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NEURAL NETWORK APPROACH TO SIGNALS' PARAMETERS ESTIMATION IN ELECTRIC POWER SYSTEMS

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ABSTRACT

Monitoring and full control of electricity flows is an important factor of an effective operation of electric power systems. It provides the possibility of an on-line analysis and optimal management of electricity distribution on the basis of modern achievements of power engineering and computer sciences. Computational intelligence techniques (mostly artificial neural networks and fuzzy inference systems) are widely used in this area during the last decades. However, specific character of signals in power systems (high levels of uncertainty and nonstationarity) makes the use of traditional neural networks inefficient and pave the way for the development of specialized architectures and learning algorithms aimed at the processing of polyharmonic nonstationary signals distorted by various types of stochastic and deterministic disturbances. In this paper, new architectures of neurons, networks and algorithms for their learning in real time are proposed. The obtained results allow improving reliability and efficiency of monitoring and diagnostic systems, especially under the circumstances of faults in the electric networks and in the presence of outliers in observations.

Index Terms **–** Neural networks, harmonic components, parameters estimation

1. INTRODUCTION

Monitoring and full control of electricity flows is an important factor of an effective operation of electric power systems. It provides the possibility of an on-line analysis and optimal management of electricity distribution on the basis of modern achievements of power engineering and computer sciences [1, 2]. Thus, it is about creating supervisory control systems for power systems based on intelligent technologies and, above all, adaptive approach [3-7] and neural networks [8-10]. They provide on-line parameter estimation and restoration of signals disturbed by random noise and parasitic components [9].

Specificity of signals in power systems (high levels of uncertainty and nonstationarity) makes the use of traditional artificial neural networks inefficient and pave the way for the development of specialized architectures and learning algorithms aimed at the processing of polyharmonic nonstationary signals, which are distorted by various types of stochastic and deterministic disturbances.

2. POLYHARMONIC SIGNALS' PARAMETERS ESTIMATION BASED ON QUADRATIC CRITERIA

Let the monitored signal be described by the following equation

$$y(t)=\sum_{j=1}^{m}\left(a_j\cos j\omega t+b_j\sin j\omega t\right)+\xi(t), \qquad (1)$$

where m – the number of harmonics, a_j, b_j – unknown parameters of separate harmonics, $\omega=2\pi f\approx 314$ rad/s – main harmonic's frequency ($f=50\text{Hz}$), t – continuous time, $\xi(t)$ – stochastic component with zero expectation value and bounded second moment.

If the monitored analog signal $y(t)$ is quantized with the step T_0, then instead of (1) its discrete counterpart may be introduced

$$y(k\mathrm{T}_0)= \\ =\sum_{j=1}^{m}\left(a_j\cos j\omega k\mathrm{T}_0+b_j\sin j\omega k\mathrm{T}_0\right)+\xi(k\mathrm{T}_0), \qquad (2)$$

where $k=1,2...$ – discrete time.

Let there be a set of N observations, defined as a vector $Y=\left(y(T)_0,y(2T_0),...y(NT_0)\right)^T\in R^N$, and a corresponding $(N\times 2m)$ harmonics matrix

$$X=\begin{pmatrix}\sin\omega T_0 & \cos\omega T_0 & \cdots & \sin m\omega T_0 & \cos m\omega T_0\\ \sin 2\omega T & \cos 2\omega T_0 & \cdots & \sin 2m\omega T_0 & \cos 2m\omega T_0\\ \vdots & \vdots & \ddots & \vdots & \vdots\\ \sin N\omega T_0 & \cos N\omega T_0 & \cdots & \sin Nm\omega T_0 & \cos Nm\omega T_0\end{pmatrix}.$$

Then we can write a system of linear equations (usually, overdefined)

$$Xw=Y\ , \qquad (3)$$

where $w=(b_1,a_1,b_2,a_2,\ldots,b_m,a_m)^T \in R^{2m}$ – unknown parameters vector from equation (2) that must be estimated.

