] have shown that modified PSO to extract the MPP for PV panels with these parameters provides the relevance of the suggested technique.

Figure 5 illustrates the flowchart of the proposed PSO MPPT tracker.

4. Shunt Active Power Filter (SAPF)

The proposed SAPF is depicted with the configuration system in figure 1. The use of the SAPF is realised via a three phase IGBTs bridge inverter which offers high bandwidth and fast switching characteristics.

The SAPF is built with two block. The first one is a controller to estimate harmonics and in literature multifarious techniques are proposed [16]. One of the most widely way to predict the reference currents is based on PQ method, proposed by Akagi [17]. This theory has good results on prediction but needs many transformations based on mathematical equations.

For this reason, this paper presents an alternative procedure built on artificial neural network (MFFNN) where it is not necessary to establish specific input-output relationships. The second block is concerned to compensate the estimated harmonics. The hysteresis controller is the most classically used current control method owing to its simplicity of construction and great dynamic behavior [18-19]. Unfortunately, results obtained with this technique are affected with a high THD value [20]. To increase this important value, fuzzy logic controller is provided in this study.

4.1. MFFNN as estimator of harmonics

In this part, the reference currents should be estimated through an artificial neural network technique, one of the most popular estimating topology based on the structure and functions of biological neural networks [21]. Since it has been used to solve many complex problems of industry, MFFNN or Multilayer Feed-Forward Neural Network is projected in this study as a structure of ANN.

MFFNN is based on three layers which are networked. The inputs to the MFFNN are the three source voltage $V_{abc,\text{res}}$ and load currents $i_L$. The output is the estimated currents $i_{\text{ref}}$. PQ is the extraction method adopted to generate the load current magnitude to be used then in building the MFFNN block.

MFFNN could be established through the neural network toolbox after the collection of the training and target data, and the followed steps resume how to build MFFNN with Matlab software.

- **step1: Define the inputs and output**
In general, \((X, T)\) are the matrices of the inputs and output (target) as defined in (16) and (17):

\[
X_{d-N} = \begin{bmatrix}
X_{11} & X_{12} & \ldots & X_{1N} \\
X_{21} & X_{22} & \ldots & X_{2N} \\
\vdots & \vdots & \ddots & \vdots \\
X_{d1} & X_{d2} & \ldots & X_{dN}
\end{bmatrix}
\]  

(16)

\[
T_{m-N} = \begin{bmatrix}
T_{11} & T_{12} & \ldots & T_{1N} \\
T_{21} & T_{22} & \ldots & T_{2N} \\
\vdots & \vdots & \ddots & \vdots \\
T_{m1} & T_{m2} & \ldots & T_{mN}
\end{bmatrix}
\]  

(17)

Where \(d\), \(N\) and \(m\) are, respectively, the number of features, the number of learning cases, and the number of the desired output. To define the input and the target of the proposed MFFNN the instruction with Matlab is:

\[
X = \begin{bmatrix} i_L(:,2); i_i(:,3); i_L(:,4); v_{res}(:,2); v_{res}(:,3); v_{res}(:,4) \end{bmatrix}
\]  

(18)

\[
T = \begin{bmatrix} i_{ref}(:,2); i_{ref}(:,3); i_{ref}(:,4) \end{bmatrix}
\]  

(19)

**Step3: Training of the MFFNN**

Once the MFFNN block is constructed in (26), now it would be trained by using the coming instruction:

\[
et = \text{train}(\text{net}, X, T)
\]  

(20)

Where \(net\) is the network net constructed at step2, \(X\) and \(T\) present the input and the target vectors.

**Step4: Evaluation of the MFFNN**

The prediction of the output is done with the next command in (28).

\[
Z = \text{sim}(\text{net}, X)
\]  

(21)

**Step5: Generation of the MFFNN**

The final step is important to obtain the Simulink block of the trained MFFNN by simply application of the command “gensim(net)”. The generated MFFNN Simulink block which is constructed with two layers, is presented in figure 6.

