Journal of Electrical Engineering and Automation (ISSN: 2582-3051)
www.irojournals.com/iroeea/

Research on improved MPPT Fuzzy Logic Control-Incremental Conductance Algorithm

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Abstract

This research discusses the limitations of the Maximum Power Point Tracking (MPPT) incremental behaviour algorithm. Although MPPT's incremental behaviour algorithm is simple and easy to implement, despite its usefulness, this method is beset by several limitations which include a slow convergence rate towards the optimal operating point, significant oscillations surrounding the maximum power point at steady state, and momentary system movement away from the maximum power point after sudden changes or variations in irradiation. For these reasons, an improved MPPT Fuzzy Logic Control-Incremental conductance (FLC-IC) algorithm is proposed in this study. And the adjustment in the input variables of the MPPT Incremental Conductance algorithm controlled by the fuzzy intelligent control algorithm increases the convergence speed, decreases the oscillations, and remains stable despite radiation variations. The algorithm is simulated and applied in a charge controller that operates using the solar energy, and the outputs observed highlights the effectiveness of the proposed algorithm that is proposed over the IC algorithm in terms of speed and efficiency.

Keywords: MPPT, photovoltaic power generation, Fuzzy Control, Boost and Incremental Conductance

DOI: https://doi.org/10.36548/jeea.2023.2.009
Received: 30.04.2023, received in revised form: 30.05.2023, accepted: 13.06.2023, published: 23.06.2023

1. Introduction

Traditional fossil fuel reserves have been decreasing year after year, and this has worried humanity in general and some countries have started to vigorously develop clean and efficient renewable energy. Since 2017, the world's installed capacity of non-fossil energy has grown by around 25% per year. Photovoltaic power generation is widely used in all walks of life because of its pollution-free, renewable, and wide application.

The PV characteristic curve is non-linear, and the efficiency is greatly influenced by irradiation and temperature. Therefore, proposing an efficient, simple and universal Maximum Power Point Tracking (MPPT) algorithm is essential [1-4], although there are already existing MPPT algorithms such as incremental conductance, Perturbation and Observation (P&O) and intelligent control methods [4], such as Fuzzy Logic Control (FLC), Particle Swarm Optimization (PSO), Artificial Neural Network (ANN). The MPPT algorithm was combined with an intelligent control method in this dissertation. In this proposed FLC-IC algorithm, the dPpv/dVpv inputs are associated with a constant value C and applied to the FLC and this, in turn, inserts this association resulting in a deltD value that is multiplied by the constant M =1. Tracking speed, MPPT algorithm oscillation and time to reach the maximum power point are greatly improved. It improves the battery charging time and allows the battery to receive voltage at the right level. Some intelligent control algorithms are analyzed and then they are compared with the improved MPPT FLC-IC algorithm in this work.

2. Intelligent Optimization Techniques

2.1 Particle Swarm Optimization

The PSO method is a technique for optimization that draws inspiration from bird navigation patterns when searching for food. Using this approach, each individual or particle focuses on finding an optimal solution to a problem by constantly repositioning itself within the swarm. The PSO algorithm is developed from a sociocognitive theory that, each particle has an individual learning (cognitive) and a learning by cultural transmission (social). In this way, the method is based on the interaction between the individual and collective search trajectories, creating a cloud of particles that converge to optimize the objective function.

Every particle provides its velocity based on past and present positions, attempting to optimize its location with respect to both the individual solution and the global swarm solution. Figure 2.1 illustrates the trajectory of a particle within a swarm, where Pbest denotes the particle's current optimal position, and gbest represents the best position identified across the entire swarm [5,6].

