Neuro-Fuzzy Control Algorithm for Active Power Filters

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Abstract: This paper proposes a combination of neural networks with fuzzy logic to produce a fuzzy controller with fast response. The fuzzy neural network uses neural nodes and links to connect input variables to fuzzifiers, to define fuzzy rules, and to combine outputs into a control action. This new method has been applied to the problem of fuzzy control of a shunt active power filter designed for harmonic current elimination. The performance of the proposed method for training and test data is examined by Matlab simulations and is found to optimize the fuzzy control performance.

I. INTRODUCTION

Although the predominance of electronic equipment in our professional environment makes work more convenient, these devices complicate demands on facility wiring and power utilities. Most facilities employ a variety of devices such as multiple switch mode power supplies, motors, fans and other nonlinear loads. Among the adverse effects of multiple nonlinear loads are voltage distortion, excessive neutral return currents, reduced utilization of available power, and power factor penalties. Harmonic currents in particular are receiving more attention as a critical power quality concern, with an estimated 60 percent of electricity now passing through nonlinear loads. Ironically, the equipment used to boost productivity and efficiency is also increasing nonproductive power consumption, power pollution, and low power factor. Additionally, the same equipment producing the harmonic distortion is also highly susceptible to its damaging effects. Power factor correction (PFC) techniques include both passive and active solutions for eliminating harmonic distortion and improving power factor [1]-[3]. Unlike traditional power factor correction techniques, active power filtering (APF) supplies only the harmonic and reactive power required to cancel the reactive currents generated by nonlinear loads. Active power filtering utilizes harmonic or current injection to achieve compensation. The APF determines the harmonic distortion on the line, and injects specific currents to cancel the reactive loads. They need a control strategy to generate appropriate switching. Fuzzy control of Active Power Filter (APF) has been investigated [4] and found to be a better alternative to conventional PI control in meeting the stringent requirements of dynamic response of this multifunction filter.

During the design process the parameters of the PI control system need to be adjusted from those derived in the original controller model. Automated tuning provides both quicker design turnaround time and an ability to adapt to the observed characteristics of the control system. This paper investigates the combination of fuzzy control with neural network to achieve automated tuning and rule generation for PI control of active power filters. Neural Network has the advantage that it can manage with less information than that needed by fuzzy logic. This fact was used to optimize the performance of a fuzzy control system in terms of speed and computational complexity. The neural network was trained to discover relationship and patterns in data to generate a fuzzy inference system (FIS) for control of an active power filter.

II. PROBLEM IDENTIFICATION

The schematic of the proposed shunt active filter with fuzzy control is shown in Fig.1. A current controlled PWM multifunctional converter has been used as active power filter. It is connected in shunt with the load. Non-linear loads comprising diode bridge rectifier with capacitive loading and a solid state ac regulator with inductive loading are taken on the APF system to demonstrate its ability for harmonic and reactive power compensation. The control only needs to sense the dc link voltage and maintain it to more than twice the peak supply voltage. There is no need to sense or calculate the load or filter current.

