Eng Int Syst (1998) 3: 131–140

Engineering
Intelligent Systems

Neural networks for real-time estimation of parameters of signals in power systems

A Cichocki*, P Kostyla†, T Łobos† and Z Waclawek†

* FRP Riken, ABS Labs, Institute of Physical and Chemical Research, Japan. Email: cia@kamo.riken.go.jp
† Technical University of Wroclaw, pl. Grunwaldzki 13, 50-370 Wroclaw, Poland. Email: lobos@elektryk.ie.pwr.wroc.pl

Fast determination of parameters of the fundamental waveform of voltages and currents is essential for the control and protection of electrical power systems. Most of the known digital algorithms are not fully parallel, so that the speed of processing is quite limited. New parallel algorithms, which can be implemented by analogue adaptive circuits employing some neural networks principles, are proposed. The problem of estimation is formulated as an optimization problem and solved by using the gradient descent method. Algorithms based on the least absolute value, the minimax, the least-squares and the robust least-squares criteria are developed and compared. The networks process samples of observed noisy signals (voltages or currents) and give as a solution the desired parameters of signal components. Extensive computer simulations confirm the validity and performance of the proposed algorithms and neural network realizations. The proposed methods seem to be particularly useful for real-time, high-speed estimation of parameters of sinusoidal signals in electrical power systems.

***Keywords:* neural networks, estimation, signal processing, electrical power systems**

1. INTRODUCTION

Real-time estimation of parameters of sinusoidal signals from noisy and distorted data has received considerable attention recently. Many sophisticated methods have been proposed including the Prony method, the Pisarenko harmonic decomposition and the Yule-Walker method. Many of these algorithms lead to a large computation burden and are rather numerically time consuming.

Fast determination of parameters of the fundamental waveform of voltages and currents is essential for the control and protection of electrical power systems. For this purpose various numerical algorithms have been developed, e.g. based on the Fourier and Kalman filtering [1, 2, 3]. Most of the algorithms are not fully parallel algorithms, so that the speed of processing is quite limited.

Recently, there has been a great interest in parallel algorithms and architectures, based on the methods of artificial neural networks [4-7]. Tank and Hopfield [4] show how optimization problems can be solved by highly interconnected networks of simple analog processors. They state that a consideration of such circuits provides a methodology for assigning function to anatomical structure in real neural circuits. They also illustrate the use of the neural networks for signal processing problems. Kennedy and Chua [5] extend the model proposed by Tank and Hopfield to the general nonlinear problem.

The purpose of this paper is to present new algorithms and along with them new architectures of analogue neuron-like adaptive processors for online estimation of parameters of sinusoidal signals, which are distorted by higher harmonics and corrupted by noise. For steady-state conditions we have developed neural networks which enable us to estimate the amplitudes and the frequency of the fundamental component of signals. When estimating the basic waveform of currents during short circuits the exponential DC component distorts the results. Assuming the known frequency, we have developed adaptive neural networks which enable us to estimate the amplitudes of the basic components as well as the amplitudes and the time constant of a DC component. The problem of estimation of signal parameters is formulated as an unconstrained optimization problem and solved by using the gradient descent continuous-time method [7]. Basing on this approach we have developed systems of nonlinear differential equations that can be implemented by analog adaptive neural networks. The solution of the optimization problem bases on some principles given by Tank and Hopfield [4] as well as by Kennedy and Chua [5]. The developed networks contain elements which are similar to the adaptive threshold elements of the perceptron presented by Widrow in [6].

2. STATEMENT OF THE PROBLEM

Consider the following sinusoidal signal distorted by a DC exponential component:

$$x(t) = X_a \sin(\omega t) = X_b \cos(\omega t) = X_c \exp(-X_d^t) \quad (1)$$

in which:

X_a, X_b	are the amplitudes of the sinusoidal signal
$\omega = 2\pi f$	where f is the frequency (50 or 60 Hz)
X_c, X_d	are the parameters of the DC component.

Let y(t) denote the noise-corrupted measurement of x(t), i.e.

$$y(t) = x(t) + e(t) \quad (2)$$

where e(t) is the error. This error includes higher harmonics, random noise and distortion caused, for example, by measurement instruments.

Consider the practical case where the signal of interest y(t) is measured during a finite duration of time and only N samples of this signal $y(t)|_{t=mT} = y(mT) = y_m$ are available. Hence, the error $e_m = e(mT)$ at the moment t = mT can be expressed as

$$e_m = y_m - x_m \quad (3)$$

where x_m=x (mT), and T is the sampling interval.

We are looking for an on-line algorithm which can provide the desired parameters on the basis of data samplesm y_m. To formulate the problem we must construct an appropriate energy function E(**X**), where **X** is the vector of the estimated parameters. The lowest energy state will correspond to the desired solution. In general, the optimization problem can be formulated as follows:

*find a vector **X** which minimizes the scalar energy function"*

$$E(\mathbf{X}) = \sum_{m=1}^{N} \sigma_m [e_m(\mathbf{X})] \quad (4)$$

where σ_m $[e_m(\mathbf{X})]$ represents a suitably chosen loss function.

In practice, the following cases have special importance [7, 8, 9, 10]:

1. for σ_m $[e_m = |e_m|$ the estimation problem is referred as the least absolute value (L_1 -norm) signal model fitting;
2. for σ_m $[e_m] = e^2_m$ we obtain the standard least-squares (L_2 -norm) optimization problem;
3. taking σ_m $[e_m] = k_m e^2_m$, with $k_m > 0$, we have a well-known weighted least-squares problem;
4. for the loss function σ_m $[e_m] = (1/\gamma) \ln\{\cosh(\gamma e_m)\}$ w obtain iteratively reweighted the least-squares problen also called the robust least-squares criterion;
5. for $E(\mathbf{X}) = \max_{1\le m\le N} \{|e_m|\}$ the optimization problem minimax (L_∞ – or Chebyshev norm) model fitting.

The proper choice of the optimization criterion use depends on the distribution of the noise error in the sample data. The standard least-squares criterion is optimal for normal (Gaussian) distribution of the noise. Often, the sig nals of voltages and currents encountered in power systen are notoriously contaminated by impulsive noise and larg isolated errors (outliers) caused by malfunctioning of som sensors or transient components. To reduce the influence o the outliers we can use the iteratively reweighted leas squares criterion. In the presence of large impulsive nois an alternative approach is to use the least absolute value cr terion. On the other hand, the minimax criterion is a appropriate to be used if the errors are uniformly distribute and the samples are relatively free from outliers.

