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Ognjen Kuljača, Krunoslav Horvat, Bruno Borović

Design of Adaptive Neural Network Controller for Thermal Power System Frequency Control

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Original scientific paper

This paper deals with analytical and simulation approach for choice of activation functions and instead of a number of nodes for a class of neural network controllers for frequency control of thermal power systems. Neural network update laws are derived via Lyapunov like stability analysis. When number of nodes is fixed, then simulation analysis is conducted to find the best performer activation function. Best performance is chosen using integral error criteria and proper statistical tests.

Key words: Choice of activation functions, Number of nodes, Neural network control

Dizajn adaptivnog regulatora s neuronskim mrežama za regulaciju frekvencije u elektroenergetskom sustavu s toplinskim turbinama. Članak opisuje analitičko-simulacijski pristup izboru aktivacijskih funkcija i broja čvorova za klasu regulatora s neuronskim mrežama za regulaciju frekvencije u elektroenergetskom sustavu s toplinskim turbinama. Zakoni učenja neuronske mreže su izvedeni kroz analizu stabilnosti primjenom funkcije Ljapunova. Nakon što je određen broj čvorova, proveden je simulacijski postupak za određivanje najbolje aktivacijske funkcije. Najbolja funkcija za dani regulator je određena korištenjem kriterija integralne pogreške i statističkim testiranjem.

Ključne riječi: izbor aktivacijskih funkcija, broj čvorova, regulacija neuronskim mrežama

1 INTRODUCTION

The paper presents novel procedure for designing neural network (NN) frequency controller for an isolated thermopower system. As power systems are rapidly entering the era of deregulation, the importance of frequency control becomes more significant and precise scheduling of loads in power system becomes increasingly complicated, if not impossible. As a result, load fluctuations in the power system are becoming more explicit. In addition, in emerging markets of ancillary services, primary controllers and turbines employed in secondary frequency and power control change constantly, typically on hourly basis.

When conventional control schemes are used, these changes of power system parameters can cause serious problems affecting the quality of frequency control, and in some cases even affect the overall system stability. In order to avoid such instabilities, conventional secondary controllers are usually implemented with smaller integral gains than the optimal performance would otherwise require ([2]).

The problem addressing the frequency and load – frequency control is well described ([2], [3], [4], [5], [6], [7], [8] and many others). Some of already mentioned non-adaptive schemes are given in [2], [3], [4], [5], [6], and [7]. However, as the recent trends in the deregulation of modern power systems lead to frequent and significant parameters changes, the quality of control is diminished when such non-adaptive controllers are used, hence calling for other approaches.

NN load-frequency control is described in [9], [10] and [11]. These NN control algorithms show satisfactory performance but, unfortunately, require off-line training. Since NN training cannot be done on real systems, this approach is constrained regarding application to power systems control because it is very hard to obtain a precise model required to train the controller.

In this paper we provide a novel design procedure and description of adaptive NN controller that does not require *a priori* training yielding the neural network capable of on-line learning ([1]). The new controller represents an advanced and performance-enhanced version of a NN control scheme given in [12].

2 MATHEMATICAL PRELIMINARIES

Let R denote the real numbers, R^n denote the real n vectors, $R^{m\times n}$ the real $m \times n$ matrices. We denote by $\|\cdot\|$ a suitable vector norm. Given a matrix $A = [a_{ij}]$, $A \in R^{n\times m}$ the *Frobenius norm* is defined by

$$\|A\|_F^2 = tr(A^T A) = \sum_{i,j} a_{ij}^2 \quad (1)$$

with $tr()$ the trace operation. The associated inner product is $\langle A, B\rangle_F = tr\left(A^T B\right)$. The Frobenius norm $\|A\|_F^2$ is denoted by $\|\cdot\|$ throughout this paper, unless otherwise specified. The trace of A satisfies $tr(A) = tr(A^T)$ for a matrix $A = [a_{ij}]$. For any mxn matrix, and nxm matrix C, we have $tr(BC) = tr(CB)$.

In proving stability we use proposition given in [13] which basically states that a system is uniformly ultimately bounded if it has a Lyapunov function whose time derivative is negative in an annulus of a certain width around the origin. As given in [13];

Lemma 1: Consider the function $g(\bullet) : R \to R$

$$g(y) = \alpha_0 + \alpha_1 y - \alpha_2 y^2, \quad y \in R^+, \quad (2)$$

where $\alpha_i > 0,\ i = 0, 1, 2$. Then $g(y) < 0$ if $y > \eta > 0$, where

$$\eta = \frac{\alpha_1 + \sqrt{\alpha_1^2 + 4\alpha_0\alpha_2}}{2\alpha_2}. \quad (3)$$

