POLE PLACEMENT APPROACH TO DISCRETE AND NEURO-FUZZY CRANE CONTROL SYSTEM PROTOTYPING

Jarosław Smoczek

AGH University of Science and Technology
Faculty of Mechanical Engineering and Robotics
Mickiewicza Ave. 30, 30-059 Krakow, Poland
tel.: +48 12 6173104
e-mail: smoczek@agh.edu.pl

Janusz Szpytko

AGH University of Science and Technology
Faculty of Mechanical Engineering and Robotics
Mickiewicza Ave. 30, 30-059 Krakow, Poland
tel.: +48 12 6173103
e-mail: szpytko@agh.edu.pl

Abstract

Today are observed rising requirements regarding increase productivity, reduced labour and maintenance cost, as well as optimizing the effectiveness of the material handling. The overhead travelling cranes play important role in selected manufacture applications. The paper presents methods of crane dynamic modelling and anti-sway discrete crane control system determining with using pole placement method (PPM). The TSK neuro-fuzzy crane controller was shown in the paper, as well as method of adaptation its control parameters to various values of rope length and masses of the load variables. The results of experiments carried out on real object were presented as well.

Presented in the paper methods of crane dynamic modelling and control algorithm determining allow to prototype the effective anti-sway crane control systems. The method of determining conventional anti-sway crane control system based on discrete controllers type of PD elaborated with using pole placement method (PPM) was described in the paper. The TSK neuro-fuzzy crane controller was shown in the paper as well as method of adaptation its control parameters to various values of rope length l and masses of the load m variables. The results of experiments carried out with using adaptive neuro-fuzzy TSK controller shown robustness on changeability of these variables and effectiveness of proposed control system.

Keywords: *pole placement method, overhead travelling crane, neuro-fuzzy control*

1. Introduction

The material handling systems that are important part of manufacturing processes support different manufacturing operations. Higher and higher requirements are put on automation of those operations to help increase productivity, reduced maintenance cost and improving worker safety. Optimizing the effectiveness of the material handling systems which can be achieved by reducing manual handling by operators and applying automation in those systems leads up to reduce delays and disturbances in the production process. The rising requirements regarding time and accuracy of transportation tasks can be met by employing advanced handling solutions and improving control quality in automated manufacturing systems.

The discussion about control solutions applicable to material handling systems, their benefits against the drawbacks is especially important in case of overhead shifting operations realized in most cases by using overhead travelling cranes. Taking into consideration the cost of applying the advanced control solutions the automated overhead shifting operations are justifiable in automated industrial processes where manufacturing operations are labour intensive and critical for assembly line. However the benefits of those applications include reduced labour cost, increase productivity, smoother flow of materials by eliminating delays and disturbances during work-in-progress, reduced damaged goods and better quality of control.

The control solutions of automated crane transport operations should be determined depending on manufacturing process requirements and transport devices characteristic. The main problems of crane control system widely considered in researches works concern following aspects:

- positioning a load shifted in *OXYZ* crane working space,
- reducing the load swing,
- determining and following the load motion trajectory taking into consideration the obstacles located in *OXYZ* crane working space,
- reducing the bevel of a crane bridge.

The problem of positioning a load shifted by an overhead travelling crane and the load swing reducing is frequently studied in researches works. In generally, the anti-sway crane control systems can be realized as open or closed loop control systems. The disadvantage of the first solution is lack of the load swing feedback signal that causes trouble with predicting behaviour of the system in transient states and lack of robustness in case of disturbances. In case of closed loop control system the load swing angle measurement system causes problem of realizing in practice. However this solution allows building robust and adaptive control systems. The most of solutions presented in scientific works concern mathematical models or laboratory models that do not express the troubles that can be found in case of real devices. The approach to the crane control system is mostly considered as the problem of ensuring precision positioning of shifted by crane load with reducing swing phenomenon. The proposed solutions in researches works concern crane control systems realized using conventional methods based on PID controller (Proportional-Integrated-Derivative), LQ (linear-quadratic), advanced methods of poles assignment, control observers and robust controllers [2-4] as well as intelligent control systems mostly based on fuzzy logic. Crane intelligent control systems are mostly based on Mamdani fuzzy inference system [1, 5, 7, 9, 10] also Sugeno models [8] as well as artificial neural networks or neuro-fuzzy hybrids [6].

The paper presents anti-sway crane control systems based on discrete conventional PD (proportional-derivative) controllers and adaptive neuron-fuzzy controller. The method of determining proposed control systems was based on parametric models achieved during identification process of the controlled object and pole placement method (PPM). Fuzzy inference system and artificial neural network were used for achieved crane dynamic model and anti-sway control system robustness on changeability of rope length and mass of the load variables.

