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# EVOLUTIONARY OPTIMIZATION OF INTERVAL MATHEMATICS–BASED DESIGN OF A TSK FUZZY CONTROLLER FOR ANTI–SWAY CRANE CONTROL

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A hybrid method combining an evolutionary search strategy, interval mathematics and pole assignment-based closed-loop control synthesis is proposed to design a robust TSK fuzzy controller. The design objective is to minimize the number of linear controllers associated with rule conclusions and tune the triangular-shaped membership function parameters of a fuzzy controller to satisfy stability and desired dynamic performances in the presence of system parameter variation. The robust performance objective function is derived based on an interval Diophantine equation. Thus, the objective of a fuzzy logic-based control scheme is to place all the closed-loop control system characteristic polynomial coefficients within desired intervals. The reproduction process in the proposed Evolutionary Algorithm (EA) is based on the arithmetical crossover, uniform and non-uniform mutation along with gene deletion/insertion mutation ensuring a diversity of genomes sizes, as well as a diversity in the parameter space of membership functions. The proposed algorithm was implemented to design a fuzzy logic-based anti-sway crane control system taking into consideration the rope length and the mass of a payload variation. The results of experiments conducted using the EA for different conditions assumed for system parameter intervals and desired closed-loop system performances are compared with results achieved using the iterative procedure which is also described in the paper.

**Keywords:** interval mathematics, pole placement method, evolutionary algorithm, fuzzy logic, TSK controller, anti-sway crane control.

## 1. Introduction

Interval mathematics (Young, 1931; Warmus, 1956; Moore, 1966) provides useful tools for robust control system synthesis and stability analysis taking into consideration the system parameter uncertainty. The uncertain system is frequently represented by a continuous-time model with interval parameters that allows designing a robust controller through combining the interval analysis of closed-loop system performances and classic methods of controller synthesis. Numerous authors, frequently inspired by Kharitonov's theorem (Kharitonov, 1978), studied the problem of robust controller design in the presence of system parameter variations (Dahleh *et al.*, 1993; Chapellat *et al.*, 1994; Mallan *et al.*, 1997). Some practical techniques of designing robust control schemes are based on iterative methods (McNichols and Fadali, 2003), modal controllers synthesis (Bańka *et al.*, 2013), methods derived based on Lyapunov stability theory (Zubowicz and Brdyś, 2013), as well as soft computing techniques, e.g., Genetic Algorithms (GAs) (Hsu *et al.*, 2007) and artificial neural networks (Lee *et al.*, 2002) applied to tune linear controller parameters in terms of acceptable ranges for phase and gain margins. In this paper, EA-based synthesis of a robust TSK (Takagi and Sugeno, 1985; Sugeno and Kang, 1988) fuzzy controller which places the coefficients of a closed-loop characteristic polynomial within desired intervals is proposed and addressed to the problem of an anti-sway crane control.

The automation of crane operations is very important owing to the necessity of ensuring safety and efficiency of the transportation process, which is involved by requirements of enhancing the productivity of manufacturing processes (Smalko and Szpytko, 2009; Szpytko and Wozniak, 2007). Those requirements motivate the development and implementation of control solutions which are robust to the rope length and the mass of payload variations, and face up the following problem: transfer a payload as fast as possible from point to point with precise positioning at a final point and reduction of sway of a payload suspended at the end of a rope.

The best known industrial applications addressing this problem are open-loop control systems applying mostly input shaping techniques (Singer *et al.*, 1997; Karajgikar *et al.*, 2011), which generally rely on calculating pulse amplitudes and the time location in regard to the natural frequency of a pendulum, which unfortunately varies in relation to the system parameters (rope length and mass of a payload). In some research works the problem under consideration is solved using time-optimal control theory (Sakawa and Shindo, 1982; Auernig and Troger, 1987) combining also feedback control schemes for the desired motion trajectory tracking (Moustafa, 2001; Fang *et al.*, 2012). Other approaches are based on an indirect adaptive control scheme, Lyapunov techniques employed for state-feedback controller design, gain-scheduling, linear quadratic Gaussian and adaptive pole-placement control schemes (Hyla, 2012).

Furthermore, soft computing techniques, especially fuzzy logic, are widely employed to the problem considered. Moon *et al.* (1996) applied fuzzy logic to perform an optimal control scheme, while Liu *et al.* (2005) incorporated a fuzzy system into a sliding mode control strategy. Linguistic-rule-based fuzzy controllers are reported by Benhidjeb and Gissinger (1995), Mahfouf *et al.* (2000), Yi *et al.* (2003) and Chang (2006), and proposed for tuning gains of a PID controller by Li and Yu (2012) or Solihin *et al.* (2010).

Some researchers adopted off-line or on-line techniques to design or tune fuzzy rule-based controllers. Trabia *et al.* (2008) proposed three fuzzy controllers with Mamdani-type rules used independently to control the crane motion, hoisting and the sway angle of a payload, and the method based on the inverse dynamic for calculating the ranges of fuzzy controller input intervals within which the membership functions were distributed. Kijima *et al.* (1995) employed a GA to tune triangular membership functions according to the objective function which was specified based on control performances evaluated during simulation. Liu *et al.* (2002) proposed two fuzzy controllers of the crane position and sway angle with singleton-type rule outputs optimized during simulation by the GA according to the cost function including the settling time, the position error and the sway angle of a payload. Chang (2007) developed a two-input (position error and sway angle) fuzzy controller with Gaussian-shaped input membership functions and output fuzzy singletons, both tuned on-line using a gradient technique. Kang *et al.* (1999) as well as Smoczek and Szpytko (2008) employed a TSK fuzzy switching scheme of linear controllers determined at selected operating points. Oh *et al.* (2004) estimated scaling factors of the TSK fuzzy-type PID controller by using a hard c-means clustering method, an artificial neural network and regression polynomials. Sadati and Hooshmand (2006) utilized a clustering method to select the operating points for a fuzzy scheduler used in tower crane control.

