



NEURO-FUZZY APPROACH FOR FAULT LOCATION AND DIAGNOSIS USING ONLINE LEARNING SYSTEM

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ABSTRACT

This paper outlines a hybrid approach of neuro-fuzzy based learning and classification approach based on the online learning systems. The effect of fault diagnosis for the suggested fault location tool is evaluated over the conventional fault diagnosis based approaches. The method of fault location based on the conventional offline neuro controller approach is compared with the suggested hybrid approach for learning and convergent time evaluation for distributed systems.

Keywords : *Neuro-Fuzzy Approach, Fault Location, Fault Diagnosis, Online Learning System, System Performance*

1. INTRODUCTION

In a power system, faults, dynamic operations, or nonlinear loads often cause various types of power quality disturbances such as voltage sags, voltage swells, switching transients, impulses, notches, flickers, harmonics, etc. ^(1,2). On the other hand, the increased use of sensitive electronic circuitry by industrial and residential customer, as well as the progress of utility deregulation and competition have imposed greater demand on the quality of power. Consequently, the studies aimed at detecting and analyzing as well as eliminating or minimizing the effects of power quality disturbances on industrial and customer loads have assumed greater importance.

One critical aspect of power quality studies is the ability to perform automatic power quality monitoring and data analysis. Usually, utilities install power quality meters or digital fault recorders at certain locations so that various power quality events can be recorded and stored in the form of sampled data for further analysis. Efficient and prompt detection, classification, and characterization of the events as well as further identification of the location of these events facilitate maintenance and control of the system, and improve system stability and reliability.

Another important aspect of a power quality study is coordination between the power system behavior and equipment performance. It is desired that the response of the sensitive equipment during the event be explained and correlated to specific features of the event, so that either the system behavior or the equipment operating characteristics can be tuned for improved ride-through ability or immunity of the equipment to specific events ⁽³⁾. It has been noted that the activities of detecting and classifying of power quality events, characterizing and locating events, studying equipment sensitivity, and modeling of the system and equipment are closely related and interdependent. Hence it is natural and desirable that the data processing and analysis as well as modeling and simulation of the system and equipment be studied in one unified framework. In this paper a new neuro-fuzzy expert system for detection and classification of various types of faults events is developed.

Fuzzy-neural networks have been proposed as a knowledge engineering technique and used for various application domains by authors including Yamakawa and Uchino ⁽¹⁾, Uchikawa and Furuhashi ⁽²⁾, and others ^(3, 4, 5, 6, 9). The fuzzy-neural approach proposed by these authors have been successfully used for learning

and tuning fuzzy rules as well as solving classification, prediction and control problems. Some recent publications suggest methods for training fuzzy neural in order to adjust to new or dynamically changing data and situations ^(4, 5).

This paper introduces a new architecture for fuzzy-neural, called FZ-NN, which stands for Fuzzy-Neural Network, and investigates some learning and adaptation strategies associated with it. In addition, the use of rule insertion and rule extraction algorithms are investigated.

2. FAULT DIAGNOSIS IN POWER SYSTEM

Power supply systems comprise three broad categories – generation, transmission and distribution. Electricity is generated at power stations from various natural resources such as coal, natural gas, hydro and wind, in large quantities where economies of scale can be achieved. These generating stations are proximate to the fuel resource, often a considerable distance from major load centres. Therefore, large quantities of electricity are transported at high voltages via the transmission network to strategically located bulk supply substations, and from there to smaller substations where the supply is further reduced for distribution. Modern power supply systems have evolved from separated utilities to large interconnected systems, with many generating stations and load centres being interconnected through power transmission lines. With the high degree of system interconnection, there is increased power exchange over larger distances at higher system voltage levels. Operation and expansion of power systems impacts society and several factors must be considered.