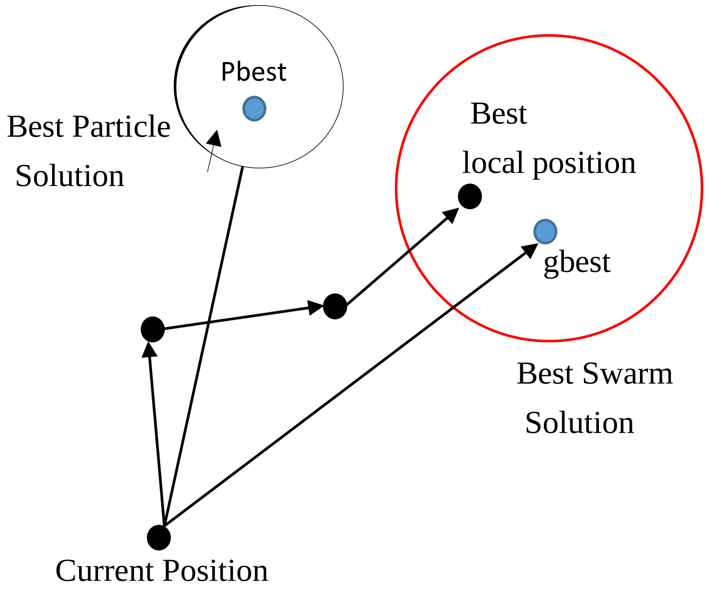

Figure 2.1. Particle Motion with the PSO Algorithm. Source[7,8]

2.2 Artificial Neural Network

ANN is a system that has computational capacity acquired through learning and generalization. The learning is related to the ability of ANNs to adapt their parameters as a consequence of interacting with the external environment and generalization, in turn, is associated with the ability of these networks to provide answers consistent for data not presented during the training step. ANNs have processing elements with a very simple structure, inspired by the functioning of the biological neuron, with connections between these processing elements. Each connection in the network has an associated weight and this weight represents the intensity of the interaction or coupling between the processing elements and its nature is excitatory. ANNs use artificial neural structures, in which the processing and storage of information are performed in a parallel and distributed manner, processing elements of relatively simple complexity. These elements can be arranged in layers responsible for inputting information, processing this information, and producing results. The structure of an artificial neural network can be seen in figure 2.2.

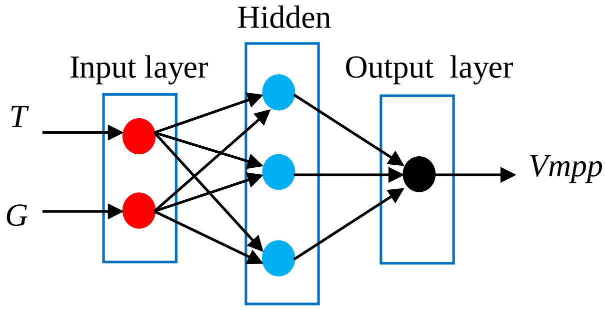

Figure 2.2. Neural Network Structure

2.3 Sliding Mode Control

The notion of implementing sliding modes in control originated from previous research on variable structure systems [9]. Using a discontinuous control, Sliding Mode Control (SMC) is a nonlinear technique that forces a nonlinear system to slide over a cross-section of its usual behavior. Rather than being a continuous function of time, the state-feedback control law can switch between different continuous structures based on the current state. Consequently, sliding mode control is a variable structure control technique. Trajectories constantly move towards a neighbouring region with a different control structure because the many control structures are built in such a way that they are interconnected. As a result, the final trajectory will not be contained by a single control structure but will instead glide along the control structures' perimeters [10-14].

As the system slides along these boundaries, it follows a specific motion known as a sliding mode, and the collection of these boundaries is referred to as the sliding (hyper)surface. In the realm of contemporary control theory, any variable structure system, including one governed by sliding mode control, can be conceived as a particular instance of a hybrid dynamical system, since the system traverses both a continuous state space and discrete control modes [15-17]. The graphical portrayal of sliding mode control can be observed in Figure 2.3.