Other examples of soft computing approaches to the crane control problem are based on neurocontrollers tuned on-line using a backpropagation method (Mendez *et al.*, 1999) or trained by the GA (Nakazono *et al.*, 2007), a cerebellar model articulation controller representing a TSK fuzzy PD-type controller with a fixed number of fuzzy rules (Yu *et al.*, 2011), and GA-based time-optimal (Kimiaghalam *et al.*, 1999), feedforward (Kimiaghalan *et al.*, 2002), or heuristically designed (Filipic *et al.*, 1999) anti-sway strategies.

Most fuzzy logic-based approaches to the anti-sway crane control problem described in the literature are linguistic rule-based strategies. The proposed evolutionary fuzzy clustering or artificial neural network-based techniques of designing a fuzzy controller are only adapted to tune the membership function shapes or parameters of rule conclusions for the assumed number of fuzzy rules or sets, and involve a set of training data obtained from simulations or experiments conducted on models or real objects. The robustness of a crane control system is also frequently analysed taking into account only the rope length variation. In the previous works, Smoczek and Szpytko (2010) proposed an iterative procedure and an evolutionary algorithm (Smoczek and Szpytko, 2011) to design a TSK fuzzy controller with respect to the rope length and mass of a payload variation. However, the proposed approaches were adapted to design a fuzzy control scheme based on the objective function relating only to the acceptable maximum value of the system response overshoot.

In this paper, a hybrid method combining an evolutionary-based searching strategy, interval analysis and the pole placement method is applied to design a TSK fuzzy controller which places the coefficients of the closed-loop control system characteristic polynomial within desired intervals. The paper describes a reproduction strategy which allows minimizing the fuzzy sets and tuning the parameters of membership functions of a TSK controller with respect to the control performance requirements taking into consideration the rope length and the payload variation. The paper proposes also an iterative procedure of designing a TSK controller which has been developed based on the method described by Smoczek and Szpytko (2010). Both methods allow to design robust fuzzy controllers. However, the results of experiments conducted for different conditions assumed for desired closed-loop system performances proved that the EA results in a number of fuzzy sets and rules of a TSK controller required to satisfy an acceptable range of closed-loop system performance deterioration specified in the form of desired intervals of closed-loop characteristic polynomial coefficients.

The paper is organized as follows. Section 2 describes a fuzzy logic-based control scheme for a planar model of a crane and the conditions assumed to design a TSK controller. In Section 3, the EA used to design a TSK fuzzy controller is presented. In Section 4, simulation examples are provided to show the effectiveness of the proposed method for anti-sway crane control system design in a bounded range of parameter variations. The results obtained by applying the EA are also compared with those derived from the iterative procedure described in Section 4. Section 5 delivers the final conclusions.

## 2. Fuzzy logic-based control scheme

The system under consideration is a planar model of a crane transferring a payload with mass *m* suspended at the end of a rope with length *l* (Fig. 1). The model is considered to be linear with varying parameters *l* and *m*. The motion equations of this system

$$\begin{cases} (M+m)\ddot{x} + ml\ddot{\alpha}\cos\alpha - ml\dot{\alpha}^2\sin\alpha = u, \\ m\ddot{x}\cos\alpha + ml\ddot{\alpha} + mg\sin\alpha = 0 \end{cases} \tag{1}$$

were derived from Lagrange's second law type equation and after linearization (assuming $\cos\alpha \cong 1$, $\sin\alpha \cong \alpha$, $\dot{\alpha}^2 \cong 0$) they were written down as two continuous transfer functions

$$\frac{\alpha(s)}{U(s)} = \frac{-K}{s^2+\omega_n^2}, \tag{2}$$

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

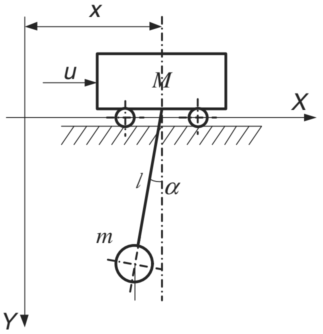


Fig. 1. Planar model of a crane, where *M*, *m*, *l*, *u* and $\alpha$ are respectively the masses of a crane and payload, the rope length, the controlling signal corresponding to the control force acting on the crane, and the sway angle of the payload.

where $K = 1/Ml$,

$$\omega_n = \sqrt{\left(1+\frac{m}{M}\right)\frac{g}{l}}$$

is the natural (not damped) pulsation, $g = 9.81$ m/s$^2$ is the gravity acceleration. The adaptive control scheme can be based on a set of linear controllers determined at selected operating points. Taking into account that the transfer function (2) represents a second-order astatic system, the two PD controllers-based crane position and sway angle of a payload control algorithm can be presented as follows:

$$U(s) = (k_1 + k_2 s)E(s) + (k_3 + k_4 s)\alpha(s), \tag{4}$$

where $e = x_r - x$ is the error of the crane position ($x_r, x$ are the reference signal and actual crane position, respectively), $k_1, k_2, k_3, k_4$ are the proportional and derivative gains of PD controllers. The control scheme can be elaborated based on a TSK fuzzy system with triangular-shaped membership functions, which is also called in the literature a P1-TS system to emphasize that membership functions of fuzzy sets for input variables are polynomial of the first order (Kluska, 2006; 2009). In the approach considered in this paper, the fuzzy logic-based adaptive control scheme is presented as a set of *N* rules with conclusions representing the linear control law (4):

$$R_k : \text{IF } l \text{ } is \text{ } \mathbf{A}_i \text{ and } m \text{ } is \text{ } \mathbf{B}_j \text{ THEN } u_k = \mathbf{K}_k^T\mathbf{X}, \tag{5}$$

where $\mathbf{A}_i$ and $\mathbf{B}_j$ are the fuzzy sets on $l$ and $m$ input variables universe of discourse, respectively, where $i = 1, 2, \ldots, n_1$ and $j = 1, 2, \ldots, n_2$ ($n_1$ and $n_2$ are the numbers of fuzzy sets defined for $l$ and $m$, respectively), $\mathbf{K}_k = [k_1, k_2, k_3, k_4]_k^T$, $\mathbf{X} = [e, \dot{e}, \alpha, \dot{\alpha}]^T$, $k = 1, 2, \ldots, N$ (where $N = n_1 \cdot n_2$).

