A Highly-Efficient Fuzzy-based Controller with High Reduction Inputs and Membership Functions for a Grid-connected Photovoltaic System

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ABSTRACT  Most conventional Fuzzy Logic Controller (FLC) rules are based on the knowledge and experience of expert operators: given a specific input, FLCs produce the same output. However, FLCs do not perform very well when dealing with complex problems that comprise several input variables. Hence, an optimization tool is highly desirable to reduce the number of inputs and consequently maximize the controller performance, leading to easier maintenance and implementation. This paper, presents an enhanced fuzzy logic controller applied to a photovoltaic system. Specifically, both inputs and membership functions are reduced, resulting in a Highly Reduced Fuzzy Logic Controller (HRFLC), to model a 100kW grid-connected Photovoltaic Panel (PV) as part of a Maximum Power Point Tracking (MPPT) scheme. A DC to DC boost converter is included to transfer the total energy to the grid over a three-level Voltage Source Converter (VSC), which is controlled by varying its duty cycle. FLC generates control parameters to simulate different weather conditions. In this study, only one input representing the current variation (△I) of the FLC is used to provide an effective and accurate solution. This reduction in simulation inputs results in a novel HRFLC which simplifies the solar electric system design with output Membership Functions (MFs). Both are achieved by grouping two rules instead of using an existing state-of-the-art method with twenty-five MFs. To the best of our knowledge, this is the first FLC able to provide such rules compression. Finally, a comparison with different techniques such as Perturb and Observe (P&O) shows that HRFLC can improve the dynamic and the steady state performance of the PV system. Notably, experimental results report a steady state error of 0.119%, a transient time of 0.28s and an MPPT tracking accuracy of 0.009s.

INDEX TERMS  Boost Converter, Current Variation, Grid Connection, High Reduced Fuzzy Based MPPT Controller (HRFLC), Photovoltaic Panel, Three level VSC.

Nomenclature

| Variables | Description |
|-----------|-------------|
| △E(t) | Error Variation |
| △I | Current Variation |
| △P | Power Variation |
| △V | Voltage Variation |
| C | Capacitor Value |
| D | Duty Cycle |
| dP_{PV}/dI_{PV} | Power derivation by current |
| E(t) | Error |
| G | Irradiation |
| I_{in} | Input Current |
| I_{out} | Output Current |
| I_{Ph} | Photo Current |
I\textsubscript{PV} Light Generated Current \\
L Induction Value \\
L\textsubscript{e} VSC Level \\
N IGBTs Number \\
R\textsubscript{o} Output Resistance \\
R\textsubscript{eq} Equivalent Resistance \\
R\textsubscript{in} Input Resistance \\
T Temperature \\
V\textsubscript{o} DC/DC Output Voltage \\
V\textsubscript{ab} Output Line to Line Voltage of the VSC \\
V\textsubscript{carrier} Carrier Voltage \\
V\textsubscript{in} DC/DC Input Voltage \\
V\textsubscript{PV} Module Output Voltage \\
X\textsubscript{i} Input Fuzzy Data \\
Y\textsubscript{COG} Output Fuzzy Controller Value \\
Y\textsubscript{i} Membership Function Value \\

**Acronyms** \\
ADC Analogic to Digital Converter \\
AI Artificial Intelligence \\
ANFIS Adaptive Neuro Fuzzy Inference System \\
ANN Artificial Neural Network \\
COG Center Of Gravity \\
DC \textendash DC Direct Current to Direct Current \\
FIS Fuzzy Inference System \\
FLC Fuzzy Logic Controller \\
HC Hill Climbing \\
Hi High \\
HRFLC Highly Reduced Fuzzy Logic Controller \\
IE Initial Error \\
InCon Incremental Conductance \\
L\textsubscript{o} Low \\
MF Membership Function \\
MPP Maximum Power Point \\
MPPT Maximum Power Point Tracking \\
NPC Neutral Point Clamped \\
P\&O Perturb & Observe \\
P\textsubscript{MPP} Power value at the Maximum Power Point \\
P\textsubscript{PV} Panel Power \\
PB Positive Big \\
PID Proportional, Integral and Derivation \\
PS Positive Small \\
PV PhotoVoltaic \\
PVG Photo Voltaic Generator \\
PWM Power Wave Modulation \\
S&H Sample and Hold \\
SSE Steady State Error \\
ST Steady Time \\
TOANC Third Order Adaptative Neuro Fuzzy Controller \\
TrC Triangular Carrier \\
TT Tracking Time \\
VSC Voltage Source Converter \\