2. Mathematical models of crane dynamic

2.1. Continuous model of a crane

The model of a crane can be simplified to the two-mass model: mass of a crane's trolley or bridge m_1 and mass of a load m_2 suspended on a rope (Fig. 1).

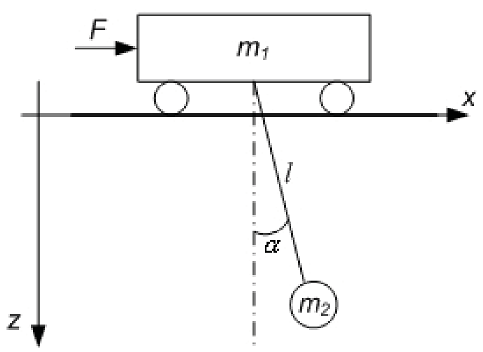

Fig. 1. The two-mass model of a crane and shifted load

The mathematical model of crane dynamic can be expressed by equation (1) which was achieved by using Lagrange's equations. It was assumed that length of a rope *l* and mass of a payload m_2 were considered as constant values and the mathematical model of driving motor was omitted.

$$\begin{cases}(m_1+m_2)\ddot{x}+m_2 l\ddot{\alpha}\cos\alpha-m_2 l\dot{\alpha}^2\sin\alpha=F,\\ m_2\ddot{x}\cos\alpha+m_2 l\ddot{\alpha}+m_2 g\sin\alpha=0\,,\end{cases} \tag{1}$$

where:

m_1, m_2 - masses of a bridge or trolley and a payload respectively,
l - rope length,
α - swing angle,
x - position of the bridge or trolley,
F - driving force,
g - acceleration of gravity.

The expression (1) for small values of swing angle α can be simplified by assuming $\sin\alpha\cong\alpha$, $\cos\alpha\cong 1$ and $\dot{\alpha}^2\sin\alpha\cong 0$:

$$\begin{cases}\ddot{x}=\dfrac{m_2\cdot g}{m_1}\alpha+\dfrac{1}{m_1}F\,,\\[2ex] \ddot{\alpha}=-(1+\dfrac{m_2}{m_1})\dfrac{g}{l}\alpha-\dfrac{1}{m_2\cdot l}F.\end{cases} \tag{2}$$

The mathematical model of the crane and shifted load motion (Fig. 2) can be expressed in form of continuous transmittances:

$$G_x(s)=\frac{X(s)}{\alpha(s)}=\frac{-ls^2-g}{s^2}\,, \tag{3}$$

$$G_\alpha(s)=\frac{\alpha(s)}{F(s)}=\frac{-\dfrac{1}{m_1 l}}{s^2+(1+\dfrac{m_2}{m_1})\dfrac{g}{l}}\,. \tag{4}$$

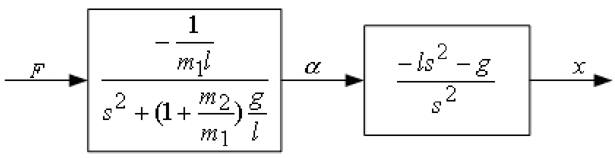

Fig. 2. Model of crane dynamic shown using continuous transfer functions

2.2. Discrete parametric model of a crane

The parametric model of a controlled object can be determined during identification process. A crane model can be assumed for simplicity as two discrete transmittances: model of crane motion mechanism $G_{\dot{x}}(z)$ and swing of the load model $G_\alpha(z)$ (Fig. 3).

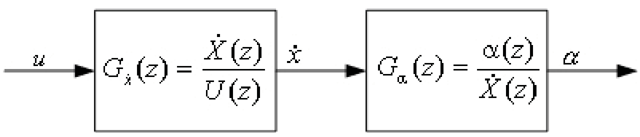

Fig. 3. Discrete model of crane dynamic

Presented in the paper parametric model of crane dynamic was assumed as two discrete transmittances linear $\dot{X}(z) = U(z) \cdot G_{\dot{x}}(z)$ and quadratic $\alpha(z) = \dot{X}(z) \cdot G_{\alpha}(z)$.

The model can be achieved in the identification process using output error method (OE) and data gathered during experiments carried out on a controlled object: input signal *u* and output signals the crane velocity $\dot{x}$ and load swing angle α. Experiments were realized with constant rope length *l* and mass of a load *m*.

