MEASUREMENT AND EVALUATION OF INSTANTANEOUS REACTIVE POWER USING NEURAL NETWORKS

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ABSTRACT -
The erratic disturbance caused by an electric arc furnace requires a fast and accurate VAr evaluation algorithm for compensation. This paper describes the development of a novel method using the approach of Artificial Neural Networks (ANN) to evaluate the instantaneous VAr. Comparing to the conventional methods, this neural network based algorithm is capable of operating at a much lower sampling rate and delivering an accurate and fast response output. By hardware implementation of this algorithm using neuron chips, the erratic VAr fluctuation can be accurately estimated for compensation.

INTRODUCTION

The electric arc furnace hitherto still provides the most efficient way of producing alloy steels from scrap metals. In the United States alone, between 1975 and 1981, some 15 million tons of newly installed arc furnace capacity brought the arc furnaces shares up to one third of the total production [1]. The arc furnace, however, is a highly non-linear plant; it generates a very fluctuating VAr caused by the rapid, large and erratic variations in furnace current which is always considered as a disturbance to the electrical-supply network. This disturbance causes an unacceptable level of voltage fluctuation and, as a consequence, causes severe light flicker to other loads connected to the same supply grid [2]. To operate such a rapidly fluctuating reactive plant requires a responsive static VAr compensation system. Although the innovation in power electronics technology has enabled the development of high speed static VAr compensators [3-5], an advancement in compensators alone cannot provide a complete solution for an electric arc furnace compensation. As the controller of the compensator must be capable of evaluating the instantaneous VAr flows into the uncompensated supply grid accurately. Overall success depends on accurate, and fast convergence in the instantaneous VAr evaluation algorithm [6].

Because the arc furnace has a highly fluctuating characteristic, there has been an interest in predicting the level of arc furnace disturbances by using statistical methods. This paper describes a novel method, which is based on artificial neural networks, to evaluate instantaneous VAr. With a more accurate and fast converging real-time instantaneous VAr evaluation algorithm, the amount of disturbance generated by the arc furnace can be better controlled and suppressed.

The first part of the paper presents a mathematical model that will be used in later sections for the analysis of conventional methods and the development of this novel instantaneous VAr evaluation algorithm. The second part of this paper briefly discusses, and compares the limitations of conventional methods used for real-time instantaneous VAr evaluation. The third part of this paper introduces the Back-propagation ANN and describes the formation of a real-time instantaneous VAr evaluation method based on this approach.

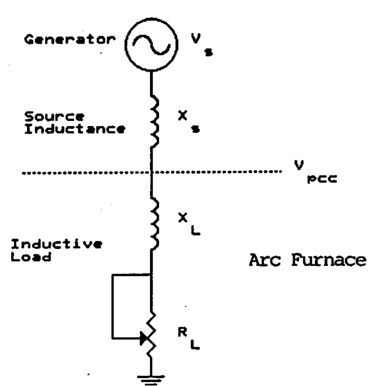

Figure 1 Single phase equivalent circuit for an arc furnace

ARC FURNACE MODEL

An arc furnace mathematical model is firstly established for the investigation of conventional VAr evaluation

94 WM 255-0 PWRD A paper recommended and approved by the IEEE Power System Instrumentation & Measurements Committee of the IEEE Power Engineering Society for presentation at the IEEE/PES 1994 Winter Meeting, New York, New York, January 30 - February 3, 1994. Manuscript submitted October 2, 1992; made available for printing December 29, 1993.

