Technical and Non-Technical Applications of Evolving Takagi-Sugeno-Kang Fuzzy Models

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***Abstract*—This paper presents a part of the results obtained by the Process Control group of the Politehnica University of Timisoara, Romania, in the field of evolving Takagi-Sugeno-Kang fuzzy models. These results concern the development of Takagi-Sugeno-Kang fuzzy models by incremental online algorithms for the description of the dynamics or static behavior of three technical and non-technical system applications, namely magnetic levitation systems, Anti-lock Braking Systems and automated translation.**

***Index Terms*—Anti-lock Braking Systems; automated translation; evolving Takagi-Sugeno-Kang fuzzy models; magnetic levitation systems.**

I. Introduction

THE specific feature of evolving Takagi-Sugeno-Kang fuzzy models is obtaining the rules in the rule bases of these fuzzy systems by a learning process, i.e., by continuous online rule base learning as shown in the representative papers [1]–[10]. The Takagi-Sugeno-Kang fuzzy models are obtained by evolving the model structure and parameters making use of online identification algorithms. The so-called adding mechanism plays an important role in online identification algorithms because it adds new local models or removes them, thus ensuring the evolving structure and parameters.

A very useful classification of online identification algorithms that compute evolving Takagi-Sugeno-Kang fuzzy models is given in [11]. This classification highlights three categories of online identification algorithms, namely I, II and III, which are briefly outlined as follows by means of their specific features.

The category I of adaptive algorithms starts with the initial structure of the Takagi-Sugeno-Kang fuzzy model, given by other algorithms or by the experience of the specialist in the modeling or operation of the nonlinear dynamic system that is modeled. The number of space partitions/clusters does not change over time, and these algorithms adapt just the parameters of the membership functions and the local models.

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The category II is represented by the incremental algorithms. Some representative examples of incremental algorithms are RAN [12], [13], SONFIN [14], [15], NeuroFAST [16], [17], DENFIS [18], [19], SCFNN [20], [21], eTS [22], [23], FLEXFIS [24], [25], and PANFIS [26]. They implement just adding mechanisms.

The category III consists of evolving algorithms. Besides the adding mechanism, these algorithms also implement removing and a part of these algorithms merging and splitting mechanisms.

This paper is built on the basis of the recent results obtained by the Process Control group of the Politehnica University of Timisoara, Romania, in the development of evolving Takagi-Sugeno-Kang fuzzy models obtained by incremental algorithms (the category II described above). The paper is the continuation of the paper [27], which offers real-world applications of evolving Takagi-Sugeno-Kang fuzzy models that describe the dynamics of nonlinear systems in crane systems [28], [29], pendulum systems [30], [31], prosthetic hand fingers [32] and twin rotor aerodynamic systems [33]. This paper applies incremental online identification algorithms to develop evolving Takagi-Sugeno-Kang fuzzy models for other technical and non-technical system applications in order to describe their dynamics or static behavior: the position of the magnetic sphere in laboratory magnetic levitation systems [34], the longitudinal slip in laboratory Anti-lock Braking Systems (ABSs) [35], and the overall paragraph score in automated translation [36].

The evolving fuzzy models treated in this paper are important because they can be next used in control. Relevant process and control applications are presented in [37]–[44], with crisp and fuzzy models [45]–[50], and the online identification algorithms must be adapted accordingly.

This paper treats the following topics: an overview on incremental online identification algorithms is presented in Section II. Useful implementation details and results on the three evolving fuzzy model applications are offered in Section III. The conclusions are pointed out in Section IV.

II. Incremental Online Identification Algorithms

The classical version of the incremental online identification algorithm is implemented using the theoretical aspects described in [27] and [33] in terms of the software support of eFS Lab presented in [51] and [52]. The flowchart of the basic version of incremental online identification algorithm is presented in Fig. 1, where TSK stands for Takagi-Sugeno-Kang. This algorithm consists of seven steps described as follows; they are also presented in [27] and [33].

