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THE DIGITAL RECURRENT NEURAL NETWORKS FOR IDENTIFICATION OF INDUSTRIAL ROBOT

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Abstract. *The nonlinear system identification via Digital Recurrent Network (DRN) has been studied in this paper. Robots are complex nonlinear dynamic systems with unmodeled dynamics and unstructured uncertainties. In this paper the identification is performed of the complex nonlinear dynamics of the two-link industrial robot. The results of simulation show that the application of the DRN to the identification of the complex nonlinear dynamics gives satisfactory results.*

Key words: *identification, industrial robot, digital recurrent network, dynamic backpropagation algorithm*

1. INTRODUCTION

The primary task of industrial robots to be performed is the motion control, such as carrying an object, painting the surface of an object or welding materials, that requires only the accurate positioning control. The manipulator control is one of the main research areas in robotics. The fine motion control of robotic manipulators has become a desired goal in the last few years as a result of the new robot morphology and the definition of new tasks involving high velocity motions and end-effector tracking precision. The conventional controllers of industrial robots are decentralized PD joint controllers. Such a classical control scheme is inadequate for precise trajectory tracking. An alternative solution to PD control is the computed torque technique. Computed torque control requires exact dynamical knowledge of industrial robots, which is apparently impossible in practical situations. The industrial robot is a multivariable nonlinear coupling dynamic system with certain uncertainties. The general task of a system identification problem is to automatically approximate the input-output behavior of an unknown plant using an appropriate model.

In order to achieve the better performance of robotic manipulators the artificial intelligence can be introduced into the control system. One way of accomplishing this is the

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application of neural nets. Neural network may be used as nonlinear function approximators. A nonlinear dynamic system, may, therefore, be identified using the techniques of neural networks. It is well known that a multilayered artificial neural network using the backpropagation learning algorithm can approximate a given nonlinear function to any desired degree of accuracy.

Recent results show that neural-network techniques seem to be very effective to identify a wide class of complex nonlinear systems when we have no complete model information, or even when we consider the controlled plant as a black box, [1].

In the paper [2] studied the stability condition when multiplayer perceptrons were used to identify and control nonlinear systems.

The author investigates the identification of nonlinear systems in [3] by utilizing the soft-computing approach. As the identification methods Feedforward Neural Network (FNN), Radial Basis Function Neural Network (RBFNN), Runge-Kutta Neural Networks (RKNN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) based identification mechanisms are studied and their performances are comparatively evaluated on the two degrees of freedom direct drive industrial robot.

In [4] an overview of neuro-fuzzy modeling methods for nonlinear systems identification is given, with an emphasis on trade off between accuracy and interpretability.

To identify a quite general class of nonlinear systems on-line, [5] proposes a new stable learning law of the multilayer dynamic neural networks. A Lyapunov-like analysis is used to derive this stable learning procedure for the hidden layer as well as for the output layer. In [6] the adaptive nonlinear identification and trajectory tracking are discussed via dynamic neural networks.

For the most part of the industrial robot control in the published literature, actuator dynamics is typically excluded from the robot dynamic behavior to simplify the control design. However, actuator dynamics plays an important part in the complete robotic dynamics, especially in the factors of highly varying loads and actuator saturation.

The neural model reference control architecture uses two neural networks: a controller network and a plant model network. The nonlinear system identification via digital recurrent network is studied in this paper. The nonlinear mapping capability of neural networks is exploited for industrial robot model. This paper is organizedin the following way. In section 2 a model of actuator and industrial robot with uncertainty is presented. Section 3 presents the architecture of the digital recurrent network used in the system identification tasks. In section 4, in order to demonstrate the validity of the proposed method, two DRN are designed and simulated in the face of large uncertainties and external disturbances. Section 5 gives the concluding remarks.

