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Research Article

ANFIS BASED INTEGRATED APPROACH FOR POWER QUALITY IMPROVEMENT OF GRID CONNECTED PHOTOVOLTAIC SYSTEM

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ABSTRACT

The term Soft Computing (SC) encompasses many techniques which include: Fuzzy Logic (FL), Neuro-Computing (NC), Probabilistic Reasoning (PR), Evolutionary Computing (EC) or Genetic Algorithms (GA), Chaotic Systems (CS), Belief Network (BN) and part of Learning Theory (LT) (Zadeh, 1965, 1994, 1995; Mellit and Kalogirou, 2008). SC techniques are different from analytical approach in that they employ computing techniques that are capable of representing imprecise, uncertain and vague concepts (Voracek, 2001a; Kulak *et al*., 2005; Kahraman, 2007; Guarino *et al*., 2009). Analytical or in other words hard computing, approaches on the other hand use binary logic, crisp classification and deterministic reasoning. In their editorial review, (Hoffmann *et al*., 2005) observed that: "In contrast with hard computing methods that only deal with precision, certainty, and rigor, soft computing is effective in acquiring vague or sub-optimal but efficient and competitive solutions. It takes advantage of intuition, which implies the human mind-based intuitive and subjective thinking is implemented here".

Techniques in SC are able to handle non-linearity and they also offer computational simplicity when compared with the analytical methods. These techniques have been shown to be able to manage large amount of information and mimic biological systems in learning, linguistic conceptualization, optimization and generalization abilities. Soft computing techniques are finding growing acceptance in materials engineering and three of them are popular, namely: (i) Fuzzy Logic (FL), (ii) Artificial Neural Networks (ANN) and (iii) Genetic Algorithms (GA). There are well established methodologies for integrating SC techniques to realize synergistic or hybrid models with which better results could be obtained (Zadeh, 2001). The use of hybrid techniques is also growing. Real world problems have to deal with systems which are non-linear, time-varying in nature with uncertainty and high complexity. The computing of such systems is study of algorithmic processes which describe and transform information: their theory, analysis, design, efficiency, implementation, and application. Conventional computing/Hard computing requires exact mathematical model and lot of computation time. For such problems, methods which are computationally intelligent, possess human like expertise and can adapt to the changing environment, can be used effectively and efficiently. Soft computing utilizes computation, reasoning and inference to diminish computational cost by exploiting tolerance for imprecision, uncertainty, partial truth and approximation. Soft Computing with its roots in fuzzy logic, artificial neural network, and evolutionary computation has become one of the most important research field applied to numerous engineering areas such as Aircraft, Communication networks, computer science, power systems and control applications. Soft Computing Techniques comprises of core methodologies: Fuzzy Systems (FS), including Fuzzy Logic (FL); Evolutionary Computation (EC), including Genetic Algorithms (GAs); Artificial Neural Networks (ANN), including Neural Computing (NC); Machine Learning (ML); and Probabilistic Reasoning (PR). Where PR and FL systems are based on knowledge-driven reasoning, whereas, ANN and EC, are data-driven search and optimization approaches.

INTRODUCTION

Fuzzy Logic System

These techniques can be deployed as individual tools or be integrated in unified and hybrid architectures. The fusion of Soft Computing techniques causes a paradigm shift in engineering and science fields, which could not be solved with the conventional computational tools. Soft Computing has gain importance in the application fields for wireless communication in the last decade. Uncertainties arising due to incomplete modeling and measurements are handled using fuzzy logic, either in stand-alone manner or in conjunction with the optimization and prediction algorithms. Various methods of using the tools for application oriented programming techniques is briefly discussed here.

Fuzzy systems are based on fuzzy logic, a generalization of traditional Boolean logic which is extended to handle the concept of partial truth i.e values between "complete true" and

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"complete False". Fuzzy Logic provides a set of mathematical methods for representing information in a way that resembles natural human reasoning and deals with system uncertainty and vagueness. Concepts of fuzzy sets, fuzzy logic and fuzzy control have been introduced and developed by L. Zadeh in a series of articles spanning several years. Fuzziness is imprecision or vagueness, a fuzzy proposition may be true to some degree. List of various problem Solving Techniques are as shown in Figure 1.

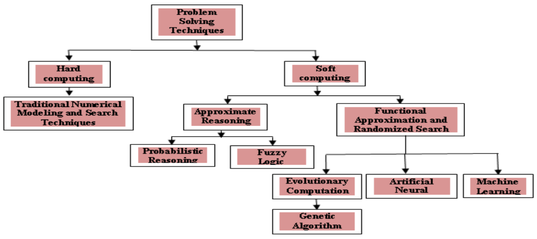


Figure 1 Various Problem Solving Techniques

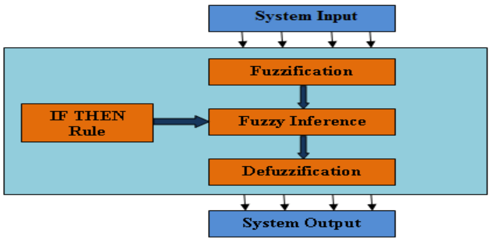


Figure 2 Fuzzy Logic System

A Fuzzy Logic System is an expert system that uses a collection of fuzzy membership functions and fuzzy IF-THEN rule base, instead of Boolean logic, to reason about data. The rules in a Fuzzy Logic System are of a form as following:
IF (a is LOW) AND *(y* is HIGH) THEN *(z* is MEDIUM), IF (premise) THEN (Conclusion) where *x* and *y* are input variables for known data values, *z* is an output variable for an output data to be computed, LOW is a membership function (fuzzy subset) defined on the set of x, HIGH is a membership function defined on the set of y, and MEDIUM is a membership function defined on the set of z. The antecedent (the rules premise, between IF and THEN) describes to what degree the rule applies, while the consequent (the rules conclusion, following THEN) assigns a membership function to each of one or more output variables. The set of rules in a Fuzzy Logic System is known as the rule base or knowledge base. Figure 2 shows the Fuzzy Logic System Block Diagram.

Fuzzification: The membership functions defined on the input variables are applied to their actual values, to determine the degree of truth for each rule premise.

***Fuzzy Inference Engine*:** The truth value for the premise of each rule is computed, and applied to the conclusion part of each rule. This results in one fuzzy subset to be assigned to each output variable for each rule. The aggregation methods min or product is used as inference rules. After Inference, the composition of all fuzzy sets is carried out. Under composition, all of the fuzzy subsets assigned to each output variable are combined together to form a single fuzzy subset for each output variable. Usually max or sum is used.

Defuzzification: It converts the fuzzy output set to a crisp number. There are many defuzzification methods. The Fuzzy Logic Algorithm steps are given in Figure 2.

Artificial Neural Networks

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the biological neural networks, which consists of massively parallel computing systems with large number of simple processors with many interconnections. An ANN methodology consists of basic architecture known as "Neurons". A neuron or nerve cell is a special biological cell that processes information in human brain. ANNs are applied to solve various challenging problems like Classification, Clustering, Function Approximation, Prediction/Forecasting, Medical Imaging Application, Optimization and Control related applications.

$$\sum_{i=1}^{N} W_i X_i = W_1 X_1 + W_2 X_2 + \cdots + W_N X_N$$

Artificial Neuron

The science of ANN has its first significance appearance during the 1940's, when researchers McCulloch and Pitts tried to emulate the functions of human brain by developing physical model of biological neuron and their interconnections. Their work was focus on a simple neuron, which were considered to be binary with fixed thresholds as shown in Figure 3. The threshold unit receives input from N other units. Input from *ith* unit is termed as X_n, and the associated weight is W_n. The total input to a unit is the weighted sum over all inputs.

