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State Observer based Elman Recurrent Neural Network for Electric Drive of Optical-Mechanical Complexes

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***Abstract* — This paper proposes an application of Elman recurrent neural networks as state observer to estimate electromechanical variable coordinates in electric drive control system of the optical-mechanical complex. The mathematical description of electric drive of the optical-mechanical complex is developed in the form of a two-mass elastic system. These elastic vibrations can be damped by using additional feedback signals from the elastic moment and the load velocity. The architecture of dynamic recurrent neural networks-based Elman scheme in investigated in the form of vector-matrix model, which allows approximating a wide class of nonlinear dynamic systems. During computer simulation in the MATLAB/Simulink environment, the comparison of the root-mean-square error between different learning algorithms for Elman's recurrent neural networks was carried out to study their accuracy estimates coordinates in a closed loop control system of optical-mechanical complex.**

Keywords — Optical-mechanical complex; Elman recurrent neural networks; neural state observer; two-mass elastic system

I. INTRODUCTION

The purpose of this article is to synthesize a neural network observer, used recurrent neural networks according to the Elman scheme, to estimate immeasurable electromechanical states in the control system of the tracking electric drive of the optical-mechanical complex guidance, taking into account the influence of nonlinear disturbances and measurement noise. Compared to the Kalman filter, the neural network observer requires less computational time, which reduces the implementation cost. In addition, in the case of a special microprocessor structure (for example: a programmable logic integrated circuit - FPGA), the time required to start one cycle of the recurrent neural networks (RNNs) algorithm can be significantly reduced due to the fact that RNNs allows parallel data processing, in contrast to the Kalman filter, the algorithm of which is consistent [1-2].

II. ELMAN RECURRENT NEURAL NETWORKS

The optical-mechanical complex guidance system is a nonlinear elastic control object. Therefore, for the synthesis of an observer of state variables, it is expedient to use recurrent neural networks made according to the Elman scheme [3-4]. Elman's dynamic recurrent neural networks are multilayer perceptrons containing input and / or output delays. Therefore, complex nonlinear objects can be processed according to Elman's scheme. The RNNs architecture according to the Elman scheme is shown in Fig. 1.

The use of delay feedback allows one to describe the Elman RNNs in the form of a state space model. Consider the RNNs according to Elman's scheme (Fig. 1), containing inputs, neurons of the first hidden layer, covered by feedback through delay elements and neurons of the output layer.

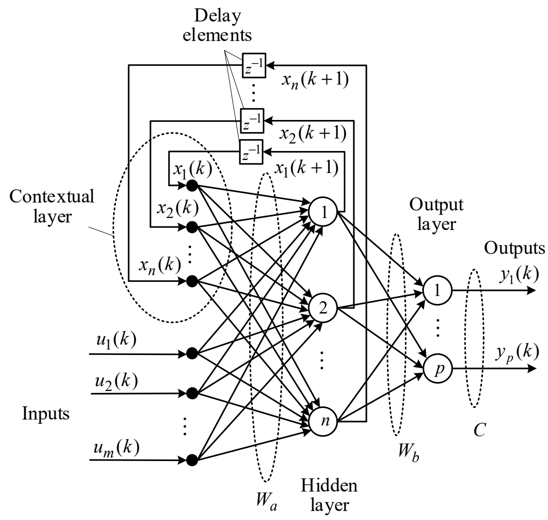

Fig. 1. Architecture of Elman neural network

Then the mathematical model of Elman's RNNs is described by a discrete nonlinear system of differential equations:

$$\begin{cases} \mathbf{x}(k+1) = f\left(W_a\mathbf{x}(k), W_b\mathbf{u}(k)\right) \\ \mathbf{y}(k) = \mathbf{C}\mathbf{x}(k) \end{cases} \tag{1}$$

where $\mathbf{x}(k)$ - n - dimensional vector of the state of the system, consisting from n neurons of the first hidden layer of the RNNs; $\mathbf{u}(k)$ - m - dimensional vector of inputs, consisting from m RNNs inputs; $\mathbf{y}(k)$ - p - dimensional vector of inputs, consisting of neurons from p the output layer; W_a - $(n\times n)$ - dimensional matrix of synaptic weight of neurons of the first hidden layer; W_b - $(n\times m)$ - dimensional matrix of the synaptic

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weight of neurons at the input of the RNNs; $\mathbf{C}$ - $(m \times p)$ - dimensional matrix of synaptic weight of output layer neurons; $f(\cdot)$ - nonlinear activation functions. Now we consider the task of training the Elman RNNs. Currently, there are two types of teaching methods: "online learning" and "offline learning".