Technical and economic factors concern the improvement of existing equipment and design of new equipment, which could offer economies. Social and demographic factors deal with the tendency of the power industry to influence social and political processes, including setting of industrial enterprises and distribution of working population. These concerns have resulted in the emergence of distributed generation, the current trend of interconnected smaller sized generating units such as Kogan Creek gas fired power station as opposed to the traditional coal fired large capacity stations such as Tarong and Stanwell. This trend is emerging as a consequence of increased Greenhouse gas issue significance, leading to consideration of alternate energy sources such as solar, wind and wave that operate with smaller

sized generation units. These smaller units are also less complex, less expensive and more rapidly constructed, allowing more rapid adaptation to the requirements of expanding industries. Therefore, interconnection of power systems yields technical, economical and environmental benefits, as excess capacity generated by hydro resources from one region may augment load supplied by fossil-fuelled generation in another.

For interconnections to operate as intended, transmission systems must have adequate capacity or load rating to transmit the quantity of power intended. If the existing transmission system does not have adequate ratings for the predicted power transfer, additional lines may be constructed in parallel with existing transmission lines, or the transmission system may be upgraded to a higher operating voltage. This is not always possible due to environmental, economic and time factors, and public opinion. In a conventional system the processing of currents and voltages are carried out to protect the devices and to make a suitable and fast control on the faults happening in the transmission line. For the analysis of the suggested controlling this paper introduces a controlling operation of fault detection and controlling based on a hybrid modeling of neural network and fuzzy logic. A system architecture for the suggested approach is as shown below:

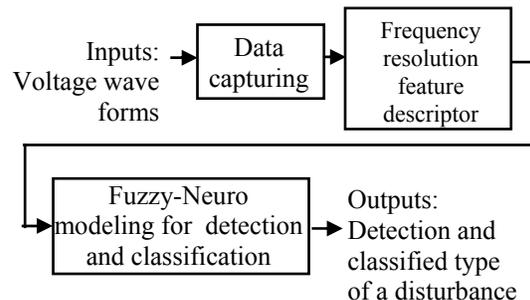


Figure 1. Suggested operational flow model for the fault diagnosis system

The application module “Detection and Classification” automatically detects and classifies the type of the disturbance captured in the recorded or simulated waveforms. The types of disturbances include the voltage sag, swell, outage, harmonic, notch, flicker, impulse and switching transient. After the disturbance is detected and classified, the module “Waveform Characterization” further processes the waveform. Eight different sub-modules corresponding to the eight types of events have been designed. The software automatically selects the appropriate sub-module for computing parameters pertinent to the event. Then, one may



proceed to the module “Equipment Sensitivity Study” for evaluating how various waveform features affect the behavior of the equipment during the event. Finally, the module “Event Location” aims at accurately pinpointing the location of the event occurrence. Presently, we are focusing on locating faults that caused the sag event using the waveforms recorded by a limited number of DFRs and related power system data. Short-circuit studies are employed to obtain an optimal fault location estimate subject to a defined performance criterion by iteratively posing faults in the system, running simulations, and comparing the simulated waveforms with the recorded waveforms. The detection and classification problem consists of two steps. The first step is feature extraction, during which the distinct and dominant features (or patterns) of various events are selected and obtained using appropriate techniques.

The second step is called decision-making, during which an inference engine to determine the types of the events further processes the extracted features. Appropriately chosen features are essential for both simplifying the Decision-Making System (DMS) and improving the correct identification rate of the system. For decision-making, a neural network based system was presented⁽⁴⁾. The author suggests using the time-delay network to capture the temporal features of the input signals. One drawback of using neural network is the difficulty of the training process. Some authors have proposed using the fuzzy logic to model the uncertainties of the training error so that the learning rate can be finely tuned to improve the convergence of the system⁽⁵⁾. However this method still belongs to the category of neural network and does not utilize fuzzy logic to model the uncertainties of the input patterns.

Fuzzy logic based DMS is well suited to solve the realworld problems. It bridges the quantitative and qualitative considerations. It has found wide applications in the areas of load forecasting, harmonic tracking, power metering, etc.^(11, 12). In this work, application of fuzzy logic techniques to the detection and classification of power quality events is explored. For the analysis of the suggested controlling this paper introduces a controlling operation of fault detection and controlling based on a hybrid modeling of neural network and fuzzy logic.

