16th Int. Conference on
Electrical Drives
and
Power Electronics
Slovakia
September 24 – 26, 2007

IDENTIFICATION OF THE PLANAR GANTRY CRANE SYSTEM USING ARTIFICIAL NEURAL NETWORKS

Mislav Crnogorac[1)] Fetah Kolonic[2)], Alen Poljugan[3)]

[1] Faculty of Electrical Engineering and Computing, HR-10000 Zagreb, Croatia*
tel./fax. +385 1 6129 824/ 6129705, e-mail: [1)] mislav.crnogorac@energocontrol.hr,
[2)]fetah.kolonic@fer.hr, [3)]alen.poljugan@fer.hr

Abstract. The paper focuses mainly on the identification of the crane electromechanical system where hanging load is transferred from one to another place, in the some limited storage area. For this purpose, Artificial Neural Network (ANN) based identification is used. Authors investigate the ANN learning problems and the identification accuracy. The comparison between an ANN identification method and an identification based on the Least Square (LS) estimation method has been done. Experimental verification is made on the scaled laboratory model of the planar gantry crane electromechanical system, (SPG-Single Pendulum Gantry).

Keywords: Identification, neural network, electromechanical system, single pendulum gantry

1. INTRODUCTION

In modern industrial systems, gantry cranes are widely used for the heavy loads transfer. When the fast and time optimal load positioning is needed, a high acceleration rate can cause considerable load swinging and consequently negative influence on the control and safety performances. In this case, apart from the load position control, a load swing angle should be undoubtedly controlled too. For an associated control problem solving, conventional solutions based on the linear mathematical model are used, such as linear state feedback controllers designed by Pole Placement (PP) or Linear Quadratic (LQ) optimal method [1, 2]. However, conventional control solutions can't solve the problems related to the system nonlinearities (e.g. a positioning error introduced by the static friction and backlash) causing a significant load positioning error and consecutively a performance deterioration. Generally, linear model derived from nonlinear differential equations, is efficient only in the system operating point, i.e. in the linearization point. If the linear controller can not keep the system in this point for any reason, systems performances deteriorate. In this connection, either advanced control strategy (nonlinear, adaptive, etc.) or intelligent control methods (neural, fuzzy, GA) are used for system performances improvement.

Nonlinear mathematical model, in any form used (as an artificial neural network, fuzzy logic, in the form of nonlinear differential equations, in the form based on the tensor product transformation etc) can be used for different tasks: for the system trajectory calculation [3], modeling of electromechanical systems [4-6], as well as for controller design [5-10]. However, as for the linear system, a main problem is to find accurate values of the model parameters, which also can be time variant.

This paper investigates neural network based system model identification. The system identification is motivated by two reasons. First is determination of the accurate gantry system mathematical model, intended to be used for the investigation of the system friction model. Second reason is the use of the ANN directly as a control block replacing the inverse dynamics of the plant.

Authors also investigate problems related to the neural network learning, such as impact of the test function and model structure on the estimation accuracy.
In the section 2 mathematical equations of the motions are presented while in the section 3 the main principle of the neural based identification is given. Simulation and experimental results (with experimental model description) are presented in the section 4 , 5 and 6.

2. MATHEMATICAL EQUATIONS OF THE MOTION

The single pendulum gantry mounted on the linear cart is presented in the Fig.1.

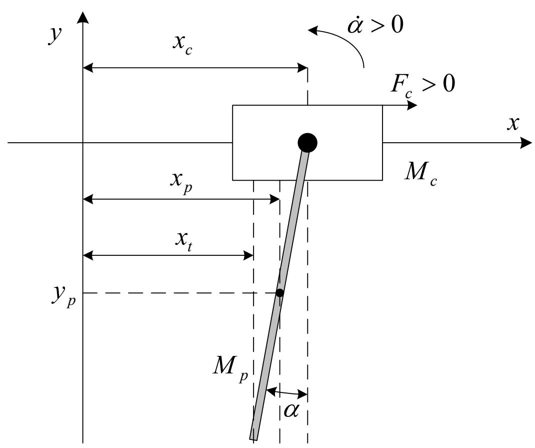


Fig. 1: Single pendulum gantry crane system

When facing the cart, a positive direction of the cart motion is to the right and a positive sense of the pendulum rotation is defined as counter clockwise. Also, the zero angle, corresponds to a suspended pendulum vertical rest down position. Single pendulum gantry can be presented as a system with one input *u* (motor voltage), and two outputs: α (pendulum angle) and x_c (cart position). Mathematical equations of the motion can be defined via Lagrange equations using a total potential and kinetic energy, [2]. Nonlinear equations of the motion are presented in (1) and (2). After linearization around pendulum angle $\alpha=0$, linear equations of the motion (3) and (4) has been derived.