The parametric model describes respectively relationships between input control signal *u* and crane velocity $\dot{x}$ (5), as well as crane velocity $\dot{x}$ and load swing angle α (6).

$$G_{\dot{x}}(z) = \frac{\dot{X}(z)}{U(z)} = \frac{D(z)}{C(z)} = \frac{d_0}{z + c_0}, \tag{5}$$

$$G_{\alpha}(z) = \frac{\alpha(z)}{\dot{X}(z)} = \frac{B(z)}{A(z)} = \frac{b_1 z + b_0}{z^2 + a_1 z + a_0}. \tag{6}$$

In the presented parametric model of the controlled object was assumed for simplicity the lack of relationship between the load swing angle α and crane velocity $\dot{x}$ variables.

2.3. Neuro-fuzzy model of crane dynamic

Presented parametric model (Fig. 3) describes the crane dynamic for constant values of rope length *l* and mass of a load *m*. The crane dynamic model which takes into consideration various parameters *l* and *m* can be expressed as neuro-fuzzy model. The model was created using fuzzy model based on Takagi-Sugeno-Kang (TSK) inference system coverted next to artificial neural network with using Adaptive-Neuro Fuzzy Inference System (ANFIS) in Matlab software environment. The example of ANFIS model is composed of two fuzzy models that describe relationships between input and output signals as the functions $\dot{x}_k = f(l, m, u, x_{k-1})$ for TSK1 model and $\alpha_k = f(l, m, \ddot{x}, \alpha_{k-1}, \alpha_{k-2})$ for TSK2 model (Fig. 4).

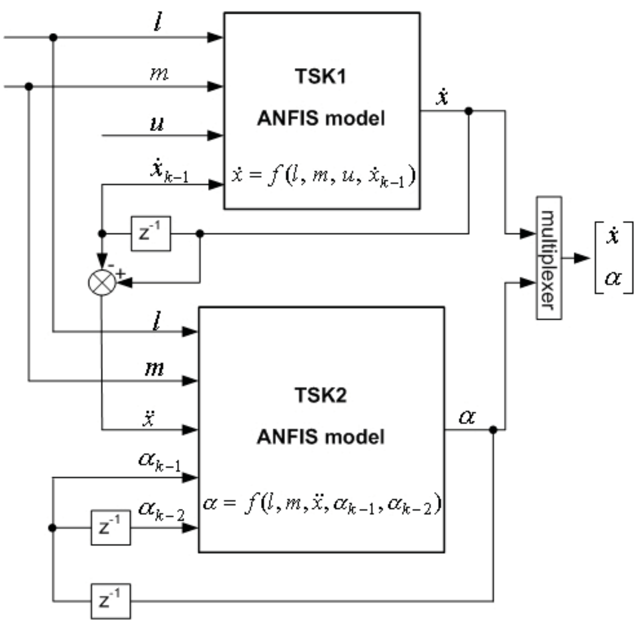

Fig. 4. ANFIS model of the crane dynamic

The ANFIS models were elaborated during learning process of artificial neural network using training data given in form of input and output variables vectors $[l, m, u, \dot{x}_{k-1}, \dot{x}_k]$ for TSK1 model and $[l, m, \ddot{x}, \alpha_{k-1}, \alpha_{k-2}, \alpha]$ for TSK2 model. Data were achieved during experiments executed on controlled object for step input signal u and chosen rope length l and masses of the load m. Consequently the training data used in the learning process is given as vectors of input/output variables that were obtained for different finite n-pairs of $\{l_i, m_j\}$ (where $n = i \cdot j$).

For both models were assumed triangular membership functions (fuzzy sets) $\boldsymbol{L_i}$ and $\boldsymbol{M_j}$ for fuzzified input signals rope length l and mass of the load m (Fig. 5).

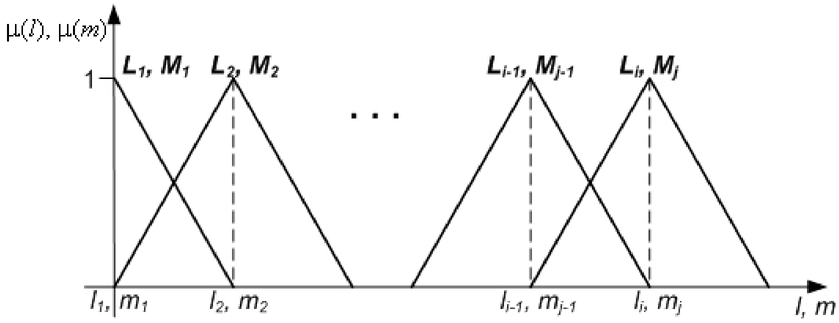

Fig. 5. Membership function used in TSK1 and TSK2 models

The knowledge base of TSK models is formulated as $n = i \cdot j$ IF-THEN fuzzy rules:

- for TSK1 model:

$$\text{IF } l \text{ is } \boldsymbol{L_r} \text{ and } m \text{ is } \boldsymbol{M_s} \text{ THEN } \dot{x}_k = f(l, m, u, \dot{x}_{k-1}), \tag{7}$$

- for TSK2 model:

$$\text{IF } l \text{ is } \boldsymbol{L_r} \text{ and } m \text{ is } \boldsymbol{M_s} \text{ THEN } \alpha_k = f(l, m, \ddot{x}, \alpha_{k-1}, \alpha_{k-2}), \tag{8}$$

where:

$\boldsymbol{L_r}$, $\boldsymbol{M_s}$ - fuzzy sets used in rules antecedent expressed in linguistic form for l and m variables respectively,

$r = 1, 2, \ldots, i$,

$s = 1, 2, \ldots, j$.

The crisp output signals $\dot{x}$ and α of respectively TSK1 and TSK2 models are calculated as a sum of input variables vector **X** and coefficients vector **K** products obtained from n-rules of models knowledge base:

$$\dot{x} = \sum_{i=1}^{n} \mathbf{X}^T \cdot \mathbf{K}_i = \sum_{i=1}^{n} \begin{bmatrix} l \\ m \\ u \\ \dot{x}_{k-1} \end{bmatrix}^T \cdot \begin{bmatrix} k_{i4} \\ k_{i3} \\ k_{i2} \\ k_{i1} \end{bmatrix}, \tag{9}$$

$$\alpha = \sum_{i=1}^{n} \mathbf{X}^T \cdot \mathbf{K}_i = \sum_{i=1}^{n} \begin{bmatrix} l \\ m \\ \ddot{x} \\ \alpha_{k-1} \\ \alpha_{k-2} \end{bmatrix}^T \cdot \begin{bmatrix} k_{i5} \\ k_{i4} \\ k_{i3} \\ k_{i2} \\ k_{i1} \end{bmatrix}. \tag{10}$$

In the process of neural networks learning was used *hybrid* method composed of back propagation learning algorithm used for optimizing parameters of rules antecedents (membership functions shapes) and least mean square (LMS) algorithm employed for rules consequents (output parameters). Proposed neuro-fuzzy model of controlled system takes consideration variety of variables rope length l and mass of the load m influence on models output signals $\dot{x}$ and α. However for simplicity swing of the load α influence on crane's velocity $\dot{x}$ is not taken into consideration in presented neuro-fuzzy model.

3. Pole placement approach to discrete anti-sway crane control system

The parametric models of the crane motion (5) and load swing (6) were identified using OE (Output Error) methods for data gathered with $T_0 = 0.1$ [s] sample time. The crane anti-sway control system (Fig. 6) was composed of two controllers: $R_\alpha(z)$ used in swing angle feedback and K_p proportional controller of crane velocity.

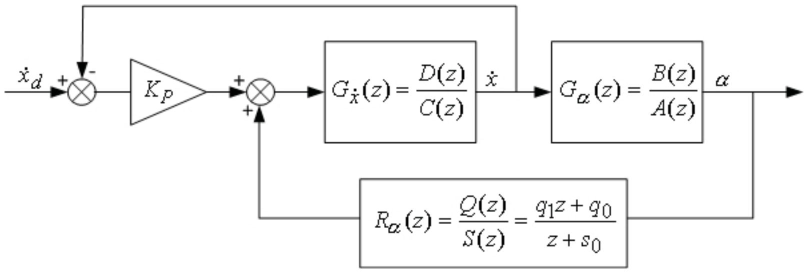

Fig. 6. Discrete anti-sway crane control system

Presented crane velocity control system was completed by adding the proportional controller of crane position. The transfer function of closed loop control system (Fig. 6) takes form (11):

$$G_C(z) = \frac{K_P \cdot S(z) \cdot D(z) \cdot B(z)}{A(z) \cdot C(z) \cdot S(z) - D(z) \cdot B(z) \cdot Q(z) + K_P \cdot D(z) \cdot A(z) \cdot S(z)}. \tag{11}$$

Diophantine equation is expressed as (12):

$$A(z) \cdot C(z) \cdot S(z) - D(z) \cdot B(z) \cdot Q(z) + K_P \cdot D(z) \cdot A(z) \cdot S(z) = P(z). \tag{12}$$

