ARTIFICIAL NEURAL NETWORKS FOR INTELLIGENT REAL TIME POWER QUALITY MONITORING SYSTEM

Ajith Abraham and Baikunth Nath
Gippsland School of Computing & Information Technology
Monash University, Churchill 3842, Australia
{Ajith, Baikunth.Nath@infotech.monash.edu.au}

ABSTRACT: Most of the modern industrial power quality monitoring systems are used for the pre-fault alarming and load flow analysis. In this paper, we present an Artificial Neural Network (ANN) model for intelligent utilization of power and for monitoring the power quality. The proposed ANN system will assist the conventional monitoring systems with added intelligence. For on-line monitoring, voltage and current are fed into the network after preprocessing and standardization. ANN is trained with the 24-hour load demand pattern as well as the different sorts of harmonics and waveform abnormalities. The performance of the proposed method is evaluated by comparing the test results with the actual expected values.

Keywords: Active power, reactive power, apparent power, power quality, power factor prediction, harmonics classification, neural networks

1. INTRODUCTION

A wide variety of real time power quality monitoring systems are serving the power industry. A quick review will show that most of the monitoring systems are used just to track the quality of the power supply and for load flow analysis [1-2], [6]. For the monitoring system to be more intelligent, we propose the use of a feedforward artificial neural network (ANN) for predicting the trend of power factor, reactive power and active power. By predicting the power factor and active power demand it is possible to automate the control of reactive power load and to better utilize the volt-amperes (VA) inflow. Efficient usage of the VA loading will not only improve the overall grid condition but also reduce the consumer's industrial tariffs. Depending on the predicted power factor, power factor corrective measures could be turned on or off to control the VA inflow into the plant. This prediction system will be extremely useful for automated control of power inflow, especially in the countries where there are limitations on the usage of consumers' peak VA maximum demand.

Modern complex manufacturing systems rely heavily on Computer Numerical Controlled (CNC) machines, variable speed drives and robotic devices which often require a high level of reliability from the incoming electricity supply. Due to the widespread usage of non-linear loads there has been a significant increase in the harmonic content of the 3-phase supply, raising serious power quality issues [5]. We attempted the usage of ANNs for classification of harmonics and abnormal waveforms. Among the commonly used neural network models, Self-Organising Maps (SOM) are reputed for pattern classification. We tried SOMs to classify harmonics and abnormal waveforms but the results were not encouraging. However, the feedforward neural networks proved efficient and were able to classify different harmonics and abnormal waveforms with almost 100% accuracy.

2. PRACTICAL IMPORTANCE OF REACTIVE POWER CONTROL

The ratio of active power (P) measured in watts to the apparent power (S) in volt-amperes is termed the power factor:

$$\text{Power factor} = \cos(\varphi) = \frac{\text{P}}{\text{S}} = \frac{\text{resistance (R)}}{\text{impedance (Z)}}.$$

It has become a normal practice to say that the power factor is lagging when the current lags the supply voltage and leading when the current leads the supply voltage. This means that the supply voltage is regarded as the reference quantity. A majority of loads served by a power utility draw current at a lagging power factor. When the power factor of the load is unity, active power equals apparent power (P = S). But, when the power factor of the load is less than unity, say 0.6, the power utilized is only 60%. This means that 40% of the apparent power is being utilized to supply the reactive power, VAR, demand of the system. It is therefore clear that the higher the power factor of the load, the greater the utilization of the apparent power [4]. For the generating and transmission stations, lower the power factor the larger must be the size of the source to generate that power, and greater must be the cross-sectional area of the conductor to transmit it. In other words, the greater is the cost of generation and transmission of the power. Moreover, lower power factor will also increase the I^2R (I denotes current) losses in lines/equipment as well as result in poor voltage regulation [9].

The apparent and active power loading patterns for a typical heavy engineering industry for a 24-hour period are shown in Figure 1. The difference between the apparent and active power contributes for the reactive power. Observed data shows that the maximum and minimum VAR requirements are 2.96 MVAR and 0.014 MVAR, respectively. If suitable power factor compensation was made when the reactive power demand was increasing, the plant might not have drawn much apparent power from the grid. The task is to predict the upward and downward trend of the reactive power demand and provide required power factor compensation. A close analysis of the daily power demand chart of the captioned plant reveals that the demand patterns are very similar every day. Neural networks are perhaps the best technique for learning relationships amongst variables. For this problem we used a feedforward artificial neural network (ANN) to learn the relationship between the power factor, voltage and current. The proposed ANN was trained on the data taken at every minute for a 24-hour period to predict the required parameters, and tested to evaluate the prediction accuracy.

