ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijareeie.com

Vol. 6, Issue 3, March 2017

Computational Analysis of Sag and Swell in Electrical Power Supply Network

K.Sathiyasekar[1], R.Kamalakannan[2], N.Ravikumar[3] , J.Suman [4], M.Tamil Selvan[5], J.Jayasrinath [6].

[1] Professor, S.A. Engineering College, Chennai, India.

[2],[3] Assistant Professor, S.A. Engineering College, Chennai, India.

[4],[5],[6] UG Scholar, S.A Engineering College, Chennai, India.

ABSTRACT: This research presents new smart approaches for the estimation and complete analysis of the two main power quality factors (sags and swells) using Neural Networks. Typical power quality (PQ) disturbances include sag, swell, harmonics, transients, over voltage, under voltage, momentary and sustained interruptions in a power supply network. Among all these disturbances, sags and swells get prime status, as they can cause necessary damage to industrial customer's equipment and can finally lead to shut down of their system. In this study Principal Component Analysis technique (PCAT) is used to pre-process the raw PQ data and reduce the number of characteristics of real PQ data. Refined data characteristics are then processed through Feed Forward Back Propagation (FFBP) & Recurrent Neural Networks (RNN) for the approximation/prediction of sag and swell. Application of RNN on PQ data demonstrates its good approximation abilities (accuracy for sag & swell approximation=96%) as compared to FFBP neural network (accuracy for sag approximation [93.5%] & swell approximation [91.5%]). The results obtained in this paper are likened with the field data of a power corporation in Australia. This research will facilitate power utilities and industrial customers on common identifications to set a base line for PQ parameters and also to evolve a complete plan for better organization of PQ problems

I. INTRODUCTION

In electrical power organization the nursing and organization of power quality data has become massively important because of the must of incessant availability of quality power supply to customers on maintainable basis. The main problem challenged by modern power values today is the unpredictability of the power system behavior due to unpredicted power quality problems. With the count of non- linear loads in electrical power supply networks, power quality problems have become common [1].

In electrical power organization, not only the count of non- linear loads leads to PQ problems, but mistakes and nonstop switching also causes PQ disturbances. Frequent PQ problems faced by electrical power supply network are harmonics, voltage unbalance, transients and voltage variations important to sag, swell and temporary or long-term breaks [2-3]. Among the mutual PQ problems that occur, sag and swell are of main worry for power businesses as they can create simple losses for industrial customers including costly apparatus damage and close down of their construction. Different researchers have obsessed on the documentation and classification of power quality problems with artificial intelligence computational techniques in electrical control industry. Chaung *et al* [6] worked on credit of many PQ disorders in two parts by wavelet-based neural networks. In the additional part he was successful in applying his method by graphical user interface (GUI) computer database but the proposed brainy system lacked the actual dimension of real PQ events and he had to use a waveform generator to false PQ disorders. Chandel *et al* [7], in their research work have also advanced a wavelet based false neural network classifier using MATLAB/SIMULINK to identify PQ disorders but their research also lacks the actual field belongings of different PQ problems met through electrical power supply network.

These researches will attention exactly on the examination of sag and swell problems in power supply network for actual ground data of a power company in Australia. Intelligent computational methods are used for the examination of sag and swell data. The objective of this exploration is to estimate the sags & swells in three phase controls of the

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power system by neural networks (NN). Principal Module Analysis Technique (PCAT) is used to reduce the large quantity of PQ data qualities. The Feed Forward Back Propagation (FFBP) and Recurrent Neural Networks (RNN) are recycled for smart processing of PQ data. The results got through NN methods are compared with the power value in Australia.

The determination of this exploration is to use forward-thinking intelligent techniques for estimation and complete analysis of sag and swell with real data of power supply network. The work aims at attaining appreciable truth with a view to benefit power values and customs to attack PQ problems and avoid the economic losses since of PQ problems.

Sections II springs the explanation of sag and swell in an electric power supply network. Section III explains the organizations used in this research for the approximation of sag & swell. The different exhibition measures tested in this research are clarified in section IV. The experimental results are recorded in section V, while the assumptions are drawn in section VI.