The fuzzy sets defined in the premises of fuzzy rules correspond to the triangular membership functions

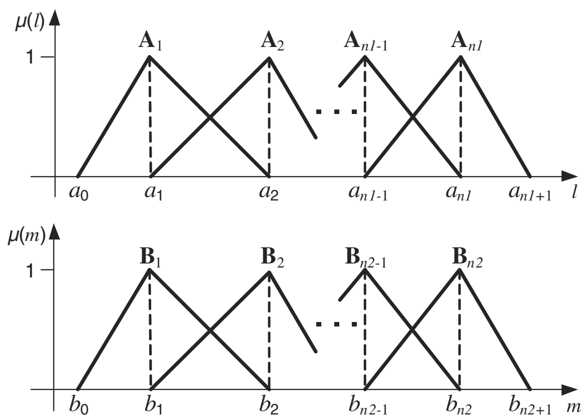


Fig. 2. Membership functions defined for fuzzy sets on the input variables $l$ and $m$.

(Fig. 2). The membership degree of a crisp input value to the fuzzy set is calculated according to the functions

$$\mu_{\mathbf{A}_i}(l)=\max\left(\min\left(\frac{l-a_{i-1}}{a_i-a_{i-1}},\frac{a_{i+1}-l}{a_{i+1}-a_i}\right),0\right), \quad (6)$$

$$\mu_{\mathbf{B}_j}(m)=\max\left(\min\left(\frac{m-b_{j-1}}{b_j-b_{j-1}},\frac{b_{j+1}-m}{b_{j+1}-b_j}\right),0\right), \quad (7)$$

where $a_{i-1} \leq a_i \leq a_{i+1}$, $b_{j-1} \leq b_j \leq b_{j+1}$, $a_i, b_j$ are the centre points of triangular membership functions of the fuzzy sets $\mathbf{A}_i$ and $\mathbf{B}_j$ (where $i = 1, 2, \ldots, n_1$ and $j = 1, 2, \ldots, n_2$).

The output of a fuzzy controller is calculated as the weighted average of all rules' output

$$u = \left(\sum_{k=1}^{N} w_k \mathbf{K}_k^T\right)\left(\sum_{k=1}^{N} w_k\right)^{-1} \mathbf{X}, \quad (8)$$

where a rule's activation degree (firing strength) is

$$w_k = \mu_{\mathbf{A}_i}(l) \cdot \mu_{\mathbf{B}_j}(m). \quad (9)$$

The problem of designing a TSK fuzzy controller consists in selecting a minimum set of operating points $\{a_i, b_j\}$ corresponding to the midpoints of triangular-shaped membership functions at which the linear controllers can be determined based on the Diophantine equation:

$$s^4 + \mathbf{s}\begin{bmatrix} 0 & 0 & Kl & 0 & K \\ \omega_n^2 & Kl & 0 & K & 0 \\ 0 & 0 & Kg & 0 & 0 \\ 0 & Kg & 0 & 0 & 0 \end{bmatrix}\begin{bmatrix} 1 \\ k_1 \\ k_2 \\ k_3 \\ k_4 \end{bmatrix}_k = s^4 + \mathbf{s}\mathbf{P}_k, \quad (10)$$

where $\mathbf{s} = [s^3, s^2, s^1, 1]$, and $\mathbf{P}_k$ is a vector of desired coefficients of a closed-loop characteristic polynomial. Thus, the vector $\mathbf{K}_k$, which is defined in the conclusion of a fuzzy rule $R_k$ (5), can be derived from

$$\mathbf{S}_k \mathbf{K}_k = \mathbf{P}_k, \quad (11)$$

where

$$\mathbf{S}_k = \begin{bmatrix} 0 & Kl & 0 & K \\ Kl & 0 & K & 0 \\ 0 & Kg & 0 & 0 \\ Kg & 0 & 0 & 0 \end{bmatrix}, \quad (12)$$

and $\mathbf{P}_k$ is a vector of the nominal values of the interval coefficients vector

$$[\mathbf{P}_k] = [[p_3]_k, [p_2]_k - \omega_n^2, [p_1]_k, [p_0]_k]^T, \quad (13)$$

where $[p_r]_k = [p_r^-, p_r^+]_k = \{p_r \in \mathbb{R} \mid p_r^- \leq p_r \leq p_r^+\}$, $r = 0, 1, 2, 3$.

Therefore, the fuzzy logic-based control scheme satisfies the desired performances for the system parameters varying within the expected ranges $l \in [l^-, l^+]$ and $m \in [m^-, m^+]$ if the condition

$$\mathbf{S}(l, m)\mathbf{K}(l, m) \in [\mathbf{P}_k], \quad (14)$$

is not violated for at least one interval vector (13) associated with a rule which has been activated with degree $w_k > 0$ to interpolate the vector $\mathbf{K}(l, m)$ according to

$$\mathbf{K}(l, m) = \left(\sum_{k=1}^{N} w_k \mathbf{K}_k\right)\left(\sum_{k=1}^{N} w_k\right)^{-1}. \quad (15)$$

## 3. Evolutionary optimization of a TSK controller

In this section the Pittsburgh-based (Smith, 1980; De Jong *et al.*, 1993) evolutionary approach to optimize the membership function parameters and the Rule Base (RB) size is proposed. A single proposition of a TSK controller can be represented by a real-valued chromosome consisting of the triangular membership functions parameters (Fig. 2)

$$\begin{aligned} \mathbf{a} &= [a_0, a_1, \ldots, a_i, \ldots, a_{n_1}, a_{n_1+1}], \\ \mathbf{b} &= [b_0, b_1, \ldots, b_j, \ldots, b_{n_2}, b_{n_2+1}]. \end{aligned} \quad (16)$$

The Fuzzy Rule-Base System (FRBS) design is a searching process consisting in exploration of the solution space composed of individuals with a different chromosome size. The EA proposed in this paper is a three-stage reproduction-based strategy combining the arithmetical crossover, uniform and non-uniform mutation (Fig. 3). In each generation the reproduction process starts from group $\lambda_1$ of individuals to increase the population to the number $\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4$. In the first step (mutation A), the genotype of the individuals selected from population $\lambda_1$ is changed through insertion or deletion of genes resulting in adding or removing fuzzy sets for the randomly chosen input variable. This leads to producing a small group of new individuals $\lambda_2$ with different sizes of the RB which are added to the population $\lambda_1$. The recombination and non-uniform mutation result in adding to the current population $(\lambda_1 + \lambda_2)$ new individuals $\lambda_3$ and $\lambda_4$. Hence the final population size in a single generation equals $\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4$, and from this group of individuals a new population $\lambda_1$ is selected using the tournament method to be the parents of the next generation.