3. ESTIMATION THE AMPLITUDES OF THE BASIC COMPONENT

During power system faults or after fault clearance in th vicinity of HVDC (High Voltage Direct Current) or TCSC (Thyristor Controlled Series Capacitors) severe waveforn distortions can occur [11]. The voltage and current wave forms may include higher frequency components, lowe frequency of which may be about only two or three times o the fundamental frequency. Their initial ratio, that is th ratio of the magnitude of higher frequency component t that of the fundamental component may be greater than 10 percent. The time constant of the decaying higher frequenc component, may reach values up to 100 ms. Waveform dis tortions like this can also occur in the case of faults nea large-capacity underground cables.

Fast estimation of parameters of the basic components o voltages and currents from measured data is very importa for measurement, control and protection tasks in electric power systems. It is difficult to filter out frequency compo nents close to the fundamental frequency, without delayin the filter response.

In this section we develop adaptive neural networks fo estimation the amplitudes X_a and X_b of distorted sinusoid signals. Three different neural networks were develope according to the three signal models:

$$y(t) = X_a \sin(\omega t) + X_b \cos(\omega t) + \varepsilon \quad (5)$$

$$y(t) = X_a \sin(\omega t) + X_b \cos(\omega t) + X_e \sin(2\omega t) + X_f \cos(2\omega t) + X_g \sin(3\omega t) + X_h \cos(3\omega t) \quad (6)$$

$$y(t) = X_a \sin(\omega t) + X_b \cos(\omega t) + [X_i \sin(\omega t) + X_j \cos(\omega_t t)]\exp(-X_t t) \quad (7)$$

As an example the development of the network according to eq (5), the simplest one, will be shown. As a loss function in eqn. (4) tl standard least-squares optimization criterion has been chosen

$$\sigma_m[e_m(\mathbf{X})] = e^2_m \tag{8}$$

The function E(X) can be minimised by implementing the steepest descent optimization algorithm

$$\frac{d\mathbf{X}}{dt} = -\frac{1}{\tau}\nabla E(\mathbf{X}), \tag{9}$$

where τ is the integration time constant and

$$\nabla E(\mathbf{X}) = \left[\frac{\partial E(\mathbf{X})}{\partial X_a};\ \frac{\partial E(\mathbf{X})}{\partial X_b}\right]$$

The gradient system can be rewritten in a scalar form as a system differential equations:

$$\frac{dX_a}{dt} = \frac{1}{\tau}\sum_{M=1}^{N} e_m \sin(m\omega T) \tag{10}$$

$$\frac{dX_b}{dt} = \frac{1}{\tau}\sum_{M=1}^{N} e_m \sin(m\omega T) \tag{11}$$

The above system of differential equations can be implemented by an adaptive analogue neural network, as shown in Fig. 1. The network consists of basic computing units: integrators, summers and multipliers. The network estimates only the amplitudes and X_a and X_b.

Neural networks according to eqns. (6) and (7) were also developed. The networks were simulated on computers and tested. The signals were simulated according to eqn:

$$y_m = \cos(2\pi 50mT/s) + \sin(2\pi f_t mT)\exp(-10mT/s) \tag{12}$$

Fig. 2 shows the estimated phasors of the basic waveforms and the time functions of the estimated amplitudes, when using the neural networks shown in Fig. 1. It was assumed that the estimation process starts with 5 samples of new transient signal. With time, the number of samples increases step by step until it reaches its final value (N=20). The accuracy of the estimation is only slightly better than that of the Fourier or Kalman algorithms [12]. A smaller dependency on the frequency of the transient component can be stated. Quite accurate results can be achieved two periods (40 ms) after a new transient. The influence of the random

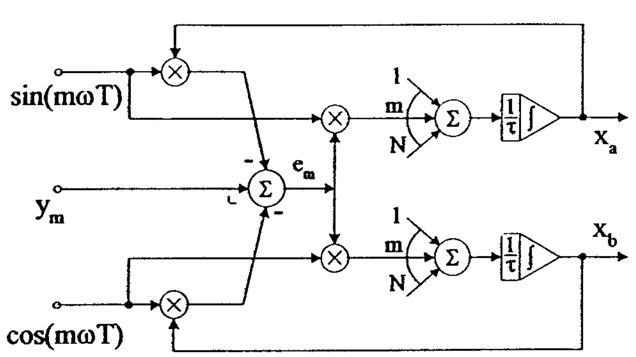

Figure 1 Artificial neural network with 2 neurones for estimation the amplitudes of the basic component

(white) noise in the measured (simulated) signal on the estimation error has also been investigated (Fig. 3).

The network developed according to eqn. (6) estimates the amplitudes of the first, second and third harmonic. The investigations (Fig. 4) show that when estimating the fundamental waveform distorted by transient components, the accuracy of the estimation depends strongly on the frequency of transient components. The most exact results (Fig. 5) can be achieved by applying a neural network developed according to eqn. (7). It can estimate all unknown parameters of the signal components X_a, X_b, X_g, X_h, X_t,ω_t. Unfortunately, it is rather complicated

4. ESTIMATION THE AMPLITUDES AND THE FREQUENCY OF THE BASIC COMPONENT

The frequency in electrical power systems can change over a small range due to generation-load mismatches. Some power system protection and control applications require accurate and fast estimates of the frequency. Most digital techniques for on-line measuring frequency have acceptable accuracy if the voltage waveforms are not distorted. On the other hand, under steady-state conditions we don't expect any exponential DC component. Thus, in this section we will develop adaptive neural networks for estimation the amplitudes X_a, X_b and the angular frequency ω of sinusoidal signals distorted by random noise and harmonics, assuming $X_c = 0$ in eqn.(1).

Up to now, the L_1- and L_∞– norm optimization criteria have seldom been used for parameter estimation, probably because their nondifferentiability causes numerical and analytical difficulties. Fortunately, the minimax and the least absolute value optimization problems can be easily reformulated as equivalent differentiable optimization problems and implemented by using artificial neural networks.