$$\ddot{x}_c = \frac{-(I_p + M_p l_p^2) B_{eq} \cdot \dot{x}_c + (M_p^2 l_p^3 + l_p M_p I_p)\sin(\alpha)\cdot\dot{\alpha}^2 + M_p l_p \cos(\alpha) B_p \cdot \dot{\alpha}}{(M_c + M_p) I_p + M_c M_p l_p^2 + M_p^2 l_p^2 \sin^2(\alpha(t))} + \frac{M_p^2 l_p^2 g \cos(\alpha)\sin(\alpha) - (I_p + M_p l_p^2)\left(\frac{\eta_g K_g^2 \eta_m K_t K_m \cdot \dot{x}_c}{R_m r_{mp}^2} + (I_p + M_p l_p^2)\frac{\eta_g K_g \eta_m K_t}{R_m r_{mp}} U_m\right)}{(M_c + M_p) I_p + M_c M_p l_p^2 + M_p^2 l_p^2 \sin^2(\alpha)} \tag{1}$$

$$\ddot{\alpha} = \frac{-(M_c + M_p) B_p \cdot \dot{\alpha} - M_p^2 l_p^2 \sin(\alpha)\cos(\alpha)\cdot\dot{\alpha}^2 + M_p l_p \cos(\alpha) B_{eq} \cdot \dot{x}_c}{(M_c + M_p) I_p + M_c M_p l_p^2 + M_p^2 l_p^2 \cdot \sin^2(\alpha)} + \frac{-(M_c + M_p) M_p g l_p \sin(\alpha) + M_p l_p \cos(\alpha)\frac{\eta_g K_g^2 \eta_m K_t K_m \cdot \dot{x}_c}{R_m r_{mp}^2} - M_p l_p \cos(\alpha)\frac{\eta_g K_g \eta_m K_t}{R_m r_{mp}} U_m)}{(M_c + M_p) I_p + M_c M_p l_p^2 + M_p^2 l_p^2 \cdot \sin^2(\alpha)} \tag{2}$$

$$\begin{bmatrix} \dot{x}_c(t) \\ \dot{\alpha}(t) \\ \ddot{x}_c(t) \\ \ddot{\alpha}(t) \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1.5216 & -11.6513 & 0.0049 \\ 0 & -26.1093 & 26.8458 & -0.0841 \end{bmatrix} \cdot \begin{bmatrix} x_c(t) \\ \alpha(t) \\ \dot{x}_c(t) \\ \dot{\alpha}(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1.5304 \\ -3.5261 \end{bmatrix} \cdot U_m(t) \tag{3}$$

$$\begin{bmatrix} x_c(t) \\ \alpha(t) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_c(t) \\ \alpha(t) \\ \dot{x}_c(t) \\ \dot{\alpha}(t) \end{bmatrix} \tag{4}$$

TABLE I
SINGLE PENDULUM GANTRY PARAMETERS

Parameters	Description
B_{eq}=5.4 [Nms/rad]	equivalent viscous damping coefficient as seen at the motor pinion
B_p=0.0024 [Nms/rad]	viscous damping coefficient as seen at the pendulum axis
η_g=1	planetary gearbox efficiency
η_m=1	motor efficiency
g=9.81 [m/s^2]	gravitational constant of earth
I_p= 0.0078838 [kgm^2]	pendulum moment of inertia
J_m= 3.9001e-007 [kgm^2]	rotor moment of inertia
K_g= 3.71	planetary gearbox gear ratio
K_m= 0.0076776	back electro-motive force (EMF) constant
K_t= 0.007683	motor torque constant
l_p=0.3302 [m]	pendulum length from pivot to center of gravity
M_c= 1.0731 [kg]	lumped mass of the cart system, including the rotor inertia
M_p= 0.23 [kg]	pendulum mass
R_m= 2.6 [Ω]	motor armature resistance
r_{mp}= 0.00635 [m]	motor pinion radius

