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Design and Simulation of Dynamic Voltage Restorer Based on Fuzzy Controller Optimized by ANFIS

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Article Info	ABSTRACT
	The fuzzy logic controller (FLC) appears to be the unique solution when the process is too complex for analysis by conventional techniques or when the available information data are interpreted qualitatively, inexactly or with uncertainty. In literature, the proposed FLC in general consists of two inputs (error and derivative of error) and one output. The number of membership functions is chosen in most cases to be five or seven regardless of the approach used for the design. In this paper, we propose Adaptive Neuro-Fuzzy Inference System (ANFIS) approach to optimize the two inputs one output FLC with seven membership functions to one input one output FLC with three membership functions without compromising accuracy. The study is applied to control a Dynamic Voltage Restorer (DVR) in voltage sag/swell mitigation. The results of simulation using MATLAB/SIMULINK show that the performance of the optimal FLC generated by ANFIS is comparable with the initial given FLC.

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1. INTRODUCTION

In recent years, an increased number of sensitive loads have been integrated in electrical power systems. Consequently, the demand for high power quality and voltage stability has been increased significantly [1]. Power quality problems like voltage sag and voltage swell are major concern of the industrial and commercial electrical consumers due to enormous loss in terms of time and money. Faults at either the transmission or distribution level may cause voltage sag or swell in the entire system or a large part of it. Also, under heavy load conditions, a significant voltage drop may occur in the system. Voltage sags can occur at any instant of time, with amplitudes ranging from 10 – 90% and a duration lasting for half a cycle to one minute [2]. Further, they could be either balanced or unbalanced, depending on the type of fault and they could have unpredictable magnitudes, depending on factors such as distance from the fault and the transformer connections. Voltage swell, on the other hand, is defined as a sudden increasing of supply voltage up 110% to 180% in RMS voltage at the network fundamental frequency with duration from half a cycle to 1 minute [2]. Voltage swells are not as important as voltage sags because they are less common in distribution systems. Voltage sag and swell can cause sensitive equipment (such as found in semiconductor or chemical plants) to fail, or shutdown, as well as create a large current unbalance that could blow fuses or trip breakers. These effects can be very expensive for the customer, ranging from minor quality variations to production downtime and equipment damage [3]. There are many different methods to mitigate voltage sags and swells, but the use of a DVR is considered to be the most cost efficient method [4].

DVR is a series custom power device intended to protect sensitive loads from the effects of voltage disturbances such as voltage sags and swells at the point of common coupling (PCC). DVR essentially consists of a series-connected injection transformer, a voltage source inverter, inverter output filter and an energy storage device connected to the dc-link. The basic operation of DVR is to inject a voltage of the required magnitude, phase angle and frequency in series with distribution feeder to maintain the desired amplitude and waveform for load voltage even when the voltage is unbalanced or distorted.

The most common choice for the control of the DVR is the so called PI controller since it has a simple structure and it can offer relatively a satisfactory performance over a wide range of operation. The main problem of this simple controller is the correct choice of the PI gains and the fact that by using fixed gains, the controller may not provide the required control performance, when there are variations in the system parameters and operating conditions. To solve these problems fuzzy logic control appears to be the most promising due to its robustness. Also, a mathematical model is not required to describe the system in fuzzy logic based design. But, the main problem with the conventional fuzzy controllers is that the parameters associated with the membership functions and the rules depend broadly on the intuition of the experts. If it is required to change the parameters, it is to be done by trial and error only. There is no scientific optimization methodology inbuilt in the general fuzzy inference system [5]. To overcome this problem of optimization, researchers have used many different methods over the past decades, these methods include genetic algorithms [6]-[9], Particle swarm [10], [11], Immune Algorithm [12], neural networks [13], [14], evolutionary programming [15], geometric methods [16], fuzzy equivalence relations [17], heuristic methods [18], gradient descent [19], [7], Kalman filtering [20], H∞ filtering [21], the simplex method [22], [23], least squares [24], backpropagation [25], and other numerical techniques [26].