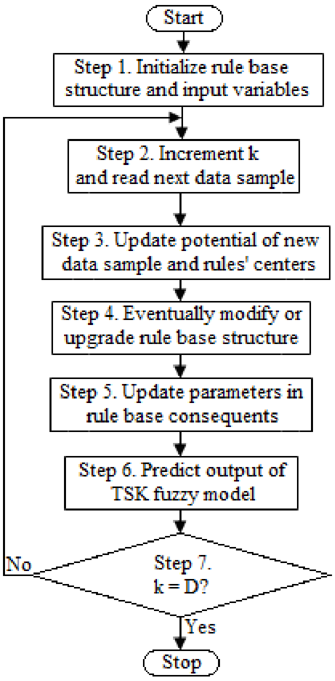

Fig. 1. Flowchart of classical version of incremental online identification algorithm [27].

Step 1. The rule base structure is initialized by setting all parameters of rule antecedents such that to initially contain just one rule, namely $n_R = 1$, where n_R is the number of rules. The subtractive clustering is next applied to compute the parameters of the evolving Takagi-Sugeno-Kang fuzzy models using the first data point $\mathbf{p}_1$, with the general expression [22] of the data point $\mathbf{p}$ in the input-output data set at the discrete time step k, with the notation $\mathbf{p}_k$:

$$\begin{aligned}&\mathbf{p}_k = [p_k^1 \;\; p_k^2 \ldots p_k^{n+1}]^T, \; \mathbf{p} = [\mathbf{z}^T \;\; y]^T \\ &= [z_1 \;\; z_2 \ldots z_n \;\; y]^T = [p^1 \;\; p^2 \ldots p^n \;\; p^{n+1}]^T \in \Re^{n+1},\end{aligned} \tag{1}$$

where T stands for matrix transposition.

The expression of the input-output data set is:

$$\{\mathbf{p}_k \mid k = 1 \ldots D\} \subset \Re^{n+1}, \tag{2}$$

and D is the number of input-output data points or data points or data samples or samples.

The rule base of Takagi-Sugeno-Kang fuzzy models with affine rule consequents, also called first-order Sugeno fuzzy inference systems in some software programs and toolboxes implementations, is:

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

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 model in the rule consequent of the rule with the index $i, i = 1 \ldots n_R$, and $a_{il}, i = 1 \ldots n_R, l = 0 \ldots n,$ are the parameters in the rule consequents.

The Takagi-Sugeno-Kang fuzzy model structure considered in this paper includes the algebraic product t-norm as an AND operator and the weighted average defuzzification method. This leads to the expression of the output y of the Takagi-Sugeno-Kang fuzzy model:

$$\begin{aligned}&y = \left[\sum_{i=1}^{n_R} \tau_i y_i\right] / \left[\sum_{i=1}^{n_R} \tau_i\right] = \sum_{i=1}^{n_R} \lambda_i y_i, \; y_i = [1 \;\; \mathbf{z}^T] \boldsymbol{\pi}_i, \\ &\lambda_i = \tau_i / \left[\sum_{i=1}^{n_R} \tau_i\right], \; i = 1 \ldots n_R,\end{aligned} \tag{4}$$

where the firing degree of the rule i and the normalized firing degree of the rule i are $\tau_i(\mathbf{z})$ and λ_i, respectively, and the parameter vector of the rule i is $\boldsymbol{\pi}_i, i = 1 \ldots n_R,$. The expression of the firing degree is:

$$\begin{aligned}&\tau_i(\mathbf{z}) = \text{AND}(\mu_{i1}(z_1), \mu_{i2}(z_2), \ldots, \mu_{in}(z_n)) \\ &= \mu_{i1}(z_1) \cdot \mu_{i2}(z_2) \cdot \ldots \cdot \mu_{in}(z_n), \; i = 1 \ldots n_R,\end{aligned} \tag{5}$$

and the expression of the parameter vector is:

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

The other parameters specific to the incremental online identification algorithm are initialized as follows using [22]:

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

where $\mathbf{C}_k \in \Re^{n_R(n+1) \times n_R(n+1)}$ is the fuzzy covariance matrix related to the clusters, $\mathbf{I}$ is the $n_R(n+1)^{\text{th}}$ order identity matrix, $\Omega = \text{const}, \Omega > 0,$ is a large number, $\hat{\boldsymbol{\theta}}_k$ is an estimation of the parameter vector in the rule consequents at the discrete time step k, and r_s, $r_s > 0$, is the spread of all Gaussian input membership functions μ_{ij}, $i = 1 \ldots n_R, j = 1 \ldots n,$ of the fuzzy sets of the input linguistic terms LT_{ij}:

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

$z_{ij}^*, i = 1 \ldots n_R, j = 1 \ldots n,$ are the membership function centers, $\mathbf{p}_1^*$ in (7) is the first cluster center, $\mathbf{z}_1^*$ is the center of the rule 1 and also the projection of $\mathbf{p}_1^*$ on the axis $\mathbf{z}$ in terms of (1), and $P_1(\mathbf{p}_1^*)$ is the potential of $\mathbf{p}_1^*$.

Other membership functions will lead to different results and will require the modification of the next steps of the algorithm. However, the membership functions given in (8) are differentiable and make these models applicable to data-driven fuzzy control.

Step 2. The data sample index k is incremented to $k+1$, and the next data sample $\mathbf{p}_k$ that belongs to the input-output data set defined in (2) is read.

Step 3. The potential of each new data sample $P_k(\mathbf{p}_k)$ and the potentials of the centers $P_k(\mathbf{p}_l^*)$ of existing rules (clusters) with the index l are recursively updated:

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

Step 4. The possible modification or upgrade of the rule base structure is carried out by means of the potential of the new data compared to the potential of the existing rules' centers. The rule base structure is modified if certain conditions mentioned in [22] and [27]–[36] are fulfilled.

Step 5. The parameters in the rule consequents are updated using either the Recursive Least Squares (RLS) algorithm or the weighted Recursive Least Squares (wRLS) algorithm. These updates result in the updated vectors $\hat{\boldsymbol{\theta}}_k$ and $\mathbf{C}_k$, $k = 2...D$.

Step 6. The output of the evolving Takagi-Sugeno-Kang fuzzy model at the next discrete time step $k+1$ is predicted as $\hat{y}_{k+1}$:

$$\hat{y}_{k+1} = \boldsymbol{\psi}_k^T \hat{\boldsymbol{\theta}}_k, \tag{10}$$

where the general expression of (10) and the expressions of the vectors are:

$$\begin{aligned} & y = \boldsymbol{\psi}^T \boldsymbol{\theta}, \boldsymbol{\theta} = [\boldsymbol{\pi}_1^T \quad \boldsymbol{\pi}_2^T \quad \ldots \quad \boldsymbol{\pi}_{n_R}^T]^T, \\ & \boldsymbol{\psi}^T = [\lambda_1[1 \ \mathbf{z}^T] \quad \lambda_2[1 \ \mathbf{z}^T] \quad \ldots \quad \lambda_{n_R}[1 \ \mathbf{z}^T]]. \end{aligned} \tag{11}$$

Step 7. The algorithm continues with the step 2 until all data points of the input-output data set presented in (2) are read.

The incremental online identification algorithm described in this section has been modified in [30] and [31] by adding and an input selection algorithm and a Gravitational Search Algorithm to replace RLS or wRLS in step 5 by updating the rule consequents. Other optimization algorithms can be used as well, with some classical and nature-inspired examples presented in [53]–[66].

Using the notation y_k for the output of the Takagi-Sugeno-Kang fuzzy models, the general expression of these models evolved by the incremental online identification algorithm presented in this section is:

$$y_k = f(\mathbf{z}_k), \tag{12}$$

where f is the nonlinear input-output map of the Takagi-Sugeno-Kang fuzzy models.

III. Technical and Non-technical Applications

A. Magnetic Levitation Systems

The incremental online identification algorithm presented in the previous section has been applied to derive evolving Takagi-Sugeno-Kang fuzzy models of the sphere position in magnetic levitation system laboratory equipment. The experimental setup is illustrated in Fig. 2.

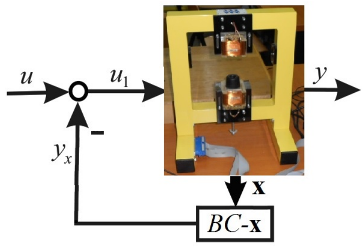

Fig. 2. Stabilized magnetic levitation system (experimental setup in the Intelligent Control Systems Laboratory of the Politehnica University of Timisoara, Romania) [34].