3. SYSTEM IDENTIFICATION USING NEURAL NETWORKS

Two structures of the system models were investigated, Nonlinear AutoRegressive model with eXogenous inputs (NARX) and Nonlinear Output Error (NOE), [11, 12]. The main goal is to correctly identify the NARX model of the process. For the model output prediction, in the case of NARX structure, the real system output has to be measured. Basically, the NARX structure gives one ahead output prediction. On the contrary, the NOE structure calculates a model output, based on its last output and system input (control signal), so there is no need for the output signal measurement. Drawback is that NOE structure output feedback can cause instability. Neural network parameters are estimated using a Modified Levenberg-Marquardt (MLM) learning algorithm with and without regularization. Although this learning algorithm is designed for the NARX neural networks, with a careful selection of the test signal this algorithm can also be used for the NOE structure. But it should be emphasized that the NOE structure is used only as a validation criteria for the NARX structure. Hereinafter these two estimator structures will be noted as NARX_NN and NOE_NN estimators. A system identification for the two different system outputs was made; for the pendulum tip position and pendulum tip velocity. This is because the model output type has considerable impact on the identification accuracy. These two models will be noted in the paper as the pendulum position and the pendulum velocity model.

MultiLayer Perceptron (MLP) two layer neural networks were chosen for the system identification, where the hidden layer uses a *tansig* and the output layer *purelin* activation function, [13]. Since only one output value is estimated all NN in the article have one neuron in the output layer.

System identifications are performed in simulations (section 4) and on the experimental setup (section 6). Identification results are compared with the LS estimator. Design of the LS estimator is not a subject of this paper, it is explained in [14].

4. SIMULATION RESULTS

In the simulation, neural network was used for the nonlinear gantry model identification (equation (1),(2)), Fig.2.

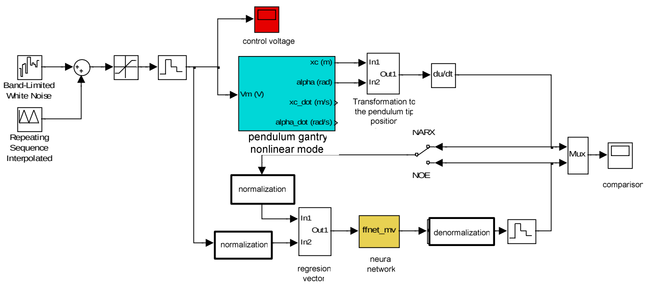
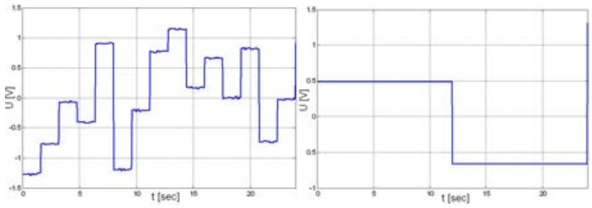


Fig.2. Simulation model of the SPG

According to the simulation results and following the parsimony principle, only one neuron in the hidden layer is enough for the proper system identification, because the nonlinearity effect is small. The simulation model, although nonlinear, for small swinging angles can be considered as linear one. This rises an important question: Why we should use the NN for identification of a process with a low "amount" of nonlinearity? The answer is simple. The real process has a nonlinearity expressed in the nonlinear friction. To simplify the NN learning task, from the NN network is first asked to learn the almost linear process (the simulation model). Then, the coefficients obtained with this simulation are set as initial learning conditions when the NN network should learn the real process. Doing that, one can compare the LS estimator with the NN identification on a linear process too; it might be interesting as well.

