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Design and Development of ANFIS based Controller for Three Phase Grid Connected System

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ABSTRACT

A proposal is presented for a low voltage (LV) grid integrated single-stage solar photovoltaic (SPV) system, accompanied by a hybrid control methodology aimed at optimizing system performance. To address prevailing challenges, the hybrid method incorporates the Adaptive Neuro-Fuzzy Inference System (ANFIS). Anticipated benefits of this initiative include efficient power distribution, load connectivity facilitated by the system, and operational functionalities such as mode zero voltage regulation and power factor adjustment. These functionalities collectively enhance energy quality by mitigating harmonic components, compensating for reactive power, and ensuring load balance. The proposed control strategy for a photovoltaic (PV) system interfaced with the grid is designed to exhibit rapid response times in both static and dynamic conditions. Comparative analyses were conducted between the output of our method and that of several competing approaches. The MATLAB/Simulink platform is employed for the purpose of demonstrating the developed system. The results show the extent to which the proposed controller works with reactive power compensation and load balancing to minimize network harmonics and maximize power consumption while keeping power factor functions at unity.

1. Introduction

Solar Photovoltaic (SPV) systems enjoy widespread popularity and are acknowledged as distributed generators (DGs) due to the abundance of their resources and the apparent positive environmental impact. Particularly in developing nations, the challenge of demand-supply imbalance can be mitigated through the integration of solar photovoltaic systems with the grid as a distributed generation source. However, integrating solar PV systems at the HV/LV network level may pose challenges such as exceeding the Point of Common Coupling (PCC) voltage limit, frequency shifts, and network instability [1], [2]. Regulatory standards outlined by authorities such as IEEE 1547, IEC 61727, and VDE-AR-N4105 delineate the norms that grid-integrated solar PV systems must adhere to [3].

To connect to the grid and power an alternating current (AC) load, solar PV systems must convert their DC output to AC through a voltage source converter (VSC). Successful coordination of the power plant with the grid relies heavily on the proper control of the VSC. The algorithm used to compute network reference currents and generate switching signals for the IGBT switches is pivotal to the success of control strategies. Hence, effective and coordinated control mechanisms are imperative for accurate synchronization when solar PV is integrated as a DG.

Researchers commonly employ single-stage and two-stage system topologies for integrating solar PV systems into the grid. Voltage source converters are typically used as the final step in creating non-conventional energy after multiple stages of power conversion, such as DC to DC or AC to DC, buck-boost stages, etc. The output of the Voltage Source Inverter (VSI) is utilized to establish a connection to the public power grid. Two controllable factors for the VSI are the Modulation Index (MI) and Theta of the reference signal, both of which require precise management.

Both the parameters on the distributed generating side and the grid side are evaluated and adjusted accordingly. Advancements in power electronics technology, coupled with ongoing policy changes and environmental concerns, are creating new possibilities for the development of distributed renewable energy systems. Renewable energy sources (RES) like fuel cells (FC), storage batteries, solar panels, wind turbines, and small-scale natural gas turbines play a crucial role in meeting the escalating energy demand. Among these, FC and PV cells are preferred choices due to the rapid development of FC technology and widespread acceptance of PV cells.

Research articles frequently report hybrid architectures combining PV and FC, where the right cell mix can provide sufficient DC voltage, subsequently transformed into AC voltage using voltage source converters (VSC). The size of solar PV varies depending on the application, from small to large ratings. Grid-connected rooftop solar PV systems significantly contribute to the nation's overall electricity production. To smoothly connect to the grid, solar PV systems require a converter circuit, which is pivotal in facilitating this connection. The interface converter, connecting the AC bus and DC bus, is underused due to the variable availability of solar irradiation. Utilization can be enhanced by delivering reactive power over the same converter circuit, achieved by modifying the control method to supply the necessary active and reactive power at the Point of Common Coupling (PCC).

Numerous control algorithms have been documented in the literature [4]-[29] for the grid integration of solar PV systems, encompassing active power supply, reactive power adjustment, and harmonic reduction. These algorithms broadly fall into three categories: traditional, intelligent, and adaptive. Theoretical frameworks, such as the Synchronous Reference Frame (SRF), Enhanced Phase Lock Loop (EPLL), Instantaneous Reactive Power (IRP), Power Balance Theory (PBT), and Conduction Frieze, exemplify various algorithms designed for network integration. A myriad of algorithms is available, and a control strategy for distribution static compensator (DSTATCOM), based on the I-COS technique, was proposed by Kannan et al. [30]. This strategy aims at effective source harmonic reduction, reactive power compensation, and load compensation. Instead of employing a traditional proportional integral (PI) controller, the authors chose a Fuzzy Logic Controller (FLC) to regulate the DC link voltage.