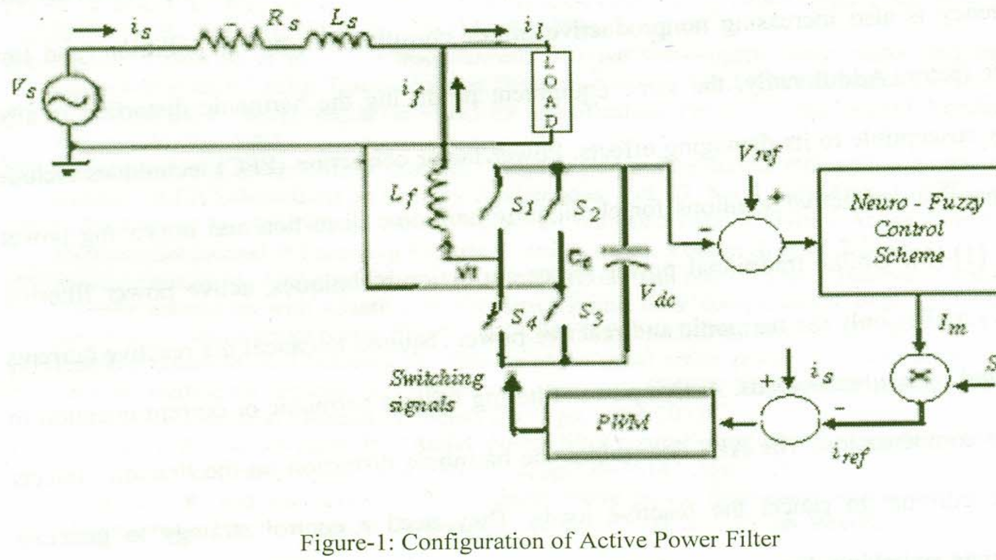

Figure-1: Configuration of Active Power Filter

The control strategy is conventional in the sense that the dc link voltage of the converter is controlled by adjusting the amplitude of the supply current [5]-[6]. The output of the controller thus generates the amplitude of reference supply current which when multiplied by a unit in-phase sine wave forms the reference current template. This is then compared with the actual supply current and fixed frequency PWM is used to generate the switching signals for the inverter. The switch control applies $+V_f$ or $-V_f$ on the ac side, forcing the compensation current to track the reference current. For proper operation of the filter the DC bus voltage V_{DC} (t) is maintained greater than the peak of the supply voltage $V_S(t)$. The filter current i_f can be forced to increase or decrease if $V_f > |V_S|$. The switches are operated on complementary basis i.e. one pair is always conducting. The switching operation can be modeled and written as one simple equation (1) including a control variable 'u'. When one pair of switches is closed the control variable is 1 and when the other pair is closed it is -1. Thus the generic expression is

$$\frac{di_f}{dt} = \frac{V_s}{L_f} + u\frac{V_f}{L_f} \qquad (1)$$

Similarly the expression for capacitor voltage taking into account the ripple due to the compensating current is written as

$$\frac{dV_{DC}}{dt} = u\,\frac{i_f}{C_{dc}} \qquad (2)$$

Though a conventional PI controller can regulate the capacitor voltage satisfactorily, the dynamics are not good as required. The fuzzy controller showed a better dynamic response under varying supply and load conditions. Though versatile, the fuzzy alternative to conventional PI control was seen to be slow and computationally intense as 49 rules were involved.

III. NEURAL NETWORKS

Neural Network (NN) consists of a number of interconnected processing elements or neurons. The arrangements and the strengths of the inter connections determine the overall behavior of an NN [7]. Fig.2. represents an artificial neuron model.

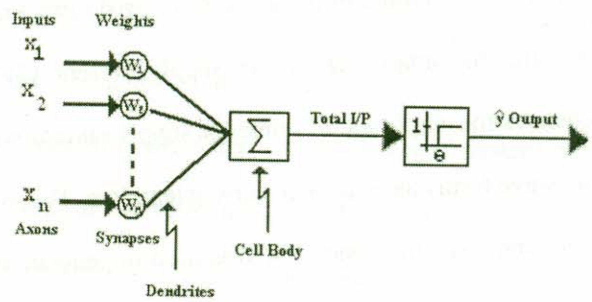

Figure-2 Artificial Neuron Model

The output $\hat{Y}$ is given by the equation

$$\hat{Y} = 1; \quad \sum w_i x_i \geq \theta$$
$$= 0; \quad \sum w_i x_i < \theta$$

Here w_i are the connection weights and no set guidelines or rules are present to select these weights. In our present study instead of choosing the membership function parameters of a fuzzy controller based on the system behavior, the artificial neural network was trained to choose membership parameters automatically. The system is modeled using the Sugeno type FIS, which is ideal for implementing neuro- adaptive learning techniques. In a Sugeno type system the output membership functions are either linear or constant. A typical rule in a Sugeno fuzzy model is given as;