For the identification accuracy is crucial to apply the test signal which will excite all system modes. Usually Band Limited White Noise Signal (BLWNS) or Pseudo Random Binary Signal (PRBS) based test signal are used. However, experimental results here confirmed that these signal give good results but not to the extent necessary. This is because these signals excite all frequencies and not only system modes. This in turn results in an identification surface whose global minimum is harder to find then the identification surface generated with the test signal that excites only system modes. Different types of the test signal are investigated and for the signals presented in the Fig.3 a) and b) best identification results are achieved. Test signal in the Fig.3.a) is used for the pendulum velocity and signal in the Fig.3.b) for the pendulum position model identification. For the comparison, system is identified with LS estimator and results are compared with neural estimators.



a) b)

Fig.3. Test signals used in simulation,
a) for pendulum velocity and b) for pendulum position model

4.1. Pendulum velocity model

Criterion function value over epochs for pendulum velocity model identification is presented in the Fig.4.

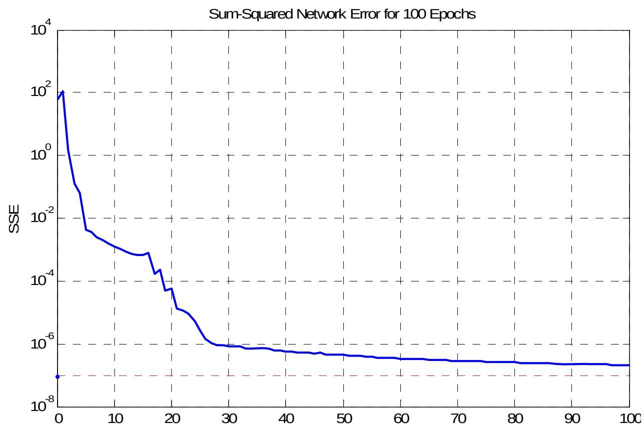


Fig.4. Criterion function over epochs for pendulum velocity model identification

After aprox. 40 epochs, MLM algorithm learning ability starts to decrease. In spite of this, identification results are quite good because criterion function has very small values indicating that the learning algorithm is near the global minimum.

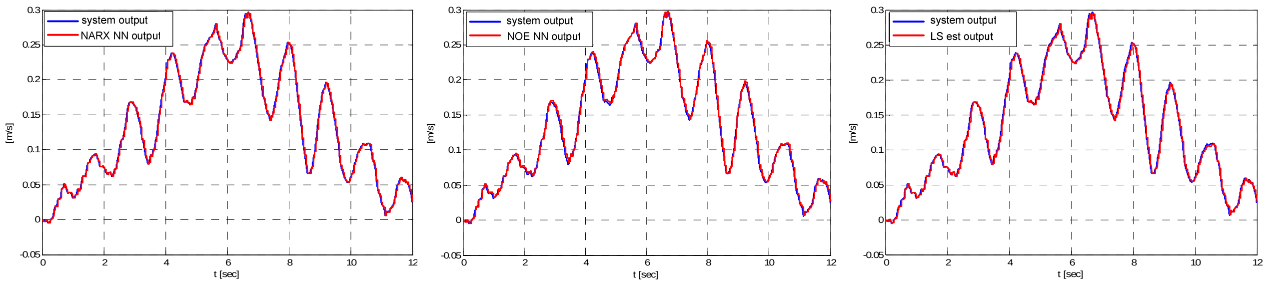
Result of the identification for the pendulum velocity model with the NARX structure is presented in Fig.5.a) and with the NOE structure in Fig.5.b). These results are compared with the results of the LS estimation in Fig.5.c). It can be noticed that identification procedures, even for the NOE structure, give good results. Careful selection of the test signal gives good results for the NOE structure even with the MLM learning algorithm.

4.2. Pendulum position model

In the Fig.6. identification results for the pendulum position model are presented. Fig.6.a) presents results for the NARX, Fig.6.b) for the NOE structure and Fig 6.c) for the LS estimator. A deterioration of the NOE_NN estimator performance compared to the NARX_NN or LS estimator can be noticed. Comparing Fig.5.b) and Fig.6.b) it is also clear that pendulum velocity model is more appropriate for identification because it gives better identification results in the NOE structure. This is expected because the velocity model regression vector is 6 dimensional. The position model regression vector is 8 dimensional, which means that the space where the learning algorithm has to find the minimum is 2 dimensions higher. In other words, the learning algorithm has a tougher job here. NN have more parameters to estimate than the LS estimator. On one hand more parameters means more model flexibility, but on the other hand the learning task becomes more complex and difficult. The LS estimator gives the transfer function which relates the pendulum tip position and the control voltage in the z-domain as

