FUZZY LOGIC AND NEURAL NETWORK APPROACH TO THE INDIRECT ADAPTIVE POLE PLACEMENT CRANE CONTROL SYSTEM

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Abstract

The problem under consideration in the paper of automation transportation operation realized by material handling devices is focused on time and accuracy of an overhead travelling crane's shifting process. The presented anti-sway crane control system was solved in the paper using combination of an indirect adaptive pole placement (IAPP) control method, fuzzy logic and artificial neural network. The presented approach to crane control is based on assuming structure of crane dynamic linear model with varying parameters, and linear closed-loop discrete control system consisting of proportional-derivative controllers with gains adjusted to changes of model's parameters using pole placement method (PPM). The parameters of crane dynamic model are estimated on-line using recursive least squares (RLS) algorithm. The estimation process is speeded up by neuro-fuzzy estimator, created using Takagi-Sugeno-Kang (TSK) fuzzy inference system, which determines the initial parameters of crane model based on scheduling variables, rope length and mass of a load changing in stochastic way. The neuro-fuzzy estimator is created in off-line process of neural network learning using least mean squares (LMS) method, based on a set of parametric output error models of crane dynamic identified for fixed values of rope length and mass of a load. The TSK estimator is next on-line improved by RLS algorithm.

***Keywords**: overhead crane, indirect adaptive, pole placement, fuzzy logic, neural network*

1. Introduction

The paper is addressed to a problem of material handling processes automation, with attention focused on transportation operations realized by the overhead travelling cranes, which belong to the class of material handling devices denoted as the Large-Dimensional Rail-Mounted Handling Devices (WSUT) [13, 14]. The problem under consideration of an anti-sway crane control system is popular in automatics and frequently discussed in scientific works in which the proposed solutions are based on both, conventional, as well as unconventional, so called intelligent, methods. However a problem of adaptive crane controlling is hardly ever addressed to applicable in industrial practice solutions, as well as verifying researches are seldom carried out on real objects. This fact is significant to meet rising demands for transportations operations time and precision, as well as for improving exploitation quality, safety and reliability of material handling devices, which important representative is an overhead travelling crane. Those requirements are the result of automation of manufacturing processes and can be met by automating and improving control quality of material handling systems and devices.

In many manufacturing processes, where cranes realize the transportation operations, the safety and precise transfer of materials is required with minimizing the load oscillations and the operation time. In the non-automatic systems the resulting performance depends on the human operator experience and capability, which can be unreliable.

The problem of positioning a payload shifted by a crane is considered in many of scientific works. The frequently presented approach to the problem under consideration is based on an openloop control system solved using the optimal control theory [2, 3]. The closed-loop approach to a crane control system is frequently addressed to a problem of nonlinear crane system controlling based on known linear model of a crane dynamic with varying parameters corresponded to rope length and mass of a load variables. This approach allows applying methods based on Quadratic Regulator (LQR) [11], gain scheduling system [6], Lyapunov-equivalence-based observer [7], feedback linearization [4], pole assignment methods [8, 13].

The unconventional methods used in crane control systems are mostly based on fuzzy logic, artificial neural network [1] or combination of both so called intelligent methods [9, 13]. Those examples are mainly based on Mamdani fuzzy implications [5, 12], however the fuzzy systems based on Takagi-Sugeno-Kang (TSK) model are also presented [10, 13].

In the paper the proposed and described crane control system was based on an indirect adaptive pole placement IAPP method with the TSK fuzzy estimator of crane dynamic model's parameters. The control algorithm was created using recursive least squares (RLS) estimator of identified model of controlled object. The crane dynamic model was assumed as a linear system with varying parameters depended on the rope length and mass of load variables. The fuzzy estimator, which was achieved in off-line process of neural network learning is used to set an initial vector of parameters close to the expected for actual values of rope length and mass of a load, and speed up the estimation realized by RLS algorithm. Simultaneously the TSK fuzzy model of a crane dynamic is improved in real-time by the RLS algorithm. The control system was based on a time-discrete closed-loop control system with crane position and speed, as well as load swing angle feedbacks. The controllers gains are adjusted using pole placement method (PPM) based on the parameters of a crane dynamic model, estimated in each sample time. The results of experiments carried out using the laboratory overhead travelling crane, with hoisting capacity Q=150 [kg], localized in the Laboratory of Automated Transportation Systems and Devices at the AGH University of Science and Technology in Krakow, are presented as well.