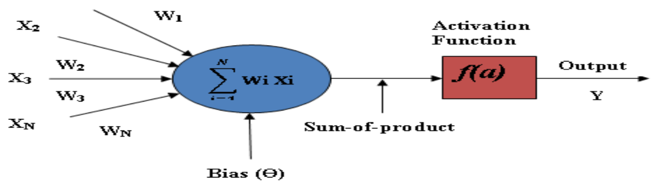


Figure 3 Artificial Neuron

If this value is below threshold t, the output of the unit is 1 and 0 otherwise. The McCulloch- Pitts model of a neuron is so simple that it only generates a binary output and also the weight and threshold values are fixed. But, it has substantial computing potential. The neural computing algorithm has diverse features for various applications. Thus, we need to obtain the neural model with more flexible computational features. In the first stage, the linear combination of inputs is calculated. Each value of input array is associated with its weight value, which is normally between 0 and 1.

Also, the summation function often takes an extra input value Theta with weight value of 1 to represent threshold or bias of a neuron.

The summation function will be then performed as:

$$\alpha = \sum_{i=1}^{N} W_i X_i = \theta$$

The sum-of-product value is then passed into the second stage to perform the activation function which generates the output from the neuron. The activation function "squashes" the amplitude the output in the range of [0,1] or [-1,1] alternately.

The behavior of the activation function will describe the characteristics of a neuron model.

In learning process, ANN updates network architecture and connection weights from training patterns. ANNs learn the underlying rules (like input-output relation) from the given collection of training data. Learning algorithms adjusts the weights of ANN using learning rules. Based on learning process there are three types of learning paradigms:

Supervised learning: also known as learning with a "teacher", means the network is provided with the correct output for every input pattern. Connection weights are then determined so allow the network to produce output very close to the correct answers. Examples of supervised learning algorithms are Boltzmann learning algorithm, Learning vector quantization, Back-propagation Adaline algorithm and Perception learning Algorithms.

Unsupervised Learning**:** also know as learning without "teacher", do not require correct output answers for each input pattern in the training set provided. It explores the network structure in data or correlations between input patterns, and organizes input patterns into categories from these correlations. Unsupervised Learning algorithms include Principal Component Analysis, Associative memory Learning, Kohonen's SOM, Adaptive resonance theory (ART) algorithms.

Hybrid learning**:** It combines supervised and unsupervised learning i.e. parts of the weights are determined through supervised learning and the remaining are obtained through unsupervised learning. Radial Basis Function (RBF) learning algorithm used for learning in RBF networks using Error-correction and competitive learning rule is an example of Hybrid learning.

Genetic Algorithms

Since 1950s several researchers have studied Evolutionary Systems as an optimization tool for engineering problems. The basic idea in all these systems is to evolve a population of candidate solutions of a given problem, using operators inspired by natural genetic variation and natural selection.

In 1970's, the pioneering work of J.H. Holland proved to be significant contribution for various engineering and scientific applications. The well known applications of GA include scheduling, sequencing, reliability design, and image processing.

Genetic Algorithms are inspired by the mechanism of natural selection, which is a biological process in which stronger individuals are more likely to be winners in a competing environment. GA assumes that the solution of a problem is an individual, which can be represented by a set of parameters. These parameters are known as genes of the chromosomes and can be represented by string of binary values. GAs is a search technique which starts with an initial set of random solutions known as population. Each individual in population is called chromosomes, which is a string of binary values.

The chromosomes evolve through successive iterations, called generations. During each iteration the chromosome evolve using some measures of fitness. Then the next generation is created, where the new chromosomes called as off-springs, are formed by either merging two chromosomes from current generation using a crossover operator or modifying a chromosome using a mutation operator.

New generation is formed by selection, based on the fitness values, some of the parents and off springs are rejected to keep the population size constant. After several iterations the algorithm converges to the best chromosome, which represents the optimum or sup-optimum solution to the problem.

Hybrid Models

The soft-computing techniques, particularly those discussed here, are complementary rather than competitive (Zadeh, 2001, 1994). This implies that a hybrid model employing a combination of artificial neural networks, fuzzy systems, and/or genetic algorithms should produce better results. There are at least four hybrid models that can be created from the above SC techniques: i) Neuro-fuzzy, ii) Fuzzy-genetic, iii) Neuro-genetic, iv) Neuro-fuzzy-genetic.

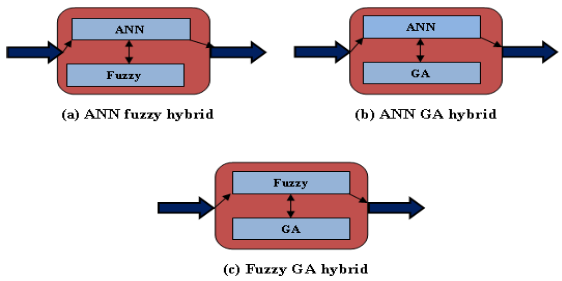


Figure 4 Hybrid soft computing models

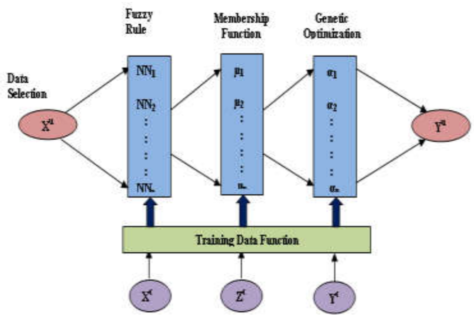


Figure 5 ANN - fuzzy- GA hybrid

Neuro-fuzzy

The neuro-fuzzy model, which involves the integration of ANN and FL techniques are perhaps the most popular hybrid technique used in materials engineering. Neuro-fuzzy models are able to take advantage of the fuzzy inference mechanism capabilities in fuzzy logic and the learning ability of neural networks.

The ANN technique is usually used as the learning algorithm for the defuzzification process in FL based models. Figure 4(a) illustrates a simple configuration of a neuro-fuzzy model.

Fuzzy-genetic

When the FL and GA techniques are combined together to develop a solution, the fuzzy-genetic model formed. The aim here is to exploit the ability of the fuzzy logic at knowledge description and the optimization capability of the genetic algorithm. Usually, the defuzzification process in fuzzy logic based model are developed using optimal selection of elements from a fuzzy set. Aside from GA, techniques that employ the concepts of interaction, variability, and voting techniques are also used to optimise the defuzzification and membership generation process. Figure 4(b) illustrates a simple configuration of a fuzzy-genetic algorithms model.

Neuro-genetic

When an ANN and GA techniques are combined to develop a solution, the neuro-genetic model results. The aim here is to take advantage of the learning ability of the ANN and optimization ability of the genetic algorithm. Figure 4(c) illustrates a simple configuration of a neuro-genetic algorithms model.

Neuro-fuzzy-genetic

When the three SC techniques discussed here are combined to develop a solution, the neuro-fuzzy-genetic model results. Usually, the GA approach is used to optimize the performance of a neuro-fuzzy system. The development of this approach is usually guided by heuristics, based on the experiences of an expert materials engineer. In (Huang, Gedeon, and Wong, 2001) the architecture in Figure 3.5 was proposed for developing a neuro-fuzzy-genetic model for predicting the permeability in petroleum reservoirs. The vector Xc and matrix Zc are the training pattern and Yc is the target output.

Soft Computing Techniques for Power Quality Improvement

In this paper, the operation of an adaptive neuro-fuzzy inference system (ANFIS)-based maximum power point tracking (MPPT) for solar photovoltaic (SPV) energy generation system. The MPPT works on the principle of adjusting the voltage of the SPV modules by changing the duty ratio of the Quasi-z-source inverter. The duty ratio of the inverter is calculated for a given solar irradiance and temperature condition by a closed-loop control scheme. The closed-loop control of the quasi ZSI regulates the duty ratio and the modulation index to effectively control the injected power and maintain the stringent voltage, current, and frequency conditions.

