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Back-Propagation Artificial Neural Network Based Power Quality Disturbances Classification of IEEE 14 Bus System

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Abstract: *In very little over 10 years, electricity power quality has fully grown from obscurity to a serious issue. Power quality is among the most things that's stressed and is taken into thought by power system utilities so as to satisfy the strain of power distributor and customers. At every passing day this issue has changing into a lot of serious and at identical time the user's demand on power quality additionally gets a lot of important. Therefore it's essential to determine an influence quality analysis system to observe power quality disturbance. Many analysis studies concerning the facility quality are done before and their aims of times targeting the gathering of information for an additional analysis, therefore the impacts of varied disturbances may be investigated. This paper deals with the implementation of IEEE f14bus system with completely different power quality disturbance conditions like voltage sag, voltage swell, momentary interruption and harmonics conditions.. Additionally a technique is shown for determinative the foremost sensitive bus and also the most sensitive load. Result analysis is completed at the sensitive bus and also the load.*
Then after these all types of power quality disturbance signals was classified using back propagation Artificial Neural Network (BP-ANN) based on IEEE 14 bus bar per unit voltage measured at different power quality conditions. The complete system was designed in MATLAB 2015R software atmosphere.
Keywords: *Artificial Neural Network, IEEE 14 Bus system, Power Quality Disturbance, Classification*

I. Introduction

The introduction of the paper should explain the nature of the problem, previous work, purpose, and the contribution of the paper. The contents of each section may be provided to understand easily about the paper.

II. Proposed Methodology

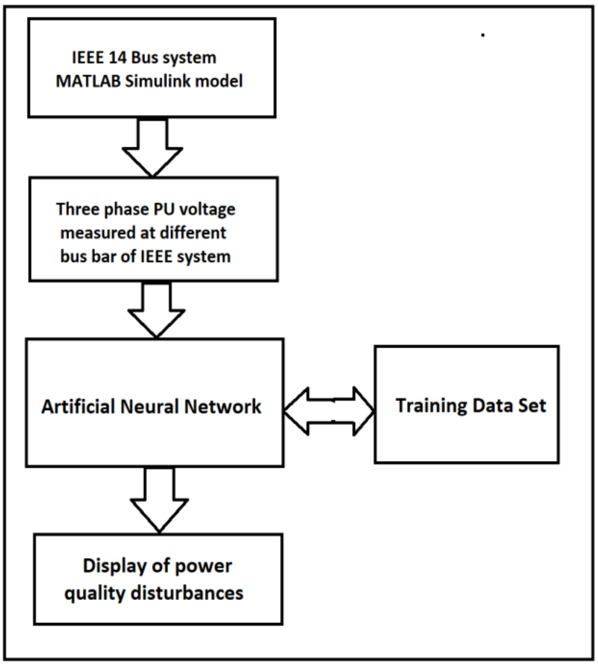

Fig.1: Block diagram of proposed approach

Figure 1 shows the block diagram of proposed approach in which IEEE 14 bus power system model was design in MATLAB 2015 software environment. Then after different power quality disturbances was simulated using circuit breaker, variable loads, harmonics generators etc. The per unit voltages was measured at different bus of IEEE 14 bus system and that measures per unit voltages was transferred to excel sheet for generation of training data set. That training data set was utilized for training ANN for classification of different power quality disturbances.

III. Power quality disturbance model

1. Normal loading condition

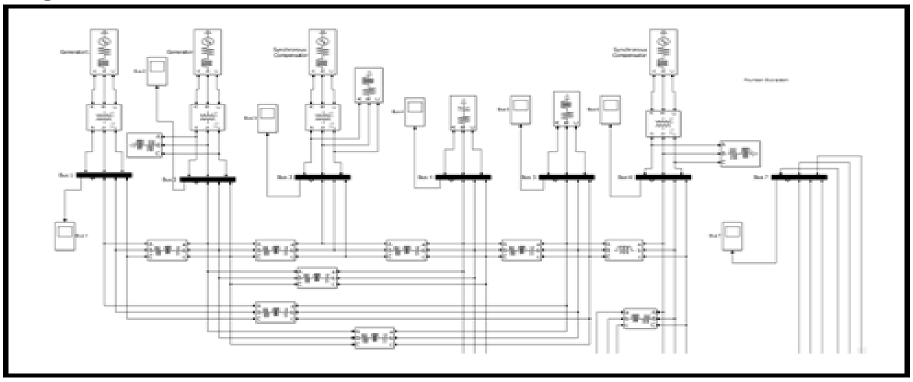

Fig.2. Zone 1 upper portion of IEEE 14 bus power system

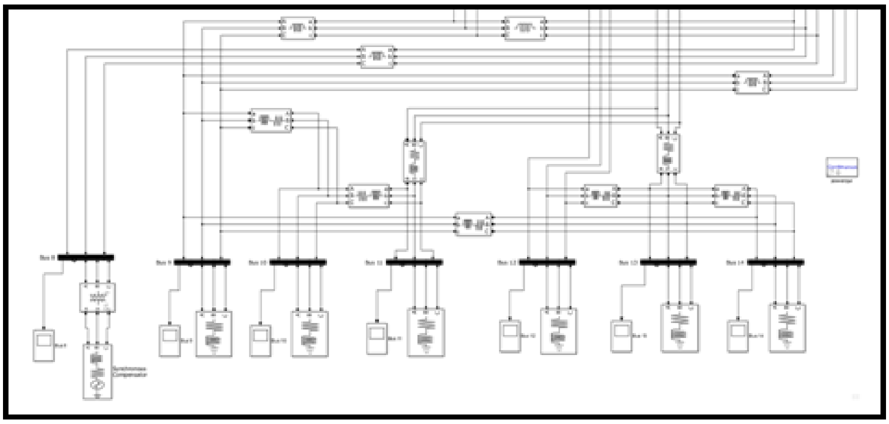

Fig.3. Zone 2 lower portion of IEEE 14 bus power system

Figure 2 and 3 shows the upper and lower portion of IEEE 14 bus system model for normal loading condition without any power quality disturbance conditions. In this model, parameters in table 1 and 2 was set and power system voltage profile was analyzed.

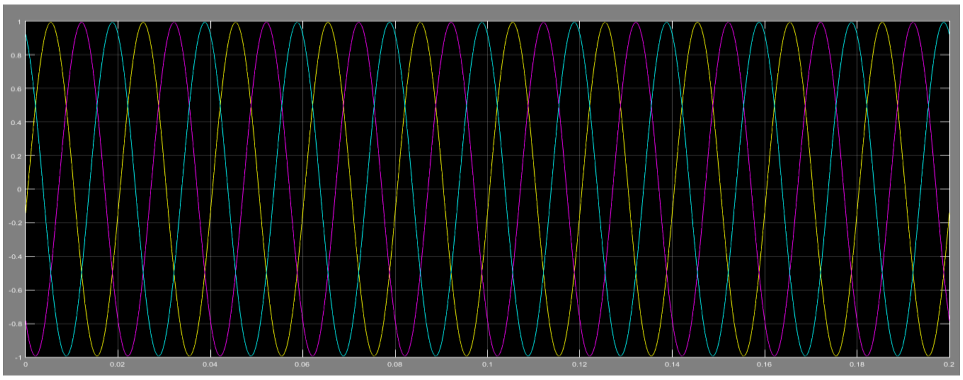

Fig.4. Normal voltage of IEEE 14 bus system at bus bar 4

Figure 4 shows the three phase voltage of IEEE 14 bus which measured at bus bar 4. In this waveform, it is cleared that voltage generated in IEEE 14 bus system is normal supply voltage and without any fluctuation as well as harmonics contents not present.