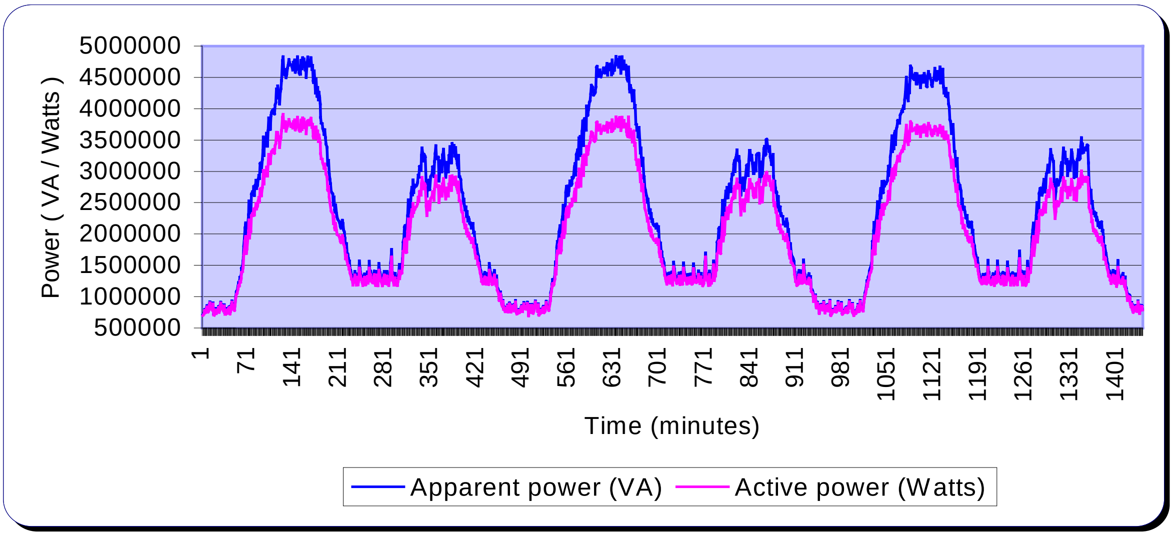

Figure 1. Active Power (Watts) and Apparent Power (VA) Demand for a heavy engineering industry.

3. POWER QUALITY ISSUES

The interest in power quality has increased during the latest years. A power quality problem can be defined as “a problem due to frequency, voltage regulation, voltage dips, flicker, transients, harmonics, power factor and 3-phase imbalance”[1], [7]. All machines affect the grid by the production of harmonics, voltage variations or by their power factors. At the same time the performance of the machines is affected by the power quality on the distribution network [5]. The number and usage of machines is increasing rapidly and thereby the power quality is being further affected. Machine drives can be disturbed by transients or other irregularities in the feeding voltage. The drives may as well disturb the network voltage by the production of harmonics, load changes and varying power factor [6]. The harmonic content and magnitude existing in any power system is largely unpredictable, and their effects will vary widely in different parts of the same system due to varying effects of different frequencies. Since the distorted wave is in the supply system, harmonic effects may occur at any point on the system where the distorted wave exists. This occurrence is not limited to the immediate vicinity of the harmonic-producing device. When power is converted to direct current or some other frequency, harmonics will exist in any distorted alternating component of the converted power. Harmonics may be transferred from one circuit or system to another by direct connection or by inductive or capacitive coupling. Harmonics of 50 Hz are in the low-frequency audio range, the transfer of these frequencies into communication, signaling, and control circuits employing frequencies in the same range may cause unacceptable interference. In addition, harmonic currents circulating within a power circuit reduce the capacity of the current-carrying equipment and increase losses without providing any useful work.

Conventional power monitoring systems are capable of identifying most of the power quality issues as well as classification of harmonics and abnormal waveforms. To further augment robustness in monitoring and to improve performance during worst conditions, we propose the use of neural networks as an alternative method for classification of the various types of harmonics and abnormal waveforms.

4. ARTIFICIAL NEURAL NETWORKS AND TRAINING GUIDELINES

A neural network is characterised by the network architecture, the connection strength between pairs of neurons (weights), node properties, and updating rules. An important feature of the artificial neural network (ANN) is its capability to learn and generalise from a set of training data. ANN can learn by adapting its weights to changes in the surrounding environment, can handle imprecise information, and are able to generalise from known tasks to unknown ones. The success of the ANN performance depends upon how accurate and generalisable the learning has been. There are three broad paradigms of learning: supervised, unsupervised (or self-organised) and reinforcement (a special case of supervised learning). The core difference between supervised and unsupervised learning is that in supervised learning the system directly compares the network output with a known correct or desired answer, whereas in unsupervised learning the output is not known. Unsupervised training allows the neurons to compete with each other until winners emerge. The resulting values of the winner neurons determine the class to which a particular data set belongs. Reinforcement learning is a form of supervised learning where the adaptive neuron receives feedback from the environment that directly influences learning.