The ANFIS is trained to generate maximum power corresponding to the given solar irradiance level and temperature. The response of the ANFIS-based control system is highly precise and offers an extremely fast response. The main objective for a grid-connected Photovoltaic (PV) inverter is to feed the harvested energy from PV panels to the grid with high efficiency and power quality. The simulation results show that the proposed ANFIS MPPT controller is very efficient, very simple and low cost.

It is well known that the output power of photovoltaic (PV) panels holds highly non-linear characteristic. For a certain temperature and irradiation, there will be a specific maximum power at certain voltage so-called maximum power point (MPP). The voltage of MPP changes with the irradiation and especially the temperature varying. Thus, the system needs to operate at the MPP of PV array by controlling the inverter, no matter how much irradiation, what temperature or other conditions.

Moreover, the generated energy from the PV system, which is mostly provided to the utility grid, not only should be of sinusoidal current, but also must satisfy the requirements of the power grids, such as no DC component of the inverter output current, minimization of the harmonics, as a result of no harmonic pollutions on the power grids, and so on. These requirements impose the inverter with a high-grade control. The challenge is how to meet the above requirements with minimum cost, which has to be faced for the majority of designers.

AI based methods are most suitable for improving the dynamic performance of maximum power point tracking. Considering the non-linear characteristics of solar PV module, the AI methods provide a fast, flexible and computationally demanding solution for the MPPT problem. Fuzzy logic controller and artificial neural networks are two main AI methods used for MPPT. In this paper, designing and implementation of ANFIS based MPPT scheme which is interfaced with Quasi-Z-Source Inverter presented.

ANFIS combines the advantages of neural networks and fuzzy logic and hence deals efficiently with non linear behavior of solar PV modules. Designing of Quasi-Z-Source Inverter is also carried out which is used for impedance matching and maximum power transfer between load and solar PV module.

Scheme for PV array Model

Irradiance level and operating temperature are taken as the input for the ANFIS reference model. The ANFIS reference model gives out the crisp value of maximum available power from the PV module at a specific temperature and irradiance level.

The actual output power from the PV module, at same temperature and irradiance level, is calculated by using multiplication algorithm on sensed operating voltage and currents. Two powers are compared and the error is given to a proportional integral (PI) controller, to generate control signals. The control signal generated by the PI controller is given the pulse to the IGBT for triggering purpose.
The generated signals control the duty cycle of quasi-z-source inverter in order to adjust the operating point of the PV module.

Pulse-width modulation (PWM) allows control and regulation of the total output voltage. A proportional and integral regulator with feed forward will adjust the shoot-through duty of the quasi ZSI. In general, the battery voltage depends on its SOC, instead of its current, and has a little change in a suitable range of the SOC. The objectives to be achieved by the proposed control system are

1. Maximum power point tracking.
2. Desired stable output power to the Grid.

The output power of the inverter should be controllable and adjustable on the basis of users demand in case of the Grid. The output voltage, magnitude and frequency should be kept constant regardless of the change in the input conditions. Solar irradiance and the temperature and other weather data are collected using weather transmitters arrangements. The outputs of the solar irradiance and temperature transducers are current/ voltage signals which are logged in real time using standard data loggers. These data are then being transferred to the PC for further processing or implementation of real-time control system using the ANFIS controller.

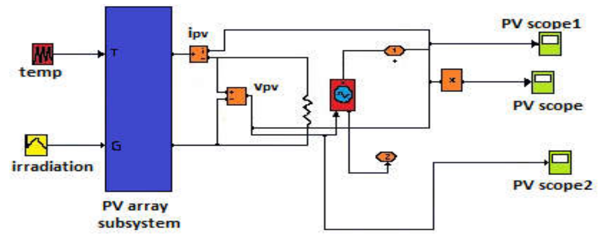


Figure 6 PV array model

The nonlinear equations depend on the incident solar irradiation, the cell temperature, and on the reference values. These reference values are generally provided by manufacturers of PV modules for specified operating conditions such as STC for which the irradiance is 1000W/m2 and the cell temperature is 25 ºC. Real operating conditions are always different from the standard and mismatch effects can also affect the real values of these meat parameters.

ANFIS for MPPT Tracking

ANFIS is capable of developing the input-output mapping of training data sets when it is trained with sufficient number of epochs. By adjusting the values of membership functions ANFIS generates the set of fuzzy rules in order to produce appropriate output for different values of inputs. Parameters of membership functions are adjusted or changed till the error is reduced to minimum value. Matlab/Simulink model of PV module is used to generate the training data set for ANFIS by varying the operating temperature in steps of 5°C from 10°C to 70°C and the solar the solar irradiance varies from 50 to 1000 W/m in a step of 50 W/m.

Once all the parameters of membership function are adjusted, the ANFIS model becomes learning model which is ready to be used in MPPT control scheme. But before using ANFIS learning model for MPPT control, its results are checked by using checking data which is different from training data. Again if error produced is more than desired value, parameters of membership functions are adjusted to bring down the error. Quasi-z-source inverter is designed to be placed between solar PV module and load in order to transfer maximum power to load by changing duty cycle of quasi-z-source inverter. The neuro-fuzzy structure shown in Figure 7 is a five-layer network. The structures shows two inputs of the solar irradiance and the cell temperature, which is translated into appropriate membership functions, three functions for the solar irradiance in Figure 11 and three functions for temperature in Figure12.

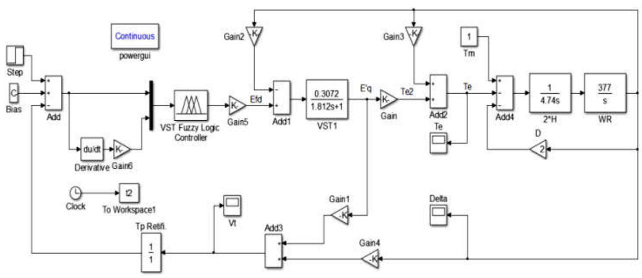


Figure7 Control circuit of ANFIS

These membership functions are generated by the ANFIS controller based on the prior knowledge obtained from the training data set.

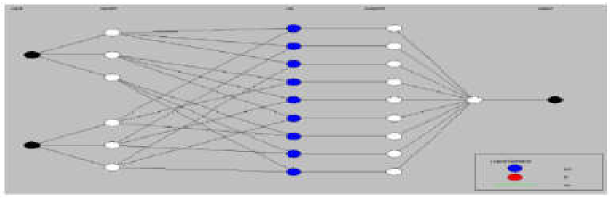


Figure 8 ANFIS-based MPPT structure

The membership function's shape varies during the training stage and the final shape obtained after the completion of the training is shown in Figure 9 and 10. These are termed as "low," "medium," and high."