![MFFNN Simulink block](image)

**Fig6. The generated MFFNN**

This block is, finally, copied to Simulink window to be ready to extract the reference currents in the shunt power active filter.

4.2. **FPWM**

Fuzzy Pulse Width Modulation or FPWM is the technique used in the second block of the proposed SAPF in order to compensate the estimated currents and to command the IGBTs with the advantage of reducing the THD value.

The principle of the FPWM topology is exposed in figure 7.
FLC is established by three processes: fuzzification phase, fuzzy rule base and defuzzification phase. Fuzzification phase aims to convert the numerical inputs to linguistic variables, the block of the fuzzy rule base or fuzzy procedure consists of the definition of the rules and the membership functions which used to obtain a suitable output and the defuzzification phase is the last procedure to obtain non-fuzzy outputs [22].

As shown in figure 7, the FPWM is built with two inputs which are the error between the reference current and the real current \( (e = i_{ref} - i_f) \) and the error variance \( (\delta e = e(k) - e(k-1)) \). Besides, the output of the designed FLC is selected as the amplitude of the current error.

FLC block is implemented by the definition of its three parts as following.

- **Fuzzification**: Seven fuzzy sets are chosen for the inputs and output such as, negative big (NL), negative medium (NM), negative small (NS), zero (Z), positive small (PS), positive medium (PM) and positive big (PB).

Figure 8 depicts the normalized triangular and trapezoidal membership functions for the inputs and output.

- **Table of rules and inference engine**: The rule table includes 49 rules and it is displayed in table 1.

The most common types of fuzzy reasoning that have been applied to different application are Mandani suggested by Ebrahimmamdani in 1975 and Sugeno in 1985 introduced by Takagi-Sugeno-Kang type models [23]. Being the first control systems based on fuzzy logic, Mamdani’s inference method is widely used for complex systems and decision processes as it lets the user to identify the command in more intuitive just like human manner. Furthermore, it generates the output membership functions, while Sugeno hasn’t. For this reason, Mamdani’s method is chosen in this paper.

**Table 1**: Fuzzy rules

<table>
<thead>
<tr>
<th>( \delta e )</th>
<th>( e )</th>
<th>NB</th>
<th>NM</th>
<th>NS</th>
<th>Z</th>
<th>PS</th>
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<td>NB</td>
<td>NM</td>
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<td>NM</td>
<td>NS</td>
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<td>PS</td>
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<td>NS</td>
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</tbody>
</table>

- **Defuzzification**: To end the defuzzification phase, it is necessary to choose one of multifarious methods which are itemized in recent researches like Mean of Maximum Method (MOM), Center of Area Method (COA) and Bisector of Area (BOA) [24-25]. The center of area method or center of gravity is chosen in this paper.

To resume, the model of the built fuzzy logic controller is defined as:

- Two inputs \( (e, \delta e) \) and one output \( (du) \) are defined with seven fuzzy sets for each variable and constructed with triangular and trapezoidal membership functions.
- Mandani procedure is employed.
- Center of area (COA) is chosen as a defuzzification method.

5. Simulation and Results

As demonstrated in Fig. 1, the system comprises a PV generator including panels connected in series and parallel, BOOST inverter and DC/AC. The system is connected to grid. The parameters of the PV array are presented in table 4, the BOOST is commanded with PSO, the DC/AC is a bridge of six IGBTs switches, the shunt power active filter is built by MFFNN to estimate harmonic currents in the first hand and FPWM to, simultaneously, eliminate harmonics, reduce reactive power and command the IGBTs switches, in the other hand. The nonlinear load is a three phase full-bridge diode rectifier supplying a RL load.
Fig9. The suggested system model under Simulink/Matlab

