CHAPTER 4
INVESTIGATION ON UPQC USING ANFIS BASED ADAPTIVE CONTROL TECHNIQUE

4.1. INTRODUCTION

The modeling of analytical method based adaptive control technique (ACT), i.e., MRAS-ACT is discussed in the previous chapter. In the previous chapter, the performance of the UPQC using MRAS-ACT is extensively analyzed for different operating conditions and compared with conventional UVTG technique. The limitations of the MRAS-ACT are discussed in the following section. This chapter deals with the major research work carried out to develop an artificial intelligence technique based ACT for better compensation capability of the UPQC.

4.2. LIMITATIONS OF THE ANALYTICAL METHOD BASED ACT

The MRAS-ACT is an analytical method which was successfully designed and validated in the previous chapter. The MRAS-ACT employed online self-tuning PI controller, reference DC link voltage estimator and power angle estimator. From the overall test result, it is observed that the MRAS based PI controller and estimators had satisfactorily functionality upto 50% sag condition. Above 50% sag conditions, the controller and estimators failed to satisfy the objective functions due to parameter dependency and estimated values were found to be varying nonlinearly. The consequences of these issues were poor regulation of the DC link voltage. However, these problems resulted in poor compensation capability of the UPQC over 50% sag. This chapter deals with overcoming of these issues with use of adaptive neuro fuzzy inference system (ANFIS).

4.3. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

The ANFIS is an hybrid artificial intelligent technique that combines applications of an adaptive neural network and fuzzy logic based decision making system [116]. It has the ability to formulate the mapping from the training and target data [117]. The ANFIS editor is a Matlab/Simulink toolbox which is used to implement the application of ANFIS.

4.3.1. ANFIS Architecture

An illustration of a generalized ANFIS architecture with two inputs (x, y), two rules (r₁, r₂) and five layered feed forward network is shown in Fig. 4.1.
It consists of adaptive (square) and non-adaptive (circle) nodes with a single output. The adaptive node parameters are updated using learning algorithm to minimize tracking error between target data and ANFIS output. Fuzzy if then rules are formed on the basis of Mamdani and Takagi-Sugeno method [118-120].

**Rule 1:** if \( x \) is \( A_1 \) and \( y \) is \( B_1 \), then \( F_1 = p_1x + q_1y + r_1 \) \( \quad (4.1) \)

**Rule 2:** if \( x \) is \( A_2 \) and \( y \) is \( B_2 \), then \( F_2 = p_2x + q_2y + r_2 \) \( \quad (4.2) \)

**Layer 1:** The parameter in this layer determines the membership function (MF) and degree of input variables (x and y) that belong to fuzzy sets \( \{A_i, B_i\} \). The function of this layer node is given as

\[
O_i = \mu_{A_1}(x); \quad \mu_{A_1}(x) = \frac{1}{1 + \left( \frac{x - c_1}{a_1} \right)^2} \quad (4.3)
\]

The shape of MF is changed by adjusting the parameters of \( \{a_i, b_i, c_i\} \)

**Layer 2:** This layer computes the firing strength or weight factor using (4.4)

\[
W_i = \mu_{A_1}(x) \times \mu_{B_1}(y); \quad (4.4)
\]

**Layer 3:** All the incoming firing strength is normalized in this layer using

\[
\overline{W}_i = \frac{W_i}{W_i + W_j}, \text{For } i = 1,2. \quad (4.5)
\]
Layer 4: Output of layer 4 ($O_i^4$) is the product of node function and the normalized firing strength is defined as

$$O_i^4 = W_i \times F_i = W_i \times (p_i x + q_i y + r_i)$$

(4.6)

Layer 5: The final ANFIS output is a summation of overall rules from the output of layer 4.

$$O_i^5 = \sum_i W_i \times F_i = \frac{\sum_i W_i \times F_i}{\sum_i W_i}$$

(4.7)

4.3.2. ANFIS Learning Algorithm

In ANFIS, a desired input/output mapping is achieved by the adaptive node parameters using learning algorithm. There are two learning algorithms used to update adaptive node parameters such as back-propagation algorithm (BPA) and hybrid learning algorithm (HLA).

In general, the BPA is found to be slow and it can be trapped in local minima condition. The hybrid learning rule combines both BPA method and least square estimation (LSE). The adaptive network under LSE learning algorithm has only one output [121-123].

$$Output = F(\vec{I}, S)$$

(4.8)

Where $\vec{I}$ is set of input variables and S is the set of adaptive parameter. The adaptive parameter S is the direct sum of two sub sets.

$$S = S_1 \oplus S_2$$

(4.9)

The matrix equation is given as $AX=B$, where $X$ is unknown vector whose elements are parameter in $S_2$ and $|S_2|=M$. The dimension of $A$, $X$ and $B$ are $P \times M, M \times 1$ and $P \times 1$, $P$ is the number of training data pair, $P$ is usually greater than $M$ (number of linear parameter).