Proposition 1: Let $x(t) \in R^m$ be the solution of the differential equation

$$\dot{x}(t) = f(x(t), t), \quad x(t_0) = x_0. \quad (4)$$

And assume there exists a function $L(x(t), t)$ that satisfies

$$m_m \|x(t)\|^2 \le L(x(t), t) \le m_M \|x(t)\|^2, \quad (5)$$

$$\dot{L}(x(t), t) \le g(\|x(t)\|) < 0 \text{ for all } \|x(t)\| > \eta > 0, \quad (6)$$

with m_m and m_M positive constants, $g(\bullet)$ as in (2) and η as in (2). Define $\delta \equiv \sqrt{m_m^{-1} m_M}$ and $d > \delta\eta$. Then $x(t)$ is uniformly ultimately bounded that is

$$\|x_0\| \le r \to \|x(t)\| \le d \text{ for all } t \ge t_0 + T(d, r), \quad (7)$$

where

$$T(d, r) = 0,\ r \le \delta^{-1} d, \quad (8)$$

$$T(d, r) = \frac{m_M r^2 - m_m R^2}{\alpha_2 R^2 - \alpha_1 R - \alpha_0},\ r > \delta^{-1} d. \quad (9)$$

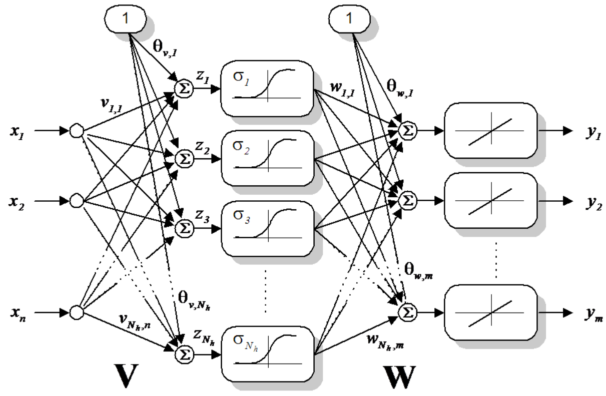

Fig. 1. Two layer neural network

3 NN POWER SYSTEM CONTROL

Given $x \in R^{n_1}$, a two-layer NN, shown in Fig. 1, has a net output given by

$$y = W^T \sigma(V^T x), \quad (10)$$

where $x = \begin{bmatrix} 1 & x_1 & \dots & x_{n_1} \end{bmatrix}^T$, $y = \begin{bmatrix} y_1 & \dots & y_{n_2} \end{bmatrix}$ and $\sigma(\bullet)$ is the activation function. If $z = \begin{bmatrix} z_1 & z_2 & \dots \end{bmatrix}^T$, we define $\sigma(z) = \begin{bmatrix} \sigma(z_1) & \sigma(z_2) & \dots \end{bmatrix}^T$. Including "1" as a first term of vector x in allows one to incorporate the thresholds as the first column of W^T. Then any tuning of NN weights includes tuning of thresholds as well [1].

The main property of NNs we are concerned with for control and estimation purposes is the function approximation property ([15], [16]). Let $f(x)$ be a smooth function from $R^{n_1} \to R^{n_2}$. Then, it can be shown that if the activation functions are suitably selected, as long as x is restricted to a compact set $S \in R^n$, then for some sufficiently large number of hidden-layer neurons *L*, there exist weights and thresholds such that

$$f(x) = W^T \sigma(V^T x) + \varepsilon(x). \quad (11)$$

The value of $\varepsilon(x)$ is called the neural network functional approximation error. In fact, for any choice of a positive number ε_N, one can find a neural network such that $\varepsilon(x) \le \varepsilon_N$ for all $x \in S$. Also, it has been shown that, if the first-layer weights *V* are fixed (not tuned), then the approximation property can be satisfied by selecting only the output weights W. For this to occur $\varphi(x) = \sigma(V^T x)$ must be a basis [1].

If one selects the activation functions suitably, then, as it was shown by Igelnik and Pao [17], the $\varphi(x)$ is a basis if is selected randomly. Activation functions should be

Gaussian, subsequent derivatives of Gaussians, sigmoidal functions or hyperbolic tangents.

3.1 Isolated Thermopower System

The model of an isolated thermopower system is shown in Fig. 2. All power values are given in per unit system ([pu]).

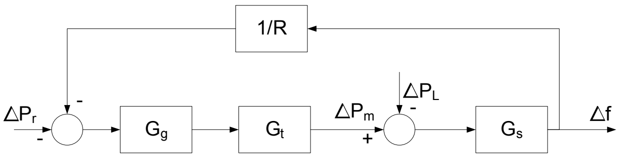

Fig. 2. The model of isolated thermo power system

The transfer functions are given as:

$$G_g = \frac{1}{1+T_g s}, \tag{12}$$

$$G_t = \frac{1}{1+T_t s}, \tag{13}$$

$$G_s = \frac{K_s}{1+T_s s}, \tag{14}$$

where G_g, G_t and G_s represent turbine governors, control turbines and the power system respectively. Such models are described in more details in [2], [3], [4], [5], [6], [7], [8], and by many others. Model parameters are: power system droop R [Hz/pu], turbine governing time constant T_g [s], turbine time constant T_t [s], load time constant T_s [s] and load system gain K_s [Hz/pu]. Model output is frequency change from operating point Δf [Hz], model inputs are load power change ΔP_L [pu] and control power reference value ΔP_r [pu], and ΔP_m [pu] is mechanical power change. These papers also show that the isolated thermopower system given in Fig. 2 is always asymptotically stable if R is a positive number. In real power systems that is always the case.