2. Voltage sag model

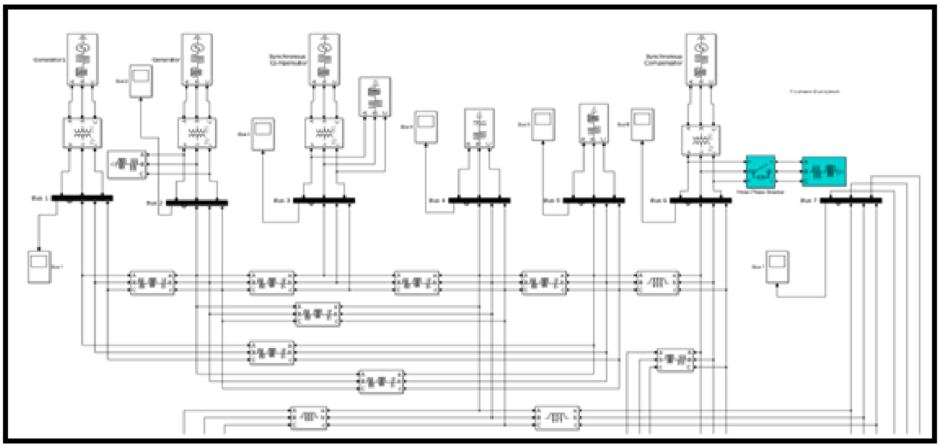

Fig.5. IEEE 14 Bus system for voltage sag power quality disturbance

Figure 5 shows the IEEE 14 bus system for voltage sag power quality disturbances. For generation of voltage sag, the highly inductive load was connected at bus bar 6 through breaker. Breaker time was simulated in such way that breaker on at 0.15 sec and OFF at 3 sec i.e. highly inductive load was connected with IEEE 14 bus system from 0.15 sec to 0.3 second duration and complete operation time of IEEE 14 bus system was 0.5 seconds. Load and breaker parameters are shown in table 3.

Table.1. Simulation blocks parameter for voltage sag generation at bus bar 6

Sr No	Simulation block	Specifications
1	Three phase breaker (Light blue color)	Initial status = open; Switching time: start time = 0.15 sec and end time = 0.3 sec; Breaker resistance (Ron) = 0.01Ω; Snubber resistance (Rs) = 1 M Ω
2	Three phase RLC Load (Light blue color)	Nominal phase to phase voltage = 1 pu; Nominal frequency = Hz; Active power P =0.5 pu; Inductive reactive power = 7 pu

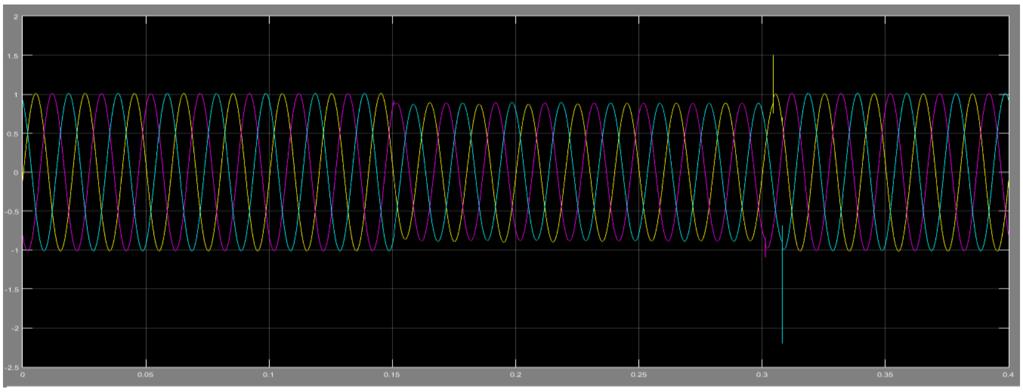

Fig.6. Voltage sag generation at bus bar

Figure 6 shows the three phase voltage measured at bus bar 2 during voltage sag conditions takes place at bus bar 6 of IEEE 14 bus system in MATLAB Simulink model. In this waveform, it is cleared that voltage of power system decrease at 0.15 sec and again maintain normal at 0.3 second when highly inductive load connect with IEEE 14 power system model.

3. Voltage swell model

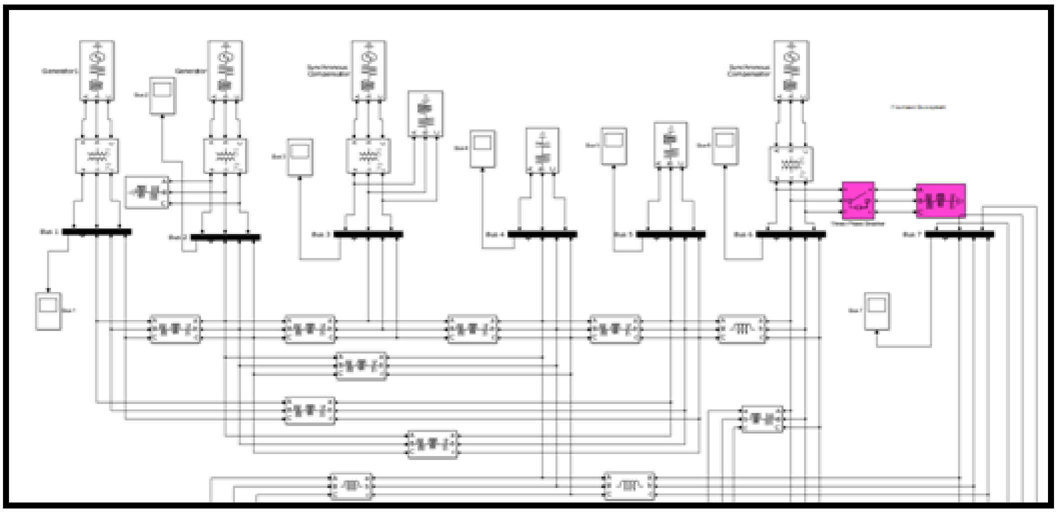

Fig.6. IEEE 14 Bus system for voltage swell power quality disturbance

Figure 6 shows the IEEE 14 bus system for voltage swell power quality disturbances. For generation of voltage swell, the highly capacitive load was connected at bus bar 6 through breaker. Breaker time was simulated in such way that breaker on at 0.15 sec and OFF at 3 sec i.e. highly capacitive load was connected with IEEE 14 bus system from 0.15 sec to 0.3 second duration and complete operation time of IEEE 14 bus system was 0.5 seconds. Load and breaker parameters are shown in table 2.

