USING OF ANFIS AND FIS METHODS TO IMPROVE THE UPQC PERFORMANCE

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Abstract:
Fuzzy Logic, which has recently drawn a great deal of attention, possesses conceptually the quality of the simplicity. However, its early application relied on trial and error in selecting either the fuzzy membership functions or the fuzzy rules. This made it heavily dependent on expert knowledge, which may not always be available. Hence, an adaptive fuzzy logic controller such as Adaptive Neuro-Fuzzy Inference System (ANFIS) removes this stringent requirement. This paper introduces the preliminary results of applying Adaptive Neuro-Fuzzy Inference System (ANFIS) to improve the performance of the Unified Power Quality Conditioner (UPQC). The theoretical foundations are introduced and details of the adaptive fuzzy system are presented. The results of its application on DC-bus voltage control are included during the compensation of several perturbations.

Keywords: PI controller, ANFIS controller, FIS controller, UPQC, DC-bus voltage control, Power Quality.

1. Introduction

The applications of power semiconductor devices are being widely used in various areas, such as large thyristor power converters, rectifiers, and arc furnaces. Complications related to the use of the non-linear loads in these systems are major issues for both power providers and users alike. Consequently, utility power system reliability and power quality has moved to the forefront. As customers increasingly use process and computer equipment, which are highly sensitive to power system interruptions, utilities are being forced to serve these loads with transmission and distribution systems that are at our exceeding capacity.

The quality of the power is effected by many factors like harmonic contamination, due to the increment of non-linear loads, such as large thyristor power converters, rectifiers, voltage and current flickering due to arc in arc furnaces, sag and swell due to the switching (on and off) of the loads etc. These problems are partially solved with the help of LC passive filters. However, this kind of filter cannot solve random variations in the load current waveform and voltage waveform. Active filters can resolve this problem, however the cost of active filters is high, and they are difficult to implement in large scale. Additionally, they also present lower efficiency than shunt passive filters [1]. One of the many solutions is the use of a combined system of shunt and series active filters like Unified Power Quality Conditioner which aims at achieving low cost and highly effective control.

The voltage sag is one of the prime factors due to which particularly production industries suffer huge loss. This is evident from many power quality survey reports [2]. Most of these voltage sensitive critical loads are non-linear in nature due to application of fast acting semiconductor switches and their specific control strategy, whose presence in a system pose some major concerns as they affect the distribution utility in some highly undesirable ways.

The aim of this paper is to design different control strategies for the Unified Power Quality Conditioner (UPQC), which is one of the major custom power solutions capable of mitigating the effect of supply voltage sag, swell, flicker and spikes at the load end or at the Point of Common Coupling (PCC). It also prevents load current harmonics from entering the utility and corrects the input power factor of the load. The control strategies used here are based on the PI Controller, the Fuzzy Controller and the Adaptive Neuro-Fuzzy Inference System (ANFIS) Controller. The relative performance of the three controls is also studied.
2. Unified Power Quality Conditioner

The basic circuit of the UPQC, (Fig. 1) [3] consists of two back to back connected IGBT based voltage source bi-directional converters with a common DC bus. One inverter is connected in series, while the other one is placed in shunt with the nonlinear load. The inverter connected in shunt with the load acts as a current source for injecting compensating current, $i_c$. While, the supply side inverter connected in series with the load acts as a voltage source feeding compensating voltage, $v_{cf}$ through an insertion transformer. A thyristor bridge rectifier feeding $RL$ load is considered as nonlinear load.

![Fig. 1. General configuration of the Unified Power Quality Conditioner (UPQC)](image)

2.1. Control Strategy for the UPQC DC bus

The control strategy for the UPQC’s shunt compensator involves not only the production of the reference currents to compensate the harmonic currents, but also the recharging of the condenser to a required active power to feed the two inverters. The two condensers $C_1$ and $C_2$ (Fig. 2) absorb the power fluctuations caused by the reactive compensation, the presence of harmonics and the control of the active power and also by the converters losses. The average voltage across these condensers must be kept at a constant value. The regulation of this voltage is absorbing or supplying active power on the grid (Fig. 2).

