Gravitational Search Algorithm-Based Evolving Fuzzy Models of a Nonlinear Process

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Abstract Implementation issues related to evolving Takagi-Sugeno-Kang (TSK) fuzzy models of a nonlinear process are offered. The nonlinear process is the pendulum dynamics in the framework of the representative pendulum-crane systems, where the pendulum angle is the output variable of the TSK fuzzy models. An online identification algorithm (OIA) is given, which continuously evolves the rule bases and the parameters of the TSK fuzzy models, adds new rules with more summarization power and modifies the existing rules and parameters. The OIA includes an input selection algorithm and a Gravitational Search Algorithm that updates the parameters in the rule consequents. The evolving TSK fuzzy models are validated by experiments conducted on pendulum-crane laboratory equipment.

Keywords Evolving Takagi-Sugeno-Kang fuzzy models · Gravitational search algorithm · Implementation issues · Pendulum Dynamics

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1 Introduction

The evolving Takagi-Sugeno-Kang (TSK) fuzzy models are characterized by the continuous online learning for rule base learning according to [1–4]. An online identification algorithm (OIA) continuously evolves the rule bases and the parameters of the TSK fuzzy models, and the models are built online by the adding mechanism (adding new or removing old local models). As shown in [5], the OIAs dedicated to evolving TSK fuzzy models are divided in three categories. The OIA proposed as follows belongs to the second category, namely the incremental algorithms, which implement only adding mechanisms. Some representative incremental algorithms are RAN, SONFIN, SCFNN, NeuroFAST, DENFIS, eTS, FLEXFIS and PANFIS.

Using the recent results related to evolving TSK fuzzy models reported in [6, 7], a new OIA will be suggested in the sequel. This OIA is inspired from [8], and it computes rule bases and parameters that continuously evolve by adding new rules with more summarization power, the existing rules and parameters are modified in terms of using the potentials of new data points. The new OIA is a modified version of that proposed in [9], which includes an input selection, and it is characterized by inserting a Gravitational Search Algorithm (GSA) [10, 11], that updates the parameters in the rule consequents.

The proposed OIA is advantageous with respect to other OIAs by the fact that the GSA replaces the recursive least squares algorithm, so there is no need to compute the covariance matrices. Therefore, the computational effort is reduced.

The presentation is dedicated to the fuzzy modeling of the pendulum dynamics in the framework of pendulum-crane systems. Some details concerning the implementation of evolving TSK fuzzy models of this process are given in the next sections. Other fuzzy models dedicated to this nonlinear process have been recently discussed in [12–17].

The following topics are treated as follows: the GSA-based OIA is presented in the next section. The case study that leads to new TSK fuzzy models for the pendulum dynamics and implementation issues are treated in Sect. 3. The conclusions are pointed out in Sect. 4.

2 Gravitational Search Algorithm-Based Online Identification Algorithm

The OIA is formulated using the details on the algorithms given in [7–9] and the GSA described in [10, 11]. The OIA consists of the following steps:

Step 1 The rule base structure is initialized by initializing the parameters in the rule antecedents. The initialization means that the initial TSK fuzzy model has a single rule, i.e., $n_R = 1$, where n_R is the number of rules. The subtractive clustering [18] is implemented to compute the parameters of the TSK fuzzy models using the first data point $\mathbf{p}_1$, where the data point $\mathbf{p}$ at the discrete time step k is

$$\mathbf{p}_k = [p_k^1 \quad p_k^2 \quad \ldots \quad p_k^{n+1}]^T, \tag{1}$$

where T indicates the matrix transposition, the data point in the input-output data space $\mathbf{R}^{n+1}$ is

$$\mathbf{p} = [\mathbf{z}^T \quad y]^T = [z_1 \quad z_2 \quad \ldots \quad z_n \quad y]^T = [p^1 \quad p^2 \quad \ldots \quad p^n \quad p^{n+1}]^T \in \mathbf{R}^{n+1}, \tag{2}$$

the rule base of the affine-type TSK fuzzy models that are identified is

$$\begin{aligned}&\text{Rule } i: \text{IF } z_1 \text{ IS } LT_{i1} \text{ AND} \ldots \text{AND } z_n \text{ IS } LT_{in}\\ &\text{THEN } y_i = a_{i0} + a_{i1}z_1 + \cdots + a_{in}z_n, i = 1 \ldots n_R,\end{aligned} \tag{3}$$

where z_j, $j = 1 \ldots n$, are the input variables, n is the number of input variables, LT_{ij}, $i = 1 \ldots n_R$, $j = 1 \ldots n$, are the input linguistic terms, y_i is the output of the local affine model in the rule consequent of the rule i, $i = 1 \ldots n_R$, and a_{il}, $i = 1 \ldots n_R$, $l = 0 \ldots n$, are the parameters in the rule consequents.