Table.3. Simulation blocks parameter for voltage swell generation at bus bar 6

Sr No	Simulation block	Specifications
1	Three phase breaker (Pink color)	Initial status = open; Switching time: start time = 0.1 sec and end time = 0.15 sec; Breaker resistance (Ron) = 0.01 Ω; Snubber resistance (Rs) = 1 MΩ
2	Three phase RLC Load (Pink color)	Nominal phase to phase voltage = 1 pu; Nominal frequency = Hz; Active power P = 0.5 pu; Inductive capacitive power = 11 pu

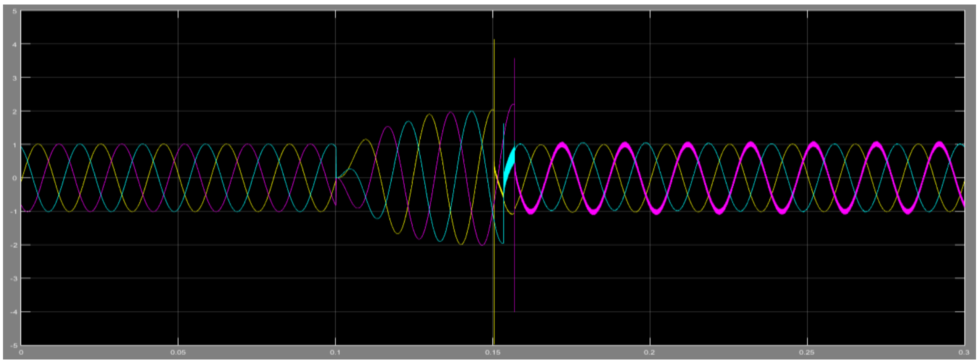

Fig.7. Voltage swell generation at bus bar 6

Figure 7 shows the three phase voltage measured at bus bar 2 during voltage swell conditions takes place at bus bar 6 of IEEE 14 bus system in MATLAB Simulink model. In this waveform, it is cleared that voltage of power system rises at 0.15 sec and again maintain normal at 0.3 second when highly capacitive load connect with IEEE 14 power system model. Similar behavior of voltage sag waveform showed in figure 14 and 15 for bus bar 4 and 14 of IEEE system model.

4. MomentaryInterruption

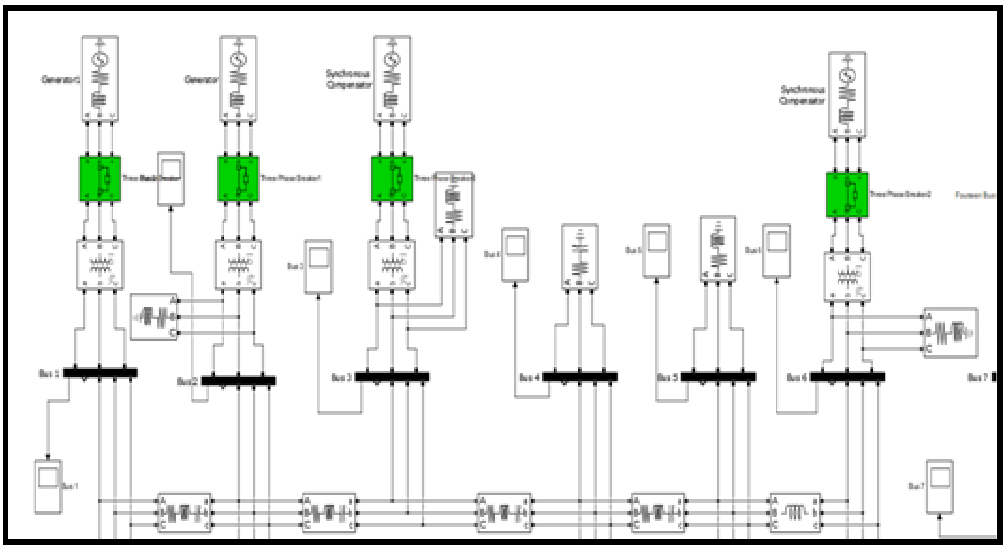

Fig.8. IEEE 14 Bus system for momentary interruption power quality disturbance (Upper zone)

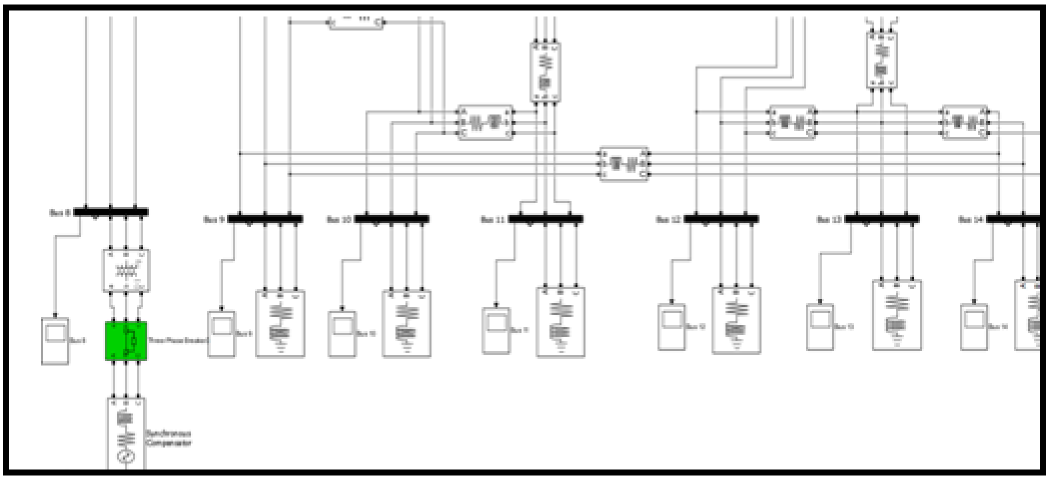

Fig.9. IEEE 14 Bus system for momentary interruption power quality disturbance (Lower zone)

Figure 8 and 9 shows the IEEE 14 bus system upper zone and lower zone in which momentary interruption of power quality disturbance was generated using breaker. Breaker was installed at before each power generator bus bar for ON and OFF of complete power system supply so that interruption was occurred. In this model, momentary interruption was generated in between 0.2 sec to 0.25 second time duration while complete power system model was run for 0.5 second simulation time. Breakers are shown in figure by green color and parameters of breaker are shown in table 5.

Figure 10 shows the three phase voltage waveform at bus bar 3 in which voltage becomes completely zero or interrupt at 0.15 seconds up to 0.3 seconds time slot. That done by simulation time adjustment of three phase breaker which were connected after each power generator sources so that voltage supply was interrupted.