**Constants** \\
A PV cell ideal factor \\
f Frequency \\
I\textsubscript{CSR} Short Circuit Current \\
I\textsubscript{mp} Optimal Current \\

$I\textsubscript{o}$ Saturation Current \\
k Boltzmann Constant \\
N\textsubscript{p} Parallel connected cells Number in a PV Module \\
N\textsubscript{s} Series connected cells Number in a PV module \\
P\textsubscript{m} Maximal Module Power \\
$q$ The electron charge \\
R\textsubscript{s} Serial Resistance in PV Cell \\
R\textsubscript{sh} Parallel Resistance in PV Cell \\
V Voltage Value \\
V\textsubscript{dc} Input VSC Voltage \\
V\textsubscript{mp} Optimal Voltage Module \\
V\textsubscript{sc} PV Module Open Circuit Voltage \\
V\textsubscript{ref} Reference Voltage

I. INTRODUCTION

In the last few years, there is a great deal of interest worldwide in searching new energy sources able to replace the dwindling fossil fuels. In this context, solar energy turned out to be the most attractive alternative due to its advantages of being cleaner, renewable and inexhaustible [1]-[2]. The main function of Photovoltaic (PV) is to transform the solar irradiance into electric power. However, the generated power from PV depends not only on irradiance but also on other factors such as temperature and spectral properties of sunlight [3]-[5]. These conditions need to be controlled in order to allow a PV panel to operate at the Maximum Power Point (MPP). It is well known from MPP theory that the power delivered to the load is maximum only when the internal impedance is equal to the load impedance. For this reason, a DC-DC converter is used. In the literature, many techniques have achieved this adaptation between the PV panel and the load impedance at different atmospheric conditions such as the well-known Perturb and Observe (P&O) [3]-[6], including the Incremental Conductance technique (InCon). P&O is cost effective and relatively easy to implement for controlling directions. However, this technique shows trade-offs between tracking speed and steady state accuracy to control atmospheric perturbations [3]-[7]. To overcome this problem, several solutions have been proposed [8]-[10]. In particular, it is worth mentioning that the perturbation step increases when the working point is far from the MPP, since the steps are proportional to the ratio $dP\textsubscript{PV}/dV\textsubscript{PV}$ (and vice-versa) [8]-[11].

In the recent years, with the emergence and development of Artificial Intelligence (AI) [12], many applications such as, text mining to biology, financial forecasting, rehabilitation systems, trust management and medical diagnosis [13]-[21] have been efficiently improved. Furthermore, AI also provided effective and robust solutions to the field of electro-control systems by developing PID, fuzzy logic [11], [22]-[38] and Artificial Neural Networks (ANNs) [39]-[41] based-control approaches. A comprehensive fuzzy system has been used by [11] to intelligently and adaptively tune the PID gain. Adaptive neuro-fuzzy controller system has been proposed for controlling MPPT with constant temperature and varying irradiance [22]-[25]. Recently, fuzzy logic is