II. DESCRIPTION OF SAG AND SWELL

Sag and swell are persons definite PQ disturbances, which can normally occur in a power supply network. Power utility engineers are troubled with these PQ disorders as they can be disastrous for customer’s equipment. The regular, sag and swell waveform for a power supply network can be shown as in Fig.1 [8]:

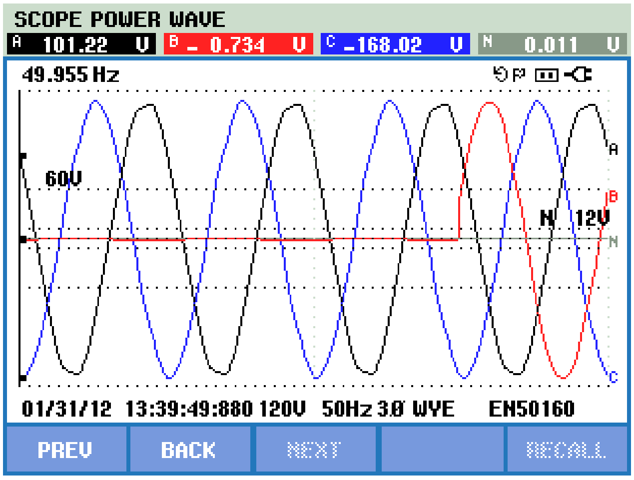

Figure 1. Normal , sag and swell waveforms [8]

A. *pre-processing by Main Section Analysis Technique (PCAT)*

Because of high suggestion in the available power quality data, it is very hard to separate those issues, which are knowingly moving the sags and swells of supply voltages. Therefore a method called Principal Component Analysis Technique (PCAT) [10] is working to amount out those qualities of PQ data, which are founded on maximum alteration. Example of the PQ data feast in two dimensions is shown in Fig. 2(a). This data is used for the clarification of PCAT algorithm. The steps used for the implementation of PCAT are potted below:

1) *Plot of PQ Data and Calculation of Data Mean:* The first step is to plot the PQ data. After this step, the mean value is calculated as shown in Fig. 2(b).

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2) *Shifting of PQ Data to Mean:* To shift the zero axis to the new axis, the mean value has to be subtracted from the value of each feature. Fig.3 (a) represents the new axis after

3) *Establishment of New Data Axis:*

The IEEE 1159-95 normal on monitoring of electrical power quality expresses sag as the discount in voltage/current among 0.1-0.9 per unit in the actual voltage/current while swell as a boost in the voltage/current between 1.1-1.8 per unit. These alterations are analyzed in a period of 0.5 series to greater than 1 min. The detail of PQ disorders with their duration as per IEEE 1159-95 values are given in Table 1[9]:

TABLE I. IEEE STANDARD 1159-1995 FOR SAG AND SWELL [9]

S/N	PQ Disturbances	Duration
1	Instantaneous Sag or Swell	0.5 cycles – 30 cycles
2	Momentary Sag or Swell	30 cycles – 3 seconds
3	Momentary Interruption	0.5 cycles – 3 seconds
4	Temporary Sag, Swell	3 seconds – 1 minute
5	Long Duration	> 1 minute

Power quality nursing and organization has become the main focus for control companies across the globe. In such a situation precise detection and estimate of PQ parameters can help power companies to take acceptable steps to avoid the unfriendly state of dim outs or harmful of customer's equipment.

III. METHODOLOGY FOR SAG AND SWELL ESTIMATE

In this research Principal Component Analysis Technique (PCAT) is employed to decrease the large quantity of power quality data qualities. Feed Forward Back Propagation (FFBP) neural network is used to approximation the values of sags and swells of a power supply network. Finally the recurrent neural network (RNN) is also used to approximation the values of sag and swell of the same supply network previous axis. Fig. 3(b) therefore shows the establishment of new data axis for generating principal components of PQ data.

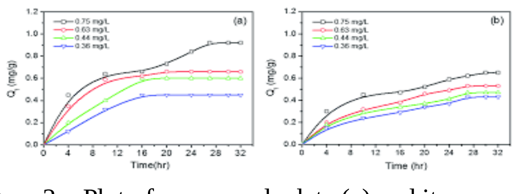

Figure 2. Plot of an example data (a) and its mean (b)

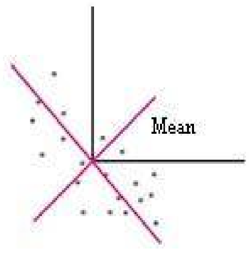

Figure 3. (a) shows the maximum variation in data (Eigen Vectors)

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4) Control of Eigen Values and Eigen Vectors from Covariance Matrix: Eigen standards represent the number of principal components and their meaning in the data; while the Eigen courses signify the dimensions in which the variance of the given data is maximum this supreme variation of data is helpful for extracting the knowledge of new qualities (dimensions) in dataset.