3. FUZZY-NEURO MODELING

The FZ-NN model is designed to be used in a distributed, and learning-based environment. The architecture provides learning from data and approximate reasoning, as well as fuzzy rule extraction and insertion. It allows for the combination of both data and rules into one system, thus producing the synergistic benefits associated with the two sources. In addition, it allows for several methods of adaptation (adaptive learning in a dynamically changing environment). FZ-NN uses a Multi-Layer Perceptron (MLP) network and a modified back propagation training algorithm. The general FZ-NN architecture consists of 5 layers of neurons with partial feed forward connections. It is an adaptable fuzzy-neural where the membership functions of the fuzzy predicates, as well as the fuzzy rules inserted before training or adaptation, may adapt and change according to new data. The interface unit for the suggested design is as briefed below :

3.1. Input layers

The input layer of neurons represents the input variables as crisp values. These values are fed to the condition element layer, which performs fuzzification. This is implemented using three point triangular membership functions with centers represented as the weights into this condition element layer. The triangles are completed with the minimum and maximum points attached to adjacent centers, or shouldered in the case of the first and last membership functions. The triangular membership functions are allowed to be non-symmetrical and any input value will belong to a maximum of two membership functions with degrees differing from zero. These membership degrees for any given input will always sum up to one, ensuring that some rules will be given the opportunity to fire for all points in the input space. This center based membership approach taken by FZ-NN avoids the problems of uncovered regions in the input space that can exist with more flexible membership representation strategies. These do not always limit centers and widths in such a way as to ensure complete coverage.

While algorithms could be formulated and used in such cases to force the memberships to cover the input space, the simple center-based approach taken by FZ-NN seems both more efficient and more natural, with fewer arbitrary restrictions. It should be noted that there are no



“bias” connections necessary for this representation in FZ-NN. The weights from the input to condition element layers of neurons can take values in $[0,1]$ only since the data are assumed to be normalised to this range. This normalisation is normally carried out as part of the FZ-NN pre-processing operations, and can be performed and reverse transparently in applications.

Initially the membership functions are spaced equally over the weight space, although if any expert knowledge is available this can be used for initialisation. In order to maintain the semantic meaningfulness of the memberships contained in this layer of connections some restrictions are placed on adaptation. When adaptation is taking place the centers are limited, remain within equally sized partitions of the weight space. This avoids problems with violating the semantic ordering of membership function labels. Therefore, under the FZ-NN architecture labels can be attached to weights when the network is constructed and these will remain valid for the lifetime of the network. For example, a membership function weight representing low will always have a center less than medium, which will always be less than high.

The condition element layer of neurons is potentially expandable during the adaptation phase with more nodes representing more membership functions for the input variables. Simple activation functions are used in the condition element nodes to perform fuzzification. An important aspect of this layer is that different inputs can have differing numbers of membership functions. The same principle applies to the output membership functions. This allows for very different types of inputs to be used together. As a simple example, temperature may be divided into seven different membership functions representing the range from cold to hot, while holiday (which is a binary variable to indicate whether it is a public holiday or not) can be represented using just two, for yes and no.

3.2. Rule layer

In the rule layer each node represents a single fuzzy rule. The layer is also expandable, in that nodes can be added to represent more rules as the network adapts. The activation function is the sigmoidal logistic function with a variable gain coefficient g (a default value of 1 is used giving the standard sigmoidal activation function). For the gain coefficient large values will make it close to the hard limited thresholding function. A value of

2.19722 would ensure that a rule node would provide activation values from 0.1 to 0.9 when the net input values are between -1 and +1. These values may be desirable as part of the architecture’s “fuzziness.” The semantic meaning of the activation of a node is that it represents the degree to which input data matches the antecedent component of the associated fuzzy rule. However the synergistic nature of rules in a fuzzy-neural architecture must be remembered when interpreting such rules. The connection weights from the condition element layer (also called the membership functions layer) to the rule layer represent semantically the degrees of importance of the corresponding condition elements for the activation of this node.