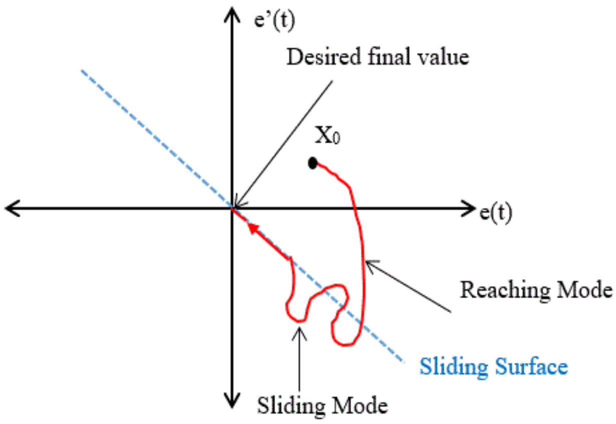

Figure 2.3. Graphical Interpretation of SMC

The depiction in Figure 2.3 illustrates the employment of phase-plane to graphically represent SMC, where the axes signify the error (e(t)) and its derivative (e`(t)). Notably, the state trajectory, beginning from any initial condition, eventually arrives at the surface within a finite period (i.e., reaching mode), and from there, slides along the surface towards the target (i.e., sliding mode). The first phase involved in designing SMC entails developing a tailored surface.

2.4 Fuzzy Logic Control Algorithm

In the area of artificial intelligence known as fuzzy logic, reasoning algorithms are used to simulate human thought and decision-making processes in computer applications. Typically, fuzzy logic methods are used when binary process data is not appropriate. Instead, they create a range of data by assigning values of 1 (representing the maximum degree) and 0 (representing the minimum grade). For example, figure 2.4 illustrates degrees of cold air, with 70 degrees Fahrenheit designated as the ideal temperature for “cold air” and given a value of 1; Any temperature above 80 degrees Fahrenheit is deemed “warm,” while temperatures below 60 degrees Fahrenheit are labeled “cold.” Therefore, temperatures below 60 and above 80 degrees are considered outside the optimal “cold” range. Another way to gauge this range is illustrated in figure 2.4. Temperatures that are neither hot nor cold are shown by the dotted line. Thus, a fuzzy logic technique frames a temperature of 65 degrees Fahrenheit as "half cold and half hot" or 50% cold/50% hot. This boundary denotes a certain degree or range of coldness, while temperatures below 60 degrees Fahrenheit are regarded as “cold” according to the fuzzy logic algorithm.

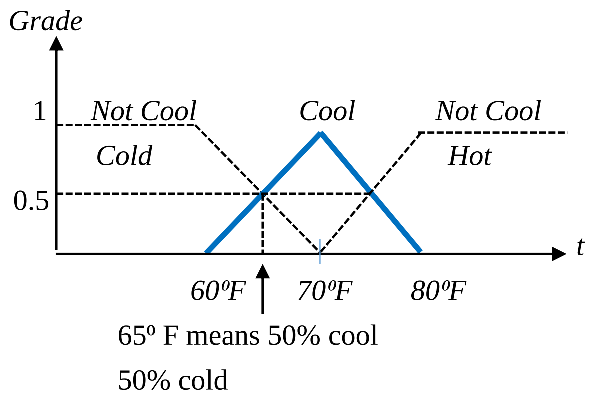

Figure 2.4. Cool Air Temperature Range and Dotted Lines Showing not Cool Range[18].

Figure 2.5 and Figure 2.6 depict the fundamental determinants of fuzzy logic, which include fuzzy sets, membership functions, linguistic variables, and fuzzy rules. These factors are essential components of the Fuzzy algorithm and are explained in detail in the figures, illustrating how the algorithm operates.