2. THE MODEL OF ACTUATOR AND INDUSTRIAL ROBOT WITH UNCERTAINTY

The dynamic model of armature-controlled dc servomotors on an n-link industrial robot can be expressed in the following form ([7]):

$$\mathbf{M}_m = \mathbf{K}_i \mathbf{i} \tag{1}$$

$$\mathbf{M}_m = \mathbf{J}_a \ddot{\boldsymbol{\theta}}_m + \mathbf{B}_m \dot{\boldsymbol{\theta}}_m + \mathbf{M}_L \tag{2}$$

$$\mathbf{u} = \mathbf{R}_i \mathbf{i} + \mathbf{L}\frac{d\mathbf{i}}{dt} + \mathbf{K}_b \dot{\theta}_m \tag{3}$$

where:

$\mathbf{M}_m \in \mathbf{R}^n$ is the vector of electromagnetic torque;
$\mathbf{K}_i \in \mathbf{R}^{n\times n}$ is the diagonal matrix of motor torque constants;
$\mathbf{i} \in \mathbf{R}^n$ is the vector of armature currents;
$\mathbf{J}_a \in \mathbf{R}^{n\times n}$ is the diagonal matrix of the actuator moment of inertia;
$\mathbf{B}_m \in \mathbf{R}^{n\times n}$ is the diagonal matrix of torsional damping coefficients;
$\mathbf{M}_L \in \mathbf{R}^n$ is the vector of load torque;
$\mathbf{u} \in \mathbf{R}^n$ is the vector of armature input voltages;
$\mathbf{R}_i \in \mathbf{R}^{n\times n}$ is the diagonal matrix of armature resistance;
θ_m, $\dot{\theta}_m$, $\ddot{\theta}_m \in \mathbf{R}^n$ denote the vectors of motor shaft positions, velocities, and accelerations, respectively;
$\mathbf{L} \in \mathbf{R}^{n\times n}$ is the diagonal matrix of armature inductance;
$\mathbf{K}_b \in \mathbf{R}^{n\times n}$ is the diagonal matrix of back electromotive force coefficients.

Physically, inductance of the armature winding is of the order of tenths of milliHenries, while its resistance is in units of Ohms. Thus, **L** is practically zero so (3) may be reduced to:

$$\mathbf{u} = \mathbf{R}_i \mathbf{i} + \mathbf{K}_b \dot{\theta}_m \tag{4}$$

In order to apply the dc servomotors for actuating an *n*-link industrial robot, a relationship between the joint position θ and the motor-shaft position θ_m can be represented as follows:

$$\mathbf{n} = \frac{\theta_m}{\theta} = \frac{\mathbf{M}_L}{\mathbf{M}} \tag{5}$$

where: $\mathbf{n} \in \mathbf{R}^{n\times n}$ is a diagonal positive-definite matrix of the gear ratios for the *n* joints; $\mathbf{M} \in \mathbf{R}^n$ is vector of torque developed at the joint side; $\theta \in \mathbf{R}^n$ is the vector of joint position.

The industrial robot is modeled as set of *n* rigid bodies connected in series with one end fixed to the ground and the other end free. The bodies are connected via either revolute or prismatic joints and a torque actuator acts at each joint. The dynamic equation of an *n*- link industrial robot is given by:

$$\mathbf{H}(\theta)\ddot{\theta} + \mathbf{C}(\theta,\dot{\theta}) + \mathbf{G}(\theta) + \mathbf{B}_d \dot{\theta} + \mathbf{M}_d = \mathbf{M} \tag{6}$$

where:

$\dot{\theta}$, $\ddot{\theta} \in \mathbf{R}^n$ are the joint velocity and acceleration vectors, respectively;
$\mathbf{H}(\theta) \in \mathbf{R}^{n\times n}$ denotes the inertia matrix;
$\mathbf{C}(\theta,\dot{\theta}) \in \mathbf{R}^n$ expresses the effect of centripetal and Coriolis forces;
$\mathbf{G}(\theta) \in \mathbf{R}^n$ is the gravity vector;
$\mathbf{B}_d \in \mathbf{R}^{n\times n}$ is the diagonal matrix of viscous and/or dynamic friction coefficients;
$\mathbf{M}_d \in \mathbf{R}^n$ represents the vector of external disturbance.