The values of the connection weights to and from the rule layer can be limited during training to be within a certain interval, say $[-1,1]$, thus introducing non-linearity into the synaptic weights. This option mimics a biologically plausible phenomenon⁽¹⁰⁾ but should be implemented in accordance with an appropriate gain factor for the activation function. For example, if the interval is $[-1,1]$ a suitable value for the gain factor may be 2.19722 as described above. The weight limitation would ensure that inputs into the rules remain within $[-1,1]$ (since the input membership functions are all between 0 and 1) and the gain factor would only allow the rules to output values in $[0.1,0.9]$. This further enhances the meaningfulness of the rules and weight saturation will not occur. As an example of the problems of rule interpretation with unrestricted weights, it is difficult to interpret a rule that has input weights that are very high values, without some form of normalization. With this weight limiting option, the necessity for such normalization is removed.

3.3. Output layers

In the action element layer, a node represents a fuzzy label from the fuzzy quantization space of an output variable, for example small, medium, or large for the output variable “required change in the velocity.” The activation of the node represents the degree to which this membership function is supported by the current data used to recall the FZ-NN. So this is the level to which the membership function for this fuzzy linguistic label is “cut” according to the current facts. The connections from the rule layer to the action element layer represent conceptually the confidence factors of the corresponding rules when inferring fuzzy output values. They are subject to constraints

that require them to remain in specified intervals as for the previous layer with the same advantages of semantic interpretability. The activation function for the nodes of this layer is the sigmoidal logistic function with the same (variable) gain factor as in the previous layer. Again, this gain factor should be adjusted appropriately, given the size of the weight boundary. The output layer performs a modified center of gravity defuzzification. Singletons, representing centers of triangular membership functions, are attached to the connections from the action to the output layer. Linear activation functions were used. For example, a small, medium and large can be represented as connection weights having values of 0, 0.5 and 1.0 respectively from the output range of [0,1] if normalized outputs are considered. Adapting the output membership functions would mean moving the centers, but the requirement that the membership degrees to which a particular output value belongs to the various fuzzy labels must always sum up to one, is always satisfied. For each center, there is a constraining band (partition) where this value can move to. This is used in the same way as the input membership function centers restrictions are. More than one output variable can be used in a FZ-NN structure and the different output variables can have different numbers of membership functions.

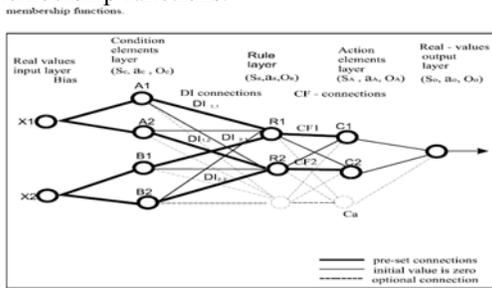


Figure 2. A FZ-NN structure for two initial fuzzy rules

- Rule 1: IF x_1 is A_1 ($DI_{1,1}$) and x_2 is B_1 ($DI_{2,1}$) THEN y is C_1 (CF_1).
- Rule 2: IF x_1 is A_2 ($DI_{1,2}$) and x_2 is B_2 ($DI_{2,2}$) THEN y is C_2 (CF_2), where D_s are degrees of importance attached to the condition elements and CF_s are confidence factors attached to the consequent parts of the rules.

One of the advantages of the FZ-NN architecture is that it manages to provide a fuzzy logic system without having to unnecessarily extend the traditional MLP. Since standard transfer functions, linear and sigmoidal, are used along with a slightly modified back-propagation algorithm, the

main departure being partitions, much of the large body of theory regarding such networks is still applicable. For those results not immediately applicable for FZ-NN the modifications are made much simpler, given FZ-NN's natural structure and algorithm.

Here the fuzzification layer and the defuzzification layer change their input connections based on simple and intuitive formulae. These changes reflect the concepts represented by the layers and must satisfy the restrictions (partitioning) imposed on the membership functions (the movements of their centres cannot take them out of the membership's partition). The same principles apply for the two layers, but different formulae are used to calculate the change of the weights. Figure 3 shows the initial membership functions of a variable x (either input or output) and the membership functions after adaptation. The amount of change has been exaggerated in order to demonstrate the concept involved. In the normal course of training changes to membership functions are limited to small, gradual movements, with the majority of weight changes occurring with the weights into and out of the rules.