methods and the later development of an ANN based instantaneous VAr evaluation algorithm. In Fig. 1, a single phase inductive load with varying resistance fed through a source impedance of negligible resistance is used to represent a typical electric arc furnace connected to the supply grid [6]. The erratic fluctuation of the furnace resistance caused by the melting of metal scraps is modelled by R_L. The system parameters are defined as:

$$v_s = V_s \sin(\omega t) \tag{1}$$

By solving the following differential equation

$$\frac{di_L}{dt} + \frac{i_L R_L}{L_L} = \frac{V_s}{L_L}\sin(\omega t)$$

$$i_L = \frac{V_s}{Z_{L2}}\left[\sin(\omega t-\phi_2) + \sin(\phi_2-\omega t_1)\, e^{-A}\right]$$

$$+ \frac{V_s}{Z_{L1}}\sin(\omega t_1 - \phi_1)\, e^{-A} \tag{2}$$

$$A = \frac{R_{L2}(t-t_1)}{L_L}$$

$$v_{pcc} = v_s - i_L X_s \tag{3}$$

where v_{pcc} is the voltage at the point of common coupling, t_1 is the time at which the load impedance varies from Z_{L1} to Z_{L2} because of the change in the arc furnace resistance from R_{L1} to R_{L2}. Where Z_{L1}, Z_{L2}, ϕ_1 and ϕ_2 are defined as follows:

$$Z_{L1} = \sqrt{R_{L1}^2 + X_L^2}$$

$$Z_{L2} = \sqrt{R_{L2}^2 + X_L^2}$$

$$\phi_1 = \tan^{-1}\left(\frac{\omega L_L}{R_{L1}}\right)$$

$$\phi_2 = \tan^{-1}\left(\frac{\omega L_L}{R_{L2}}\right)$$

Based on the above equations, Fig. 2 are the simulation of the variation of the v_{pcc} and load current i_L due to R_L varying at pseudo-random in the range between 50Ω to 250Ω, and the frequency of variation ranged from 2 Hz to 100 Hz.

In later sections of this paper, analysis and development of different types of real-time VAr evaluation algorithms will all be based on this arc furnace model.

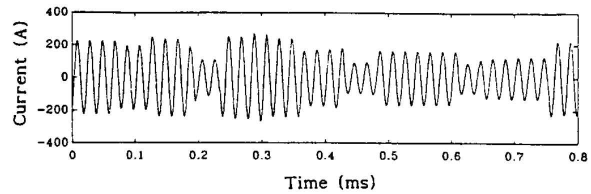

Figure 2a Variation in arc furnace current with time

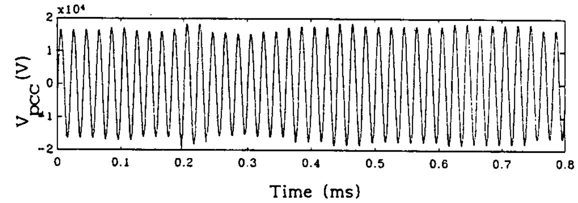

Figure 2b Variation in v_{pcc} with time

STATEMENT OF PROBLEMS

There are four conventional methods commonly used for the evaluation of VAr [6]. The instantaneous VAr can be evaluated by A) current sampling at voltage cross over, B) volt-ampere product, C) parameter cross product and D) rate of change of parameters. Using Eqtns. (1-3), the performance of each VAr evaluation algorithms will be discussed and compared.

A) Current sampling at voltage Cross Over

The output of this algorithm is a quantised level corresponding to the inductive component of the load current given by

$$I_x = I_{Lm}\sin(x\pi - \phi_x) + \text{dc component} \tag{4}$$

where I_x is the load current measured at the x^{th} v_{pcc} zero cross over, and I_{Lm} is the peak value of the load current. To minimise the effect of current harmonics and transients, the average value is used. The load VAr over M cycles is then proportional to

$$\bar{I}_{LM} = \sum_{x=1}^{2M} \frac{I_x}{2M} \tag{5}$$

In Fig. 3c, it shows that the output response of this algorithm has a noticeable delay. Although the response seems to be fast, it has a significant overshoot. Apparently, the overall step response of this algorithm cannot cope with an abrupt change in load current satisfactorily. This algorithm is not suitable for the application of arc furnace VAr compensation.