![Fig. 2. Evolution of the $V_{dc}$ voltage](image)
The correction of this voltage ($V_{DC}$) must be done by adding the fundamental active currents in the reference currents of the UPQC’s parallel part (shunt compensator) [4]. From a deference between the measured voltage ($V_{DC}^2$) and the reference voltage ($V_{DC-ref}^2$), the active power $P_{ref}$ in output of the controller is added to the fluctuant active power and gives rise to a fundamental active current correcting the voltage $V_{DC}$. To get the signal of $P_{ref}$, it’s possible to choose a proportional controller or a proportional integral controller. The latter is often preferable because it allows the canceling of the static error [5].

$$\omega^2 = \frac{2K_i}{C} \text{ and } \xi = K_p \sqrt{\frac{1}{2CK_i}}$$

3. **Fuzzy control**

The Fuzzy control is basically a nonlinear and adaptive in nature, giving the robust performance in the cases where in the effects of parameter variation of controller is present. It is claimed that the Fuzzy logic controller yields [6, 7] the results which are better than those obtained with the conventional controllers such as PI, PID etc.

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Inputs to the fuzzy controller are categorized as various linguistic variables with their corresponding membership values as shown in the Table 1. Depending upon the range (very large, large, medium, small and zero) and the sign (positive or negative) of the error signals $E_1$ and $E_2$, the FLC searches the corresponding output from the linguistic codes given in the Table 1 [8].
4. ANFIS control

The basic principle of the ANFIS method is the using of the network neuron to optimize the membership’s functions of the fuzzy controller in other words; an ANFIS is one optimized FIS.

In the Neuro-Fuzzy controller, the simplicity of a Fuzzy controller is combined with the intelligent and adaptiveness of the Neuron Network optimization.

4.1. ANFIS architecture

In this section, we will describe the ANFIS architecture and its learning algorithm for the Sugeno fuzzy model [9]. For simplicity, we assume that the fuzzy inference system under consideration has two inputs \(m\) and \(n\) and one output \(f\). For a first-order Sugeno fuzzy model, a typical rule set with two fuzzy if / then rules can be expressed as:

Rule 1:
If \((m\ \text{is} \ A_1)\ \text{and} \ (n\ \text{is} \ B_1)\) then \(f_1 = p_1 m + q_1 n + r_1\)  \hspace{1cm} (2)

Rule 2:
If \((m\ \text{is} \ A_2)\ \text{and} \ (n\ \text{is} \ B_2)\) then \(f_2 = p_2 m + q_2 n + r_2\)  \hspace{1cm} (3)

where \(p_1, p_2, q_1, q_2, r_1\) and \(r_2\) are linear parameters, and \(A_1, A_2, B_1\) and \(B_2\) are nonlinear parameters.

The corresponding equivalent ANFIS architecture is as shown in Fig. 4. The entire system architecture consists of five layers, namely, a fuzzy layer, a product layer, a normalized layer, a defuzzy layer and a total output layer. The following sections discuss the relationship between the output and input of each layer in the ANFIS.

Layer 1 is the fuzzy layer, in which \(m\) and \(n\) are the input of nodes \(A_1, A_2, B_1\) and \(B_2\), respectively. \(A_1, A_2, B_1\) and \(B_2\) are the linguistic labels used in the fuzzy theory for dividing the membership functions. The membership relationship between the output and input functions of this layer can be expressed as:

\[
O_{1,i} = \mu_{A_i}(x), \quad i = 1,2;
\]

\[
O_{1,j} = \mu_{B_j}(x), \quad j = 1,2;
\]

where \(O_{1,i}\) and \(O_{1,j}\) denote the output functions and \(\mu_{A_i}\) and \(\mu_{B_j}\) denote the membership functions.

Layer 2 is the product layer that consists of two nodes labeled \(\Pi\). The output \(w_1\) and \(w_2\) are the weight functions of the next layer. The output of this layer is the product of the input signal, which is defined as follows:

\[
O_{2,i} = \mu_{A_i}(x) \mu_{B_1}(y), \quad i = 1,2;
\]

where \(O_{2,i}\) denotes the output of Layer 2.