A least Square Estimation (LSE) of $X$ is $X^*$ required to minimize the squared error $\|AX - B\|^2$. Where $X^*$ is $X^* = (A^T A)^{-1} A^T B$, $A^T$ is the transpose of $A$, $A^T A$ is non singular matrix and $(A^T A)^{-1} A^T$ is the pseudo inverse of $A$.

Let $i^{th}$ row vector of matrix $A$ is $a_{i1}$ and $i^{th}$ row vector of matrix $B$ is $b_{i1}$. The sequential formulae to compute LSE of $X$ is given as

$$X_{i+1} = X_i + S_{i1} a_{i1} (b_{i1}^T - a_{i1}^T X_i)$$

(4.10)
\[ S_{i+1} = S_i - \frac{S_i a_{i+1} a_{i+1}^T S_i}{1 + a_{i+1}^T S_i a_{i+1}}, i = 0, 1, \ldots, P - 1 \]

(4.11)

Where \( S_i \) is the covariance matrix and LSE of \( X^* \) is \( X_p \).

The hybrid learning procedure combines BPA and LSE to update the adaptive parameter \( S_1 \) and \( S_2 \). For each and every epoch, the hybrid learning process is composed of a forward pass and backward pass. In forward pass, the input data are given, the functional signals go in forward path until matrix \( A \) and \( B \) are attained and the error signal is computed. In backward pass, the error rate is measured with respect to each node output and it propagates from output end to the input end.

\( S_1 = \) weight and threshold of hidden layer
\( S_2 = \) weight and threshold of output layer

In the hybrid learning algorithm, the back propagation learning algorithm is adopted to tune \( S_1 \) (hidden layer parameter) and \( S_2 \) (output layer parameter) is identified by applying LSE technique. The hybrid learning algorithm not only reduces the convergence time [124].

### 4.3.3. ANFIS Training Procedure

The ANFIS is trained to achieve optimum input/output mapping and its procedure is elaborately discussed in this section. The procedure of training ANFIS is shown in Fig. 4.2. The ANFIS is trained successfully following five major processes.

**Process I – Load Training Data**

The training data contains both input data and output data (target data). The optimum output data for the input data is identified using heuristic method [125]. After obtaining the output data, both input and output data are arranged in a single data file in column wise. This data file is a training data used to train the ANFIS. In the proposed work, the training data contains three columns – first two columns represent the input data and the third column is an output or target data.

**Process II – Fuzzification and Membership Function**

In this process, the crisp training data is converted into fuzzy set using appropriate membership function. The appropriate membership function must be selected to minimize the tracking error between target data and ANFIS output. In ANFIS editor, there are eight types of membership functions available.
Process III – Fuzzy Rule Frame
The fuzzy if then rules are framed according to the weighed fuzzified input.

Process IV – Set Learning Algorithm
The learning algorithm is used to update or change the membership function parameter to minimize the mapping error between the target data and ANFIS data [126]. Two algorithms are used to train the ANFIS are BPA and HLA.

Process V – Defuzzification and Extraction
The defuzzification is the process of converting ANFIS fuzzified outcome to the crisp output. The final process is to extract the fis file to the workspace [126,127].

4.4. ANFIS BASED ADAPTIVE CONTROL TECHNIQUE
The ANFIS based ACT (ANFIS-ACT) is proposed in this chapter to overcome the limitations of the MRAS based ACT. In proposed ANFIS based ACT, the ANFIS is trained to operate as DC link voltage controller, reference DC link voltage estimator and power angle estimator. As similar to MRAS-ACT, ANFIS-ACT is also classified into shunt ANFIS-ACT and series ANFIS-ACT.
4.4.1. **Shunt ANFIS Adaptive Control Technique**

The function of the shunt adaptive control technique has been elaborately discussed in the previous chapter. The block diagram of the proposed shunt ANFIS based ACT is shown in Fig. 4.3. In the proposed shunt ANFIS-ACT, the ANFIS is trained to play two major functions such as reference DC link estimator and DC link voltage controller. In MRAS-ACT, the reference DC link voltage is estimated with the function of voltage sag factor whereas in ANFIS-ACT, reference DC link voltage is estimated with the function of voltage sag factor and load power factor. Hence in the proposed work, the value of reference DC link voltage is varied with respect to voltage sag and load. The DC link voltage error is computed from the difference of reference and actual DC link voltage. The DC link voltage error is minimized using DC link voltage controller. In the proposed work, ANFIS is trained to operate as DC link voltage controller and it is termed as ANFIS controller. The ANFIS controller minimizes the DC link voltage error and estimates the reference source current magnitude ($I_{ANFIS}^*$). $I_{ANFIS}^*$ is a real fundamental component of load current and reference source current is the product of $I_{ANFIS}^*$ and three phase unit sine vector and is given in (4.12). The next step is computation of current error signal using (4.13) and it is the difference of reference and actual source current. The current error signal is also termed as current related PQ distortions. The current error signal is processed by the
hysteresis current controller and the hysteresis controller produces firing pulses using (4.14). These firing pulses controls the duty cycle of the shunt VSI. Consequently, the actual source current tracks the reference current.