If input1 = x and input 2 = y, then output z = ax + by + c

The output level 'z_i' of each rule is weighted by the firing strength w_i of the rule. For an AND rule in the above case the firing strength is

$$w_i = \text{AND Method } [F1\ (x), F2\ (y)]$$

where F(.) are the membership functions for inputs 1 & 2. The final output of the system is the weighted average of all rule outputs computed as

Final output $\hat{Y} = \sum w_i z_i / \sum w_i$

Fig (3) shows how the Sugeno rule operates. The Sugeno system is computationally efficient and compact and hence was chosen to construct the fuzzy models.

[-10 10]. A limiting block was introduced before the fuzzy block in order to truncate values beyond these ranges before supplying them to the fuzzy logic controller. The 49 fuzzy if-then weighted rule base was designed using the pendulum analogy. The output was represented by a set of 9 membership functions whose shape was taken similar to the shape of the input membership functions. The range of output was set to [-35 35]. The AND method used during interpretation of the If-then rules was 'min' and the OR method used 'max'. Also 'min' was used as the implication method whereas 'max' method was used for aggregation. The Mamdani type FIS described above, though effective was found to be very slow because of its inherent complexity. It was also seen that computation speed depended on the number of rules used to model the system. Hence a neural network trained FIS was investigated to optimize the performance of the fuzzy system. The results of the developed Mamdani type FIS were used to train the neural network to generate membership functions for a Sugeno type FIS with reduced number of rules.

V. NEURO-FUZZY CONTROL ALGORITHM

The neural network was used to customize the membership functions so that the fuzzy system best models the control data. In a fuzzy neural system, the neural network essentially implements the functions of a fuzzy system. The first network fuzzifies the crisp input data and the second or hidden network layer implements the fuzzy rules. Finally defuzzification of the fuzzy output is done by the third network to provide the crisp data output. In the proposed scheme of developing an Artificial Neural Network based Fuzzy Inference System (ANFIS) for control of the active power filter the following inputs were provided to the ANFIS

1. *Training Data*: An array containing error values (range: [–30,30]; Step: 0.5), change of error (range: [-10,10]; Step: 0.5) & the output (generated by the Mamdani Type FIS, with 49 rules and Triangular MFs, for the corresponding inputs of error & change of error) was provided as training data.

2. *Checking Data*: An array containing error values (range: [–30,30] ; Step: 1, change of error (range: [-10,10] ; Step: 1) & the output (generated by the Mamdani Type FIS, with 49 rules and triangular MFs, for the corresponding Inputs of error & change of error) was provided a checking data.

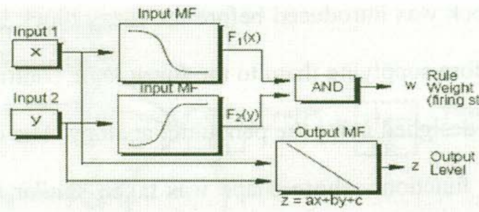

Figure-3 Sugeno Inference Method

IV. NEURO-FUZZY CONTROL SYSTEM

Neural Network has been used to generate the switching signals directly for control of APF [8]-[13] however the computation involved increases the response time considerably. The authors in this paper have instead used neural network to customize the membership functions so that the fuzzy system best models the control data. The basic structure of fuzzy inference system is a model that maps input characteristics to input membership functions, input membership function to rules, rules to a set of output characteristics, output characteristics to output membership functions, and the output membership function to a single-valued output or a decision associated with the output. Because of the complexity of the system and the amount of computation involved these FIS models were seen to be slow. Also deciding weights for the Membership Functions is not a very easy task. Moreover the system's speed can be considerably enhanced if the number of Membership Functions & hence the number of rules governing them can be reduced. Normally the membership functions are fixed and somewhat arbitrarily chosen. The shape of the membership functions depend on system parameters and changing these parameters will change the shape of the membership function. In this alternative scheme, instead of choosing the membership function parameters based on understanding of the system, neural network is trained to choose membership function parameters automatically.