The laboratory equipment includes two electromagnets, the ferromagnetic sphere, the sensors to detect the position of the sphere, the computer interface, the drivers, the power supply unit, the connection cables, the acquisition board, and appropriate software support. If both electromagnets are used, the control signal applied to the lower electromagnet can be used as an additional force but it can also be used as a disturbance input. The main notations for this experimental setup are [34]: u_1 (V) – the control signal applied to the upper electromagnet, $\mathbf{x} = [x_1 \ x_2 \ x_3]^T$ – the state vector with the components x_1 (m) – the sphere position, x_2 (m/s) – the sphere speed, x_3 (A) – the current in the upper electromagnet, and $y = x_1$ (m) – the process output and also the output of the evolving Takagi-Sugeno-Kang fuzzy models.

The laboratory equipment is a nonlinear unstable system. Linearizing the process model at seven operating points, the process is next stabilized using a state-feedback control system as shown in Fig. 2, where BC-**x** is the state-feedback compensator, and y_x is the output of the block BC-**x**, obtained as a linear combination of the state variables. The notation u is used for the reference input of the stabilized state-feedback control system for which Takagi-Sugeno-Kang fuzzy models are evolved and derived, and also as an input variable to the evolving Takagi-Sugeno-Kang fuzzy models that are exemplified as follows.

Setting the sampling period to $0.5 \cdot 10^{-3}$ s, the values of u have been generated in order to cover different ranges of magnitudes and frequencies, and the output y has been measured from the equipment. The evolution of the system input versus time is presented in Fig. 3, which includes the input data for both training and validation (testing). The past input and output values have been obtained by shifting the training and validation data samples.

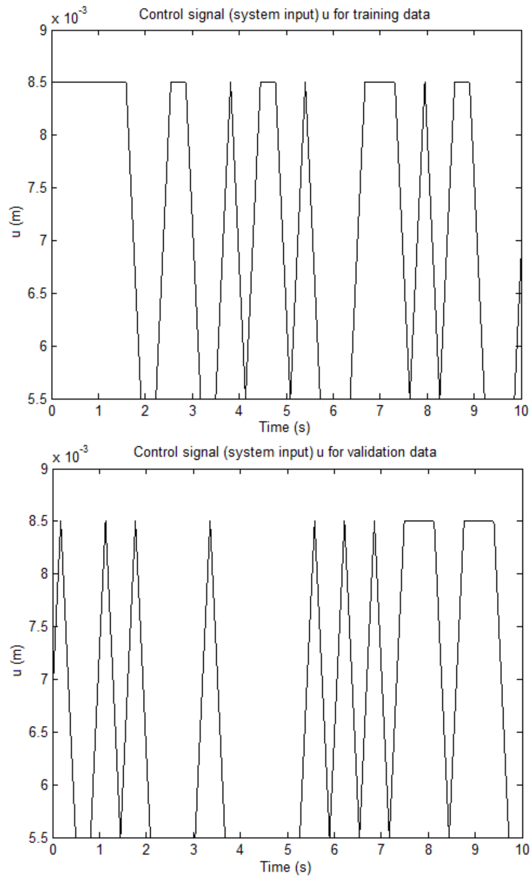

Fig. 3. System inputs of magnetic levitation system versus time: training data and validation (testing) data [34].

The input signal shown in Fig. 3 has been applied to the laboratory equipment to generate the input-output data points $(\mathbf{z}_k, y_k),\ k = 1...D$. Fig. 3 illustrates the inputs that correspond to the set of $D = 20000$ data points of the training data and the inputs of the other set of $D = 20000$ data points of the testing data. The output values will be next illustrated.

The value of the parameter Ω in the step 1 has been set to $\Omega = 10000$. The dynamics is introduced in the evolving Takagi-Sugeno-Kang fuzzy models by inserting several past values of the input and/or output. The parameters in the rule consequents have been updated in the step 5 of the algorithm described in Section II using either RLS or wRLS.