2. Identification of a crane dynamic model

The assumed structure of a time-discrete crane dynamic model is shown in the Fig. 1. The model of controlled object consists of two sub-models which are expressed as the discrete transfer functions $G_{\dot{x}}(z)$ and $G_{\alpha}(z)$. In presented in the Fig. 1 model, the swing of a load influence on a crane speed was omitted for simplicity. Consequently the parametric model of the controlled object consists of two models that present relationship between the load swing α and crane velocity $\dot{x}$ (transfer function $G_{\alpha}(z)$), as well as relationship between crane speed $\dot{x}$ and input function u (transfer function $G_{\dot{x}}(z)$). The models can be identified separately based on data measured for the constant values of rope length l and mass of a load m_2.

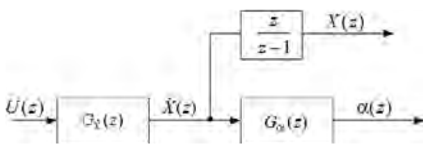

Fig. 1. The assumed parametric model of a crane dynamic consisting of two models expressed in a form of discrete transfer functions $G_{\dot{x}}(z)$ and $G_{\alpha}(z)$

The model, which expresses dynamic behaviour of a crane power transmission, can be simplified to a first-order system, denoted as the transfer function $G_{\dot{x}}(z)$:

$$G_{\dot{x}}(z) = \frac{D(z)}{C(z)} = \frac{d_0}{z + c_0}. \tag{1}$$

The model that expresses dynamic behaviour of oscillating object can be formulated as a second-order system, denoted as the transfer function $G_\alpha(z)$:

$$G_\alpha(z) = \frac{B(z)}{A(z)} = \frac{b_1 z + b_0}{z^2 + a_1 z + a_0}. \tag{2}$$

The presented models (1) and (2) can be identified off-line using output error (OE) method based on data measured during experiments carried out for fixed values of rope length, denoted as *l*, and mass of a load, denoted as m_2 (the mass of a crane is denoted as m_1). In the proposed indirect adaptive pole placement crane control system the parameters of assumed models are determined using recursive least squares (RLS) algorithm that improves the identification's performances in each step time. The estimators of both models are as follows:

$$\hat{\Theta}_{\dot{x}}(t) = \begin{bmatrix} d_0(t) \\ c_0(t) \end{bmatrix},\ \hat{\Theta}_\alpha(t) = \begin{bmatrix} b_1(t) \\ b_0(t) \\ a_1(t) \\ a_0(t) \end{bmatrix}. \tag{3}$$

The estimators of outputs $\hat{\dot{x}}$ and $\hat{\alpha}$ of the controlled object are calculated based on estimators of parameters $\hat{\Theta}_{\dot{x}}(t-1)$ and $\hat{\Theta}_\alpha(t-1)$ derived in previous step time:

$$\hat{\dot{x}}(t) = \varphi_{\dot{x}}^T(t) \cdot \hat{\Theta}_{\dot{x}}(t-1), \tag{4}$$

$$\hat{\alpha}(t) = \varphi_\alpha^T(t) \cdot \hat{\Theta}_\alpha(t-1). \tag{5}$$

The vectors $\varphi_{\dot{x}}(t)$ and $\varphi_\alpha(t)$ are composed of delayed outputs and inputs of the assumed models:

$$\varphi_{\dot{x}}(t) = \begin{bmatrix} u(t-1) \\ -\dot{x}(t-1) \end{bmatrix},\ \varphi_\alpha(t) = \begin{bmatrix} \dot{x}(t-1) \\ \dot{x}(t-2) \\ -\alpha(t-1) \\ -\alpha(t-2) \end{bmatrix}. \tag{6}$$