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used in several applications due to its simplicity and its interpretability. Note that the main advantage of such technique is the addition or withdrawal of membership functions (MFs) without rehabilitation or re-learning. Fuzzy logic allows to model natural language rules and also complex dynamic systems. For this reason, fuzzy-based MPPT algorithms have gained a great deal of attention [11], [22]–[31]. Notably, high tracking performance have been obtained by using fuzzy-based MPPT [11], [22]–[31]. Hitherto, most of the works used two inputs and one output with five MFs to generate twenty-five rules [22]–[32]. Others used one output and two inputs of seven MFs, resulting in forty-nine rules [22]. In [23], two inputs were used with three MFs, yielding nine rules. Vicente Salas et al. [42] employed the variation of current as the unique input in MPPT controller. Specifically, the authors used one input with two MFs, one output with two MFs and only two rules. To the best of our knowledge, this was the first approach able to provide a significant reduction in number of inputs and MFs. It is to be noted, as reported in the literature, that different inputs can be selected. In particular, some used the temperature and irradiance variation [23], whereas others used error variation and momentum [24]–[28]. In [32], the proposed fuzzy controller employed different input variables, such as: (1) slope of solar power vs. solar voltage and slope changes; (2) slope and power variation ($\Delta P$); (3) $\Delta P$ and voltage variation ($\Delta V$); (4) $\Delta P$ and current variation ($\Delta I$); (5) sum of conductance and conductance increment; (6) sum of conductance arc tangent angles and increment conductance arc tangent. In [41] the inputs were $\frac{dP_{PV}}{dt}$ and the error $E(t)$ (defined as $E_{MPPT} - P_{PV}$); or, $E(t)$ and error variation ($\Delta E(t)$). However, for computational reasons, the best inputs turn out to be the $\Delta P_{PV}$ and $\Delta V_{PV}$ (or $\Delta I_{PV}$), power variation and voltage (or current) variation, respectively [22]–[41]. Hence, as reported in the aforementioned works, all controllers based on MPPT used at least two inputs. In contrast, this paper propose a highly-efficiency fuzzy-based MPPT controller with high reduction inputs and MFs for a grid-connected photovoltaic system. Notably, only two MFs were used. Furthermore, $\Delta I_{PV} = (I_{PV}(k) - I_{PV}(k - 1))$ is selected as unique input. Consequently, the calculation time, the number of variables and the circuitry (Analog to Digital Converter (ADC), Sample and Hold (S&H), filter, etc.) are significantly reduced. Moreover, the proposed fuzzy-based controller approach is able to decrease the tracking time and concurrently increase the tracking accuracy as compared with other state-of-the-art controllers.

The rest of the paper is organized as follows: in Section II mathematical details of a PV panel are introduced; in Section III the design of the DC-DC converter is presented; Section IV and V describe the fuzzy based MPPT controller and the Pulse Width Modulation (PWM) used for the three level voltage source converter, respectively. In Section VI the model and simulation of the PV system with HRFLC based MPPT controller is presented. In Section VII the experimental results are discussed and in Section VIII conclusions are addressed.

II. MATHEMATICAL MODELING FOR A PHOTOVOLTAIC PANEL

A solar cell is composed of two types of semiconductors, called $p$-type and $n$-type. Photovoltaic transformation occurs when solar cell is exposed to sunlight, by converting the electromagnetic solar irradiance to electricity. Incident irradiance produces proportional electron-hole pairs if their energy is greater than the energy of the semiconductor’s band-gap. Fig. 1 shows the circuit model of a standard photovoltaic model. The photocurrent $I_{ph}$ is the current source of the PV cell, generated when irradiation $G$ occurs [42]–[48]. Intrinsic shunt and series PV cell resistances are $R_{sh}$ and $R_{s}$, respectively. It is to be noted that $R_{sh}$ assumes typically high values and vice-versa, $R_{s}$ low values. PV cells associated to larger units result in PV modules; these, interconnected together in parallel-series configurations, lead to the production of PV arrays. Equation (1) shows the current output when the mathematical model of the PV panel is simulated [43].

$$I_{PV} = N_{p}I_{ph} - N_{p}I_{0}[exp\left(\frac{q * (V_{PV} + I_{PV}R_{s})}{N_{p}AKT}\right) - 1].$$

(1)

In this work, the SunPower SPR-305-WHT PV panel is used with the following characteristics: Maximal Module Power ($P_m$) of 305W, optimal voltage ($V_{mp}$) of 54.7V, optimal current ($I_{mp}$) of 5.88A, saturation current ($I_{s}$) of 1.1753e-08A, photo-current ($I_{ph}$) of 5.9602A, short circuit current ($I_{sc}$) of 5.96A, open circuit voltage ($V_{oc}$) of 64.2V, serial resistance ($R_{s}$) of 0.037998Ω, parallel resistance ($R_{sh}$) of 993.51Ω and number of cells equal to 96. As regards the PV array, its characteristics are: serial modules number of 5 and parallel modules number of 66. Hence, the PV has a power of about 100kW, obtained as follows $66 \times 5 \times 305W= 100650W= 100.65kW$. Irradiance of 1kW/m² and cell temperature of 25°C are the electrical specifications under test conditions. I-V and P-V curves of the array are depicted in Fig. 2. Here, the PV panel is directly connected to a DC-DC converter. This converter is an impedance adapter and allows to transfer the power captured from the PV panel to the grid toward a three-level voltage source converter.
III. DESIGN THE DC-DC CONVERTER

A simple DC-DC boost converter transfers the power consumption from the PV Generator (PVG) to the load, when the adaptation condition (between PVG and load) occurs. The adaptation is characterized by an adequate duty cycle signal \((0 < D < 1)\). Note that the PWM signal controls the valve gate, IGBT, in the boost converter. The wiring Simulink diagram of the DC-DC boost is shown in Fig. 3.