In this paper we present an unconstrained optimization based on Adaptive Neuro-Fuzzy Inference System (ANFIS) to generate an optimal fuzzy controller from a given un-optimized fuzzy controller. The given fuzzy controller consists of two inputs and one output with seven membership functions, but the generated optimal fuzzy controller consists of one input and one output with only three membership functions. The generated optimal fuzzy controller is used to control DVR in sag/swell compensation and the results are compared with that given by the initial un-optimized fuzzy controller.

2. DYNAMIC VOLTAGE RESTORER (DVR)

A Dynamic Voltage Restorer (DVR) is a series connected solid state device that injects voltage into the system in order to regulate the load side voltage. The DVR was first installed in 1996 [27], [28]. It is normally installed in a distribution system between the supply and the critical load feeder. Its primary function is to rapidly boost up the load-side voltage in the event of a disturbance in order to avoid any power disruption to that load [29]. There are various circuit topologies and control schemes that can be used to implement a DVR [30], [31]. In addition to its main task which is voltage sags and swells compensation, DVR can also added other features such as: line voltage harmonics compensation, reduction of transients in voltage and fault current limitations [32]. The general configuration of the DVR consists of a voltage injection transformer, an output filter, an energy storage device, Voltage Source Inverter (VSI), and a Control system as shown in Figure 1.
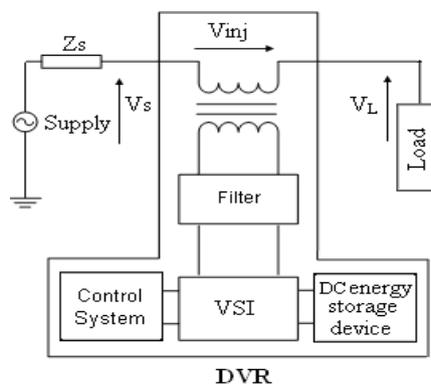

Figure 1. DVR general configuration

2.1. Operating Principle

The basic function of the DVR is to inject a dynamically controlled voltage Vinj generated by a forced commutated converter in series to the bus voltage by means of a voltage injection transformer. The momentary amplitudes of the three injected phase voltages are controlled such as to eliminate any detrimental effects of a bus fault to the load voltage V_L. This means that any differential voltages caused by disturbances in the ac feeder will be compensated by an equivalent voltage. The DVR works independently of the type of fault or any event that happens in the system. For most practical cases, a more economical design can be achieved by only compensating the positive and negative sequence components of the voltage disturbance seen at the input of the DVR (because the zero sequence part of a disturbance will not pass through the step down transformer which has infinite impedance for this component).

The DVR has two modes of operation which are: standby mode and boost mode. In standby mode (Vinj=0), the voltage injection transformer's low voltage winding is shorted through the converter. No switching of semiconductors occurs in this mode of operation, because the individual inverter legs are triggered such as to establish a short-circuit path for the transformer connection. The DVR will be most of the time in this mode. In boost mode (Vinj>0), the DVR is injecting a compensation voltage through the voltage injection transformer due to a detection of a supply voltage disturbance.

2.2. Voltage Reference Calculation Method

There are lots of methods for DVR voltage correction generating reference voltage that DVR must inject it into the bus voltage [33]-[39]. The strategy of voltage reference calculation used in this work is shown in Figure 2.
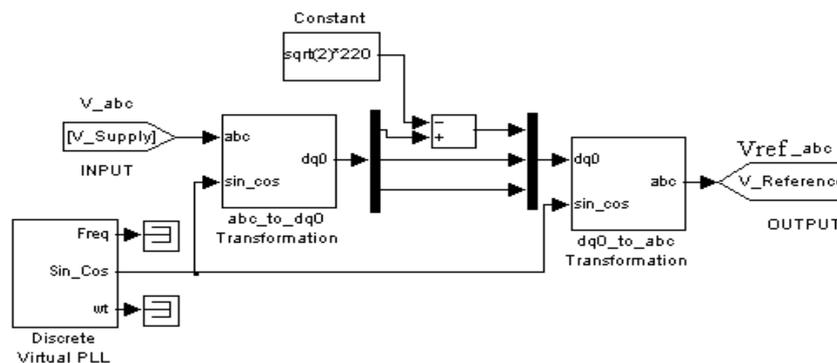