The learning process of the "offline learning" RNNs, considered in this article, assumes that the object state variable is obtained at the output of Elman's RNNs. In this case, the training set of Elman's RNNs consists of control signals of the object and measured state variables with delays as in the NARMA [5] models.

$$\mathbf{M}_{\text{ом}} = \left[\mathbf{u}(k),\, \mathbf{u}(k-1), \ldots, \mathbf{d}(k),\, \mathbf{d}(k-1), \ldots\right]^T \tag{2}$$

where $\mathbf{M}_{\text{ом}}$ is the training set of Elman's RNNs; $\mathbf{u}(k)$ - the vector of the control signal of the control object at the moment of time k; $\mathbf{d}(k)$ - vector of real values of measured state variables.

The learning process of Elman's RNNs refers to the calculation of synaptic matrices W_a and W_b in (1) with a training set (2), it is necessary to optimize the quality functional of the RNNs. For this, the quality functional of the RNNs $E(w)$ can be written in the form of the root mean square error (RMSE) over the entire number of images N of the training set:

$$E(w) = \frac{1}{N}\sum_{i=1}^{N}\left(\mathbf{d}_i(k) - \hat{\mathbf{y}}_i(k)\right)^2 = \frac{1}{N}\sum_{i=1}^{N}\mathbf{e}_i^2(k) \tag{3}$$

where i - the index of the training image; $\mathbf{e}_i(k) = \mathbf{d}_i(k) - \hat{\mathbf{y}}_i(k)$ - the error vector between the value of the output signal vector of the Elman RNNs $\hat{\mathbf{y}}_i(k)$ and its real value $\mathbf{d}_i(k)$ at the k-th iteration.

The most popular learning algorithms for Elman's RNNs for optimizing the quality functional (3) include: backpropagation gradient descent (traingd) algorithm; adaptive gradient descent backpropagation (*traingdx*), Levenberg – Marquardt backpropagation (*trainlm*); a backpropagation gradient descent algorithm on scaling conjugation (*trainscg*) [5].

III. Neural Network Observer for Optical-Mechanical Complexes Electric Drive.

The considered electric drive optical-mechanical complex, as a control object, is a nonlinear two-mass elastic system [6, 7]. The mathematical description of control object can be written in the form of a system of differential equations as:

$$\begin{cases} \dfrac{dM_m}{dt} = -\dfrac{1}{T_e}T_m - \dfrac{\beta_e}{T_e}\omega_1 + \dfrac{\beta_e}{T_e}u_{sr}; \\ J_1\dfrac{d\omega_1}{dt} = T_m - T_{21} - b_{21}\left(\omega_1 - \omega_2\right) - T_{f1}; \\ \dfrac{dT_{21}}{dt} = c_{21}\left(\omega_1 - \omega_2\right); \\ J_2\dfrac{d\omega_2}{dt} = T_{21} + b_{21}\left(\omega_1 - \omega_2\right) - T_{f2} - T_L; \\ \dfrac{d\varphi_2}{dt} = \omega_2. \end{cases} \tag{4}$$

where J_1 - total moment of inertia of the motor rotor, axle shaft and inner rings of bearings (first mass); J_2 - moment of inertia of the optical-mechanical complex pipe (second mass); b_{21} - shaft damping coefficient; c_{21} - stiffness coefficient; ω_1 - angular speed of the first mass; φ_2, ω_2 - angular position and speed of the second mass, respectively; φ_0 - clearance in the gearbox kinematics; T_{21} - the torque of elastic connection between the masses; T_{f1}, T_{f2} - nonlinear moments of friction of motion in bearings of the first and second masses; T_L - external disturbing torque acting on the second mass; $\hat{M}_{21}$, $\hat{\omega}_2$ - estimates of the elastic torque, the angular speed of the second mass at the output of the neural network observer Elman; β_e, T_e - the transfer ratio and constant time of the current regulator; $\mathbf{K} = \left[k_1, k_2, k_3, k_4\right]$ - vector of coefficients of the optimal speed controller; φ_{ss} - setting signal of the angular position at the input of the position regulator, φ_{ss} - setting speed φ. k_{sr} - coefficient of speed regulator.