Introducing identification criterion

$$E_{LS}^N(w)=\frac{1}{2}\|Y-Xw\|^2=\frac{1}{2}\|e\|^2=\frac{1}{2}e^Te \quad (4)$$

and using the least squares technique, we obtain a well-known result

$$w=(X^TX)^+X^TY, \quad (5)$$

where $(\cdot)^+$ – preudoinverse symbol.

In [9, 10], it is stated that in the tasks of on-line signals monitoring in power systems the least squares method in batch and recurrent forms is too awkward. It is proposed to estimate parameters by solving the system of differential equations

$$\frac{dw}{dt}=\nabla_t w=-\eta X^T(Y-Xw)=-\eta X^Te \quad (6)$$

or in a scalar form

$$\begin{cases}\dfrac{da_j}{dt}=-\eta\sum\limits_{k=1}^{N}e(k)\cos j\omega kT_0,\\ \dfrac{db_j}{dt}=-\eta\sum\limits_{k=1}^{N}e(k)\sin j\omega kT_0,\end{cases} \quad (7)$$

where $e(k)=y(kT_0)-\sum\limits_{j=1}^{m}\left(a_j\cos j\omega kT_0+b_j\sin j\omega kT_0\right)$, η – positive parameter.

In [10], an analog neural network architecture is proposed, which is formed by integrators, adders and multipliers. An elementary neuron implements main harmonic's parameters estimation in the form

$$\begin{cases}\dfrac{da_1}{dt}=-\eta\sum\limits_{k=1}^{N}e(k)\cos k\omega T_0,\\ \dfrac{db_1}{dt}=-\eta\sum\limits_{k=1}^{N}e(k)\sin k\omega T_0.\end{cases} \quad (8)$$

As most real-world signal processing problems in power systems are being solved using digital hardware, it is practical to introduce a discrete neuron formed by adders, multipliers and delay units z^{-1}. Its learning algorithm is presented as difference equations

$$\begin{cases}a_1(k)=a_1(k-1)+\eta(k)\sum\limits_{k=1}^{N}e(k)\cos k\omega T_0,\\ b_1(k)=b_1(k-1)+\eta(k)\sum\limits_{k=1}^{N}e(k)\sin k\omega T_0,\end{cases} \quad (9)$$

where $\eta(k)$ – learning step parameter (generally, variable), which defines speed and smoothing properties of the procedure.

Artificial neural network for parameters estimation of equation (2) consists of N neurons working in parallel. Fig. 1 shown one of these neurons using symbols defined in [9]. The neuron is tuned with the procedure (9).