In an effort to mitigate current harmonics resulting from PV output current distortion, Hamid et al. [31] suggested installing a power conditioner unit (PCU) in parallel with the power plant, running it in forward mode to compensate for PV output current distortion. Additionally, in [32], the authors proposed a gradient descent back propagation (GDBP) method based on I-COS learning for a distributed static compensator, constituting a hybrid ANN-based methodology DSTATCOM. The authors of [33] introduced a PV-STATCOM to enhance power transfer, allowing more power to be transmitted to the grid using the same converter infrastructure. To ensure power quality, the voltage source converter is managed with appropriate control computations, particularly crucial when dealing with highly inductive and nonlinear coupling points. Due to the significant distortion of grid currents and voltages caused by highly inductive and nonlinear loads, the power factor on the grid side tends to be weak. Thus, power quality improvement is imperative in the context of a PV system.

To address power quality issues such as harmonics, reactive power load, and load imbalance, a DSTATCOM is employed. Due to its simplicity, quick response, and robust activity, DSTATCOM proves to be a more appealing method of load compensation compared to passive methods. Operating in current control mode as a shunt-associated compensator, DSTATCOM switches based on the generated reference currents using a suitable control strategy.

The inherent nonlinearities of solar PV systems pose challenges for traditional control procedures of VSCs outlined in the literature. This leads to responses with noticeable spikes and slow decays. Despite these challenges, control solutions based on intelligent algorithms can effectively address the nonlinearities in solar PV systems, offering more reliable and efficient control compared to traditional approaches. Researchers have explored the use of artificial neural networks (ANNs) in various contexts [34]-[48], but limited literature focuses on integrating solar PV with grid-related applications. Despite the downsides of ANNs, such as their functioning as a black box, lack of rules for structure construction, and difficulties with network instruction, they have shown promise.

In contrast, Fuzzy Logic Control (FLC), commonly used in microprocessor-based control systems, involves the rule base selection through the "trial and error" method. Alternatively, the combination of neuro-fuzzy systems and robust control CI methods can create neuro-fuzzy systems, offering advantages such as quick and efficient learning, parallel input processing, generalizability, independence from system design parameters, and a nonlinear, flexible structure.

The proposed approach introduces an innovative control method for Voltage Source Converters based on an artificial neural network and fuzzy logic hybrid algorithm. This novel algorithm facilitates efficient transfer of active power to both the grid and the load, simultaneously providing reactive power support and compensating for harmonics. The multi-layer perceptron architecture of the ANN-based algorithm aids in analyzing system nonlinearity. The effectiveness of back propagation (BP) learning for multilayer feedforward neural networks is dependent on both the learning rate and model complexity.

A Neuro-Fuzzy Inference System integrates fuzzy logic and neural systems, with the fuzzy system's parameters determined by the neural network. ANFIS significantly reduces the need for manual optimization of fuzzy parameters. The neural network automatically adjusts system parameters, such as membership function boundaries, enhancing overall performance. Unlike traditional neural networks where the training process effectively creates the system, a neuro-fuzzy scheme employs fuzzy logic definitions to design the system, refined through neural network training methods. ANFIS offers several benefits, including defining the behavior of complex systems by modifying fuzzy if-then rules, requiring no prior human expertise, accommodating a wide range of datasets, providing a large selection of membership functions, and achieving rapid convergence. VLSI technology offers the potential for power-efficient implementations [49]-[51]. This is particularly important in grid-connected systems, where minimizing power consumption is a key consideration.

The work proposed here demonstrates reductions in static error, improvements in convergence speed, dynamic load adaptation, and resilience. Additionally, an Incremental Conductance (INC) based Maximum Power Point Tracking (MPPT) algorithm is developed to monitor and adjust the solar PV system's Maximum Power Point (MPP) as needed based on changes in solar intensity.

2. System Description and Development of Controller

More power can be generated from the sun by connecting additional solar photovoltaic modules in series and parallel. A photovoltaic cell is the building block of an active inverter PV module. When PV cells are exposed to direct sunlight, the photon energy from the sun is transformed into electricity. To get 10 kWp, we used a single solar PV module from Vikram Solar, the ELDORA 270, with a power output of 270.66 Wp. In order to change the DC voltage into the AC voltage, a

VSC with a 10 kVA, 415 V three-phase is suggested. Fig. 1 shows the schematic of the system. The system used is same as was used by [11].