The aim of the first mutation is to bring the diversity of genome sizes into the current population through changing the number of fuzzy sets for the randomly chosen input variable. The probability of insertion $p_I$ or deletion $p_D$ of a gene depends on the average $\overline{n}$, minimum $n_{\min}$ and maximum $n_{\max}$ numbers of fuzzy sets defined for the input variable

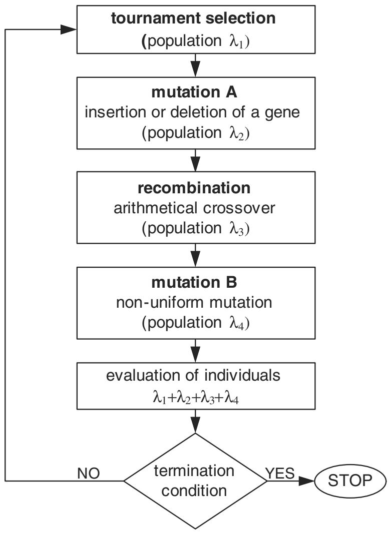


Fig. 3. EA flowchart.

$$p_D = \frac{\overline{n} - n_{\min}}{n_{\max} - n_{\min}}, \quad p_I = 1 - p_D. \tag{17}$$

Fuzzy set reduction is obtained using a randomly selected method: through removing a fuzzy set or merging the randomly selected two neighboring membership functions according to the formula

$$\begin{aligned} a'_i &= za_i + (1-z)a_{i+1}, \\ b'_j &= zb_j + (1-z)b_{j+1}, \end{aligned} \tag{18}$$

where $a'_i, b'_j$ are the new genes of a chromosome (16) obtained through merging $a_i$ and $a_{i+1}$, or $b_j$ and $b_{j+1}$ centre points of membership functions (where $i = 1, 2, \ldots, n_1 - 1, j = 1, 2, \ldots, n_2 - 1$), $z$ is a uniformly distributed random number in the interval $[0, 1]$.

An increase in the chromosome size is performed through uniform mutation, depending on the locus of a new gene corresponding to the midpoint of a new membership function:

$$\begin{aligned} [a'_{i-1}, a'_i] &= [a_{i-1}, a_i] - z(a_i - a_{i-1}), \quad i = 1, \\ a'_i &= za_{i-1} + (1-z)a_i, \quad 1 < i < n_1 + 1, \\ [a'_i, a'_{i+1}] &= [a_{i-1}, a_i] + z(a_i - a_{i-1}), \quad i = n_1 + 1, \end{aligned} \tag{19}$$

and

$$\begin{aligned} [b'_{j-1}, b'_j] &= [b_{j-1}, b_j] - z(b_j - b_{j-1}), \quad j = 1, \\ b'_j &= zb_{j-1} + (1-z)b_j, \quad 1 < j < n_2 + 1, \\ [b'_j, b'_{j+1}] &= [b_{j-1}, b_j] + z(b_j - b_{j-1}), \quad j = n_2 + 1. \end{aligned} \tag{20}$$

The crossover is conducted on the population $\lambda_1$ and the small population $\lambda_2$ of frequently worse individuals. Thus, random selection of parents ensures that the crossover can be also conducted between individuals from both populations. Simultaneously, tournament selection guarantees that the recombination is performed on the best individuals $\lambda_1$ from the previous generation ($\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4$). The recombination process is performed using the arithmetical crossover method conducted on the two individuals A and B that leads to obtaining the offspring A' and B' (21). If the number of fuzzy sets for a given input variable is different in the chromosomes A and B, the crossover is performed between genes representing the closest pairs of membership function midpoints, which is illustrated in Fig. 4. The offspring A' and B' inherit the chromosome size from the parents A and B, respectively:

$$\begin{aligned} {a'_i}^{(A')} &= z{a_i}^{(A)} + (1-z){a_i}^{(B)}, \\ {b'_j}^{(A')} &= z{b_j}^{(A)} + (1-z){b_j}^{(B)}, \\ {a'_i}^{(B')} &= z{a_i}^{(B)} + (1-z){a_i}^{(A)}, \\ {b'_j}^{(B')} &= z{b_j}^{(B)} + (1-z){b_j}^{(A)}. \end{aligned} \tag{21}$$

The last stage of the reproduction process (mutation B) is based on non-uniform mutation (Michalewicz and Janikow, 1991) conducted on a randomly chosen gene of a randomly selected chromosome. The offspring is created according to a randomly selected formula

$$\begin{aligned} a'_i &= \begin{cases} a_i + (1 - z^\gamma)(a_{i+1} - a_i), & i < n_1 + 1, \\ a_i + (1 - z^\gamma)(a_i - a_{i-1}), & i = n_1 + 1, \end{cases} \\ b'_j &= \begin{cases} b_j + (1 - z^\gamma)(b_{j+1} - b_j), & j < n_2 + 1, \\ b_j + (1 - z^\gamma)(b_j - b_{j-1}), & j = n_2 + 1, \end{cases} \end{aligned} \tag{22}$$

or

$$\begin{aligned} a'_i &= \begin{cases} a_i - (1 - z^\gamma)(a_{i+1} - a_i), & i = 0, \\ a_i - (1 - z^\gamma)(a_i - a_{i-1}), & i > 0, \end{cases} \\ b'_j &= \begin{cases} b_j - (1 - z^\gamma)(b_{j+1} - b_j), & j = 0, \\ b_j - (1 - z^\gamma)(b_j - b_{j-1}), & j > 0, \end{cases} \end{aligned} \tag{23}$$

in which the exponent $\gamma$ of the random number $z$ equally distributed in the interval [0, 1] is determined based on the ratio of the number of the current generation *t* to the maximum number of generations $t_{\max}$ (24),

$$\gamma = \left(1 - \frac{t}{t_{\max}}\right)^\beta, \tag{24}$$

where $\beta > 0$ is a parameter determining the degree of dependency on the generation number (in the numerical experiments presented in Section 4 this parameter was assumed as 2).