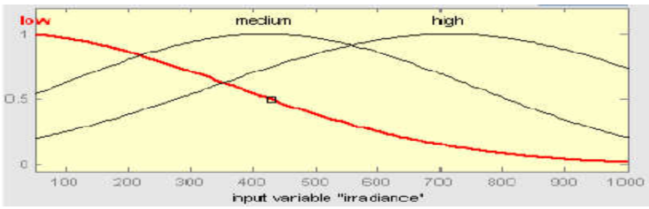


Figure 9 Membership function of solar irradiance

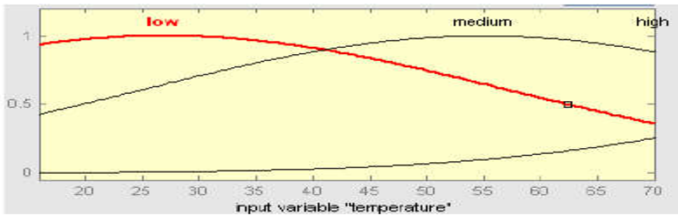


Figure 10 Membership function of PV cell temperature

Improvement of MPP for grid connected PV System

The solar irradiance varies from a certain minimum value to the maximum value and then goes down to another minimum value to simulate a real time scenario, the solar irradiance and temperature is varied accordingly. The PV voltage nearly 450v without ANFIS controller, and with the controller it can boost nearly 550v. As shown in figure 11 and figure 12 with the irradiance from nearly 50 to 1000 W/m with a peak value of 50 KW/m. The temperature is varied from 16^{o} C to 70^{o} C with the step of 5^{o} C.

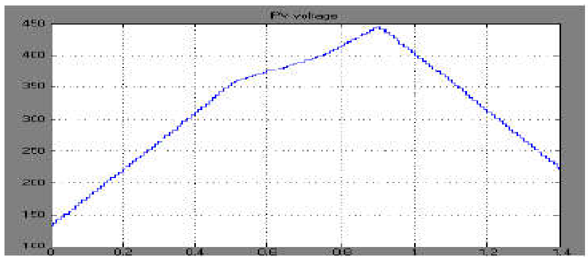


Figure 11 PV Output Voltage without ANFIS controller

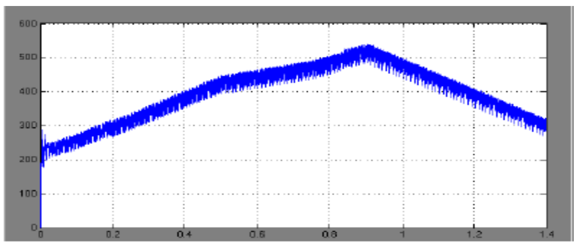


Figure12 Membership function of solar irradiance

The output voltage from the PV panel attains 450v constantly, and the current reaches 16 Amps from the panel for the various temperature and irradiance. Shows in figure11 and figure12 for the various weather conditions the voltage and current constantly draws from PV panel by using this MPPT technique.

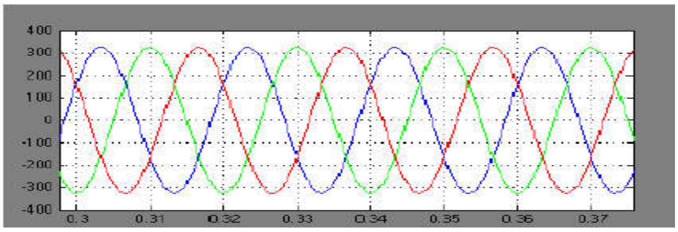


Figure 13 Grid output voltage

Figure13. shows the three phase output of the grid, connected with the PV system. The voltage reaches up to 300V.

Grid Power Quality Enhancement Using Fuzzy Control-Based Shunt Active Filtering

Active filtering has proved efficient for the mitigation of harmonics in distribution grids. This paper deals with the design of fuzzy control strategies for a three-phase shunt active filter to enhance the power quality via the regulation of the DC bus voltage of the distribution network. The proposed control scheme is based on Interval Type 2 Fuzzy Logic controller. A simulation study is performed under Simulink/Matlab to evaluate the performance and robustness of the proposed control scheme.

Power quality issues have become a major concern in recent years due to the widespread use of nonlinear loads such power electronic converters, variable speed motor drives and consumer electronics. Nonlinear loads introduce harmonics into the power network which cause a number of disturbances such as distortion of the current and voltage waveforms, electromagnetic interference, overheating of power distribution components inducing losses and reducing their lifetime. Active Power Filters (APFs) also called Active Power Line Conditioners (APLCs) are a relatively new technology which offers a more flexible alternative and provides superior filtering performance characteristics and faster transient response as compared to conventional passive filters consisting of custom designed LC filters which are tuned to provide fixed frequency compensation . AFPs basically consist of a power electronic inverter and a control circuit.

The performance of these filters systems depends mainly on the converter topology employed, the adopted reference current generation strategy for harmonic compensation as well as the controller for the regulation of the DC bus voltage. The regulation of the DC bus voltage consists of maintaining the voltage across the capacitor connected to the inverter at the desired level. The role of the capacitor voltage is to compensate for inverter losses and any transient fluctuations in real power between the AC and DC sides following load changes. Various DC bus voltage control strategies have been proposed in the literature.

This paper presents a simplified design approach of an Interval Type-2 fuzzy logic controller (IT2FLC) for DC bus voltage regulation. The presented control strategies are evaluated through extensive simulation under various operating conditions of the SAPF such as system's parameters and nonlinear load variations.

Shunt AFP Configuration and Control Scheme

Shunt AFP Configuration

The APF concept is to use an inverter to produce specific currents or voltages harmonic components to cancel the harmonic components generated by the load. The most commonly used AFP configuration is the Shunt APF (SAPF) which injects current harmonics into the point of common coupling (PCC). Figure 14 shows basic principle of SAPF.

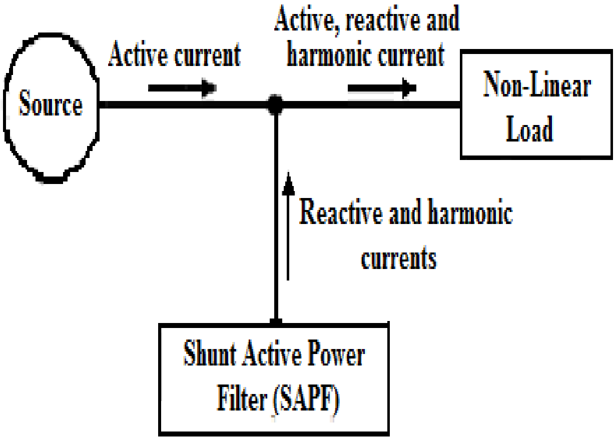


Figure 14 Basic principle of a SAPF

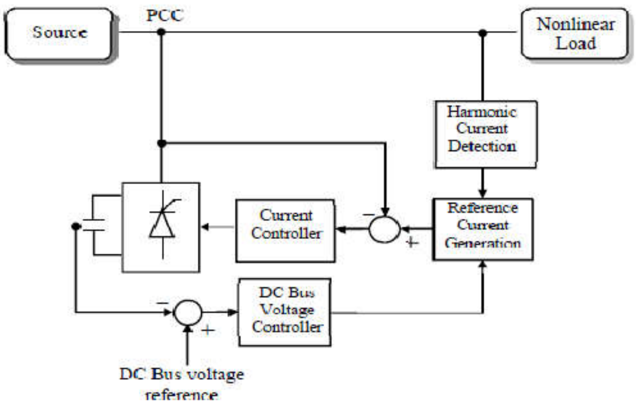


Figure 15 SAFP control system implementation

Control Scheme of the SAPF

The SAPF control strategy is implemented in three basic stages: The first is the harmonic detection method to identify harmonic level in the system. The second part is to derive the compensating currents and the third one is the control technique of the inverter for injecting these currents into the power system. The overall control system of the SAFP is depicted in Figure 15.The Synchronous Detection Method (SDM) is used here to calculate the reference current for SAPF due to its simplicity. It is based on the idea that the APF forces the source current to be sinusoidal and in phase with the source voltage despite the load variations.