B) VAr evaluation by volt-ampere product

The integral over one period of the product of voltage and a quarter of cycle delayed current can be used to evaluate the steady state VAr flow.

$$Q_L = -\frac{1}{T}\int_{-T}^{0} v_{pcc}(\omega t)\ i_L[\omega(t-\frac{T}{4})]d(\omega t) \qquad (6)$$

where T is the period of supply. This Volt-Ampere Product algorithm can be implemented by the voltage and current samples as given by

$$Q_{L,Pn} = -\sum_{x=P+1}^{P+n} \frac{v_{pcc,x}\ i_{L,x-n/4}}{n} \qquad (7)$$

where $Q_{L,Pn}$ corresponds to the running average of the volt-ampere product and n is the number of samples per cycle of supply voltage.

The integral properties of this algorithm has an effect of reducing the bandwidth and results in attenuating higher order harmonics. The output of this algorithm shown in Fig. 3d is a closer approximation to the steady state fundamental VAr flowing in the network because of the reduced bandwidth. The output response of this algorithm is slightly sluggish. This may not be acceptable to a fast response compensation system.

C) VAr evaluation by parameter cross product

The reactive power flow in the system may also be evaluated by obtaining the differential cross product of the alternately delayed voltage and current parameters as given by

$$Q_L = \frac{1}{2}(P_2 - P_1) \qquad (8)$$

where

$$P_2 = v_{pcc}[\omega(t-\frac{T}{4})]\ i_L(\omega t) \qquad (9)$$

$$P_1 = v_{pcc}(\omega t)\ i_L[\omega(t-\frac{T}{4})] \qquad (10)$$

This can be represented by discrete parameter samples and implemented as follows,

$$Q_{L,x} = \frac{v_{pcc,x-n/4}\ i_{L,x} - v_{pcc,x}\ i_{L,x-n/4}}{2} \qquad (11)$$

To implement this technique as a running average and hence reduce the distortion due to isolated voltage and current spikes, we have

$$Q_{L,PN} = \sum_{x=P+\frac{n}{4}}^{P+N} \frac{v_{pcc,x-n/4}\ i_{L,x} - v_{pcc,x}\ i_{L,x-n/4}}{n} \qquad (12)$$

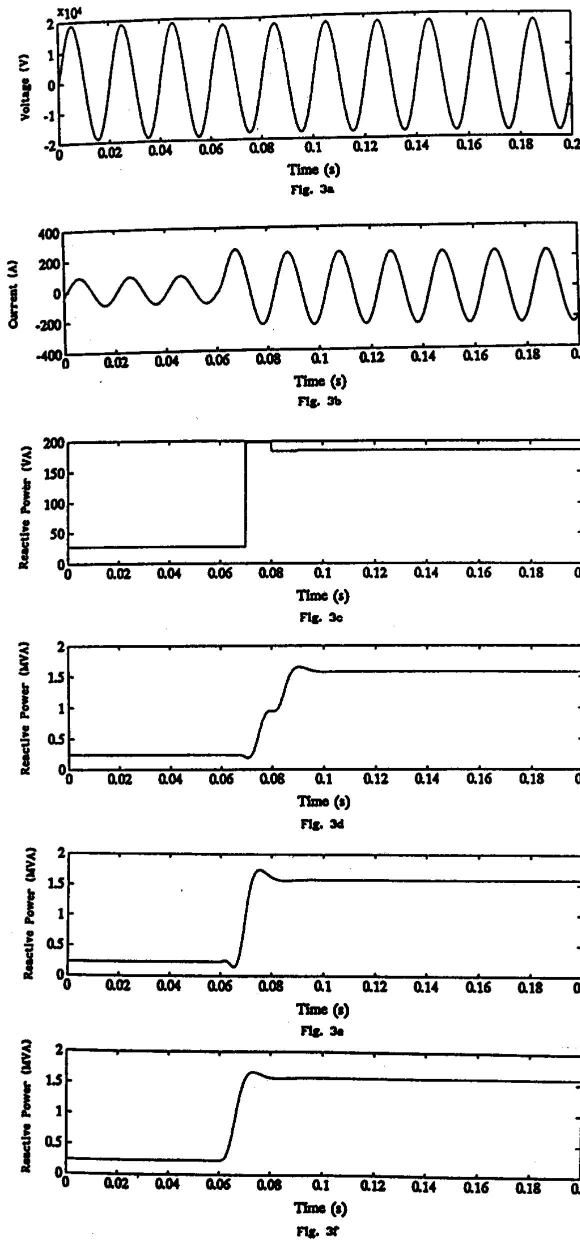

Figure 3a & 3b - Computer simulation of V_{pcc} and i_l
3c - The output of algorithm A
3d - The output of algorithm B (N=25)
3e - The output of algorithm C (N=25)
3f - The output of algorithm D (N=25)

where P represents the running average summation point and N is the number of samples representing the summation period.