In supervised learning, the training patterns can be thought of as a set of ordered pairs $\{(x_1, y_1), (x_2, y_2), \ldots , (x_p, y_p)\}$ where x_i represents an input pattern and y_i represents the output pattern vector associated with the input vector x_i. The process of training the network is of finding the gradient of the error surface (in weight space) of the actual output produced by the network with respect to the desired result.

The following guideline will be of help as a step by step methodology for training a network.

- **Choosing the number of neurons**

The number of hidden neurons affects how well the network is able to separate the data. A large number of hidden neurons will ensure the correct learning and the network is able to correctly predict the data it has been trained on, but its performance on new data, its ability to generalise, is compromised. With too few a hidden neurons, the network may be unable to learn the relationships amongst the data and the error will fail to fall below an acceptable level. Thus, selection of the number of hidden neurons is a crucial decision. Often a trial and error approach is taken starting with a modest number of hidden neurons and gradually increasing the number if the network fails to reduce its error. A much used approximation for the number of hidden neurons for a three layered network is $N= \frac{1}{2} (J + K) + \sqrt{P}$, where J and K are the number of input and output neurons and P is the number of patterns in the training set.

- **Choosing the initial weights**

The learning algorithm uses a steepest descent technique, which rolls straight downhill in weight space until the first valley is reached. This valley may not correspond to a zero error for the resulting network. This makes the choice of initial starting point in the multidimensional weight space critical. However, there are no recommended rules for this selection except trying several different starting weight values to see if the network results are improved.

- **Choosing the learning rate**

Learning rate effectively controls the size of the step that is taken in multidimensional weight space when each weight is modified. If the selected learning rate is too large then the local minimum may be overstepped constantly, resulting in oscillations and slow convergence to the lower error state. If the learning rate is too low, the number of iterations required may be too large, resulting in slow performance. Usually the default values of most commercial neural network packages [8] are in the range 0.1 – 0.3 providing a satisfactory balance between the two consequences. If the network fails to reduce its error, then reducing the learning rate may help improve convergence to a local minimum of the error surface.

- **Choosing the activation function**

The learning signal is a function of the error multiplied by the gradient of the activation function $\frac{df}{d(net)}$. The larger the value of the gradient, the more weight the learning will receive. For training, the activation function must be monotonically increasing from left to right, differentiable and smooth.

5. PROPOSED ANN MODEL AND EXPERIMENTATION RESULTS

The experimental system consists of three stages: Problem modeling and data simulation, network training and performance evaluation.

- **Modeling the problem and data simulation**

A heavy engineering manufacturing plant is considered for the prediction of power factor, reactive power and active power. For a typical 24-hour load demand pattern of the plant 1440 data sets were generated. The input parameters considered are the voltage and current. The voltage (V) was taken as a random value (i.e +/- 2.5% of the normal value) to cater for worst conditions in the grid voltage regardless of the plant load. Using the known values of current (I), power factor (cos(φ)) and random value of voltage, active power and reactive power values were calculated [7].

- **ANN training for prediction and classification**

    a) **Prediction of power demand**: We used a feedforward neural network with 2 hidden layers in parallel, 2 input neurons corresponding to the input variables and 3 output neurons. Each of the input neurons was directly connected to each of the neurons in the hidden layers as well as to each of the neurons in the output layer. The predicted outputs were power factor, active power (Watts) and reactive power (VAR). The network was trained using 70% of the simulated data and the remaining 30% data was used for testing and validation. Initial weights, learning rate and momentum used were 0.3, 0.1 and 0.1, respectively. The training error was set at 0.00075.

    b) **Classification of harmonics:** The network used in this case consists of 30 input neurons corresponding to the input variables, 2 hidden layers in parallel and 6 neurons for the output layer. Each of the input neurons was directly connected to each of the neurons in the hidden layers. ANN was trained using 114 data sets. Each data set was represented by values taken at 30 sampling instants. In addition to the normal waveform, the 3^{rd}, 5^{th}, 7^{th}, 9^{th} and 11^{th} harmonics were considered. For training, 80% of the **data sets were** used. The remaining 20% data sets were used for testing and validation. Initial weights, learning rate and momentum used were 0.3, 0.1 and 0.1, respectively. The training was terminated after 30,000 epochs

    c) **Classification of abnormal waveforms:** We used a feedforward network with input layer consisting of 60 neurons corresponding to the input variables and output layer consisting of 4 neurons. Each of the 60 input neuron was directly connected to each of the neurons in the 2 hidden layers. ANN was trained using 60 data sets. Each data set was represented by values taken at 60 sampling instants. Besides the normal waveform, the other waveforms considered were spikes or abnormalities on the positive cycle, spikes or abnormalities on the negative cycle and a mixture of spikes or abnormalities on both the positive and negative cycle. Initial weights, learning rate and momentum used were 0.3, 0.1 and 0.1, respectively. The training was terminated after the error had settled.