Minimax criterion

The minimax estimation problem can be reformulated as follows:*"find a vector of parameters X which minimizes the energy function"*

$$E(X_a,X_b,\omega) = \max_{1\le m\ge N}\{|e_m(X_a,X_b,\omega)|\} \tag{13}$$

Using the steepest descent continuous-time optimization algorithm we obtain the set of nonlinear equations [7, 10]:

$$\frac{dX_a}{dt} = \frac{1}{\tau}\sum_{M=1}^{N} S_m \mathrm{sign}(e_m)\sin(m\omega T) \tag{14}$$

$$\frac{dX_b}{dt} = \frac{1}{\tau}\sum_{M=1}^{N} S_m \mathrm{sign}(e_m)\cos(m\omega T) \tag{15}$$

$$\frac{d\omega}{dt} = \frac{1}{\tau}\sum_{M=1}^{N} S_m mT \mathrm{sign}(e_m)[X_a\cos(m\omega T) - X_b\sin(m\omega T)] \tag{16}$$

where the coefficient represents the time constant of integrators, and

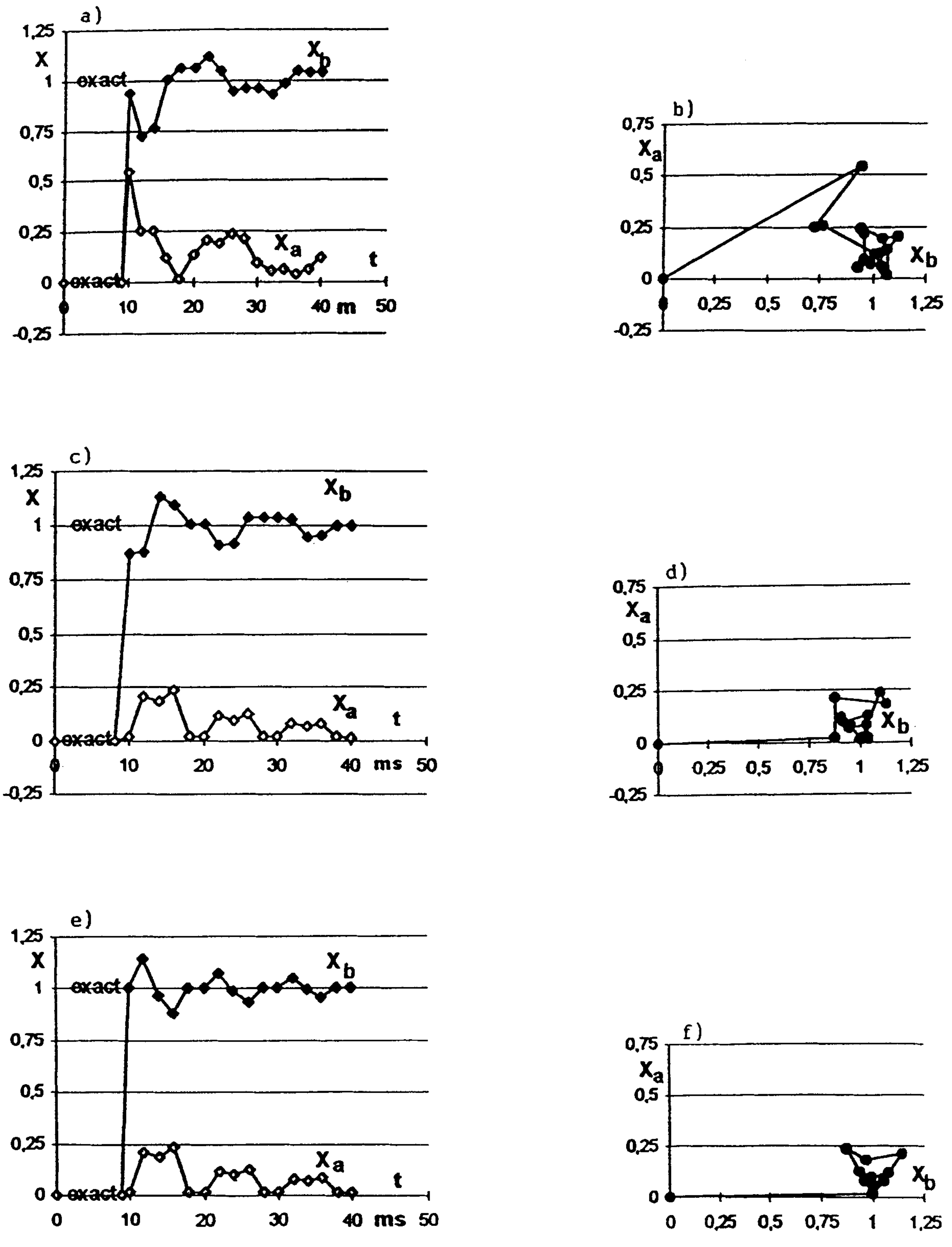

Figure 2 Estimated time functions of the parameters X_a and X_b (a, c, e) and the phasors (b, d, f) of the basic (50Hz) component of the signal (12), when using the neural network with two neurons (Fig 1); sampling frequency –500 Hz, number of samples taken into the estimation 520, frequency of the transient component: a,b) –105 Hz: c,d) –125 Hz, e,f) – 150 Hz

$$S_m = \begin{cases} 1 & \text{if } |e_m| = \max\{|e_i|\} \\ 0 & \text{otherwise.} \end{cases}$$

The set of differential equations can be implemented by a neuron-like network shown in Fig. 6. The network consists of basic computing units: integrators, summers, multipliers, signum activation functions and trigonometric functions generators. The switches S are controlled by a special subnetwork called Winner-Take-All (WTA) circuit. The function of the WTA is to select the largest in absolute value instantaneous error. The sign of the selected error is transmitted for further processing, while the other error signals are completely

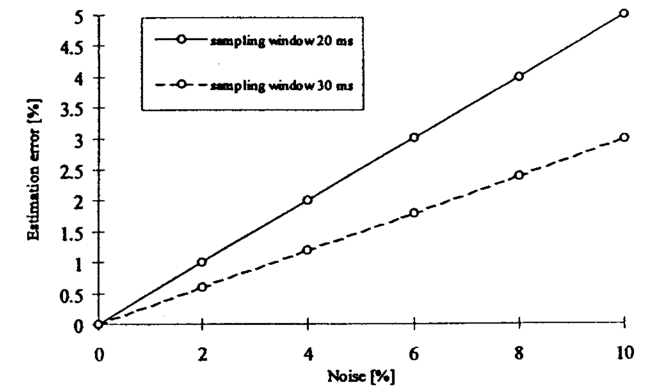

Figure 3 Errors of the amplitude estimation when using the networks acc. to Figure 1

inhibited by opening corresponding switches.