The system is linear and the need for adaptive control or use of the function approximation property of the neural network is not obvious. However, as it was mentioned before, all of the system parameters can and do change during the operation. This is especially true in modern power systems where ancillary services are bought and utilized on free market on the hourly base. Thus, with constantly changing parameters it is conceivable that adaptive control scheme would perform better than non-adaptive control.

The conventional way to control thermopower plant is to use linear PI controllers. The controller has the change of power system frequency Δf as the input and produces the control signal ΔP_r at output. That signal is fed to available turbine governors in order to counter the changes caused by the change in the load ΔP_L. The turbine output is the mechanical power ΔP_m. However, the presence of integral action means that the system can become unstable. Instead, the full state space adaptive NN controller acting as a nonlinear proportional gain parallel to $1/R$ will guarantee stability and provide required accuracy.

The system shown in Fig. 2 can be represented in state space form as

$$\begin{aligned} \dot{x} &= \begin{bmatrix} -\frac{1}{T_g} & 0 & -\frac{1}{RT_g} \\ \frac{1}{T_t} & -\frac{1}{T_t} & 0 \\ 0 & \frac{K_s}{T_s} & -\frac{1}{T_s} \end{bmatrix} x \\ &+ \begin{bmatrix} -\frac{1}{T_g} & 0 \\ 0 & 0 \\ 0 & -\frac{K_s}{T_s} \end{bmatrix} \begin{bmatrix} \Delta P_r \\ \Delta P_L \end{bmatrix} \\ \dot{x} &= Ax + Bu \\ \Delta f &= \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} x. \end{aligned} \tag{15}$$

The state vector *x* is defined as

$$x = \begin{bmatrix} y_g & \Delta P_m & \Delta f \end{bmatrix}^T, \tag{16}$$

where y_g is the output from the turbine controllers. In practice, these states are physically available, and this representation allows for the NN control scheme design.

3.2 Adaptive Neural Network Control

We use the neural network shown in Fig. 1. When the first layer weights are initialized randomly and then fixed to form a basis $\varphi(x)$, the NN output (10) becomes

$$y = W^T \varphi(x) \tag{17}$$

similarly to the tracking NN controller described in [18], [19], [14], [20], [21] and numerous other papers.

However, as the problem here is control and not tracking, we need different controller architecture. First of all there is no special robustifying term within the controller and, second, the PD controller parallel to NN controller is absent. Actually, nor derivative nor proportional part parallel to $1/R$ is needed to initially stabilize the system since uncontrolled system is always stable. Even though the proportional gain K parallel to $1/R$ was still used in the scheme in [12], simulation analysis had shown that proportional gain does not improve the performance of the control scheme. Therefore, the controller developed below does not use proportional part in control, but only NN alone.

It is assumed that the load disturbance ΔP_L is bounded so that

$$\Delta P_L \leq \Delta P_M. \tag{18}$$

This assumption is true as long as the power system is in normal mode of operation. If the load disturbance is

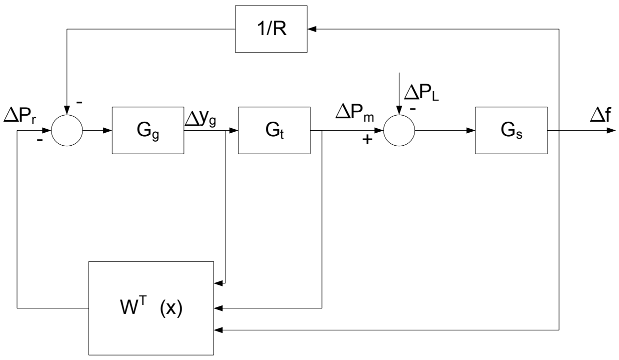

Fig. 3. NN control scheme

too big there will not be any control action since the system just does not have enough power generation capability available. In that case, the protection functions take over and some loads have to be disconnected.