Table.4. Simulation blocks parameter for momentary interruption generation

Sr No	Simulation block	Specifications
1	Three phase breaker (Green color)	Initial status = closed; Switching time: start time = 0.2 sec and end time = 0.25 sec; Breaker resistance (Ron) = 0.01 Ω; Snubber resistance (Rs) = 1 MΩ

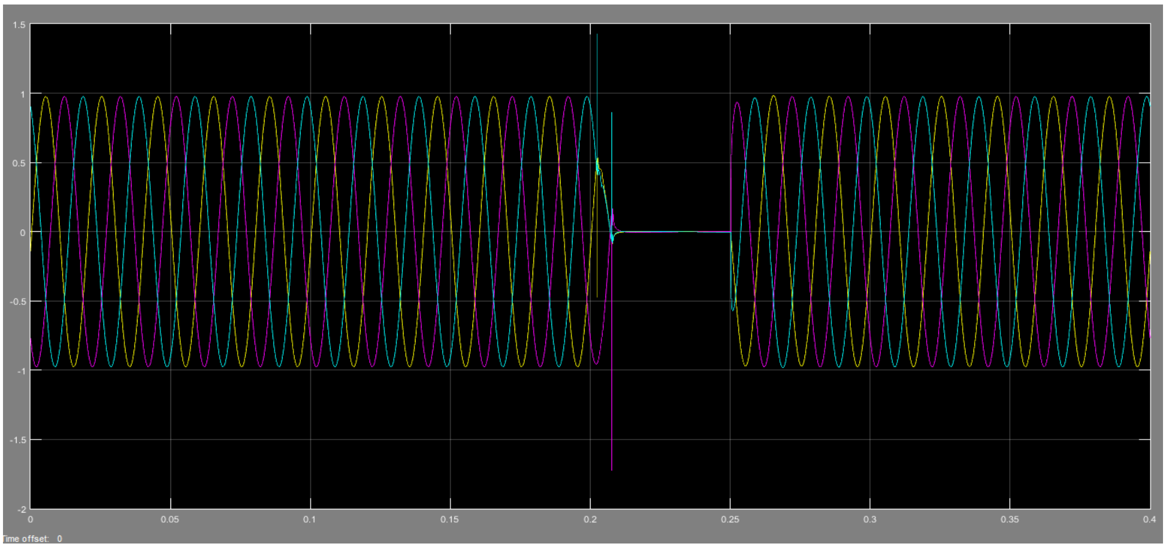

Fig.10. Momentary interruption voltage waveform measured at bus 3

5. Voltage harmonics model

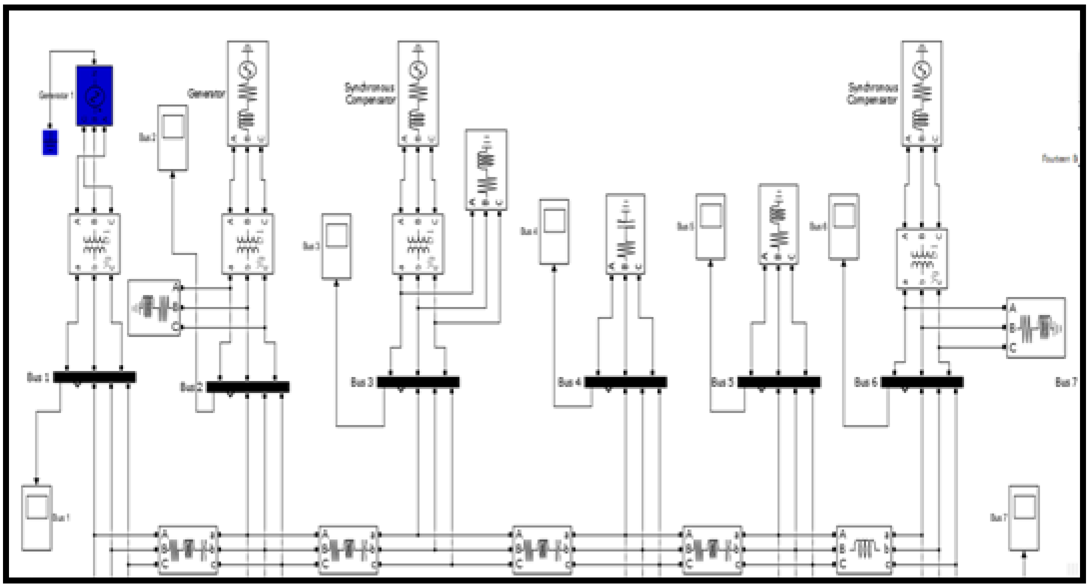

Fig.11. MATLAB Simulation model for momentary interruption voltage generation

Figure 11 shows the IEEE 14 bus system for generation of harmonics as power quality disturbance in power system. For harmonics generation, programmable voltage source was connected at bus bar 1 which simulated for generation of 5^{th} harmonics and 7^{th} harmonics from simulation time of 0.1 sec to 0.15 sec time slot while complete simulation time is sec. The complete parameters of programmable voltage source is shown in table 6.

Table.5. Simulation blocks parameter for harmonics waveform generation at bus bar 1 For IEEE 14 bus system

Sr No	Simulation block	Specifications
1	Three phase programmable voltage source (Blue color)	Amplitude of ph to ph voltage = 1 PU; Phase angle = -30 Degree; Frequency = 50Hz; 5^{th} order harmonics data: Amplitude of harmonics = 0.4 pu; Phase difference = -45 Degree; 7^{th} Order harmonics data:Amplitude of harmonics = 0.2 pu; Phase difference = -36.7 Degree; Time for entering the harmonics into system: Start time: 0.1 Sec; End time: 0.15 Sec;

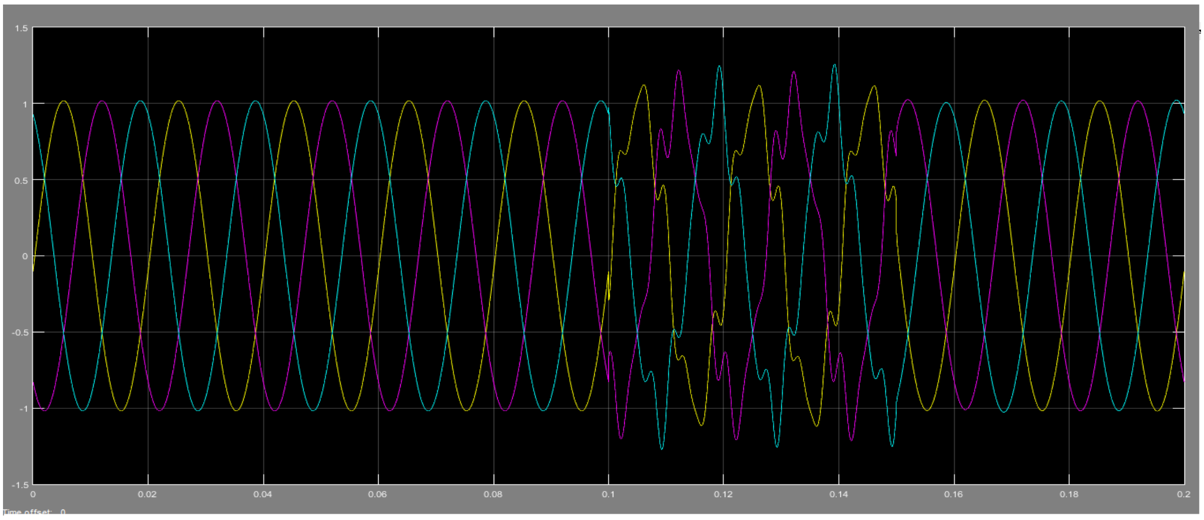

Fig.12. Harmonics voltage measured at bus bar 1

Figure 12 shows the three phase voltage measured at bus bar 1 in which it is observed that harmonics was generated from 0.1 to 0.15 sec simulation time slot. While the effect of harmonics was decreases when transmission impedance included due to transmission interconnection between different bus bar. Figure 23 to 25, it is observed that harmonics decreases with increasing with transmission lone impedance.