The one-step prediction errors are determined based on the actual and estimated values of outputs (7, 8). On the basis of the vectors $\varphi_{\dot{x}}(t)$ and $\varphi_\alpha(t)$ the auxiliary matrixes $\mathrm{P}_{\dot{x}}(t)$ and $\mathrm{P}_\alpha(t)$ are determined according the expressions (9) and (10) respectively:

$$\begin{aligned} e_{\dot{x}}(t) &= \dot{x}(t) - \hat{\dot{x}}(t) = \dot{x}(t) - \varphi_{\dot{x}}^T(t) \cdot \hat{\Theta}_{\dot{x}}(t-1) = \\ &= \dot{x}(t) - \begin{bmatrix} u(t-1) \\ -\dot{x}(t-1) \end{bmatrix}^T \cdot \begin{bmatrix} d_0(t-1) \\ c_0(t-1) \end{bmatrix}, \end{aligned} \tag{7}$$

$$\begin{aligned} e_\alpha(t) &= \alpha(t) - \hat{\alpha}(t) = \alpha(t) - \varphi_\alpha^T(t) \cdot \hat{\Theta}_\alpha(t-1) = \\ &= \alpha(t) - \begin{bmatrix} \dot{x}(t-1) \\ \dot{x}(t-2) \\ -\alpha(t-1) \\ -\alpha(t-2) \end{bmatrix}^T \cdot \begin{bmatrix} b_1(t-1) \\ b_0(t-2) \\ a_1(t-1) \\ a_0(t-2) \end{bmatrix}, \end{aligned} \tag{8}$$

$$\mathrm{P}_{\dot{x}}(t) = \frac{\mathrm{P}_{\dot{x}}(t-1)}{\beta} - \frac{\mathrm{P}_{\dot{x}}(t-1) \cdot \varphi_{\dot{x}}(t) \cdot \varphi_{\dot{x}}^T(t) \cdot \mathrm{P}_{\dot{x}}(t-1)}{\beta \cdot \left(\beta + \varphi_{\dot{x}}^T(t) \cdot \mathrm{P}_{\dot{x}}(t-1) \cdot \varphi_{\dot{x}}(t)\right)}, \tag{9}$$

$$\mathrm{P}_\alpha(t) = \frac{\mathrm{P}_\alpha(t-1)}{\beta} - \frac{\mathrm{P}_\alpha(t-1)\cdot\varphi_\alpha(t)\cdot\varphi_\alpha^T(t)\cdot\mathrm{P}_\alpha(t-1)}{\beta\cdot\left(\beta+\varphi_\alpha^T(t)\cdot\mathrm{P}_\alpha(t-1)\cdot\varphi_\alpha(t)\right)}, \tag{10}$$

where:
$\beta = 0{,}98$ - assumed forgetting coefficient which determines speed of learning process.

The Kalman's vectors are determined basis of auxiliary matrixes $\mathrm{P}_{\dot{x}}(t)$ and $\mathrm{P}_\alpha(t)$, and delayed input and outputs of controlled object:

$$\mathrm{K}_{\dot{x}}(t) = \mathrm{P}_{\dot{x}}(t)\cdot\varphi_{\dot{x}}(t) = \mathrm{P}_{\dot{x}}(t)\cdot\begin{bmatrix} u(t-1) \\ -\dot{x}(t-1)\end{bmatrix}, \tag{11}$$

$$\mathrm{K}_\alpha(t) = \mathrm{P}_\alpha(t)\cdot\varphi_\alpha(t) = \mathrm{P}_\alpha(t)\cdot\begin{bmatrix} \dot{x}(t-1) \\ \dot{x}(t-2) \\ -\alpha(t-1) \\ -\alpha(t-2)\end{bmatrix}. \tag{12}$$