Fig. 3e shows that the response of this algorithm converges much faster than the previous two, but it has a significant overshoot and undershoot.

D) VAr evaluation as a function of the rate of change of parameters.

The steady state value of VAr-flow in the electrical supply network can be evaluated by the function shown below

$$Q_L = \frac{1}{k}\int_0^k \bar{Q}_L \, d(\omega t) \tag{13}$$

where k is the desired integration interval and $\bar{Q}_L$ is defined by

$$\bar{Q}_L = \frac{v_{pcc}(\omega t)}{2}\frac{d i_L(\omega t)}{d(\omega t)} - \frac{i_L(\omega t)}{2}\frac{d v_{pcc}(\omega t)}{d(\omega t)} \tag{14}$$

and Q_L can be simplified to

$$Q_L = \frac{1}{2} V_m I_{Lm} \sin\phi \tag{15}$$

By using the voltage and current samples, Eqtn. (14) is given as

$$\bar{Q}_{L,x} = \frac{v_{pcc,x}\left(i_{L,x} - i_{L,x-1}\right) - i_{L,x}\left(v_{pcc,x} - v_{pcc,x-1}\right)}{2\tau\omega} \tag{16}$$

where τ is the sampling period.

$Q_{L,PN}$ is the running average of $Q_{L,x}$ over the integration period k.

$$Q_{L,PN} = \frac{1}{N}\sum_{x=P+1}^{P+N} \bar{Q}_{L,x} \tag{17}$$

$$k = N\tau$$

where P represents the running average summation point and N is the number of samples representing the summation point.

Figure 3f shows that the response of this algorithm is capable of providing a very good balance in response time and damping. Because of its differential property, this algorithm has an effect on increasing the bandwidth and results in higher order harmonics amplification. Although this algorithm has the drawback of high frequency noise amplification, it can generally be compensated by the system low-pass filter.

In accordance with the above analysis, algorithm D is selected for the development of an ANN based algorithm. From Eqtn. (17), the evaluated $Q_{L,PN}$ can be assumed as an instantaneous VAr by reducing the integration interval k. It is also noticed that the evaluation accuracy is affected by the number of sampling point N. In order to achieve a very small integration interval, k, and a very large sampling point, N, a very high sampling frequency, $1/\tau$, is required. In later section, the development of a new VAr evaluation algorithm, based on back-propagation neural networks, will be thoroughly described. With a special training procedure, the output of this neural network based algorithm can be very close to the instantaneous VAr and is capable of delivering a higher accuracy without the requirement of operating at a higher sampling frequency.

BACK-PROPAGATION NEURAL NETWORKS

A neural network is a parallel, distributed information processing structure consisting of processing elements known as neurons interconnected together with unidirectional signal channels called connections. Each neuron has a single output connection that branches into as many collateral connections as desired. Each collateral connection carries the same signal. The strength of connection between neurons is represented by a value called a weight. Each neuron can have its local memory, which represents the state of neuron. The neuron output depends only upon the current values of the input signals arriving at the neuron via impinging connections and upon values stored in the neuron's local memory. The input to output characteristics of each neuron are described by the activation function and local memory of each neuron.