Both mutations A and B play a significant role preventing from premature convergence of population to the suboptimal regions. The mutation A results in a diversity of genome sizes, while the mutation B leads to a diversity in the parameter space of rule antecedents,

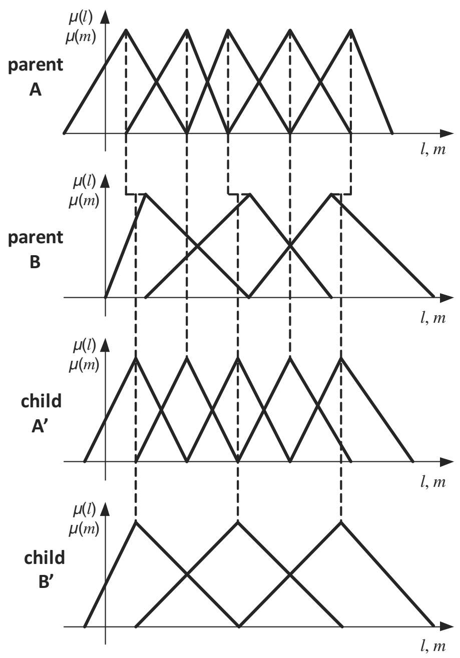


Fig. 4. Illustration of crossover between individuals which differ in the genome size.

and the conclusions. The recombination mechanism ensures fine exploration of the best promising regions of the solution space by tuning the membership function parameters.

The fitness of an individual is determined through testing the condition (14) for the most hazardous operating points corresponding to all possible combinations of the crossover points of triangular membership functions (Fig. 2), their midpoints, and the bounds of system parameter intervals $[l^-, l^+]$ and $[m^-, m^+]$. Each vector $\mathbf{K}_k$ in a rule's conclusion (5) is derived from the system (11) for the midpoints of $N$ interval vectors of the coefficients of the desired closed-loop characteristic polynomial. The fitness of an individual is calculated as a sum of the normalized distances between the coefficients of the closed-loop system characteristic equation at the most hazardous operating points and the closest bounds of desired polynomial coefficient intervals:

$$f = \sum_{h=1}^{H}\sum_{k=1}^{N}\sum_{r=0}^{3}\left(\beta_1\beta_2\frac{\min(|p_r - p_r^-|_k, |p_r - p_r^+|_k)}{|p_r^+ - p_r^-|_k}\right)_h, \tag{25}$$

where

$$\beta_1 = \begin{cases} 0, & w_k = 0, \\ 1, & w_k > 0, \end{cases}$$

$$\begin{cases} \beta_2 = 1 & \text{if} \quad \mathbf{S}(l,m)\mathbf{K}(l,m) \in [\mathbf{P}_k], \\ \beta_2 > 1 & \text{if} \quad \mathbf{S}(l,m)\mathbf{K}(l,m) \notin [\mathbf{P}_k], \end{cases}$$

$p_r$ is the closed-loop characteristic polynomial coefficient, $H$ is the number of operating points at which the condition (14) is tested, $\beta_2$ is the penalty factor, which is $\beta_2 > 1$ if the condition (14) is violated (in the numerical experiments this factor was assumed to be 4).

## 4. Simulations results

The proposed hybrid method combining the evolutionary-based searching strategy, interval mathematics and pole assignment-based closed-loop control synthesis was applied to design a TSK fuzzy controller for performance requirements defined in the form of the desired stable poles intervals

$$[s_r]_k = [s_r^-, s_r^+]_k = \left[-\omega_n \mp \sqrt{\frac{2g}{l}}(1-\zeta)\right]_k, \tag{26}$$

where $\zeta$ is the parameter which determines the width of a desired stable pole interval.

Thus, a vector $\mathbf{K}_k$ in the conclusion of each rule $R_k$ (5) were determined at the operating point $\{a_i, b_j\}$ through assigning all closed-loop system poles at a nominal value of the interval (26). The EA described in Section 3, with the population composed of 48 individuals ($\lambda_1 = 12$, $\lambda_2 = 4$, $\lambda_3 = 28$, $\lambda_4 = 4$), was employed to find the numbers of membership functions and the distribution of their parameters to satisfy the closed-loop system performances for two pairs of rope length and mass of payload intervals: [1 m, 8 m], [10 kg, 600 kg] and [1 m, 10 m], [10 kg, 1000 kg]. For each pair of those intervals, two experiments were conducted for assumed $\zeta = 0.69$ and $\zeta = 0.76$, which were used to specify an acceptable range of closed-loop system performance deterioration. Tables 1 and 2 present the results of experiments, where $n_1$ and $n_2$ are respectively the numbers of fuzzy sets determined for variables $l$ and $m$, $N$ is the number of fuzzy rules of the TSK fuzzy controller, $\mathbf{a}$ and $\mathbf{b}$ are the vectors (19) representing the best chromosome obtained in the last generation. The termination condition of the EA was assumed as the maximum number of generations equal to 100.