According to (1), (2), (5), (6), the vector of armature input voltages in (4) could be rewritten:

$$\mathbf{u} = \frac{\mathbf{R}_i\mathbf{n}}{\mathbf{K}_i}\{[\mathbf{J}_a + \mathbf{H}(\theta)]\ddot{\theta} + (\mathbf{B}_m + \mathbf{B}_d + \mathbf{K}_b)\dot{\theta} + \mathbf{C}(\theta,\dot{\theta}) + \mathbf{G}(\theta) + \mathbf{M}_d\} \quad (7)$$

The $\mathbf{H}(\theta)$, $\mathbf{C}(\theta,\dot{\theta})$ and $\mathbf{G}(\theta)$in (7) are functions of physical parameters of industrial robots links' masses, links' lengths, the moments of inertia and the payload parameter. The precise values of these parameters are difficult to acquire due to measuring errors, environment and the payload variations. In this paper $\mathbf{M}_d$ in (7) has to be replaced by $\mathbf{M}_u(\theta,\dot{\theta},\ddot{\theta},t)$ because it should represent not only external disturbance but also the payload variation. So (7) can be rewritten as:

$$\mathbf{u} = \frac{\mathbf{R}_i\mathbf{n}}{\mathbf{K}_i}\{[\mathbf{J}_a + \mathbf{H}(\theta)]\ddot{\theta} + (\mathbf{B}_m + \mathbf{B}_d + \mathbf{K}_b)\dot{\theta} + \mathbf{C}(\theta,\dot{\theta}) + \mathbf{G}(\theta) + \mathbf{M}_u(\theta,\dot{\theta},\ddot{\theta},t)\} \quad (8)$$

3. DIGITAL RECURRENT NETWORKS

The recurrent network has dynamic nonlinear mapping ability since it has the recursive structure in it, which is suitable for dynamic system, while FNN represents the static nonlinear mapping.

The Digital Recurrent Networks (DRN) are the generalization of the Feedforward Network (FNN). The FNN is a static network, in the sense that the network output can be computed directly from the network input, without the knowledge of the initial network states. A DRN can contain feedback loops and time delays (D).

Figure 1 is an example of DRN. The layer outputs and the net inputs in the DRN are explicit functions of time. The output of the network is a function not only of the weights, biases, and network input, but also of the outputs of some of the network layers at previous points in time. In [8] the dynamic backpropagation algorithm is used to adapt weights and biases.