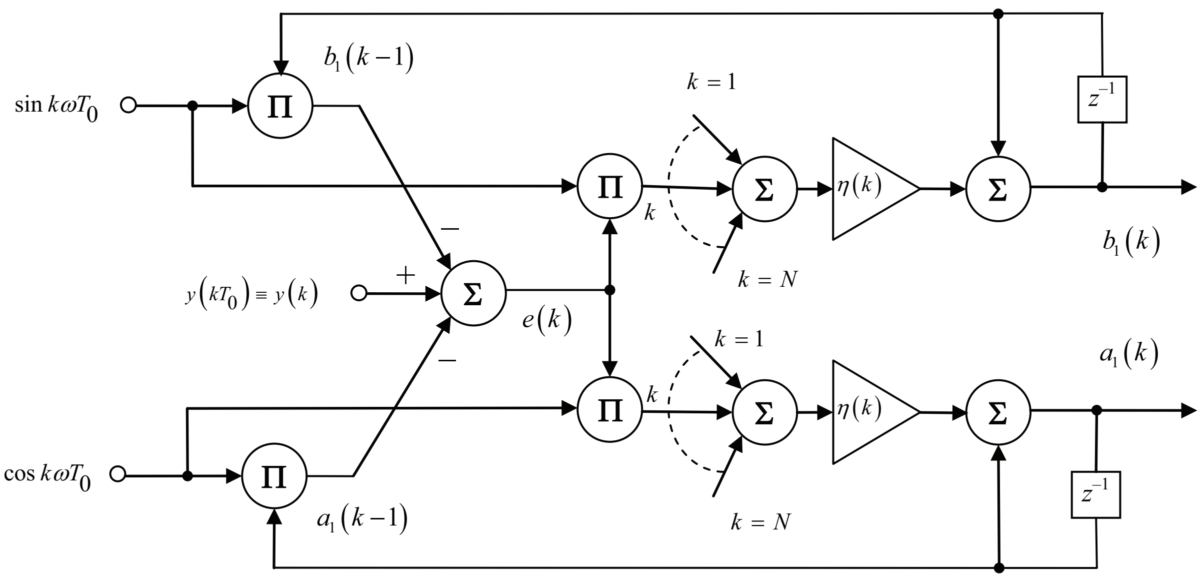

Fig. 1 – Artificial neuron for main harmonic's parameters estimation

One prerequisite for the efficient use of the least squares method is the assumption that the matrix of independent variables X is defined precisely, and disturbances are present only in the response vector Y. In circumstances where the main frequency $f = 50$ Hz is unstable, the least squares method loses its efficiency. An alternative may be the so-called total least squares method [11], implying the presence of disturbances in the independent variables as well.

In this case, the following system of equations is introduced instead of (3)

$$\left(X^* + \Xi\right) w = Y^* + \xi , \tag{10}$$

where $X^* \in R^{N\times 2m}, Y^* \in R^N$ – precise, but unknown observation matrices, $\Xi \in R^{N\times 2m}, \xi \in R^N$ – matrices of errors caused by disturbances.

In the general case, the estimation problem by means of total least squares method reduces to the problem of minimizing the function

$$E_{TLS}^N = \|\Xi\|^2 + \|\xi\|^2 \tag{11}$$

under the constraints (10), or (after the chain of transformations [11]) – to minimize the sum of squared errors

$$e = \frac{Y - Xw}{\left(1 + w^T w\right)^{\frac{1}{2}}} , \tag{12}$$

that is, to find the minimum of the identification criterion

$$\begin{aligned} E_{TLS}^N(w) &= \frac{1}{2}\frac{\|Y - Xw\|^2}{1 + w^T w} = \\ &= \sum_{k=1}^{N} \frac{\left(y(k) - \sum_{j=1}^{2m} x_j(k) w_j \right)^2}{1 + \sum_{j=1}^{2m} w_j^2}. \end{aligned} \tag{13}$$

Because the procedure for minimizing (13) is quite cumbersome, total least squares method has not received proper distribution in the theory and practice of identification.

To simplify the numerical implementation of this method, in [10], a modified error was introduced

$$\begin{aligned} \tilde{e}(t) &= s^T(t)\left(Xw - Y\right) = s^T(t) e = \\ &= \sum_{k=1}^{N}\left(\sum_{j=1}^{2m} x_j(k) w_j - y(k) \right) s_k(t) = \\ &= \sum_{j=1}^{2m} \tilde{x}_j(t) w_j - \tilde{y}(t), \end{aligned} \tag{14}$$

where $s(t) = \left(s_1(t), s_2(t), \ldots, s_N(t)\right)^T \in R^N$ – vector of identically distributed external excitation signals with zero mean and bounded variance,

$$\tilde{x}_j(t) = \sum_{k=1}^{N} x_j(k) s_k(t) , \tag{15}$$

$$\tilde{y}_j(t) = \sum_{k=1}^{N} y(k) s_k(t) . \tag{16}$$

In this case, the estimation problem is reduced to minimization of the following identification criterion

$$E_{TLS}^N(w) = \frac{1}{2} \cdot \frac{\tilde{e}^2(t)}{1 + w^T w} \tag{17}$$

with the gradient procedure

$$\begin{aligned} \frac{dw_j(t)}{dt} &= -\eta \frac{\partial E_{TLS}^N(w)}{\partial w_j} = \\ &= -\eta \tilde{e}(t) \frac{\tilde{x}_j(t)\left(1 + w^T \tilde{w}\right) - \tilde{e}(t) w_j(t)}{1 + w^T w}, \end{aligned} \tag{18}$$

which after some transformations can be brought to a form

$$\frac{dw_j(t)}{dt} = -\eta \tilde{e}(t)\left(\tilde{x}_j(t) + \tilde{y}(t) w_j(t)\right) . \tag{19}$$