The algebraic product t-norm to model the AND operator and the weighted average defuzzification method in the TSK fuzzy model structure lead to the output y of the TSK fuzzy model

$$y = \left[\sum_{i=1}^{n_R} \tau_i y_i\right] / \left[\sum_{i=1}^{n_R} \tau_i\right] = \sum_{i=1}^{nR} \lambda_i y_i = \sum_{i=1}^{n_R} \lambda_i [1 \quad \mathbf{z}^T]^T \boldsymbol{\pi}_i, \tag{4}$$

where the firing degree and the normalized degree of the rule i are $\tau_i(\mathbf{z})$ and $\lambda_i(\mathbf{z})$, respectively:

$$\begin{aligned}&\tau_i(\mathbf{z}) = \text{AND}(\mu_{i1}(z_1), \mu_{i2}(z_2), \ldots, \mu_{in}(z_n)) = \mu_{i1}(z_1) \cdot \mu_{i2}(z_2) \cdot \cdots \cdot \mu_{in}(z_n), i = 1 \ldots n_R,\\ &\lambda_i(\mathbf{z}) = \tau_i(\mathbf{z}) / \left[\sum_{i=1}^{n_R} \tau_i(\mathbf{z})\right], i = 1 \ldots n_R,\end{aligned} \tag{5}$$

and the vector $\boldsymbol{\pi}_i$, $i = 1 \ldots n_R$, in (4) is the parameter vector of the rule i

$$\boldsymbol{\pi}_i = [a_{i0} \quad a_{i1} \quad a_{i2} \quad \ldots \quad a_{in}]^T, i = 1 \ldots n_R. \tag{6}$$

The parameters are initialized as a part of the parameters specific to the OIAs given in [7–9]

$$\begin{aligned}&\hat{\boldsymbol{\theta}}_1 = [(\boldsymbol{\pi}_1^T)_1 \quad (\boldsymbol{\pi}_2^T)_1 \quad \ldots \quad (\boldsymbol{\pi}_{n_R}^T)_1]^T = [0 \quad 0 \quad \ldots \quad 0]^T, r_s = 0.4,\\ &k = 1, n_R = 1, \mathbf{z}_1^* = \mathbf{z}_k, P_1(\mathbf{p}_1^*) = 1,\end{aligned} \tag{7}$$

and the parameters of the GSA [10, 11], related to the generation of the initial population of agents, namely the $n_R(n+1)$-dimensional search space of the parameters in the rule consequents, the number of agents N, and initialize randomly the agents' velocity vector $\mathbf{V}_{i,0} \in \mathbf{R}^{n_R(n+1)}$ of ith agent, $i = 1 \ldots N$. $\hat{\boldsymbol{\theta}}_k$ in (7) is an estimation of the parameter vector in the rule consequents at the discrete time step k, r_s, $r_s > 0$, is the spread of all Gaussian input m.f.s μ_{ij}, $i = 1 \ldots n_R$, $j = 1 \ldots n$, of the fuzzy sets of the input linguistic terms LT_{ij}

$$\mu_{ij}(z_j) = \exp[-(4/r_s^2)(z_j - z_{ij}^*)^2], i = 1 \ldots n_R, j = 1 \ldots n, \tag{8}$$

and z_{ij}^*, $i = 1 \ldots n_R$, $j = 1 \ldots n$, are the centers of these m.f.s. $\mathbf{p}_1^*$ in (8) is the first cluster centre, $\mathbf{z}_1^*$ is the centre of the rule 1 and also a projection of $\mathbf{p}_1^*$ on the axis $\mathbf{z}$ defined in (2). $P_1(\mathbf{p}_1^*)$ in (7) is the potential of $\mathbf{p}_1^*$.

The input selection algorithm proposed in [7] is next applied in order to select the important input variables from all possible input variables. This algorithm ranks the inputs according to their importance factors and is described in [9].