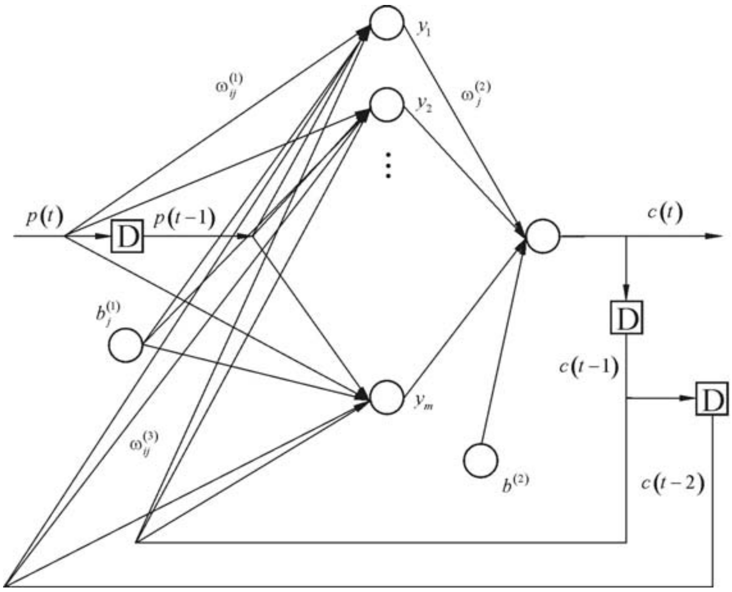

Fig. 1. Digital Recurrent Network

DRN network is composed of a nonlinear hidden layer and a linear output layer. The inputs $p(t)$ and $p(t-1)$ are multiplied by weights $\omega_{ij}^{(1)}$, outputs $c(t-1)$ and $c(t-2)$ are multiplied by weights $\omega_{ij}^{(3)}$ and summed at each hidden node. Then the summed signal at a node activates a nonlinear function $f(\cdot)$, called a hyperbolic tangent sigmoid function. The outputs from all y_j are weighted with $\omega_{ij}^{(2)}$ and summed at each output node.

The output of the network is:

$$c(t) = \sum_{j=1}^{m} \omega_j^{(2)} y_j + b^{(2)} \tag{9}$$

where:

$$y_j = \frac{e^{n_j} - e^{-n_j}}{e^{n_j} + e^{-n_j}} \tag{10}$$

$$n_j = p(t)\omega_{1j}^{(1)} + p(t-1)\omega_{2j}^{(1)} + c(t-1)\omega_{1j}^{(3)} + c(t-2)\omega_{2j}^{(3)} + b_j^{(1)}, \; j = 1,2,...,m \tag{11}$$

where m is the number of hidden neurons.

The performance index for the network is:

$$F(\mathbf{x}) = \sum_{t=1}^{Q} [c_d(t) - c(t)]^2 \tag{12}$$

where:

Q is number of data for training;

$c_d(t)$ is the desired response at time step t;

$c(t)$ is the output network at time step t and $\mathbf{x}$ is a vector containing all of the weights and biases in the network.

The network should learn the $\mathbf{x}$ vector that minimizes F. In order to use gradient descent, we need to find the gradient of F with respect to the network parameters:

$$\frac{\partial F}{\partial \mathbf{x}} = \sum_{t=1}^{Q} \left[\frac{\partial c(t)}{\partial \mathbf{x}} \right]^T \cdot \frac{\partial^e F}{\partial c(t)} \tag{13}$$

where the superscript e indicates an explicit derivative, not accounting for indirect effects through time. To find the complete derivatives that is required in (13) we need additional equation:

$$\frac{\partial c(t)}{\partial \mathbf{x}} = \frac{\partial^e c(t)}{\partial \mathbf{x}} + \frac{\partial^e c(t)}{\partial c(t\text{-}1)} \cdot \frac{\partial c(t\text{-}1)}{\partial \mathbf{x}} + \frac{\partial^e c(t)}{\partial (t\text{-}2)} \frac{\partial c(t\text{-}2)}{\partial \mathbf{x}} \tag{14}$$

The term $\frac{\partial c(t)}{\partial \mathbf{x}}$ must be propagated forward through time.

4. SIMULATION RESULTS

To illustrate validity of the proposed method, a two-link industrial robot shown in Fig. 2 is simulated, whose dynamic model can be described by (8). With respect to the robot, the matrices in (6) are listed as follows:

$$H(\boldsymbol{\theta})=\begin{bmatrix} a+b+2c\cos\theta_2 & b+c\cos\theta_2 \\ b+c\cos\theta_2 & b \end{bmatrix};\quad C(\boldsymbol{\theta},\dot{\boldsymbol{\theta}})=\begin{Bmatrix} -2c\dot{\theta}_1\dot{\theta}_2\sin\theta_2-c\dot{\theta}_2^2\sin\theta_2 \\ c\dot{\theta}_1^2\sin\theta_2 \end{Bmatrix};$$

$$G(\boldsymbol{\theta})=\begin{Bmatrix} dg\cos\theta_1+eg\cos(\theta_1+\theta_2) \\ eg\cos(\theta_1+\theta_2) \end{Bmatrix}$$