\[
\begin{bmatrix}
I_{saA}^* \\
I_{sbA}^* \\
I_{scA}^*
\end{bmatrix} = \begin{bmatrix}
I_{ANFIS}^* U_a \\
I_{ANFIS}^* U_b \\
I_{ANFIS}^* U_c
\end{bmatrix}
\]

(4.12)

\[
\begin{bmatrix}
I_{CaA} \\
I_{CbA} \\
I_{CcA}
\end{bmatrix} = \begin{bmatrix}
I_{saA}^* \\
I_{sbA}^* \\
I_{scA}^*
\end{bmatrix} - \begin{bmatrix}
I_{sa} \\
I_{sb} \\
I_{sc}
\end{bmatrix}
\]

(4.13)

\[
S_{shaA} = \begin{cases}
OFF & I_{CaA} > +hb \\
ON & I_{CaA} < -hb
\end{cases}
\]

(4.14)

### 4.4.2. Series ANFIS Adaptive Control Technique

The function of series ACT has been discussed in the previous chapter. The block diagram of the series ANFIS-ACT is shown in Fig. 4.4. In proposed series ANFIS-ACT, ANFIS is trained to estimate power angle with the function of voltage sag and load power factor. After identifying the optimum power angle, the training data file is to be prepared. This training data is used to train ANFIS for estimating the power angle and the power angle estimated by the ANFIS is given as \( \delta_A \). After obtaining \( \delta_A \), the reference load voltage signal is generated using (4.15). The reference load voltage signal is product of \( V_{Lm} \) and three-phase unit sine vector with \( \delta_A \). The next stage in the series ACT is the capturing of voltage related PQ distortions. And it is termed voltage error signal and it is computed from the difference of reference and actual load voltage using (4.16). The voltage error signal is processed by the hysteresis controller and it produces firing pulses to the series VSI using (4.17). These firing pulses control the duty cycle of the series VSI. Consequently, the actual load voltage tracks the reference load voltage.

\[
\begin{bmatrix}
V_{LA}^* \\
V_{LB}^* \\
V_{LC}^*
\end{bmatrix} = \begin{bmatrix}
V_{Lm}^* \sin(\omega t + \delta_A) \\
V_{Lm}^* \sin(\omega t + 120^\circ + \delta_A) \\
V_{Lm}^* \sin(\omega t - 120^\circ + \delta_A)
\end{bmatrix}
\]

(4.15)
4.5. IDENTIFICATION OF SUITABLE MEMBERSHIP FUNCTION AND NEURAL LEARNING ALGORITHM

The ANFIS based controller and estimators are implemented in ACT using ANFIS editor. In ANFIS editor, the ANFIS is trained using eight input MFs, two output MFs and two neural learning algorithms. The eight input MFs are triangular MF (trimf), trapezoidal MF (trapmf), generalized bell MF (gbellmf), gaussian curve MF (gaussmf), gaussian combination MF (Gauss2mf), Π-shaped MF (pimf), difference between two sigmoidals MF (dsigmf) and product of two sigmoidals MF (psigmf). Two output MFs are constant MF and linear MF. In constant MF, the boundary of the MF is maintained constant whereas in linear MF, the MF boundary register linear variations with respect to the input/output data pairs. The two neural learning algorithms are BPA and HLA. In this section, suitable MF and Neural learning algorithm are to be identified for optimum compensation of PQ distortions.

4.5.1. Load Training Data Set

Initial stage in the ANFIS training is to prepare and load the training Data set. In the proposed work, ANFIS plays three major roles which are DC link voltage
controller, reference DC link voltage estimator and power angle estimator. And three different training data sets are to be prepared. As discussed earlier, the structure of training data set is found to be a single data file with three columns and the first two columns represent the input data and third column is an output or target data. For ANFIS controller, the first two columns of the training data set are error and integral error of the DC link voltage and the third column is the reference source current magnitude. The training data sets for shunt ANFIS controller are obtained from the numerical simulations using MRAS based PI controller and fixed gain PI controllers. For upto 60% sag, the training data sets are obtained from the MRAS based PI controller and beyond that, the training data sets are prepared from the different fixed gain PI controllers. For ANFIS based reference DC link voltage estimator, the first two columns are found to be voltage sag factor and load power factor and the third column refers to the values of the reference DC link voltage. For ANFIS based power angle estimator, the first two columns are found to be voltage sag factor and load power factor and the third column is the optimum values of the power angle.