A [7×7, 9] Mamdani type Fuzzy Inference System (FIS) using standard triangular membership functions with equal partitions was first developed and tested to control the APF. The 49 rule FIS accepts error and change of error in the capacitor voltage as inputs and gives the required magnitude of supply current I_m. The error between the reference generated by the fuzzy logic controller I_s* and the sensed supply current I_s is fed directly to the PWM generator, which uses it to generate the APF switching signals. The two inputs are represented by sets of seven membership functions and the output by a set of nine membership functions. The range for the 'error' input was set as [-30 30] and that for 'change of error' was set as

Case 1. NeuroFuzzy FIS with 3 MFs for each input & 9 rules generated using the Backpropagation training algorithm.

Case 2. NeuroFuzzy FIS with 5 MFs for each input & 25 rules generated using the Backpropagation training algorithm.

Case 3. NeuroFuzzy FIS with 3 MFs for each input & 9 rules generated using the Hybrid training algorithm.

Case 4. NeuroFuzzy FIS with 5 MFs for each input & 25 rules generated using the Hybrid training algorithm.

The active power filter system was simulated under fixed and varying load conditions to study the dynamic response of the controllers. The harmonic spectrum was plotted and the reduction in percentage total harmonic distortion of supply current was observed. The response to a large negative error was also studied. The comparative study of the performance of APF system under fuzzy and neuro-fuzzy controllers is given in Table.I. It was observed that the 25 rule neuro-fuzzy system trained by Hybrid method gave optimized performance in terms of dynamic response and reduction in % THD. The input membership functions of this system are shown in Fig.4 and the generated fuzzy inference system is shown in Fig.5.

Table I: Comparative study of Neuro-Fuzzy control schemes for control of APF

	Input MF's for error and change of error	Output MF's	Training Method	Reduction in %THD of supply current	Rate of compensation for large error	Dynamic response for step change in load
Fuzzy Control Scheme [7 x 7, 9]	7 x 7, 49 rules with assigned weights Triangular MFs	9 Triangular MF's	–	97.88%	≈ .037ms	< half cycle
Neuro-Fuzzy control scheme-1 [5 x 5]	5 x 5, 25 rules NN optimized MFs, weights=1	Constant	Backpropogation	97.1%	≈ .038ms	Quarter cycle
Neuro-Fuzzy control scheme-2 [3 x 3]	3 x 3, 9 rules NN optimized MFs, weights=1	Constant	Backpropogation	95.32%	≈ .038ms	Quarter cycle
Neuro-Fuzzy control scheme-3 [5 x 5]	5 x 5, 25 rules NN optimized MFs, weights=1	Constant	Hybrid	98.46%	≈ .037ms	Quarter cycle
Neuro-Fuzzy control scheme-4 [3 x 3]	3 x 3, 9 rules NN optimized MFs, weights=1	Constant	Hybrid	94.8%	≈ .038ms	Quarter cycle

The Sugeno FIS was selected with triangular input MFs. The number of input MFs was taken first as 5 and then as 3. Thus the number of rules generated was either 25 or 9. Constant MFs were selected for output. Both Backpropagation and Hybrid Methods were tried for training the FISs generated. Training was limited to 1000 epochs and the tolerance limit was set at 0.

VI. SIMULATION RESULTS

A voltage source converter with four IGBT's, $C_d = 2000uF$ and $L_f = 3.13mH$ was modeled as an active power filter connected in parallel with the load. There are many kinds of linear and non-linear loads which draw harmonic and reactive current from the ac source and must be compensated by the APF system. The proposed system was tested for two such typical loads. A single-phase bridge rectifier with RC ($R=430\Omega$ & $C = 1000\mu F$) was first considered as a non-linear load fed from a 230 V, 50 Hz supply. The supply voltage and current drawn by this load are shown in Fig. 3(a). From the harmonic spectrum shown in Fig.3 (b), it is evident that the load draws a distorted current from the supply and the total harmonic distortion is found to be 149.7%.