The actual estimators $\hat{\Theta}_{\dot{x}}(t)$ and $\hat{\Theta}_\alpha(t)$ are determined based on one-step prediction errors (7) and (8) according to equation (13) and (14):

$$\hat{\Theta}_{\dot{x}}(t) = \hat{\Theta}_{\dot{x}}(t-1) + \mathrm{K}_{\dot{x}}(t)\cdot e_{\dot{x}}(t), \tag{13}$$

$$\hat{\Theta}_\alpha(t) = \hat{\Theta}_\alpha(t-1) + \mathrm{K}_\alpha(t)\cdot e_\alpha(t). \tag{14}$$

The IAPP control system under consideration requires to start with non-adaptive controller gains or/and initial values of estimators $\hat{\Theta}_{\dot{x}}(t)$ and $\hat{\Theta}_\alpha(t)$ to excite the controlled object outputs and prompt the RLS algorithm to estimation.

3. The indirect adaptive pole placement crane control system

3.1. The neuro-fuzzy estimator of crane model's parameters

The crane nonlinear model simplified to a linear model with varying parameters (1, 2) characterizes stochastic changes of parameters corresponded to changes of rope length and mass of a load variables, which can be used as scheduling variables to solve both problems, robust control, as well as modelling a crane system. Considering a given controlled object, e.g. an overhead travelling crane, the range of those parameters changes are usually known ($l = \langle l_{\min}, l_{\max}\rangle [m]$ and $m_2 = \langle m_{2\min}, m_{2\max}\rangle [kg]$) during control system designing. Simultaneously, the parameters of controlled object can change, in the extreme case, from minima to maximal, or vice versa, value, which can caused the deterioration of RLS algorithm and adaptive system performances. For this reason in the IAPP system was employed the fuzzy estimator which speeds up estimation by determining the initial values of estimators $\hat{\Theta}_{\dot{x}}(t)$ and $\hat{\Theta}_\alpha(t)$, based on the actual values of scheduling variables l and m_2.

The TSK estimator of the OE models parameters (1, 2) is determined based on the models identified for chosen values of rope length $l = \{l_1, l_2, ..., l_n\}$ and mass of a load $m_2 = \{m_{21}, m_{22}, ..., m_{2m}\}$. In the result of crane dynamic models identification a set of vectors $\mathrm{Y}_k = [d_{0k}, c_{0k}, b_{1k}, b_{0k}, a_{1k}, a_{0k}]^T$, are obtained for input vectors $\mathrm{X}_k = [l, m_2]^T$ consisting of the scheduling variables of the TSK system. The variables l and m_2 are fuzzy using the triangular membership functions $LM(l)$ and $LM(m_2)$, that take value one (membership coefficient $\mu(l)=1$, $\mu(m_2)=1$) for rope length and mass of a load constant values assumed during identification of *N* models (Fig. 2).

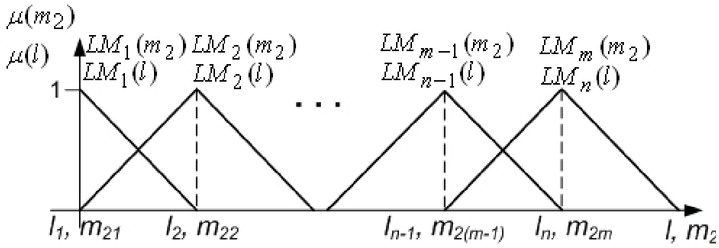

Fig. 2. The triangular membership functions defined for l and m_2 input variables of TSK fuzzy estimator

The set of determined OE models corresponds to the $N=n\cdot m$ fuzzy implications in TSK knowledge base, where a single *k*-rule if-then is expressed as follows:

IF

l is $LM_i(l)$ and m_2 is $LM_j(m_2)$

THEN

$$\mathbf{Y_k}=\left[d_{0k}, c_{0k}, b_{1k}, b_{0k}, a_{1k}, a_{0k}\right]^T,$$

where:

$k=1,2,...,N$,

$i=1,2,...,n$,

$j=1,2,...,m$.