Fig. 4.5 ANFIS training data (a) Controller, (b) Reference DC link voltage estimator and (c) Power angle estimator
From the various simulation analyses, the optimal value of power angle is identified and UPQC was shown the best performance on coordinated sharing of load reactive power demand. For different operating conditions, optimum targets for corresponding inputs are identified and collected in a single training data set. Fig. 4.5 (a), Fig. 4.5 (b) and Fig. 4.5 (c) represents the training data set of ANFIS controller, ANFIS based reference DC link voltage estimator and power angle estimator respectively.

Fig. 4.6 (a) DC link voltage control using constant type MFs, (b) DC link voltage control using linear type MFs and (c) Training error using linear type MFs
4.5.2. Identification of Suitable Membership Function

After loading training data, the ANFIS is trained using eight MFs under two types such as constant and linear types [128]. After training ANFIS, it is tested in the simulation for 440 V/50 Hz utility system under trained operating conditions. The simulation result for DC link voltage control using constant MFs is shown in Fig. 4.6 (a). The control of DC link voltage using constant MFs resulted in high oscillation and peak overshoot. Hence, ANFIS using constant MFs is not suitable for compensating PQ distortions. The simulation response for the DC link voltage control using linear type MFs is shown in the Fig. 4.6 (b). From the obtained response, it is observed that the robust control DC link voltage is achieved using linear type MFs. The bar chart of the percentage of training error of various types of linear MFs is shown in Fig. 4.6 (c). Among all linear MFs, minimum training error is achieved using triangle MF. Hence, ANFIS using triangle MF is suitable for controlling UPQC.

![Fig. 4.7 Training error and ANFIS response using (a) Linear triangle MF with BP, (b) Constant triangle MF with HLA and (c) Linear triangle MF with HLA](image)

4.5.3. Selection of Optimum Neural Learning Algorithm

Selection of better neural learning algorithm is a key process for achieving optimum compensation capability of the UPQC. This process is done using three
combinations such as linear triangle MF with BP, constant triangle MP with HLA and linear triangle MF with HLA [129-131]. The simulation results of training error and ANFIS tracking response using linear triangle MF with BP and linear triangle MF with HLA are shown in Fig. 4.7 (a) and Fig. 4.7 (b). Using linear triangle MF with BP, the training error is high and ANFIS output completely fails to track the target data. Using constant triangle MP with HLA, the training error is minimized. However, ANFIS output is poorly tracks the target data. The simulation result of training error and ANFIS tracking response using linear triangle MF with HLA is shown in Fig. 4.7 (c). Using linear triangle MF with HLA, the training error is considerably minimized and the target data is optimally tracked by ANFIS output. Hence from these investigations, it is concluded that the linear triangle MF with HLA is suitable for compensating PQ distortions and it is implemented for further investigations.

![Simulation results for trained and untrained operating conditions](image)

Fig. 4.8 Simulation results for trained and untrained operating conditions (a) Source voltage magnitude in per unit, (b) Reference DC link voltage estimation using ANFIS-ACT and (c) Power angle estimation using ANFIS-ACT
4.6. PERFORMANCE ANALYSIS ON ANFIS ESTIMATORS

The performance of ANFIS based reference DC link voltage and power angle estimators are analyzed for trained and untrained operating conditions. The voltage sag considered are 0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80% and 90% and power factor considered are 1 PF, 0.9 PF, 0.8 PF, 0.7 PF, 0.6 PF, 0.5 PF, 0.4 PF, 0.3 PF, 0.2 PF and 0.1 PF. For untrained operating conditions, the voltage sag and load PF are varied from these values. Fig. 4.8 (a) shows source voltage magnitude in per unit (p.u.). In this waveform, from 0 sec to 1.1 sec is considered as trained operating conditions and from 1.1 sec to 2.6 sec is considered as untrained operating condition. In untrained operating condition, the voltage fluctuation is introduced between 0.23 to 0.24 sec and notch of 2 p.u. magnitude is introduced at 0.244 sec. The simulation results for ANFIS based reference DC estimator and power angle estimator for trained and untrained operating conditions are shown in Fig. 4.8 (b) and Fig. 4.9 (c). From the obtained results, it is found that the proposed ANFIS based estimators are optimally worked for both trained and untrained operating conditions.

