International Journal of Petroleum and Gas Engineering Research

Vol.2, No.1, pp.1-7, August 2018

Published by European Centre for Research Training and Development UK (www.eajournals.org)

THE USE OF WAVENET-REGULATOR IN CONTROL SYSTEMS OF GAS TURBINE ENGINES

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ABSTRACT: *The applicability of the method of managing an aero gas turbine engine using wavelet neural networks is considered in this article. The use of wavelet functions provides the traditional neural network of local approximation, which provides rapid training of the network and reduces the typical for multi-layer perceptrons dependence of the quality of learning from the sequence of submission of training data. The structural scheme of the control system and algorithm for determination of the number of wavelet-bases and the size of the network are developed.*

KEYWORDS: Aviation Gas Turbine Engine, Wavelet Neural Network, Control System, Algorithm.

INTRODUCTION

Neurocontrollers are the controlling adaptive systems’ development and like them, they can be contingently divided into two classes: indirect (model of the object is adjusted) and direct (etalon model). In the tasks of technological processes controlling indirect systems in which the model neural net which is connected in parallel with the controlled object are more widespread. Options of such a neural net are adopting permanently up to the object functioning. These options are the initial information based on which the controlling actions are calculated. Undoubtedly that the synthesized control quality is completely defined with the accuracy of the model which is adjusted, the imperious problem is the rapidity of the process.

Taking into consideration the control theory, a great majority of processes in gas turbine engines are dynamic and non-stationary. It is quite understandable that effective object controlling cannot be implemented based on the classical methods of automatic controlling including classical adaptive approach but more developed methods on the basis of computational intelligence hybrid systems are required. First of all it is using of neurocontrollers on the basis of which artificial neural nets are set, and which have the universal approximate properties, that gives them an opportunity to successfully solve the problems of any type of nonlinearity that may arise.

This problem is often complicated with the small amount of samples, when there are no sufficient data about the object and it is impossible to create accurate neural model. Thereby in [4] the technological processes’ adaptive controlling system was proposed. Neo-fuzzy model characterized with high rapidity, tracing and filtering properties instead of usual neural model is proposed. This model provides piece-lined approximation of the controlled object of non-linear characteristics but in some cases the appropriate accuracy is not reached.

ISSN: Print 2514-9253, Online 2514-9261

Experimental Methods

Wavenet-analysis for neural networks.

For efficiency of the controlling electronic system of gas turbine engines wavenet the adjusting model can be successfully used. It combines in itself the approximate capabilities of the neural nets and the local unsteady capabilities of the wavenet disorder.

We will select function $\varphi(x) \in L^2(R)$ which is called mother wavelet and which meets the following circumstances:

- condition of finite energy:

$$\int_{-\infty}^{\infty} |\varphi(t)|^2 dt < \infty ; \quad (1)$$

- acceptable state:

$$\int_R \frac{|\hat{\varphi}(\omega)|}{|\omega|} d\omega < \infty ; \quad (2)$$

where $\hat{\varphi}(\omega)$ - Fourier transform $\varphi(x)$. Then, the appropriate family of the stretched and transformed wavelets can be defined in such a way:

$$\left\{ \varphi_{j,k}(x) = a^{-2/j} \varphi(a^{-j} x - kb), (j,k) \in Z^2 \right\} \quad (3)$$

where a and b, are stretching and transforming parameters respectively. Correctly a and b, $\{\varphi_{j,k}(x)\}$ can be called as "cleared" wavenet which includes the frame $L^2(R)$.

$$A\|f\|^2 \leq \sum_{(j,k)\in Z^2} \left|\langle \varphi_{j,k}, f \rangle\right|^2 \leq B\|f\|^2 \quad (4)$$

where $f \in L^2(R)$, $\langle \varphi_{j,k}, f \rangle = \int_R \varphi_{j,k}(t) f(t) dt$ is an internal product $A>0$ and $B>0$ - frame limits. If $A = B$, $\{\varphi_{j,k}(x), (j,k) \in Z^2\}$ - nonslack frame. In this case, it leads to:

$$f(x) = A^{-1} \sum_{(j,k)\in Z^2} \langle \varphi_{j,k}, f \rangle \cdot \varphi_{j,k}(x) \quad (5)$$

while $A = B = 1$, $\{\varphi_{m,n}(x), (m,n) \in Z^2\}$ becomes orthonormal basis. Then

(6)

It should be noted that wavenet transformation has the ability of the variable time-frequency localization. Points of the grid of the mother wavenet $\{\varphi_{j,k}(x)\}$ are located on $(kbaj, \pm a\text{-}j\omega o)$; therefore the width of a time interval $\varphi_{j,k}(x)$ can be changed with frequency change. Thus, this property is very useful to the analysis of non-stationary signals and learning of non-linear functions. (Often used wavenet example – second derivative Gaussian function).