The third layer is the normalized layer, whose nodes are labeled \(N\). Its function is to normalize the weight function in the following process:

\[
O_{3,i} = \bar{w} = \frac{w_i}{w_1 + w_2}, \quad i = 1,2
\]

Where \(O_{3,i}\) denotes the Layer 3 output.

Layer 4 is the defuzzy layer, whose nodes are adaptive. The output equation is \(w_i(p_i x + q_i y + r_i)\), where \(p_i, q_i\) and \(r_i\) denote the linear parameters or so-called consequent parameters of the node. The defuzzy relationship between the input and output of this layer can be defined as:

\[
O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i)
\]

where \(O_{4,i}\) denotes the Layer 4 output.

The fifth layer is the total output layer, whose node is labeled \(\Sigma\). The output of this layer is the total of the input signals, which represents the vehicle shift decision result. The results can be written as:
where $O_{5,i}$ denotes the Layer 5 output [7].

4.2. Learning method of ANFIS

The task of training algorithm for this architecture is tuning all the modifiable parameters to make the ANFIS output match the training data [11]. Note here that $a_i, b_i$ and $c_i$ describe the sigma, slope and the center of the bell membership functions, respectively. If these parameters are fixed, the output of the network becomes:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 = \bar{w}_1 f_1 + \bar{w}_2 f_2$$

$$\Rightarrow f = (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1 r_1) + (\bar{w}_2 x)p_2 + (\bar{w}_2 y)q_2 + (\bar{w}_2 r_2)$$

This is a linear combination of the modifiable parameters.

For this observation, it’s possible to divide the parameter set $S$ into two sets

$$S = S_1 \oplus S_2$$

$S_1$ = set of total parameters
$S_2$ = set of premise (nonlinear) parameters
$S_2$ = set of consequent (linear) parameters
$\oplus$ = direct sum

For the forward path (see Fig 4), it’s possible to apply least square method to identify the consequent parameters.

Now for a given set of values of $S_i$, we can plug training data and obtain a matrix equation:

$$A \Theta = y$$

Where $\Theta$ contains the unknown parameters in $S_2$. This is a linear square problem, and the solution for $\Theta$, which is minimizes $\|A \Theta - y\|^2$, is the least square estimator:

$$\Theta^* = (A^T A)^{-1} A^T y$$
We can use also recursive least square estimator in case of on-line training. For the backward path (see Fig. 4), the error signals propagate backward. The premise parameters are updated by descent method [12], through minimizing the overall quadratic cost function

\[ J(\Theta) = \frac{1}{2} \sum_{n=1}^{N} [y(k) - \hat{y}(k, \Theta)]^2 \]  

(14)

In a recursive manner with respect \( \Theta(S) \). The update of the parameters in the \( i^{th} \) node in layer \( L^{th} \) layer can be written as

\[ \hat{\Theta}_i^L(k) = \hat{\Theta}_i^L(k - 1) + \eta \frac{\partial^+ E(k)}{\partial \hat{z}_i^L} \]  

(15)

Where \( \eta \) is the learning rate and the gradient vector

\[ \frac{\partial^+ E}{\partial \hat{z}_i^L} = \epsilon_{L,i} \frac{\partial \hat{z}_{L,i}}{\partial \hat{z}_i^L} \]  

(16)

\( \hat{z}_{L,i} \) being the node’s output and \( \epsilon_{L,i} \) is the back-propagated error signal.

5. Case Study

For the purpose of analyzing the performance of the designed UPQC using the control strategies discussed above. A three phase supply of 230V, 50Hz is considered to be feeding a diode rectifier (non-linear load). The both series and shunt inverters are modeled using universal bridges with IGBT/diodes.

The element values of the passive filter, connecting the shunt inverter to the system are:

- \( R_{fp} = 1 \) ohm, \( L_{fp} = 30 \) mH.
- The element values of the passive filter, connecting the series inverter to the system are:
  - \( R_{fs} = 0.1 \) ohm, \( L_{fs} = 12 \) mH, \( C_{fs} = 700 \) \( \mu \)f.
- The value of the condenser providing the DC bus voltage is 700\( \mu \)f. Sags and swells are injected using three phase voltage sources.
- The values of proportional and integral constants of the DC bus PI controller are taken to be 0.5 and 500 respectively.