where:

$$a=m_1a_1^2+(m_2+m_T)l_1^2+J_{\zeta 1};\quad b=m_2a_2^2+m_Tl_2^2+J_{\zeta 2};\quad c=(m_2a_2+m_Tl_2)l_1;$$

$$d=m_1a_1+(m_2+m_T)l_1;\quad e=m_2a_2+m_Tl_2,$$

m_i is the mass of the i-th link, m_T is the mass load, l_i is the length of the i-th link, a_i is the position centre of mass of the i-th link and $J_{\zeta j}$ is the moment of inertia of i-th link.

In this simulation the plant outputs is bounded within the approximation region [-1.57 1.57] which corresponds to armature inputs voltage in the interval [-10 10]. The training data are obtained by applying different inputs to the system, then a block of 1000 observations are selected to train the DRN 1 and DRN 2, as described in section 3.

The two-layer DRN is used to the identification of an industrial robot, Fig. 3.

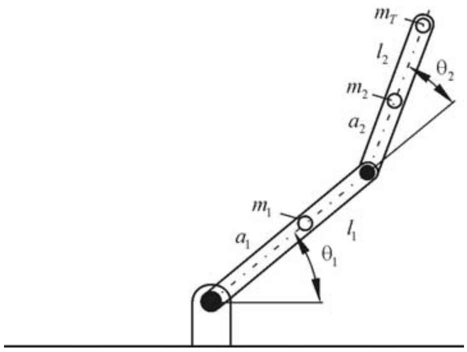

Fig. 2. A two-link industrial robot

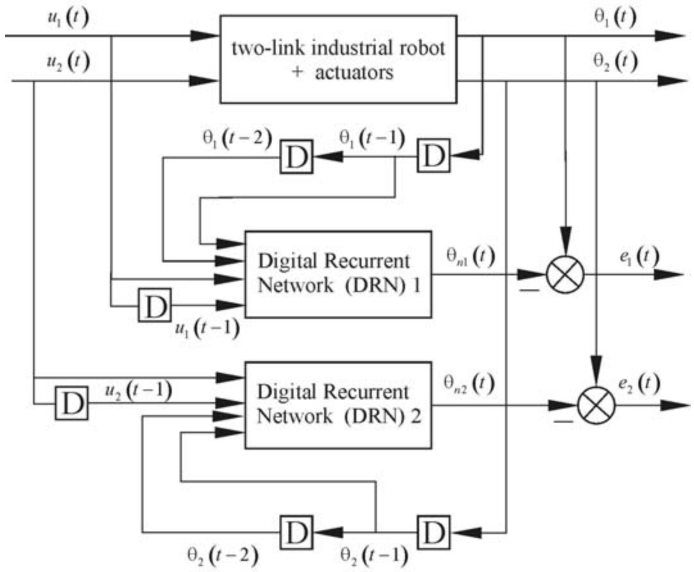

Fig. 3. The identification of an industrial robot

The parameters of the DRN 1 are given in Table 1. The number of the hidden neurons is 10.

Table 1. Parameters of the DRN 1

j	$\omega_{1j}^{(1)}$	$\omega_{2j}^{(1)}$	$\omega_{1j}^{(3)}$	$\omega_{2j}^{(3)}$	$b_j^{(1)}$	$\omega_j^{(2)}$
1	0.6756	-0.6968	1.2764	-1.3655	8.3455	-0.0014
2	0.0009	-0.0027	0.8931	1.004	1.7489	0.0002
3	0.0002	0.0002	0.3327	-0.1527	0.6613	4.3376
4	0.0005	0.0005	0.717	-0.3619	1.9828	0.3877
5	0.8378	-0.2689	-2.5506	-4.1931	2.847	0.0012
6	-0.0002	-0.0001	-0.4816	0.1228	0.0136	2.7535
7	-0.4032	0.4195	1.508	-1.7804	-3.0111	0.0012
8	-0.5782	0.5798	0.5896	-0.1379	1.3202	-0.0012
9	-0.0002	-0.0002	-0.3527	0.1644	0.885	4.4162
10	-0.0002	-0.0001	-0.4971	0.1476	0.0085	-2.9235

$b^{(2)} = 0.2658$

The parameters of the DRN 2 are given in Table 1.