NN tuning law is derived in [24] as follows. NN control scheme in shown in Fig. 3. Control signal is given by

$$\Delta P_r = W^T \varphi(x) \tag{19}$$

and the weight updates are provided by

$$\dot{W} = F\varphi(x)\Delta f - k_w \|x\| FW, \tag{20}$$

with F any symmetric and positive definite matrix and k_w positive design parameter. Then, the system states x and neural network weights W are ultimately uniformly bounded (UUB) and the system is stable in Lyapunov sense as long as

$$\|x\| > \frac{d_M \sigma(P)_{\max} + \frac{D^2}{4k_w^2}}{\frac{1}{2}\sigma(Q)_{\min}}, \tag{21}$$

or

$$\|W\| > \frac{D}{2k_w} + \sqrt{\frac{D^2}{4k_w^2} + \frac{d_M \sigma(P)_{\max}}{k_w}}. \tag{22}$$

Proof is provided in [24] in the way that rewrites equation (15) into the form that is more suitable for the stability analysis

$$\dot{x} = Ax + B_2 \Delta P_L + B_1 W^T \varphi(x) \tag{23}$$

where

$$B_1 = \begin{bmatrix} -\frac{1}{T_g} & 0 & 0 \end{bmatrix}^T, \tag{24}$$

$$B_2 = \begin{bmatrix} 0 & 0 & -\frac{K_s}{T_s} \end{bmatrix}^T. \tag{25}$$

We will also redefine the disturbance as

$$d = B_2 \Delta P_{L.} \tag{26}$$

Note that *d* is also bounded by a constant d_M because ratio $\frac{K_s}{T_s}$ has always a finite value. We can now rewrite (23) as

$$\dot{x} = Ax + d + B_1 W^T \varphi(x) \tag{27}$$

Let us now define the Lyapunov candidate:

$$\dot{L} = \frac{1}{2} x^T P x + \frac{1}{2} W^T F^{-1} W \tag{28}$$

with P a diagonal and positive definite matrix. In this design W is a vector because we have only one output. The Lyapunov derivative is:

$$\dot{L} = \frac{1}{2}(\dot{x}^T P x + x^T P \dot{x}) + W^T F^{-1} \dot{W}. \tag{29}$$

By introducing (27) into (29) we obtain

$$\begin{array}{l} L = \frac{1}{2}\dot{x}^T (A^T P + PA)x + x^T P d \\ \quad + x^T P B_1 W^T \varphi(x) + W^T F^{-1} \dot{W}. \end{array} \tag{30}$$

The first term in (30) is a well known Lyapunov function for linear system and can be easily rewritten by introducing (20) into (30)

$$\begin{array}{l} L = \frac{1}{2}\dot{x}^T Q x + x^T P d \\ \quad + W^T \varphi(x)(x^T P B_1 + \Delta f) + k_w \|x\| \|W\|^2, \end{array} \tag{31}$$

with Q positive definite (note that uncontrolled system is asymptotically stable, so positive definite Q always exists). Let us define *D* as $D = \max(\|\varphi(x)\| (\|PB_1\| + 1))$. Activation functions are bounded so we can replace $\varphi(x)$ by $\|\varphi(x)\|$. Let us define $\sigma(Q)_{\min}$ and $\sigma(P)_{\max}$ as the minimum and maximum singular values of matrices Q and P respectively. After introducing norms and some arithmetic we obtain the following inequality:

$$\dot{L} \le -\|x\| \left(\begin{array}{l} \frac{1}{2}\|x\| \sigma(Q)_{\min} - \\ d_M \sigma(P)_{\max} - \|W\| D + k_w \|W\|^2 \end{array} \right). \tag{32}$$

Lyapunov derivative is negative as long the term in parentheses in (32). This term will be positive as long as (21) and (22) hold, meaning as long as x and W are outside a compact set. Vectors x and W are thus UUB and the system is stable.

4 CHOICE OF NUMBER OF NODES AND ACTIVATION FUNCTIONS

The important step in structuring the neural network is choice of number of nodes and type of activation functions. Exact solution for choice of number of nodes or activation functions does not exist. Instead, various iterative methods can be applied. Here, we will illustrate an novel iterative method for choice of NN controller's activation functions and number of nodes.

Let us first deal with choice of number of nodes. We will assume some minimal knowledge about the nature of controlled plant. We can see that, in essence, controlled plant is built out of three first order transfer functions with nonconstant parameters. The state vector in our case has three states. It is shown in [25] and [26] that bound of function approximation error decreases with number of nodes as well as the number of inputs.

So, a simple way to estimate number of nodes is to pick transfer function with any parameters corresponding to the control plant architecture - in our case, we have three first order transfer functions so we choose the first order transfer function as a common representative for all three states of the system. Then, the transfer function is persistently excited with the appropriate signal ([27]) and the inputs, u, and the output, y, are recorded. This step can be easily done by simulation. Error can be calculated as $e = y - u$.

Now, the next step is to setup feedforward network with less or the same number of inputs as is our state vector, x. In our case, inputs are u and e. Generally, the initial number of NN nodes for the approximation of the first order transfer function can be heuristically determined and typically turns out to be two. Furthermore, hyperbolic tangents, any member of the family of the sigmoid or the Gaussian type of activation functions can be used during this step.