B. Feed Forward Back Propagation Neural Network (FFBP- NN)

Feed Forward Back Propagation (FFBP) is used to estimation the sag and swell in the power distribution network. The Multilayer Perceptron algorithm faces the problem of non- convergence due to which FFBP procedure is proposed. In this algorithm, supervised techniques are castoff. The error in the assessed sag and swell is calculated using least mean squared error algorithm [11]. The mass at each node of FFBP is calculated using (3).

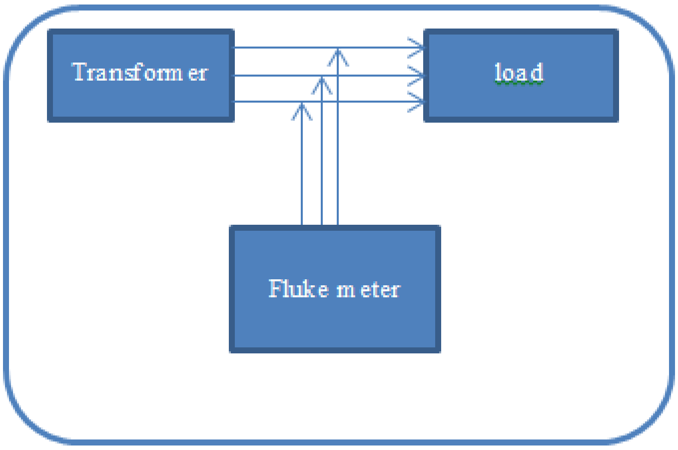

Figure 4 Block diagram

IV. PERFORMANCE MEASURES

It is always wanted to check the reply of a classifier/algorithm to checked its applicability. The different actions like sensitivity, specificity, accuracy and area under receiver operating characteristics (AUROC) give the act measures of a classifier/algorithm.

Figure 5. Testing of power quality issues

Feed-forward networks have the following physiognomies:

1.	Perceptron's are agreed in layers, with the principal layer taking in inputs and the previous layer producing outputs. The middle layers have no connection with the outside world, and later are called hidden sheets.
2.	Each perceptron in one sheet is connected to each perceptron on the following layer. Hence information is constantly "fed forward" from one layer to the next. And this explicates why these grids are named feed-forward networks.
3.	There is not at all joining among perceptron's in the same layer

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C. Recurrent Layer Neural Network (RNN)

Recurrent neural networks (RNN) have chance topologies. The copies using RNN can be industrialized using their central states.
Thus accuracy defines the general sag & swells detection competences of the classifiers/algorithms. Thus the compassion shows the algorithm's capability to accurately estimate the sags & swells whereas the gen of non-false alarm discovery is specified by specificity.

Lastly the classifier/algorithm's compromise between specificity and compassion can be analyzed by receiver operating characteristics curves (ROC). The general accuracy presentation can be analyzed by the area under ROC curves (AUROC) [13].

The "Scaling Bias Weights Method" (SBWM) [14] remains used in this research to analyze the compromise between compassions and specificities (i.e. ROC) of predicted sags and swells values. In this method the output at all node of neural network is processed finished the sigmoid purpose, which is exposed in (7). (FFBP) algorithm, Because of its typical nature of internal States, delays are linked with different exact weights of Neural network the style of RNN is shown in Fig. 5. It takes start response which helps this network to recollect the past inputs. The change between RNN and FFBP neural nets is that of feedback which is available at the effort.

V. EXPERIMENTAL RESULTS

Power quality data is taken from a power distribution company in Melbourne, Australia. PQ monitoring device at the power distribution network site consists of fifteen parameters/attributes of PQ data. The dataset consists of different values of these fifteen different parameters and has been monitored for 92 days consecutively.

The first task in the computational analysis of sags and swells of distribution system is to find those attributes which have maximum variation using PCAT. Only two major components (nonzero Eigen values) were found which could represent the whole dataset. Thus these two highly correlated attributes (principal components) were used to train the neural networks. After the pre-processing using PCAT, the capability of two different neural networks was tested to perfectly estimate the sag and swell values of a distribution network. In feed forward back propagation algorithm, the power quality data is trained from input (pre-processed data) to the output (sag or swell) of a neural network to estimate/predict the sag & swell values.