4.7. ANALYSIS ON PROPOSED AND CONVENTIONAL UPQC

The compensation capability of proposed and conventional UPQC is investigated in this section. The results obtained from the conventional UPQC are given in the label UVTG, the results of proposed UPQC using analytical adaptive control technique are given as MRAS-ACT and the results of proposed UPQC using ANFIS adaptive control technique are given as ANFIS-ACT.

4.7.1. Reference DC Link Voltage and Power Angle Estimations

In proposed ACT, the reference DC link voltage and power angle estimators play a vital role under voltage sag condition. The performance of these estimators is analyzed using MRAS-ACT and ANFIS-ACT for various sag conditions and corresponding results are represented in Fig. 4.9 (a) to Fig. 4.9 (d). Fig. 4.9 (a) shows the results of reference DC link voltage estimation using MRAS-ACT for 0% to 90% sag conditions. In MRAS-ACT, the value of reference DC link voltage is estimated using the mathematical model and it varies linearly for each sag conditions.
Fig. 4.9 (a) Reference DC link voltage estimation using MRAS-ACT, (b) Reference DC link voltage estimation using ANFIS-ACT, (c) Power angle estimation using MRAS-ACT and (d) Power angle estimation using ANFIS-ACT
After 60% sag condition, the reference DC link voltage is settled at 430 msec and it significantly increases the transient in the regulation of actual DC link voltage. The simulation result for estimation of reference DC link voltage using ANFIS-ACT is shown in Fig. 4.9 (b) and the result is plotted for various sag conditions and different loads. In ANFIS-ACT, the reference DC link voltage is estimated with the function of source voltage sag and load power factor. Using ANFIS-ACT, the optimum value of reference DC link voltage is estimated with 2 msec settling time for all operating conditions. Hence the reference DC link voltage estimator using ANFIS-ACT is suitable for better regulation of DC link voltage.

The simulation result for the power angle estimation using MRAS-ACT is shown in Fig. 4.9 (c). In MRAS-ACT, the power angle is estimated using mathematical model and it is the function of source voltage sag and load power factor. From the obtained result, the power angle is successfully estimated upto 60% for linear loads i.e., R and RL loads and upto 50% sag for nonlinear load, i.e., rectifier load. The settling time of the power angle estimated by the MRAS-ACT is found to be 140 msec. The simulation response for the power angle estimation using ANFIS-ACT is shown in Fig. 4.9 (d) and the response is taken for different load under 0% to 90% sag conditions. Using ANFIS-ACT, the optimum value of power angle is estimated upto 80% sag with settling time of 2msec. From the obtained results, it is found that the ANFIS based estimators are suitable for regulating the UPQC and compensating the PQ distortions.

4.7.2. DC Link Voltage Control

The DC link voltage control using conventional UVTG, proposed MRAS-ACT and ANFIS-ACT is investigated for nonlinear load and linear load with respect to 0% to 90% voltage sag conditions. The simulation results of DC link voltage control for nonlinear load and linear load are shown in Fig. 4.10 (a) and Fig. 4.10 (b) respectively. In conventional UVTG, constant reference value is used to control actual DC link voltage that resulted in constant voltage across the DC link voltage. And the conventional UVTG technique failed to control reference and actual DC link voltage above 30% sag condition. In proposed technique, the variable reference value is used to control the actual DC link voltage that resulted in variable voltage across the DC link capacitor. The MRAS-ACT failed to control reference and actual DC link voltage over 50% sag for nonlinear load and 60% sag for linear load. Using ANFIS-ACT, DC
link voltage is successfully controlled upto 80% voltage sag condition for both nonlinear and linear load. From this investigation, it is confirmed that a wide range of DC link voltage control is achieved using proposed ANFIS-ACT.

![DC link voltage control using UVTG, MRAS-ACT and ANFIS-ACT](image)

**Fig. 4.10** DC link voltage control using UVTG, MRAS-ACT and ANFIS-ACT (a) Nonlinear load and (b) Linear load

### 4.7.3. Reactive Power Compensation

The compensation of load reactive power demand of nonlinear load and linear load are analyzed using conventional UVTG, proposed MRAS-ACT and ANFIS-ACT. For nonlinear load, the rectifier load is considered and RL load is taken as linear load. The simulation results of load reactive power demand compensation for nonlinear and linear loads are presented in Fig. 4.11 (a) and Fig. 4.11 (b). From the obtained responses, the conventional UVTG failed to compensate load reactive power demand over 30% sag for both nonlinear and linear loads. This issue is mainly due to failure in the control of DC link voltage. The MRAS-ACT failed to mitigate the load reactive power demand over 50% sag for nonlinear load and 60% sag for linear loads. The ANFIS-ACT successfully compensated the load reactive power demand upto
80% sag for both nonlinear and linear loads. This investigation confirmed that the UPQC using ANFIS-ACT has wide range of compensation of load reactive power demand.