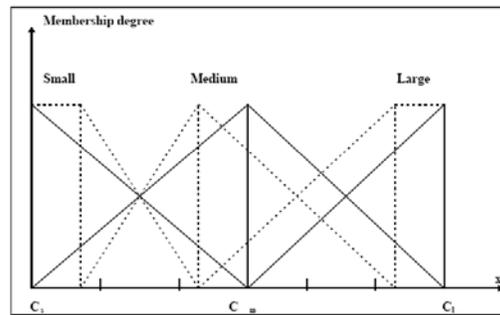


Figure 3. Initial membership functions of a variable x in the FZ-NN and the membership functions after adaptation (dotted lines).

4. SYSTEM MODELING

The suggested FZ-NN has a flexible architecture, which allows for different training and adaptation strategies to be tested before the most suitable is selected for a certain application. Some of the issues involved in this adaptation are discussed below:

4.1. Initialization

Uniformly distributed triangular membership function can be used as initial values for the input variables, and uniformly distributed



singletons can be used as initial values for the output variables. These are the defaults that are used in the absence of other information.

4.2. Membership function insertion

If some expert knowledge is available then this can be used to initialize the memberships, or atleast initialize those for which knowledge exists with the remained being initialized using the default method.

4.3. Rule insertion

If initial set of rules is available, it is used for initialization of the FZ-NN structure through rules insertion mode. The rules are represented as weights as well as inserting the existence of a rule, the relative importance of that rule and its sensitivity to input variables can be provided.

4.4. Training

The FZ-NN can be accomplished either for the inner two rule weight layers, in which case the system adapts its fuzzy rules but does not adapt the membership functions, or for the four weight layers, in which case the system adapts both the rules and the membership functions. The only difference between these two options is that the connections in the fuzzification and defuzzification layers are “frozen” in the former case and they are subject to change in the latter case.

4.5. Aggressive

A section of new data is used for further training and adaptation without using any of the old, previously used, data.

4.6. Conservative

New data is added to the entire old data and training is performed on the entire set.

Obviously, these concepts of aggressiveness and conservatism in training are fuzzy. In fact, some compromise of using the new data with a percentage of old data tends to be most efficient. The amount of old data retained depends on operating requirements (since for on-line adaptation using a large data set may not be feasible), the stationary of the relationships, and the length of time that changes tend to persist for until returning, if at all, to the original relationships. An example here is that of the stock market. This tends

to exhibit long-term trends with occasional departures from that trend. However except in unusual circumstances, such as a large financial market crash, the long-term pattern will eventually be restored. The fuzzy condition making is as suggested below:

The core of the rule set of the implemented fuzzy expert system is illustrated as follows:

1) Detection: For detection, one rule follows.

Rule 1: If THD_n is A_2 or PS_n is B_2 or V_n is C_3 or V_n is C_1 then $DETECT=1$

2) Classification: Fifteen rules follows.

Rule 1: V_{n1} is A_4 and N_n is F_1 and OS_n is G_1 then $IMPULSE=1$

Rule 2: V_n is A_1 or V_{n1} is A_1 then $OUTAGE=1$

Rule 3: V_n is A_6 or V_{n1} is A_6 then $SWELL=1$

Rule 4: V_n is A_5 and PS_n is C_1 and PS_{n1} is C_1 and EW_{n1} is D_1 and $\{TS_{n1}$ is H_2 or $[TS_{n1}$ is H_4 & TS_{n2} is $H_1]\}$ then $SWELL=1$

Rule 5: V_{n1} is A_5 and $\{PS_n$ is C_2 or PS_{n1} is $C_2\}$ then $SWELL=1$

Rule 6: V_{n1} is A_2 then $SAG=1$

Rule 7: V_{n1} is A_3 and $\{PS_n$ is C_2 or PS_{n1} is $C_2\}$ then $SAG=1$

Rule 8: V_{n1} is A_3 and $\{PS_n$ is C_1 and PS_{n1} is $C_1\}$ and $\{THD_{n1}$ is B_1 or $[THD_{n1}$ is B_2 and OS_{n1} is $G_4]\}$ then $SAG=1$