Neural net models are specified by the net topology, node characteristics, and training or learning rules. In our application, a neural network of a feedforward architecture was used. This network is made up of sets of neurons arranged in three or more layers. These are an input layer, an output layer and one or more hidden layers. In this network, the output of neurons in a layer are transmitted to neurons in the upper layers. A neuron of the feedforward network does not interact with other neurons in the same layer. Except for the input layer neurons, the net input to each neuron is the sum of the weighted outputs of the neurons in the prior layer. Therefore, the net input to neuron j is described by

$$net_j = \sum w_{ji} o_i + \theta_j \tag{18}$$

w_{ji} is the weight of connection from neuron i to neuron j, o_i is the output of neuron i in the previous layer, θ_j is the local memory (threshold) of neuron j. The output of neuron j is then obtained by the operation of a nonlinear function on the net input. This can be described as

$$o_j = f(net_j) \tag{19}$$

The function $f(net_j)$ is the nonlinear activation function of the neurons, given by the sigmoidal function:

$$f(x) = \frac{1}{1 + \exp(-x)} \tag{20}$$

The learning ability of neural networks is mainly due to its capability to adjust the weights. Back-propagation training algorithm devised by Rumelhart [7] is used to modify the weights of multilayer feedforward neural network. In our application, it is appropriate to consider back-propagation neural networks as a method to solve nonlinear function approximation problems. The output of a feedforward neural network can be considered as a function $\hat{f}(x,W)$ of input vector x and weight matrix W. Assume a feedforward network is used to approximate a bounded function $f(x) : A \subset \mathbb{R}^n \rightarrow \mathbb{R}^m$. In the training stage, examples (x_1,y_1), (x_2,y_2), ...,(x_k,y_k), ... of the mapping $y_k = f(x_k)$ are presented to the neural network. The neural network can approximate the function by adjusting its weights W so that the error E can be reduced, where E is defined as

$$E = \frac{1}{2} \sum \{y_i - \hat{f}(x_i)\}^2, \quad x_i \in A \tag{21}$$

The weights are updated in the gradient descent direction of E, i.e.

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}}, \quad \text{where } w_{ji} \in W \tag{22}$$

where Δw_{ji} is the amount of change for the weight component w_{ji}, and the positive constant η determines the learning rate of the neural network. The larger the constant η is, the faster the change in the weights is. However, a large η may lead to oscillation in weight space. For a feedforward neural network with sigmoidal activation function, the evaluation of $\frac{\partial E}{\partial w_{ji}}$ has been determined [7]. In order to speed up the convergence of the training process without leading to oscillation, Rumelhart suggested to modify the training algorithm in Eqtn. (22) to include momentum term, such that

$$\Delta w_{ji}(n+1) = -\eta \frac{\partial E}{\partial w_{ji}} + \alpha \Delta w_{ji}(n) \tag{23}$$

where n labels the iteration in the learning process and α is a constant which determines the effect of past weight changes on the current direction of movement in weight space. This momentum term provides a damping effect and reduces the amount of oscillations during the training process.

INSTANTANEOUS VAr EVALUATION VIA ANN

The back-propagation neural network is applied to model the Eqtns (16) & (17) for the evaluation of instantaneous VAr.

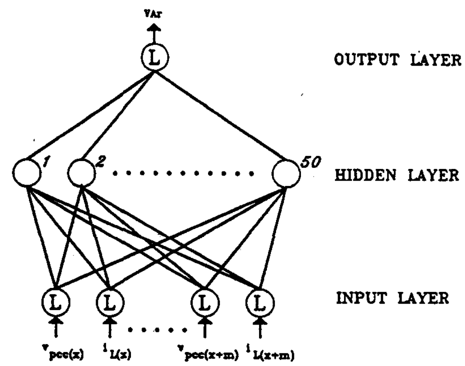

Figure 4 Back-propagation neural network for VAr evaluation

The learning capability of ANN is exploited to develop a special training procedure such that the modified algorithm is capable of delivering a better performance than the conventional approaches.