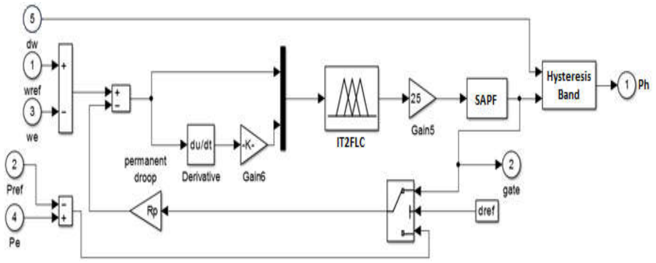


Figure 16 Implementation of IT2FLC controller for the SAPF

Control Strategy for the DC Bus Voltage

The capacitor that powers the active filter acts as voltage source and its voltage must be kept constant to ensure that the performance of the filter is maintained and the voltage fluctuations of the semi-conductors do not exceed the limits prescribed. The Interval Type 2 Fuzzy Logic Controller (IT2FLC) is implemented as shown in Figure 16. Type-2 fuzzy logic systems, introduced by Zadeh (1975) as an extension of ordinary Type-1 fuzzy logic systems, are characterized by fuzzy membership functions represented by fuzzy sets in [0, 1] unlike a Type-1 fuzzy which have crisp membership functions. T2FLC consists of five components including fuzzifier, rule base, fuzzy inference mechanism, type reducer and defuzzifier as depicted in Figure17. In a IT2FLC at least some of the fuzzy sets used in the antecedent and/or consequent parts and each rule inference output are type-2 fuzzy sets. Generally speaking, in a T2FLC, the crisp inputs are first fuzzified, usually into Type-2 fuzzy sets. The fuzzified Type-2 fuzzy sets then activate the inference engine and rule base to yield output Type-2 fuzzy sets by performing the union and intersection operations of Type-2 fuzzy set and compositions of Type-2 relations.

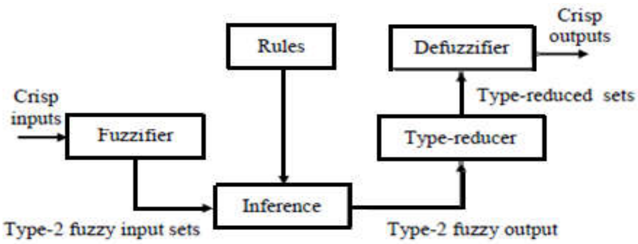


Figure 17 Interval Type-2 fuzzy system (IT2FLS)

Then a type reduction process is applied to these output sets in order to generate Type-1 fuzzy sets (called type-reduced sets) by combining these output sets and performing a centroid calculation. Finally, the type-reduced Type-1 set is defuzzified to produce crisp output. A generalized rule for Type-2 fuzzy system is:

IF x_1 is A_{k1} and x_2 is A_{k2} and … x_n is A_{kn} THEN $uk = \sum_{i=1}^{N} P_{ik}X_i + b$k,

Where x_k and u_k are the input and output linguistic variables respectively; $A_{ki's}$ are Type-2 fuzzy sets for the k_{th} rule and ith input; P_{ki} and b_k are consequent parameters of the rules which are Type-1 fuzzy sets. The fuzzy controller inputs (DC bus voltage error *(e)* and change of error *(de)* are implemented using Gaussian membership functions as shown in Figure18. The fuzzy labels are negative (N), environ zero (EZ), positive (P). The control rules are given in Table1.

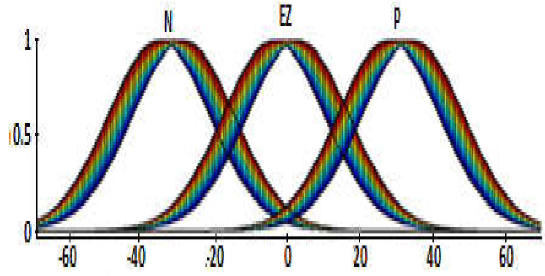


Figure 18(a) error signal (e) of Membership functions

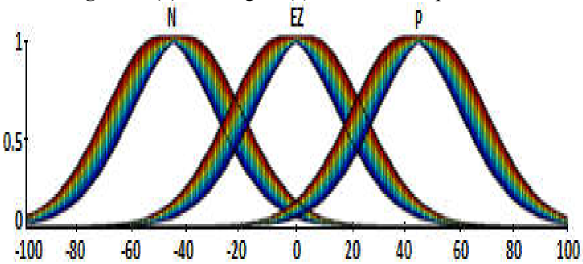


Figure 18(b) change in error signal (de) of Membership functions

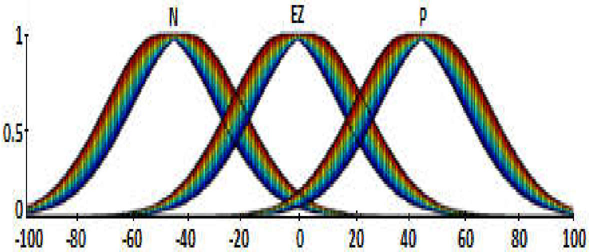


Figure 18 (c) control signal for (u) Membership functions

Table1 IT2FLC Fuzzy Control Rules

de e	**N**	**EZ**	**P**
N	N	N	EZ
EZ	N	EZ	P
P	EZ	P	P

SIMULATION RESULTS

The SAPF model and controller have been implemented using Simulink and Sim Power Systems toolboxes. The model parameters used for these simulations are listed in Table1. In this simulation study, the performance of IT2FLC designed for the DC bus voltage are first analyzed in terms of current waveforms and related Total Harmonic Distortion (THD). The robustness of these controllers is then compared with respect to changes in the filter inductance L_f.

Simulation Results Using without filter

Initially, the system is simulated without the SAPF. Figure 19(a) and Figure 19(b) show the load voltage and current respectively which demonstrates a considerable distortion in the current waveform. The THD in Figure 19(c) has been estimated to
23.74 %.

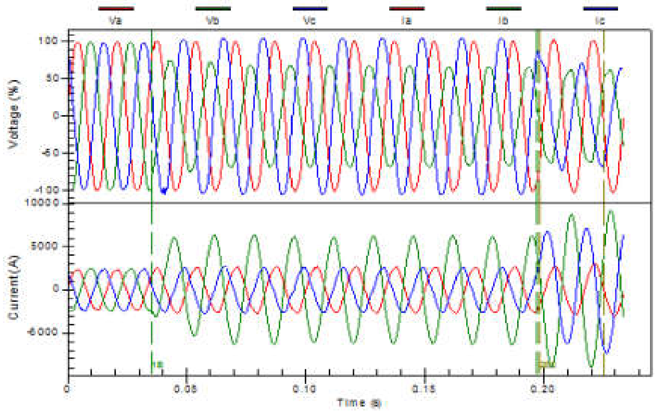


Figure 19 (a) Source voltage and (b) current without SAPF

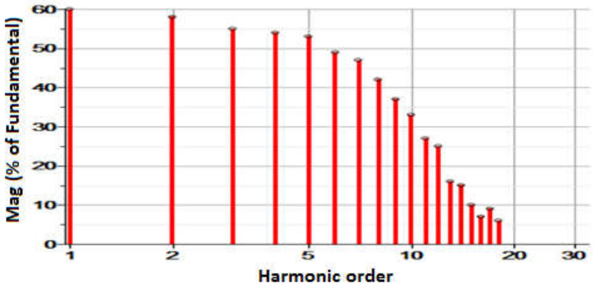
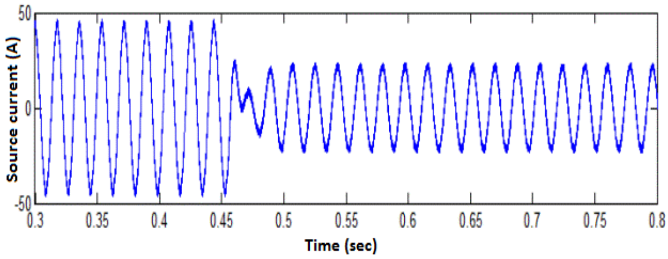