The equations $P(z)$, $A(z)$ and $C(z)$ are the monic polynomials and $P(z)$ is desired characteristic equation with desired stable poles z_i:

$$P(z) = z^n + \sum_{i=0}^{n-1} p_i \cdot z^i, \tag{13}$$

where:

$$n = \deg(P(z)) = \deg(A(z) \cdot C(z) \cdot S(z) - D(z) \cdot B(z) \cdot Q(z) + K_p \cdot D(z) \cdot A(z) \cdot S(z)). \tag{14}$$

Consequently the desired characteristic equation $P(z)$ for $n = 4$ takes form (15):

$$P(z) = z^4 + p_3 z^3 + p_2 z^2 + p_1 z + p_0. \tag{15}$$

The vector of coefficients $[p_3\ p_2\ p_1\ p_0]$ in desired polynomial $P(z)$ was determined for two the same pairs stable poles calculated for assuming damping coefficient ξ and known pulsation of the load swinging ω_0 measured in closed-loop control system:

$$z_i = \exp\left((-\xi\omega_0 \mp j\omega_0\sqrt{1-\xi^2})T_0\right), \tag{16}$$

where:
T_0 - sample time.

The parameters of the discrete control system can be calculated according the equations system (17):

$$\begin{bmatrix} a_1 & 0 & 0 \\ a_0 & a_1 & 0 \\ 0 & a_0 & a_1 \\ 0 & 0 & a_0 \end{bmatrix}\begin{bmatrix} 1 & 0 \\ c_0 & 1 \\ 0 & c_0 \end{bmatrix}\begin{bmatrix} 1 \\ s_0 \end{bmatrix} + d_0\left(K_P \begin{bmatrix} 1 & 0 \\ a_1 & 1 \\ a_0 & a_1 \\ 0 & a_0 \end{bmatrix}\begin{bmatrix} 1 \\ s_0 \end{bmatrix} - \begin{bmatrix} 0 & 0 \\ b_1 & 0 \\ b_0 & b_1 \\ 0 & b_0 \end{bmatrix}\begin{bmatrix} q_1 \\ q_0 \end{bmatrix}\right) = \begin{bmatrix} p_3 \\ p_2 \\ p_1 \\ p_0 \end{bmatrix}. \tag{17}$$

The example of parametric models $G_{\dot{x}}(z)$ and $G_\alpha(z)$ achieved in the process of controlled object identification carried out for constant values l =1.2 [m] and m =30 [kg] are shown as equations (18) and (19):

$$G_{\dot{x}}(z) = \frac{D(z)}{C(z)} = \frac{0.4671}{z - 0.8704}, \tag{18}$$

$$G_\alpha(z) = \frac{B(z)}{A(z)} = \frac{-0.0008839z + 0.0008851}{z^2 - 1.919z + 0.9966}. \tag{19}$$

According the equation (17) two pairs of discrete control parameters (Fig. 6) were determined for the pulsation of the load swinging $\omega_0 = \pi$ measured in closed-loop control system, sample time T_0 = 0.1 [s] and assuming damping coefficient $\xi = 1$ (20):

$$\begin{gathered} K_{P1} = 1{,}8\ ; \quad R_{\alpha 1}(z) = \frac{506.1z - 458.8}{z - 0{,}0766}, \\ K_{P2} = 0{,}129\ ; \ R_{\alpha 2}(z) = \frac{525.33z - 514.1}{z - 0{,}073}. \end{gathered} \tag{20}$$

Presented method allowed to determine control parameters for selected values of variables $l = \{0.7,\ 1.2,\ 1.7\}$ [m] and $m = \{10,\ 30,\ 50,\ 70\}$ [kg]. Consequently the twelve solutions of controller's parameters $\{K_{pi}, q_{1i}, q_{oi}, s_{0i}\}$ were obtained for twelve $\{l_i, m_i\}$ pairs.

4. Adaptive neuro-fuzzy anti-sway crane control system

The problem of anti-sway crane control system was considered taking into account the rope length *l* and mass of the load *m* variables influence on amplitude and frequency of the load swing. The proposed control system was based on Takagi-Sugeno-Kang (TSK) inference system (Fig. 7).