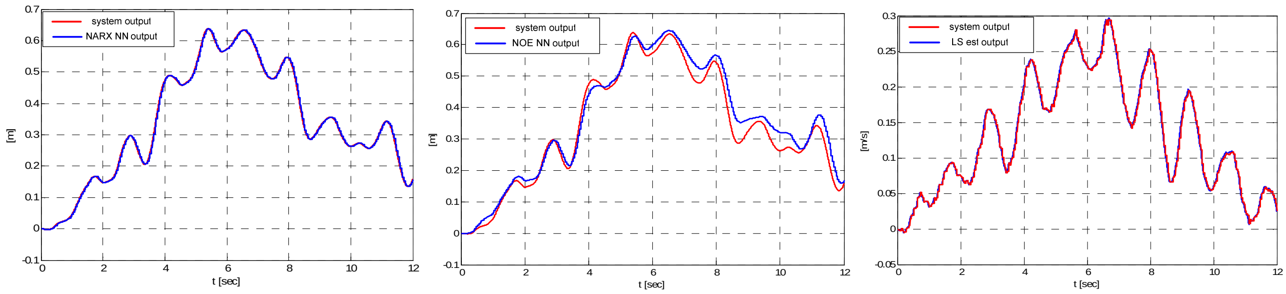
$$F(z)=\frac{x_t(z)}{U_m(z)}= \\ =\frac{-0.0004201z^3+0.0005222z^2+0.0003298z-0.0003615}{z^4-3.584z^3+4.806z^2+0.6254} . \quad (5)$$

The same transfer function can be obtained form equation (3) using the ZOH transformation. That means the process estimation with LS estimator has been performed correctly.



a) b) c)

Fig.5. Simulation results for the pendulum velocity model identification, a) NARX_NN, b)NOE_NN, c) LS estimator



a) b) c)

Fig.6. Simulation results for the pendulum position model identification, a) NARX_NN, b) NOE_NN, c) LS estimator

5. SINGLE PENDULUM GANTRY EXPERIMENTAL SETUP

Experimental tests have been performed on the scaled laboratory model of the planar gantry crane electromechanical system, (SPG-Single Pendulum Gantry). The experimental model of a SPG consists of two basic parts: cart with pendulum and digital control system implemented on the personal computer with AD interface, [1,6,10,15].

The cart is driven by DC servo motor by the rack and pinion mechanical interface, Fig.7. Driving motor, two encoders and additional weight are placed on the cart. Encoders are used for the cart position and the pendulum angle measurement, and additional weight is used to ensure better cart fitting to the pinion on the rack. The cart position resolution is 22.75 µm, the swing angle resolution is 0.0015 rad. and available cart distance (the length of the rack) is 1 m (maximum).

Digital control system consists of a personal computer (PC), data acquisition board (DAC), terminal board and power supply with amplifier unit (UPM).Terminal unit is connected to DAC board supplied with 16 differential 14 bit analogue inputs, 4 analogue 12 bit outputs, 6 optical encoder inputs, 48 programmable digital inputs. Universal power module (UPM) with +/-15V, 3A has amplifier for electromechanical plant's actuators (DC motors). This laboratory system use microprocessor of personal computer (PC) for simulation and software development as well as for real-time control. Control algorithm, designed and simulated in MATLAB/Simulink environment, use graphically oriented software interface for real-time code generation. This application oriented code is running under the same PC.