IV. MATLAB Simulation model for power quality classification

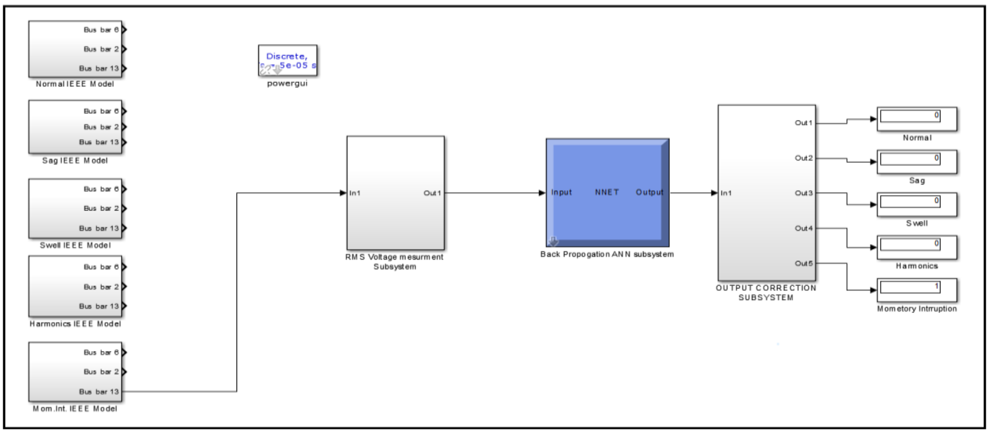

Fig.13. MATLAB Simulation model for power quality disturbance classification using back propagation Artificial Neural Network

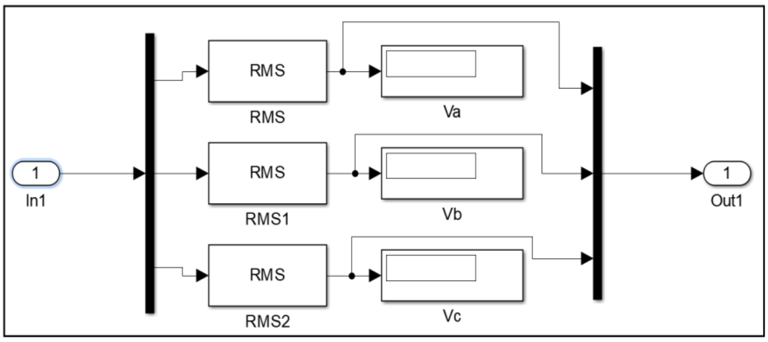

Fig.14. RMS Voltage measurement subsystem model

1. ANN MATLAB Subsystem model

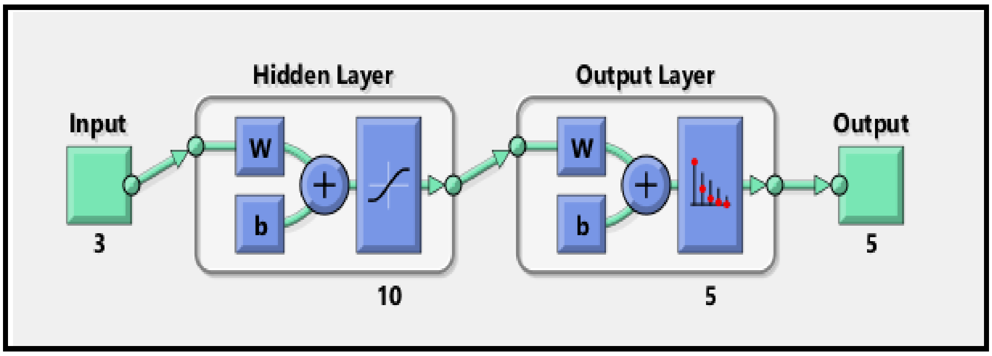

Fig.15. Generalized structure of Neural network in MATLAB Simulink model

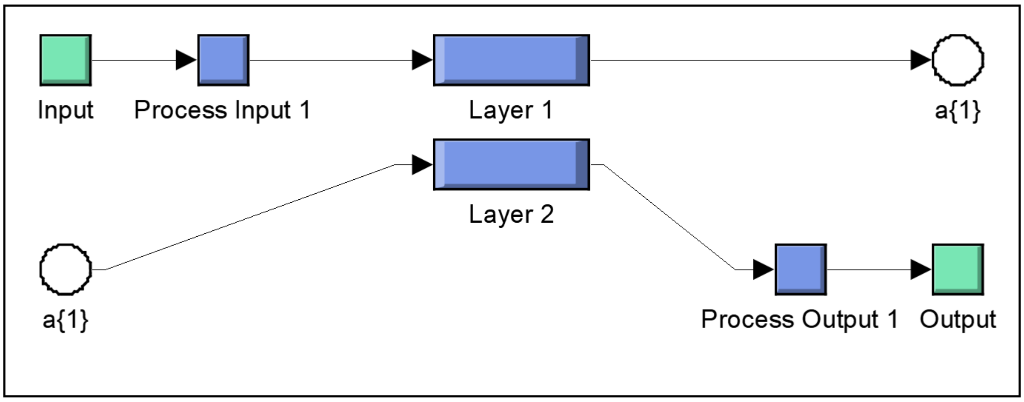

Fig.16. ANN Structure in ANN Subsystem model

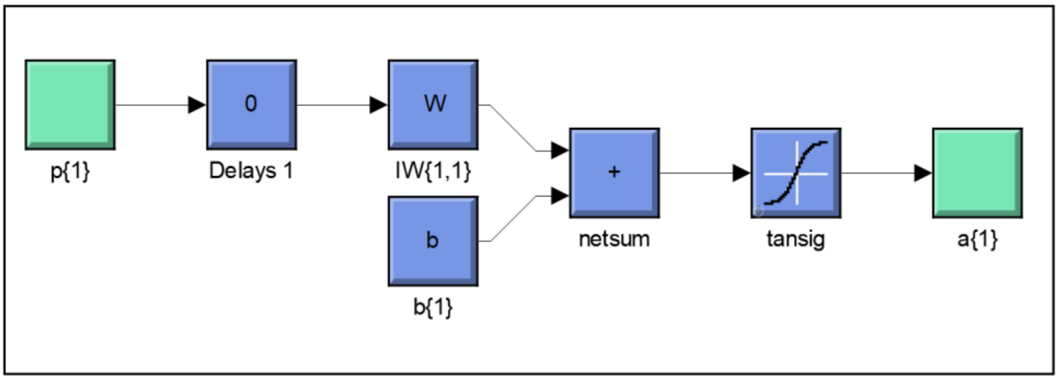

Fig.17. ANN layer 1 in MatlabSimulink with biasand sigmoidal activation function

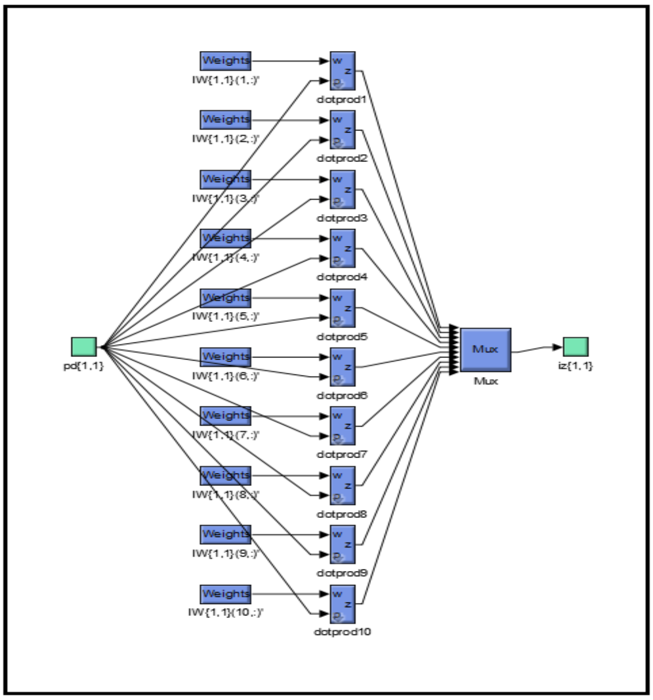

Fig.18. Neurons layer 1 in MATLAB Simulink model with updated weights of each input

