RAPORT ȘTIINȚIFIC ȘI TEHNIC
privind implementarea proiectului în perioada februarie – decembrie 2021 (etapa 1)

A. REZUMATUL ETAPEI

Echipa de cercetare care a desfășurat activități de cercetare în cadrul proiectului "Reglare fuzzy data-driven cu validare experimentală", contract de finanțare nr. 192 / 19.02.2021, codul de depunere PN-III-P4-ID-PCE-2020-0269, este cea nominalizată în cererea de finanțare: prof.dr.ing. Radu-Emil Precup (director de proiect), ș.l.dr.ing. Claudia-Adina Bojan-Dragoș, ș.l.dr.ing. Adriana Albu, ș.l.dr.ing. Alexandra-Iulia Szedlak-Stînean, lect.dr. Ciprian Hedrea, as.dr.ing. Raul-Cristian Roman, drd.ing. Ion-Cornel Mitulețu, as.drd.ing. Elena-Lorena Hedrea.

Obiectivul principal urmărit în cadrul proiectului a fost îndeplinit conform planului de realizare și este descris în cele ce urmează:

(1) Analiza cercetărilor teoretice privind îmbunătățirea soluțiilor de reglare existente și proiectarea de noi regulatoare pentru a îmbunătăți performanțele sistemelor de reglare automată pentru diverse procese neliniare care includ procese cu aliaje cu memoria formelor (engl. Shape Memory Alloy, SMA). Activitățile desfășurate pentru atingerea acestui obiectiv se referă la:

   1.1. Analiza stadiului actual al cercetărilor teoretice și al aplicațiilor experimentale realizate pe diverse echipamente de laborator care includ și procese cu aliaje cu memoria formei (SMA). A fost efectuată analiza menționată și în capitolul B sunt prezentate date sintetice aferente acestei analize, însoțite de bibliografia aferentă. Procesele și echipamentele analizate sunt: servosisteme [C1], [C3], [C7], populație și epidemie [C2], SMA [C4], politică monetară [C5], ambreiaje acționate electromagnetic [C6], volume mari de date [C8], macarale turn [C9], roboți mobili [C10].

   1.2. Cercetarea posibilităților de îmbunătățire a soluțiilor de reglare existente pentru diverse procese neliniare care includ și procese cu aliaje cu memoria formei (SMA) și proiectarea de noi soluții de reglare de tip data-driven și fuzzy. Au fost analizate și propuse regulatoare noi de tip fuzzy [C1], [C6], [C10], bazate pe Iterative Feedback Tuning [C9], bazate pe rețele neuronale artificiale combinate cu învățare prin reîntărire (sau prin recompensă) și algoritmi metaeuristici de optimizare [C3], cu detalii prezentate în lucrările [C1], [C3], [C6], [C9] și [C10].

Rezultatele prevăzute a fi obținute în cadrul proiectului în această etapă conform conform planului de realizare sunt:

➢ Valorificarea rezultatelor prin publicarea unei lucrări într-o revistă din domeniu cu factor de impact ridicat și prin participarea și prezentarea a două lucrări în cadrul unor conferințe cu vizibilitate ridicată.
➢ Pregătirea rapoartelor pentru documentarea activităților.

Rezultatele principalele obținute în cadrul proiectului în această etapă depășesc rezultatele prevăzute. Acestea sunt:

➢ Raport de cercetare.
➢ Zece lucrări publicate: [C1]-[C10].
➢ Detalii privind lucrările publicate: 2 lucrări [C1], [C2] publicate în reviste indexate în Clarivate Analytics Web of Science (cu una din denumirile anterioare ISI Web of Knowledge) cu factor de impact, 2 lucrări [C3], [C4] acceptate în reviste indexate în Clarivate Analytics Web of Science (cu una din denumirile anterioare ISI Web of Knowledge) cu factor de impact, 1 lucrare [C5] publicată în volum de conferință indexată în Clarivate Analytics Web of Science (cu unele din denumirile anterioare ISI Web of Knowledge sau ISI Proceedings), 1 lucrare [C6] publicată în volum de conferință indexată în baze de date internaționale (IEEE Xplore, INSPEC, Scopus, DBLP), 3 lucrări [C7], [C9], [C9] prezentate la conferințe ale căror

volume vor fi indexate în baze de date internaţionale (IEEE Xplore, INSPEC, Scopus, DBLP), 1 capitol de carte publicat în Springer.