The relationship between inputs and outputs variables of the boost converter is represented by the following equations [44]:

\[
V_o = V_{in}/(1 - D). \tag{2}
\]

\[
I_{out} = (1 - D)I_{in}. \tag{3}
\]

whereas, Equation (4) shows the equivalent resistance \((R_{eq})\) of the DC-DC boost converter:

\[
R_{eq} = R_{in}(1 - D)^2. \tag{4}
\]

The maximum power is transferred to the load when \(R_{eq}\) is equal to the output resistance \((R_o)\) of the PV system [45]– [46]. Hence, according to the maximum power transfer theorem the duty cycle can be obtained as follows:

\[
R_{in} = V_{in}/I_{in} = R_o(1 - D)^2 \implies D = 1 - \sqrt{\frac{R_{in}}{R_o}} \tag{5}
\]

Inductor \((L)\) and capacitor \((C)\) functions of the DC-DC boost converter are instead defined as:

\[
L = \frac{(V_o - V_{in})V_{in}}{f(\Delta I)V_o}. \tag{6}
\]

\[
C = \frac{(V_o - V_{in})I_{out}}{f(\Delta V)V_o}. \tag{7}
\]

where \(D\) is the duty cycle; \(f\) is the frequency (5 kHz in this study); \(V_{in}\) and \(V_o\) are the inputs and outputs voltages, respectively; \(\Delta I\) and \(\Delta V\) are the current and voltage ripple. Here, \(L = 5e^{-3}H\) and \(C = 12000e^{-6}F\). Fig. 4 depicts the I-V curve of the panel studied with different working zone. In particular, A-B area denotes the buck working zone, B-C the boost working zone and finally A-C the buck-boost working zone [47]. In this work, the boost converter’s working zone (B-C) is the most important and, \(\Delta I\) is the variable of greatest interest. Note that in Fig. 4, B is the MPP point and C is the open circuit point. At the B point \(R_o = R_{in}\). Furthermore, in this area, \(R_o >> R_{in}\) with \(R_{in} = R_o(1 - D)^2\). In order to have a stable voltage at the grid, the VSC voltage must be stable and constant. In this study, the voltage supplied to the VSC is kept constant (\(V = 500\)V) as shown in Fig. 10.

IV. FUZZY BASED MPPT CONTROLLER

A. FUZZY INFERENCE SYSTEM

A standard Fuzzy Inference System (FIS) consists of three modules, as shown in Fig. 6. In the first stage, called fuzzification, input variables are expressed in linguistic variables by assigning a MF. Secondly, IF-THEN rules are applied. Finally, in the defuzzification step, linguistic variables are transformed into specific output values and parameters are adjusted based on the input-output data relation [22]– [33].

B. FUZZY LOGIC CONTROLLER

A Fuzzy Logic Controller (FLC) is based on a FIS [32]. In fuzzification, the selected linguistic variables are the Positive Small (PS) and the Positive Big (PB). These linguistic values attribute a fuzzy score to the input. In this paper, both input and output MFs are triangular for its simplicity and ease of implementation (Fig. 5). It is to be noted that a high number of MFs lead to an increase of rules and consequently, the control program is difficult to implement.

In this work, two rules are necessary to efficiently develop the control and provide accurate results. Moreover, only one input is used for the FLC, that is the current variation \(\Delta I_{PV}\), defined as follows:

\[
\Delta I_{PV}(n) = I_{PV}(n) - I_{PV}(n - 1). \tag{8}
\]
Table 1 reports the rules used in this paper. As can be seen only two MFs are involved. In contrast, in [22]–[32] higher number of rules are employed (i.e., from 9 to 49). Note that the rules define the relationship between $\Delta I$ and $D$, represented by the IF-THEN instructions. For example, if the change in current is $PS$ then $D$ will be high.

$$Y_{COG} = \frac{\sum_{i=1}^{n} Y_i(X_i)X_i}{\sum_{i=1}^{n} Y_i(X_i)} .$$

where $COG$ stands for Centre Of Gravity. The final level of FLC is the defuzzification able to produce a signal that controls the $MPP$. The $PV$ panel current and the $PV$ current variation $\Delta I$ are illustrated in Fig. 7. As can be seen, $\Delta I$ is always positive in all irradiance variations.