The experiments resulted in designing TSK controllers placing the coefficients of the characteristic polynomial of the closed-loop system within the desired intervals for operating points lying within the expected intervals of the rope length and payload mass. The performances of the EA employed to find an appropriate number of fuzzy sets and tune the membership function parameters for system parameter intervals [1 m, 8 m] and [10 kg, 600 kg], and for $\zeta = 0.69$ and $\zeta = 0.76$ are illustrated in the form of the best value of the fitness function in each epoch (Fig. 5) and as the comparison of RB sizes of the 12 best individuals selected as the parents of the next generation (Figs. 6 and 7). The experiments proved the ability of the developed evolutionary strategy to optimize the number of the TSK controller's fuzzy rules. Figures 6 and 7 illustrate the influence of a mutation process (gene insertion and deletion) on the diversity of the genome size in the current population that allows finding a suitable solution of a TSK controller with a minimum number of fuzzy sets, which satisfies an acceptable range of performance deterioration. Figure 6 presents the number of individuals of population $\lambda_1$ representing the different RB sizes in the first 25 generations. The solutions with 20 ($n_1 = 5$, $n_2 = 4$), 15 ($n_1 = 5$, $n_2 = 3$), 10 ($n_1 = 5$, $n_2 = 5$) and 12 ($n_1 = 4$, $n_2 = 3$) rules dominated in the consecutive epochs until the 14th generation, while the population representing 8 rules started to growth up from the 12th epoch, completely dominating the population from the 18th epoch. Figure 7 illustrates the evolution of population during the first 40 generations in the second experiment conducted for more rigorous acceptable range of performance deterioration ($\zeta = 0.76$). During the first 13 generations the population is dominated by chromosomes representing fuzzy controllers with respectively 36 ($n_1 = 6, n_2 = 6$), 30 ($n_1 = 6, n_2 = 5$), 24 ($n_1 = 6, n_2 = 4$) and 20 ($n_1 = 5, n_2 = 4$) rules. From the 17th until the 100th epoch, the best solutions are mostly represented by the RB consisting of 15 if-then rules ($n_1 = 5, n_2 = 3$).

Examples of closed-loop system performances of the fuzzy control system designed for scheduling variables intervals [1 m, 8 m] and [10 kg, 600 kg] are presented in Figs. 8 and 9 in the form of unit-step system responses (the crane position and the sway angle of the payload) at selected most hazardous operating points corresponding to the crossover points of membership functions. The solid line (a) in Fig. 8 represents the response at the operating point corresponding to the crossover points of membership functions $\mathbf{A}_1$ and $\mathbf{A}_2$, and $\mathbf{B}_1$ and $\mathbf{B}_2$ with the centre points $a_1 = 0.9\,\text{m}$, $a_2 = 2.28\,\text{m}$, $b_1 = 32\,\text{kg}$ and $b_2 = 530\,\text{kg}$ determined using the EA for $\zeta = 0.69$ (Table 2). The dotted lines (s-) and (s+) represent the responses of a classic PD controller-based closed-loop control system designed at $\{a_1, b_2\}$ through assigning the poles at right and left bounds of the desired interval (26). The condition (14) is satisfied for the examined operating point $\{(a_1 + a_2)/2, (b_1 + b_2)/2\}$, because the characteristic polynomial coefficients

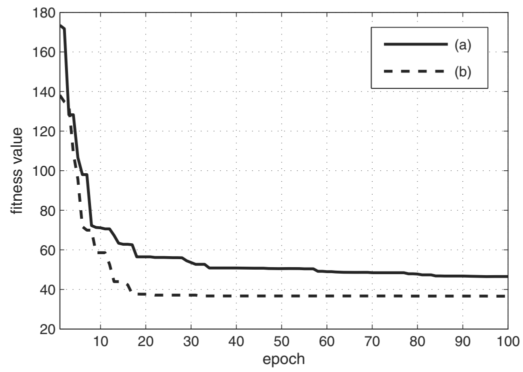


Fig. 5. Comparison of the best value of the fitness function in each epoch—experiments for parameters [1 m, 8 m], [10 kg, 600 kg], $\zeta = 0.76$ (a), [1 m, 8 m], [10 kg, 600 kg], $\zeta = 0.69$ (b).

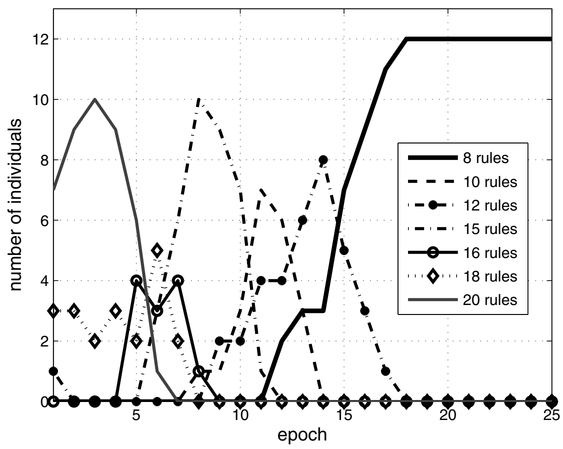


Fig. 6. Size comparison of the best individuals in the first 25 epochs—experiment for $\zeta = 0.69$, [1 m, 8 m], [10 kg, 600 kg].

Table 1. Results of experiments obtained using the EA.

| $l$ and $m$ intervals | $\zeta$ | $n_1$ | $n_2$ | $N = n_1 \cdot n_2$ |
|---|---|---|---|---|
| $[1, 8]$ m | 0.69 | 4 | 2 | 8 |
| $[10, 600]$ kg | 0.76 | 5 | 3 | 15 |
| $[1, 10]$ m | 0.69 | 5 | 3 | 15 |
| $[10, 1000]$ kg | 0.76 | 6 | 3 | 18 |

Table 2. Parameters of membership functions tuned using the EA.