Step 2 At the next time step, k is set to $k = k + 1$, and the next data sample $\mathbf{p}_k$ is read.

Step 3 The potential of each new data sample is calculated as

$$\begin{aligned} &P_k(\mathbf{p}_k) = (k-1)/[(k-1)(\vartheta_k + 1) + \sigma_k - 2\nu_k], \vartheta_k = \sum_{j=1}^{n+1} (p_k^j)^2, \\ &\sigma_k = \sum_{j=1}^{n+1} \sum_{l=1}^{k-1} (p_l^j)^2, \nu_k = \sum_{j=1}^{n+1} (p_k^j \sum_{l=1}^{k-1} p_l^j). \end{aligned} \tag{9}$$

Step 4 The potentials of the centers of existing rules (clusters) are recursively updated in terms of

$$P_k(\mathbf{p}_l^*) = (k-1) P_{k-1}(\mathbf{p}_l^*) / \left[k - 2 + P_{k-1}(\mathbf{p}_l^*) + P_{k-1}(\mathbf{p}_l^*) \sum_{j=1}^{n+1} (d_{k(k-1)}^j)^2 \right], \tag{10}$$

where $P_k(\mathbf{p}_l^*)$ is the potential at the discrete time step k of the cluster centre, which is a prototype of the rule l.

Step 5 The possible modification or upgrade of the rule base structure is carried out using the potential of the new data compared to the potential of existing rules' centers. The rule base structure is modified if certain conditions specified in [7, 8] are fulfilled.

Step 6 The parameters in the rule consequents are updated using the velocity and position update equations specific to the GSA

$$\begin{aligned} &\mathbf{V}_{i,k} = \rho_i \mathbf{V}_{i,k-1} + \mathbf{A}_{i,k-1}, \\ &\hat{\boldsymbol{\theta}}_{i,k} = \hat{\boldsymbol{\theta}}_{i,k-1} + \mathbf{V}_{i,k}, k = 2 \ldots D, i = 1 \ldots N, \end{aligned} \tag{11}$$

where $\rho_i, 0 \le \rho_i \le 1$, is a uniform random variable and $\mathbf{A}_{i,k-1} \in \mathbf{R}^{n_R(n+1)}$ is the acceleration vector of ith agent. The fitness function used in the GSA is

$$f_k = y_k - \boldsymbol{\psi}_{k-1}^T \hat{\boldsymbol{\theta}}_{k-1}, k = 2 \ldots D. \tag{12}$$

The parameter vector $\hat{\boldsymbol{\theta}}_k$ is obtained as

$$\hat{\boldsymbol{\theta}}_k = \min_{i=1\ldots N} \hat{\boldsymbol{\theta}}_{i,k}. \quad (13)$$

The output of the TSK fuzzy model given in (4) is expressed in the vector form

$$\begin{aligned} &y = \boldsymbol{\psi}^T \theta, \theta = [\,\boldsymbol{\pi}_1^T \quad \boldsymbol{\pi}_2^T \quad \ldots \quad \boldsymbol{\pi}_{n_R}^T\,]^T, \\ &\boldsymbol{\psi}^T = [\,\lambda_1[1 \quad \mathbf{z}^T] \quad \lambda_2[1 \quad \mathbf{z}^T] \quad \ldots \quad \lambda_{n_R}[1 \quad \mathbf{z}^T]\,]. \end{aligned} \quad (14)$$

Step 7 Using (14), the output of the evolving TSK fuzzy model at the next discrete time step $k+1$ is predicted

$$\hat{y}_{k+1} = \boldsymbol{\psi}_k^T \hat{\boldsymbol{\theta}}_k. \quad (15)$$

The algorithm continues with the step 2 until all data points from the set of input-output data are used.

$$\{\mathbf{p}_k | k = 1 \ldots D\} \quad (16)$$

The step 1 of the OIA is conducted offline. The steps 2–7 are conducted online.

3 Case Study and Experimental Results

The laboratory setup built around the pendulum-cart system [19] has been used to exemplify and validate the OIA and the evolving TSK fuzzy models. The laboratory setup is illustrated in Fig. 1.