Figure 2. SIMULINK model of SRF method for voltage reference calculation

Figure 2 shows the basic control scheme and parameters that are measured for control purposes. When the supply voltage is at its normal level the DVR is controlled to reduce the losses in the DVR to a minimum. When voltage sags/swells are detected, the DVR should react as fast as possible and inject an ac voltage into the grid. It can be implemented using the synchronous reference frame (SRF) technique based on the instantaneous values of the supply voltage. The control algorithm produces a three phase reference voltage to the PWM inverter that tries to maintain the load voltage at its reference value. The voltage sag/swell is detected by measuring the error between the d-voltage of the supply and the d-reference value. The d-reference component is set to a rated voltage. The MATLAB/Simulink environment is a useful tool to implement this method (SRF) because it has many tool boxes that can be used easily. The SRF method can be used to compensate all type of voltage disturbances, voltage sag/swell, voltage unbalance and harmonic voltage, but in this work we have studied only voltage sag/swell. The difference between the reference voltage and the injected voltage is applied to the VSI to produce the load rated voltage, with the help of pulse width modulation (PWM) through the PI (or fuzzy) controller.

3.   UN-OPTIMIZED FUZZY CONTROLLER

We suppose that we have already a fuzzy controller of two inputs and one output with seven membership functions that gives satisfactory results in controlling the DVR. The inputs are the error and the derivative of the error, denoted as ε and Δε respectively. Figure 3 shows the Membership function curves of the inputs and the output, Table 1 gives the rule base.
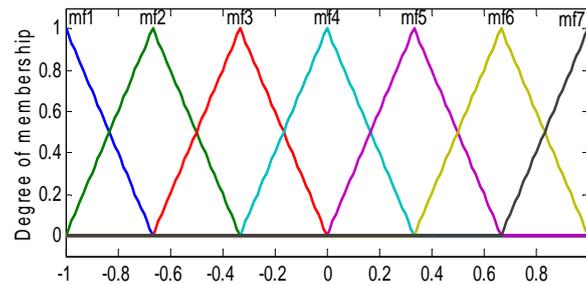
Figure 3. Membership function curves of the inputs ε and Δε and the output

Table 1. The rule base

ε /Δε	mf1	mf2	mf3	mf4	mf5	mf6	mf7
mf1	mf1	mf1	mf1	mf1	mf2	mf3	mf4
mf2	mf1	mf1	mf1	mf2	mf3	mf4	mf5
mf3	mf1	mf1	mf2	mf3	mf4	mf5	mf6
mf4	mf1	mf2	mf3	mf4	mf5	mf6	mf7
mf5	mf2	mf3	mf4	mf5	mf6	mf7	mf7
mf6	mf3	mf4	mf5	mf6	mf7	mf7	mf7
mf7	mf4	mf5	mf6	mf7	mf7	mf7	mf7

The MATLAB/SIMULINK implementation of the fuzzy controller for one phase is shown in Figure 4

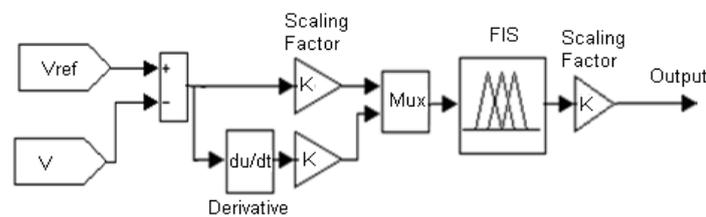
Figure 4. SIMULINK model of the fuzzy logic controller (FLC)