- ➢ Factor de impact cumulat al lucrărilor publicate conform 2020 Journal Citation Reports (JCR) publicat de Clarivate Analytics în 2021 = 14.098.
- ➢ Reviste cu factor de impact ridicat în care au fost publicate lucrările: Information Sciences (Elsevier), Scientific Reports (Nature), International Journal of Systems Science (Taylor and Francis).
- ➢ Conferinţe cu vizibilitate ridicată în volumele cărora au fost publicate lucrările: 4th IFAC Conference on Embedded Systems, Computational Intelligence and Telematics in Control CESCIT 2021, 30th International Symposium on Industrial Electronics ISIE 2021, 8th International Conference on Information Technology and Quantitative Management ITQM 2020 & 2021.

Remarci:

1. În acest raport ştiinţific textele, figurile şi parţial relaţiile au fost preluate din lucrările elaborate de echipa de cercetare. Din acest motiv formulările sunt în limba engleză. La unele relaţii va fi păstrată numerotarea din raportul de cercetare.

2. Toate lucrările publicate sau în curs de publicare şi care conţin rezultate de cercetare obţinute în cadrul acestui proiect au menţionat sprijinul UEFISCDI în secţiunea de Acknowledgements, alături de specificarea codului de depunere a cererii de finanţare.

B. DESCRIEREA ŞTIINŢIFICĂ ŞI TEHNICĂ

Descrierea este concentrată asupra prezentării sintetice a cercetării efectuate în cadrul activităţii 1.1, analiza stadiului actual al cercetărilor teoretice şi al aplicaţiilor experimentale realizate pe diverse echipamente de laborator, în speţă SMA conform [C4]. Sunt propuse modele fuzzy evolutive de tip Takagi-Sugeno pentru un proces reprezentativ construit în jurul SMA. Conform remarcii 1 din capitolul A, descrierea este continuată în limba engleză.

As analyzed in [1], the analysis of the state-of-the-art of control theory and applications related to Shape Memory Alloy (SMA) actuators shows that they are in continuous progress because of their special features. A comprehensive review on the challenges for practical applications of SMA actuators is given in [2]. As all actuators, the SMA ones have to ensure very good control system performance indices as they are integrated in control systems in various critical applications. The special features of SMA actuators, which justify their success, are maintaining a deformed shape until heat is applied to recover the original shape [3], capability to high strain recovery and withstanding the higher load and high damping and supporting large reversible changes of mechanical and physical characteristics [4], [5].

Due to the above features and the need to validate the control system structure, testing equipment was designed in both simple cases to demonstrate the SMA behavior and complicated ones to model the specific processes and next to design controllers including nonlinear robust ones for position and tracking control. Suggestive examples of testing equipment are reported in [6]–[8].

SMA actuators are implemented and validated by means of both simulation and experimental results in a wide variety of applications as biomedical engineering [9], industry, vibration control systems [4], [5], [9], [10]–[13], aeronautics and aviation [6], [14]. The recent literature highlights their attractiveness in robotics control system especially for hand prostheses which can follow a two-dimensional motion with a relatively high accuracy driven by SMA coils [15] and for the development of a low-cost five-fingered prosthetic hand because they ensure a biological-like behavior that reacts fast but smoothly as the natural muscular fibers [16]. A bidirectional SMA rotating actuator using a rotating frame and two SMA wire-based actuating units similar to human skeletal muscle systems was designed in [17] to provide angular displacements in both clockwise and counter-clockwise directions with compliance.