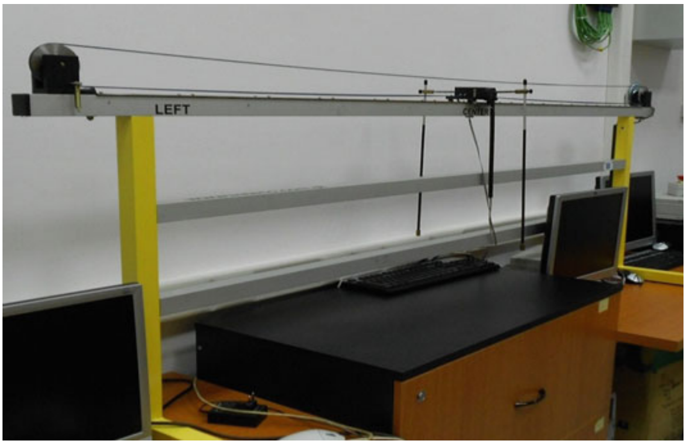

Fig. 1 Laboratory setup in the Intelligent Control Systems Laboratory of the Politehnica University of Timisoara

The expression of the state-space model of the process in the pendulum-cart system is

$$\begin{aligned}
\dot{x}_1 &= x_3,\\
\dot{x}_2 &= x_4,\\
\dot{x}_3 &= \left\{ \frac{J_p}{(m_c+m_p)l_d} \left[\frac{p_1 u}{(m_c+m_p)l_d} - x_4^2 \sin x_2 - \frac{(f_c - p_2)x_3}{(m_c+m_p)l_d}\right] + \left[g \sin x_2 \right.\right.\\
&\quad \left.\left. - \frac{f_p x_4}{(m_c+m_p)l_d}\right] \cos x_2 \right\} / \left[\frac{J_p}{(m_c+m_p)l_d^2} - \cos^2 x_2\right],\\
\dot{x}_4 &= \left\{ \left[\frac{p_1 u}{(m_c+m_p)l_d} - x_4^2 \sin x_2 - \frac{(f_c - p_2)x_3}{(m_c+m_p)l_d}\right] \cos x_2 + \frac{1}{l}\left[g \sin x_2 \right.\right.\\
&\quad \left.\left. - \frac{f_p x_4}{(m_c+m_p)l_d}\right]\right\} / \left[\frac{J_p}{(m_c+m_p)l_d^2} - \cos^2 x_2\right],\\
y &= x_2,
\end{aligned} \tag{17}$$

where the variables are: x_1—the cart position (the distance between the cart and the centre of the rail), x_2—the angle between the upward vertical and the ray pointing at the centre of mass cart, x_3—the cart velocity, x_4—the pendulum angular velocity, u—the control signal represented by a constrained PWM voltage signal, $|u| \le u_{\max} > 0$, m_c—the equivalent mass of the cart, m_P—the mass of the pole and load, and l_d—the distance from the axis of rotation to the centre of mass. The parameters in (17) are: J_p—the moment of inertia of the pendulum-cart system with respect to the axis of rotation, p_1—the ratio between the control force and the control signal, p_2—the ratio between the control force and x_3, f_c—the dynamic cart coefficient, and f_p—the rotational friction coefficient. The parameter values of the laboratory setup are [7, 9, 19]

$$\begin{aligned}
&u_{\max} = 0.5,\ m_c = 0.76 \text{ kg},\ m_p = 0.052 \text{ kg},\ l_d = 0.011 \text{ m},\ J_p = 0.00292 \text{ kg} \cdot \text{m}^2,\\
&p_1 = 9.4 \text{ N},\ p_2 = -0.548 \text{ N s/m},\ f_c = 0.5 \text{ N s/m},\ f_p = 6.65 \cdot 10^{-5} \text{ N m s/rad}.
\end{aligned} \tag{18}$$

The OIA presented in the previous sections has been applied in order to obtain evolving TSK fuzzy models of the process that can be characterized by the nonlinear crisp model given in (17). The OIA has been implemented starting with the eFS Lab code given in [20, 21] and adding the functionalities taken from [7–11].

