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Identification of multiconnected dynamic objects with uncertainty based on neural technology and reference converters

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ABSTRACT

The proposed method of identification in the presented article allows evaluating with sufficient accuracy the “black box” model of multiconnected non-stationary dynamic objects with uncertainty in any short time. One of the key advantages of the proposed method is that it allows determining an adaptable "black box" model and creating an adaptive control system in the case of non-measurable derivatives of the m-th order state variables of a multiconnected object.

1. Introduction

In modern production processes, control objects in robotic and mechatronic devices operate in intensive mode and in uncertainty conditions. The requirements for quality in the automatic control systems of such dynamic objects are tightened. Therefore, it is important and relevant to obtain (identify) aprior and aposterior information about such objects, e.g. dynamic characteristics.

It is known that the estimation of the structure and parameters of the mathematical model of an object is important for the design of an optimal performance indicator management system [1-6]. However, in some cases the estimates of the structure and parameters of the mathematical model of an object are unknown.

High-quality management of dynamic objects, which can be described (defined) as non-stationary and uncertain, can be achieved by means of adaptive systems [2-4]. However, in such adaptive control systems, the object's state variables must be fully observable, in other words, n-th order derivatives of the object's output variables and themselves must be observable (measurable) [2, 3].

It should be noted that a mathematical model of a number of robotic and mechatronic devices – differential equations – can be developed on the basis of physics, electrical engineering, mechanics, e.g. the Lagrange-Euler approach. However, these types of mathematical models have sufficient nonlinearity and uncertainty [6-8]. For the experimental study of such models, it is necessary to observe (measure) the first, second and third order derivatives [6-8].

In most cases, the m-th order derivatives of input and output variables in real objects cannot be measured physically. Therefore, for the high-quality management of such uncertain dynamic

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objects, it is necessary to use reference converters, methods of identification, and means of artificial intelligence – neural technology. For instance, it is necessary to propose more efficient methods and tools for designing intelligent and adaptive control systems without the direct use of m-th order derivatives of the object's real state variables [1,5]. That is, it is necessary to develop such an identification method that makes it possible to continuously estimate the parameters of the mathematical model based on observations of only input and output variables during the normal operation of an uncertain object, or to observe on the basis of the object's "black box" model [10].

In view of the above, the present paper proposes a method for the identification of multiconnected dynamic objects with uncertainty based on neural technology and reference converters.

2. General statement of the problem

Let's assume that, in general, the movement of the dynamic object with uncertainty could be written by vector differential equations or matrix transfer function:

$$\dot{\boldsymbol{y}}\,(\boldsymbol{t}) = \boldsymbol{\psi}(\vec{\boldsymbol{a}}(\boldsymbol{t}), \boldsymbol{y}(\boldsymbol{t}), \boldsymbol{u}(\boldsymbol{t})), \tag{1a}$$

Here $\boldsymbol{y}(\boldsymbol{t}), \boldsymbol{u}(\boldsymbol{t})$ are n-dimensional output and control-input vectors, which are measurable (observable); $\dot{\boldsymbol{y}}\,(\boldsymbol{t})$ is $\boldsymbol{m}$-th order derivatives vector of the multiconnected dynamic object with uncertainty and it is not observable.

It is assumed that the additivity feature is met for the multi-connected dynamic object. Then object (1a) can be described by operator equations as follows:

$$\left.\begin{array}{l} Y_1(s) = W_{11}(t,s)U_1(s) + W_{12}(t,s)U_2(s) + \cdots + W_{n1}(t,s)U_n(s) \\ Y_2(s) = W_{21}(t,s)U_1(s) + W_{22}(t,s)U_2(s) + \cdots + W_{n2}(t,s)U_n(s) \\ \quad\vdots \qquad\qquad \vdots \qquad\qquad\qquad \vdots \qquad\qquad\qquad \vdots \\ Y_n(s) = W_{n1}(t,s)U_{n1}(s) + W_{n2}(t,s)U_{n2}(s) + \cdots + W_{nn}(t,s)U_n(s) \end{array}\right\} \tag{1b}$$

Here $U_j\,, (j = \overline{1,n})$ j-th control input effect, $W_{ij}(t,s)$ - relevant transfer functions of the object through directly straight ($i = j$) and cross ($i \neq j$) channels, are the elements of $n \times n$ size matrix (2)

$$W_{ob}(t,s) = \begin{vmatrix} W_{11}(t,s) & W_{12}(t,s) \ldots & W_{1n}(t,s) \\ W_{1n}(t,s) & W_{22}(t,s) \ldots & W_{2n}(t,s) \\ \vdots & \vdots & \vdots \\ W_{n1}(t,s) & W_{n2}(t,s) \ldots & W_{nn}(t,s) \end{vmatrix} \tag{2}$$