ISSN: Print 2514-9253, Online 2514-9261

$$\varphi(x)=(1-x^2)e^{-\frac{x^2}{2}} \Leftrightarrow \varphi(\omega)=\sqrt{2\pi\omega^2}e^{-\frac{\omega^2}{2}} \qquad (7)$$

This function has excellent localization on time and frequency and satisfies a condition of the allowed state.

From the point of view of the given above results the wavenet - base of function (VBF) of a neural network can be defined as:

$$f(x)=\sum_{j=1}^{K} w_j\varphi_j(x)=\sum_{j=1}^{K} w_j\varphi_j(a_jx-b_j) \qquad (8)$$

where $w_j \in R$, $a_j \in R^d$, $b_j \in R^d$, d - input dimension and K – number of wavenet -bases.

In the multidimensional case, you can use the product of one-dimensional wavelet:

$$\psi(x)=\psi(x_1,x_2,\ldots x_n)=\prod_{i=1}^{n}\varphi(x_i) \qquad (9)$$

$x=[x_1,x_2,\ldots x_n]^T$ are inputs of a network. In general, any function can be approximated by a wavenet-network which nodes of activation functions are scaled and turned into a mother wavenet, $\varphi_{ab}(x)$:

$$\varphi_{ab}(x)=\sqrt{a}\ \ \varphi(ax-b), \qquad (10)$$

Normalization constant $\sqrt{a}$ is found in such a way, that energy $\varphi_{ab}(x)$ is such as in $\varphi(x)$

$$\varphi_{a_jb_j}(x_i)=\sqrt{a_{ij}}\varphi(a_{ij}x_i-b_{ij}) \qquad (11)$$

$$\psi_j(x)=\prod_{i=1}^{n}\varphi_{a_jb_j}(x_i) \qquad (12)$$

$$f(x)=\sum_{j=1}^{K} w_j\psi_j(x) \qquad (13)$$

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If the output of the system is multidimensional $(y \in R^m)$:

$$y_i = \sum_{j=1}^{K} w_{ij}\psi_j(x) + e_i, \quad i = 1,2,\ldots,m \qquad (14)$$

$$y_i \cong \sum_{j=1}^{K} w_{ij}\psi_j(x), \quad i = 1,2,\ldots,m \qquad (15)$$

Thus, wavenet network consists of the three layers: the wavenet layer for computation of wavenet functions as functions of nodes activation (11), the product layer for computation of wavenet bases (12) and the output layer for determination of the outputs (15).

The configuration of control system is shown in fig. 1.