4. ANFIS PRINCIPLES

This section introduces the basics of ANFIS network architecture and its hybrid learning rule. Inspired by the idea of basing the fuzzy logic inference procedure on a feed forward network structure, Jang [40] proposed an Adaptive Network-based Fuzzy Inference System (ANFIS) or semantically equivalently, the Adaptive Neural Fuzzy Inference System, whose architecture is shown in Figure 5. He reported that the ANFIS architecture can be employed to model nonlinear functions, identify nonlinear components on-line in a control system, and predict a chaotic time series.

It is a hybrid neuro-fuzzy technique that brings learning capabilities of neural networks to fuzzy inference systems. The learning algorithm tunes the membership functions of a Sugeno-type Fuzzy Inference System using the training input-output data. The ANFIS is, from the topology point of view, an implementation of a representative fuzzy inference system using a back propagation (BP) neural network-like structure. It consists of five layers [41], [42]. The role of each layer is briefly presented as follows: let O_i^l denote the output of node i in layer l, and x_i is the i_{th} input of the ANFIS, $i = 1, 2,...,p$. In layer 1, there is a node function M associated with every node:

$$O_i^1 = M_i(x_i) \tag{1}$$

The role of the node functions M_1, M_2 ...Mq here is equal to that of the membership functions $\mu(x)$ used in the regular fuzzy systems, and q is the number of nodes for each input. Gaussian shape functions are the typical choices. The adjustable parameters that determine the positions and shapes of these node functions are referred to as the premise parameters. The output of every node in layer 2 is the product of all the incoming signals:

$$O_i^2 = M_i(x_i) \ AND \ M_j(x_j) \tag{2}$$

Each node output represents the firing strength of the reasoning rule. In layer 3, each of these firing strengths of the rules is compared with the sum of all the firing strengths. Therefore, the normalized firing strengths are computed in this layer as:

$$O_i^3 = \frac{o_i^2}{\Sigma_i o_i^2} \tag{3}$$

Layer 4 implements the Sugeno-type inference system, i.e., a linear combination of the input variables of ANFIS, x_1, x_2, ...x_p plus a constant term, c_1, c_2, ...,c_p, form the output of each IF −THEN rule. The output of the node is a weighted sum of these intermediate outputs:

$$O_i^4 = O_i^3 \sum_{j=1}^{p} P_j x_j + c_j \tag{4}$$

Where parameters P_1, P_2, ...,P_p and c_1,c_2, ...,c_p, in this layer are referred to as the consequent parameters. The node in layer 5 produces the sum of its inputs, i.e., defuzzification process of fuzzy system (using weighted average method) is obtained:

$$O_i^5 = \sum_i O_i^4 \tag{5}$$

The flowchart of ANFIS procedure is shown in Figure 6. ANFIS distinguishes itself from normal fuzzy logic systems by the adaptive parameters, i.e., both the premise and consequent parameters are adjustable. The most remarkable feature of the ANFIS is its hybrid learning algorithm. The adaptation process of the parameters of the ANFIS is divided into two steps. For the first step of the consequent parameters training, the Least Squares method (LS) is used, because the output of the ANFIS is a linear combination of the consequent parameters. The premise parameters are fixed at this step. After the consequent parameters have been adjusted, the approximation error is back-propagated through every layer to update the premise parameters as the second step. This part of the adaptation procedure is based on the gradient descent principle, which is the same as in the training of the BP neural network. The consequence parameters identified by the LS method are optimal in the sense of least squares under the condition that the premise parameters are fixed [43].
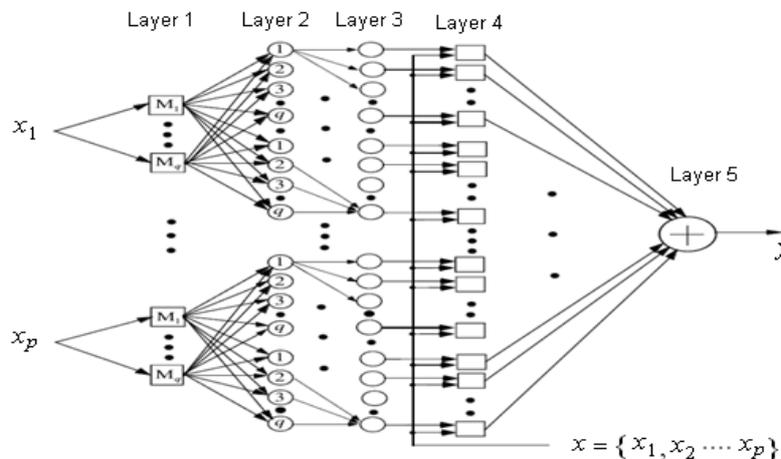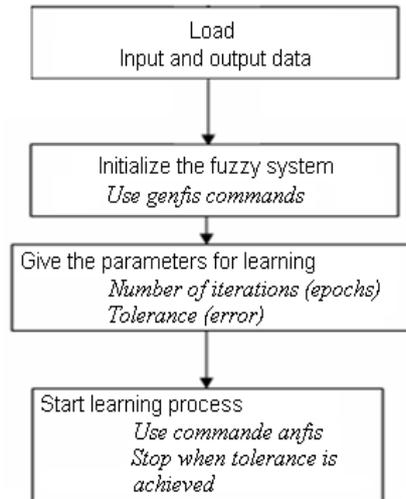

Figure 5. Structure of ANFIS

Figure 6. ANFIS procedure

The MATLAB/SIMULINK implementation of the Sugeno fuzzy controller for one phase in our case is shown in Figure 7. From this figure we can observe that the generated optimal Sugeno fuzzy controller does not need scaling factors (tuning gains).
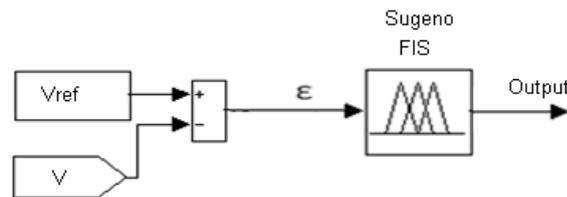

Figure 7. SIMULINK model of the Sugeno fuzzy logic controller (SFLC)

5. SIMULATION RESULTS AND DISCUSSION

To generate the optimal fuzzy controller represented by a Sugeno fuzzy inference system (SFIS) we have used ANFIS Editor GUI from MATLAB/SIMULINK Fuzzy Logic Toolbox, we have began by loading a Training data set that contains the desired input/output data of the given fuzzy controller from the simulation of DVR. This data set is an array with the input data arranged as the first column vectors, and the output data in the last column. ANFIS structure with Sugeno model containing 3 rules has been considered. Hybrid learning algorithm method was used to adjust the parameter of membership function. All the variables' fuzzy subsets for the input ε are defined as (M1, M2, M3) with triangular membership function. The membership functions and initial universes of the input generated by ANFIS training are illustrated in Figure 8. The output variable Y given by ANFIS training is a vector of constants. Y= [y_1, y_2, y_3] where, y_1= -1222, y_2= 82.57, y_3= 1387. The control rules are the following:
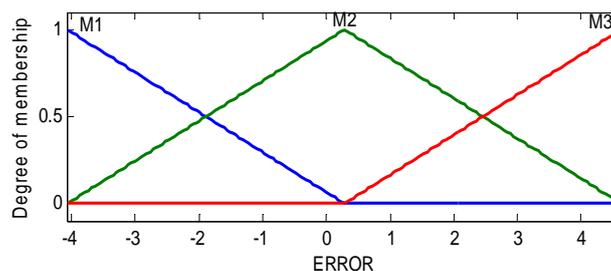
Figure 8. Membership function curves of the input ε

a) If (input ε is M1) then (output is y_1)
b) If (input ε is M2) then (output is y_2)
c) If (input ε is M3) then (output is y_3)