Table 2. Parameters of the DRN 2

j	$\omega_{1j}^{(1)}$	$\omega_{2j}^{(1)}$	$\omega_{1j}^{(3)}$	$\omega_{2j}^{(3)}$	$b_j^{(1)}$	$\omega_j^{(2)}$
1	0.7326	0.7812	1.3481	1.8925	5.0934	0.065
2	0.1679	-0.3247	1.2673	-1.3108	3.2674	-0.0563
3	-0.2952	-0.0341	0.2814	-0.0057	0.0347	2.765
4	0.1275	-0.3714	1.9159	0.7096	3.1207	0.5184
5	0.6284	0.1983	-1.8367	-2.3967	2.0986	0.0738
6	0.0065	-0.0034	-1.3827	3.2903	-0.9834	4.9152
7	-0.6245	0.8713	0.3861	-1.9314	2.9671	0.0367
8	-0.9478	0.2597	-0.2967	-3.1098	-1.4967	0.06206
9	-0.0001	-0.0352	1.3094	0.3769	0.9977	-3.496
10	-0.0782	-0.0017	2.2001	0.2394	0.0192	1.5031

$b^{(2)} = 0.4903$

To validate the model, the input signal (Fig. 4 a)) is applied simultaneously to both the model and plant and their responses are then compared. Fig. 4 b) and Fig 4 d) illustrate the responses of the system and the DRN 1 network. Fig. 4 c) illustrates the error $e_1(t)$.

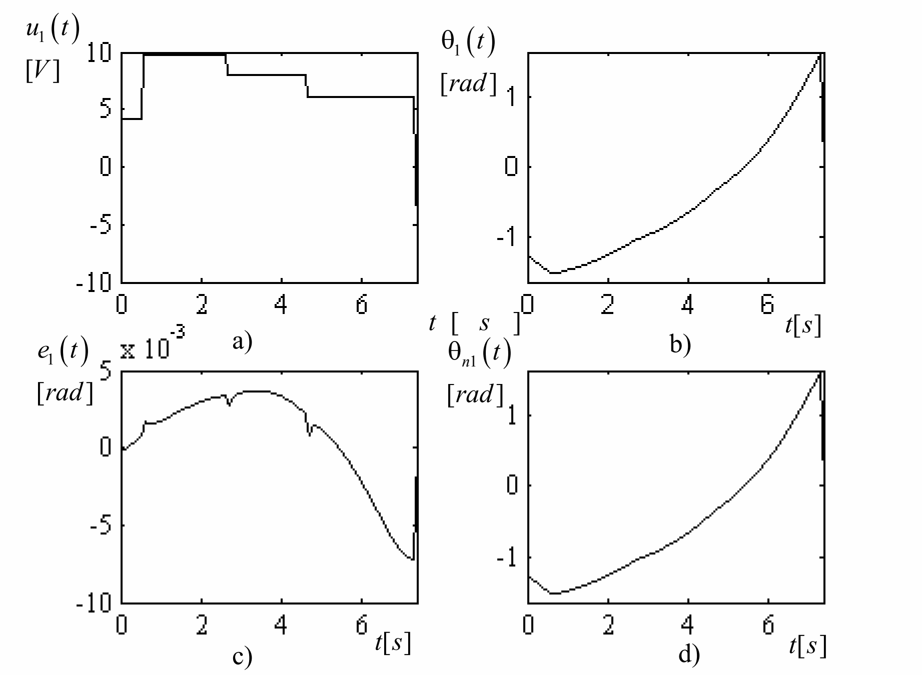

Fig. 4 a) input signal, b) response of the DRN 1 c) the error variation d) the response of the model