The final output vector **Y** of the TSK system is calculated as weighted average of all rules outputs:

$$\mathrm{Y}=\begin{bmatrix} d_0 \\ c_0 \\ b_1 \\ b_0 \\ a_1 \\ a_0 \end{bmatrix}=\frac{\sum_{k=1}^{N} w_k\cdot \mathrm{Y}_k}{\sum_{k=1}^{N} w_k}=\frac{\sum_{k=1}^{N} w_k\cdot \begin{bmatrix} d_{0k} \\ c_{0k} \\ b_{1k} \\ b_{0k} \\ a_{1k} \\ a_{0k} \end{bmatrix}}{\sum_{k=1}^{N} w_k}. \tag{15}$$

The weight of a *k* fuzzy rule w_k is calculated as a product of membership coefficients for *l* and m_2 input values to the triangular membership functions $LM_i(l)$ and $LM_j(m_2)$ shown in the Fig. 2:

$$w_k=\mu_i(l)\cdot\mu_j(m_2). \tag{16}$$

The TSK fuzzy system can be presented in a form of neural network, that allow to used learning algorithm to set the parameters of fuzzy implications consequences based on training data. Data gathered from identification can be used to set the TSK system parameters in the process of neural network learning based on a training data matrix **TD** composed of input and output variables of fuzzy system, and using least mean squares algorithm to learn the consequences of fuzzy rules:

$$\mathrm{TD} = [l, m_2, y_i]. \tag{17}$$

The TSK fuzzy estimator of the OE model parameters, obtained in off-line process of neural network learning is improved in real-time process by using recursive least squares algorithm. In each step time the RLS algorithm determines the estimators $\hat{\Theta}_{\dot{x}}(t)$ and $\hat{\Theta}_{\alpha}(t)$ for actual values of rope length l and mass of a load m_2. The actual values of estimators $\hat{\Theta}_{\dot{x}}(t)$ and $\hat{\Theta}_{\alpha}(t)$ are changed in each k fuzzy implication of the TSK fuzzy system, if a weight of this implication is $w_k(t) > 0$, according to the equation:

$$\hat{\Theta}_{\dot{x}k,\alpha k}(t) = \frac{\hat{\Theta}_{\dot{x}k,\alpha k}(t-1)}{w_k(t)} \quad \forall\ k = 1, 2, \ldots, N. \tag{18}$$

3.2. Pole placement approach to crane control

The assumed structure of control algorithm used in the IAPP crane control system is based on the proportional controllers of crane position and speed (gains K_{Px} and $K_{P\dot{x}}$) and discrete load swing controller R_{α} (19). The control system for assumed crane dynamic model (1, 2) is presented in the Fig. 3.

$$R_{\alpha}(z) = \frac{Q(z)}{S(z)} = \frac{q_1 z + q_0}{z + s_0}. \tag{19}$$

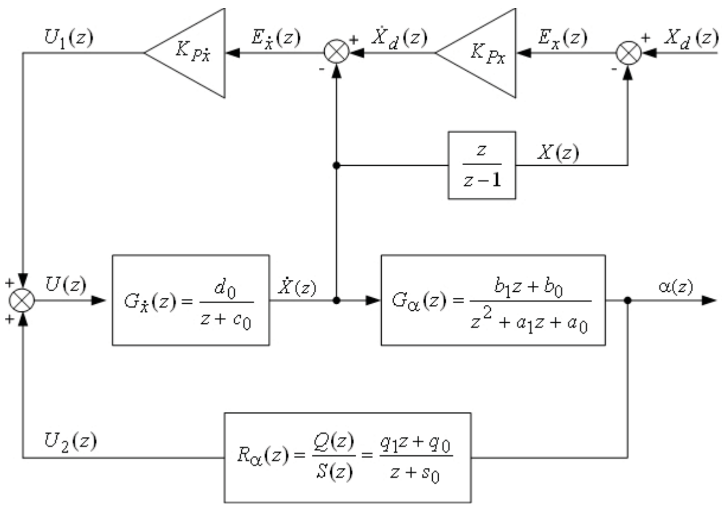

Fig. 3. The time-discrete crane position and speed, as well as the load swing control system