Switching to discrete time, it is possible to obtain quite a simple learning algorithm

$$\begin{aligned} w_j(k) &= w_j(k-1) + \\ &+ \eta(k)\tilde{e}(k)\left(\tilde{x}_j(k) + \tilde{y}(k) w_j(k-1)\right), \end{aligned} \tag{20}$$

which provides higher estimation accuracy, however requires the introduction of probing perturbations in the monitored signal. In this regard, the use of total least squares method for signals' parameters estimation in power systems has some limitations.

3. FOURIER NEURAL NETWORK FOR SIGNALS' PARAMETERS ESTIMATION IN POWER SYSTEMS

Some awkwardness of the neural network architecture described above as well as assumptions on the nature of the disturbances $\xi(k)$ limit its use in situations where there are outliers in observations that drastically worsen the results of the incoming data processing. That is why we propose to use a digital version of the

Fourier neural network architecture [12] tuned by a robust estimation procedure.

So let the monitored signal be described by equations (1), (2), but the disturbances distribution is different from normal and is characterized by the presence of "heavy tails". The criterion to identify is the Huber function [13] in the form

$$E_H(k) = \sigma_H(e(k)), \tag{21}$$

where

$$\sigma_H(e) = \begin{cases} \frac{1}{2}e^2 & \text{when } |e| \le \beta, \\ \beta|e| - \frac{\beta^2}{2} & \text{when } |e| > \beta, \end{cases} \tag{22}$$

$\beta > 0$ – parameter defining a critical outlier level.

Gradient minimization of the criterion (21) taking into account (2) leads either to a continuous learning algorithm [9]

$$\begin{cases} \frac{da_j}{dt} = \eta\psi(e(k))\cos k\omega T_0, \\ \frac{db_j}{dt} = \eta\psi(e(k))\sin k\omega T_0, \end{cases} \tag{23}$$

where

$$\psi(e) = \begin{cases} -\beta & \text{when } e < -\beta, \\ e & \text{when } |e| \le \beta, \\ \beta & \text{when } e > \beta, \end{cases} \tag{24}$$

or to its difference modification –

$$\begin{cases} a_j(k) = a_j(k-1) + \eta_j(k)\psi(e(k))\cos k\omega T_0, \\ b_j(k) = b_j(k-1) + \eta_j(k)\psi(e(k))\sin k\omega T_0. \end{cases} \tag{25}$$

Fig. 2 shows the Fourier neural network architecture for robust signals' parameters estimation in power systems.