The network is trained to check if sufficiently small error can be achieved where the sufficiently small error depends on required precision in actual system. If this is achieved, the chosen number of nodes remains two. If not, one node is added. The procedure is repeated until the sufficiently small error is achieved. Software tools for NN training and simulation needed for carrying out the procedure are numerous and readily available.

Now, for the system shown in Fig. 2, we can choose two nodes for each of the three transfer functions, totaling six nodes in neural network hidden layer. Actually, the dimension of $\varphi(x)$ is in this case 7×1 with bias included.

Choice of activation functions is more complex. Again, as for the choice of number of nodes, there is no exact solution for choice of activation functions. Therefore, we will assume that we know the basic information of system architecture and we will find activation function through simulation.

The procedure starts with setting up the network with number of nodes found by the procedure described above. The activation functions are the ones that are to be checked. Persistently excited input or disturbance signal is fed into the system from Fig. 2 controlled by (11) and with weights updated by (12) and performance indicators recorded. The procedure is repeated to evaluate all activation functions candidates with expected parameter changes.

Of course, we must assume that we don't have complexity issues with hardware. In the other words, our hardware is good enough to withstand numerical burdens of Radial basis functions (RBF) or sigmoid activation functions. With contemporary hardware pieces this is always almost the case.

5 SIMULATION EXAMPLE

In order to illustrate the procedure described above, the simulation example is provided. Simulations were performed with following parameters and signals: $T_g = 0.08s$, $T_t = 0.3s$, $T_s = 20s$, $K_s = 120\frac{Hz}{pu}$, $R = 2.4\frac{Hz}{pu}$, $F = diag(0.07)$, $k_w = 0.05$, and $\Delta P_L = 0.1\sin(0.02\pi\, t)pu$. Matrix $\varphi(x)$ has dimensions 7x1 and *W* and *V* initialized as random numbers between -0.5 and 0.5. Simulations were performed for given plant parameters as well as for plant parameters increased and decreased by 10%. Simulation time was 480 s. Recorded performance indicators for each simulation were Integral of Absolute Error (IAE)

$$J_{IAE} = \int_0^{\infty} |e(t)|\, dt \tag{33}$$

and Integral of Squared Error (ISE)

$$J_{ISE} = \int_0^{\infty} e^2(t)dt. \tag{34}$$

Since neural network weights were initialized randomly, it was necessary to perform a number of simulations in order to obtain samples with different IAE and ISE values that allow us to compare mean values and choose the best candidate. We performed fifty simulations for every activation function and every set of parameters. Simulation was performed for Gaussian activation function given by

$$f(x) = e^{-a^2(x-b)^2}, \tag{35}$$

$tanh$ activation function given by

$$f(x) = \frac{e^{2a(x-b)} - 1}{e^{2a(x-b)} + 1}, \tag{36}$$

and $sigm$ (sigmoid) activation function given by

$$f(x) = \frac{1}{e^{-a(x-b)} + 1}. \tag{37}$$

Resulting IAE and ISE mean values for the three activation functions from above are given in Table 1, Table 2 and Table 3.

Simulation was also performed for nominal parameters and $\pm 10\%$ parameter changes for the system controlled with conventional PI controller with proportional