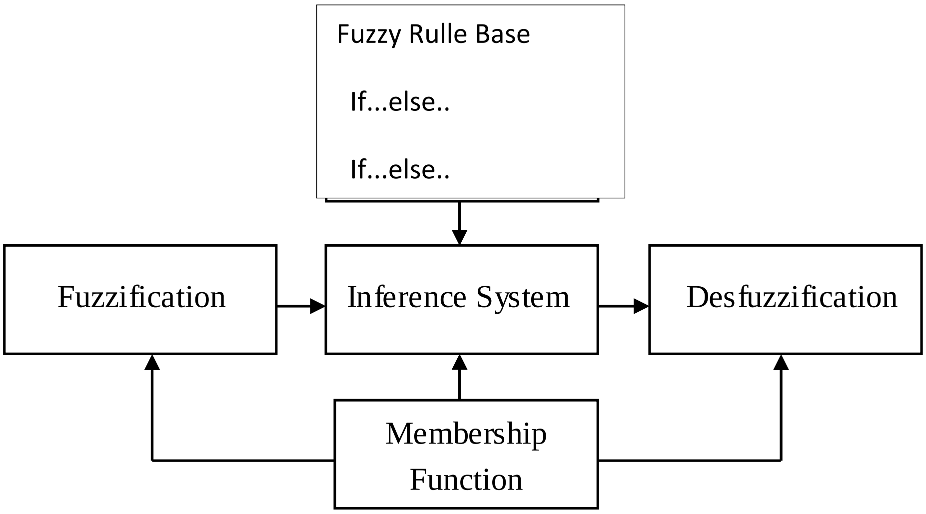

Figure 2.5. Basic Structure Diagram of Fuzzy Logic Controller

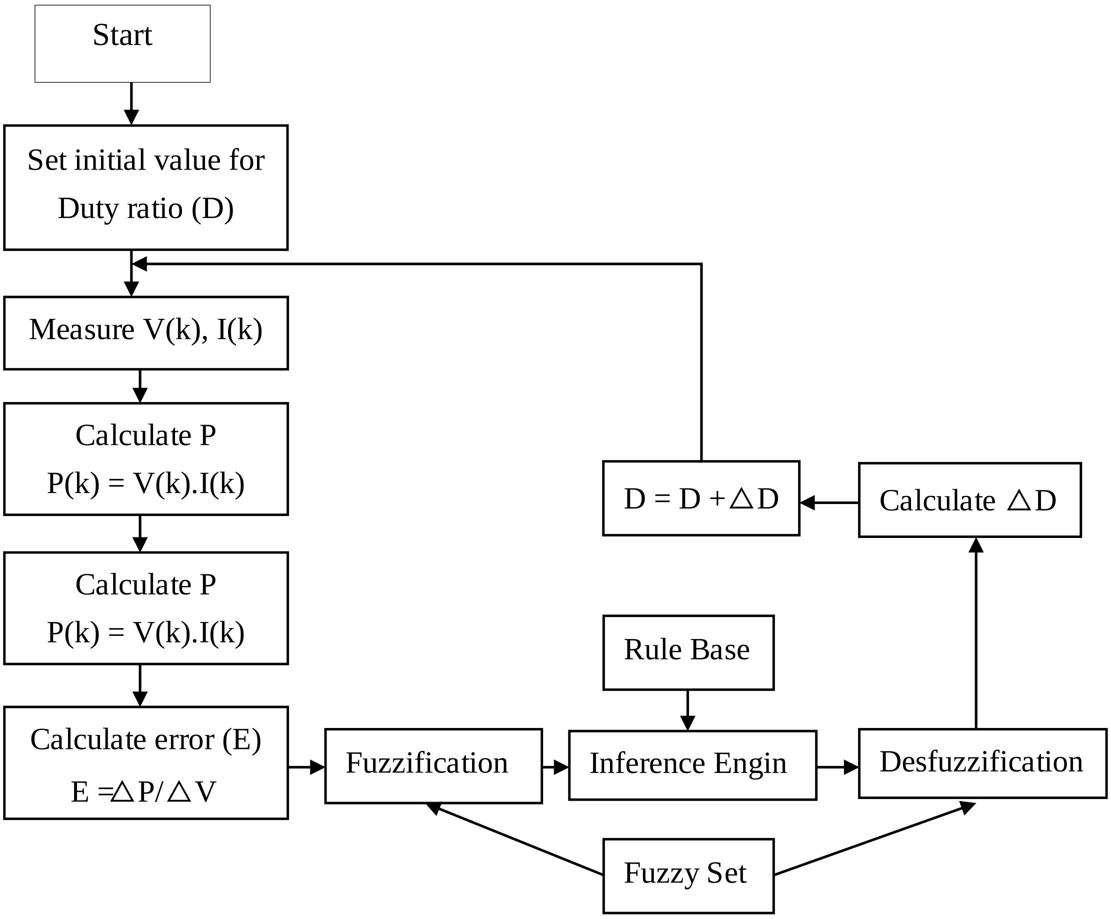

Figure 2.6. Fuzzy Flowchart

2.5 Comparison of Intelligent Control Techniques

All comparative analysis of the presented algorithms is shown in Table 2.1.