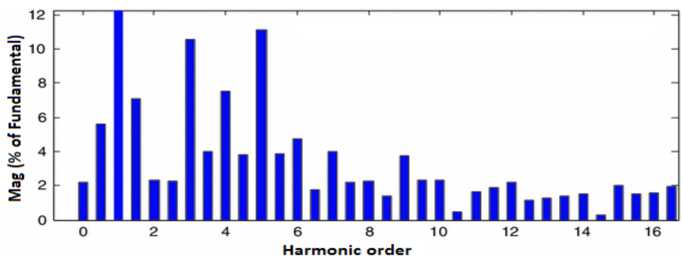
Figure 19(c) Harmonics without SAPF

Simulation Results using with SAPF

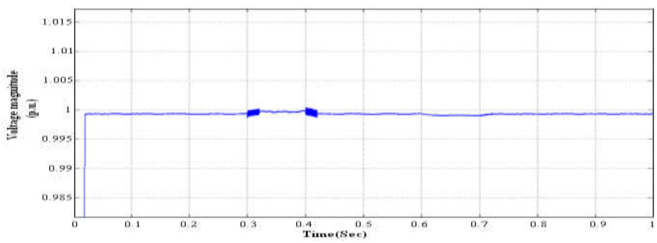
The source current waveform and its harmonic spectrum (THD) after introducing the SAPF application using IT2FLC are respectively shown in Figure 20 (a) and (b). The output DC capacitor voltage is given in Figure 20 (c).



(a)



(b)



(c)

Figure 20 SAPF control using T2FLC (a) source current (b) THD (c) V_{DC}

The ability of the SAPF to compensate for the harmonic current of the load is demonstrated in Figure20 (a) and (b). The THD dropped from 23.74 % to 3 % when using the SAPF.

IT2FLC Performance Under Changing System's Parameters

In order to assess the robustness of these controllers, the filter inductance L_f has been increased by 50%. Figure 21 shows the DC bus voltage response under PI controller and IT2FLC was performed. In recent years, many different techniques are applied in order to draw maximum power from photovoltaic (PV) modules for changing solar irradiance and temperature conditions. Generally, the output power generation of the PV system depends on the intermittent solar insulation, cell temperature, efficiency of the PV panel and its output voltage level.

Consequently, it is essential to track the generated power of the PV system and utilize the collected solar energy optimally. The aim of this paper is to simulate and control a grid-connected PV source by using an adaptive neuro-fuzzy inference system (ANFIS) . The data are optimized by IT2FLC and then, these optimum values are used in network training.

The simulation results indicate that the ANFIS controller can meet the need of load easily with less fluctuation around the maximum power point (MPP) and can increase the convergence speed to achieve the MPP rather than the conventional method. Moreover, to control both line voltage and current, a grid side P/Q controller has been applied. A dynamic modeling, control and simulation study of the PV system is performed with the Matlab/Simulink program. Using fuzzy logic can dramatically solve the two problems mentioned.

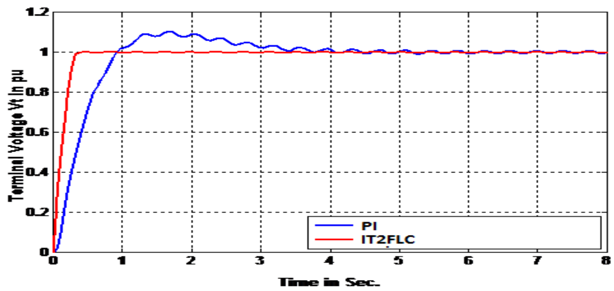


Figure 21 Comparison of (a) PI (b) T2FLC

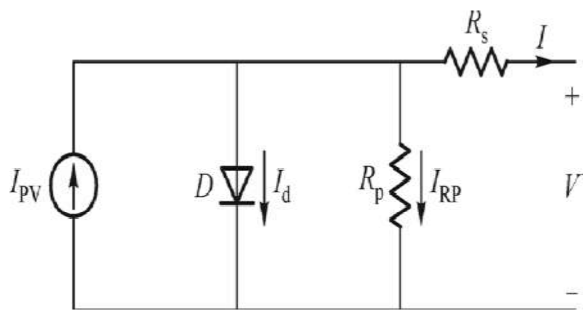


Figure 21 Equivalent circuit of the photovoltaic

Array Under Parameter Variations

In fact, fuzzy logic controller can reduce oscillations of output power around the MPP and losses. Furthermore, in this way, convergence speed is higher than the other two ways mentioned.

A weakness of fuzzy logic in comparison with ANN refers to oscillations of output power around the MPP. Nowadays, artificial intelligence (AI) methods have numerous applications in determining the size of PV systems, MPPT control and optimal structure of PV systems. In most cases, multilayer perceptron (MLP) neural networks or radial basis function network (RBFN) are employed for modeling PV module and MPPT controller in PV systems.

The ANN can be considered as a robust technique for mapping the inputs-outputs of nonlinear functions, but it lacks subjective sensations and acts as a black box. On the other hand, fuzzy logic has the ability to transform linguistic and mental data into numerical values. However, the determination of membership functions and fuzzy rules depends on the previous knowledge of the system. Neural networks can be integrated with fuzzy logic and through the combination of these two smart tools, a robust AI technique called adaptive neuro-fuzzy inference system (ANFIS) can be obtained. IT2FLC is used for data optimization and then, the optimum values are utilized for training neural networks and the results show that the ANFIS controller technique has less fluctuation in comparison with the conventional methods. However, one of the major drawbacks in the mentioned techniques is that they are not practically connected to the grid in order to ensure the analysis of PV system performance.

In this paper, first, the 360 data of temperature and irradiance as the input data are given to IT2FLC and optimal voltage (VMPP) corresponding to the MPP delivery from the PV system. Then the optimum values are utilized for training the ANFIS. The characteristic of the solar array is explained as

$$I_{PV} + I_d + I_{RP} + I \quad (1)$$

where I is the output current, V is the output voltage, IPV is the generated current under a given isolation, Id is the diode current, IRP is the shunt leakage current, I0 is the diode reverse saturation current, n is the ideality factor (1.35) for a p-n junction, Rs is the series loss resistance (0.2 Ω), RP is the shunt loss resistance (161.24 Ω).

Adaptive Neuro-Fuzzy Interference System

ANFIS refers to adaptive neuro-fuzzy inference system. An adaptive neural network has the advantages of learning ability, optimization and balancing. However, a fuzzy logic is a method based on rules constructed by the knowledge of experts. The good performance and effectiveness of fuzzy logic are approved in nonlinear and complicated systems. ANFIS combines the advantages of adaptive neural network and fuzzy logic. For a fuzzy inference system, with 2 inputs and 1 output, a common rule set is obtained with 2 fuzzy if-then rules by Equations (2) and (3). The fuzzy rules can typically be

Rule 1: If x is A1 and y is B1; then f1 +p1x + q1y + r1 (2)

Rule 2: If x is A2 and y is B2; then f2 + p2x + q2y + r2 (3)

where x and y are the inputs and f is the output. [A1, A2, B1, B2] are called the premise parameters. [pi, qi, ri] are called the consequent parameters, i = 1, 2. These parameters are called result parameters. The ANFIS structure of the above statements is shown in Figure 22.