The rules surface of the fuzzy controller it’s as follow:

![Fig. 5. FIS controller rules surface](image-url)
The rules surface of the ANFIS controller it’s as follow:

![ANFIS controller rules surface](image)

**Fig. 6. ANFIS controller rules surface**

![The ANFIS structure](image)

**Fig. 7. The ANFIS structure**

### 5.1. Simulation Results And Analysis

A three-phase sinusoidal supply voltage (voltage corrected by the series filter) of 230V, 50Hz is applied to the non-linear load (diode rectifier feeding a RL load) this load injects harmonic currents into the system, as it’s shown in the fig. 8 (a).

The UPQC through its shunt inverter is able to reduce the harmonics in the grid side. The measured THD (Total Harmonic Distortion) in load current (Fig. 8 (a)) is found to be 18.18%. The THD of the source current is also 18.18% before compensation. It’s effectively reduced to 4.01 %, 3.76% end 3.93% with PI controller, Fuzzy controller and ANFIS controller after compensation as can be seen from the fig. 8 (c).

The compensating currents (Fig. 8 (b)) generated by the shunt inverter contain harmonic components of the load current but with opposite polarity such that when they are injected at the point of common coupling. The harmonic components of the supply current are successfully reduced. Fig. 8 (d) presents the DC bus voltage (voltage across the condensers) that they feed the both of the shunt and the series inverters. The condenser is well charged to the reference voltage, \(V_{DCref} = 735.603V\) absorbing the charging current from the supply. Once the condensers are charged to required value, the DC bus voltage appearing constant when the three
controllers are used. There aren’t big oscillations in the condenser voltage when it feeds the shunt inverter, because this inverter passes only the reactive power to compensate the load current harmonics. From the fig. 8 (d) is noticed that there is a difference between the three controllers during the transitory regime time to recharge the condensers, such as the PI controller gives a long rise time and an overtaking of 1.5 % with a maximal value equals 746.65 V. On the other hand, the Fuzzy controller gives a good rise time and an overtaking equals 0 % than the third controller (Neuron-Fuzzy) the rise time is very good with an overtaking equals 0 %.

The behavior of these controllers influences the waveform of the injected current (Fig. 8 (b)) and as a consequence on the source current waveform (Fig. 8 (c)).

Fig. 8. UPQC-mitigating the effect of harmonics load current, by the shunt inverter using the three controllers PI, Fuzzy (FIS) and Neuron-Fuzzy (ANFIS) – phase a -

(a) Load current.
(b) Injected current by the shunt inverter
(c) Source current.
(d) DC bus voltage
At the moment $t = 0.9$ s, the power asked by the load (phase a) is increased (fig. 9 (a)). This phenomenon influences on the $V_{DC}$ voltage waveform (Fig. 9 (d)). To discuss the waveform of this voltage, two things must be noticed; the overtaking and the time of the transitory regime. It’s noticed in the case of FIS regulator that the overtaking is important compared with two other cases. It’s also noticed that the time of transitory regime is longer in the case of the PI regulator. On the other hand, the ANFIS regulator groups together the advantages of these two regulators FIS and PI such it’s noticed for the ANFIS regulator an overtaking almost equals to that provoked by the PI and a transitory regime time inferior than that engendered in the case of the FIS regulator.

A three-phase supply voltage (230V, 50Hz) is imposed with voltage sag of 20%. It’s applied to the non-linear load (diode rectifier feeding a RL load) (Fig. 10 (a)). The UPQC with its series voltage control detects and calculates the required voltage to be injected in series with the line to compensate the voltage sag. In effect, the series inverter in combination with the insertion transformer produces the series injected voltage as calculated to mitigate the effects of the fluctuations of supply voltage by asking the required power from the DC bus.

Fig. 10 (c) shows the compensated supply voltage that is supplied to the load when the fig. 10 (d) shows the DC bus voltage, which reflects the disturbance in the supply voltage. Soon after, as can be seen from the fig. 10 (d), the condenser voltage (DC bus voltage) tries to come back to the reference value, after compensation.