Assume the movement of the multiconnected dynamic object with uncertainty for each $i,j = \overline{1,n}$ channel is described by the transfer function as follows

$$W_{ij}(t,s) = {k_{ij}}\Big/{\sum_{l=0}^{m} a_{m-l,ij}\,(t)s^l}\,, \tag{3a}$$

Here $k_{ij},\ a_{m-l,ij}\,(t)$ – are unknown non-stationary parameters of the object with uncertainty described by the (3a) expressions of straightforward and cross effect channels.

Based on the knowledge about the identified dynamic object (our aprior information), we assume that the parameters $a_{l,ij},\ l = \overline{1,m}, k_{ij},\ i,j = \overline{1,n}$ in mathematical model (3a) can obtain estimates in the bounded regions, i.e.

$$a_{l,ijmin}\ \leq a_{l,ij}\,(t)\ \leq\ a_{l,ijmax}\,, \forall l \in L, L = [\overline{0,m}],\ k_{ij}, i,j = \overline{1,n} \tag{3b}$$

The structural diagram of the multiconnected dynamic object with uncertainty can be described as follows.

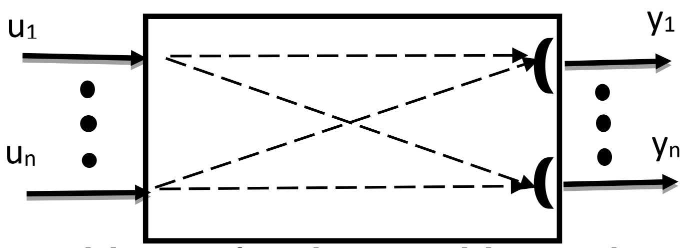


Fig. 1. Structural diagram of a multiconnected dynamic object with uncertainty.

Based on Fig. 1.1 and the record of operator (1b), the problem of identifying a multiconnected dynamic object could be considered as an identification problem with n-inputs in n number and single output. In the latter case, it is only possible to apply the proposed approach for the identification of the multiconnected dynamic object [8], which can be measured by input and output variables.

3. Solving the identification problem of a multiconnected dynamic object with uncertainty based on reference converters and neural technology

To identify a multiconnected dynamic object with uncertainty, i.e. in order to evaluate $a_{l,ij}$, $l=\overline{1,m}, k_{ij},\ i,j=\overline{1,n}$ parameters, m-th order derivatives $y_j^l(t),\ j=\overline{1,n},\ l=\overline{1,m}$ of the output variables must be measurable. However, in the case under consideration, m-th order derivatives are not observable (measurable). Therefore, it is proposed to use linear conversions – reference filters [5, 8] - of output $y(t)$ and input $u(t)$ vectors (signals) linear conversions measured (observed) in real time to estimate (determine) the dynamic parameters $a_{l,ij},\ l=\overline{1,m}, k_{ij},\ i,j=\overline{1,n}$ of a multiconnected object with uncertainty.

Assume that input variables of vector *u(t)* are not periodic, i.e. they meet following conditions:

$$\boldsymbol{u(t)} \neq \mathbf{u}\left(\boldsymbol{t}+\boldsymbol{T_p}\right) \quad -\infty<t<\infty,\ 0<T_p<\infty, \tag{4}$$

(4), (1b.), (3b.) $y(t)$ – output and $u(t)$ – input variable vectors of the multiconnected dynamic object with uncertainty and their derivatives $y_j^l(t),\ u_j^l(t),\ j=\overline{1,n},\ l=\overline{1,m}$ are not periodic functions. Linear converters – (reference converters) – $W_{FYj}\ (s)$ and $W_{FUj}\ (s)$, $j=\overline{1,n}$ are added to the outputs of each output and input for the object. *m*-th order derivatives $s^l Y_{Fj}\ (s)$, $s^l U_{Fi}\ (s)$, $l=\overline{0,m}$ of outputs for the reference filters $Y_{Fj}\ (s),\ U_{Fj}\ (s)$ are observable (see Fig. 2).