The results presented in [34] show that the best performance as far as the root mean square error (RMSE) on the validation data is obtained by the Takagi-Sugeno-Kang fuzzy model with the input vector:

$$\mathbf{z}_k = [u_k \ \ y_{k-1}]^T \tag{13}$$

with RLS applied in the step 5. A sample of real-time experimental results is shown in Fig. 4 as the time responses of y versus time of this fuzzy model 4 and the real-world system.

This fuzzy model has evolved to 7 rules and has 49 parameters. The results show that a reduced number of model inputs is needed for this process in order to have acceptable model performance expressed, for example, in terms of RMSE.

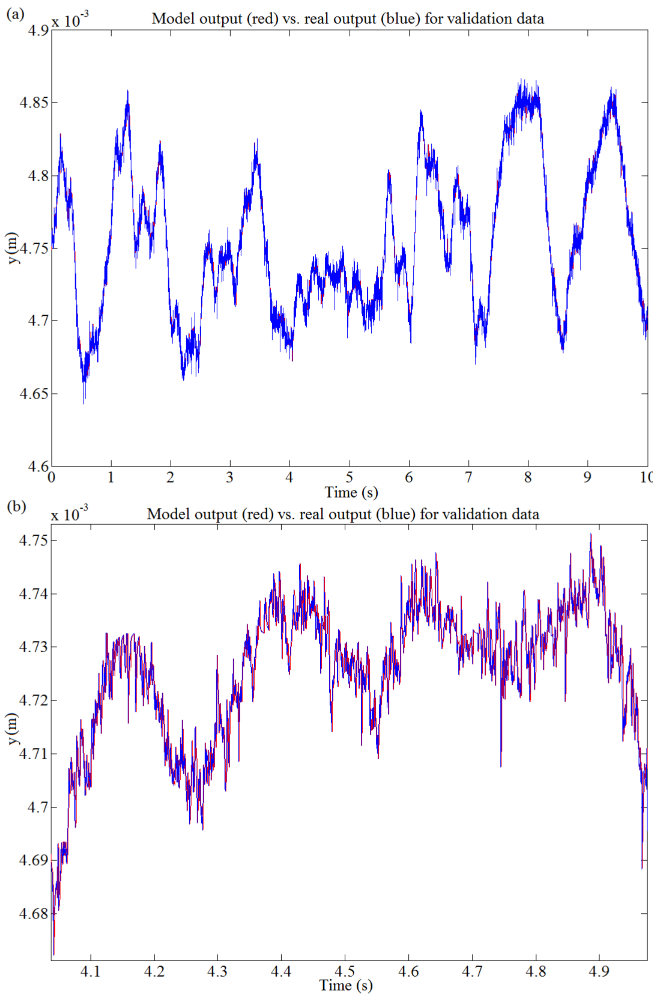

Fig. 4. (a) Sphere position y versus time of Takagi-Sugeno-Kang fuzzy model (red) and real-world system (blue) on the validation (testing) data set, (b) zoomed plots of sphere position versus time [34].

B. *Anti-lock Braking Systems*

The continuous-time nonlinear state-space model of the ABS process is derived starting with [35], [67]:

$$\begin{aligned} J_1 \dot{x}_1 &= F_n r_1 \mu(\lambda) - d_1 x_1 - M_{10} - M_1, \\ J_2 \dot{x}_2 &= -F_n r_2 \mu(\lambda) - d_2 x_2 - M_{20}, \\ \dot{M}_1 &= c_{31}(b(u) - M_1), \end{aligned} \tag{14}$$

where λ is the longitudinal slip, J_1 and J_2 are the inertia moments of wheels illustrated in Fig. 5, x_1 and x_2 are the angular velocities, d_1 and d_2 are the friction coefficients in the axes of the wheels, M_{10} and M_{20} are the static friction torques that oppose the normal rotation, M_1 is the brake torque, r_1 and r_2 are the radii of wheels, F_n is the normal force that the upper wheel pushes upon the lower wheel, $\mu(\lambda)$ is the friction coefficient, $\dot{x}_1$ and $\dot{x}_2$ are the angular accelerations of the wheels, u is the control signal applied to the actuator, namely the direct current (DC) motor which drives the upper wheel, and the actuator's nonlinear model is reflected in the nonlinear map $b(u)$.