The sampling period has been set to 0.01 s. The control signal u has been generated as two weighted sums of pseudo-random binary signals (Fig. 2) to cover different ranges of magnitudes and frequencies. This process input has been applied to the laboratory setup to generate the input-output data points $(\mathbf{z}_k, y_k)$, $k = 1 \ldots D$, and a total number of 6000 data points has been used in the tests. The data points are separated in training data and validation data. The first $D = 2500$ data points (the time domain from 0 to 25 s) in Fig. 2 belong to the validation data, and the rest of $D = 3500$ data points (the time domain from 25 to 60 s) in Fig. 2 belong to the

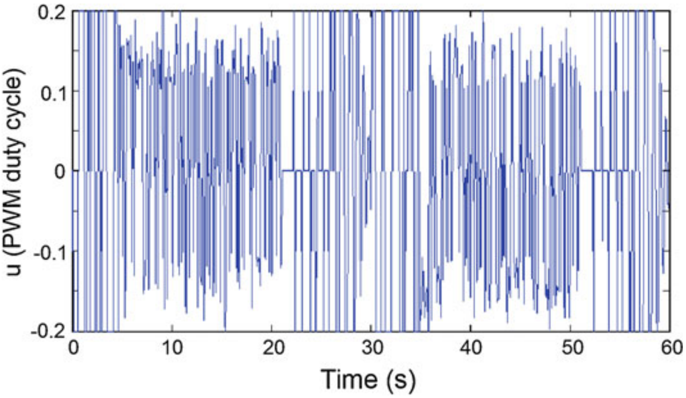

Fig. 2 Control signal versus time, corresponding to training data (0–25 s) and testing data (25–60 s)

testing (validation) data. The process output y is not presented in Fig. 2, but it will be illustrated as follows.

The input selection algorithm, which belongs to the step 1 of the OIA has been applied for three values of the importance threshold, as in [9], $\lambda = 0.4$, 0.3 and 0.2, and one value of the significance threshold, $\tau = 0.5$. This has lead to three final TSK fuzzy models with the following inputs: the TSK fuzzy model 1, with the input u_k, the TSK fuzzy model 2 with the inputs u_k and y_{k-1}, and the TSK fuzzy model 3 with the inputs u_k, y_{k-1} and y_{k-2}. The output of all these three TSK fuzzy models is y_k.

The number of inputs of the TSK fuzzy models is variable during the iterations of the OIA, and that is the reason why the considered fuzzy models are the final ones. The inputs of the three TSK fuzzy models have been obtained from delayed system inputs and/or outputs, which have been extracted from the training and validation data sets. The values of the parameters of the GSA included in the step 6 of the GSA have been set to: number of agents $N = 100$, zero initial velocity vectors, exponential type depreciation law of the gravitational constant with the initial gravitational constant $G_0 = 5$.

The final results are similar to those obtained for the OIA given in [9], but with the recursive least squares algorithm employed in the step 6. Therefore, the TSK fuzzy model 1 has evolved to $n_R = 2$ rules, the TSK fuzzy model 2 has evolved to $n_R = 7$ rules, and the TSK fuzzy model 3 has evolved to $n_R = 9$ rules.

The OIA and the TSK fuzzy model performance have been compared with other OIAs that result in evolving TSK fuzzy models, ANFIS [22], DENFIS [23] and FLEXFIS [24]. The comparison of all fuzzy models has been carried out using the root mean square error (RMSE) as performance index:

$$RMSE = \sqrt{(1/D) \sum_{k=1}^{D} (y_k - x_{2,k})^2}, \qquad (19)$$

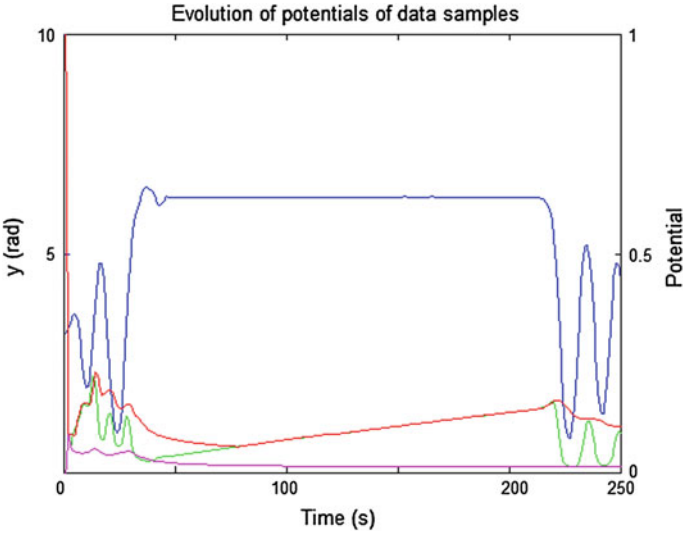

Fig. 3 Evolution of output (*blue*) and potential of data points of TSK fuzzy model 3 on training data

the same inputs, numbers and shapes of m.f.s as those of the three TSK fuzzy models, and the numbers of rules n_R have been set such that to be very close. The variable y_k in (19) is the output (the pendulum angle) of the TSK fuzzy models and $x_{2,k}$ is the output (the pendulum angle) of the laboratory setup at the discrete time moment k. The RMSE has been computed and measured for the training data and for the testing (validation) data as well.