The imposed sage voltage influences the $V_{DC}$ waveform at the moment $t=0.5$ s (Fig. 10 (d)). During the application of this sage voltage, it’s observed that in the case of the PI regulator the $V_{DC}$ voltage oscillates approximately in beside of the reference voltage. On the other hand, for the two other regulators (FIS and ANFIS) the $V_{DC}$ voltage oscillates in beside of an axis under the reference voltage. It’s a deficiency in the $V_{DC}$ voltage. It’s provokes a call up in the source current (Fig. 10 (g))
Fig. 10. UPQC–mitigating the effect of sag voltage, by the series inverter using the three controllers PI, Fuzzy (FIS) and Neuron-Fuzzy (ANFIS) – phase a -

(a) Supply voltage
(b) Injected voltage by the series inverter
(c) Load voltage
(d) DC bus voltage
(e) Load current
(f) Injected current by the shunt inverter
(g) Source current
A three-phase supply voltage (230V, 50Hz) is imposed with harmonics voltage. It’s applied to the non-linear load (diode rectifier feeding an RL load) (Fig. 11(a)). The UPQC with its series voltage control detects and calculates the required voltage to be injected in series with the line to compensate the voltage harmonics in
the supply. In effect, series inverter in combination with the insertion transformer produces the series injected voltage to mitigate the effects of the supply voltage fluctuations by asking the required power from the DC bus. Fig. 11(c) shows the compensated supply voltage that it’s supplied to the load, while the fig. 11(d) shows the DC bus voltage, which reflects the disturbance in the supply voltage. Soon after, as can be seen from the fig. 11(d), the condenser voltage (DC bus voltage) tries to come back to the reference value after compensation. The voltage harmonics imposed at the moment t=0.7s influence slightly the $V_{DC}$ curve (Fig. 11(d)). By what the series filter absorb the reactive energy from the condenser to compensate the voltage harmonics. It appeared from the fig. 11 (d), which the voltage undulation is the order of 0.2V for all three used regulators.

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<thead>
<tr>
<th>Factor</th>
<th>PI Controller</th>
<th>FUZZY Controller</th>
<th>ANFIS Controller</th>
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<tr>
<td>1 Line current THD after filtering</td>
<td>4.01%</td>
<td>3.76%</td>
<td>3.96%</td>
</tr>
<tr>
<td>2 Multi mode oscillations in voltage waveform</td>
<td>Observed</td>
<td>Not observed</td>
<td>Not observed</td>
</tr>
<tr>
<td>3 Charging of DC link</td>
<td>Slower</td>
<td>Faster</td>
<td>Too faster</td>
</tr>
<tr>
<td>4 Time taken for condenser’s voltage to reach the first overshoot</td>
<td>0.07 sec</td>
<td>0.045 sec</td>
<td>0.025 sec</td>
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<tr>
<td>5 Sag, Swell, in supply voltage are eliminated.</td>
<td>Eliminated</td>
<td>Eliminated</td>
<td>Eliminated</td>
</tr>
<tr>
<td>6 Load harmonics current are eliminated</td>
<td>Eliminated</td>
<td>Eliminated</td>
<td>Eliminated</td>
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<tr>
<td>7 Overtaking condenser’s voltage</td>
<td>1.5%</td>
<td>0%</td>
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6. Conclusion

The Unified Power Quality Conditioner (UPQC) is a device expected to solve almost all power problems. It takes advantages of series and shunt active power filters to compensate the distortions of both source voltages and load currents.

In this paper, artificial intelligence of Adaptive Neuron-Fuzzy Inference System (ANFIS) has been used for the control of UPQC DC bus voltage. The novelty of this paper lies in the comparison between a PI, Fuzzy and Fuzzy-Neuron controller to regulate the DC bus voltage. The performance of the system for applications such as voltage sag, voltage swell, control of condenser’s voltage, current harmonics elimination has been successfully examined and analyzed. ANFIS controller presents good results then a PI controller and Fuzzy controller.

The UPQC has been developed with different DC bus controllers (PI, Fuzzy and Neuron-Fuzzy) and simulated results have been described which establishes the fact that in both the cases the compensation is done but the response of Neuron-Fuzzy controller is faster and the value of THD is minimum for the both of the voltage and the current which is evident from the figures and the comparison table (Table-1).

References