The unknown gains of closed loop control systems for estimated parameters of controlled object's model are derived based on Diophantine equation (20) formulated for the characteristic equation of considered closed loop control system transmittance, and expected characteristic equation, denoted as $P(z)$ (21) and determined for desired poles. In the expression (20) the Diophantine equation was formulated based on the **A**, **B**, **C**, **D** matrixes consisting of crane dynamic model parameters, and **P** vector of desired characteristic equation coefficients.

$$(\mathrm{z}-1)\cdot(\mathrm{A}\cdot\mathrm{C}\cdot\mathrm{S} + K_{P\dot{x}}\cdot\mathrm{A}\cdot\mathrm{D}\cdot\mathrm{S} - \mathrm{B}\cdot\mathrm{Q}\cdot\mathrm{D}) - K_{Px}\cdot K_{P\dot{x}}\cdot\mathrm{zA}\cdot\mathrm{D}\cdot\mathrm{S} = \mathrm{P}. \tag{20}$$

The $P(z)$ is the $n = 5$ order desired characteristic equation (21) of the closed loop control system (Fig. 3).

$$P(z) = z^5 + p_4 z^4 + p_3 z^3 + p_2 z^2 + p_1 z + p_0. \tag{21}$$

The coefficients $[p_4, p_3, p_2, p_1, p_0]^T$ of the desired equation $P(z)$ are derived based on desired poles (22), which can be specified for pulsation ω_0 of closed loop control system and dimensionless dumping coefficient ξ.

$$z_{1,2,3,4} = exp\left[\left(-\xi\omega_0 \mp j\omega_0\sqrt{1-\xi^2}\right)T_0\right], \quad z_5 = exp[-\omega_0 T_0]. \tag{22}$$

3.3. Indirect adaptive pole placement crane control system

The IAPP crane control system with the TSK fuzzy estimator simplified algorithm is presented in the Fig. 4.