Note that for each of the outputs and inputs, $W_{FYj}\ (s)$ and $W_{FUj}\ (s)$, $j=\overline{1,n}$ transfer function structures of the *m*-th order linear converters (reference filters) can be selected as follows:

$$W_{FYj}\ (s) = {Y_{Fj}\ (s)}\Big/{y_j\ (s)} = 1\Big/{\textstyle\sum_{l=0}^m} d_{m-l,Fj}\ (t) s^l,$$

$$W_{FUi}\ (s) = {U_{Fi}\ (s)}\Big/{u_i\ (s)} = 1\Big/{\textstyle\sum_{l=0}^m} d_{m-l,Fi}\ (t) s^l. \tag{5}$$

If we select the structures and parameters of the transfer functions for the linear converters (– reference filters) of the input and output variables as equal ($W_{FYj}\ (s) = W_{FUi}\ (s) = W_F(s),\ j,i=\overline{1,n}$) and steady, then using the operator model, the identification system (see Fig. 2 and 3) can be written as follows:

$$\left.\begin{array}{l} W_F(s)Y_1(s) = W_F(s)W_{11}(t,s)U_1(s) + W_F(s)W_{12}(t,s)U_2(s) + \cdots + W_F(s)W_{n1}(t,s)U_n(s) \\ W_F(s)Y_2(s) = W_F(s)W_{21}(t,s)U_1(s) + W_F(s)W_{22}(t,s)U_2(s) + \cdots + W_F(s)W_{n2}(t,s)U_n(s) \\ \qquad \vdots \qquad\qquad \vdots \qquad\qquad\qquad \vdots \qquad\qquad\qquad \vdots \\ W_F(s)Y_n(s) = W_F(s)W_{n1}(t,s)U_1(s) + W_F(s)W_2(t,s)U_{n2}(s) + \cdots + W_F(s)W_{nn}(t,s)U_n(s) \end{array}\right\}$$

If we consider $W_F(s)Y_j(s) = Y_{Fj}$, $W_F(s)U_i(s) = U_{Fi}$, then the relation between transformed variables Y_{Fj} and U_{Fi} can be described as follows;

$$\boldsymbol{Y_F(s) = W_{ob}(t,s)U_F}, \tag{6a}$$

or

$$Y_{Fj}\,(s) = W_{obij}(t,s)U_{Fi}, \quad i,j = \overline{1,n} \tag{6b}$$

Here $W_{obij}(t,s)$ – is the transfer function “of j-th output relative to i-th input”, described as (6a).

Thus, in the case when (4) conditions are met, state variables of the object are not observed, we have shown the possibility of identification of the multiconnected dynamic object by measuring $s^lY_{Fj}\,(s),\ s^lU_{Fj}\,(s), l = \overline{0,m}$ derivatives of reference converters-filters, i.e. we have proved that.

If during the quasi-stationarity period the object needs parametric identification, then, $a_{l,ij}$, $l = \overline{1,m}, k_{ij},\ i,j = \overline{1,n}$ can be estimated using the methods proposed in [5, 8] or LSM (least squares method). However, in the synthesis and technical implementation of adaptive control systems for multiconnected dynamic object the use of such models has some difficulties, and its practical efficiency may not be sufficient [1, 5, 8-10].

Mathematical models-differential equations of several technical objects like robotics, drones, mechatronic devices can be determined on the basis of electrical engineering, mechanics, e.g. Euler-Newton and Lagrange-Euler approach. However, the mathematical models developed on the basis of existing approaches have sufficient nonlinearity and uncertainty or non-stationarity [8-10]. Control systems that can change object parameters should be intelligent or adaptive. Adaptive control system controllers adjust the controller parameters based on object information in either online or offline mode. In such systems, to ensure optimization of control system and its stability, computer simulation of intelligent ACS by using existing tools is an important issue and its effective solution is relevant [9].

In the paper, taking into account the above, the problem of determining the “black box” model of the multiconnected dynamic object with uncertainty using the Neural Network technology and linear converters in the case of uncertainty of the structure and parameters of mathematical model is solved.

In most methods of identification of dynamic objects $\boldsymbol{\psi}(\cdot)$ – structure of mathematical model (1) is accepted as the total sum of certain functions (for instance, linear and nonlinear functions) [1-10]. If initial information and studies about the dynamic object is not sufficient and the structure of the identified mathematical model is not selected correctly (sufficiently), then the solution to the control synthesis problem will be complicated and inefficient [9, 10].

In the case of a lack of information in dynamic objects with uncertainty, in order to solve the synthesis problem of high-quality intelligent control system, determination of the mathematical model of the object is more effective due to the use of new information technology based on Neural Network Toolbox [9, 10]. However, as in [10], identification based on Neural Network (NN) is not defined with $a(t)$ parameters due to the difference between $k-1$ and m tacts, it is directly defined with $\boldsymbol{y}(t)$ output state variables of the object. In other words, it is identified as the output of the “black box” model of the real dynamic objects in Neural Network.