Table 2.1. Comparison of Intelligent Control Techniques

Algorithm	Convergence rate	Complexity	Sensitivity	Analogue / digital	Accuracy	Periodic Tuning
PSO	Fast	Low	High	Digital	High	No
ANN	Medium	High	Moderate	Both	Medium	No
SMC	Fast	Medium	Low	Digital	High	Yes
FLC	Fast	High	Moderate	Digital	High	Yes

Table 2.1 shows that although the FLC has a high degree of complexity compared to other algorithms presented in the table, FLC is fast, has a high sensitivity, and exact, that is, it offers little probability of errors. And according to other research, other advantages noticed are: (1) Fuzzy Logic is based on words and not numbers, or that is, truth values are expressed linguistically. Better handling of inaccuracies; (2) Ease in specifying the control rules, in language close to natural; (3) The use of linguistic variables brings us closer to thinking human; (4) Simplifies trouble shooting, provides a quick prototype of the systems; (5) Simplifies the acquisition of the knowledge base and requires few rules, few values and few decisions.

3. FLC-IC

3.1 Modeling and Simulation of the Proposed FLC-IC

In the photovoltaic system to obtain a great productivity of the system, it is necessary to have the control of the maximum power point. Considering that, a new algorithm is proposed based on Incremental Conductance (IC) and fuzzy logic control, which resulted in an algorithm called FLC-IC, which aims to minimize the weaknesses of the IC algorithm. Although it is known because of its simplicity and construction, but has some problems such as:

(1) Its slow speed when reaching the point of maximum power;

(2) Large fluctuations before, during and after reaching the MPP;

(3) When a momentary change in irradiation occurs, instabilities are checked for some period of time.

Therefore, the FLC-IC algorithm was improved to minimize the problems mentioned above, through the FLC, which controls the step size and the dP/dV ratio during the entire process.

Figure 3.1 represents the modeling of the circuit used for the simulation and is made up of 3 main elements, namely: (1) Solar panel-1Soltech 1STH-250WH, (2) Boost-type converter, (3) Load controller using the improved fuzzy based on IC. And for the performance of the converter, the following parameters were also used: C_1 = 0.1mF, L=5mH, C_2 = 0.1mF, Lead-Acid battery 48V,100wh.