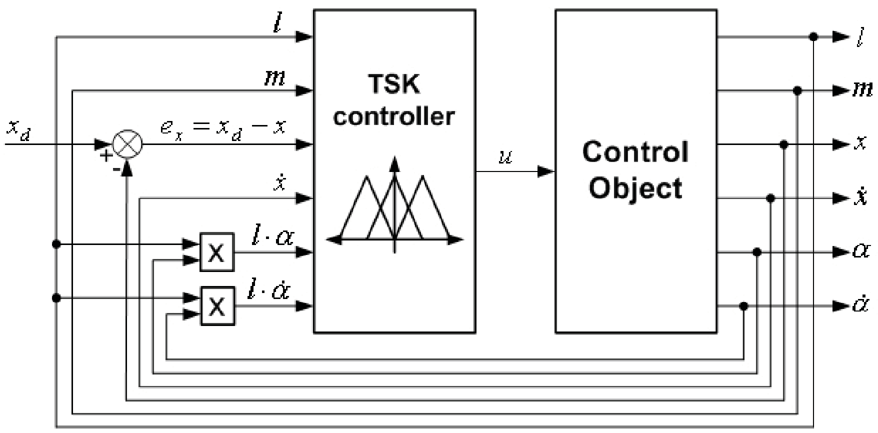

Fig. 7. Anti-sway crane control system with TSK fuzzy controller

The TSK fuzzy controller is composed of sixth input signals: rope length *l*, mass of the load *m*, error of crane position $e_x = x_d - x$ (where x_d is expected final crane position), crane velocity $\dot{x}$, deviation of the load from vertical symmetry axis of the rope drum $l \cdot \alpha$ (calculated as a product of rope length *l* and load swing angle α) and velocity of this deviation $l \cdot \dot{\alpha}$ (calculated as a product of rope length *l* and velocity of swing angle $\dot{\alpha}$). Input signals that were defined as linguistic terms *rope length* and *mass of the load* were taken into consideration in the fuzzification process as well as formulated in fuzzy rules IF-THEN (fuzzy knowledge base). Triangular membership functions used in fuzzification process were formulated in the fuzzy knowledge base of TSK controller by using linguistic terms: *very small*, *small*, *medium* and *big* {***VS, S, M, B***}. Maximum values of membership functions coefficients $\mu = 1$ were assumed for values of *rope length l* = {0.7, 1.2, 1.7} [m] and *mass of the load m* = {10, 30, 50, 70} [kg]. The fuzzy knowledge base of the TSK controller was composed of 12th IF-THEN implications type of:

IF *rope length* is $\boldsymbol{L_r}$ = {***S, M, B***} and *mass of the load* is $\boldsymbol{M_s}$ = {***VS, S, M, B***},
THEN $u_k = f(l, m, e_x, \dot{x}, l \cdot \alpha, l \cdot \dot{\alpha})$.

The aim of control strategy included in fuzzy knowledge base is to choose right vector of controller gains basis on information about input variables *rope length* and *mass of the load* used in rules antecedents. The crisp output signal *u* of the TSK controller is calculated as sum of output variables u_i obtained from each fuzzy rules as a product of vector input signals **X** and vector control coefficients **K** (21):

$$u = \sum_{i=1}^{n} \mathbf{X}^T \cdot \mathbf{K}_i = \sum_{i=1}^{n} \begin{bmatrix} l \\ m \\ e_x \\ \dot{x} \\ l \cdot \alpha \\ l \cdot \dot{\alpha} \end{bmatrix}^T \cdot \begin{bmatrix} k_{i6} \\ k_{i5} \\ k_{i4} \\ k_{i3} \\ k_{i2} \\ k_{i1} \end{bmatrix}, \tag{21}$$

where *n* - the number of rules formulated in the knowledge base of TSK controller.

The TSK controller was presented as the neural network structure. The parameters ($\mathbf{K}_n$ *n*-vectors of control gains) of TSK controller were determine in the process of learning artificial neural network using training data obtained from discrete control systems that were determine for pairs of $\{l_i, m_i\}$ using pole placement method. Training data (learning data) has a form of **TD** matrix (22) which was columns vectors of input and output variables:

$$\mathbf{TD} = [l \quad m \quad e_x \quad \dot{x} \quad l \cdot \alpha \quad l \cdot \dot{\alpha} \quad u]. \tag{22}$$

Process of artificial neural network learning was realized by using Adaptive Neuro-Fuzzy Inference System (ANFIS) in Matlab program as well as back propagation and least mean square (LMS) learning algorithms.

5. Results of experiments

Presented in the paper the TSK neuro-fuzzy anti-sway crane control system was tested in experiments that were carried out using the double girder overhead travelling crane with 150 [kg] hoisting capacity localized in the Automated Transport Laboratory of AGH University of Science and Technology. Measurement system was built with using A/B phases encoders and resistance strain gauge installed on crane's bridge that enable to measure signals of crane position and speed, load swing angle and mass of the load. Hardware-software architecture of the control-measurement circuit was based on PC with control-measurement card and Matlab program.