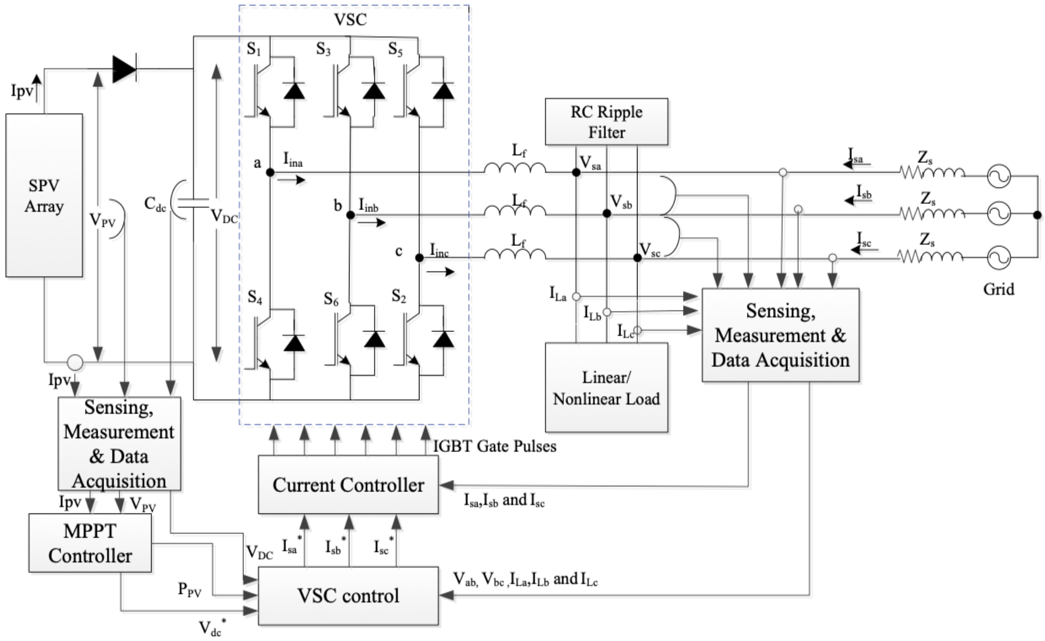

Fig. 1. Schematic of the system used

In the pursuit of tracking the Maximum Power Point of a solar PV array under diverse climatic conditions, an extensive array of Maximum Power Point Tracking methods has been documented. Among these, the Incremental Conductance technique has been formulated and exhibits superior performance when compared to alternative approaches.

This article introduces a hybrid control modeling approach for a Solar Photovoltaic system, propelled by a Voltage Source Converter. The presented method utilizes a Neuro-Fuzzy Inference System, where the parameters of the fuzzy system are computed employing a neural network within ANFIS, amalgamating the strengths of both systems. The neural network's capacity to autonomously adjust system parameters, such as membership function boundaries, eliminates the necessity for manual optimization of fuzzy parameters.

The amalgamation of the learning capabilities of a neural network with a rule-based fuzzy system yields significant performance enhancements, enabling the incorporation of historical data into the classification process. The development of a neuro-fuzzy system involves constructing the system using fuzzy logic definitions and fine-tuning it through neural network training methods while simultaneously training the neural network. Through the implementation of the ANFIS controller, an adaptive network is constructed from nodes and directed connections linking neurons. The adaptability of individual nodes influences the output of intermediary nodes, leading to network settings adjustments based on optimization principles to minimize a specified error metric. Common learning principles for adaptive networks include the chain rule and gradient descent.

Furthermore, FLC proves to be a valuable tool for managing complex, poorly characterized, nonlinear systems. The ANN exhibits increasing intelligence, power, speed, and adaptability over time. ANFIS combines the advantages of ANN and FLC, employing a data-driven learning approach that utilizes Fuzzy Logic to transform inputs into desired outputs through a highly interconnected Neural Network, mapping inputs and outputs numerically using weights. Tuning the parameters of a Fuzzy Inference System using ANFIS is akin to tuning the parameters of a Fuzzy Logic system using a Neural Network, albeit with fewer steps and variables. The ANFIS toolbox constructs a Fuzzy Inference System from input/output mapping data, adjusting membership function parameters through back propagation or a combination of back propagation and least squares methods.

The term "Hybrid Learning" encapsulates this educational paradigm, allowing fuzzy systems to acquire knowledge from the information they model. ANFIS accomplishes its tasks through Neural Network learning, excelling in modeling, learning, nonlinear mapping, and pattern recognition. The benefits of ANFIS include the refinement of fuzzy if-then rules to better characterize the actions of complex systems, fast convergence rates, autonomy from human input, the ability to approximate any dataset of interest, and expanded options when selecting membership functions [30].

2.1. Training Procedure

The ANFIS constitutes a fuzzy Sugeno model configured within an adaptive system format. This methodology, by imparting a structured framework, streamlines ANFIS modeling and diminishes the dependence on domain specialists. To illustrate the ANFIS architecture, two fuzzy if-then rules grounded on a first-order Sugeno model have been deliberated.

First rule: $(z1 \ = \ p1x \ + \ q1y \ + \ r1) \ if \ (x \ is \ A1)$ and $(y \ is \ B1)$.

Condition 2: $(z2 \ = \ p2x \ + \ q2y \ + \ r2)$ if $(x \ is \ A2)$ and $(y \ is \ B2)$.

The inputs x and y, the fuzzy sets Ai and Bi, the outputs Zi within the fuzzy region indicated by the fuzzy rule, and the desired parameters pi, qi, and ri obtained during training are all part of this formula. The ANFIS architecture shown in Fig. 2 is what is responsible for enforcing these two rules.