The architecture of Elman's neural network observer for assessing state variables in the optical-mechanical complex guidance system is shown in Fig. 2.

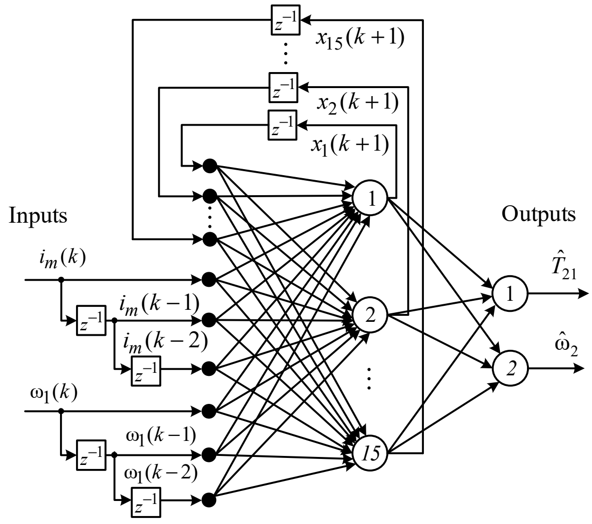

Fig. 2. The architecture of Elman's neural network observer

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In the case under consideration, Elman's neural network observer is used to restore unmeasured state variables: elastic torque ($\hat{T}_{21}$), angular speed of the second mass ($\hat{\omega}_2$). This neural network observer has three-layer Elman RNNs with a dimension of 6-15-3, which consists of 6 neurons in the input layer, 15 neurons in the hidden layers and two neurons in the output layer. As input signals of the neural network observer, the data of the motor current (i_m ; m- motor) and the angular speed of the motor (ω_1) with a delay are used. The depth of unit delays at the Elman RNN input is two. The activation functions in the hidden layers are hyperbolic tangential (*tansig*), and in the output layer they are linear with constraints (*satlins*).

The simulation model of the closed-loop system of the tracking electric drive position of the optical-mechanical complex in the MATLAB / Simulink environment is shown in Fig. 3. In the Subsystem 1 block, there is a mathematical model of the optical-mechanical complex in the form of a two-mass elastic system, the electromechanical parameters of which are shown in detail in [6]. The Subsystem 2 block is the optimal speed controller and the Subsystem 3 block is the PI position regulator.

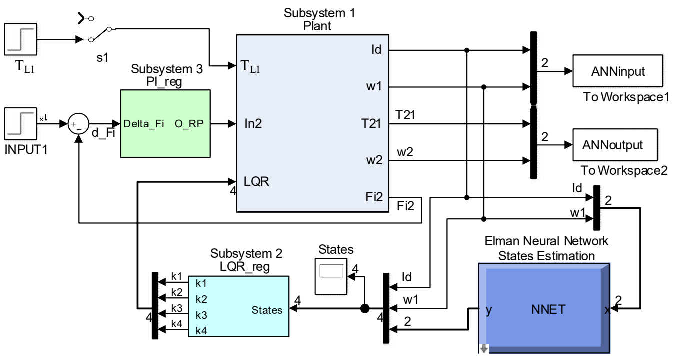

Fig. 3. A simulation model of a closed system in the MATLAB / Simulink

In the block diagram of modeling shown in Fig. 3, the Elman Neural Network block is implemented using the Neural Networks Tool application package.

IV. Simulation Results

The training set data for the training process is collected by the motor current (i_m) and motor speed (ω_1) sensors. The amount of data in the training and test sets is 10^6 samples. The discrete for the Elman RNNs learning process is $T_s = 10^{-4}$ s. The value of the reference angular velocity entering the input of the speed controller is equal to 10^{-2} rad/s. The external disturbing moment of resistance acts on the second mass 2 s after the beginning of the transient process.

To study the effect on the RMSE of the estimation of state variables when training the neural network observer Elman, various training algorithms are used for the same time intervals and constant computational parameters of the computer.