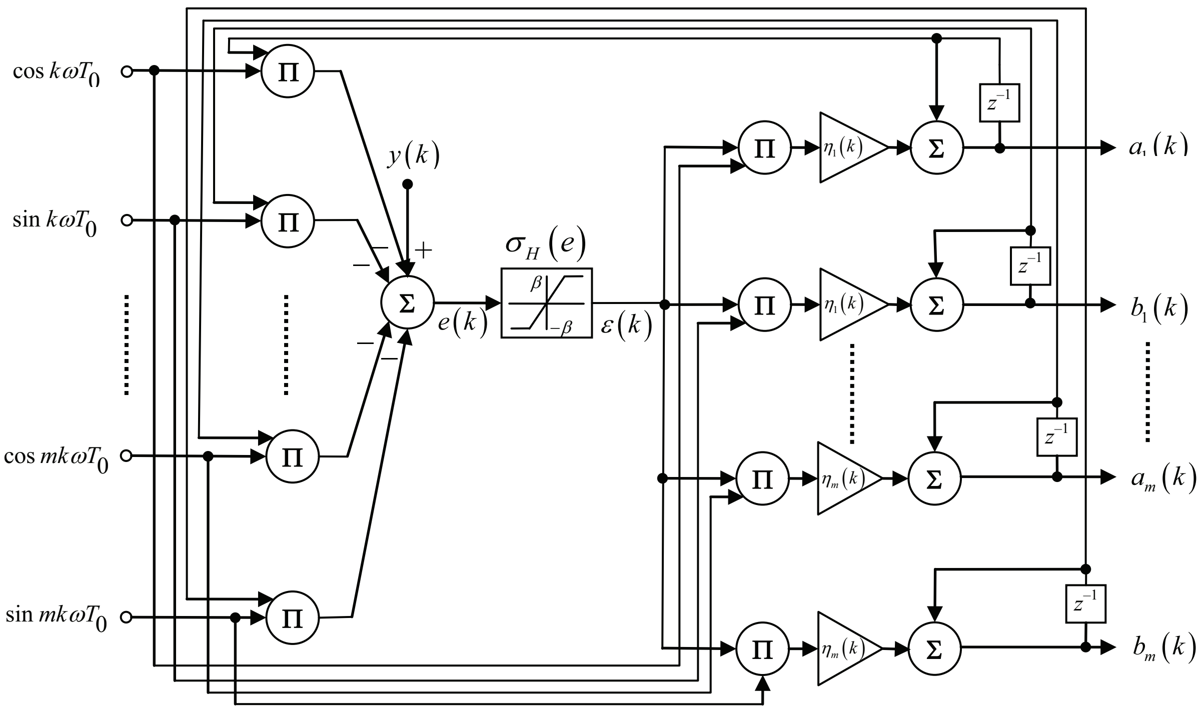

Fig. 2 – Fourier neural network architecture for robust harmonic signals' parameters estimation

The principal difference between learning procedures (9) and (25) is in the amount of information they use. The algorithm (9) refers to the procedures with a "window" memory and has a filter (smoothing) properties, the algorithm (25) is a typical one-step procedure designed to monitor the changing characteristics of the signal, it suppresses rare outliers with the saturation function (24). In principle, the algorithm (25) can be given smoothing properties as well. For this purpose, the step parameters $\eta_j(k)$ should be changed during the learning process following the Dvoretzky's conditions.

4. ESTIMATION OF PARAMETERS OF A HARMONIC SIGNAL DISTORTED BY A DECAYING EXPONENT AND OUTLIERS

In emergency conditions encountered in power systems, the harmonic components of currents and voltages may contain exponentially decaying DC terms, which may be imposed by stochastic disturbance with outliers. Analysis and evaluation of such situations is important for rapid diagnosis of the conditions of electric power systems.

Let the monitored signal be described either by an equation in continuous time

$$\tilde{y}(t) = a\cos\omega t + b\sin\omega t + g\exp(-ht), \quad (26)$$

or in discrete time

$$\tilde{y}(kT_0) = a\cos k\omega T_0 + b\sin\omega T_0 + g\exp(-hkT_0), \quad (27)$$

where the parameters vector $w = (a,b,g,h)^T \equiv \equiv (w_1, w_2, w_3, w_4)^T$ is to be estimated. Note that instead of (26) and (27) the following expressions may be used

$$\tilde{y}(t) = c\sin(\omega t + \varphi) + w_3\exp(-w_4 t) \quad (28)$$

and

$$\tilde{y}(t) = c\sin(k\omega T_0 + \varphi) + w_3\exp(-w_4 kT_0), \quad (29)$$

where

$$c = \sqrt{w_1^2 + w_2^2} = \frac{w_1}{\cos\varphi}, \quad (30)$$

$$\varphi = \arctan\frac{w_1}{w_2}. \quad (31)$$

It is also assumed that there is a set N disturbed observations $y(k) = y(kT)_0 = y(t)$, where $t = kT_0$, $k = 1,2,...,N$. Introducing instantaneous error

$$e(k) = y(k) - \tilde{y}(k), \quad (32)$$

and identification criterion of the type (4)

$$E_{LS}^N(w) = \frac{1}{2}\sum_{k=1}^{N} e^2(k), \quad (33)$$

we arrive at a standard nonlinear estimation problem, which can be solved by well-known procedures of nonlinear least-squares method of Hartley or Marquardt [14].