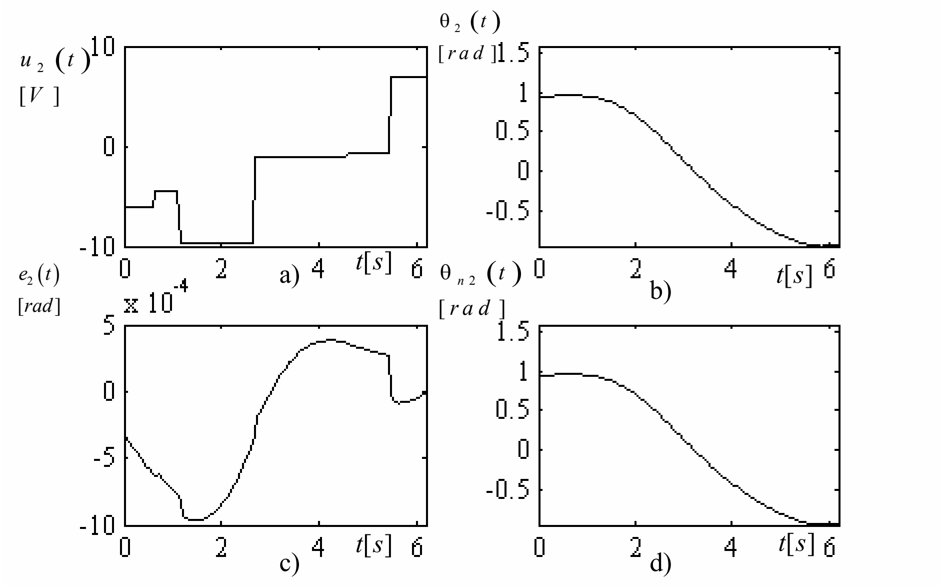

Fig. 5 a) input signal, b) response of the DRN 2 c) error variation d) response of the model

The approximating capability of the model (DRN 2) was tested with the input, Fig. 5 a) not previously used in the training phase. Fig. 5 b) and Fig. 5 d) illustrate the responses of the system and the DRN 2, Fig. 5 c) illustrates error $e_2(t)$.

5. CONCLUSIONS

The robot motion problem consists of obtaining the dynamic model of manipulator and using this model, it determines the control inputs. The main task of control system here is to track the required trajectory with given accuracy even in the presence of disturbances. During the design of the control system we commonly assume that all parameters of robot are constant and precisely known in advance. This assumption is valid for the majority of the robot parameters. However, some parameters in robotic systems are not sufficiently precisely defined and can vary during the task execution.
The numerous simulations are performed on two degrees of freedom industrial robot. DRN has been applied very successfully in the identification industrial robot model. When computing training gradient in recurrent networks, there are two different effects that we must account for, [8]. The first is a direct effect, which explains the immediate impact of a change in the weights on the output of the network at the current time. The second is an indirect effect, which accounts for the fact that some of the inputs to the network are previous network outputs, which are also the functions of the weights.

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IDENTIFIKACIJA INDUSTRIJSKOG ROBOTA DIGITALNOM REKURENTNOM NEURONSKOM MREŽOM

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U ovom radu je proučavana identifikacija nelinearnih sistema pomoću digitalne rekurentne mreže. Roboti su složeni nelinearni dinamički sistemi sa nemodeliranom dinamikom i nestrukturnim neodređenostima. U ovom radu je predstavljena identifikacija složene nelinearne dinamike dvosegmentnog industrijskog robota. Rezultati simulacije pokazuju da primena DRN u identifikaciji kompleksne nelinearne dinamike daje zadovoljavajuće rezultate.

Ključne reči: *identifikacija, industrijski robot, digitalna rekurentna mreža, dinamički algoritam sa propagacijom greške unazad*