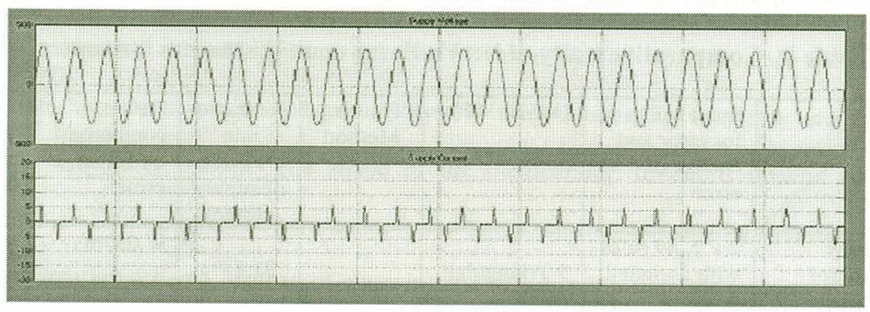

Figure-3 (a): Simulation Results: Nonlinear Load; diode bridge rectifier with RC load: Supply voltage & supply current before compensation

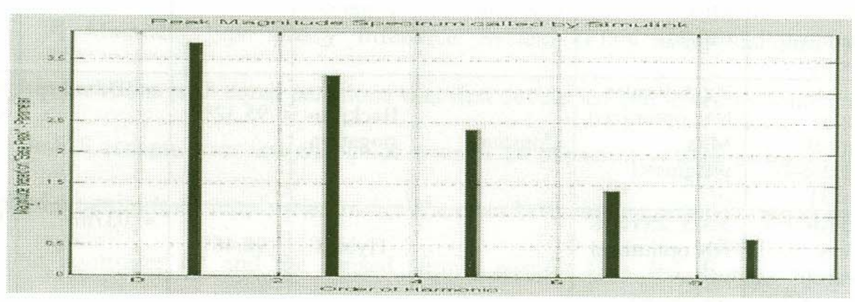

Figure-3 (b): Harmonic spectrum of uncompensated supply current

The effectiveness of the neural network training method was tested by simulating the active power filter system for each of the four NeuroFuzzy FISs described below:

The variation of the generated output with the training data provided to the neuro-fuzzy system is shown in Fig.6. It also depicts the training error for every iteration, to guard against over fitting of the training data set. The simulation results of the same are given in Fig. 7 (a)-(g). An excellent dynamic response for addition and removal of load is observed from Fig.7 (b). Supply current settles smoothly to a new steady state value within a quarter cycle of change in load at 0.1ms and 0.3ms. There is a small change in DC bus voltage (Fig.7 (e)) at the instant of disturbance in load to balance extra energy due to increased or decreased level of compensation. DC bus voltage settles to its steady state value within a few cycles. Harmonic spectrum of the compensated supply current is shown in Fig. 7(f). It was observed that the supply current after compensation becomes sinusoidal with a 98.46% reduction in total harmonic current distortion.