Real dynamic model of object (1a) can be described in the formal reduction form, i.e.

$$\boldsymbol{y(t) = F\big(a(t), \dot{y}(t), u(t)\big),\ y \subset R^n, u \subset R^n} \tag{7}$$

After each input and output variable has been converted through the $W_F(s)$ reference converters (linear converters), by measuring $s^l Y_{Fj}(s)$, $s^l U_{Fj}(s)$, $l = \overline{0,m}$ derivatives, it is possible to determine the “black box” NN of the multiconnected dynamic object with uncertainty.

Assume the “black box” type mathematical model of the object based on neural network can be determined by NN with r intermediate layers through each i-th input j-th output channel:

$$\boldsymbol{Y_{Ni}} = \boldsymbol{\phi_i}\left(\boldsymbol{w_{ij,r}}, \dot{\boldsymbol{y}}(\boldsymbol{t}), \boldsymbol{u}(\boldsymbol{t})\right), \boldsymbol{w_{ij,r}} \in \boldsymbol{W_{ij,r}}, \boldsymbol{i}, \boldsymbol{j} = \overline{\boldsymbol{1}, \boldsymbol{n}} \quad , \boldsymbol{r} = \overline{\boldsymbol{1}, \boldsymbol{g}} \quad , \tag{8a}$$

or

$$\boldsymbol{Y_N} = \boldsymbol{\phi}\left(\boldsymbol{w}, \dot{\boldsymbol{Y}}_{\boldsymbol{F}}(\boldsymbol{t}), \boldsymbol{U_F}(\boldsymbol{t})\right), \boldsymbol{w} \in \boldsymbol{W} \tag{8b}$$

Here $w_{ij} \in W_{ij}$, $i \in [1, n]$, $r \in [1, g]$, i-th are weighted coefficient of the neurons in the g-th intermediate layers through the j-th output channel and can get values in the $W_{ij,r}$ region.

The problem of determining the “black box” (neural network) model of a dynamic object with uncertainty can be formulated as follows.

We need to determine such “black box” model with NN of an object with observable (measurable) all state variables $\boldsymbol{Y_F}(t) = [Y_{F1}(t), Y_{F2}(t), \dots, Y_{Fn}(t)]$ and input effects $U_F(t) = [U_{F1}(t), U_{F2}(t), \dots, U_{Fn}(t)]^{\mathrm{T}}$ of a real dynamic object, i.e. as in model (8b), that the square of the difference (error) between the outputs of NN and of the real object (state variables) is minimum for $t_k = T_0\, k$ ($T_0 = const, k = 1,2,3,\dots,K$):

$$\mathbb{E} = \frac{1}{2}\sum_{k=1}^{K}(E^k)^2 = \frac{1}{2}\sum_{k=1}^{K}[\,Y_F(t_k) - Y_N(t_k)]^2 =$$

$$= \frac{1}{2} \sum_{k=1}^{K}\sum_{i=1}^{n}[Y_{Fi}^k - \phi_i(w_{ij}, \dot{Y}_{Fi}^k, {U_{Fj}}^k)]^2 = \rightarrow \min \tag{9}$$

If one model, i.e. $i = 1$, is sufficient and if the possible value-accuracy of error ε is given, then in optimization problem (9) we can be satisfied that $\lim_{k\to\infty} \frac{1}{2}\sum_{k=1}^{K}(E^k)^2 =$ is less than ε .

The modeling system in the form of “black box” of a real multiconnected dynamic object with uncertainty based on NN can be described as Fig. 2:

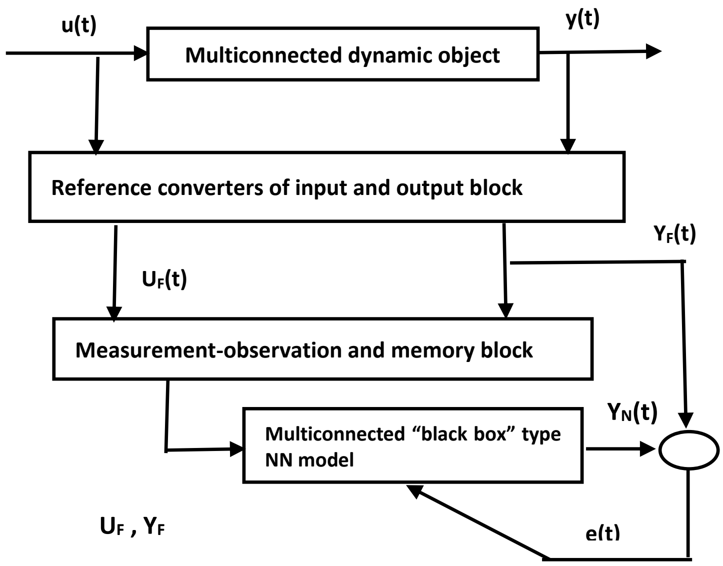


Fig. 2. The structure of NN-based modeling system in the form of “black box” of a multiconnected dynamic object with uncertainty based on the observation of transformed sate variables