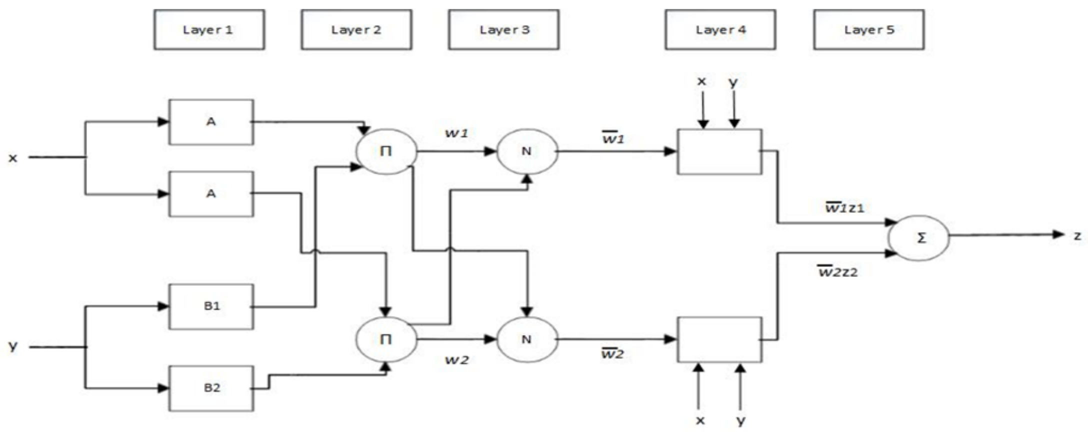

Fig. 2. General ANFIS architecture

A node's status in this design is represented by its shape; a circle represents a node that is always in the same location, whereas a square represents an adaptable node. It consists of a fuzzification layer, a rule layer, a normalization layer, and a single summation neuron in a five-layer feed forward neural network.

First-layer nodes are all able to adapt to their surroundings. This layer's outputs are the inputs' fuzzy membership grades, and they are defined as:

$$O1, i \ = \ \mu \, Ai \, (x), \qquad i = 1,2 \tag{1}$$

$$O1, i \ = \ \mu \, Bi - 2 \, (y), \qquad i = \ 3,4 \tag{2}$$

where $Ai(x)$ and $Bi(y)$ are fuzzy membership functions that can take on any value.

For example, if the bell shaped membership function is employed: $\mu \ Ai \ (x)$, is provided by:

$$\mu_A(x) =\rightleftarrows \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}} \tag{3}$$

Bell-shaped membership functions can be controlled by adjusting the parameters a_i, b_i, and c_i. The nodes in the second layer are rigid and are marked with a symbol representing basic multiplication. It is possible to express this layer's output as:

$$O_{2,1} = w_i = \mu Ai(x)\mu Bi(y), \quad i = 1,2 \tag{4}$$

They are referred to as the "firing strengths" of the regulations.

The N labels on the nodes of the third layer indicate that they are immovable and permanent, normalize firepower levels carried over from the preceding tier. These layers' outputs can be interpreted as:

$$O_{3,1} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{5}$$

which are so called normalization firing strengths.

Adaptive nodes are used in the fourth layer. Every layer 2 node's output is a first-order polynomial multiplied by its normalised firing strength (for a first-order Sugeno model). Thus, the output of this layer is given by:

$$O_{4,1} = w`izi = (pix + qiy + ri), O_{4,1} \quad i = 1,2 \tag{6}$$

In the fifth layer, there is a single anchored node indicated by the symbol. At this node, data from all incoming sources is added together. Accordingly, the full model output is:

$$O_{5,1} = \sum_i \bar{w}_i z_i = \frac{\sum w_i z_i}{\sum_i w_i} \tag{7}$$

The first and fourth layers of this ANFIS architecture are adaptive ones. There are three premise parameters (a_i, b_i, c_i) in the first layer that can be adjusted to change how the input membership functions are calculated. Similarly, the first-order polynomial's succeeding parameters (pi, qi, ri) on the fourth layer are all open to tweaking. This means that the adaptive network can be compared to a fuzzy inference system of the Sugeno type.

2.2. ANFIS Editor GUI

Input data for the ANFIS editor GUI (or the ANFIS command line function) must be in the form of a matrix, with all columns but the last containing vectors. One can use this to access the Beginning of FIS training again, store the trained model, launch a new Sugeno instance, or read the FIS model in any graphical user interface. The final column must include the output data. Input into an example ANFIS editor's graphical user interface is depicted in Fig. 3.