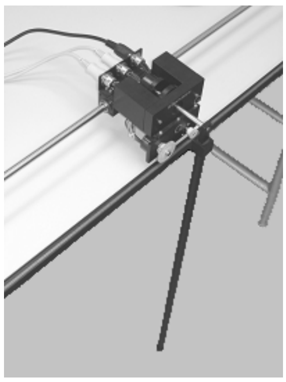


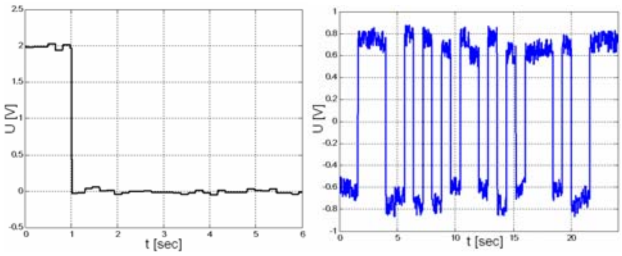
Fig. 7. Single pendulum gantry laboratory model

6. EXPERIMENTAL VERIFICATION

From the simulation results can be concluded that LS estimator gives, in overall, the best results for the system identification. However, in the real system a big influence of unmodelled nonlinearities can be expected, so LS estimator performance could be deteriorated. The largest influence on the system performance has the nonlinear friction presented in simulation and modeled as linear (viscous) friction. Backlash is so small in the real system and it couldn’t be identified with the sample time of 0,06 s. Lower sampling rates are not advisable because the system possesses measurement noise. In this case neural network identification should give better performance compared to the LS estimator. Because of the nonlinearities, a number of the network hidden layer neurons should be reviewed.

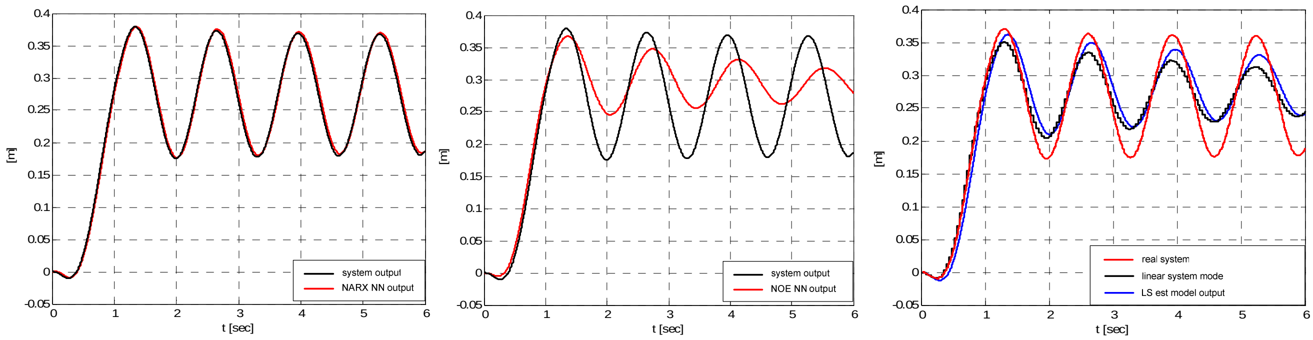
For the identification of the pendulum velocity model, six neurons in the hidden layer are used, and for the pendulum position model only three neurons in the hidden layer are used. The number of neurons in the hidden layer was determined experimentally. In both cases the simulation model of the process can be used to set up initial coefficients of the NN. If this is done, the NN learning algorithm has a much simpler task, it has to learn only the nonlinear components of the process. Better generalization of such NN is also expected. The model order can also be estimated using the linear model. The linear model order regression dimensions are 6 and 8. In order to acknowledge the nonlinear friction these dimensions can be increased to 8 and 10. Experimental results show that this in not necessary. The learning algorithm uses regularization which reduces the order of the model, if it is selected to big. But, as stated, the regularization did not have a considerable influence, because the model order are optimally chosen by experimentation.

Like in simulation, selection of the test signal is important for the identification accuracy. Experimental testing showed that the best results are achieved for the test signals presented in the Fig.8. Experimental results are presented in Fig.9 and Fig 10. For the both models the results with NOE structure are not suitable. Only the results obtained with NARX neural network track the real system output. A reason for that is the nonlinearity which can not be identified with LS estimator, or in the case of the NOE_NN structure, unmatched learning algorithm. Poor results with the NOE structure are predictable because the NOE_NN is intended only as validation criteria for the NARX_NN. Also experimental results confirmed that in the case of neural network identification pendulum velocity model is more suitable to use.