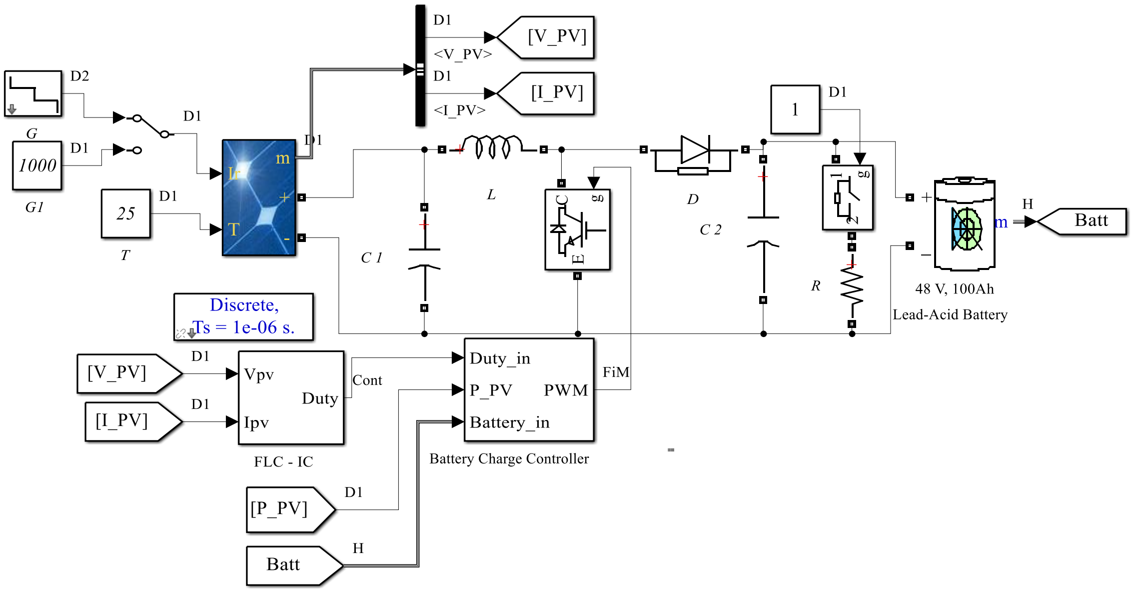

Figure 3.1. MPPT Solar Charge Controller Model Using the Improved FLC-IC

In Fig.3.1, the FLC-IC is connected with a battery charge controller, but inside it is the union of FLC with the improved IC algorithm; more details can be seen below in Fig. 3.2.

The functioning of the improved FLC-IC algorithm, illustrated in Figure 3.3, can be outlined as follows:

(1) Initially two input variables called I(t)=Ipv and V(t)=Vpv in which the variable " t " indicates the time and are applied, from these two variables $\Delta I, \Delta V$ and ΔP are calculated.

(2) Then the ratio between "$\Delta P / \Delta V$" is calculated, which together with the size of the step called "C", is inserted into the fuzzy logic control, and it is Fuzzified, generating a "deltaD" as seen in Fig. 5.6. This last variable, together with the variables "V" and "I", become input variables to determine the output value called "D". But to find the value of "D", it follows some ΔV conditions as seen in Fig.5.7 and $M = 1$ is considered. If $\Delta V = 0$ and $\Delta I = 0$, there will be no change, but if $\Delta I > 0$, the value of D grows ($D = Dold + M \times deltaD$), if $\Delta I < 0$ the value of D decreases ($D = Dold - M \times deltaD$). But if the value of ΔV is not equal to zero

and the value of the current voltage is equal to the previous voltage as well there will be no change; if the current voltage is greater than the previous voltage and ΔV and ΔI are greater than zero respectively, the value of "D" increases otherwise it decreases. But if also current voltage is less than the previous voltage, "D" grows.