It is also known that in the presence of outliers in observations, identification procedures based on the least squares criteria (4) and (33) become inefficient. Therefore it is expedient to move to robust procedures based on objective functions that suppress the influence of outliers. In contrast to the Huber function (22) discussed above, here, we consider criteria based on the logistic function [15] that generate the estimation procedures, which are very convenient for neural network implementation [16, 17].

A robust criterion that takes into account N observations has the form

$$E_w^N(w) = \sum_{k=1}^{N}\delta_w(e(k)), \quad (34)$$

where

$$\delta_w(e) = \beta^2\ln\cosh\frac{e}{\beta}, \quad (35)$$

parameter $\beta > 0$ has the same meaning, as in (22).

To tune the parameters, in the general case, either a continuous procedure can be used

$$\frac{dw_j}{dt} = -\eta\frac{\partial E_w^N(w)}{\partial w_j}, \; j = 1,2,3,4, \quad (36)$$

or a discrete one

$$w_j(k) = w_j(k-1) - \eta_j\frac{\partial E_w^N(w)}{\partial w_j}, \; j = 1,2,3,4, \quad (37)$$

here, using the chain rule, the derivative in the right hand side can be written in the form

$$\frac{\partial E_w^N(w)}{\partial w_j} = \sum_{k=1}^{N}\frac{\partial E_w^N(w)}{\partial\sigma_w}\cdot\frac{\partial\sigma_w}{\partial e(k)}\cdot\frac{\partial e(k)}{\partial w_j} = \sum_{k=1}^{N}\psi(e(k))\frac{\partial e(k)}{\partial w_j}, \quad (38)$$

where

$$\psi(e(k)) = \beta\tanh\frac{e(k)}{\beta}. \quad (39)$$

Then, either a continuous procedure can be used to tune all the unknown parameters

$$\begin{cases} \frac{dw_1}{dt} = \eta_1 \sum_{k=1}^{N} \psi\left(e(k)\right)\cos k\omega T_0 = \eta_1 \sum_{k=1}^{N} \varepsilon(k)\cos k\omega T_0, \\ \frac{dw_2}{dt} = \eta_2 \sum_{k=1}^{N} \psi\left(e(k)\right)\cos k\omega T_0 = \eta_2 \sum_{k=1}^{N} \varepsilon(k)\cos k\omega T_0, \\ \frac{dw_3}{dt} = \eta_3 \sum_{k=1}^{N} \psi\left(e(k)\right)\exp\left(-w_4 kT_0\right) = \\ = \eta_3 \sum_{k=1}^{N} \varepsilon(k)\exp\left(-w_4 kT_0\right), \\ \frac{dw_4}{dt} = \eta_4 \sum_{k=1}^{N} \psi\left(e(k)\right) w_3 kT_0 \exp\left(-w_4 kT_0\right) = \\ = \eta_4 \sum_{k=1}^{N} \varepsilon(k) w_3 kT_0 \exp\left(-w_4 kT_0\right), \end{cases} \quad (40)$$

or its difference modification

$$\begin{cases} w_1(k) = w_1(k-1) + \eta_1(k) \sum_{k=1}^{N} \varepsilon(k)\cos k\omega T_0, \\ w_2(k) = w_2(k-1) + \eta_2(k) \sum_{k=1}^{N} \varepsilon(k)\sin k\omega T_0, \\ w_3(k) = w_3(k-1) + \\ +\eta_3(k) \sum_{k=1}^{N} \varepsilon(k)\exp\left(-w_4(k-1)kT_0\right), \\ w_4(k) = w_4(k-1) + \\ +\eta_4(k) \sum_{k=1}^{N} \varepsilon(k) w_3(k-1)kT_0 \exp\left(-w_4(k-1)kT_0\right). \end{cases} \quad (41)$$