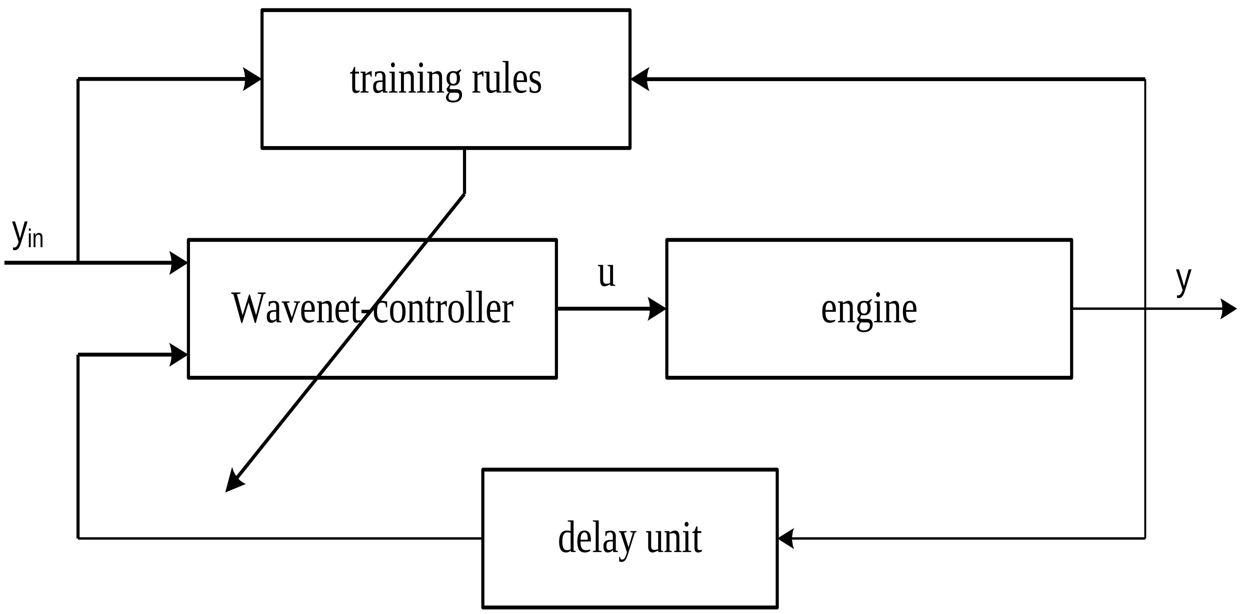

Figure 1 - The proposed configuration of control system

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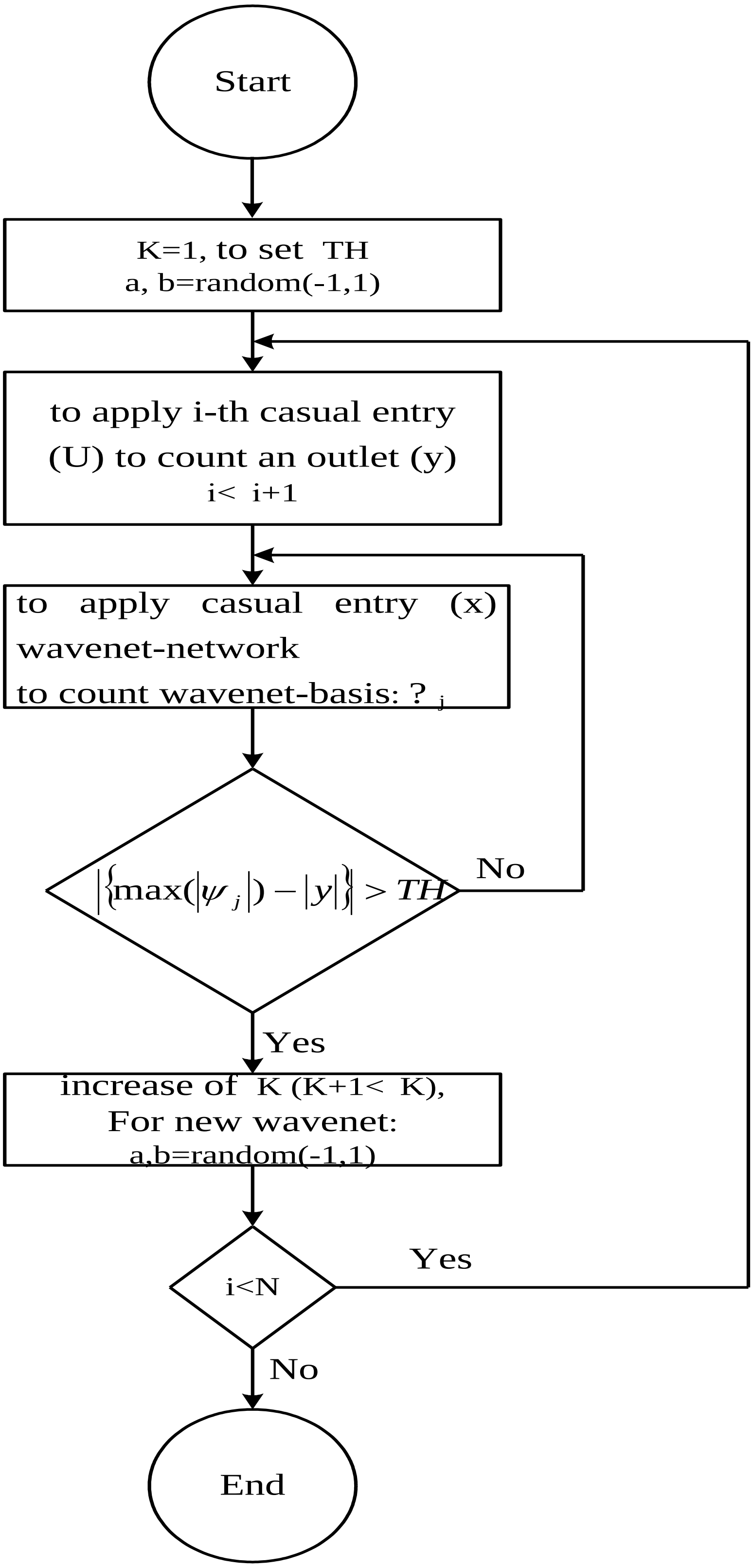

Figure 2 - Algorithm of determination of the wavenet-bases amount and the size of a network

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Execution of the two controllers operation and the comparison of their results are given in fig. 3 and fig. 4.