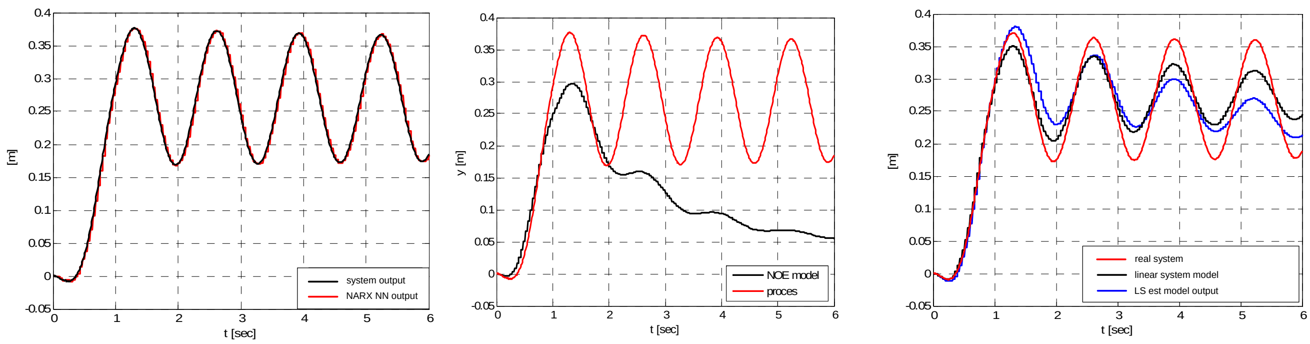
a) b)

Fig.8. Test signals used in experimental verification, a) for pendulum velocity and b) for pendulum position model



a) b) c)

Fig.9. Experimental results for the pendulum velocity model identification, a) NARX_NN, b) NOE_NN, c) LS estimator



a) b) c)

Fig.10. Experimental results for the pendulum position model identification, a) NARX_NN, b) NOE_NN, c) LS estimator

7. CONCLUSION

Using artificial neural network, the identification of the planar gantry electromechanical crane model has been successfully done. Two neural network estimator structures are compared; NOE and NARX. The identification of the two different models for different outputs is performed too, and the identification results of the neural network estimation are compared with the results obtained with the LS estimator.

The simulation testing showed identification accuracy dependence on the test signals profiles. The simulation results shows that both types of the neural network estimators give good results in comparison with the LS estimator.

For the experimental testing, number of neurons in hidden layer has to be increased due to the system nonlinearities (mainly friction, backlash can be neglected in this specific experiment). The experimental results confirm that the LS estimator can not estimate system nonlinearities.

Poor results with the NOE structure are predictable because the applied learning algorithm is mainly design for NARX structure. From this reason, the NOE_NN is intended only as validation criteria for the NARX_NN. To obtain better results an appropriate NOE (on-line) learning algorithm must be applied. However, this implicates neural network stability problems and also problems related to the algorithm complexity (real world implementation problems).

Identification of the nonlinear friction was done with the NARX_NN. Though results obtained with the NARX structure shows good performance, the well known drawback of the NARX estimator is the need for the system output measurement. If the linear model of the process exists, a method for simplifying the learning task is suggested.

The simulation and experimental results indicate that in the case of the neural network estimators, pendulum velocity model is more suitable to be used.

In the future work the obtained results will be used to implement the inverse dynamic ANN controller for the electromechanical system described in this paper.

8. REFERENCES

[1] T.Popadić, F.Kolonić, A.Poljugan: A Fuzzy Control Scheme For The Gantry Crane Position And Load Swing Control, Proceedings of the 29th International conference on Computers in Technical Systems, pp. 15-20, May 22.-26, Opatija Croatia, 2006

[2] ………., Linear Experiment #4: Pole Placement: Single Pendulum Gantry, Instructor Manual, Linear Motion Servo Plants IP02, Quanser.

[3] H.H. Lee and S.G. Choi: A Model-Based Anti-Swing Control of Overhead Cranes with High Hoisting Speeds, Proceedings of 2001 IEEE International Conference on Robotics & Automation, Seoul, Korea, May 21-26, 2001.

[4] P.Korondi: Tensor Product Model Transformation-based Sliding Durface Design, Acta Politechnica, Journal of Applied Sciences at Budapest Tech Hungary, vol 3., No. 4, pp. 23-35, 2005.