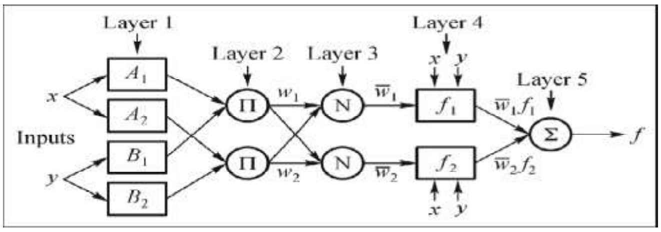


Figure 22 ANFIS architecture of a 2-input first-order Sugeno fuzzy model with 2 rules

The PV system is designed in order to obtain optimum values by ANFIS. A set of 360 data of temperature and irradiance are regarded as inputs for rule formation as shown in Figure 26 and the output is VMPP corresponding to the MPP delivery from the PV panels as depicted in Figure 24 and Figure 25. Then these optimum values are utilized for training the ANFIS. By following Figure 26, all input are 360 data in which a set of 330 data are used for training the developed ANFIS model. Besides, a set of 30 data samples are not included in the training. The input temperatures range from 5°C to 55°C in the steps of 5°C and irradiances vary from 50 W/m2 to 1000 W/m2 in the steps of 32 W/m2. The ANFIS input structure is depicted in Figure 23 which includes five layer. The inputs of ANFIS can be considered irradiance.

The structure shows two inputs of the solar irradiance and cell temperature, which are translated into appropriate membership functions. Three functions for the solar irradiance are displayed in Figure 24 and three functions for the temperature are illustrated in Figure 25. They have 9 fuzzy rules in total as exhibited in Figure 26. These rules have a unique output for each input. The network is trained for 5000 epochs. After training, the output of the trained network should be very close to the target outputs as shown in Figure 3.27.

According to Figures28, VMPP is compared with the target values while in Figure 29 and 30 the output of ANFIS test is compared with the target values, showing high precision with less than 2% absolute error between estimated voltage and real measured data. This error can be reduced by increasing the number of the training data for ANFIS. The proposed approach has the capability of estimating the amount of generated PV power at a specific time. The ANFIS based temperature and irradiation confirms satisfactory results with minimal error and the generated PV power is optimized significantly with the aids of the ANFIS algorithm

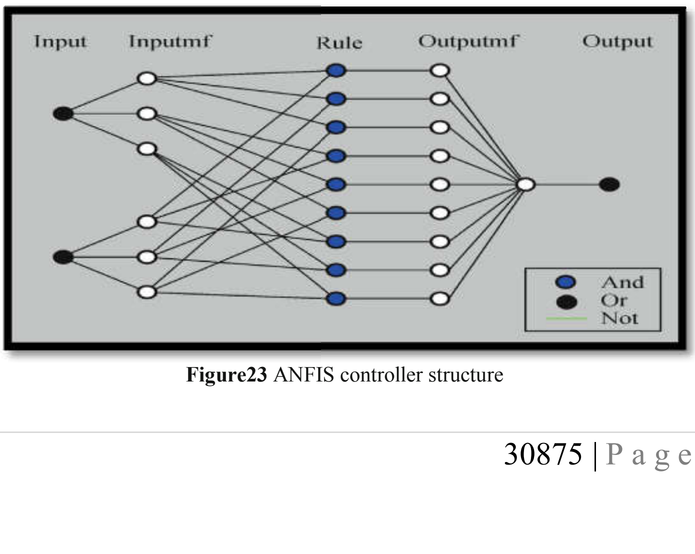


Figure23 ANFIS controller structure

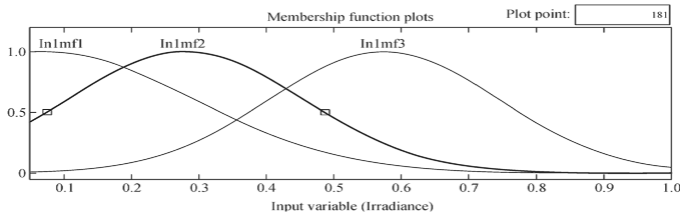


Figure 24 Solar irradiance membership function for ANFIS

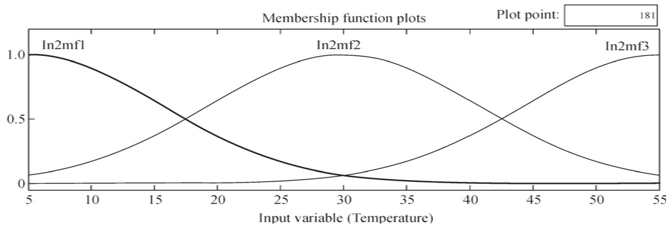


Figure 25 Temperature membership functions for ANFIS

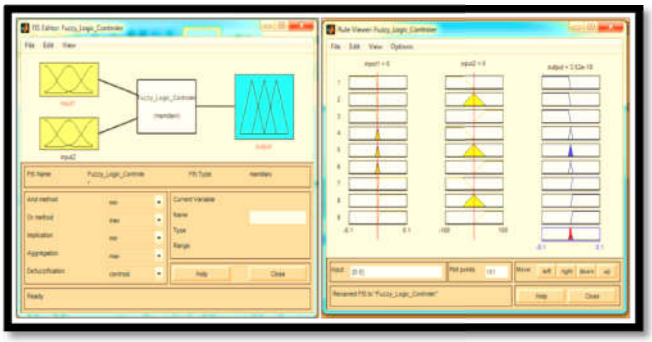


Figure 26 Fuzzy Rule

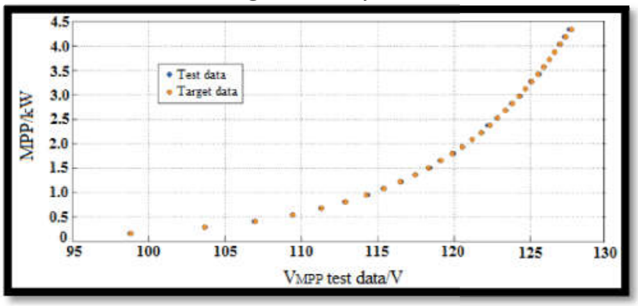


Figure 27 Output of ANFIS test with the amount of target data

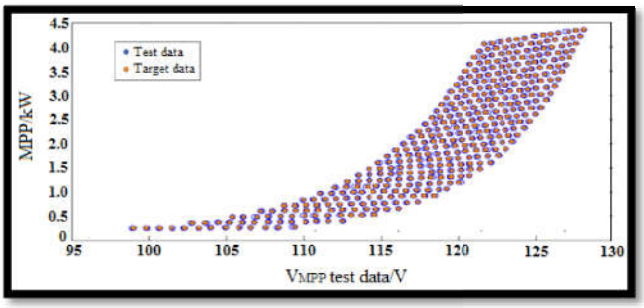


Figure 27 Output of ANFIS test of VMPP with the amount of target data

To compare the accuracy and efficiency of the four MPPT algorithms selected in this paper, Matlab/Simulink is used to implement the tasks of modeling and simulation. The main objective of this case is to investigate the comparative study of MPPT algorithms under variations of irradiance and temperature conditions in the PV system. The system is connected to the main grid that includes the 4.4 kW PV system and the amount of load is 4.4 kW. There is no power exchange between the PV system and the grid in normal condition. The simulation is conducted for different isolations at a fixed temperature of 25°C as shown in Figure 29(a). The output voltage and the current of PV are depicted in Figure 29(b) and Figure29(c), respectively. When the irradiance is increased to t = 4 s and t = 8 s, it leads to an increase in the output current of PVs shown in Figure 29(c). The evaluation of the proposed controller is compared and analyzed with the conventional techniques of fuzzy logic, P&O and IC. It is worth mentioning that the proposed MPPT algorithm can track accurately the MPP when the irradiance changes continuously. Besides, this method has well regulated PV output power and it produces extra power rather than aforementioned methods as indicated in Figure 29(d).