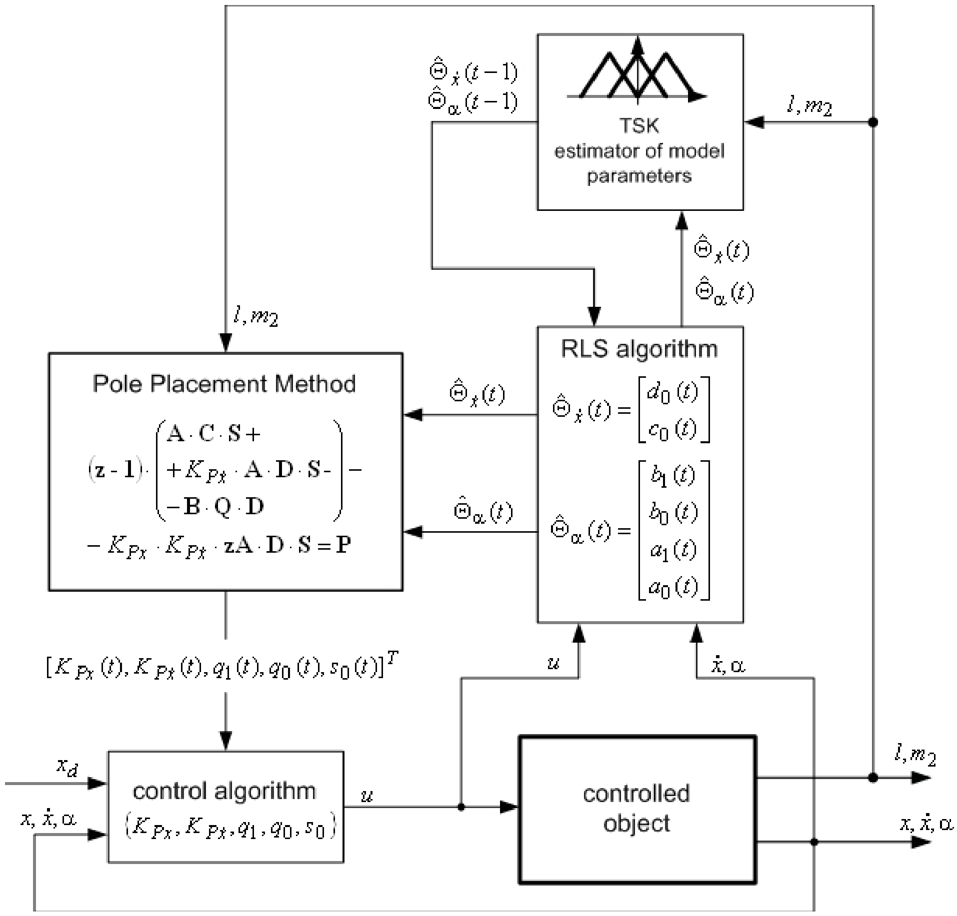

Fig. 4. The indirect adaptive pole placement crane control system with the TSK fuzzy estimator of crane model parameters

The control algorithm is based on the time-discrete closed loop control system (Fig. 3) which gains are adjusted by using pole placement method for estimated by RLS and TSK algorithms parameters (3) of assumed crane dynamic model (1, 2), and desired poles (22) determined for assumed dumping coefficient $\xi = 1$ (lack of oscillations and overshoots of output signals, crane position x and the load swing angle α), and for pulsation of the load swing angle (23).

$$\omega_0 = \sqrt{\left(1 + \frac{m_2}{m_1}\right)\frac{g}{l}}. \tag{23}$$

4. Experimental results

The experiments were carried out using the laboratory object, the double-girder overhead travelling crane with hoisting capacity *Q*=150 [kg]. The control system with IAPP control algorithm was realized using the PC platform with I/O board (PCI-1710HG control-measurement card manufactured by Advantech firm).

The control assumptions and aims were formulated as expected positioning accuracy for crane's mechanism and shifted a payload, and acceptable tolerance of oscillations and overshoots of output signals equal 0.02 [m], as well as the setting time about 7 seconds. The examples of experimental results for chosen values of rope length l ={0.7; 1.7}[m] and mass of a load m_2 ={10; 30; 50; 70}[kg], and expected position of crane and payload $x_d = 1[m]$, are presented in the Fig. 5-8 in the form of time characteristics of crane position $x[m]$ and the load deviation assumed as a product of rope length and load swing angle $l \cdot \alpha [m]$.

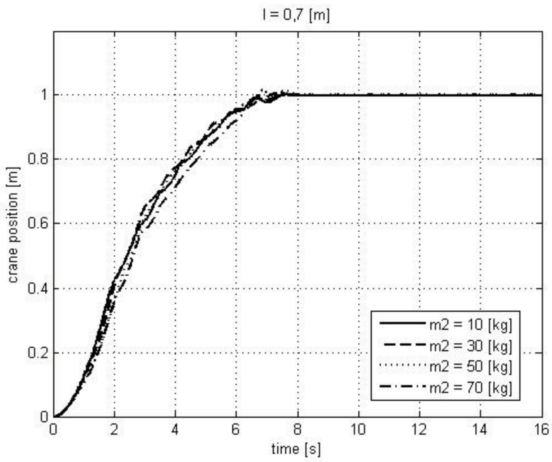

Fig. 5. The crane position for $l = 0.7\ [m]$ *and* $m_2 = \{10,\ 30,\ 50,\ 70\}[kg]$