The network topology is shown in Fig. 4. The network inputs are m pairs of $v_{pcc(x)}$ and $i_{L(x)}$, and the output is the corresponding instantaneous VAr. Before the neural network can be applied for VAr evaluation, a large number of training patterns, which include the v_{pcc}, i_L and $Q_{L,PN}$, are generated using the model. The special training procedure is explained in Fig. 5. In this example, 101 pairs of v_{pcc} and i_L are sampled from one cycle of voltage and current variation. A sampling frequency of 5000 Hz is required for a 50 Hz line frequency. The VAr, $Q_{L,P100}$ is evaluated from these samples by the algorithm D. This $Q_{L,P100}$ shown in Fig. 5 is used as a target value for the network training. Instead of using the 101 pairs of v_{pcc} and i_L samples as inputs to the neural network, Fig. 5 shows that only 5 pairs of v_{pcc} and i_L are sub-sampled from the same sample train as the 101 sets for the network inputs (i.e. m=5). With this arrangement, the output of the trained network is equal to $Q_{L,P100} + \varepsilon$, where ε is the network error inherited from the training procedure. Throughout this investigation, this network error has always been kept below 2%. Apparently, a very small network error is preferred but its corresponding training time will be much longer. This method has two advantages. Firstly, the network size is much smaller because the number of input neuron is reduced from 202 to 10. Secondly, the sampling frequency can be much lower. In this neural network approach, the sampling frequency is only 250 Hz. Although the data are sampled from one cycle in Fig.5, data can be collected from a fraction of the cycle to reduce the integration period k, so that the evaluated result can be closer to the instantaneous VAr.

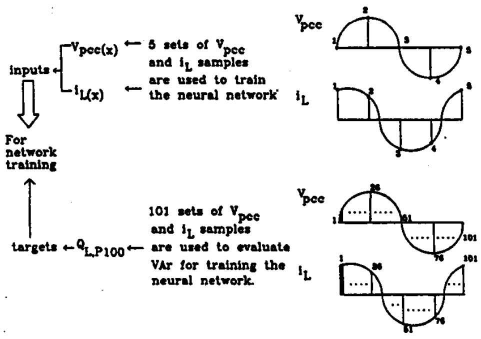

Figure 5 Neural network training mechanism

RESULTS

Figure 4 shows a three-layer back-propagation network employed for this application. The input layer contains 10 neurons for 5 pairs of v_{pcc} and i_L samples. The output layer has one neuron, which gives the instantaneous VAr. The number of neurons in the hidden layer was chosen to be 50. The learning rate η and momentum term α were chosen to be 0.2. It was found that the network worked well with this number of hidden neurons and parameters. In this investigation, all simulations were carried out using a 33MHz 80386 PC AT with 80387 coprocessor.

Each training set contains numerous patterns. Each pattern consists of a $Q_{L,P100}$ and 5 pairs of corresponding v_{pcc} and i_L samples. The training set was generated so that the values of $Q_{L,P100}$ were evenly distributed in the range of VAr variation. After having been trained, the network was applied to evaluate the VAr using inputs samples different from that for training. It was found that the network is very capable of generating $Q_{L,P100}$ from any 5 sets of inputs.

Very promising results have been obtained and are shown in Fig. 6. In these simulations, the v_{pcc} and i_L samples for each $Q_{L,P100}$ were collected in one cycle as discussed in the last section. Using the algorithm D, the mean percentage error between the evaluated VAr based on 101 sets and 5 sets data sub-sampled from the same 101 sets of current and voltage samples was found to be about 20 %. This illustrates that five samples per cycle is insufficient to represent one cycle. After 100,000 training iterations, the neural network is applied to evaluate VAr. The dotted line in Figure 6 represents the output of trained neural network using 5 sets of data sub-sampled from the same sample train as the 101 sets. The mean percentage error between the output of neural network and the evaluated VAr based on 101 sets of current and voltage samples is below 2%.