Therefore, the injected power from the main grid to the PV system is decreased as demonstrated in Figure 29(e). The P&O and IC methods perform a fluctuated PV power even after the MPP operating has been successfully tracked. To precisely analyze the performance of the ANFIS technique, the simulation is conducted for different temperatures at a fixed isolation of 1000 W/m2 as shown in Figure 30(a). The grid voltage is indicated in Figure 30(b). Figure 30(c) shows the variation of the output current of PV.

Consequently, the grid power injection to the PV system declines as illustrated in Figure 30(e). In the view of power stabilization, the PV power controlled by ANFIS is more stable than that controlled by the conventional methods, which confirms that the PV with the proposed MPPT method can operate in the MPP for the whole range of assumed solar data (irradiance and temperature).

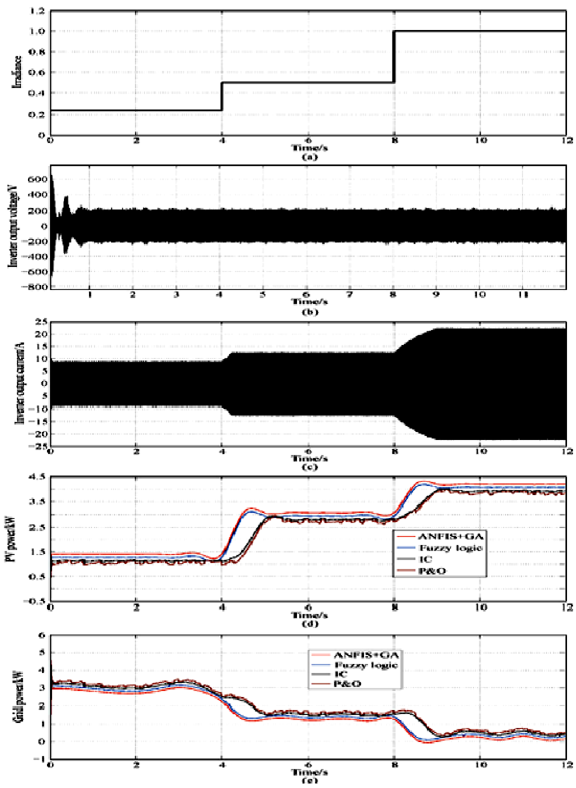


Figure 29 Simulated results for PV (variation of irradiance) in case 1(a) Irradiance; (b) inverter output voltage; (c) inverter output current; (d) PV power; (e) grid power

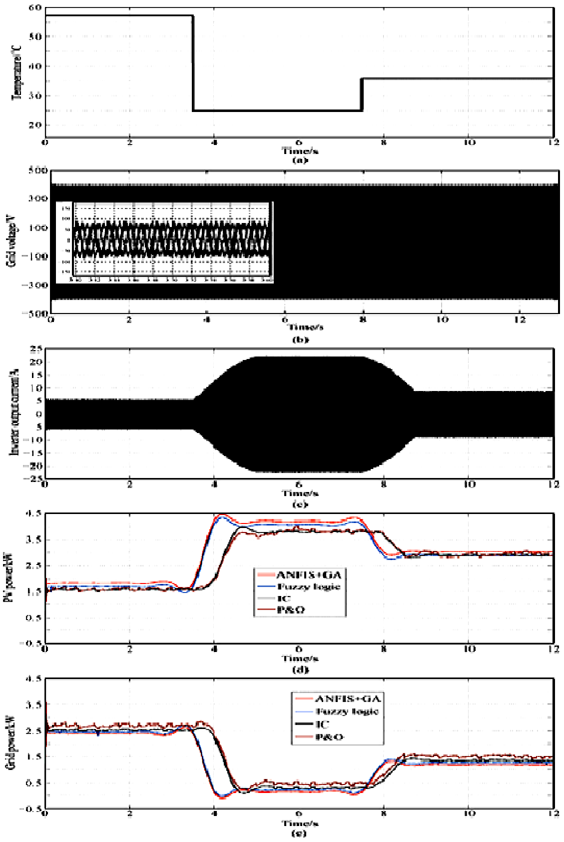


Figure 30 Simulated results for PV (variation of temperature) in case 1 (a) Temperature; (b) grid voltage; (c) inverter output current; (d) PV power; (e) grid power

CONCLUSION

This paper discussed the modeling and simulation of a PV system and the implementation of an MPPT algorithm. With the aid of proposed method, the PV system was able to perform and enhance the production of electrical energy at an optimal solution under various operating conditions. To achieve the maximum power from the PV system, the ANFIS technique was used. The ANFIS was used to provide the reference voltage corresponding to the maximum power for any environmental changes. Then optimized values were used for training the ANFIS. For different conditions, the proposed algorithm was verified and it was found that the error percentage of VMPP is from 0.06% to 1.35%. This error could be reduced by increasing the number of the training data for the ANFIS. By means of the ANFIS algorithm, the disadvantages of previous approaches could dramatically be reduced, the oscillations of power output around the MPP could be decreased, and the convergence speed could be increased to achieve the MPP in comparison with the conventional method. To control the grid current and voltage, a grid-side controller was applied.

References

1. Abraham, N.T. *et al*. (2014), Literature Survey of SAR Algorithm in Photovoltaic System, International Journal of Electrical and Computer Engineering, Vol. 4, no. 2, 154-155.
2. Altin, N. (2013), Interval type-2 fuzzy logic controller based maximum power point tracking in photovoltaic systems, Advances in Electrical and Computer Engineering, Vol. 13, no.3, 65–70.
3. Angalaeswari, S., Thejeswar, M.G., SanthanaPoongodi, R., ValeedBasha, W. and Sasikumar, P. (2014), Power Quality Improvement of Standalone Hybrid\Solar-Wind Power Generation System using FACTS Devices, Vol. 3, no. 3, 7987-7992.
4. Blaabjerg, F., Teodorescu, R., Liserre, M. and Timbus, A. (2006), Overview of control and grid synchronization for distributed power generation systems, IEEE Transaction on Industrial Electronics, Vol.53, no. 5, 1398-1409.
5. Blasko, V. and Kaura, V. (1997), A novel control to actively damp resonance in input LC filter of a three-phase voltage source converter, IEEE Trans. Ind. Appl., Vol. 33, no. 2,542–550.
6. Calais M., Myrzik J., Spooner T., and Agelidis V. G., (2002), Inverters for single-phase grid connected photovoltaic systems—An overview,‖ in Proc. IEEE PESC‘02, Vol. 2, 1995–2000.
7. Calais, M. and Agelidis, V. G. (1998) , Multilevel converters for single-phase grid connected photovoltaic systems—an overview,‖ in Proc. IEEE ISIE‘98, vol. 1, 224–229.
8. Chaturvedi, D. K., Satsangi, P. S., and Kalra, P. K., (1999) , Load frequency control: A generalized neural network approach,‖ Int. J. Electr. Power Energy Syst., vol. 21, 405–415.
9. Kalbat, A., (2013), PSCAD Simulation of Grid-Tied Photovoltaic Systems and Total Harmonic Distortion Analysis‖, 3rd International Conference on Electric Power and Enegy Conversion Systems, 1-6.
10. Kumari, J. S. and Babu, C. S. (2012), Mathematical modeling and simulation of photovoltaic cell using Matlab-Simulink environment, *International Journal of Electrical and Computer Engineering*, Vol. 2, no. 1, 25-26.
11. Lai, J.S. and Peng, F.Z.,(2002), Multilevel inverters: A survey of topologies, controls, andapplications,‖ IEEE Trans. Ind. Electron., vol. 49, no. 4, 724–738.
12. Levi , E., (2004), Editorial - Special Issue on Multi-Phase Motor Drives‖, EPE Journal, Vol. 14, No. 3, pp. 4.

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