In Fig. 4-6 show the results of modeling the estimation of the angular velocity of the second mass and the elastic moment between the masses after the learning process of the neural network observer Elman, where: fig. 4 – estimation results with the a gradient descent training algorithm (traingd); fig. 5 – estimation results with the gradient descent training algorithm for scaling conjugation (trainscg); fig. 6 – estimation results with the Levenberg - Marquardt training algorithm (trainlm).

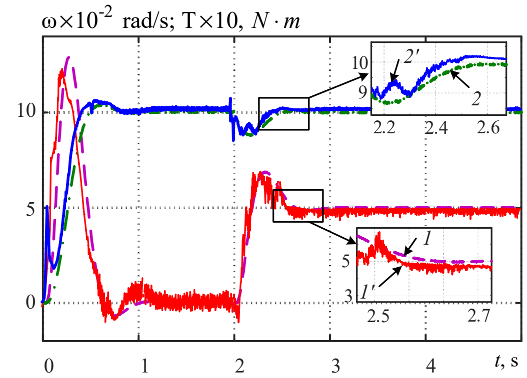

Fig. 4. Estimation results with the gradient descent training algorithm (traingd)

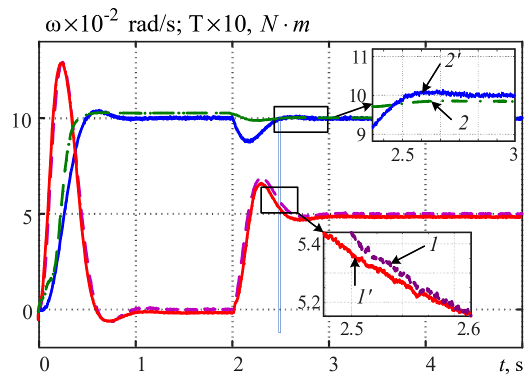

Fig. 5. Estimation results with the gradient descent training algorithm for scaling conjugation (trainscg)

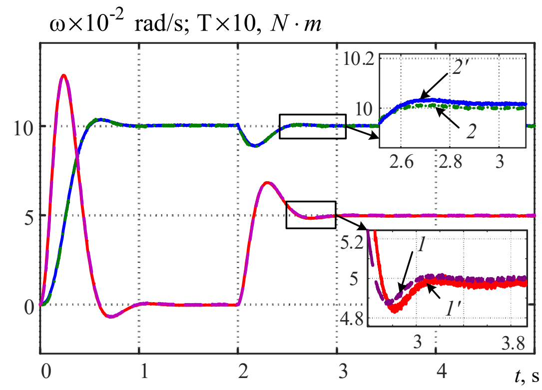

Fig. 6. Estimation results with the Levenberg - Marquardt training algorithm (trainlm)

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The curves in Fig. 4-6 represent transient processes of elastic moment between masses, angular speed of the second mass and are designated as follows: *1* – elastic torque between masses (T_{21}); *1'*– estimated elastic torque between masses ($\hat{T}_{21}$); *2* – angular speed of the second mass (ω_2); *2'* – estimated angular speed of the second mass ($\hat{\omega}_2$).

The results of comparing the value of the RMSE training RNNs Elman as a neural network observer of the state between the training algorithms are shown in Table 1.

TABLE 1: PERFORMANCE COMPARISIONS

Learning algorithm type	**RMSE training**	**Epoch training**
Gradient descent algorithm (*traingd*)	26.3	31
Gradient descent algorithm for blending scaling (*trainscg*)	12.1	458
Levenberg – Marquardt Algorithm (*trainlm*)	0.25	166

The simulation results presented in Fig. 4-6 and in table 1 show that such learning algorithms as the gradient descent algorithm and the gradient descent algorithm for scaling the conjugation do not cope with the task at all due to the large value of the standard deviation. The Levenberg - Marquardt learning algorithm best copes with the task with a small value of RMSE = 0.25.

V. CONCLUSION

In this article, the method for synthesizing a neural network observer based on Elman's recurrent neural networks was proposed , which allows identifying electromechanical state variables in the control system of the tracking electric drive of guidance for the optical-mechanical complex based on the feedback signals of the current and the angular speed of the motor. The simulation results showed that the efficiency of using a neural network observer depends on the chosen architecture, the training algorithm of Elman's recurrent neural networks and is related to the accuracy of their estimation.

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