![Graph showing reactive power compensation using UVTG, MRAS-ACT and ANFIS-ACT](image)

**Fig. 4.11** Reactive power compensation using UVTG, MRAS-ACT and ANFIS-ACT
(a) Nonlinear Load and (b) Linear load

### 4.7.4. THD Compensation

The compensation of source current THD for nonlinear load and linear load is examined using conventional UVTG, proposed MRAS-ACT and ANFIS-ACT. The simulation results of source current THD compensation for nonlinear and linear loads are presented in Fig. 4.12 (a) and Fig. 4.12 (b). The conventional UVTG failed to compensate source current THD over 30% sag for nonlinear and linear loads. The MRAS-ACT failed to mitigate the load reactive power demand over 50% sag for nonlinear load and 60% sag for linear loads. The ANFIS-ACT successfully compensated the load reactive power demand upto 80% sag for nonlinear and linear
loads. Under rated voltage condition, the source current THD of nonlinear load using UVTG is 4.8%, using MRAS-ACT is 3.24% and ANFIS-ACT mitigated to 3.21%. For 50% voltage sag condition, the source current THD of nonlinear load using UVTG is 6.4%, using MRAS-ACT is 2.9% and ANFIS-ACT mitigated to 1.5%. For 80% voltage sag condition, the source current THD of nonlinear load using UVTG is 8.9%, using MRAS-ACT is 6.3% and ANFIS-ACT mitigated to 1.8%. This investigation confirmed that the UPQC using ANFIS-ACT has better compensation capability on mitigation of source current THD.

Fig. 4.12 THD compensation using UVTG, MRAS-ACT and ANFIS-ACT (a) Nonlinear load and (b) Linear load
4.7.5. Voltage Drop Compensation

Voltage drop is a serious problem that significantly affects the performance of the load under voltage sag condition. The compensation of load voltage drop of the nonlinear and linear loads are analyzed for without and with UPQC using the conventional UVTG, proposed MRAS-ACT and ANFIS-ACT. The simulation results of the load voltage drop compensation for nonlinear and linear loads with respect to 0% to 90% sag are presented in Fig. 4.13 (a) and Fig. 4.13 (b). Under rated voltage, it is maintained at load terminal using the proposed and conventional schemes. For 50% sag condition, the load voltage drop for without UPQC is 50.46%, for UVTG is 14.3%, for MRAS-ACT it is 6.3% and for ANFIS-ACT it is 4.1%. Hence, the percentage of load voltage drop compensated using UVTG is 71.6%, using MRAS-ACT is 87.5% and using ANFIS-ACT is 91.8%. For the 80% sag condition, the load voltage drop for without UPQC is 80.6%, for UVTG it is 64.8%, for MRAS-ACT it is
76.2% and for ANFIS-ACT it is 45.7%. Hence the percentage of load voltage drop compensated using UVTG it is 19.6%, using MRAS-ACT it is 5.45% and using ANFIS-ACT it is 43.3%. From the obtained results, it is observed that the conventional UVTG failed to maintain rated load voltage over 30% sag condition and this issue is mainly due to constant DC link voltage. The MRAS-ACT failed to minimize the load voltage drop over 50% sag condition and the ANFIS-ACT is successfully minimized upto 80% sag. From this investigation, it is confirmed that constant DC link voltage resulted in increased load voltage drop whereas the variable DC link voltage significantly minimized the load voltage drop.

4.7.6. Power Drop Compensation

Power drop is the result from load voltage drop that significantly increases the economical losses to the end users. The compensation of load power drop of the nonlinear and linear loads is analyzed for without and with UPQC using conventional UVTG, proposed MRAS-ACT and ANFIS-ACT. The simulation results of the power voltage drop compensation for nonlinear and linear loads with respect to 0% to 90% sag are presented in Fig. 4.14 (a) and Fig.4.14 (b). Under rated voltage, the actual power is maintained at load terminal using the proposed and conventional schemes. For 50% sag condition, the load power drop for without UPQC is 75.38%, for UVTG it is 25.7%, for MRAS-ACT it is 12.2% and for ANFIS-ACT it is 7.3%. Hence the percentage of load power drop compensated using UVTG is 65.9%, using MRAS-ACT it is 83.8% and using ANFIS-ACT it is 90.3%. For 80% sag condition, the load power drop for without UPQC is 96.1%, for UVTG it is 89.1%, for MRAS-ACT it is 95.7% and for ANFIS-ACT it is 69.9%. Hence the percentage of load voltage drop compensated using UVTG is 7.3%, using MRAS-ACT it is 0.41% and using ANFIS-ACT it is 27.2%. From the obtained results, it is observed that the conventional UVTG failed to maintain the actual load power over 30% sag condition and this problem is due to constant DC link voltage. The MRAS-ACT failed to minimize load voltage drop over 50% sag condition and ANFIS-ACT is minimized upto 80% sag condition. From this investigation, it is confirmed that constant DC link voltage resulted in increased load power drop and the variable DC link voltage significantly minimized the load power drop.
4.7.7. Power Flow Analysis