The solution to the above formulated identification problem is function $\boldsymbol{Y_N} = \boldsymbol{\phi}\left(\boldsymbol{w}, \dot{\boldsymbol{Y}}_{\boldsymbol{F}}(\boldsymbol{t}), \boldsymbol{U_F}(\boldsymbol{t})\right)$. These solutions are known as input-output pairs $(\boldsymbol{Y_F^1}, \boldsymbol{Y_N^1})$,$(\boldsymbol{Y_F^2}, \boldsymbol{Y_N^2})$,...,$(\boldsymbol{Y_F^K}, \boldsymbol{Y_N^K})$ (formulated from the measurments). Identification process, i.e. NN training directly synthesizes such function $\boldsymbol{\phi}(\cdot)$ in n number that can be close to function $\boldsymbol{F}(\cdot)$ realized by the object. Thus, training of Neural Networks becomes a multivariate optimization issue.

Since function (9) can be arbitrary, in general, training of n Neural Network is a multiextremal nonconvex optimization problem. The number of iterative algorithms given in [9] can be used to solve above-mentioned optimization problem(9). Currently the most widely used method of NN training (minimizing the mean square (quadratic) error of function (9)) is an iterative gradient algorithm.

This training algorithm mentioned in most studies [9-12] is called error back propagation. Therefore, there is no need to give detailed explanation on error back propagation method. However, we consider it appropriate to give the identification of the multiconnected dynamic object with uncertainty as above formulated n-number "black box" for the mechatronic device implementation (according to Fig. A1.1 in Appendix 1) based on Neural Networks Toolbox, to provide "M" language program (Fig. A1) of MATLAB and training procedures with an explanation as follow.

In order to determine the "black box" model for a single channel, the explanation of NN training procedures can be summarized as follows.

In subsystems in Fig. 3 – object's output, reference converter-filter variables in the input and output, intervals Δt (Δt=0.002s) in K (K=4000, researcher selects) number, observation-measurements, i.e., input matrices $\boldsymbol{P} = [\boldsymbol{X}] = [\boldsymbol{u_1}; \boldsymbol{u_2}; \boldsymbol{s^2\, Y_{F1}}; \boldsymbol{sY_{F1}}\,; \boldsymbol{y_2}; \boldsymbol{s^2\, Y_{F2}}; \boldsymbol{sY_{F2}}\,; \boldsymbol{s^2\, U_{F1} s^2\, U_{F1}}; \boldsymbol{sU_{F1}}\,; \boldsymbol{U_{F1}}; \boldsymbol{s^2\, U_{F2}}; \boldsymbol{sU_{F2}}\,; \boldsymbol{U_{F2}};]$ are formed:

Observational matrices of state variables $y_1^k; y_2^k\ k = \overline{1, K}\ (K = 4000\,, researcher\ selects)$ of the real multiconnected object

$\boldsymbol{T} = [\boldsymbol{y}] = [\boldsymbol{y_1}; \boldsymbol{y_2}]$ (or separately) are formed:

$$\mathbf{net = newff(min\,max(P), [300, 300, 2], \{`purelin', 'logsig', 'tansig', 'traingd'\});}$$

Creation and training of first NN (with appropriate transfer functions $'tansiq','\,logsiq', purlin'$) named **d** with 3 layer (300 neurons in two layers, 2 neurons in output layer). Number of neuron layers and etc. parameters are selected iteratively by the constructor).

$\mathbf{net.train\ Param.goal = 0.001}$; – the value of accuracy omission error of the NN training – $\mathbf{e^k} = (\mathbf{e_1^k}$ (heuristically selected by the constructor).

$\mathbf{net.trainParam.show = 50}; -$ from one of the fifty examples Param the first NN output $\mathrm{y_1^k},\ \mathrm{k} = \overline{1, \mathrm{K}}$ should be shown (defined heuristically by the constructor).