The neural network implementing this approach to the estimation problem consists of N neurons for processing errors $e(k)$ connected in parallel. The scheme of one of them for time k is shown in Fig. 3. This network is a kind of hybrid of structures described above.

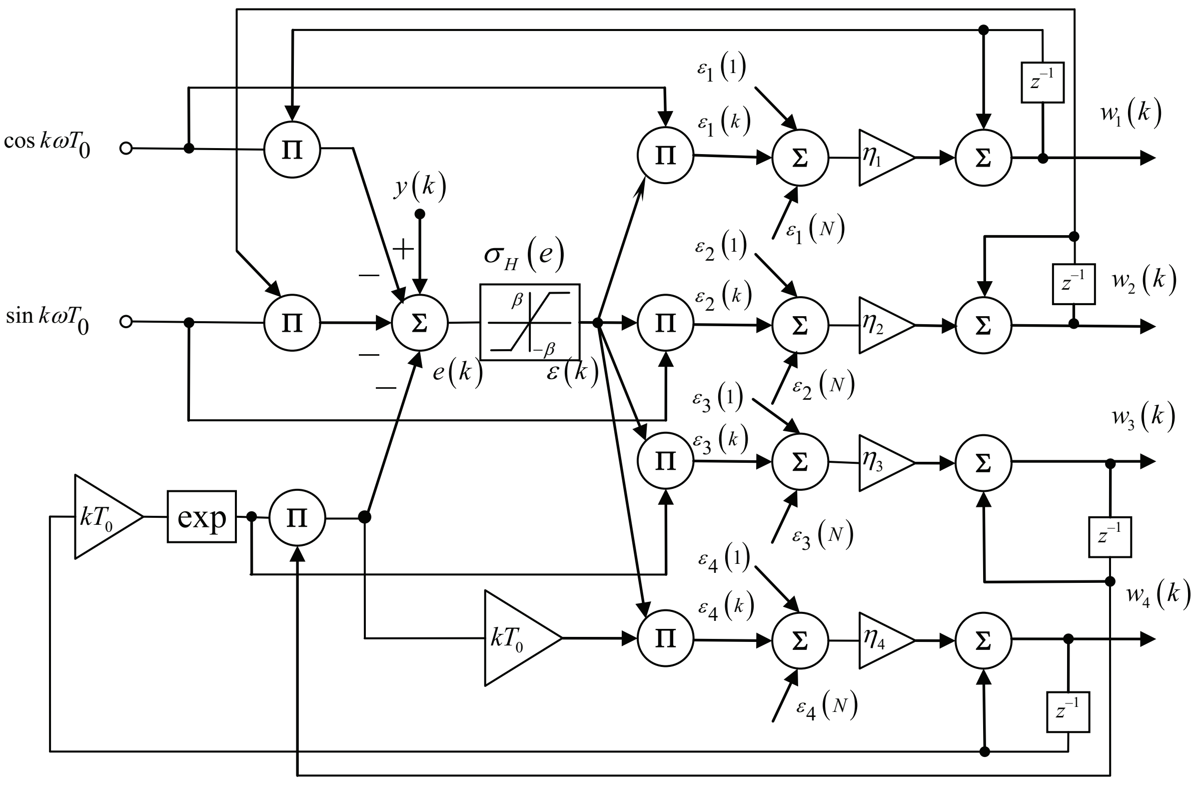

Fig. 3 – Artificial neuron for estimating the parameters of signal (27)

5. CONCLUSIONS

The problem of signals' parameters estimation in power systems based on neural network approach is considered. Architectures of neurons, networks and algorithms for their learning in real time are proposed. The obtained results allow improving the reliability and efficiency of monitoring and diagnostic systems, especially when faults in the power grids occur and outliers are present in the observations.