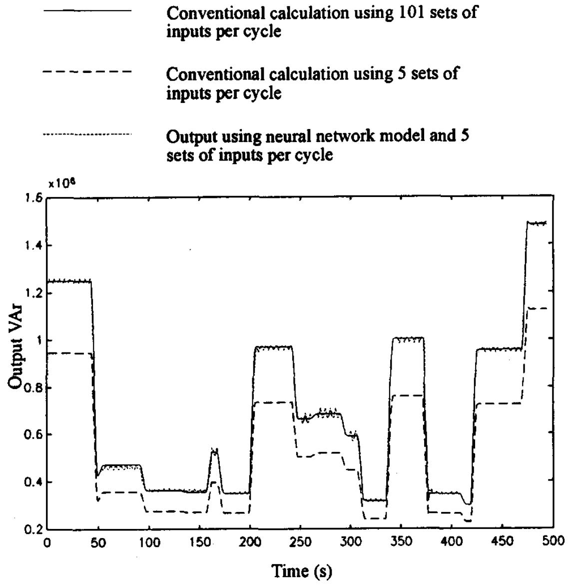

Figure 6 Output comparison based on samples collected in one cycle

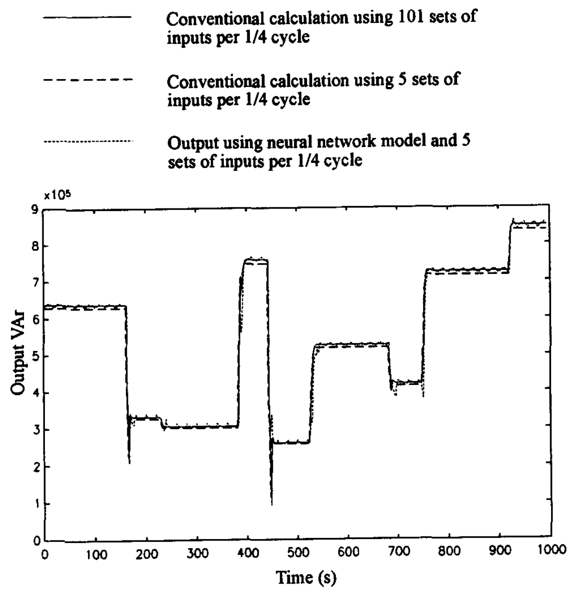

Figure 7 Output comparison based on samples collected in 1/4 cycle

In Fig. 7, the voltage and current samples for each $Q_{L,P100}$ were collected in one-quarter of a cycle and the neural network was trained with the same number of training iterations. A sampling frequency of 20,000 Hz is required. With a faster sampling frequency and the same N, the response to the changing VAr is faster. Fig. 7 shows that the trained neural network can deliver an accurate VAr with sampling frequency of 1000 Hz. The mean percentage error between the evaluated VAr using 101 sets and 5 sub-sampled sets of data is about 2 %. The mean percentage error between the output of neural network model and the evaluated VAr using 101 sets of samples is less than 2%. Figure 7 also shows that using 5 samples to represent 1/4 cycle is more acceptable in conventional approach.

The effect of training iterations on network performance is illustrated in Fig. 8. When the number of training iterations is 5,000, Fig. 8a shows that the VAr generated from the output neuron cannot converge to their target values. In addition, after a change in furnace resistance, the mean values of VAr do not converge to the target value. Figure. 8b shows the comparison between VAr output by the neural network after 100,000 iterations and that evaluated by conventional approach using 101 sets of samples. The error and fluctuation between the VAr output from the neural network and the target values is negligible. The relationship between error and number of training iterations is shown in Fig. 9. By increasing the number of training iterations, it is possible to further reduce the error in the network output.

DISCUSSIONS

Eqtn. (17) can only evaluate the VAr at a certain instant after the voltage and current samples are captured. The evaluated VAr lags the sampling process. By reducing the

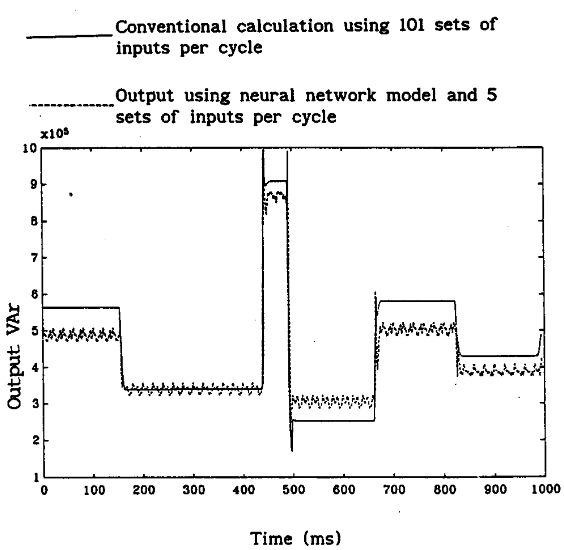

Figure 8a Output comparison after the network has been trained for 5,000 iterations