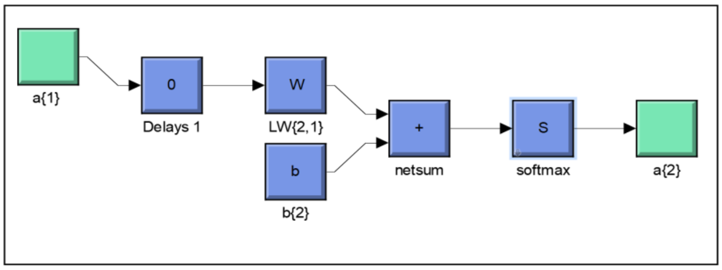

Fig.19. ANN layer 2 in MatlabSimulink with bias and soft competitive activation function

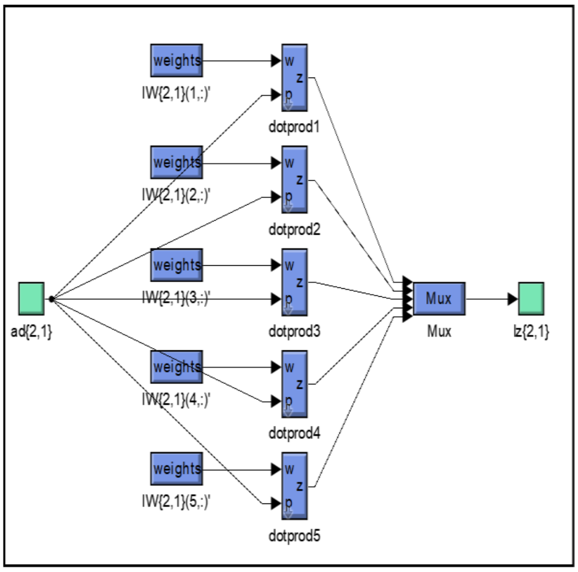

Fig.20. Neurons layer 2 in MATLAB Simulink model with updated weights of each input

2. Output correction subsystem model

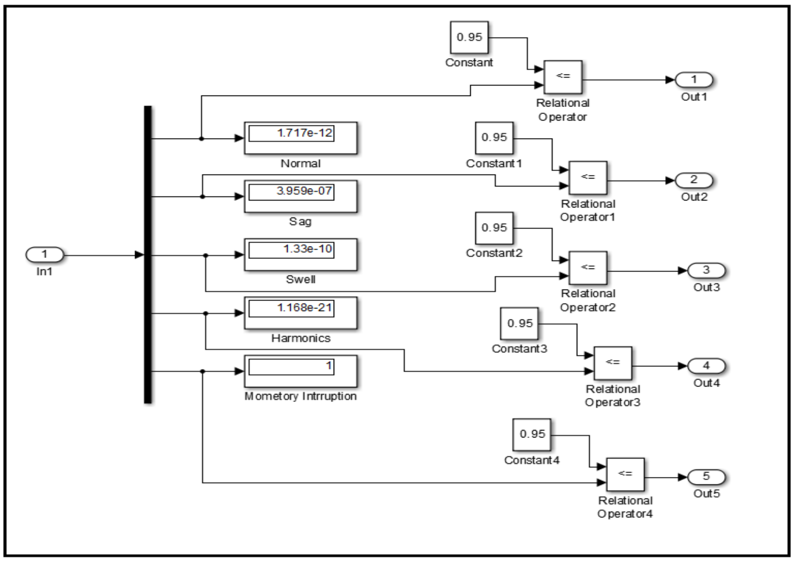

Fig.21. Output correction subsystem MatlabSimulinkmodel

3. Training of Artificial Neural Network

Neural network training for power quality disturbance classification was presented. For that separate neural network structure are utilized and input for Neural network was IEEE 14 bus system three phase per unit voltage which measured at different bus bar location like bus bar 2, bus bar 6 and bus bar 13. Similarly, three phases per unit voltage will be measured at different bus bar location and will be utilized for training of neural network for considering the different bas bar voltage effect for different power quality disturbances.

Neural network train for 15 power quality disturbance cases at different bus bar location i.e. bus bar 2, 6 and 13. These Power quality disturbance cases simulate in IEEE 14 bus subsystem models by taking different loading conditions and by taking harmonics effect on IEEE 14 bus system model.

Table.6. Training input data set for Artificial Neural Network

Sr No	Condition	Bus Bar No.	Va (PU)	Vb (PU)	Vc (PU)
1	Sag	2	0.04816	0.7403	0.7884
2	Swell	2	0.5557	0.2415	0.7971
3	Harmonics	2	0.2728	0.7145	0.9875
4	Mom. Intrp.	2	0.001019	0.007503	0.008522
5	Normal	2	0.1122	0.8105	0.9227
6	Sag	6	0.007236	0.4524	0.4597
7	Swell	6	2.06	1.027	1.033
8	Harmonics	6	0.1884	0.7772	0.9656
9	Mom. Intrp.	6	0.001375	0.003376	0.00475
10	Normal	6	1.20E-01	8.05E-01	0.9255
11	Sag	13	0.02887	0.4568	0.4857
12	Swell	13	1.895	0.9111	0.9839
13	Harmonics	13	0.204	0.7488	0.9528
14	Mom. Intrp.	13	0.001429	0.0022781	0.00421
15	Normal	13	0.1383	0.7743	0.9126

The three phases per unit voltage was measured during power quality disturbance like voltage sag, swell, harmonics, momentary interruption and normal condition for simulation time of 2.5 seconds. Because all types of power quality disturbances was simulated in between 1.5 sec to 3 sec time duration so that 2.5 sec was best time for measurement of power quality disturbances voltages.

Table 6 shows the per unit three phases voltage measures at bus bar 2, bus bar 6 and bus bar 13 for input training data set for Neural network. Similarly table 7 shows the required target output for corresponding serial number power quality disturbance for corresponding three phases input per unit voltages.