| $l$ and $m$ intervals | $\zeta$ | parameters of membership functions |
|---|---|---|
| $[1, 8]$ m, $[10, 600]$ kg | 0.69 | **a**=$[-1.2,\ 0.9,\ 2.28,\ 5.82,\ 7.94,\ 8.98]$, **b**=$[-60; 32; 530; 819]$ |
| $[1, 8]$ m, $[10, 600]$ kg | 0.76 | **a**=$[-0.13,\ 1.06,\ 1.85,\ 3.26,\ 5.00,\ 7.60,\ 13.41]$, **b**=$[-93, 9, 334, 611, 799]$ |
| $[1, 10]$ m, $[10, 1000]$ kg | 0.69 | **a**=$[-0.45,\ 1.04,\ 2.00,\ 3.41,\ 5.82,\ 10.66,\ 18.15]$, **b**=$[-42, 61, 615, 999, 1646]$ |
| $[1, 10]$ m, $[10, 1000]$ kg | 0.76 | **a**=$[-0.15,\ 0.86,\ 1.40,\ 2.17,\ 3.84,\ 6.09,\ 10.68,\ 12.68]$, **b**=$[-13, 45, 348, 1008, 1615]$ |

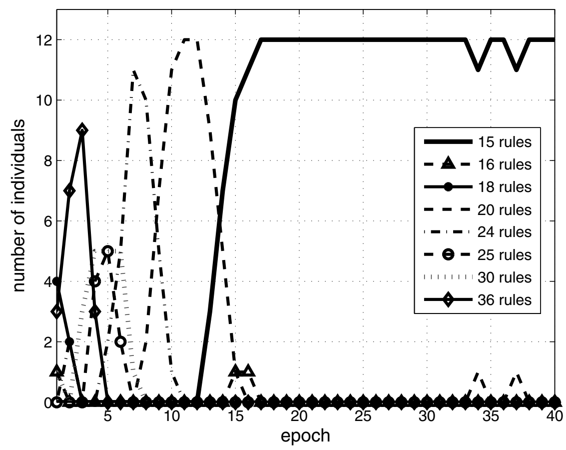


Fig. 7. Size comparison of the best individuals in the first 25 epochs—experiment for $\zeta = 0.76$, [1 m, 8 m], [10 kg, 600 kg].

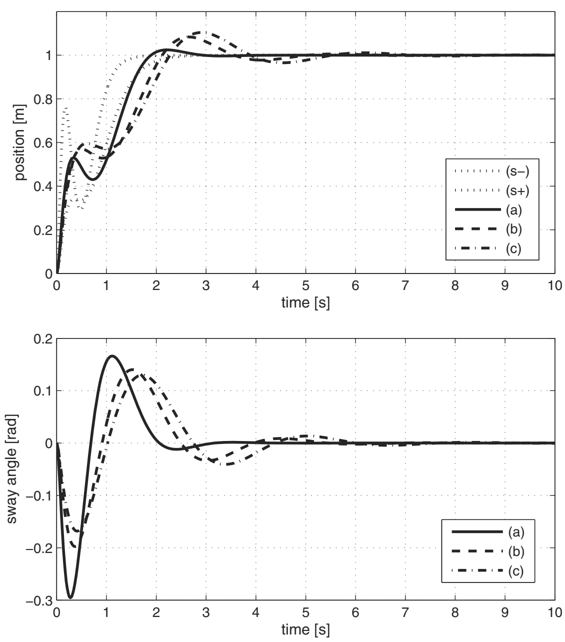


Fig. 8. Crane position and payload sway angle—example of simulations for a TSK controller designed for [1 m, 8 m], [10 kg, 600 kg] and $\zeta = 0.69$.

lie within the desired interval vector (13) characterizing the acceptable deviation from the nominal point $\{a_1, b_2\}$. The coefficients of the characteristic polynomial are close to the right bounds of the vector (13), therefore the response (a) satisfies an acceptable deterioration of the control system performances specified for the nominal point $\{a_1, b_2\}$, and the settling time of the response (a)

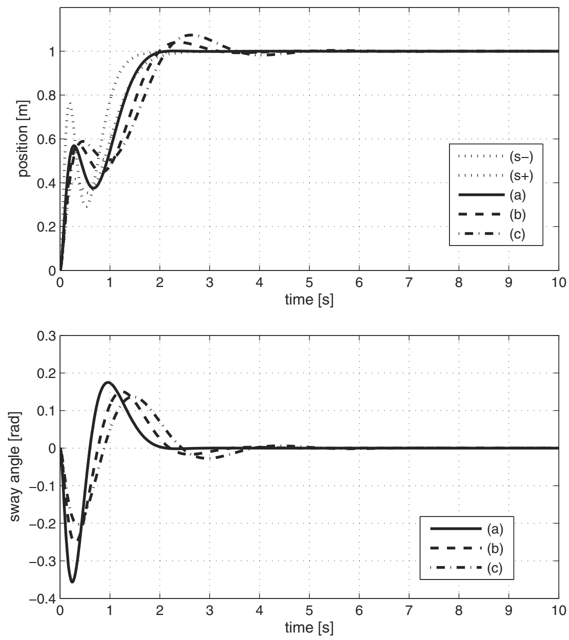


Fig. 9. Crane position and payload sway angle—example of simulations for a TSK controller designed for [1 m, 8 m], [10 kg, 600 kg] and $\zeta = 0.76$.

is close to the settling time of the response (s+), despite the overshoot of about 0.02. In comparison, the responses (b) and (c) are examples of control system performances at the operating point $\{(a_1 + a_2)/2, (b_1 + b_2)/2\}$ for $a_2 = 4\,\mathrm{m}$ and $a_2 = 5\,\mathrm{m}$, respectively. The condition (14) is not satisfied at $\{(a_1 + a_2)/2, (b_1 + b_2)/2\}$ for any interval vector (13) specifying the acceptable range of the performance deterioration for operating points lying between the nominal points $\{a_1, b_1\}$, $\{a_1, b_2\}$, $\{a_2, b_1\}$ and $\{a_2, b_2\}$, which results in arising oscillations and extending the settling time of the responses (b) and (c) in comparison with the response (a).