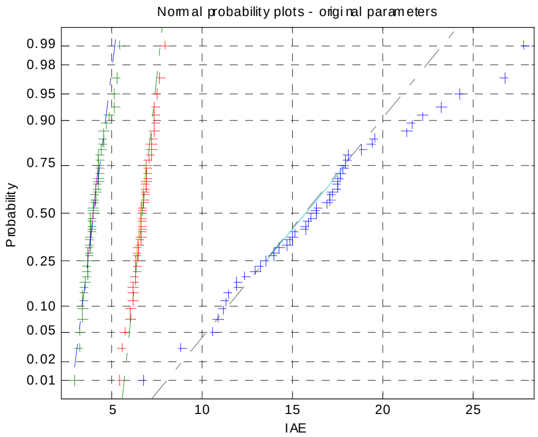

Fig. 4. Normal probability plots for IAE and original parameters

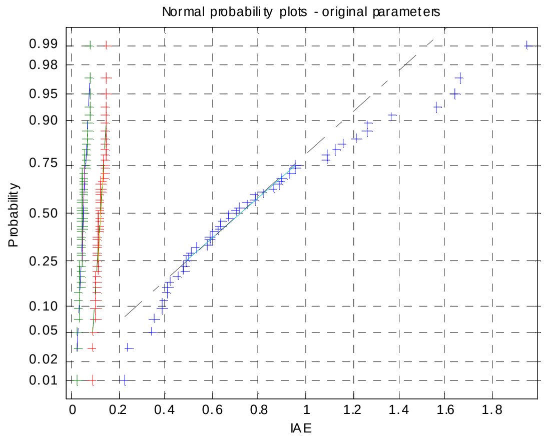

Fig. 5. Normal probability plots for IAE and decreased parameters

Table 1. Mean values of IAE and ISE with original parameters

	IAE	ISE
Gauss	4.0426	0.0476
tanh	16.2409	0.7912
sigm	6.7312	0.1214

Table 2. Mean values of IAE and ISE with original parameters decreased by 10%

	IAE	ISE
Gauss	4.0844	0.0475
tanh	16.1705	0.7654
sigm	6.7234	0.1234

Table 3. Mean values of IAE and ISE with original parameters increased by 10%

	IAE	ISE
Gauss	4.1132	0.0503
tanh	16.1597	0.7799
sigm	6.7229	0.1271

gain, $k_p = 0.08$, and integral gain, $k_i = 0.1\,Hz$. Results are shown in Table 4.

From tables 1-4 it can be seen that control with neural networks with Gaussian and sigmoidal functions outperforms by far control with PI or tanh activation function. However, the question is whether these differences are statistically significant.

To answer that question, we will first check the distribution of recorded IAE and ISE simulation results for every activation function. Normal probability plots varying the criteria, system parameters, and initial weights within V-layer are shown in Figures 4-9.

From Figures 4-9 we can see that distributions are normal, so samples can be compared by standard t test for hypothesis testing, with $H0$ hypothesis stating the means are the same and $H1$ hypothesis stating that one mean is smaller than the other, i.e. left tailed t test. We will perform test with 0.025 level of significance. In case of comparison with PI controller we use one sample t test.

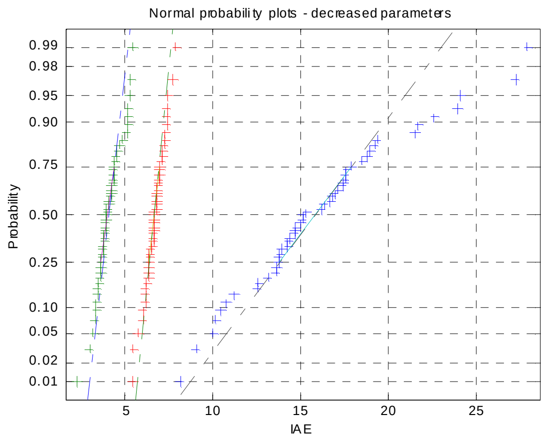

Fig. 6. Normal probability plots for ISE and original parameters

T test results are given in Tables 5-10. Subscripts assigned to the criteria name denote activation function for obtained mean value of integral error.

Very small p values and relatively big t values point on small effect on precision by consecutive testing on samples. Therefore, there was no need to perform multivariable statistical testing.

T tests confirm that the tests leading to results in Tables 1-4 are statistically significant. Now we can state that NN control with Gaussian activation functions outper-

Table 4. IAE and ISE for PI controlled system

	IAE	ISE
Nominal	17.0659	0.8122
-10%	17.0639	0.8119
+10%	17.0674	0.8124

Table 5. T test results for IAE and original parameters

	Test result	p value	t value
$IAE_{tanh} < IAE_{PI}$	no	0.0864	-1.3836
$IAE_{sigma} < IAE_{tanh}$	yes	$1.5037 \cdot 10^{-21}$	-15.8608
$IAE_{Gauss} < IAE_{sigma}$	yes	$1.0431 \cdot 10^{-44}$	-25.1142

Table 6. T test results for ISE and original parameters

	Test result	p value	t value
$ISE_{tanh} < ISE_{PI}$	no	0.3538	-0.3773
$ISE_{sigma} < ISE_{tanh}$	yes	$1.5006 \cdot 10^{-16}$	-12.0192
$ISE_{Gauss} < ISE_{sigma}$	yes	$1.7594 \cdot 10^{-41}$	-23.5823

Table 7. T test results for IAE and decreased parameters

	Test result	p value	t value
$IAE_{tanh} < IAE_{PI}$	no	0.0741	-1.469
$IAE_{sigma} < IAE_{tanh}$	yes	$5.0414 \cdot 10^{-21}$	-15.4241
$IAE_{Gauss} < IAE_{sigma}$	yes	$3.3138 \cdot 10^{-39}$	-22.2924

Table 8. T test results for ISE and decreased parameters

	Test result	p value	t value
$ISE_{tanh} < ISE_{PI}$	no	0.1902	-0.8853
$ISE_{sigma} < ISE_{tanh}$	yes	$8.0349 \cdot 10^{-17}$	-12.2194
$ISE_{Gauss} < ISE_{sigma}$	yes	$4.7662 \cdot 10^{-41}$	-25.8554

Table 9. T test results for IAE and increased parameters

	Test result	p value	t value
$IAE_{tanh} < IAE_{PI}$	no	0.0716	-1.4875
$IAE_{sigma} < IAE_{tanh}$	yes	$6.0808 \cdot 10^{-21}$	-15.3564
$IAE_{Gauss} < IAE_{sigma}$	yes	$1.7644 \cdot 10^{-46}$	-26.3856