Least absolute value criterion

The network shown in Fig. 6 can easily be modified to perform the parameters estimation according to L_1- and L_2-norm criteria. By closing all the switches S or by removing them and the associated WTA circuit, the network will act according to the least absolute value criterion, realizing the set of differential equations:

$$\frac{dX_a}{dt} = \frac{1}{\tau} \sum_{M=1}^{N} \mathrm{sign}(e_m)\sin(m\omega T) \quad (17)$$

$$\frac{dX_b}{dt} = \frac{1}{\tau} \sum_{M=1}^{N} \mathrm{sign}(e_m)\cos(m\omega T) \quad (18)$$

$$\frac{d\omega}{dt} = \frac{1}{\tau} \sum_{M=1}^{N} mT\mathrm{sign}(e_m)[X_a\cos(m\omega T) - X_b\sin(m\omega T)] \quad (19)$$

Least-squares criterion

In order to estimate parameters according to the least-squares criterion all signum activation functions must be replaced by linear functions, and all switches S must be closed or removed. In this case the neural network can be described by a system of differential equations:

$$\frac{dX_a}{dt} = \frac{1}{\tau} \sum_{M=1}^{N} (e_m)\sin(m\omega T) \quad (20)$$

$$\frac{dX_b}{dt} = \frac{1}{\tau} \sum_{M=1}^{N} (e_m)\cos(m\omega T) \quad (21)$$

$$\frac{d\omega}{dt} = \frac{1}{\tau} \sum_{M=1}^{N} mTe_m[X_a\cos(m\omega T) - X_b\sin(m\omega T)] \quad (22)$$

Computer simulation

Extensive computer simulation experiments have confirmed that the neural network shown in Fig. 5 allows us to estimate in real-time desired parameters of noisy sinusoidal signals. Owing to limited space, we shall present only some illustrative results. For all examples presented in this paper, we have chosen the following parameters: the number of samples N = 30, the integration time constant for all three integrators was $\tau = 20.10^{-8}$ for the L_1- and L_2-norm, and $\tau = 2.10^{-8}$ for the L_∞-norm. Let us consider a sinusoidal signal $x(t) = 140\sin(\omega t) + 60\cos(\omega t)$, $\omega = 100\pi$, contaminated by uniformly distributed noise. Fig. 7 shows the trajectories of estimated parameters for the sampling window NT = 30 ms (sampling frequency f_s= 1000 Hz) and the noise level of 2%. The figure shows that the trajectories of the estimated parameters X_a and X_b converge to almost the same values, independent of the criterion used. The best results have been obtained using the minimax criterion (Figs. 8 and 9a). In the presence of higher harmonics the L_2– norm shows the best accuracy (Fig. 9b).

5. ESTIMATION THE PARAMETERS OF SHORT-CIRCUIT CURRENTS

During short circuit the waveform of currents can be additionally distorted by an exponential DC component. For the application the sinusoidal signal model has to be extended with an exponential term as in eqn. (1). We have assumed that at the beginning of a short circuit the frequency remains constant. In this section we shall present adaptive neural networks which enable us to estimate the amplitudes X_a and X_b and of the basic waveform as well as the amplitude X_c and the time constant $T_t = 1/X_d$ of the exponential component.

Robust least-squares criterion

The criterion is preferable if additive impulsive noise is expected. Using the loss function shown in the Section 2 we determine the first derivative of this function with respect to the unknown parameters X_a, X_b, X_c, X_d. The function can be minimized with respect to each parameter by implementing a dynamic gradient system [7] as in eqn. (9), which can be rewritten in a scalar form, as a system of differential equations [9]:

$$\frac{dX_a}{dt} = \frac{1}{\tau} \sum_{M=1}^{N} (\varepsilon_m)\sin(m\omega T) \quad (23)$$

$$\frac{dX_b}{dt} = \frac{1}{\tau} \sum_{M=1}^{N} (\varepsilon_m)\cos(m\omega T) \quad (24)$$

$$\frac{dX_d}{dt} = \frac{1}{\tau} \sum_{M=1}^{N} \varepsilon_m\exp(-X_d mT) \quad (25)$$

$$\frac{dX_d}{dt} = \frac{1}{\tau} \sum_{M=1}^{N} (\varepsilon_m)X_c mT\exp(-X_d mT) \quad (26)$$

where $\varepsilon_m = \tanh(\gamma e_m)$.

The system of differential equations can be implemented by a neuron-like, adaptive analogue processor shown in Fig.10. Each channel consists of a sigmoidal function (hyperbolic tangent) generator and exponential function generator. The slope of the sigmoid function depends on the