Overall accuracy of 96% is achieved [sensitivity sag & swell=95.5% and specificity of sag & swell=92.5%] for the estimation of sag and swell using this network.Table II summarizes overall accuracy sensitivity and specificity of FFBP and RNN for saga and swell data.

TABLE II. OVERALL ACCURACY, SENSITIVITY AND SPECIFICITY OF DIFFERENT CLASSIFIERS FOR (I) SAG (II) SWELL

Classifier/ Algorithm	Performance	Sag	Swell
FFBP (Feed Froward Back Propagation)	Accuracy	93.50%	91.5%
	Sensitivity	95.23%	92.30%
	Specificity	82.84%	79.2%
	AU-ROC	0.945	0.925
RNN (Recurrent Layer Neural Network)	Accuracy	96%	96%
	Sensitivity	95.5%	95.5%
	Specificity	92.5%	92.5%
	AU-ROC	0.960	0.960

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The comparison of the two classifiers/algorithms (FFBP & RNN) show that RNN achieved better accuracy than FFBP as a feedback loop in this network enables the RNN to attain the state representations by remembering the neural network weights. These neural network weights are trained through PQ parameters in a way to decrease the false positive and false negative values and increases the overall accuracy.

Fig. 9 shows the ROC curves for both classifiers for sag and swell. The plot of curves above the normal diagonal lines (AUROC>0.5) clearly indicates the usefulness of intelligent computational techniques for identification monitoring and management of PQ problems in electric power system. The area under ROC curve using RNN was calculated to be 0.96, which showed a significant improvement in sag & swell estimation using RNN technique as compared to FFBP.

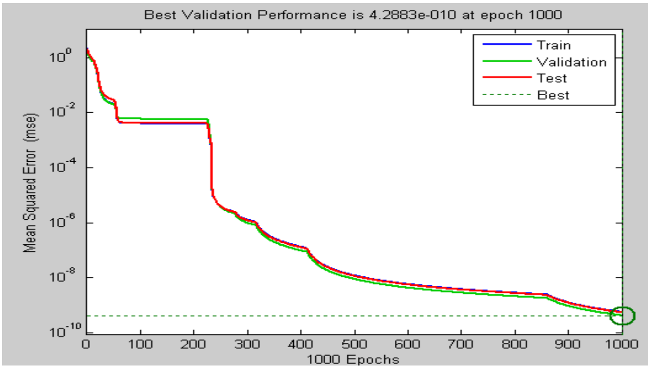


Figure 6. The training, testing and validation error curves for sag using FFBP-NN.

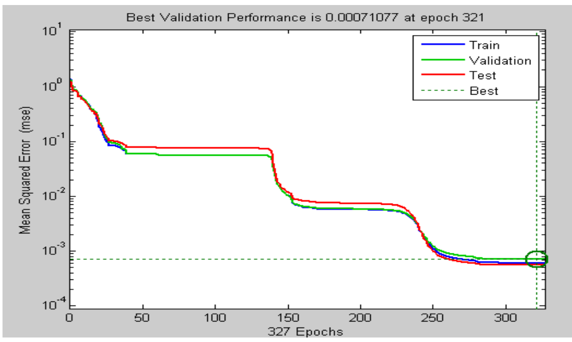


Figure 7. The training, testing and validation error curves for swell using FFBP-NN

The training, testing and validation error curves for sag & swell are shown in Fig. 6 and Fig. 7 respectively. The FFBP estimated the sags and swells values with an overall accuracy of 93.50% (sag) & 91.5% (swell). For sag estimation, the sensitivity was calculated to be 95.23% and the specificity of 82.84% was observed. While the sensitivity and specificity of swell estimation using the same model were 92.30% & 79.2% respectively. The area under ROC curve using FFBP neural network for sag and swell was calculated to be 0.945 and 0.925 respectively.

The recurrent layer neural network (RNN) was also trained with PQ data and convergence is achieved in 30 epochs. In this case the network was trained for both sag and swell estimation at the same time. The training, cross validation and testing mean squared training error curves are shown in Fig.8.