Table.7. Training target data set of Artificial Neural Network

Sr No	Condition	Bus Bar No.	Normal	Sag	Swell	Harmonics	Momentary Interruption
1	Sag	2	0	1	0	0	0
2	Swell	2	0	0	1	0	0
3	Harmonics	2	0	0	0	1	0
4	Mom. Intrp.	2	0	0	0	0	1
5	Normal	2	1	0	0	0	0
6	Sag	6	0	1	0	0	0
7	Swell	6	0	0	1	0	0
8	Harmonics	6	0	0	0	1	0
9	Mom. Intrp.	6	0	0	0	0	1
10	Normal	6	1	0	0	0	0
11	Sag	13	0	1	0	0	0
12	Swell	13	0	0	1	0	0
13	Harmonics	13	0	0	0	1	0
14	Mom. Intrp.	13	0	0	0	0	1
15	Normal	13	1	0	0	0	0

Figure 22 shows the selection of percentage of training data set, validation data set and testing data set from entire 15 numbers of samples. Training data set: These are presented to the network during training, and the network is adjusted according to its error.Validation data set: These are used to measure network generalization, and to halt training when generalization stops improving.Testing data set: These have no effect on training and so provide an independent measure of network performance during and after training.

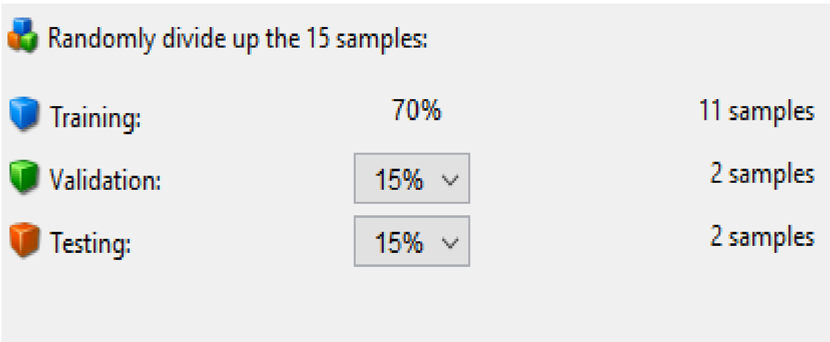

Fig.22. MATLAB NNSTART window for training data set selection for training data, validation data and testing data

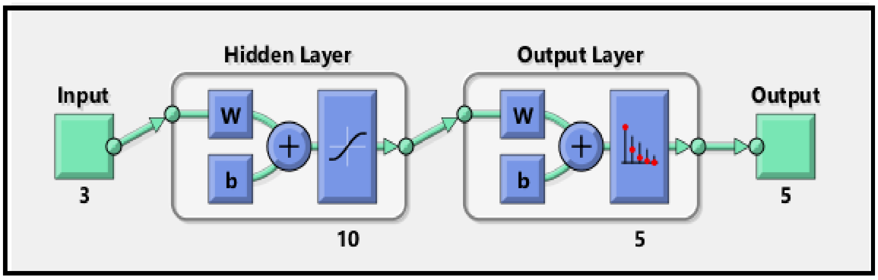

Fig.23. Generalized structure of ANN for training

Figure 23 shows the generalized structure of back propagation based Artificial Neural Network in which input are three phases per unit voltage and then corresponding targets are different power quality disturbance as shown in table 5.7 and 5.8 respectively. Hidden layer is consist of 10 neurons and having sigmoidal activation function of each neuron while output neuron is consist of 5 neurons and having soft competitive activation function.

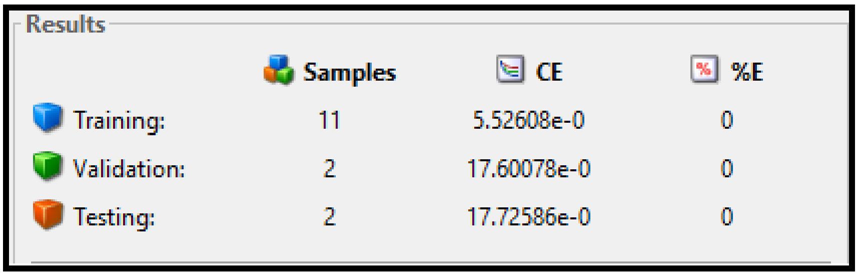

Fig.24. Training performance parameter for neural network for power quality disturbance classification

Figure 24 shows, For training of ANN, 15 data sample was utilized out of 11 power quality disturbance three phase voltage sample cases data set i.e. 70% data utilized for training. For validation and testing 30% dataset was utilize i.e. 4 sample data set. Also MSE (Mean square error) for all data set was zero after successful training of ANN.