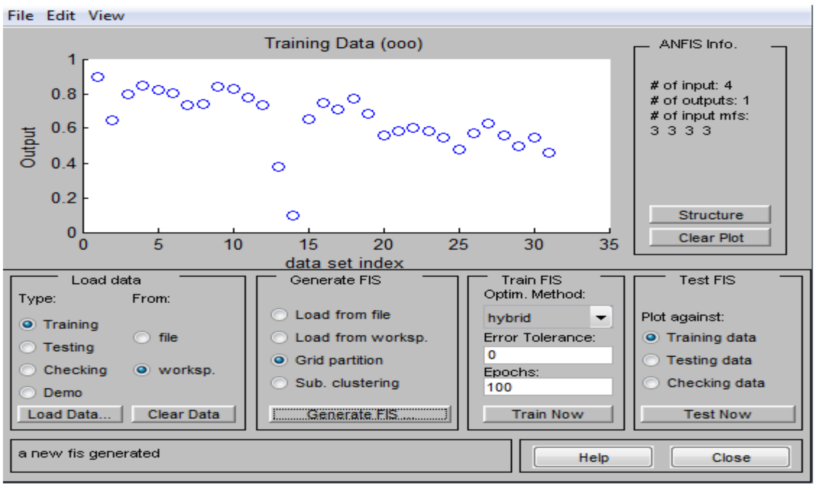

Fig. 3. ANFIS Editor GUI

2.3. FIS Generation

The basic framework of the FIS model is created before the training process begins. The model's framework can be specified by carrying out one of the following operations: -

- The user can: Recall a Sugeno-type FIS structure from a MATLAB file or workspace
- The first step is to generate a basic FIS model with one of the following partitioning strategies
- Grid Split: Converts the input data into a single-output Sugeno-style FIS
- Applying subtractive clustering to the data generates an initial model for ANFIS training

The grid partitioning approach is employed in the development of the FIS structure. The several kinds of input/output membership functions are listed when you click the generate FIS button. The proposed model was developed with the help of the "trimf" membership function. The introductory FIS generation conversation box is depicted in Fig. 4.

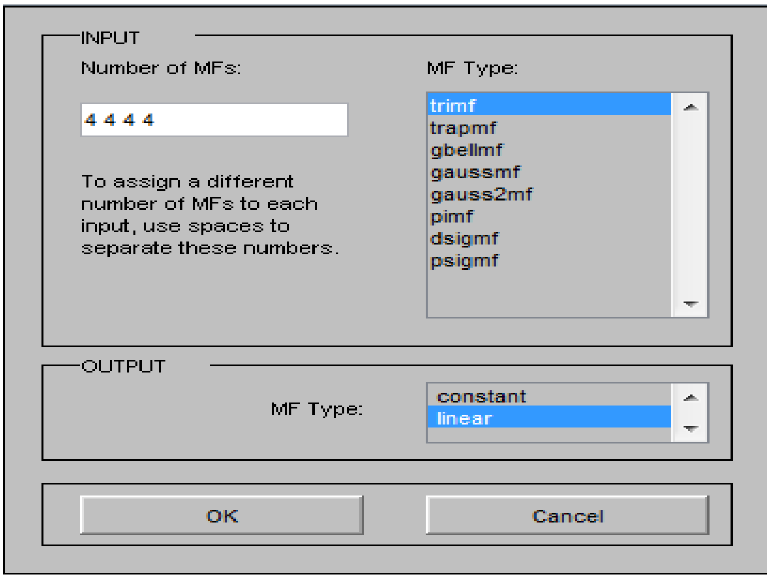

Fig. 4. Initial FIS Generation

2.4. Structure of the Model Proposed

Finishing the FIS generation, the model's structure can be inspected by selecting the structure button in the GUI's center right panel. The ANFIS architecture in use is seen in Fig. 5. This graph has color-coded nodes to make it easier to follow the various paths. The rules are represented by a tree whose branches are colored according to whether or not they are employed by the rules themselves. The node on the left is the input, while the node on the right is the output. An individual node stands in for a rule's normalization factor. Information about the structure can be viewed by clicking on the nodes.

The modelling approach taken by ANFIS is similar to that taken by several system identification methods. To begin, it is expected that the parameterized model has a specific structure (one that maps membership functions to rules, outputs, and other membership functions). We then record the inputs and outputs of a format suitable for ANFIS's training purposes. By modifying the FIS model's membership function parameters in accordance with the selected error criterion, ANFIS can teach it to behave like the training data. In Fig. 6, we can see the ANFIS output and the training error. The ANFIS output is a reflection of its training, and the training error serves as a guiding metric to assess the model's learning progress. A well-trained ANFIS should exhibit low training error, indicating its ability to accurately predict outputs for given inputs.