6. REFERENCES

[1] O.V. Danilyuk, Z.M. Bakhor, N.B. Batyuk, and V.V. Romanishin, "On-line diagnostics of power systems' operation modes based on artificial neural

networks technologies," Informaciyni tekhnologii i systemy, 4(1/2), pp. 100-103, 2001.
[2] O.V. Danilyuk, and R.O. Tkachenko, "Artificial neural networks technologies in power systems supervision tasks," Electroenergetika '98: Zbornik Prednasok z IX Vedeckej Konference, pp. 169-172, 1998.
[3] L. Lovisolo, E.A.B. da Silva, M.A.M. Rodrigues, and P.S.R. Diniz, "Efficient coherent adaptive representations of monitored electric signals in power systems using damped sinusoids," IEEE Trans. Signal Processing, 53(10), pp. 3831-3846, 2005.
[4] S. Osowski, "SVD technique for estimation of harmonic components in a power system: a statistical approach," IEE Proc. C, 141, pp. 473-479, 1994.
[5] D. Levicky, M. Drutarovsky, P. Galajda, D. Kocur, and S. Marchevsky, "Adaptive Goertzel's algorithm for harmonic analysis of power voltage," 40. Int. Wissenschafliches Koll. Vortragsreichen, 1, pp. 473-478, 1995.
[6] Ye. Bodyanskiy, S. Vorobyov, and V. Timofeev, "Adaptive recognition of the states of dynamic objects with periodic output signal," Pattern Recognition and Image Analysis, 9(3), pp. 505-509, 1999.
[7] H. Li, P. Stoica, and J. Li, "Computationally efficient parameter estimation for harmonic sinusoidal signals," Signal Processing, 80, pp. 1937-1944, 2000.
[8] S. Osowski, "Neural network for estimation of harmonic components in a power system," IEE Proc. C, 139(2), pp. 129-135, 1992.
[9] A. Cichocki, and R. Unbehauen, Neural Networks for Optimization and Signal Processing, Teubner, Stuttgart, 1993.
[10] A. Cichocki, P. Kostyla, T. Lobos, and Z. Waclawek, "Adaptive neural networks for robust estimation of signal parameters," Proc. IFAC-IFIP-IMACS Conf. “Control of Industrial Systems”, 1/3, pp. 621-626, 1997.
[11] G.H. Golub, and C.F. Van Joan, "An analysis of the total least squares problem," SIAM Journal on Numerical Analysis, 17(6), pp. 883-893, 1980.
[12] R.J. Schalkoff, Artificial Neural Networks, McGraw-Hill, New York, 1997.
[13] W.J.J. Rey, Robust Statistical Methods, Springer, Berlin-Heidelberg-New York, 1978.
[14] J. Bard, Nonlinear parameters estimation, Statistics, Moscow, 1979.
[15] P.W. Holland, and R.E. Welsch, "Robust regression using iteratively reweighted least squares," Communication Statistics – Theory and Methods, A6(9), pp. 813-827, 1977.
[16] Ye. Bodyanskiy, and O. Vynokurova, "Robust learning algorithm for radial-basis adaptive fuzzy-wavelet-neural network," Adaptyvni systemy avtomatychnogo upravlinnya, 11(31), Systemni technologii, Dnipropetrovs’k, pp. 3-15, 2007.
[17] Ye. Bodyanskiy, O. Pavlov, and O. Vynokurova, Outliers-resistant learning algorithm for radial-basis fuzzy-wavelet-neural network in stomach acute injury diagnosis tasks, in K. Markov, K. Ivanova, and I. Mitov, eds., Int. Book Series “Information Science & Computing”, Institute of Information Theories and Applications FOI ITHEA, Sofia, 2008, pp. 55-62.