The TSK neuro-fuzzy controller which was tested for different values of rope length and masses of the load and $x_d = 1$ [m] expected crane position. Chosen results are presented in form of time charts for crane position (Fig. 8, 10 and 12) and for load deviation from vertical symmetry axis of the rope drum $l \cdot \alpha$ (Fig. 9, 11 and 13).

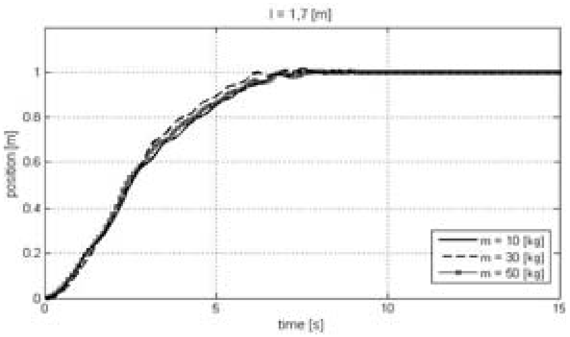

Fig. 8. Crane's position for l = 1.7 [m] and m = {10, 30, 50} [kg]

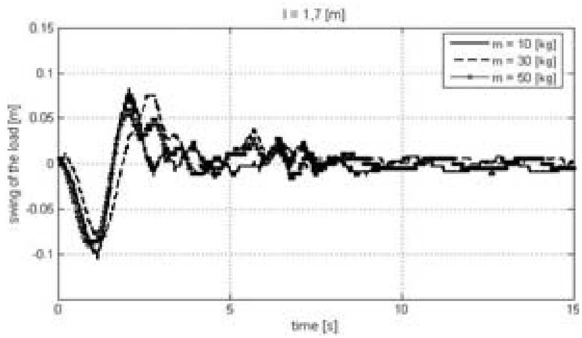

Fig. 9. Load deviation from vertical symmetry axis of the rope drum for l = 1.7 [m] and m = {10, 30, 50} [kg]

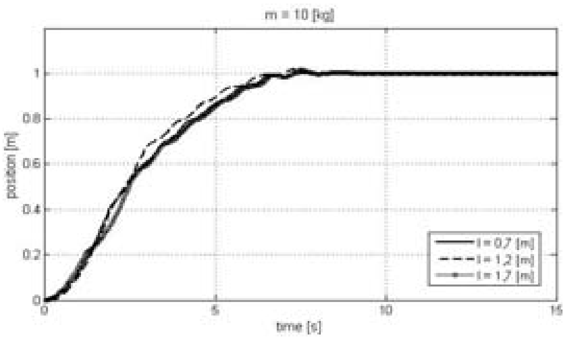

Fig. 10. Crane's position for m = 10 [kg] and l = {0.7, 1.2, 1.7} [m]

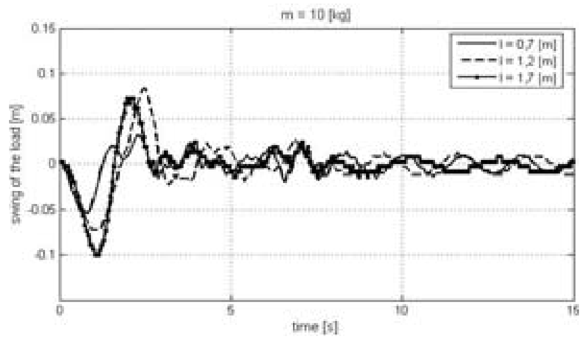

Fig. 11. Load deviation from vertical symmetry axis of the rope drum for m = 10 [kg] and l = {0.7, 1.2, 1.7} [m]

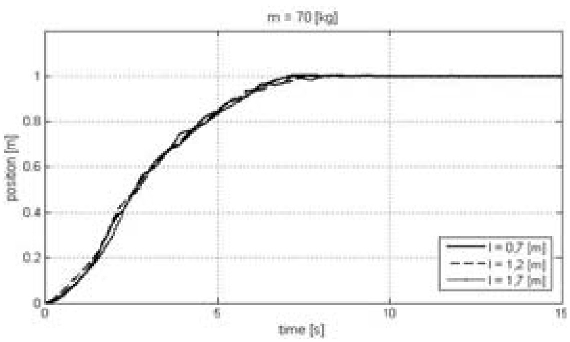

Fig. 12. Crane's position for m = 70 [kg] and l = {0.7, 1.2, 1.7} [m]