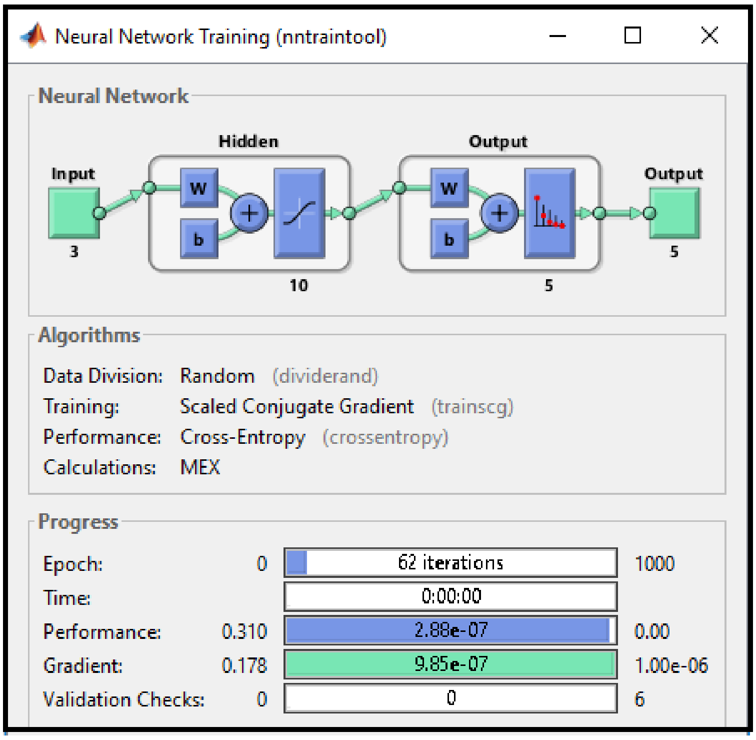

Fig.25. Training performance window for ANN

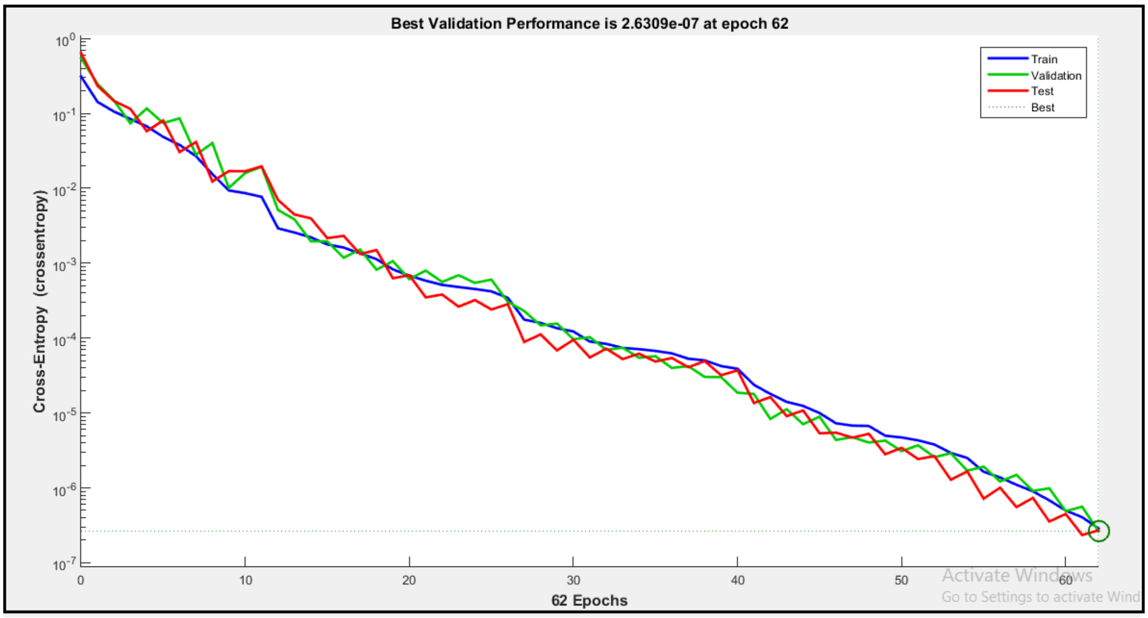

Fig.26. Training performance characteristics of ANN for power quality disturbance classification

Figure 26 shows the training performance window for training of power quality classification neural network. In this total 62 epochs are required for complete training of ANN using back propagation algorithm. Gradient for this training was measures as $9.85*10^{-7}$. During training of neural network for fault classification, neural network takes 28 epochs and mean square error becomes minimum of $2.639*10^{-7}$ shows by green line in figure 27.

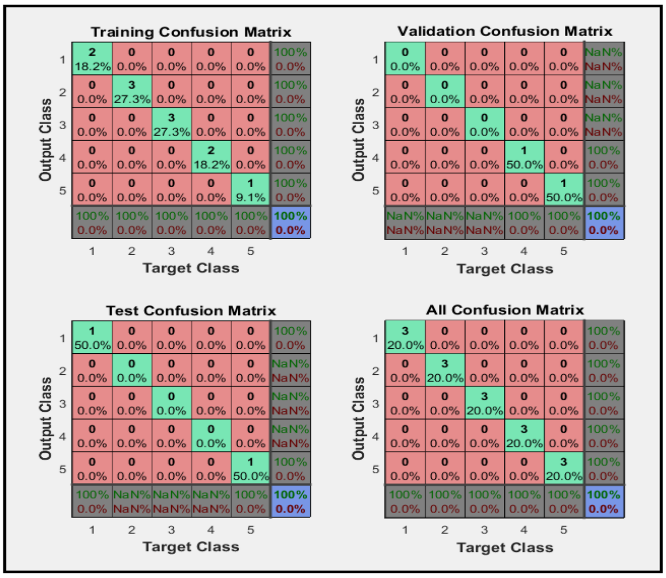

Fig.27. Confusion matrix for training of neural network for power quality disturbance classification

Figure 27 shows that 100% data are perfectly classify the power quality disturbances and not confused for any other data set classification. It means that for remaining 0% data set neural network was in confusion state for classify the fault i.e. not confused for training of data. Perfectly classify all types for power quality disturbances.

V. Conclusion

The proposed method is very much efficient and having efficiency of different power quality disturbance classification is 100 %. In these work neural network was train for different location voltage data base for different power quality disturbance conditions. That technique is also done load flow analysis on IEEE 14 bus system during different power quality conditions. The entire system was design in MATLAB R2015 version software and in which power system toolbox, neural network toolbox and load flow analysis toolbox utilized for system analysis and designing.

References

[1]. E. W. Gunther and H. Mehta, "A survey of distribution system power quality preliminary results," IEEE Transactions on Power Delivery, vol. 10, no. 1, Jan. 1995, pp. 322-329.

[2]. M. B. Hughes, J. S. Chan, and D. O. Koval, "Distribution customer power quality experience," IEEE Transactions on Industrial. Applications, vol. 29, no. 1, Nov./Dec. 1993, pp. 1204-1211.

[3]. J. J. Burke, D. C. Grifith, and J. Ward, "Power quality—Two different perspectives," IEEE Transactions on Power Delivery, vol. 5, no.3, June 1990, pp. 1501-1513.

[4]. I. Daubechies, "Ten Lectures on Wavelets", CBMS-NSF Regional Conference Series in Applied Mathematics for the Society for Industrial and Applied Mathematics, Philadelphia, 1992.

[5]. S. G. Mallat, "Multiresolution approximations and wavelet orthonormal bases" Transactions of American Mathematical Society, vol. 315, no. 1, 1989, pp. 69-87.

[6]. M. P. Collins, W. G.Hurley, and E.Jones, "The application of wavelet theory in an expert system for power quality diagnostics," 30th Universal Power Engineering Conference, 1995.

[7]. Oliver Poisson, Pascal Rioual and Michel Meunier, "New Signal processing tools applied to power quality analysis", IEEE transactions on Power Delivery, vol. 14, no. 2, July 1999, pp. 324-327.

[8]. Oliver Poisson, Pascal Rioual and Michel Meunier, "Detection and Measurement of Power quality disturbances using Wavelet transform", IEEE transactions on Power Delivery, vol. 15, no. 3, July 2000, pp. 214-219.

[9]. P K Dash, B K Panigrahi and G Panda, "Power quality analysis using S transform", IEEE transactions on power delivery, vol. 18, no. 2, April 2003, pp. 23-29.

[10]. M. P. Collins, W. G. Hurley, and E. Jones, "The application of wavelet theory to power quality diagnostics," 29th Universal Power Engineering Conference, 1994.

[11]. Y. Xu, X. Xiao,Y.Yang, and X. Chen, "Application of wavelet transform in power quality analysis," Automated Electric Power Systems, vol. 23, no. 23, 1999, pp.87-93.

[12]. A. M. Gouda, M. M. A. Salama, M. R. Sultan, and A. Y. Chikhani, "Application of multi resolution signal decomposition for monitoring short-duration variations in distribution systems," IEEE Transactions on Power Delivery, vol. 15, no. 1, Apr. 2000, pp. 137-145.

[13]. A. M. Gaouda, M. M. A. Salama, A. Y. Chikhani, and M. R. Sultan, "Application of wavelet analysis for monitoring dynamic performance in industrial plants," North American Power Symposium, Laramie, WY, 1997.

[14]. S. Santoso, E. J. Powers,W. M. Grady, and P. Hoffman, "Power quality assessment via wavelet transform analysis," IEEE Transactions on Power Delivery, vol. 11, no.1, Apr. 1996, pp.56-62.

[15]. Yuan Liao, Automated Analysis of Power Quality Data and Transmission Line Fault Location, Dissertation of Texas A&M University, College Station, Texas, 2000.

[16]. S.Madan and K. E.Bollinger, "Applications of Artificial Intelligence in Power Systems," Electric Power Systems, vol. 41, 1997, pp. 117-131.

[17]. R.C. Bansal, "Bibliography on the fuzzy set theory applications in power systems", IEEE Transactions on Power Systems, vol. 18, no.4, Nov. 2003, pp. 1291- 1299.