A similar example of performance comparison for a fuzzy control system designed using the EA for $\zeta = 0.76$ assumed for specifying the desired intervals of poles (26) is presented in Fig. 9. The solid line (a) is the system response at the operating point $\{(a_1 + a_2)/2, (b_2 + b_3)/2\}$ (where $a_1 = 1.06$ m, $a_2 = 1.85$ m, $b_2 = 334$ kg and $b_3 = 611$ kg), at which the condition (14) is satisfied for the interval vector (13) representing an acceptable deviation from the nominal point $\{a_1, b_3\}$. The settling time of this response is close to that of the response (s+) associated with the right bound of the desired pole interval (26). Moving, e.g., the centre point of the membership function $\mathbf{A}_2$ to the right-hand side (Fig. 2) causes a deterioration of closed-loop system performances at the crossover point $\{(a_1 + a_2)/2, (b_2 + b_3)/2\}$, which is illustrated in Fig. 11 by the responses (b) and (c)

Table 3. Results of experiments obtained using the iterative procedure.

| $l$ and $m$ intervals | $\zeta$ | $n_1$ | $n_2$ | $N = n_1 \cdot n_2$ |
|---|---|---|---|---|
| $[1, 8]$ m<br>$[10, 600]$ kg | 0.69<br>0.76 | 4<br>5 | 3<br>3 | 12<br>15 |
| $[1, 10]$ m<br>$[10, 1000]$ kg | 0.69<br>0.76 | 5<br>6 | 3<br>4 | 15<br>24 |

obtained for the TSK controller with the centre point of the membership function $\mathbf{A}_2$ assumed as $a_2 = 3$m and $a_2 = 4$m, respectively. The condition (14) is not satisfied for $\{(a_1 + a_2)/2, (b_2 + b_3)/2\}$, which means that performance deterioration (responses (b) and (c)) exceeds the acceptable range assumed for the operating points lying within the points $\{a_1, b_2\}$, $\{a_1, b_3\}$, $\{a_2, b_2\}$, $\{a_2, b_3\}$.

The results obtained using the EA (Table 1) were compared with those of the iterative method employed to design a TSK fuzzy controller. In the iterative method, the rope length $[l^-, l^+]$ and payload mass $[m^-, m^+]$ ranges were divided into even intervals (respectively, 0.1 m and 10 kg). In the two-stage iterative procedure, starting from $l_i = l^-$ and $m_j = m^-$, $i$ and the next $j$ are incremented to find the minimum number of membership function midpoints between the lower and upper bounds of intervals $[l^-, l^+]$ and $[m^-, m^+]$. At each iteration, $l_i$ and $m_j$ are assumed as the temporary center points $\{a_i, b_j\}$ of membership functions, which leads to creating temporary fuzzy rules with the parameters of controllers $\mathbf{K}_k$ determined in their conclusions according to system (11).

The condition (14) is tested for the crossover points of memberships functions. If it is satisfied, the temporarily fuzzy sets and rules are removed. If the condition (14) is violated at a sample point $l_i$ or $m_j$, a new fuzzy set is created with a point of a membership function at $l_{i-1}$ or $m_{j-1}$, respectively. Creating Tables 3 and 4 present the results of this procedure applied to design a TSK fuzzy controller for the same conditions which were assumed during experiments conducted using the EA. The method does not lead to obtaining an optimal solution due to assuming the initial set of membership functions with midpoints at the bounds of intervals $[l^-, l^+]$ and $[m^-, m^+]$ before starting an iterative process. Therefore, in the two cases, for the parameter intervals [1 m, 8 m] and [10 kg, 600 kg], and [1 m, 10 m] and [10 kg, 1000 kg] (Table 3), the iterative procedure resulted in obtaining a larger size of RB: 12 and 24 rules, respectively.

## 5. Conclusions

The hybrid method combining the evolutionary-based search strategy, interval mathematics and pole assignment-based closed-loop control synthesis was

Table 4. Parameters of membership functions determined using the iterative procedure.

| $l$ and $m$ intervals | $\zeta$ | parameters of membership functions |
|---|---|---|
| $[1, 8]$m,<br>$[10, 600]$ kg | 0.69 | **a**=[1.0, 2.4, 5.8, 8.0],<br>**b**=[10, 520, 600] |
| $[1, 8]$m,<br>$[10, 600]$ kg | 0.76 | **a**=[1.0 1.9, 3.7, 7.3, 8.0],<br>**b**=[10, 370, 600] |
| $[1, 10]$m,<br>$[10, 1000]$ kg | 0.69 | **a**=[1.0, 2.0, 4.1, 8.4, 10.0],<br>**b**=[10, 520, 1000] |
| $[1, 10]$m,<br>$[10, 1000]$ kg | 0.76 | **a**=[1.0, 1.7, 2.9, 5.0, 8.7, 10.0],<br>**b**=[10, 360, 900, 1000] |

proposed in this paper to design a TSK fuzzy controller. Closed-loop system performance conditions are derived from the interval Diophantine equation and applied to define the objective function of the evolutionary algorithm used to optimize the number of fuzzy sets on inputs of a TSK fuzzy controller. The proposed method was implemented to design an anti-sway crane control system robustness to the rope length and mass of a payload variation.

The evolutionary-based strategy used to optimize the design process of a fuzzy controller provides effective reproductions techniques for searching the solution space in RB optimization through minimizing the numbers of fuzzy sets determined for input variables. The hybridization of arithmetical crossover, uniform and non-uniform mutation, and deletion/insertion mutation ensures the diversity of genome sizes, as well as diversity in the parameter space of rule antecedents. The recombination mechanism ensures fine exploration of the best promising regions of the possible solution space by tuning the triangular-shaped membership function parameters.

The results of experiments conducted for different conditions assumed for system parameter intervals confirm that the developed method of robust fuzzy controller synthesis allows designing a TSK controller placing the coefficients of a closed-loop characteristic polynomial within the desired intervals. The paper also describes an iterative procedure of designing a TSK controller. Both the methods, the EA and the iterative procedure, allows designing the robust fuzzy controller. However, the results of experiments conducted for different conditions assumed for desired closed-loop system performances proved that the EA results in a smaller number of fuzzy sets and rules of a TSK controller required to satisfy the acceptable range of closed-loop system performance deterioration specified in the form of desired intervals of closed-loop characteristic polynomial coefficients.

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