- **Performance and results achieved**

    a) **Prediction of power demand:** The three outputs are the power factor, active power (Watts) and reactive power (VAR). Figures 2, 3 and 4 illustrate the test results for each of the predicted outputs. The network performance is given below.

Training time taken:	*8.11 minutes (on Gateway Solo Intel 233MHz Pentium platform)*
Learning epochs:	*1024*
Error achieved:	*0.000732 (Training set), 0.000079 (Test set)*
Correlation:	*0.9998 (Watts), 0.9938 (Power factor), 0.9992 (VAR)*
R squared:	*0.9997(Watts), 0.9876 (Power factor), 0.9984 (VAR)*

From the experimental results, it is clear that the proposed neural network performed extremely well in predicting the output parameters.

b) Classification of harmonics: Error achieved for harmonics classification = 2×10^{-9}

Harmonics	Actual Quantity	ANN Classified	Correctly classified (%)
Normal	19	19	100
3rd	19	19	100
5th	19	19	100
7th	19	19	100
9th	19	19	100
11th	19	19	100
Total	114	114	100

c) Classification of waveforms: Error achieved for waveform abnormality classification = 1.5×10^{-7}

Abnormality	Actual Quantity	ANN classified	Correctly classified (%)
Normal	16	16	100
+ve cycles	15	15	100
-ve cycles	14	14	100
+/- cycles	15	15	100
Total	60	60	100