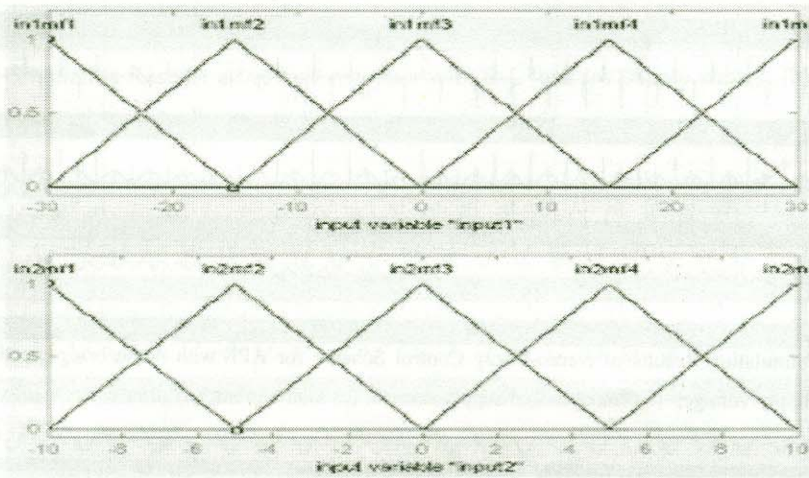

Figure-4: Input membership functions generated by Neuro-Fuzzy controller

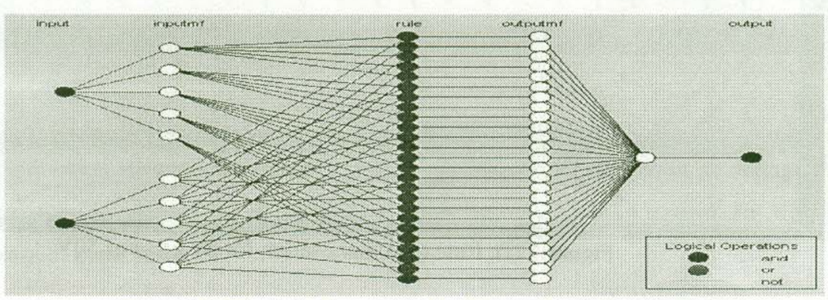

Figure-5: FIS model generated by Neuro-Fuzzy controller

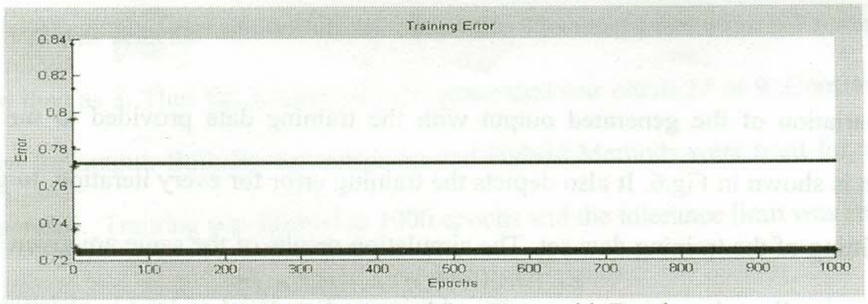

Figure-6: Variation in Training Error with Epoch no.

The performance of the APF system was also studied for ac regulator fed inductive load. It consists of a series resistive–inductive load with back to back connected thyristors. Fig.8(a)-(e) show the simulation results for this load. It is found that the supply current remains sinusoidal and the APF is able to compensate harmonic and reactive power. The THD of the supply current is reduced from 29.48% to 1.24%.