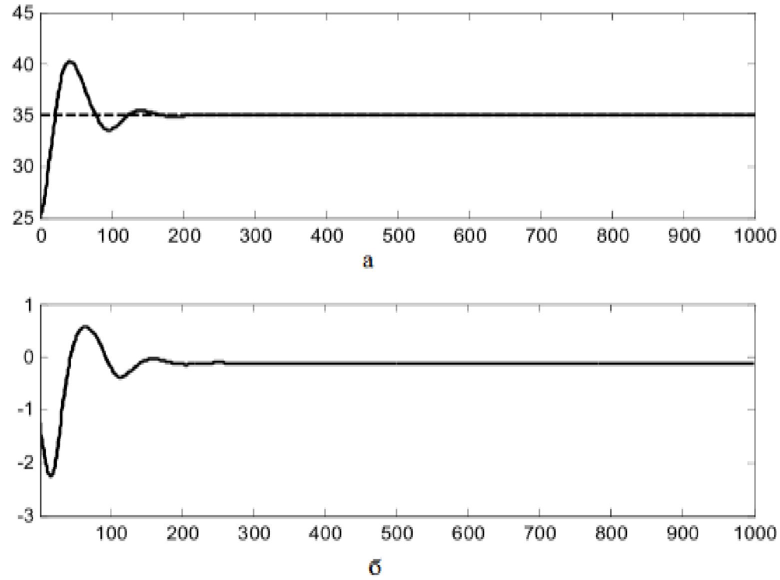

Figure 3 - Execution of the proposed controller (a wavenet -neural network)

a - a surge characteristic;

b - the controlling signal (TH = 0,8; K = 2, structure: 1-2-2-1)

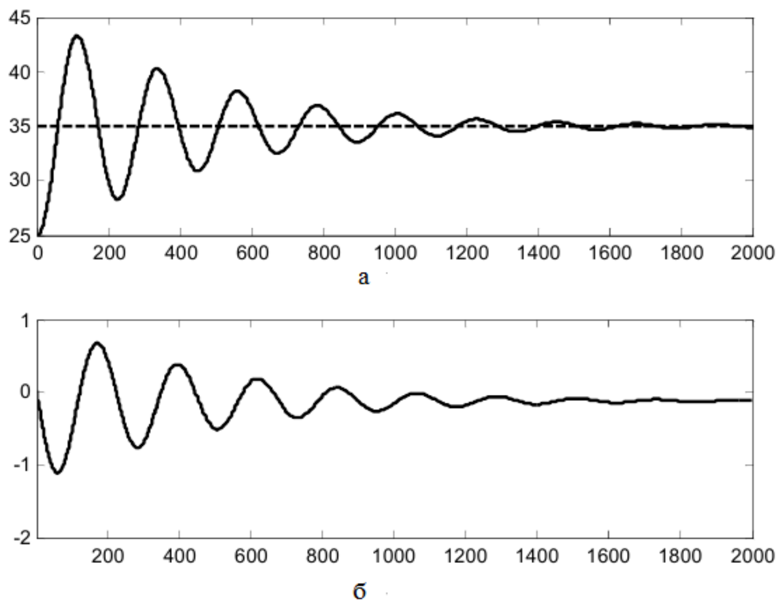

Figure 4 – Execution of the proposed controller (a neural network)

a - a surge characteristic;

б - the controlling signal (HM: 2-5-5-1)

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CONCLUSION

Proposed method of solving GTE controlling tasks based on the WAVENET-regulator supposes that on the contrary to the existed classical methods which use tight limits of the controlling options and also the variation coefficient rigid boundaries using of the WAVENET neural nets based on the adaptation of the design mathematical model to the real GTE taking into consideration specific external conditions can sufficiently improve the controlling characteristics and also reduce the cost of the options updating by reducing the number of the regulated options.

Further research is to develop practical implementation of this technique for the specific GTE.

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ISSN: Print 2514-9253, Online 2514-9261