[5] P.Korondi, P.Bartal, F.Kolonić: Friction Model Based on Tensor Product Transformation, Proceedings of the 7th International Symposium of Hungarian Researchers on Computational Intelligence, 24-25.11.2006, pp. 83-94, Budapest, Hungary, 2006

[6] F.Kolonic, A.Poljugan, I.Petrovic: Tensor Product Model Transformation-based Controller design for Gantry Crane Control System – An Application Approach, Acta Politechnica, Journal of Applied Sciences at Budapest Tech Hungary, vol 3., No. 4, pp. 95-112, 2005.

[7] G. Corriga, A. Giua i G. Usai: An Implicit Gain-Scheduling Controller for Cranes, IEEE transactions on control system technology, vol 6, NO. 1, january 1998.

[8] Y. Tabata, K. Ichise, S. Ouchi i K.Z. Liu: Anti-sway control of a rotational crane using a non-linear controller, Proceedings of SICE2002, Osaka, Japan, 5-7 Aug 2002.

[9] J.Yanai, M. Murakami, S.Ouchi, K.Z. Liu and Y. Todaka. Anti sway control system of a rotational crane using non-linear controller, Proceedings of 2000 ACM, Nagoya, Japan, 2000.

[10] P.Zoltán, P.Baranyi, F.Kolonić, A.Poljugan: Approximation Trade-Off by TP Model Transformation, Proceedings of the 6th International Symposium of Hungarian Researchers on Computational Intelligence, Budapest, Hungary, p.p, 731-741, 2005.

[11] L.R. Castro, J.L. Figueroa, O.E. Agamennoni: " BIBO Stability for NOE Model Structure using HL CPWL Functions", Proceedings of the IASTED Conference on Modelling, Identification and Control MIC 2005, pp. Xx-yy, Insbruck, Austria, February 16.-18, 2005.

[12] I.Petrović, M. Baotić, N.Perić: Regularization and validation of neural network models of nonlinear systems, Elektrotechnik und Informationstechnik (e&i) (0932-383X) 117 (2000), 1; 24-31

[13] S.V.Kartalopoulos: Understanding Neural Networks and Fuzzy Logic, The Institute of Electrical and Electronics Engineers, Inc., New York, 1996

[14] K.J.Aström, B. Wittenmark: Adaptive control- second edition, Addison Wesley Series in Electrical Engineering, Control Engineering, 1995.

[15] F.Kolonic, A.Poljugan, Z.Jakopovic: Laboratory-based and industrial- oriented course in mechatronics, Proceedings of the 13th International Conference of Electrical Drives and Power Electronics, EDPE 2005, CD-ROM, paper E05-117, Dubrovnik, Croatia

THE AUTHOR(S)

Fetah Kolonić (1956) received his Ph.D.E.E. in 1997, M.S.E.E. in 1990 and B.S.E.E. in 1980 at the University of Zagreb, Croatia. He is currently associate professor at the Faculty of Electrical Engineering and Computing, University of Zagreb. His areas of interest are control of electrical drives and power converters, optimal and robust control of industrial systems and integration structure in complex mechatronic systems. As a principal investigator and project leader he has been conducting several projects funded by international and Croatian industry as well as by the Croatian government. His teaching and research include application of advanced control techniques in industrial applied systems. He has been co-author of many papers published in journals and presented at the national and international conferences. He is the member of KOREMA, Croatian National Committee CIGRE and IEEE (Robotics and Automation Society).

Mislav Crnogorac (1983) received his B.S.E.E. in 2006 at the University of Zagreb, Croatia. He is currently employed as a designer at EnergoControl Zagreb in Croatia. His filed of interests are control of electrical drives and power converters, optimal predictive and robust control of industrial systems and integration structure in complex mechatronic systems.

Alen Poljugan (1977) received his M.S.E.E. in 2005 and B.S.E.E. in 2001 at the University of Zagreb, Croatia. From 2001 he works as assistant at the Faculty of electrical engineering and computing (Department of electrical machines, drives and automation). His filed of interests are control of electrical drives and power converters, optimal and robust control of industrial systems and integration structure in complex mechatronic systems. He has been co-author of several papers published at the national and international conferences