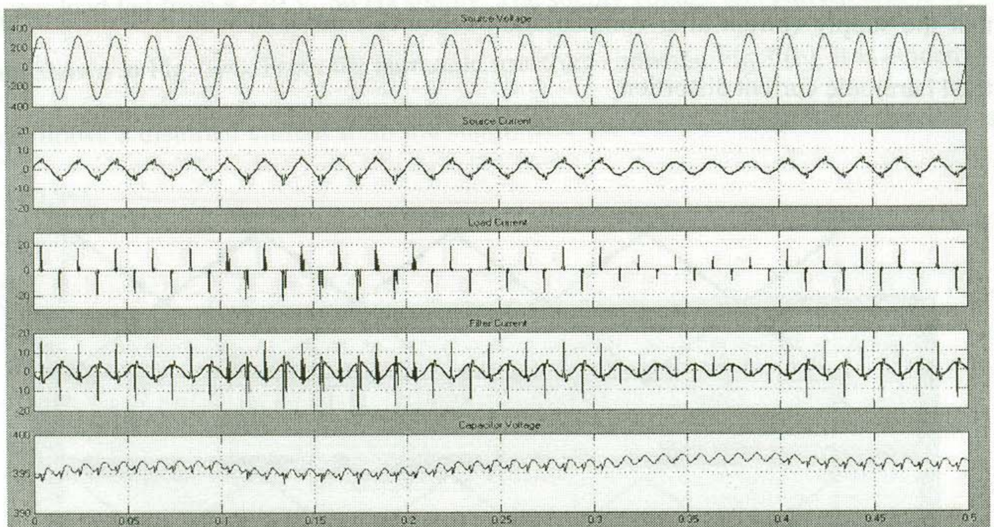

Figure-7: Simulation Results of Neuro-Fuzzy Control Scheme for APF with diode bridge rectifier feeding RC load: (a) supply voltage, (b) compensated supply current, (c) load current, (d) filter current, (e) voltage across dc capacitor