Fig. 5. ABS experimental setup in the Intelligent Control Systems Laboratory of the Politehnica University of Timisoara, Romania [67].

The longitudinal slip λ is defined as:

$$\lambda = (r_2 x_2 - r_1 x_1)/(r_2 x_2), x_2 \neq 0, \quad (15)$$

the controlled output of the ABS process is λ in the context of longitudinal slip control, and the notation $y = \lambda$ is employed in this sub-section for the sake of model development.

Setting the sampling period to $0.01\,\mathrm{s}$, several values of u have been generated in order to cover different ranges of magnitudes and frequencies. The output $y = \lambda$ has been measured from the ABS equipment. The evolution of the system input versus time is presented in Fig. 6, which includes the input data for both training and validation (testing).

The input signal illustrated in Fig. 6 has been applied to the laboratory equipment to generate the input-output data points $(\mathbf{z}_k, y_k)$, $k = 1...D$, needed to be applied to the algorithm. Fig. 6 outlines the inputs that correspond to the set of $D = 240$ data points of the training data and the inputs of the other set of $D = 60$ data points of the testing data. The output values computed by the Takagi-Sugeno-Kang fuzzy models and measured from the equipment will be presented as follows.

A part of the real-time experimental results is exemplified in Fig. 6 as the time responses of y versus time of the Takagi-Sugeno-Kang fuzzy model with the input vector

$$\mathbf{z}_k = [u_k \;\; u_{k-1} \;\; y_{k-1} \;\; y_{k-2}]^T, \quad (16)$$

with wRLS applied in the step 5 of the incremental online identification algorithm, and the real-world ABS.

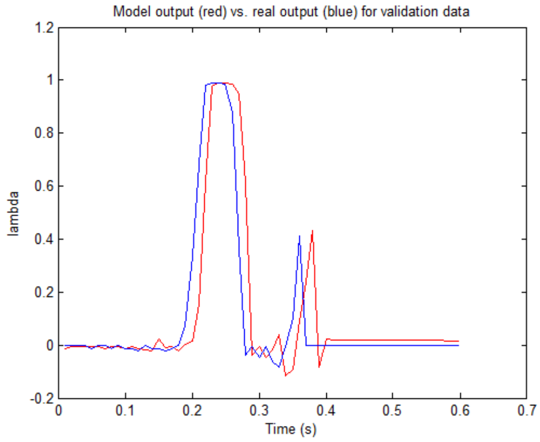

Fig. 6. (a) Longitudinal slip position y=λ versus time of Takagi-Sugeno-Kang fuzzy model (red) and real-world ABS (blue) on the validation (testing) data set [67].

This fuzzy model has evolved to 9 rules and has 117 identified parameters. The performance is acceptable, it can be improved but this is constrained by the number of data samples considered for this process, which is rather small.

C. Automated Translation Systems

The problem considered in automated translation systems is defined as follows in terms of [36]: the text T1 in English will be translated into French with the help of an online translation memory software application. Google Translate and Systran have been used as representative online translation memory software applications in [26]. The translation leads to the text T2 in French. The text T2 is next introduced in the same application; it is translated into English leading to the result T3. T2 is compared T1 to T3 resulting in the degree of concordance between them by means of a statistical test. Fuzzy models have been evolved, which give the Overall Paragraph Score (OPS) viewed as the Takagi-Sugeno-Kang fuzzy model output, namely $y_k = \mathrm{OPS}_k$, using $n = 7$ categories of primary errors as input variables. The general expression of the input vector to the Takagi-Sugeno-Kang fuzzy models is:

$$\mathbf{z}_k = [\mathrm{WT}_k \;\; \mathrm{SE}_k \;\; \mathrm{OM}_k \;\; \mathrm{SA}_k \;\; \mathrm{SP}_k \;\; \mathrm{PE}_k \;\; \mathrm{ME}_k]^T, \quad (17)$$

where: WT – Wrong Term, SE – Syntactic Error, OM – Omission, SA – Word Structure and Agreement error, SP – MisSPelling, PE – Punctuation Error, and ME – Miscellaneous Error. The weights of these seven categories of primary errors categorized as serious errors/minor errors are given in [68].