In this section, the real power flow and reactive power flow are investigated using proposed ANFIS-ACT based UPQC for 0.8 PF RL load. The simulation results for real power flow and reactive power flow are shown in Fig. 14.5 (a) and Fig. 14.5 (b) respectively. During rated source voltage, the load real power demand is delivered from the source and load reactive power demand is supplied from the shunt APF. Under source voltage sag, the shunt APF absorbs real power from the source and it passes to series APF through a common DC link capacitor. From the series APF, the required real power is delivered to the load. In the proposed ANFIS-ACT, the power angle is injected at 40% sag for 0.8 PF load. Upto 30% sag, the shunt APF is completely delivers the load reactive power demand, i.e., 9.018 KVAR delivered. At 40% sag, the load reactive power is found to be 8.806 KVAR and the reactive power delivered by the shunt APF is 6.318 KVAR and the reactive power delivered by the series APF is 2.636 KVAR. After the power angle is injected, the 28.5% of
load reactive power demand is delivered by the series APF. This investigation proves that up to 80% sag, the power flow is maintained and coordinated sharing of load reactive power demand is successfully achieved.

![Graph showing real and reactive power flow analysis](image)

Fig. 4.15 Results of ANFIS-ACT for 0.8 PF load (a) Real power flow analysis and (b) Reactive power flow analysis

4.7.8. Voltage and Current Profile Enhancement Using ANFIS-ACT

The proposed ANFIS-UPQC is designed to compensate the typical real time power quality distortions such as voltage and current related PQ distortions and the corresponding simulation result is shown in Fig. 4.16. The voltage related PQ distortions are notch with 2 p.u. (0.3 sec), 30% voltage sag (0.4 to 0.5 sec), 30% swell (0.55 to 0.65 sec) and unbalance source (0.7 to 0.8 sec).
Fig. 4.16 Compensation of voltage and current related PQ distortions using ANFIS-ACT,
(a) Source voltage, (b) Load Voltage, (c) Compensation Voltage, (d) Source current, 
(e) Load current and (f) Compensation current
The current related PQ distortions are harmonic distortion generated by the rectifier load (0.85 to 1.05 sec) and reactive power demand load (1.05 sec). The source voltage, load voltage and compensation voltage are shown in Fig. 4.16 (a), Fig. 4.16 (b) and Fig. 4.16 (c) respectively. Under the notch condition, the magnitude of phase A and phase B of source voltage is increased to 1.3 p.u. and 1.5 p.u. respectively. With the support of series APF, the notch is mitigated in the load side and load voltage of phase A and phase B are found to be 1.08 p.u. and 1.2 p.u. respectively. During voltage related power quality problems, series APF plays vital role on compensation and maintains rated load voltage across load shown in Fig. 4.16 (b). The source current, load current and compensation current are shown in Fig. 4.16 (d), Fig. 4.16 (e) and Fig. 4.16 (f) respectively. For current related PQ distortions, the shunt APF plays a major role and it maintains the source free from harmonic distortions and reactive power demand.