**V. THREE LEVEL PWM VOLTAGE SOURCE CONVERTER**

In the literature, several multilevel inverter topologies have been introduced, such as the diode clamped multilevel inverter, the flying capacitor multilevel inverters, and the cascaded H-bridge multilevel inverter. The most used is the well-known Neutral Point Clamped (NPC) [49]–[50]. In this paper, a three-level Voltage Source Converter (VSC) is employed, since it is suitable for higher voltage inverters and provides the following advantages than a common two-level inverters: i) low output current ripples; ii) reduced harmonic power as a result of a smaller output voltage that leads to cleaner AC output waveform; iii) the IGBTs are subjected to the half of the bus voltage; iv) the NPC inverter is characterized by a low common-mode and line-to-line voltage step. However, the three-level VSC provides a double effective switching frequency, an augmented number of IGBTs and a complex control strategy while increasing in level. This means that the cost and magnitude of its components is higher than the well-known two-level inverters, due to the reduced output voltage steps. In order to achieve such voltages, $N$ IGBTs are added in each level:

$$N = 2(Le - 1) .$$

where $Le$ the desired level. In this study $Le = 3$, so, four IGBTs are needed for one leg, as shown in Fig. 8. In this topology, half of the voltage ($V_{dc}/2$) is applied to the IGBT achieved by the two equal capacitors in series. Furthermore, two clamp diodes in each leg are responsible for driving the half voltage to each specific IGBT [49]. For each of the three phases, produced in each leg (Fig. 8), the output voltage switches between $-V_{dc}/2$ and $V_{dc}/2$. These voltages are obtained by turning on at the same time: 1) A1 and A2; 2) A2 and A3; 3) A3 and A4 as reported in
The corresponding control signals for the IGBTs can be
expressed as follows:

\[ V = \begin{cases} 
1 & \text{if } V_{\text{carrier}} > V_{\text{ref}} \\
0 & \text{if } V_{\text{carrier}} < V_{\text{ref}} 
\end{cases} \]  

(11)

A zoom of the line-to-line voltage \((V_{ab})\), obtained at the VSC, is illustrated in Fig. 10. Here, the total harmonic distortion calculated for \(V_{ab}\) is 0.39%.

VI. MODELING AND SIMULATION OF PV SYSTEM WITH HRFLC BASED MPPT CONTROLLER

The simulation model of the incremental conductance technique was performed by using constant temperature and by varying irradiance. Fig. 11 depicts irradiance and temperature selected as input to the PV panel. Fig. 12 represents the proposed HRFLC of a PV panel connected to the grid. In particular, Fig. 12 (a) depicts the synoptic scheme of the panel connected to the grid toward the VSC with the High Reduced Fuzzy based MPPT controller; whereas, Fig. 12 (b) illustrates the global scheme of the PV panel connected to the grid toward the boost DC-DC converter and the VSC.

The power transfer between the PV panel and the boost DC-DC converter at 25°C is shown in Fig. 13 (a); while, comparison results with 40°C, 20°C are reported in Fig. 13 (b). The steady state error (SSE) and tracking time (TT) are shown in Fig. 14 and 15, respectively. Fig. 16 (a) depicts the Steady Time (ST), SSE and TT at 40°C; whereas, Fig. 16 (b) highlights ST, SSE and TT at 20°C.