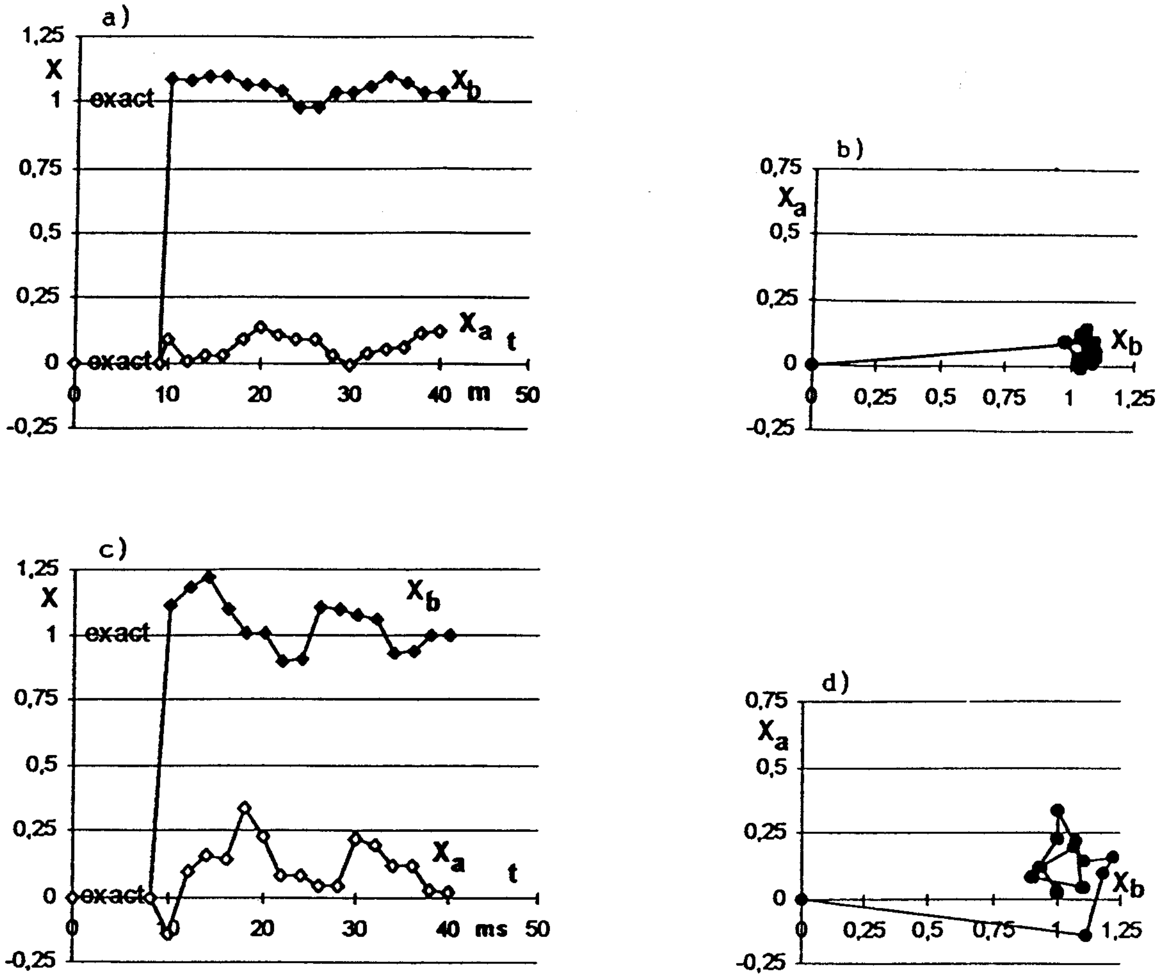

Figure 4 Estimated time functions of the parameters X_a and X_b(a,c) and the phasors (b,d) of the basic (50) Hz component of the signal (12), when using the neural networks according to the signal (12), when using the neural networks according to the eqn. (6); sampling frequency –500 Hz, number of samples taken into the estimation 5 ⇒20, frequency of the transient component: a,b) –105Hz; c, d) –125 Hz

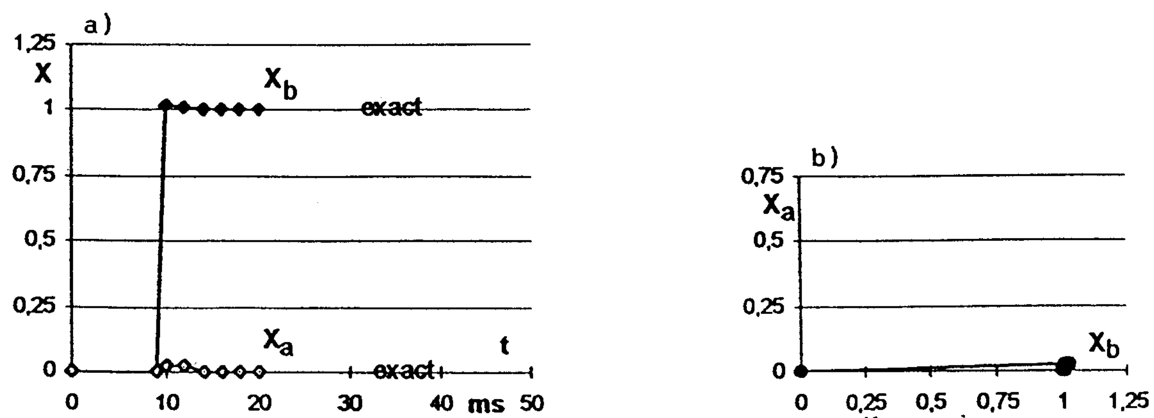

Figure 5 Estimated time function (a) and the phasor (b) of the basic(50Hz) compnent of the signal (12), when using the neural networks according to the eqn (7); sampling frequency –500Hz, number of samples taken into the estimation 5 ⇒ 10, Frequency of the transient component – 105Hz

parameter γ. If γ is small, say less than 0.1,the hyperbolic tangent can be approximated by its argument. The sigmoid function is almost linear in a wide range, and the network acts according to the standard least-squares criterion. If the parameter γ is large, say greater than 1000, then the sigmoid function approximates the hard limiter (signum function) and the network is able to solve the problem according to the least-absolute value criterion.

We have simulated the network on computer and extensively tested for a variety of sinusoidal signals corrupted by noise and distorted by exponential DC components. The simulations fully confirmed correctness of the presented approach. For the results presented in Figs. 11 and 12 we have chosen the number of samples N = 30 and the integration time constant for all integrators $\tau = 2 \times 10^{-8}$s. Fig. 11 shows trajectories of the estimated parameters for the signal without and with outliers. The figure illustrates that the trajectories converge to almost the same values, independent of impulsive noise.

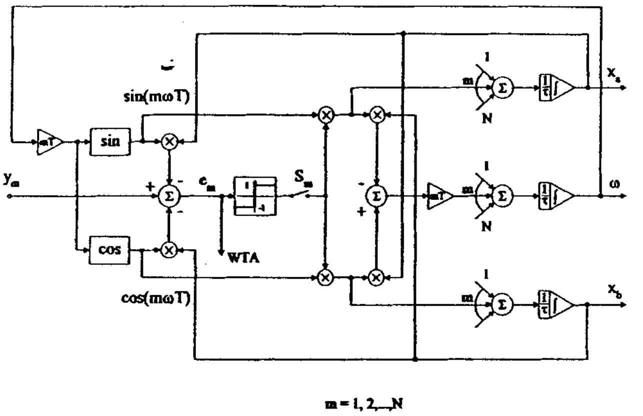

Figure 6 Artificial neural network for estimation the amplitudes and the frequency of noisy sinusoidal signals