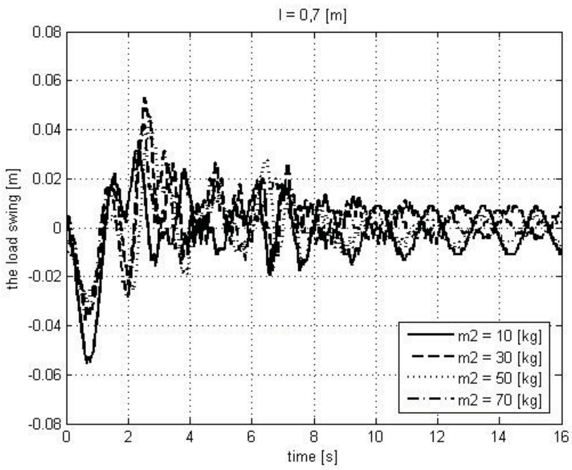

Fig. 6. The load swing for $l = 0.7\ [m]$ *and* $m_2 = \{10,\ 30,\ 50,\ 70\}[kg]$

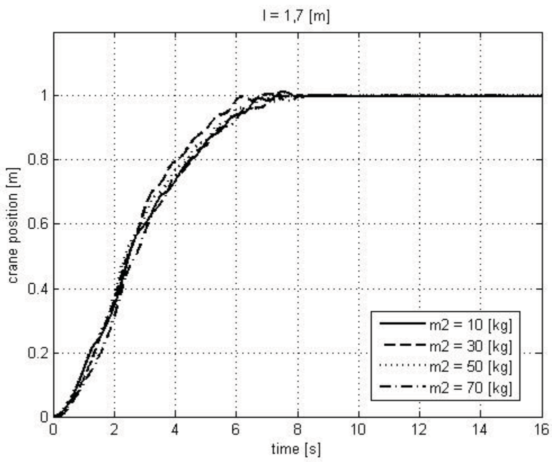

Fig. 7. The crane position for $l = 1.7\ [m]$ *and* $m_2 = \{10,\ 30,\ 50,\ 70\}[kg]$

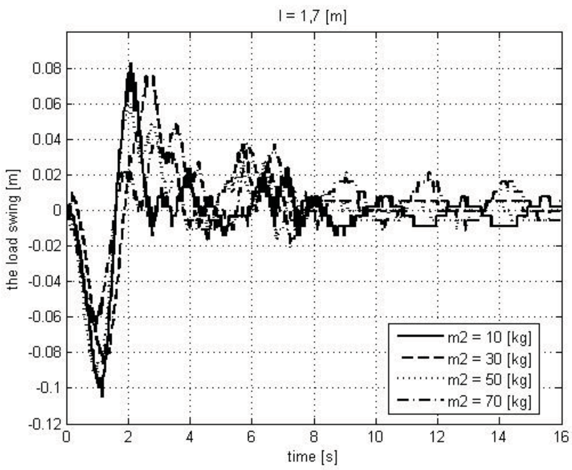

Fig. 8. The load swing for $l = 1.7\ [m]$ *and* $m_2 = \{10,\ 30,\ 50,\ 70\}[kg]$

The results obtained using the IAPP control system (Fig. 4) with TSK fuzzy estimator are satisfied for the assumed control conditions. The oscillations of a payload are reduced about expected tolerance (0.02 [m]) just between 3-4 seconds, and next dumped in expected setting time, about 7 seconds to the assumed acceptable tolerance 0.02 [m]. The results of experiments confirm effectiveness of the proposed adaptive control system.

5. Final remarks

The aim of researches, which results are presented in the paper, was to elaborate an automated transportation system realized by overhead travelling crane. The problem of automating, with ensuring expected time and precision of operations realized by overhead travelling crane, as well as improving exploitation quality of transportation device, was solved using indirect adaptive pole placement control algorithm. The stochastic varying parameters of considered system, which corresponds to rope length and mass of a payload changes in expected ranges, are estimated using combination of recursive least squares (RLS) algorithm and neuro-fuzzy system, that speeds up estimation process and improves control quality of the IAPP crane control system. The proposed solution was tested with satisfactory results on the laboratory object, and examples of performances were presented in the paper.

Acknowledgements

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