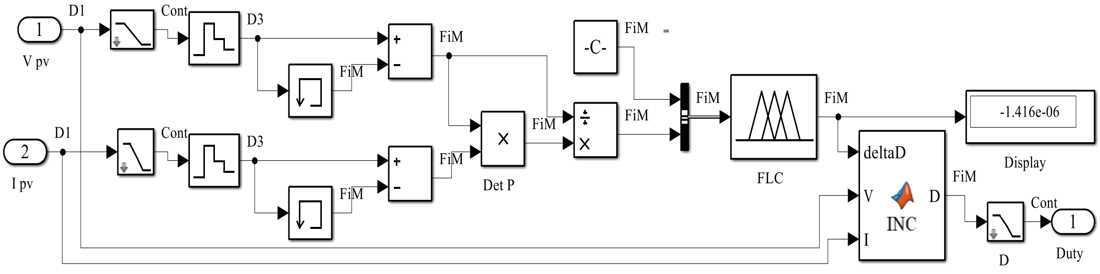

Figure 3.2. Improved FLC-IC Circuit

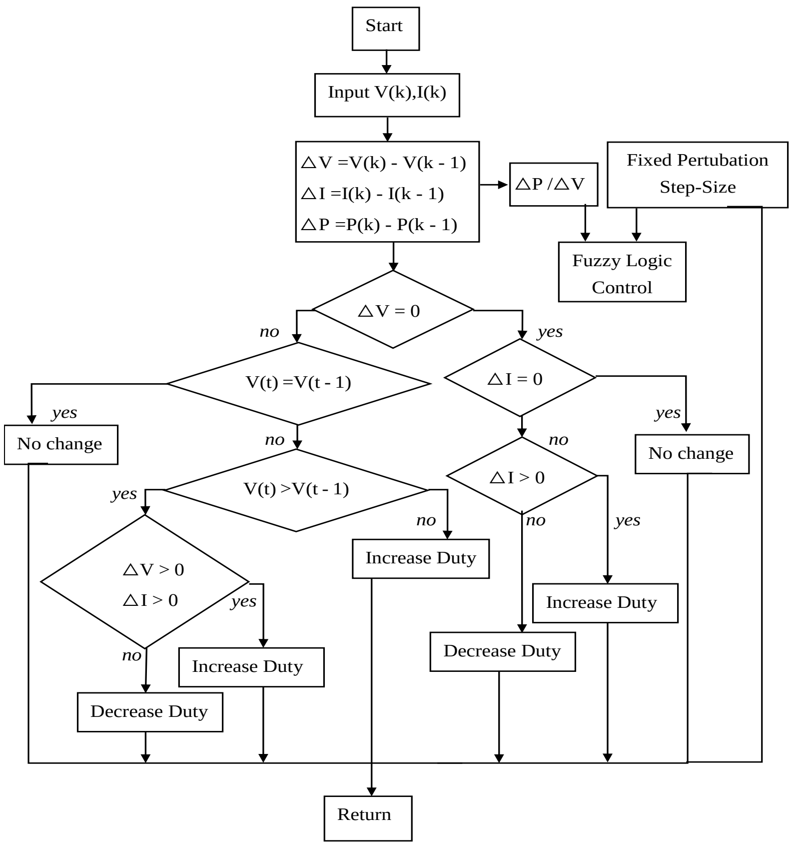

Figure 3.3. Flowchart of the Improved FLC-IC Algorithm

3.2 Simulation Results with FLC-IC

(1) Figure 3.4 shows 3 simulated waves, being the photovoltaic power (Ppv), the photovoltaic current (Ipv) and the photovoltaic voltage, using improved FLC-IC. And the simulation data are as follows: the simulation time is set t = 0.8 s, the light intensity decreases between 1000 w/m^2 to 200 w/m^2 and the temperature T = 25 °C. During this external condition, with irradiance of 1000 w/ m^2, the output power of the system is 250 W.

(2) For the photovoltaic output voltage obtained in the simulation, it can be seen that regardless of the unstable conditions of the environment, the voltage always remains at the same level.

(3) Whereas for the current, it tends to have an inverse behavior of the voltage, because it is noticed that while the voltage seeks to stabilize itself, the current tends to decrease according to the behavior of solar irradiation.