Table 10. T test results for ISE and increased parameters

	Test result	p value	t value
$IAE_{tanh} < IAE_{PI}$	no	0.298	-0.5337
$IAE_{sigma} < IAE_{tanh}$	yes	$9.4429 \cdot 10^{-15}$	-10.7030
$IAE_{Gauss} < IAE_{sigma}$	yes	$8.4833 \cdot 10^{-36}$	-21.4119

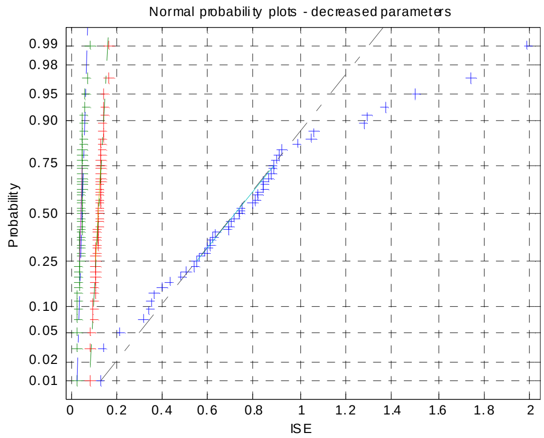

Fig. 7. Normal probability plots for ISE and decreased parameters

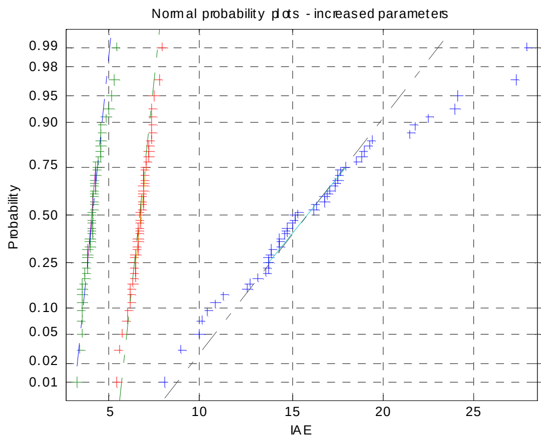

Fig. 8. Normal probability plots for IAE and increased parameters

forms other cases since it generates the smallest integral errors.

Comparison in responses of the system with original parameters controlled by neural network with Gaussian activation function vs. PI controller is shown in Fig. 10 and Fig. 11. Disturbance input was set to be $\Delta P_L = 0.1\sin(0.02\pi t)$.

Unwanted frequency variation is shown in Fig. 10 and is about three times smaller in magnitude for the system controlled by NN than in the case of system controlled with conventional PI controller. However, as shown in Fig. 11, the power required to achieve such performance is essentially equal in both cases. Thus, the requests for action from ancillary systems required to keep the system frequency within the nominal bounds will be much lower if NN control scheme is used resulting in reduced overall cost

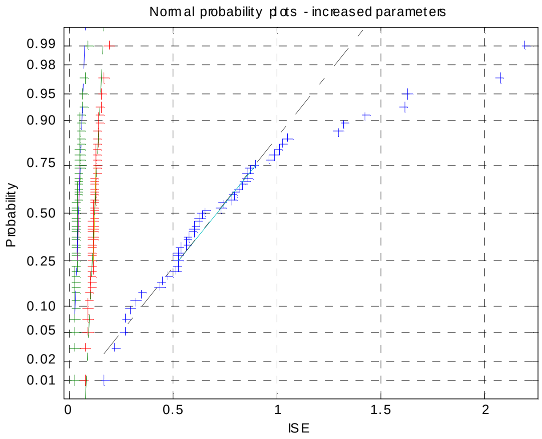

Fig. 9. Normal probability plots for IAE and increased parameters

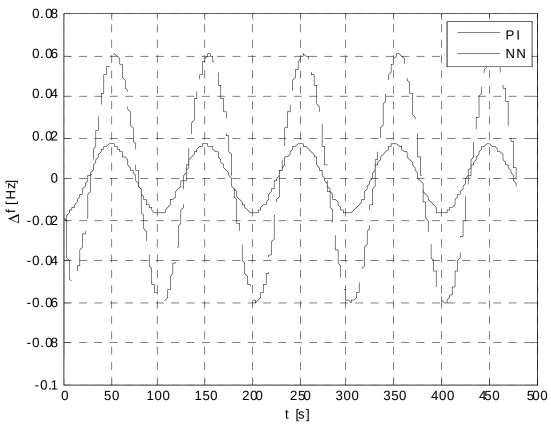

Fig. 10. Frequency changes

of the frequency control.