Rule 9: V_{n1} is A_3 and PS_n is C_1 and PS_{n1} is C_1 and OS_n is G_2 and THD_{n1} is B_2 and THD_{n2} is B_2 and THD_{n3} is B_2 then $NOTCH=1$

Rule 10: V_{n1} is A_3 and N_n is F_2 and OS_n is G_2 then $NOTCH=1$

Rule 11: V_{n1} is A_4 and PS_n is C_1 and PS_{n1} is C_1 and THD_n is B_3 and THD_{n3} is B_1 and $\{OS_n$ is G_4 or OS_{n1} is $G_4\}$ then $TRANSIENT=1$

Rule 12: V_{n1} is A_4 and TS_{n1} is H_3 and TS_{n2} is H_3 and TS_{n3} is H_3 and OS_{n1} is G_4 then $HARMONIC=1$

Rule 13: THD_{n1} is B_4 and THD_{n2} is B_4 and THD_{n3} is B_4 and OS_{n2} is G_4 then $HARMONIC=1$

Rule 14: TS_{n1} is H_4 and TS_{n2} is H_4 and TS_{n3} is H_4 and OS_{n2} is G_4 then $HARMONIC=1$

Rule 15: If RN_{iK_1} then $FLICKER=1$

In the above rules, $A_i, B_i, C_i, D_i, F_i, G_i, H_i$, and K_i are the membership functions for the input patterns, and the following trapezoidal and triangular functions are used.

5. SIMULATION RESULTS

A number of power quality events of various types have been simulated and corresponding waveforms are obtained. The following eight distinct features inherent to different types of power quality events have been extracted: the Fundamental Component (V_n), Phase Angle Shift (δn), Total Harmonic Distortion (THD_n), Number of Peaks of the Wavelet Coefficients (N_n), Energy of the Wavelet Coefficients (EW_n), Oscillation Number of the Missing Voltage (OS_n), Lower Harmonic Distortion (TS_n), and Oscillation Number of the rms Variations (RN). The formulae for computing these features are given as follows:

$$V_n = \sqrt{2}absV^n[1] / N$$

$$\alpha_n = angle(V^n[1]) - angle(V^1[1])$$

$$THD_n = \sqrt{\sum_{k=2}^{int(N/2)} \{abs(V^n[k])\}^2} / V^1[1]$$

$$N_n = peak(abs(WC^5))$$

$$EW_n = \sum_{k=1}^{le} abs(WC^n[k])$$

$$OS_n = root(V^5_{miss})$$

$$TS_n = \sqrt{\sum_{k=2}^{10} \{abs(V^n[k])\}^2} / V^1[1]$$

$$RN = root(V^s_{rms} - mean(V^s_{rms}))$$

For the evaluation of the suggested work a distribution system with the DFR units interfaced at the load side is developed as shown in figure 4.

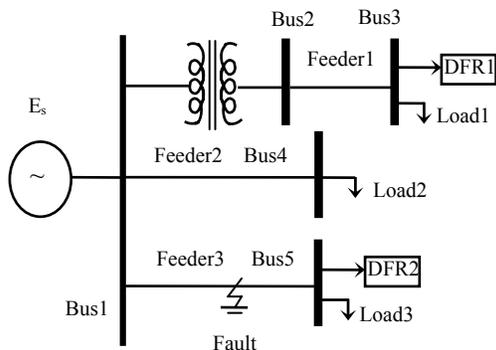


Figure 4. Distributed system considered for the electrical system

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Enter the total shunt admittance of the line= 100
Enter the real series impedance of the line= 20
Enter the imaginary series impedance of the line= 50
Enter the inductive reactance of the line= 12
Enter the reactance of the series capacitor= 50
enter the resistance of the line= 10

Total_Y =
      0 +1.0000e+002i
Total impedance of the line=
Z1 =
      10.0000 + 9.1200i
Enter the Harmonic level 5
    
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Figure 5. The passed query values for the developed electrical system