A DVR is connected to the system through a series transformer with a capability to insert a maximum voltage of 90% of the phase to ground system voltage. In the following simulations, the main characteristics of the DVR are set as: voltage source full-bridge IGBT based inverter controlled with PWM signal generator with commutation frequency of 12kHz, capacitor energy storage bank 8.8mF, coupling transformer ratio 1:1, nominal dc link voltage 850V, LC output filter values C=80μF in series with a damping resistance Rd = 0.1Ω, L = 1mH, source voltage 220Vrms and source frequency of 50Hz. The load is 80kVA with 0.92p.f., lagging. The given fuzzy controller tuning is made such to have high transient speed and to have very low tracking error for the fundamental (50Hz).

A case of Three-phase 50% balanced voltage sag is simulated and the result is shown in Figure 9. Voltage sag is initiated at 200ms and it is kept until 300ms, with total voltage sag duration of 100ms. As a result of the control of DVR by the optimal fuzzy controller; the load voltage is kept at 1.00p.u throughout the simulation including the voltage sag period. We can notice that during normal operation, the DVR is doing nothing but once voltage sag is detected, it quickly injects necessary voltage components to smooth the load voltage. Except the slight amelioration in dynamic performance of the given controller, we can say that the two controllers have the same performance.
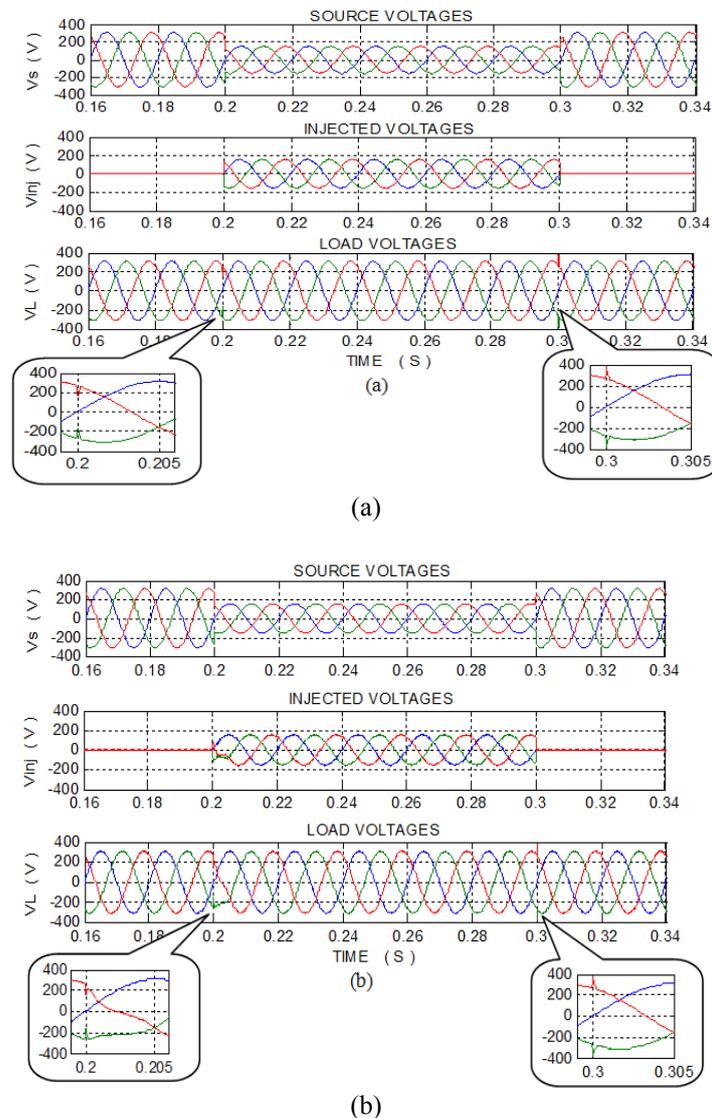