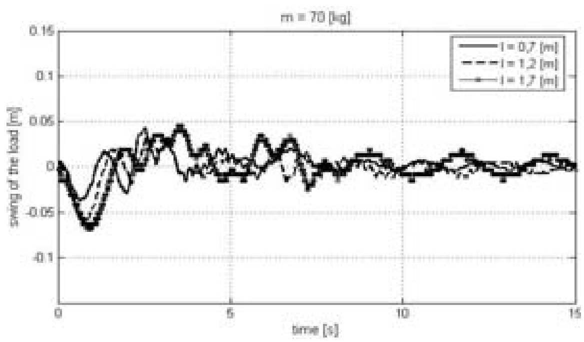

Fig. 13. Load deviation from vertical symmetry axis of the rope drum for m = 70 [kg] and l = {0.7, 1.2, 1.7} [m]

On the basis of presented results it can be stated that the aims of the control system were achieved with satisfactory results. The setting time was at about 7 [s] for various values of rope length l and masses of the load m. At this time, when expected position $x_d = 1$ [m] was achieved, the load swing (load deviation from vertical symmetry axis of the rope drum $l \cdot \alpha$) was reduced with satisfactory accuracy ±0,015 [m]. Simultaneously the load deviation was reducing under ±0,03 [m] value already at 3-4 second after starting.

The comparison of results that were obtained using discrete controller type of PD and TSK fuzzy controller are presented in time charts of crane position and load swing (Fig. 14 and 15).

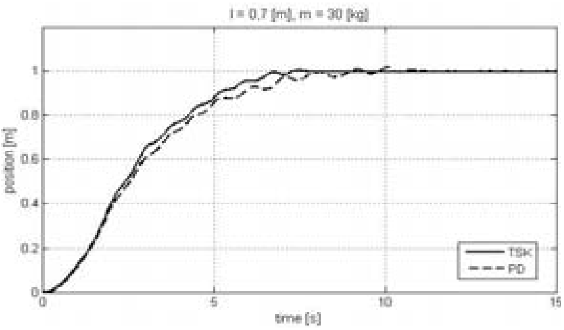

Fig. 14. Crane's position for l = 0.7 [m] and m = 30 [kg]

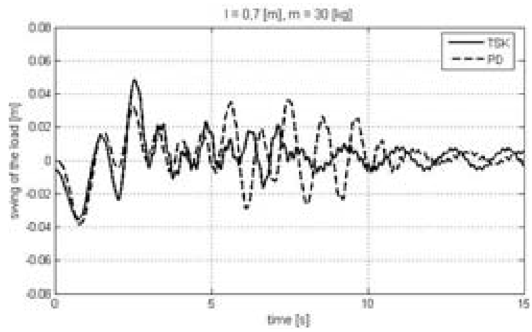

Fig. 15. Load deviation from vertical symmetry axis of the rope drum for l = 0.7 [m] and m = 30 [kg]

Simulations and experiments carried out on models and real object showed that conventional discrete control systems that were determined using pole placement method are not robustness against changes of rope length l and masses of the load m. Experiment with discrete controller determined for parametric model which was identified for constant values $l = 1.7$ [m] and $m = 30$ [kg] was carried out with the same mass of the load but with changing rope length to the value $l = 0.7$ [m]. The results of experiments (Fig. 14 and 15) carried out on real object show that setting time is less above 1 [s] in case of applying the TSK controller compared with discrete controller. Oscillations of load deviation that were appeared after obtaining expected position by crane and were reduced at about 10 [s] shows the lack of discrete controller robustness.

6. Conclusions

Rising expectations regarding increase productivity, reduced labour cost, optimizing the effectiveness of the works transport operations require developing automated material handling systems as well as determining and implementing new advanced solutions for control quality improvement. The overhead travelling cranes are frequently important elements of material handling systems used in automated manufacturing processes. Requirements regarding time and accuracy of overhead shifting operations realized in automated manufacturing processes can be met by automated solutions applying in crane mechanisms for reducing manual handling operations as well as determining advanced control systems to achieve expected time and precision of transportation tasks.

Presented in the paper methods of crane dynamic modelling and control algorithm determining allow to prototype the effective anti-sway crane control systems. The method of determining conventional anti-sway crane control system based on discrete controllers type of PD elaborated with using pole placement method (PPM) was described in the paper. The TSK neuro-fuzzy crane controller was shown in the paper as well as method of adaptation its control parameters to various values of rope length *l* and masses of the load *m* variables. The results of experiments carried out with using adaptive neuro-fuzzy TSK controller shown robustness on changeability of these variables and effectiveness of proposed control system.

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