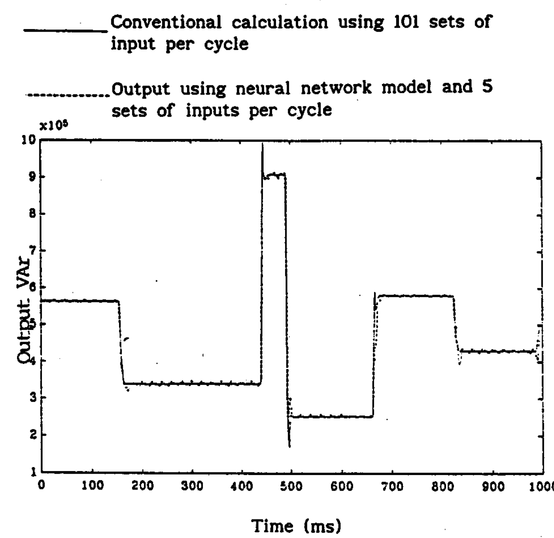

Figure 8b Output comparison after the network has been trained for 100,000 iterations

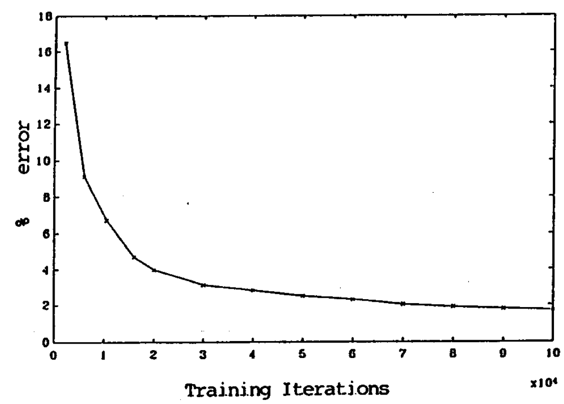

Figure 9 Variation in error with different number of iterations

portion of each cycle taken for samples, the evaluated VAr will approach to the true VAr flowing in the power supply network. In the present investigation, although samples were only taken in one-quarter of a cycle. In practice it is possible to reduce the portion of the cycle down to 1/400 cycle. In addition, the new algorithm can deliver the same accuracy as conventional methods with substantially less voltage and current samples. Thus, the evaluation system can be operated at a lower sampling rate.

The long computational time required by serial computers can be eliminated by hardware implementation of this algorithm using neuron chips . Recently, the VLSI technology allows 8 neurons with 8 synapses each (the number of synapses can be expanded by adding external hardwares) to be fabricated in a single MD1220 Neural Bit Slice. This neuron chip has an equivalent processing power of 55 MIPS [8]. The compensation system constructed by these neuron chips can evaluate the instantaneous VAr with negligible processing time after the weights obtained from the learning process are download to the RAM of these chips. This performance can never be achieved by the conventional methods.

In this study, it has also been demonstrated that the neural network model using only 5 sets of input can deliver an equivalent accuracy of 101 input sets. This suggests that the performance of this algorithm can be further enhanced by selecting appropriate sets of input for training. The error of the network output is found to be decreased by increasing the number of patterns in the training set. In addition, Fig. 9 illustrates the error can substantially be decreased by increasing the number of iterations.

CONCLUSIONS

By introducing back-propagation neural network for approximating the VAr evaluation function, it is possible to estimate the instantaneous VAr as accurately as that obtained by conventional methods operating at a very high sampling rate. The methodology developed in this paper is successful and results are promising. The neural network model and training mechanism developed in this paper are very flexible and versatile to provide any specified output requirement. Because of the fast convergence and high accuracy properties of this ANN based algorithm, the erratic fluctuation of VAr generated by an electric arc furnace can be accurately estimated for compensation.

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