However, it is to be noted that a significant improvement was observed when the proposed HRFLC is employed. In particular, as regards the simulation carried out at 25°C, TT, ST and SSE were of 0.008s, 0.08s, 0.12 kW, respectively. This resulted in an error percentage of 0.12kW/100.65kW= 0.119%. In relation to the simulation at 20°C, instead, TT, ST and SSE were of 0.01s, 0.04s, 0.005kW, respectively. In this case the error percentage was of 0.005kW/100.65kW=0.0049%. Finally, as regards the experiment at 40°C, TT, ST and SSE were of 0.01s, 0.22s, 0.01kW, respectively, achieving an error of 0.01kW/100.65kW=0.0099% and an initial loss of about 9.5kW. The relationship between the boost power and grid power is depicted in Fig. 17. Specifically, Fig. 17(a) reports the simulation results at 25°C. In this scenario, TT is less than 0.004s (Fig. 19), ST is about 0.3s and SSE is of 100.54kW-98.83kW = 1.71kW (Fig. 18), providing an error percentage of 1.71kW/100.65kW = 1.69%. Results show high tracking efficiency and a good performance due to the use of the three level converter. Note that this performance can be improved when using five level converter or more. As regards simulation performed at 20°C as shown in Fig. 20(b), the ST is 0.02s, TT is 0.005s, SSE is 2kW, resulting in an error of 2kW/100.65kW=1.98%. As regards the 40°C simulation (see Fig. 20(a)), the following errors 0.03s TT, 0.17s ST and 1.4kW SSE were achieved, resulting an error percentage of 1.4kW/100.65kW=1.39%. It is to be noted that in 20°C simulation there is a gain in power due to the materials characteristics of the PV. In this work, a stable voltage (i.e., 500V) was used to supply the VSC. By this assumption, the power variation depends on the current. Hence, the power estimated at the grid is 98.83kW and the power of the boost is 100.54kW, as shown in Fig. 18. The global power transfer between the PV panel and the grid at
25°C is shown in Fig. 21. In this case, $TT$ (Fig. 23), $ST$ and $SSE$ (Fig. 22) were of 0.005s, 0.09s and 1.82kW, respectively. For 20°C simulation, as shown in Fig. 24 (b) the $ST$ was 0.02s, $TT$ 0.02s, $SSE$ 1.8kW, leading to an error percentage of 1.8kW/100.65kW=1.78%. Finally, as regards the 40°C simulation (Fig. 24 (a)) reports 0.04s of $TT$, 0.17s $ST$ and 1.4kW of $SSE$, resulting in an error of 1.4kW/100.65kW=1.39%.
been taken into account. Note that three temperatures have to grid with only one input is developed. More specifically, in this paper, a HRFLC, based is observed. In Fig. 24 (a), with the proposed HRFLC, the efficiency was 98.83kW power transmission from the PV panel to grid out of 100.65 kW, meaning 98.19% of transmitted power for 25°C, 89.8kW for 40°C and 100.2kW for 20°C as illustrated in Fig. 24 (b). The variation of the duty cycle was between only two values: 0.463 and 0.478 to get the highest and lowest irradiance, respectively.

For the power transferred from the panel to the grid in the case of 25°C the tracking time error was about 0.005s as shown in Fig. 23. Fig. 22 depicts a steady state error of 1.82 kW and a steady time of about 0.09s. Since the panel power was 100.65kW, the steady state error was 1.8% (or 98.19% tracking efficiency). Hence, for 20°C and 40°C the tracking times were 0.02s and 0.04s respectively; whereas, the steady state error were 1.8kW and 1.4kW, respectively. It is to be noted that even the steady state error for 40°C was less than 20°C the power transmitted from the panel to the grid was higher than those achieved in 40°C (i.e., 100.2kW and 89.8kW respectively). As regards PV-Boost simulations high accuracy and efficiency were reported (Fig. 13 - 15). The tracking time was 0.009s, the steady state error was 0.12 kW and the transit time was 0.08s for 25°C. For 20°C and 40°C the efficiencies are 99.99% and 90.7% respectively. This was due to: i) the use of few MFs which reduce the calculation time of the output; ii) the adequate, simple and fast choice of the duty cycle D by only two MFs. In relation to the results obtained between the boost and the grid at 25°C, a duty cycle of about 0.01s and a tracking time of 0.004s, were achieved (Fig.19). In Fig.18 the steady state error was of 1.71 kW which means an error of 1.69% for 20°C and 40°C. Fig. 20 (a) and (b) report, instead, the efficiency values that are 99.51% and 89.7% respectively. Most state-of-the-art works performed simulations at 25°C. For example, in [31], the best fuzzy system reported a transit time of 0.91s, a tracking accuracy of 99.93% with an error of 5.86Wh and a steady state error of 0.37%. The P&O (0.5%) in [31] reported a transit time of 0.25s and a steady state error of 7.16%. The ANNs used in the literature, the steady state error was approximately 3W for 30W (10% of error) [52]. The ANN-based system proposed in [53] provided a transit time of 0.05s with a steady state error of 0.6%. In [54] the proposed fuzzy system reported a transit time of 0.25s, and a mean steady state error of 2.36%. In [22] using adaptive neuro-fuzzy controller the steady state error was about 0.5%. In [24] the tracking time error estimated was 1.58s. For further evaluation, Table 3 illustrates the results presented in [45]– [46] such as Third Order B-spline Adaptive Neuro-fuzzy Controller (TOANC), fuzzy logic controller, PID–incremental conductance (PID–InCon) and PID–Hill climbing (PID–HC). As can be observed, TOANC achieved the highest efficiency and the lowest error as it employed the MPPT error and its derivative.