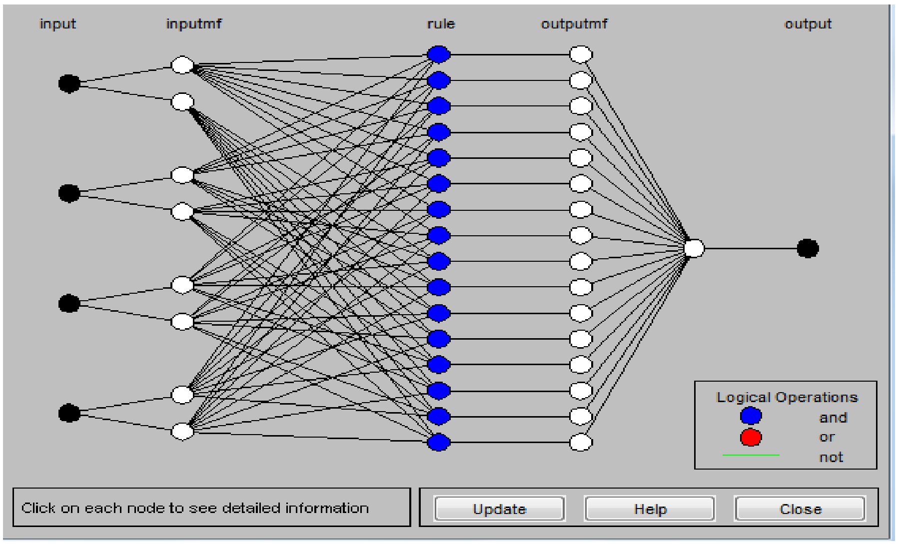

Fig. 5. ANFIS model structure

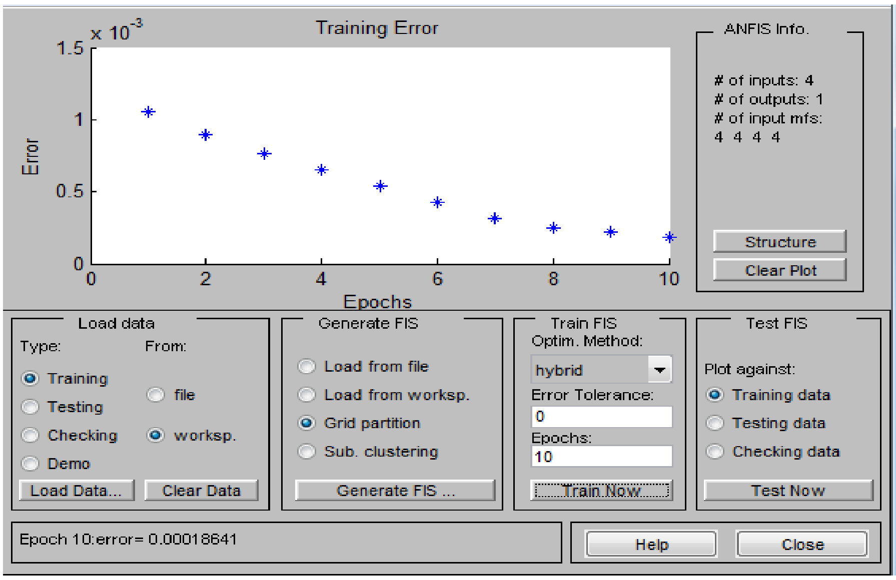

Fig. 6. ANFIS model structure

3. Results and Discussions

The MATLAB/Simulink simulation environment is used to test the suggested control strategy for a solar photovoltaic system that is connected to the grid. In this work, a solar PV array with a 10 kW nominal MPP is used. Power factor correction (PFC) mode, fluctuating solar radiation, and other scenarios have all been analyzed.

3.1. Analysis Under Linear Load

Fig. 7 depicts the system's operation in the ZVR mode while subjected to dynamic linear loading. All waveforms are shown in the output, including those for the line voltage (v_s), line current (i_{abc}), load currents for phases "a" and "c," inverter current (i_c), terminal voltage (V_t), DC link voltage (V_{dc}), photovoltaic power (P_{pv}), and photovoltaic current (P_{vc}) (I_{pv}). The voltage between the PCC terminals may fluctuate if the load draws reactive power from the mains (V_t). Disconnecting the specified load's phase 'c' after 1.1 s maintains sinusoidal currents in the network (i_{abc}). There are no noteworthy shifts in either the terminal voltage (V_t) or the intermediate circuit voltage from their respective reference values.