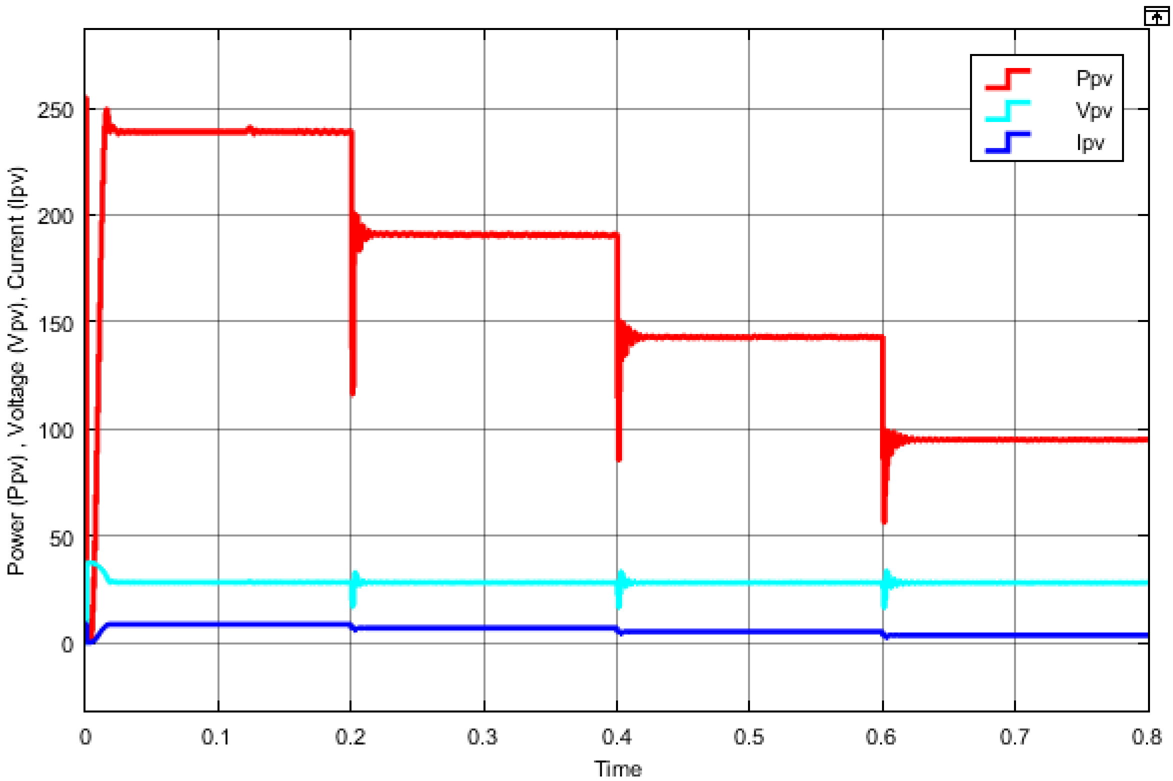

Figure 3.4. Simulation Results Involving the Improved FLC-IC

All data related to the simulation of the charge controller using the improved FLC-IC algorithm are expressed in Table 3.1. The values help us conclude that the algorithm used has strong performance and is effective.

Table 3.1. Solar Controller Result Table Using Improved FLC-IC

MPPT solar charge controller	Improved FLC-IC
Output power	249.5W
Output Current	8.099A
Output voltage	30.81V
Battery voltage	48V
Battery current	-7.52A
SOC (%)	50 to 50.006
Efficiency (%)	98.0

3.3 Summary

The simulation results lead to the following three conclusions. Firstly, the improved FLC-IC algorithm demonstrates a high capacity for speed of range to MPP, as the photovoltaic power sign (PPV) rapidly reaches the maximum power point in under 0.025 seconds. Secondly, the fluctuations in the PPV sign, whether they are lasting, occur only once, or are numerous, have significantly reduced or almost eliminated. Thirdly, despite unstable environmental conditions such as varying solar radiations, the algorithm remains stable, as evidenced by the simulation times of 0.2s, 0.4s, and 0.6s, during which the signal decreases due to decreasing variation in irradiation, but easily recovers the maximum power point. These three observations conclusively demonstrate that the flaws observed in the incremental conductance algorithm have been resolved through the implementation of the FLC-IC algorithm.

The primary goal of the FLC-IC algorithm is to enhance the speed of range to the maximum power point and minimize fluctuations and instabilities commonly observed in photovoltaic systems. Compared with the algorithm discussed in chapter 2 of this study, the FLC-IC algorithm presents several advantages such as ease of implementation, reduced range time to the maximum power point, and high stability.

4. Conclusion

Based on the results obtained with the control technique using improved FLC-IC, a PV array is used whose power is 250W, and improved boost converter to obtain results, and with these results, the output power obtained is 249.5w. This value is very close to the desired patency of the solar panel. The output current obtained which is 8.099A, is also a value very close to that of the solar panel which is 8.15A. The voltage obtained in this simulation is 30.81v, and the voltage of the panel used is 30.7v. A tiny increase is obtained, but that should not be discarded. All these acquired values are obtained with a constant temperature of 25ºC and solar irradiation of 1000w/m^2. And the results of this simulation show that with this algorithm, the maximum power point can be reached even under conditions of variable solar radiation. Other results that that influence the battery charge is noticed. When the improved FLC-IC algorithm is applied, the battery is charging because it goes from its initial value of 50% to 50.006%. Although it reaches that lowest value, it tends to charge and for a time of 0.8 seconds it is very good. The battery current and the voltage take values of different signs, and that the charge controller obtained an efficiency of 98%, missing only 2% to reach the maximum level of efficiency is noticed. This improved algorithm has great advantages because it is fast. The point of maximum power was reached in less than 0.1 seconds, that is in hundredths, it remains stable even in conditions whose irradiation is unstable and it considerably reduces voltage and power fluctuations encountered. The maximum power point is always easily reached and when applied to a battery charge controller it shows reasonable efficiency. Therefore, the use of this algorithm for future work is advisable.

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