$\mathbf{net.train\ Param.epoch = 1000;}$ Circulation of NN training – **'epoch'** (number of cycles selected heuristically by the constructor).

net.train(net,P,T); Launching NN training procedure.

view (net); – automatic installation of a "black box" model object in the Simulink and description of the flow chart (See Fig. 4).

gensim (net); **or display (net)**; – Decription of information on NN in MATLAB: – method of training (e.g. training method "Gradient Decent"), criteria ("mse"), number of iterations ("epoch") and others (See Fig. 3).

Dependence of the training error on the number of iterations (the "epoch"), the intended target – the "min" value of the error (a), and the description of the "black box" as subsystem (b) in Simulink are given in Fig. 4.

The graphs (a, b) of NN outputs (e.g. $y_{N1}(t) = y_{N1}(kT_0) = y_{N1}^k$, $k = \overline{1{,}4000}$, $T_0 = 0.01s$) after the training of NN and the transition processes of the real object (e.g. $y_1(t) = y_1^k, k = \overline{1{,}4000}$, $T_0 = 0.01s$) as well as for $u_1(t) = 1[t] = 1[kT_0]$, $u_2(t) = 0$ to estimate the input-control effects are shown in Fig. 5.

Based on a comparative analysis of the transition processes in Fig. 5, $\boldsymbol{y_N(t)}$ – NN output and $\boldsymbol{y(t)}$ derivative is exactly the same as nonlinear dynamic object with uncertainty, i.e. $y(t) \cong y_N(t)$. Thus, in the problem of control influence or regulator synthesis, the possibility of using the trained NN (“black box” model of the real dynamic object) for the dynamic object with uncertainty in “offline” mode has been confirmed.

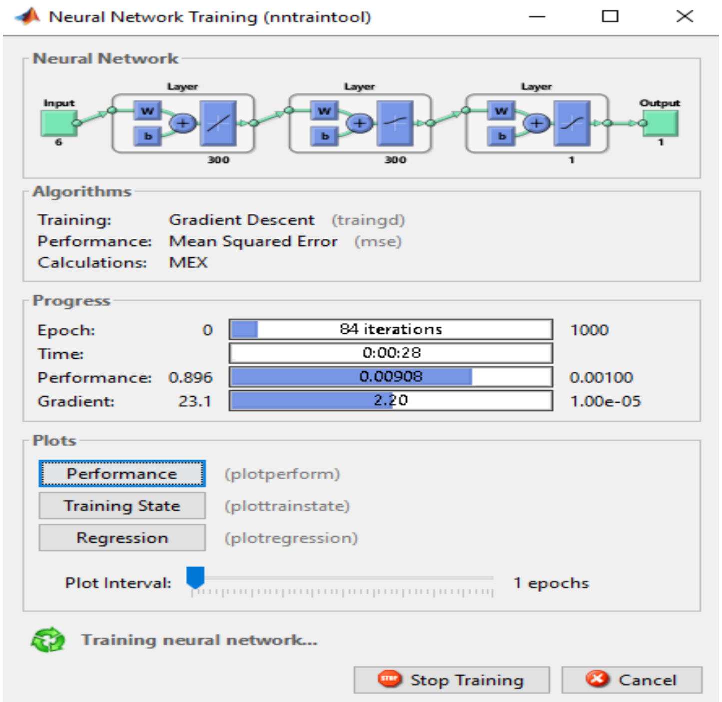
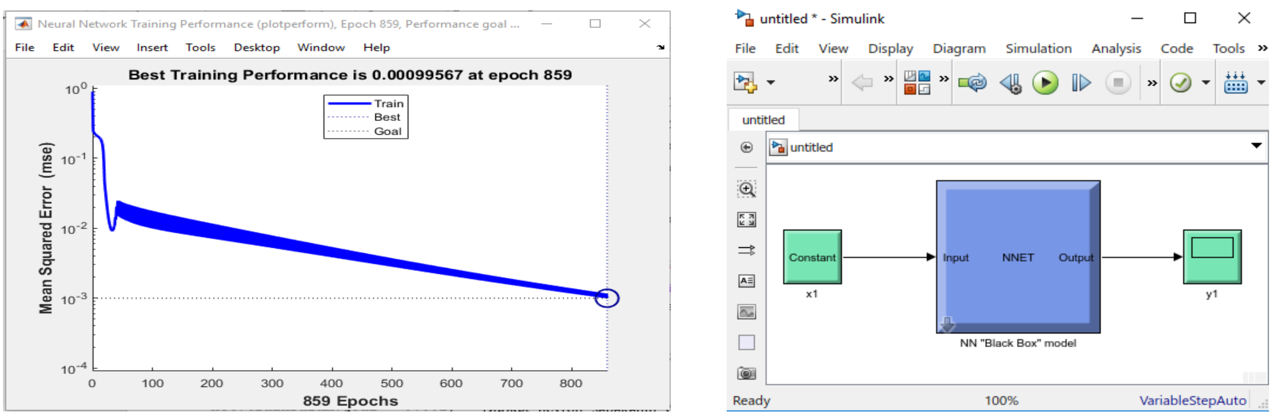