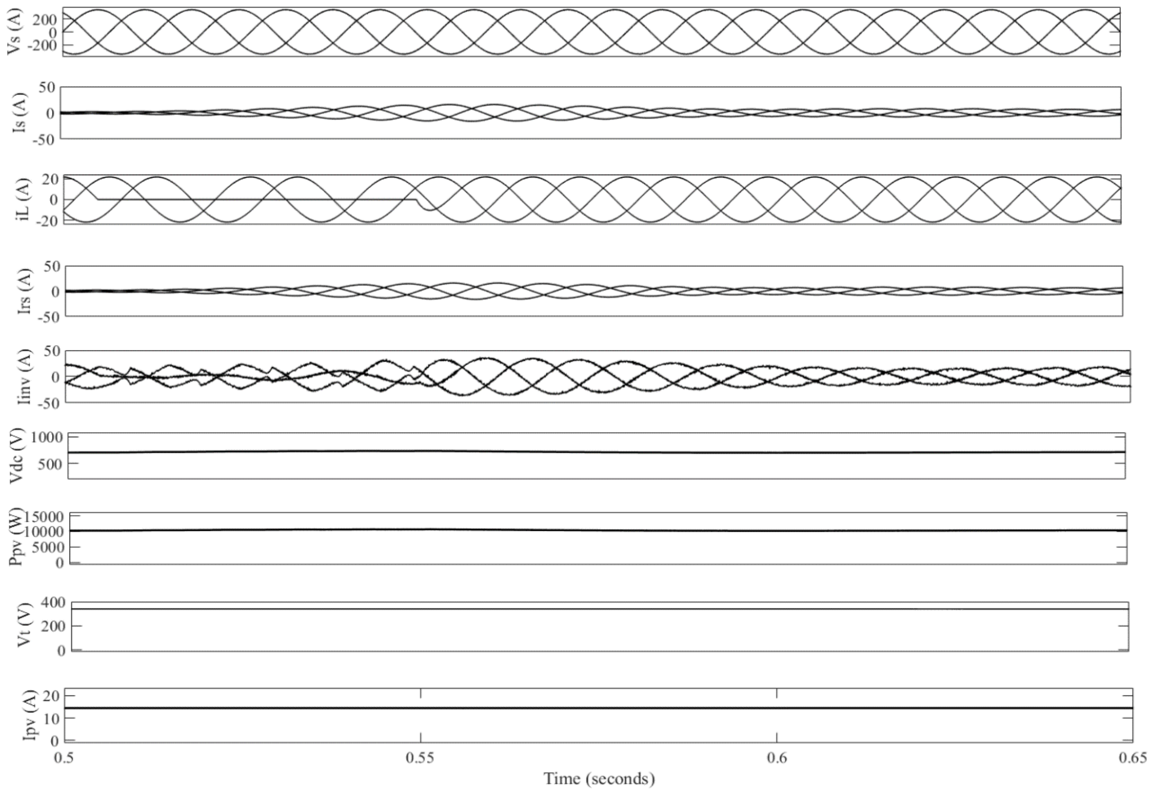

Fig. 7. Under linear load in ZVR mode

3.2. Analysis Under Non-Linear Load

As can be seen in Fig. 8, the controller's performance analysis takes the dynamic behaviour of the non-linear load into account. The suggested control is able to keep sinusoidal network currents even the load on 3rd phase 'c' is eliminated at 1.1 seconds (i_{abc}). Equally stable are the terminal voltage (V_t) and DC link voltage (V_{dc}). The suggested controller additionally mitigates mains current harmonics to below the thresholds set by a number of regulations. The regulator reliably provides harmonic correction and load balancing.

3.3. Variation in Solar Irradiance

Fig. 9 displays the results of a performance analysis conducted on the suggested controller under varying levels of solar radiation. Radiation from the sun (S) doubles in intensity every half a second, from 600 to 1000 W/m2. While PV power (PVP) increases as solar radiation levels rise, grid power (Pg) drops. Uniform power factor operation mode is possible, and MPP functioning is maintained, under these conditions. When subjected to nonlinear, dynamic loading, the suggested controller method outperforms state-of-the-art alternatives. Table 1 provides a snapshot of the system's performance under ZVR mode, showcasing its ability to maintain a high grid current while keeping the Total Harmonic Distortion at the Point of Common Coupling low.

Table 1. Performance analysis

Mode	Criteria	Control algorithm
ZVR	Grid current (A), %THD at PCC	24.27A, 4.16 %
	Grid current (A), %THD at PCC	41A, 42 %
	V_{dc} (V)	717 V