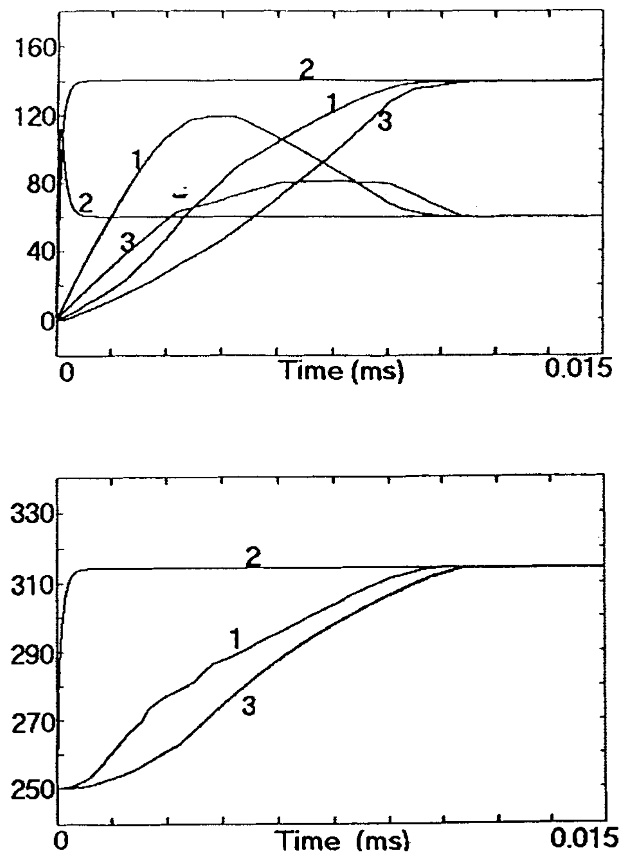

Figure 7 Computer simulated state trajectories of estimated parameters of a signal x(t) =140sin(ωt) = 60cos(ωt) corrupted by noise (2%) using 1) L_1 – norm, 2) L_2 – norm, 3) L_∞– norm; N=30, NT =30ms

Minimax criterion

The optimization problem can be transformed into an equivalent differentiable minimization problem:

"*minimize* X_0 *subject to* $-X_0 \leq e_m \leq X_0$, *where* $X_0 \geq 0$"

The optimal value of is simultaneously the minimum of the energy function. By applying the standard penalty function approach [7] the constrained minimization problem can be mapped into an unconstrained problem:

"*minimize* E_∞ (X), *where*"

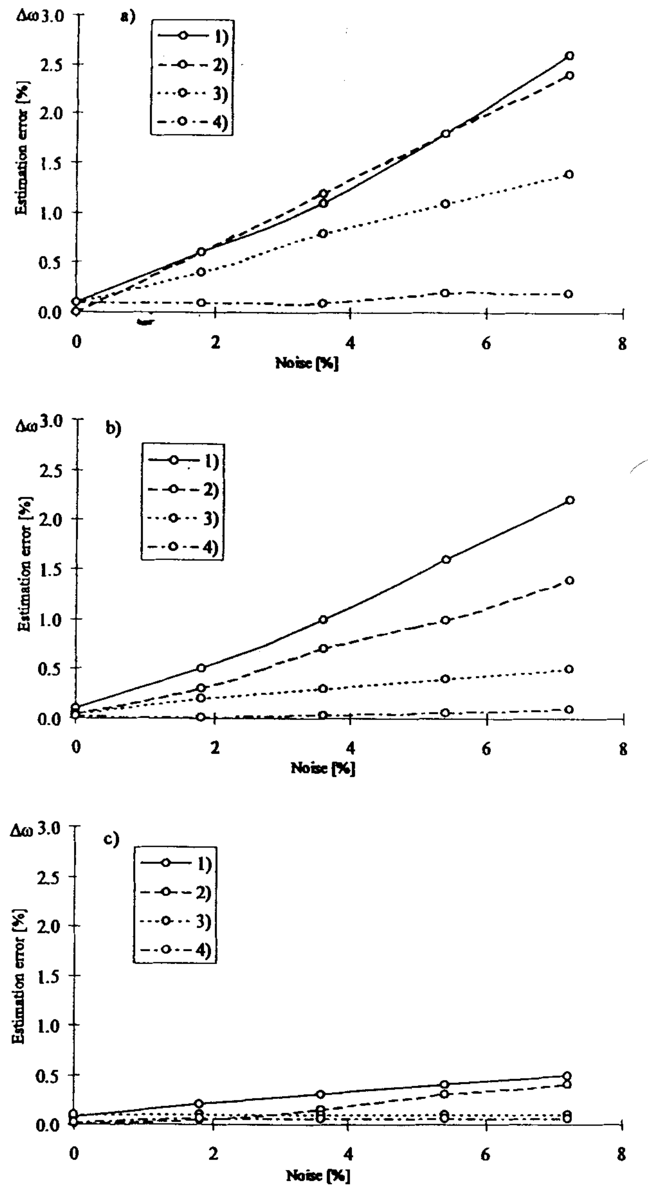

Figure 8 Errors of the frequency estimation using: a) L_1 – norm, b) L_2 – norm, c) L_∞ – norm criterion; N=30; sampling window: 1) 10ms (f_s = 3000Hz), 2) 15ms (f_s=2000 Hz), 3) 20ms (f_s = 1500 Hz), 4) 30ms (f_s =1000 Hz)

$$E_\infty(\mathbf{X}) = vX_0 + \frac{k}{2}\sum_{m=1}^{N}[\min\{0, e_m + X_0\}]^2 + \frac{k}{2}\sum_{m=1}^{N}[\min\{0, e_m + X_0\}]^2 \quad (27)$$

$v > 0$; $k > 0$ are penalty terms (typically $v = 1$, $k = 10$).

By applying the gradient strategy i.e. the steepest descent continuous time algorithm [7], we obtain a gradient system:

$$\frac{d\mathbf{X}_0}{dt} = -\frac{1}{\tau_0}\left(v - k\sum_{m=1}^{N}|g_m(e_m, X_0)|\right) \quad (28)$$

$$\frac{d\mathbf{X}_i}{dt} = -\frac{1}{\tau}\sum_{m=1}^{N} g_m(e_m, X_0)\frac{\partial e_m}{\partial X_i} \quad (29)$$

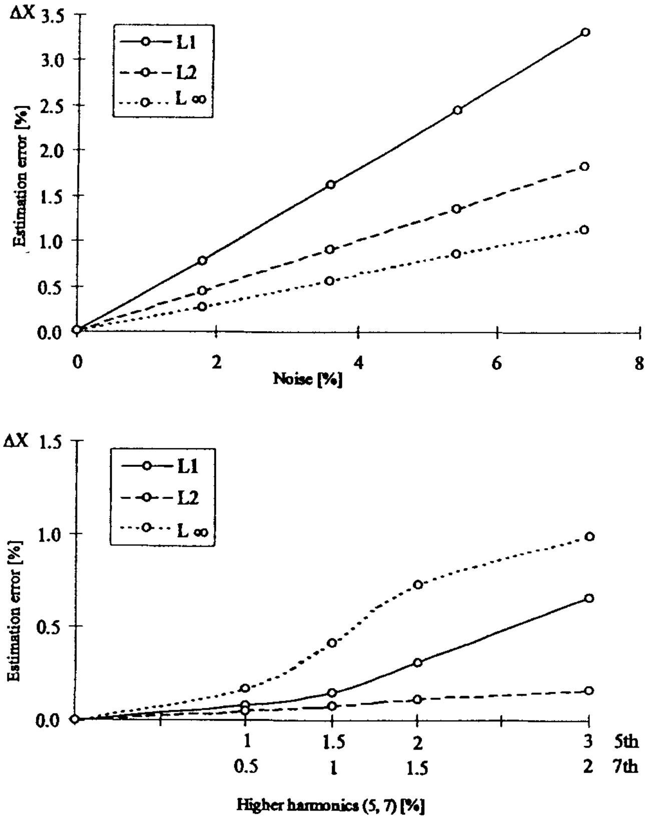

Figure 9 Errors or the amplitude estimation; signal contaminated by (a) uniformly distributed noise, and (b) 5th and 7th harmonies; N=30; NT = 20ms