Fig. 3. Description of the parameters for the NN training (object identification) of the “black box” model in the NN Toolbox of MATLAB



a) b)

Fig. 4. Graph of dependence of the NN training error on the number of cycles (epochs) and description of NN in the form of “black box” in Simulink (b)

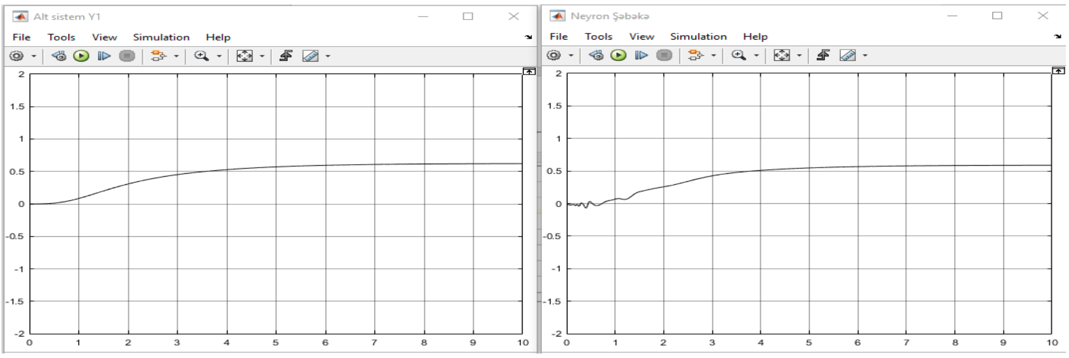


Fig. 5. The transition processes Y_{N1} of the first NN with output signal Y_{F1} of the first reference filters in the object's output

4. Conclusion.

A theoretical method for solving the determining problem of **"black box"** model for the multiconnected dynamic object with uncertainty based on neural technology and reference converter-filters, as well practical realization in MATLAB have been developed in the case when information is not sufficient and state variables are not measurable. It has been proved that the modeling of real multiconnected uncertain dynamic objects based on conversion of input and output variables is correct and efficient. "Black box" NN model for the doubly-connected 2-nd order object has been trained according to error back propagation algorithm, and in order to overlap measured state variables vectors $\mathrm{U_{Fi}}, \mathrm{Y_{Fj,}}(\mathrm{i},\mathrm{j} = 1{,}2)$ of the 2-nd order reference converters with state variables vector of NN output $\mathrm{y_N}(\mathrm{t})$, the structure of NN (layers-3), the number of the neurons in the layer (300, 300,1), transfer functions, accuracy of training (0.001) and other parameters have been identified.

One of the advantages of the proposed method is that it allows parametric identification when state variables of a multi-connected dynamic object are not measurable, as well as the creation of an adaptive control system.

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Reviewer: Professor V.A. Mustafayev, DSc (Engineering)

Appendix: In order to model multiconnected dynamic objects with uncertainty based on reference converters-filters and NN, the experiments have been conducted for the following identification system in MATLAB (Fig. A6).