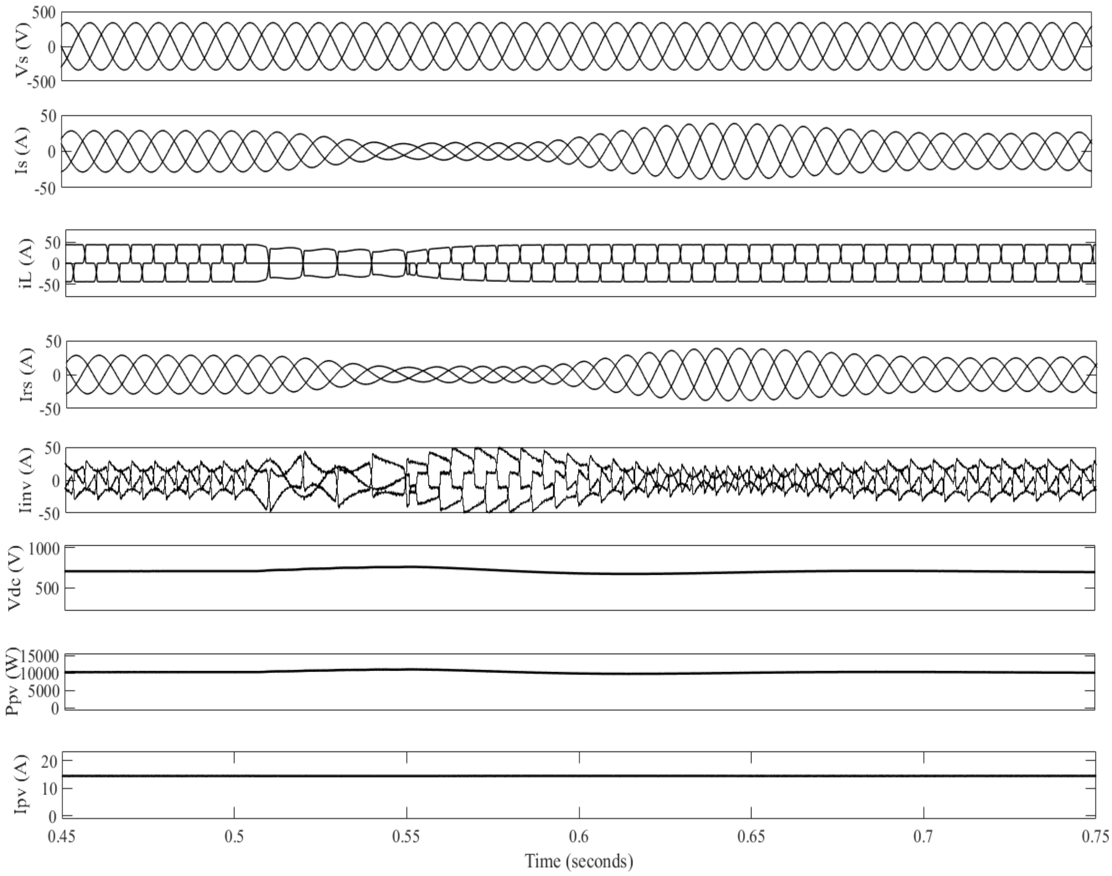

Fig. 8. For dynamic nonlinear load, PFC mode

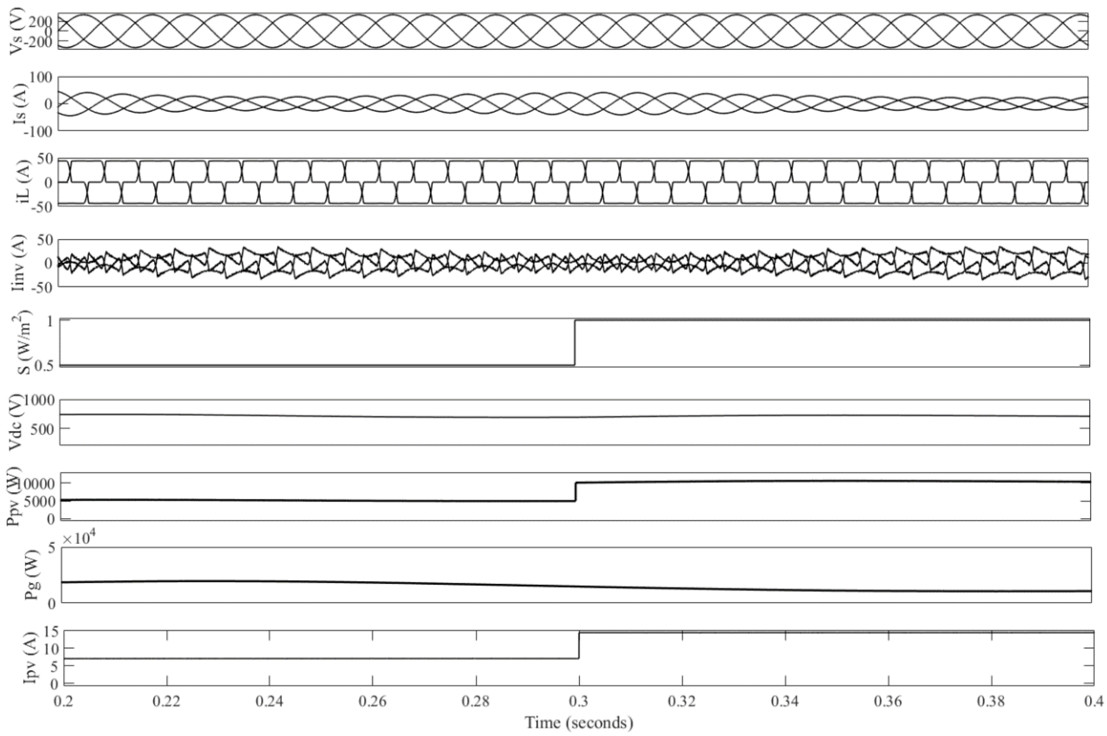

Fig. 9. Considering non-linearity in the load and solar irradiance changing

4. Conclusion

A MATLAB/Simulink model was used to evaluate the effectiveness of the proposed method. The efficiency of the proposed regulation is evaluated by simulating the effects of a load imbalance and variations in solar radiation. The results demonstrate the presented controller's efficacy in minimizing network harmonics and maximizing power draw while maintaining unity power factor functions with reactive power compensation and load balancing. The proposed controller is responsive quickly during transient events as well. Harmonics in the line voltage and current are much below the thresholds set by IEEE-519 and IEEE-1547.

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