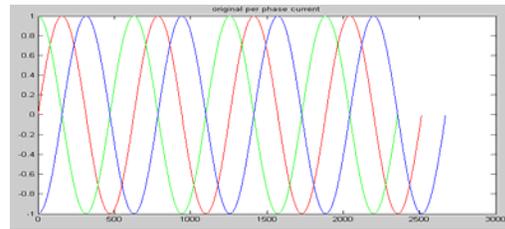


Figure 6. Passed three phase pulse as observed at the generation side

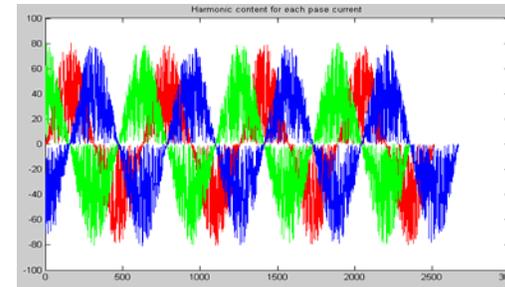


Figure 7. The distorted phase observed in the transmission line due to fault introduced

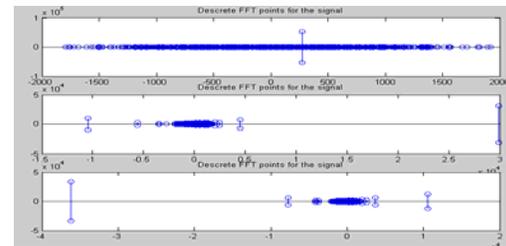


Figure 8. The discrete feature coefficient observed for the three current pulses after distortion

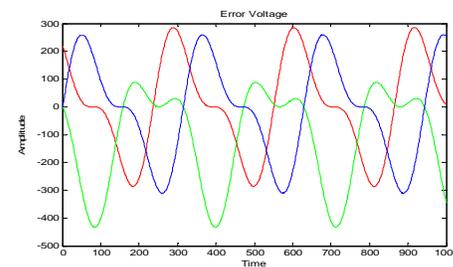


Figure 9. Effective phase voltage observed for the developed system with sag effects

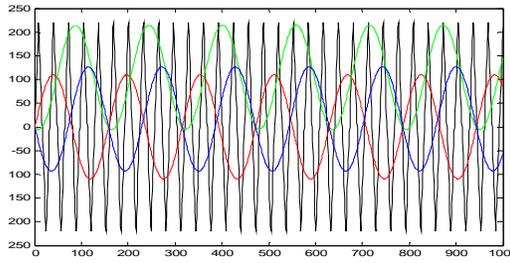


Figure 10. The effective phase observation obtained after the reference model comparison

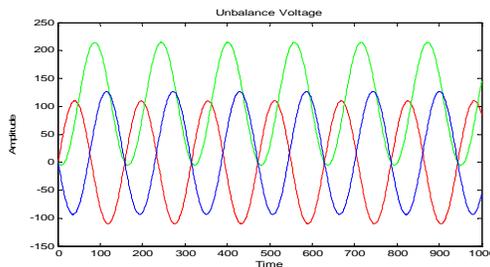


Figure 11. The compensated voltage observation after application of Neuro modeling for the compensation

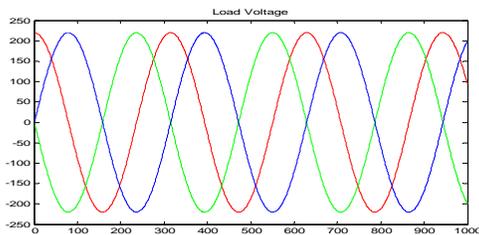


Figure 12. The compensated load voltage observed after the correction applied to the developed system

6. CONCLUSIONS

In this paper a fuzzy neural network architecture for digital fault processing in distributed power system is introduced. The adaptive learning algorithms used along with the rule extraction and rule insertion techniques show that this is a promising approach to building adaptive intelligent information processing systems, which is suitable for fault diagnosis, is developed. The developed system is evaluated over a fault current signal extracted with the resolution feature description and passed to fuzzy neuro model for the classification and detection of fault condition in the observing power system. The effects of harmonic, power disturbances were studied and were observed to be improved by the suggestive approach.

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