6 CONCLUSION

Paper has shown a practical approach to neural network design for frequency control for thermal power systems. First, we defined linear-in-parameter (LIP) neural network (i.e. hidden layer weights are fixed and initiated as random numbers). Then, we performed Lyapunov stability analysis in order to find weight updates laws. It was followed by initiation of hidden layer and output weights as random numbers covering the expected state space of controlled plant. The procedure for determining number of nodes was described in details. The structure of NN was finalized by choosing the type of activation function through proper statistical testing.

The comparative analysis of the NN and conventional PI controller showed that the power necessary to keep the

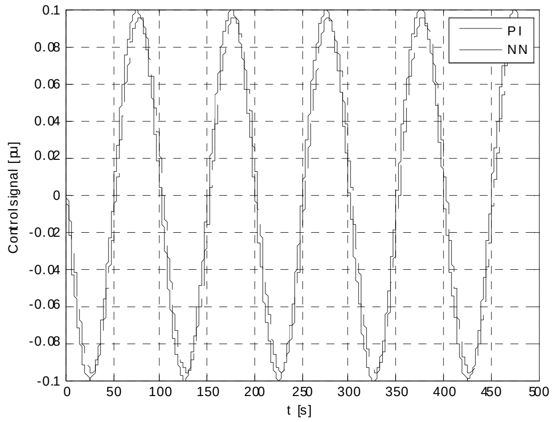

Fig. 11. Control signals

system frequency within the nominal bounds will be much lower when NN control scheme is used. It results in significantly reduced cost of the frequency control.

Described procedure can be easily carried out using a digital computer and can be applied to systems exhibiting similar dynamics as described in this paper, for example hydropower systems, hydraulic pistons or water turbines. Moreover, future work will comprise application of the given procedure on systems with different dynamics as well as systems with nonlinearities, therefore expanding its use to a wider class of systems.

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Ognjen Kuljača received his B.Sc and M.Sc. degrees from Faculty of Electrical Engineering and Computing in Zagreb, University of Zagreb in 1994 and 1998, respectively. Between 1994 and 1999 he was with Control Systems Department, Brodarski Institute, Zagreb, Croatia. He finished his Ph.D. study in Electrical Engineering at The University of Texas in Arlington in 2003. In 2004 he joined Alcorn State University, Mississippi, USA where he served as Assistant Professor at Department of Advanced Technologies and Associate Director of Sensors and Automation Laboratory at Systems Research Institute. From 2010 he is again with Brodarski Institute, Zagreb, Croatia as lead researcher. His research and professional interests are in optimal control, neural networks and fuzzy control, power systems control and industrial automation.

Krunoslav Horvat received his B.Sc degree from Faculty of Electrical Engineering and Computer Science, University of Maribor, in 1996, and M.Sc. and Ph.D. degrees from Faculty of Electrical Engineering and Computing in Zagreb, University of Zagreb in 2000 and 2006, respectively. From 1996 he is with Brodarski Institute, Zagreb, where he currently serves as lead researcher and Head of Control Systems Department Electrical Group. Dr. Horvat has served as project manager for more than ten major turbine governing projects in hydropower plants in Croatia. He is recipient of Young Researcher of the Year award in Croatia. He is also author of numerous publications. His research interests are in turbine governing, fault tolerant control, neural networks and fuzzy systems.

Bruno Borović received his B.S. and M.S. degrees in Control Engineering from Faculty of Electrical Engineering and Computing, University of Zagreb, Croatia in 1996 and 1999, respectively, and PhD from University of Texas at Arlington in 2005. Between 1997 to 2001 he was a research scientist and design engineer at the Brodarski Institute, Zagreb, Croatia, where he was involved in various projects involving process automation and control systems. From 2001 to 2005, he was a research assistant with Automation & Robotics Research Institute, Fort Worth, Texas, where he worked on the modeling and motion control of MEMS actuators. In 2006, Dr. Borovic joined startup, nowadays successful company, Invensense Inc. as a design engineer and worked there on the development of MEMS inertial sensors until 2010. In 2010, Dr. Borovic returned back to Croatia and joined Faculty of Electrical Engineering and Computing as a senior researcher on EU sponsored CURE project. Dr. Borovic's current interests include low-cost navigation sensors, marine technology and control systems. He is an author or co-author of over thirty journal and conference papers and a two book chapter in the areas of control systems and MEMS. He is also a Senior Member of the IEEE and a member of ASME.

AUTHORS' ADDRESSES

Ognjen Kuljača, Ph.D.
Krunoslav Horvat, Ph.D.
Brodarski Institute,
Avenija Većeslava Holjevca 20, HR-10000 Zagreb, Croatia
email: okuljaca@hrbi.hr, kruno@hrbi.hr
Bruno Borović, Ph.D.
Faculty of Electrical Engineering and Computing,
University of Zagreb,
Unska 3, HR-10000 Zagreb, Croatia
email: bruno.borovic@fer.hr

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