(a)

(b)

Figure 9. Simulation result of DVR response to a balanced voltage sag;
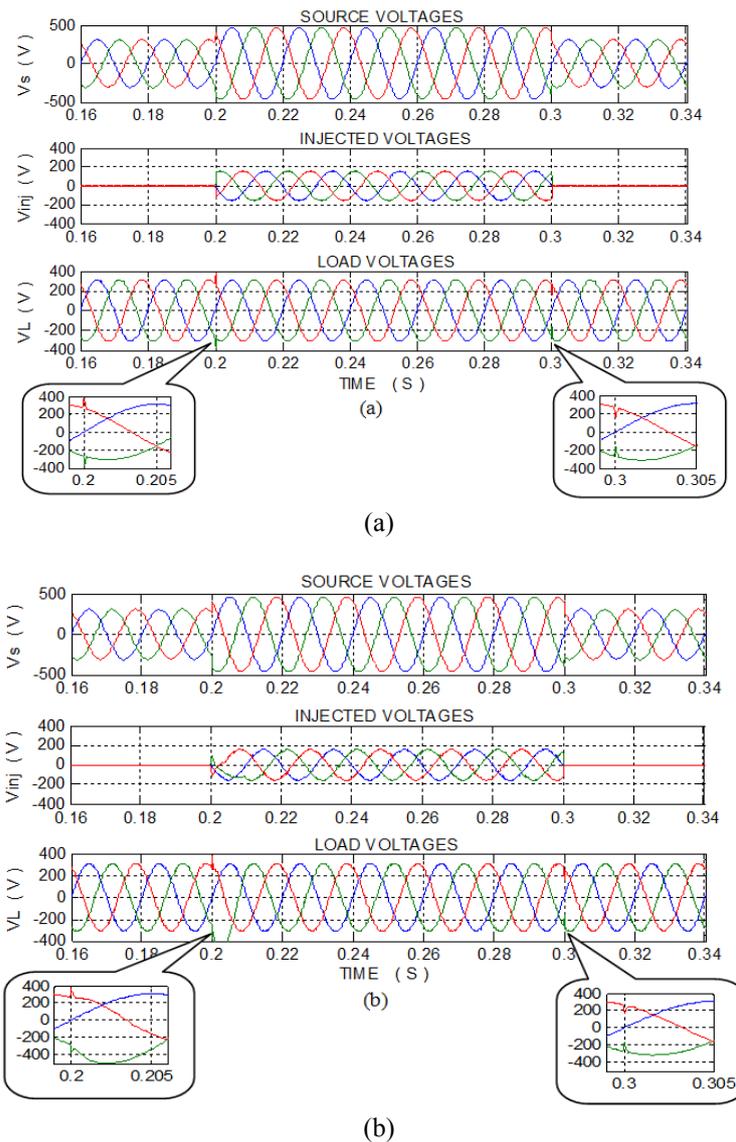(a) The given fuzzy controller, (b) The optimal fuzzy controller

(a)

(b)

Figure 10. Simulation result of DVR response to a balanced voltage swell;
(a) The given fuzzy controller, (b) The optimal fuzzy controller

For the case of balanced voltage swell compensation represented by Figure 10, the load voltage is kept at the nominal value with the help of the DVR. Similar to the case of voltage sag, the DVR reacts quickly to inject the appropriate voltage component (negative voltage magnitude) to correct the supply voltage.here, also except the slight amelioration in dynamic performance of the given controller; we can say that the two controllers have the same performance.