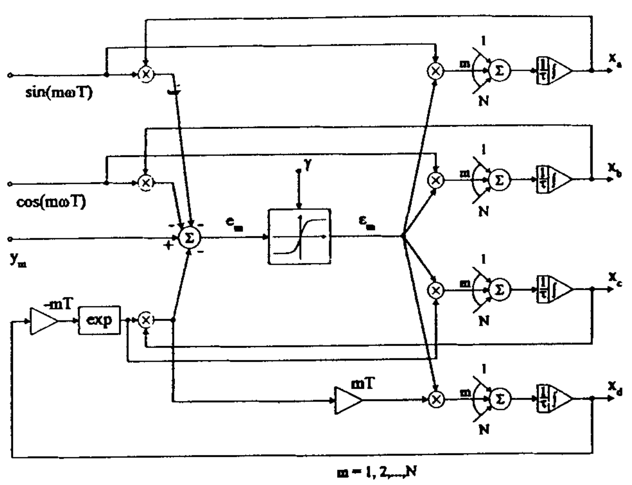

Figure 10 Artificial neural networks for estiomation of parameters of sinusoidal signals with exponential DC components, using the robust least- squares criterion

for i = a, b, c, d; where $\tau_0 > 0$, $\tau_i > 0$

$$g_m(e_m, X_0) = \begin{cases} e_m - X_0 & \text{if } e_m > X_0 \\ 0 & \text{if } -X_0 \le e_m \le X_0 \\ e_m + X_0 & \text{if } e_m < -X_0 \end{cases}$$

Taking into account (1) the gradient system (28, 29) can be

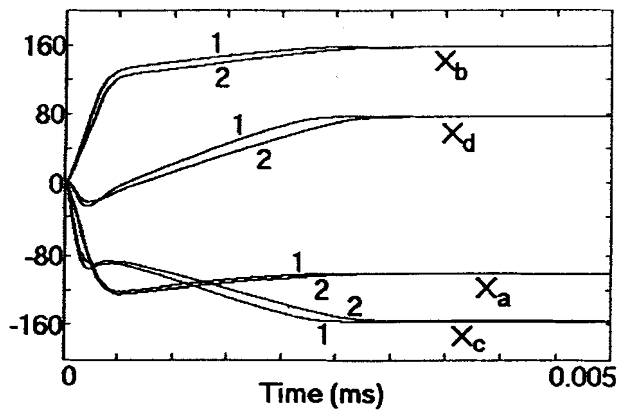

Figure 11 Trajectories of estimated parameters of the signal:
x(t) = –100 sinωt + 160 cosωt – 160exp (-80t)
contaminated by white noise (2%) and additive impulsive noise, without (1) and with wild noise (2), γ=1

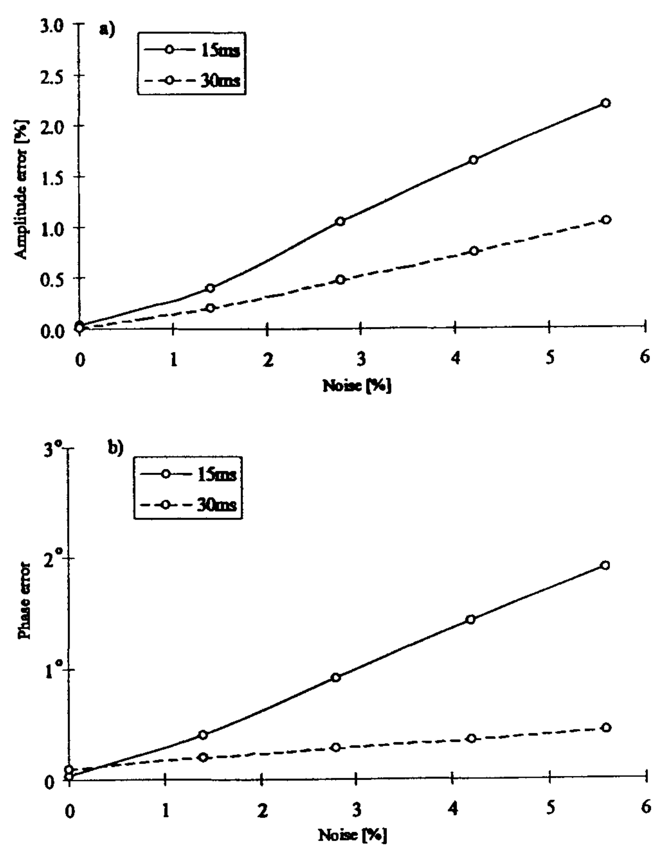

Figure 12 Errors of the amplitude (a) and phase (b) estimation by using the network in Fig 9; N= 30; γ= 1; sampling window: 1) 15ms, 2) 30ms

rewritten as a system of differential equations:

$$\frac{dX_0}{dt} = -\frac{1}{\tau_0}\left\{\frac{\nu}{k}\sum_{m=1}^{N}\left[(e_m+X_0)S_{ml} - (e_m-X_0)S_{m2}\right]\right\} \quad (30)$$

$$\frac{dX_a}{dt} = -\frac{1}{\tau}\sum_{m=1}^{N}\left[(e_m+X_0)S_{ml}+(e_m-X_0)S_{m2}\right]\sin(m\omega T) \quad (31)$$

$$\frac{dX_b}{dt} = -\frac{1}{\tau}\sum_{m=1}^{N}\left[(e_m+X_0)S_{ml}+(e_m-X_0)S_{m2}\right]\cos(m\omega T) \quad (32)$$