Some of the results for the TSK fuzzy model 3 on the training data are presented in Fig. 3 as clusters in the input space and in Fig. 4 as clusters in the input space. The time responses of the system output versus time of the TSK fuzzy model 3 and of the real-world process on the validation data are shown in Fig. 5.

The RMSE can be used as an objective function in appropriately defined optimization problems solved by several classical and nature-inspired optimization algorithms [24–33]. These optimization problems can be inserted in the OIA, and they must be accompanied by real-world constraints.

The comparison of results reads to the conclusion that the best performance on the validation (testing) data is exhibited by the TSK fuzzy model 3 obtained by the OIA presented in the previous section. In addition, the performance is very close to that achieved by the TSK fuzzy model obtained by the OIA proposed in [9].

As shown in [9], the evolving TSK fuzzy models obtained by the OIA outperform the evolving fuzzy models obtained by ANFIS, DENFIS and FLEXFIS. However, the performance depends on the parameters of both the input selection algorithm and the GSA.

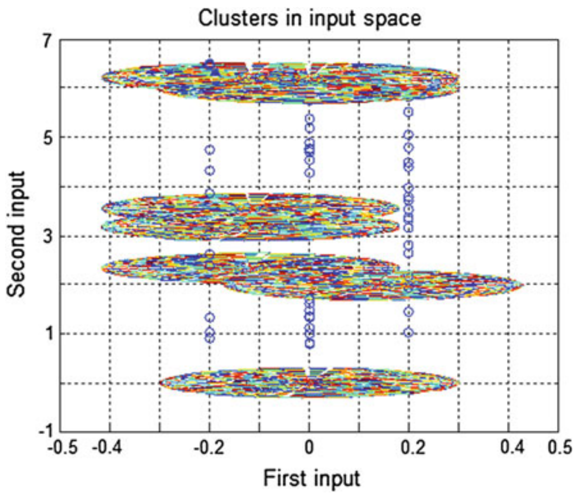

Fig. 4 Clusters in input space of TSK fuzzy model 3 on training data

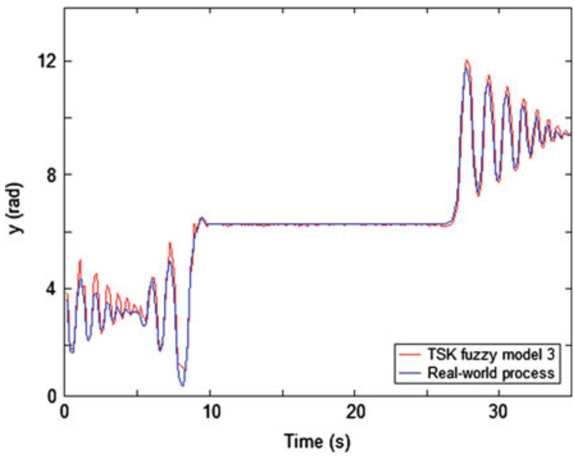

Fig. 5 Pendulum angle versus time of TSK fuzzy model 3 and real-world process for validation data

4 Conclusions

An OIA for evolving TSK fuzzy models has been proposed. The new features of this OIA are the inclusion of an input selection algorithm and of a nature-inspired optimization algorithm represented by the GSA. This offers not only a more systematic approach but also the alleviation of the computational effort. But the random parameters specific to the GSA and the parameters of the input selection algorithm affect the results and the models are sensitive with respect to the choice of these parameters.

The real-time experimental results related to the fuzzy modeling of the pendulum dynamics in pendulum-crane systems validate the OIA and the evolving TSK fuzzy models as well. Future research will be focused on considering other fuzzy models for several applications [34–44] accounting for the further simplification of the OIA.

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