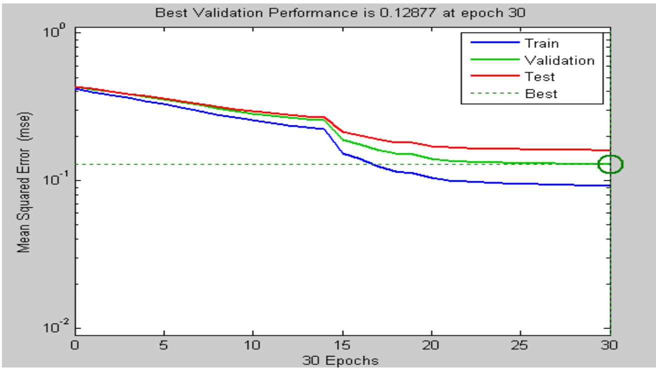
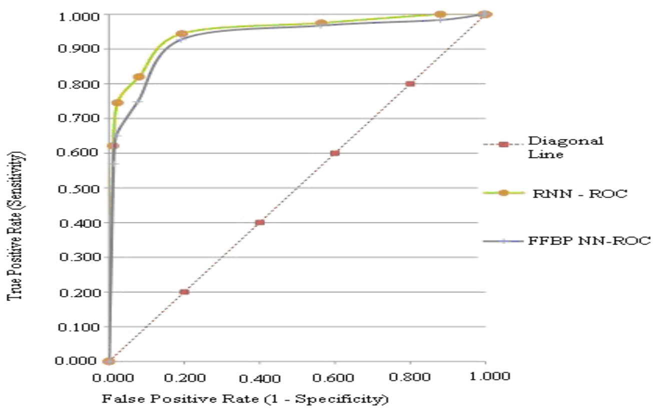
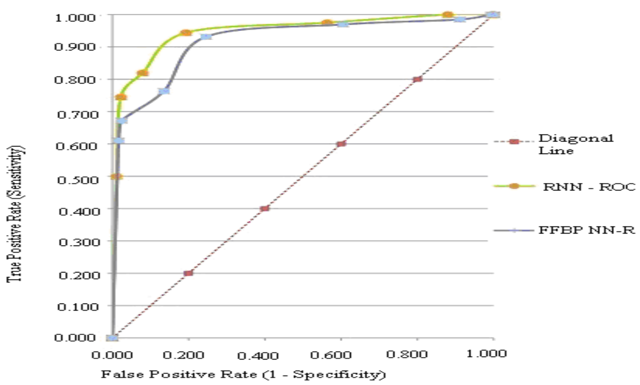


Figure 8. The training, testing and validation error curves for sag & swell using RNN.





transients etc) and sags and swell of electrical power distribution network of the power company under study. However in order to achieve accuracy beyond 96%, other PQ parameters need to be explored for computational analysis. These parameters can be integrated with PQ dataset to improve the accuracy in estimation and predictions of sag and swell for the power distribution network.

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VI. CONCLUSION

Problems related to sag and swell faced by industrial customers and power companies can be controlled by efficiently estimating/predicting their values and comparing them with allowable standards. In this research sag and swell values are efficiently predicted with appreciable accuracies for an electric power company in Melbourne, Australia. The outcome of this research is that PQ problems can be identified and classified with high accuracy using artificial intelligence computational techniques. ANN techniques in this research can be used to develop adaptive PQ meters with multiple threshold of sag and swell as compared to normal practice of monitoring PQ disturbances with particular threshold. The accuracy in prediction and estimation of PQ parameters help power. which showed a significant improvement in sag & swell estimation using RNN technique as compared to FFBP.

REFERENCES

[1]Irfan I.Mujawar,Komal S.Duba V.Ittam,Sneha N.navgire,Isak I.Mujawar,"Power Quality Audit of NKOCET-A case study", International conference on Energy systems and Applications(ICESA),2015.

[2]Ibrahim Sefa,Necmi Altin,Erdem Asa,Kerim Colak,"Power Quality Analyzer for Three phase systems",International conference on Renewable Energy Research and Applications,Madrid,Oct 2013.

[3]Cui Lina,Huang Yanqiu,Jiao Deqiang,yu Weibo,"Detection of Power Quality Analyzer", "International conference on computer,Mechatronics,Control and Electronic Engineering(CMCE),2010.

[4]Xuesong Zhou, Tianxi ren, Youjie Ma and Zhiqiang GAO,"The Discussion on Smart Distribution Grid system","Internaional Conference on Mechatronics and Automation, 2016.

[5]Marcos Vinicius Eloy Xavier, "High Performance Power Quality Monitoring System", 2016.

[6]Almeida, Bar bosa, "Study of Financial Losses Due to Harmonic Distortion in a telephone Switching office, 2016.

[7]Ollen, Math H.J."Solving Power Quality problems: voltage sags and interruptions", New York: IEEE Press, 1999.