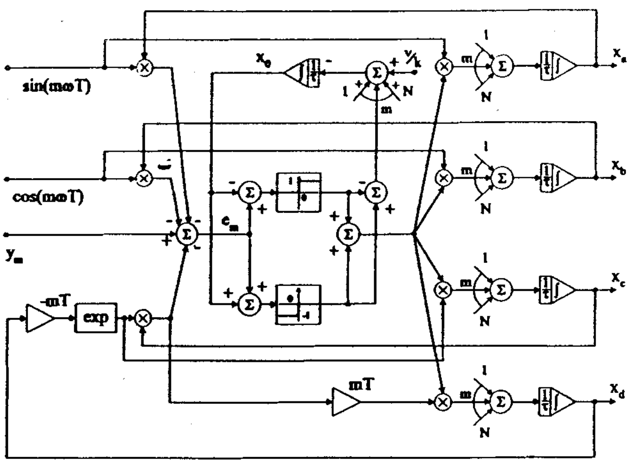

Figure 13 Artificial neural network for estimation of parameters of sinusoidal signals with exponential DC components, by using the minimax criterion

$$\frac{dX_c}{dt} = -\frac{1}{\tau}\sum_{m=1}^{N}[(e_m+X_0)S_{m1}+(e_m-X_0)S_{m2}]\exp(-X_d mT) \qquad (33)$$

$$\frac{dX_d}{dt} = -\frac{1}{\tau}\sum_{m=1}^{N}[(e_m+X_0)S_{m1}+(e_m-X_0)S_{m2}] \, X_c(-mT)\exp(-X_d mT) \qquad (34)$$

where $S_{m1} = \begin{cases} 1 & \text{if } e_m < -X_0 \\ 0 & \text{otherwise} \end{cases}$ $\quad S_{m2} = \begin{cases} 1 & \text{if } e_m > X_0 \\ 0 & \text{otherwise} \end{cases}$

The system of differential equations can be implemented by an analogue neural network whose functional block diagram is shown in Fig. 13. The network has also been simulated on computer and extensively tested. Good agreement with theoretical considerations has been obtained. As an example Fig. 14 shows the trajectories of estimated parameters of a sinusoidal signal distorted by an exponential DC component and Fig. 15 errors of the amplitude estimation for signals contaminated by uniformly distributed noise.

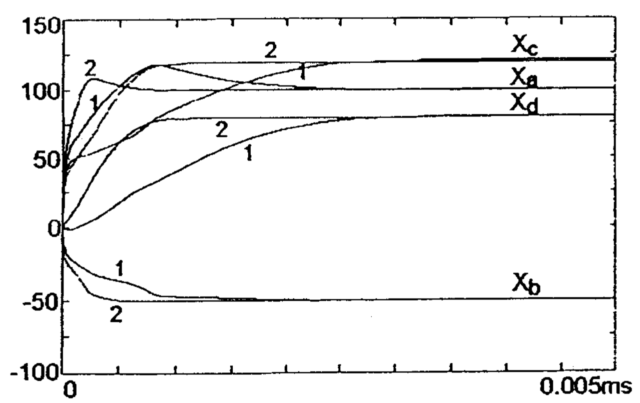

Figure 14 Computer simulated trajectories of estimated parameters of the signal: x(t) = 1090sinωt − 50cosωt + 120exp(−80 t) corrupted by noise (2%). N=20, sampling window: 1) 20ms, 2) 40ms

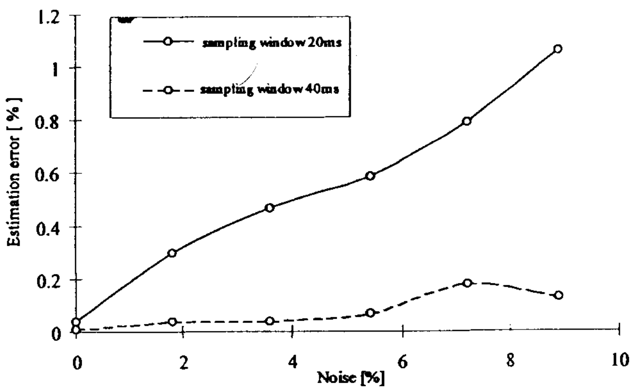

Figure 15 Errors of the amplitude estimation; signal contaminated by uniformly distributed noise

6. CONCLUSIONS

Adaptive analogue neural networks represent a very promising approach for high-speed estimation of parameters of signals. In this paper new algorithms and architectures of neuron-like adaptive circuits have been proposed. The algorithms for steady-state conditions enable us to estimate the amplitudes and the frequency of the fundamental component of voltages and currents. The algorithms for short-circuit conditions allow us to estimate the amplitudes of the basic component and the parameters of a DC exponential component of currents. The choice of a proper network also depends on the expected distribution of noise in the measured signal. Extensive computer simulation experiments confirmed the validity and performance of the proposed algorithms.

REFERENCES

1. A. G. Phadke, J. S. Thorp and M. G. Adamiak: *A New Measurement Technique for Tracking Voltage Phasors, Local Frequency and Rate of Change of Frequency*, IEEE Trans. on Power Apparatus and Systems, vol. PAS-102, pp. 1025-1038, May 1983.
2. T. Lobos: *Nonrecursive Methods for Real-Time Determination of Basic Waveforms of Voltages and Currents*, IEE Proc.- C., vol. 136, pp. 347-351, No. 6, Nov. 1989.
3. K.Fr. Eichhorn, and T. Lobos: *Recursive Real-Time Calculation of Basic Waveforms of Signals*, IEE Proc. - C., vol. 138, pp. 469-470, No. 6, Nov. 1991.
4. D.W. Tank and J. Hopfield: *Simple Neural Optimization Networks: an A/D Converter, Signal Decision Circuit and a Linear Programming Circuit*, IEEE Trans. on Circuit and Systems, vol. CAS-33, pp. 533-541, May 1986.
5. M.P. Kennedy, and L.O. Chua: *Neural Networks for Nonlinear Programming*, IEEE Trans. on Circuits and Systems, vol. CAS-35, pp. 554-562, May 1988.
6. B. Widrow and M. Lehr: *30 Years of Adaptive Neural Networks: Perceptron, Madaline and Back Propagation*, Proc. of the IEEE, vol. 78, pp. 1415-1442, No. 9, September 1990.
7. A. Cichocki and R. Unbehauen: *Neural Networks for Optimization and Signal Processing*, Stuttgart: Teubner - J. Wiley, 1993.
8. S. Osowski: *Neural Networks for Estimation of Harmonic Components in a Power Systems*, IEE Proc.-C, vol. 139, pp. 129-135, No. 2, March 1992.
9. A. Cichocki and T. Lobos: *Adaptive Analogue Network for*