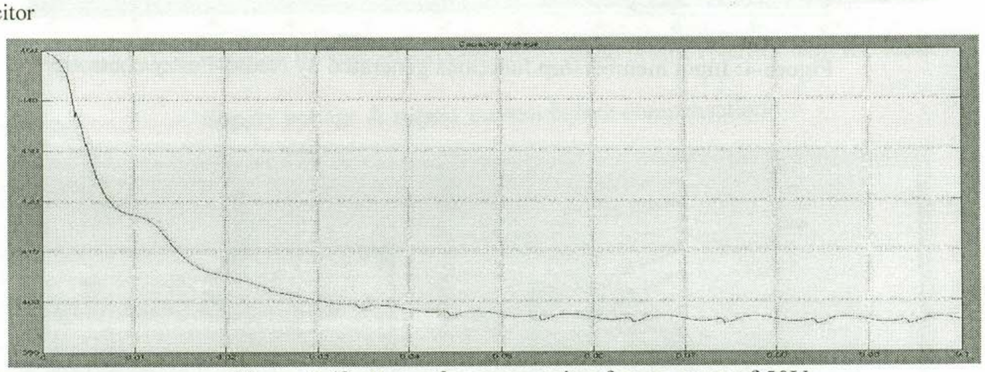

Figure-7 (f): Rate of compensation for an error of 50V

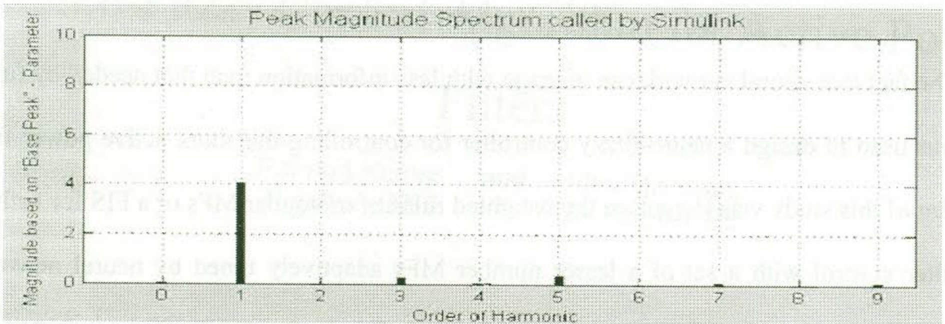

Figure-7 (g): Harmonic spectrum of compensated supply current

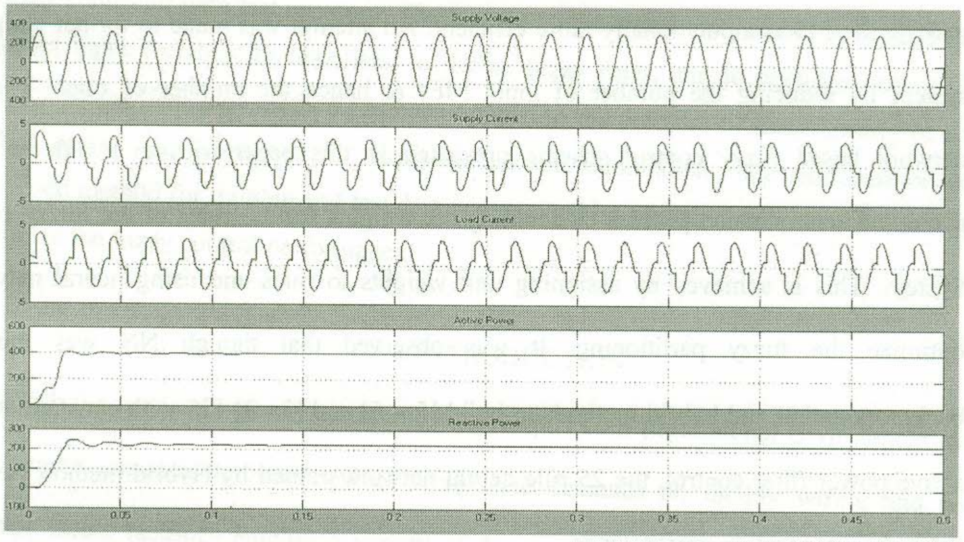

Figure-8: Simulation Results: ac voltage regulator with R-L load (a) Supply voltage (b)supply current before compensation (c) load current (d) active power (e) reactive power

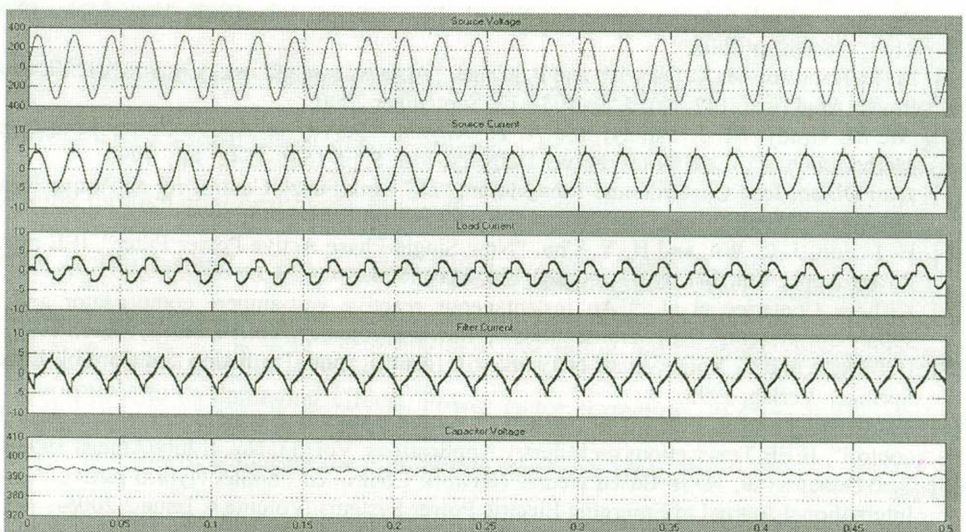

Figure-9: Simulation Results of Neuro-Fuzzy Control Scheme for APF with ac voltage regulator fed RL load: (a) supply voltage, (b) compensated supply current, (c) load current, (d) filter current, (e) voltage across dc capacitor

V. CONCLUSION

The fact that neural network can manage with less information than that needed by fuzzy logic was used to design a neuro-fuzzy controller for controlling the shunt active power filter. The aim of this study was to replace the weighted rules of triangular MFs of a FIS for active power filter control with a set of a lesser number MFs adaptively tuned by neural networks. The Sugeno system used for constructing the fuzzy model eliminated the need for de-fuzzification, making the FIS computationally more efficient. An attempt was made to further simplify the system by reducing the number of input MFs & hence the number of rules. The neural network based fuzzy control scheme presented in this paper tries to avoid the lengthy sometimes-complicated process of deciding the weights for the rules of the Fuzzy Inference System. This is achieved by assigning unit weights to rules and using neural networks to optimize the fuzzy partitioning. It was observed that though NN was trained by backpropogation and hybrid methods to build [5×5] and [3×3] FIS with constant output for active power filter control, the 25 rule neural network trained by Hybrid method yielded the desired compensation performance.

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