At the end Three-phase unbalanced voltages condition is investigated (40% swell, 20% sag and 60% sag). According to Figure 11, the DVR is able to produce the required voltage components for different phases rapidly and help to maintain a balanced and constant load voltage at 1.00pu. In this case no difference between the two controllers is apparent so, we can say that the two controllers have the same performance. As a result, the performance of DVR under the two controllers in mitigating voltage sags/swell and voltage unbalance is almost the same. In addition the proposed fuzzy controller (generated by ANFIS) has only one input with minimum number of membership functions and do not need gains which make its implementation practically very easy with a minimum cost.
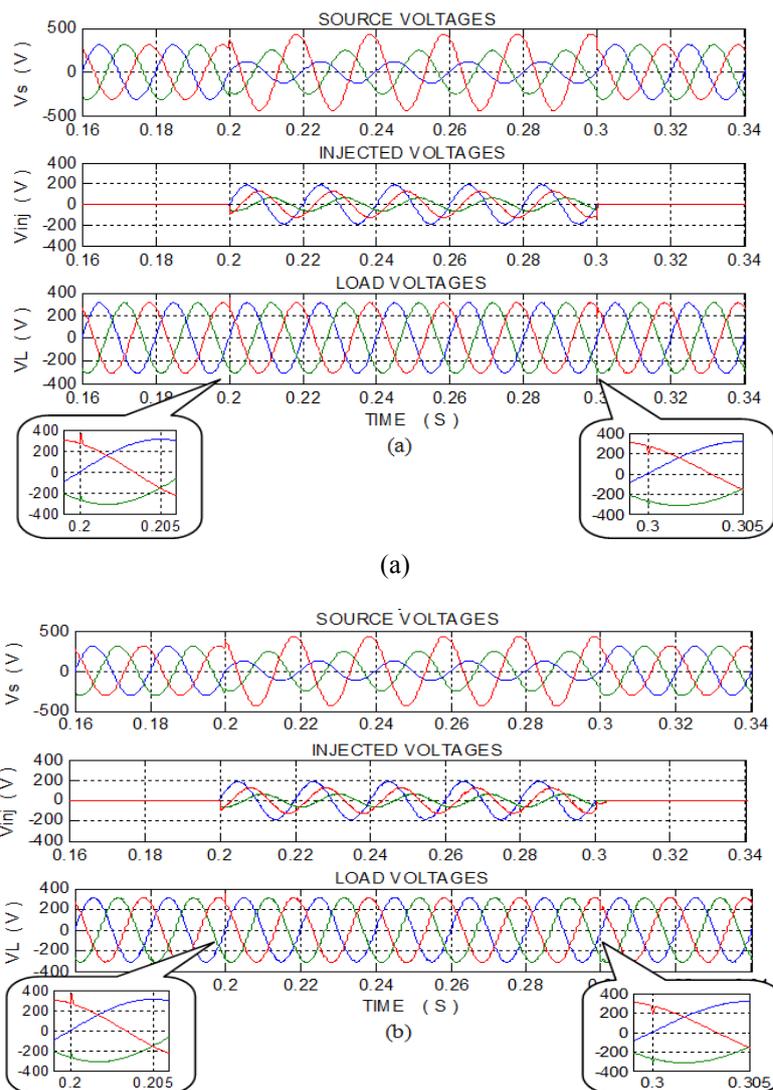
Figure 11. Simulation result of DVR response to unbalanced voltages;
(a) The given fuzzy controller, (b) The optimal fuzzy controller

6.   CONCLUSION

This paper presents a simple unconstrained optimization method based on ANFIS to optimize the inputs and the number of membership functions of a given fuzzy controller. The method was applied to a fuzzy controller of two inputs and one output with seven membership functions in controlling a DVR. The proposed controller is generated by ANFIS training according to a given input output data taken from the DVR simulation. The simulation results have shown almost a same performance with a slight negligible difference in dynamic respence of the two conttrollers. Compared to the given fuzzy controller, the proposed one is the simplest; it consists only of one input and output with three membership functions (3 rules only) and the most cost efficient controller. In addition this controller has no gains to adjust and solve the problem of traditional fuzzy controller gains tuning.

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