The system inputs are presented in Fig. 7, which illustrates the input data for both training and validation (testing). The real system output is the actual value of OPS obtained by the application of Google Translate or Systran in the translation from English to French, which has been investigated in [36].

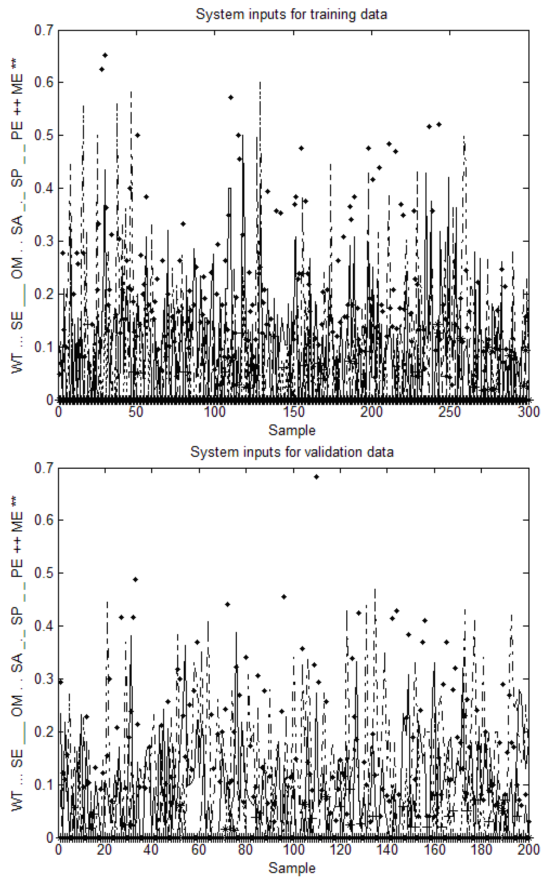

Fig. 7. System inputs of automated translation systems versus data sample for training data and validation (testing) data [36].

On of the evolved Takagi-Sugeno-Kang fuzzy models, which corresponds to Google Translate using wRLS in the step 5 of the algorithm given in the previous sections, has evolved to $n_R = 6$ rules, and it consists of 132 parameters. The outputs of this fuzzy model and of the real system output are illustrated in Fig. 8 for validation (testing) data, and the results are encouraging.

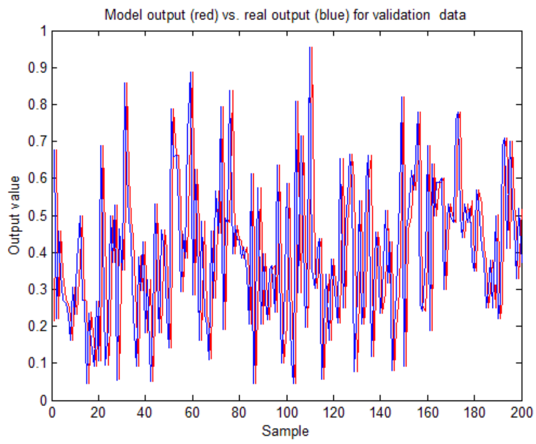

Fig. 8. System output (OPS) versus data sample of evolving Takagi-Sugeno-Kang fuzzy model and real system for validation (testing) data [36].

IV. Conclusion

This paper has presented some results obtained by the Process Control group of the Politehnica University of Timisoara, Romania, in the application of evolving Takagi-Sugeno-Kang fuzzy models to three nonlinear systems. Two technical dynamical systems and one non-technical static system have been modeled. An incremental online identification algorithm organized in a cost-effective manner has been applied to produce the Takagi-Sugeno-Kang fuzzy models.

The performance of the Takagi-Sugeno-Kang fuzzy models, expressed as system responses and assessed by RMSE, is encouraging. But the performance is affected by the parameters of the incremental online identification algorithm, which leads to parametric sensitivity and eventually robustness problems.

Future research will be focused on the application of the Takagi-Sugeno-Kang fuzzy models to control these processes. This should be combined with the proper definition of the control goals.

Acknowledgment

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