Kamal et al. [45]– [46] compared the proposed method

FIGURE 16. Errors between panel power and boost power at 40°C (a) and 20°C (b).

FIGURE 17. Simulation results of boost power and grid power at 25°C (a) and 40°C, 20°C, 25°C (b).

VII. EXPERIMENTAL RESULTS

In this paper, a HRFLC-based MPPT controller connected to grid with only one input is developed. More specifically, here, the variation of irradiance and temperature in time has been taken into account. Note that three temperatures has been studied 40°C, 25°C, and 20°C. An excellent tracking between the power grid and the PV panel power was achieved as reported in Fig. 21, 22, 23 for the 25°C; in Fig. 24 (a) and Fig. 24 (b) for 40°C and 20°C, respectively. In addition, a complete adaptation was observed in the results related to the PV panel power and the boost power as illustrated in Figs 13, 14 and 15 for the 25°C; Fig. 16 (a) and 16 (b) for 40°C and 20°C, respectively. It is worth mentioning that a fast reaction and adaptation to different working conditions was observed.

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TOANC with sliding mode controller, integral backstepping controller, predictive, MPPT with irradiance sensor, ANFIS and three point weighted. Comparative results are reported in Table 4. Hence, the proposed HRFLC-based MPPT, which achieved an efficiency of 99.12%, with only one input, one output, and two rules. This FLC can be easily implemented and widely used. Results are summarized Table 5.

The results achieved for 20°C and 40°C are reported in Table 6. The proposed HRFLC provided high performances with a reduced number of MFs and rules, making its architecture very simple. In fact, the main idea was to keep the voltage stable while the current control the irradiance variation. The choice of the single input $\Delta I$ simplifies considerably the implementation. The reasons of using $\Delta I$ can be summarized as follows: first, the voltage of the VSC must be kept constant and stable in order to supply the grid with fixed AC voltage.

### VIII. CONCLUSIONS

In this work, an HRFLC-based MPPT method is proposed as an accurate, simple and representative approach. The design and simulation of the method are discussed in detail. In this paper, only the current variation is used under different weather conditions (i.e., irradiation at 20°C, 25°C and 40°C), achieving high accuracy and efficiency, by employing a number of inputs less than usually used in the literature, mainly twenty-five rules or over. This reduction means that the calculation is simplified significantly. Comparing to the conventional P&O method, the proposed MPPT method can satisfactorily address the trade-off between the tracking speed and steady state oscillations. Moreover, a connection to a grid is achieved. This connection provided high performances. Moreover, the use of Fuzzy in MPPT control (HRFLC) achieves better results than the classical approach, especially for static error and tracking time. Furthermore, in comparison with other controllers like fuzzy, ANNs and so on, the HRFLC reported higher accuracy and efficiency in tracking time, transit time, and steady state with a high reduction in variables and functions. This reduction allows not only to simplify the implementation process but also to achieve a significant gain in terms of time and cost (by using a smaller number of components). This will make an easy process for installation and maintenance. As an alternative perspective, in the future, exploitation of deep and/or reinforcement learning methods [13]–[18], [55] will be also
FIGURE 20. Errors between boost power and grid power at 40°C (a) and 20°C (b).

FIGURE 21. Simulation results of panel power and grid power at 25°C (a) and 40°C, 20°C, 25°C (b).

FIGURE 22. Simulation results of the steady time and steady state error of the grid power and PV Panel power at 25°C.

FIGURE 23. Simulation results of the tracking time between the grid power and PV panel power at 25°C.

FIGURE 24. Errors between panel power and grid power at 40°C (a) and 20°C (b).

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