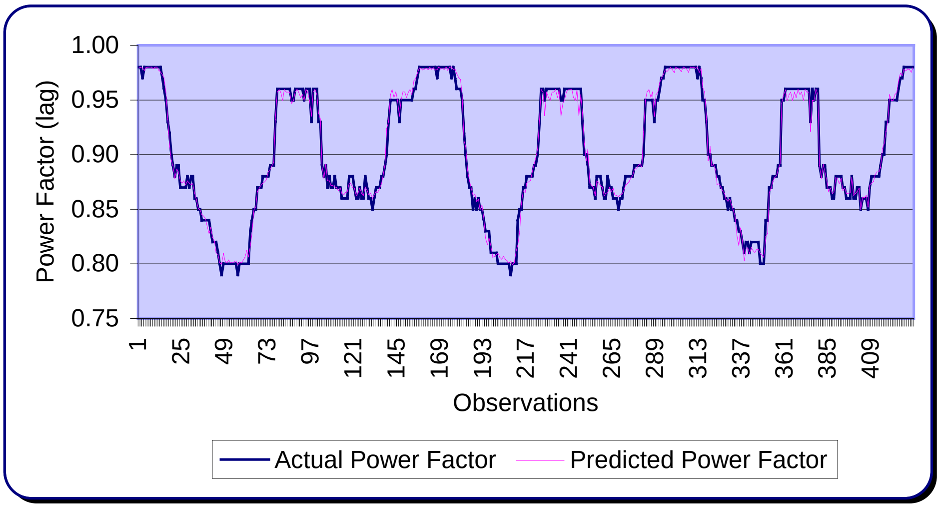

Figure 2. Test Result – Predicted Power Factor

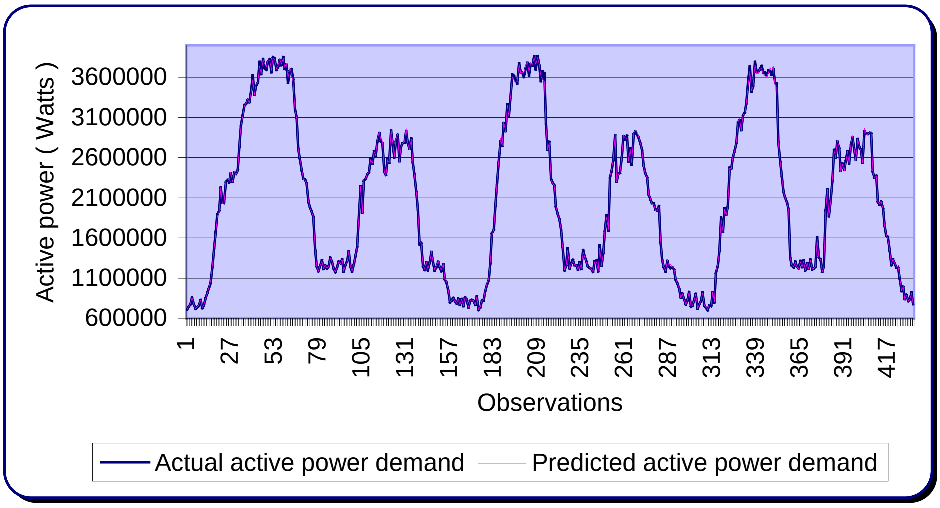

Figure 3: Test Result - Predicted Actual Power Demand

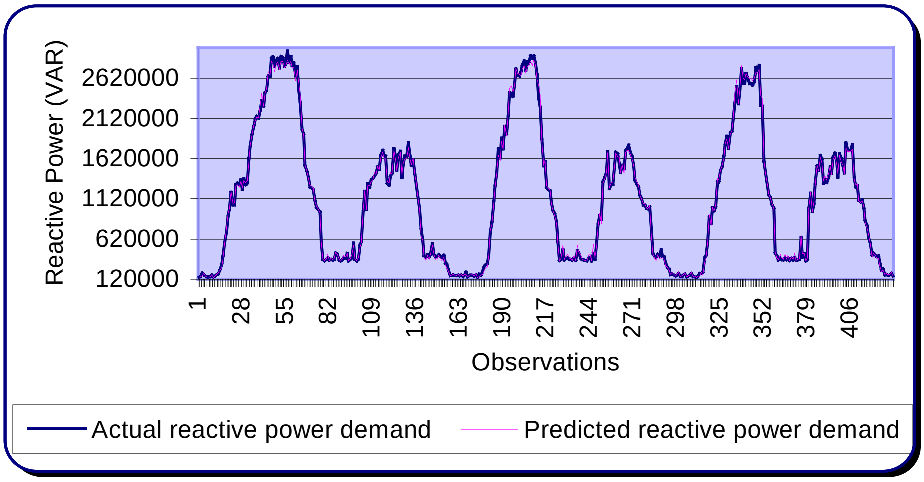

Figure 4: Test Result – Predicted reactive power demand (VAR)

6. CONCLUSIONS

In this paper, we propose the usage of Artificial Neural Networks (ANNs) to make the conventional real-time power monitoring systems more intelligent. We attempted to make use of the fault tolerant prediction and classification capability of ANNs [3]. Using a feedforward ANN, the power factor, active power and reactive power for a heavy engineering industry were predicted and the test results obtained were completely satisfactory. For the predicted power factor, active power and reactive power the R-squared values obtained were *0.9876, 0.9997 and 0.9984,* respectively. The high values indicate that the ANN is fully trained and is capable of predicting the results within the prescribed error range. For this problem, we have considered random values of input parameter voltage to test the learning ability of ANN during worst conditions. The performance could have been even better if the observed rather than simulated values of voltage were used. We also attempted to classify the harmonics and abnormal waveforms using feedforward ANNs and the errors achieved were of the order 2×10^{-9} and 1.5×10^{-7}, respectively, indicating that classification is almost 100% accurate. Moreover, ANNs are very robust, capable of handling the noisy and approximate data that are typical in power systems, and therefore may prove to be more reliable during worst conditions.

ACKNOWLEDGMENTS

The authors wish to thank the two anonymous referees for their constructive comments that improved clarity of the paper.

REFERENCES

1 Allan Collinson, Power Quality: the volts and amps of electricity supply, IEE Review, Volume 45 (3), May 1999.

2 David Sawyer, Non-stop Monitoring, *IEE Review*, Volume 45(3), May 1999.

3 Erdinc Turckan, Real-time Spectral pattern recognition using neural network for condition monitoring, *Proceedings of the Maintenance and Reliability Conference, Volume 2, Chapter 56*, May 1998.

4 Miller T J E, Reactive Power Control in Electric Systems, *Wiley – Interscience*, 1982.

5 Peter Lynch, An active approach to harmonic filtering, *IEE Review*, Volume 45(3), May 1999.

6 Peter J Tavner and James Penman, Condition Monitoring of Electric Machines, *Research Studies Press Ltd, England*, 1987.

7 Richard C Dorf, The Electrical Engineering Handbook, *CRC-IEEE press*,1997.

8 Ward Systems Group, Neuro Shell 2 version 4, 1998.

9 Westinghouse Electric Corporation (Central Station Engineers), Electrical Transmission and Distribution Reference book, 1964.