Table 4.1 Power quality issues compensation using UVTG, MRAS-APF and ANFIS-APF

<table>
<thead>
<tr>
<th>Sag (%)</th>
<th>Technique</th>
<th>( V_{dc}^* ) (V)</th>
<th>( V_{dc} ) (V)</th>
<th>( Q_s ) (VAR)</th>
<th>( V_L ) Drop(%)</th>
<th>( P_L ) Drop(%)</th>
<th>( I_s ) THD (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>UVTG</td>
<td>762.1</td>
<td>762.3</td>
<td>-69.3</td>
<td>0.18</td>
<td>1.7</td>
<td>4.8</td>
</tr>
<tr>
<td></td>
<td>MRAS-APF</td>
<td>762.1</td>
<td>762.1</td>
<td>-49.7</td>
<td>0.15</td>
<td>0.4</td>
<td>3.24</td>
</tr>
<tr>
<td></td>
<td>ANFIS-APF</td>
<td>723.9</td>
<td>724</td>
<td>-19.1</td>
<td>0.09</td>
<td>0.2</td>
<td>3.21</td>
</tr>
<tr>
<td>30</td>
<td>UVTG</td>
<td>762.1</td>
<td>762.2</td>
<td>-75.1</td>
<td>1.1</td>
<td>3.34</td>
<td>3.4</td>
</tr>
<tr>
<td></td>
<td>MRAS-APF</td>
<td>877.5</td>
<td>877.6</td>
<td>-96.7</td>
<td>0.91</td>
<td>1.3</td>
<td>2.01</td>
</tr>
<tr>
<td></td>
<td>ANFIS-APF</td>
<td>761.8</td>
<td>762.1</td>
<td>-33.6</td>
<td>0.8</td>
<td>1.12</td>
<td>1.55</td>
</tr>
<tr>
<td>40</td>
<td>UVTG</td>
<td>762.1</td>
<td>573.6</td>
<td>9701</td>
<td>3.5</td>
<td>9.26</td>
<td>6.8</td>
</tr>
<tr>
<td></td>
<td>MRAS-APF</td>
<td>918.1</td>
<td>918.2</td>
<td>-171</td>
<td>1.3</td>
<td>2.3</td>
<td>1.7</td>
</tr>
<tr>
<td></td>
<td>ANFIS-APF</td>
<td>876.7</td>
<td>876.8</td>
<td>-128</td>
<td>1.5</td>
<td>2.2</td>
<td>1.1</td>
</tr>
<tr>
<td>50</td>
<td>UVTG</td>
<td>762.1</td>
<td>510</td>
<td>7711</td>
<td>24.3</td>
<td>47.55</td>
<td>6.4</td>
</tr>
<tr>
<td></td>
<td>MRAS-APF</td>
<td>959</td>
<td>959.2</td>
<td>-259.3</td>
<td>4.8</td>
<td>9.5</td>
<td>2.9</td>
</tr>
<tr>
<td></td>
<td>ANFIS-APF</td>
<td>1028</td>
<td>1028.7</td>
<td>-218</td>
<td>3.3</td>
<td>6.3</td>
<td>1.5</td>
</tr>
<tr>
<td></td>
<td>UVTG</td>
<td>762.1</td>
<td>273.1</td>
<td>3985</td>
<td>53.7</td>
<td>82.5</td>
<td>7.4</td>
</tr>
<tr>
<td>70</td>
<td>MRAS-APF</td>
<td>1045</td>
<td>928.7</td>
<td>11630</td>
<td>44.1</td>
<td>74.5</td>
<td>5.3</td>
</tr>
<tr>
<td></td>
<td>ANFIS-APF</td>
<td>1067</td>
<td>1068</td>
<td>-440</td>
<td>28.5</td>
<td>49.6</td>
<td>1.4</td>
</tr>
<tr>
<td>80</td>
<td>UVTG</td>
<td>762.1</td>
<td>151.2</td>
<td>3514</td>
<td>65.7</td>
<td>90.1</td>
<td>8.98</td>
</tr>
<tr>
<td></td>
<td>MRAS-PI</td>
<td>1075</td>
<td>400</td>
<td>9052</td>
<td>77.7</td>
<td>96.1</td>
<td>6.3</td>
</tr>
<tr>
<td></td>
<td>ANFIS-APF</td>
<td>1067</td>
<td>1068</td>
<td>-490</td>
<td>55.5</td>
<td>71.4</td>
<td>1.8</td>
</tr>
</tbody>
</table>
The rectifier load produces 33% THD in load current, whereas the shunt APF maintains sinusoidal source current with 3.21% THD exposed in Fig. 4.15 (d). Comparative analyses on compensation of power quality issues with respect to various voltage sag conditions using conventional UVTG, proposed MRAS-ACT and ANFIS-ACT are given in the Table. 4.1. From the overall investigation it is concluded that the conventional UPQC failed to compensate the PQ distortions over 30% sag, proposed UPQC using MRAS-ACT failed to compensate PQ distortions over 50% sag and ANFIS-ACT successfully compensated the PQ distortion upto 80% sag condition.

4.8. CONCLUSIONS

The performance of the proposed UPQC using ANFIS-ACT is investigated for different operating conditions. The procedure for collecting of training data set and ANFIS training are elaborately discussed. The drawbacks of mathematical modeling based estimator and controller are highlighted. The conventional UVTG failed to control DC link voltage over 30% sag condition. The MRAS-ACT failed to control DC link voltage over 50% sag for nonlinear load and over 60% sag for linear loads. The ANFIS-ACT controlled the reference and actual DC link voltage upto 80% sag condition. From the obtained test result, it is concluded that UPQC using ANFIS-ACT exhibited robust regulation of DC link voltage and it has better compensation capability and wide range of operating condition.