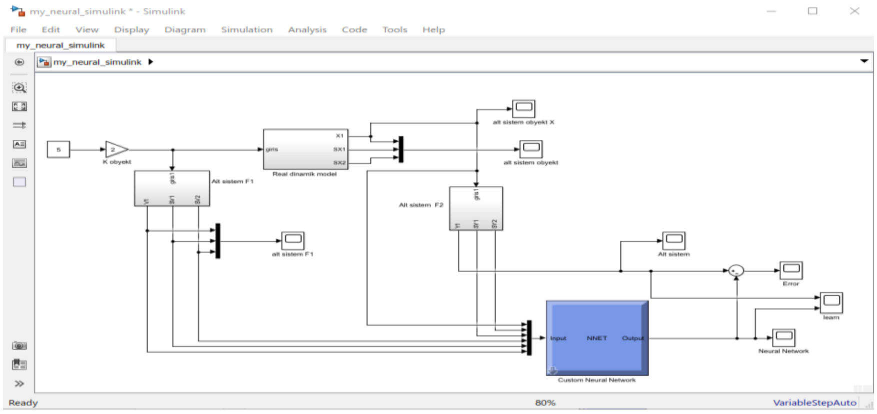
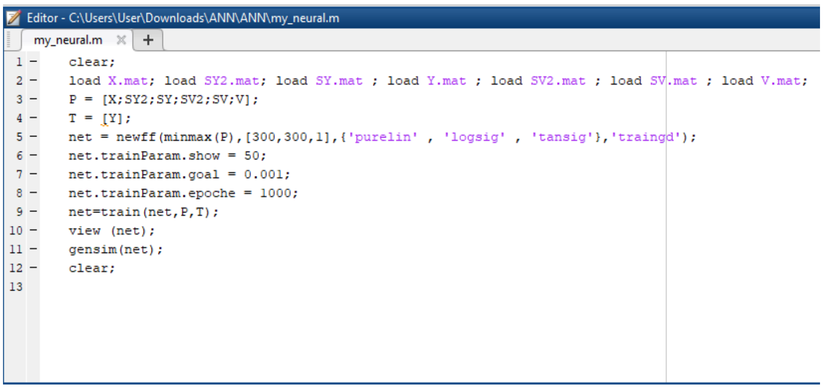


Fig. A6. Structural diagram of the identification system with reference converters and NN for dynamic object in MATLAB

The program in the "M" language of the NN implementation of the black box model of a multiconnected dynamic object for single channel based on MTLAB's Neural Networks Toolbox package is described in Fig. A7.



```
Editor - C:\Users\User\Downloads\ANN\ANN\my_neural.m
my_neural.m

clear;
load X.mat; load SY2.mat; load SY.mat ; load Y.mat ; load SV2.mat ; load SV.mat ; load V.mat;
P = [X;SY2;SY;SV2;SV;V];
T = [Y];
net = newff(minmax(P),[300,300,1],{'purelin' , 'logsig' , 'tansig'},'traingd');
net.trainParam.show = 50;
net.trainParam.goal = 0.001;
net.trainParam.epoche = 1000;
net=train(net,P,T);
view (net);
gensim(net);
clear;
```

Fig. A7. The program in the "M" language of the NN implementation of the black box model of a multiconnected dynamic object for single channel based on Neural Networks Toolbox in MATLAB

An example of a 2[nd] order benchmark filter-converter structure used for conversion of input and output variables, and the time diagram of the error of a real-dynamic object (the "black box").

The structural diagram of 2-nd order reference converter-filter used for the conversion of input and output variables (Fig. A8 – to the left) and time diagram of NN error (“black box” model) for the real dynamic object (Fig. A8 – to the right) are given as follows (See Fig. A8).

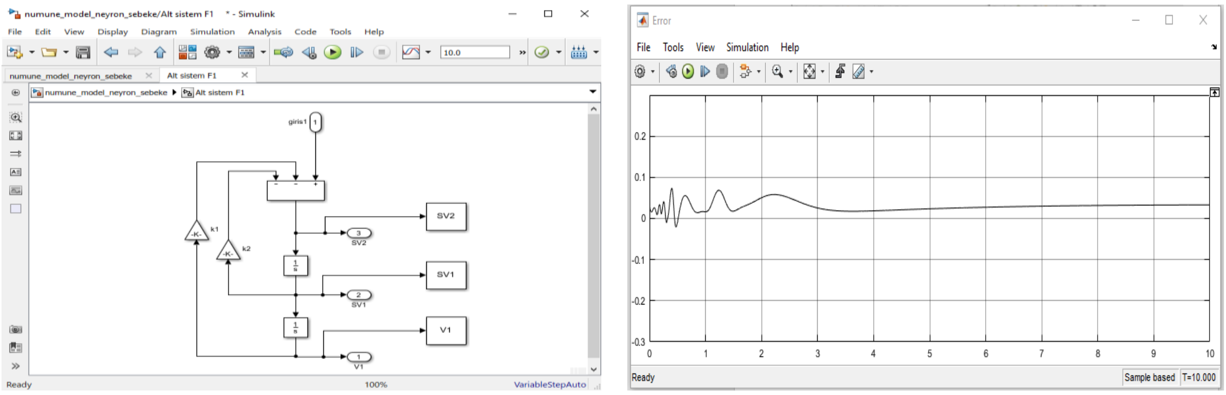


Fig. A8. Structural diagram of 2-nd order reference converter-filter used for the conversion of input and output variables and time diagram of NN error (“black box” model) for the real dynamic object (to the right)