Table2 PV array parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of cells (Ns)</td>
<td>36</td>
</tr>
<tr>
<td>Reference temperature (T_r)</td>
<td>25</td>
</tr>
<tr>
<td>Series resistance (R_s)</td>
<td>0.02</td>
</tr>
<tr>
<td>Shunt Resistance (R_p)</td>
<td>1000</td>
</tr>
<tr>
<td>Short-Circuit Current (I_{sc})</td>
<td>3.2</td>
</tr>
<tr>
<td>Band-gap Energy (E_{g0})</td>
<td>1.12</td>
</tr>
<tr>
<td>Ideality Factor (A)</td>
<td>1.75</td>
</tr>
</tbody>
</table>

As shown in figures 3a,3b,3c and 3d the Simulink results of the system for different temperature and radiation demonstrates that the I-V characteristics of PV module relies strongly on temperature and solar irradiation.

fig10. a Three phase source voltage

fig10. b Three phase source current

Fig11. Currents after filtration for a phase

The objective of the PV system and converters is to deliver a clean power to the grid, which is demonstrated by figures 10.a and 10.b. Indeed, the waveforms of the three
phase source currents voltages are sinusoidal which demonstrate the effectiveness of the proposed SAPF.

The load current is the sum of the source current and the compensation current for a phase as shown in equation (29).

\[ i_L = i_s + i_c \] (29)

Therefore, to demonstrate this equation, figure 11 illustrates the load current (in red), the source current (in green) and the compensated current (in blue) after filtration. The proposed SAPF generates a sinusoidal source current with a good compensation of harmonics.

\[ \text{Fig12.} \] Power curve with PSO

The role of the proposed boost with PSO MPPT controller, is to maintain the PV system operating at its maximum power point. The importance of the use of PSO tracker is to differentiate between the global maximum point and the local maximum point which is demonstrated by figure 12.

\[ \text{Fig13.} \] The dynamic performance of the MFFNN- SAPF

The MFFNN method is established after the application of the instantaneous active and reactive power theory (PQ), as a benchmark procedure to test the estimation preciseness of the proposed model MFFNN. Figure 13 shows the actual fundamental active load current extracted by PQ method compared to the estimated fundamental active load current by MFFNN method. The figure shows the closeness of both curves which proves the effectiveness of the proposed MFFNN as an estimator.

Besides, MFFNN method and fuzzy logic techniques improve the robustness of the proposed SAPF with decreasing value of THD (total harmonic distortion) from 15.14% with the instantaneous active and reactive power method and classical PWM, to 0.94 with PQ and FPWM, to 0.17 with MFFNN and FPWM as shown in figures 14a, 14b and 14c.

\[ \text{Fig14.a} \] THD with PQ and PWM
\[ \text{Fig14.b} \] THD with PQ and FPWM
\[ \text{Fig14.c} \] THD with MFFNN and FPWM

6. Conclusion

For grid-connected PV power generation system, MPPT based on PSO is proposed to step-up the dc voltage and to track the global MPP when multiple peaks exist in the PV curve under partially shaded conditions. Moreover, with the aim of compensation harmonic currents and reactive power, shunt power active filter with MFFNN and FPWM techniques is introduced. Simulation results prove the success of the suggested system, with reduction on the THD value which is within the limit of the harmonic standard recommendation.
Nomenclature

- $V_{pv}$: PV cell voltage (V)
- $I_{pv}$: PV cell output current (A)
- $V_{oc}$: Solar module open circuit voltage
- $I_{sc}$: Short circuit current
- $V_T$: Thermal junction voltage (KT/q)
- $Q$: Electron charge (e)
- $K$: Boltzmann’s constant (J/K)
- $T$: Temperature
- $A$: Diode ideality factor
- $N_p$: Number of cells in parallel
- $N_s$: Number of cells in series
- $N_{mp}$: Number of modules in parallel
- $N_{ms}$: Number of modules in series
- $\lambda$: The irradiation on the surface (w/m²)
- $K_I$: Current/temperature coefficient (A/K)
- $R_s$: The equivalent series resistance
- $R_p$: The equivalent parallel resistance
- PSO: Particle Swarm Optimiztion
- MFNNN: Multilayer feed forward neural network
- FPWM: Fuzzy pulse width modulation

References