As shown in [C4], the modeling of SMA actuators is a hot topic in the framework of model-based design. In addition, since the experiments are expected to have certain costs, accurate process models are important in order to ensure the convenient digital simulation of SMA actuators

as controlled process and the control systems as well. The mathematical model of SMA as a dynamical system is highly nonlinear, which makes it complicated to design an appropriate controller. SMAs can exist in two different phases depending on the applied temperature and stress. The difference between the heating and the cooling transition gives rise to hysteresis. Therefore, for modeling the SMA behavior it is more convenient to use several system identification approaches implemented in Matlab's System Identification Toolbox in order to describe the system model as a linear one with uncertainties and then apply the robust stability method to control the system efficiently as illustrated in [6] and [18]. Other two approaches to SMA model design implementation are based on Liang's constitutive model and discussed in [10]; the first one is a stress-driven model and the second one is a strain-driven model (used only to implement the SMA-based actuator). In stress-driven model, stress and temperature are inputs, whereas strain is output. In strain-driven model, temperature and strain are inputs, whereas stress is output. In [14], the model of SMA actuator system consists of four dynamic equations including the temperature dynamics based on thermal energy conservation equation, phase transformation equation between martensite and austenite, SMA constitutive law and the mechanical dynamics. The discrete-time nonlinear dynamical system described in the Single-Input-Single Output (SISO) form is equivalently represented in [7] as an equation by linearization using Taylor's formula around the origin, obtaining a linear dynamic model along with its unmodeled dynamics.

Although all the modeling approaches briefly discussed in [C4] and specifically above ensure good modeling performance, there is still room for performance improvement. One direction in this regard is to develop nonlinear models of SMA actuators. Representative nonlinear models are the fuzzy models as they are relatively easily understandable and also may embed the human expert's knowledge in dealing with the processes they model aiming their control. As specified in [19], the concept of evolving fuzzy (or rule-based) controllers was proposed by Angelov back in 2001 and further developed in his later works [20]–[25]. These controllers employ evolving Takagi-Sugeno-Kang (TSK) fuzzy models, which are characterized by computing the rule bases by a learning process, i.e., by continuous online rule base learning. Some recent illustrative results on evolving fuzzy models are offered in [26]–[29]. The TSK fuzzy models are developed in terms of evolving the model structures and parameters by means of online identification algorithms.

The paper [C4] is built upon authors' recent papers on evolving TSK fuzzy models [19], [30]–[32] mainly focusing on modeling the midcarpal joint angles in the framework of human hand dynamics, and produces two evolving TSK fuzzy models for SMA wire actuators with the technical description described in [6]. The output of these system models is the position of the SMA wire actuators, and the input is the current signal which supplies the actuator (it flows through the wire). This current signal is actually the control input or control signal involved in position control system structures and it is produced by the controller. Moreover, additional TSK fuzzy model inputs and outputs obtained from past inputs and/or outputs are included in the model structure. The experimental results highlight that the proposed fuzzy models are consistent with training and validation data.

The online identification algorithm is implemented by adapting the theory treated in [33], with the aid of the eFS Lab software developed by Dourado and his team according to the description given in [34] and [35]. The flowchart of the incremental online identification algorithm is presented in Fig. 1. This algorithm is organized in terms of the following steps, also given in [19] and authors' recent papers highlighted in [C4]:
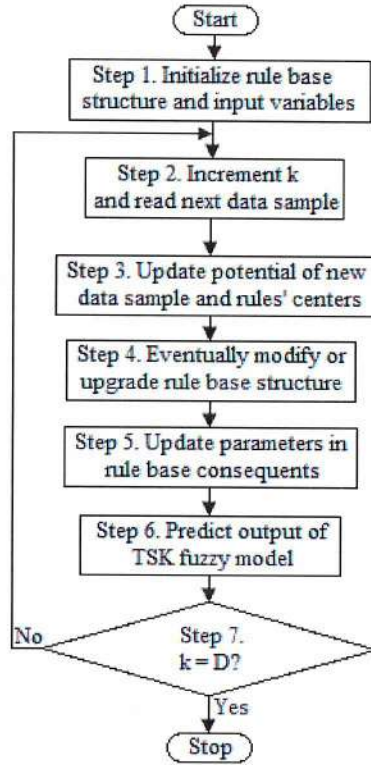
Fig. 1. Flowchart of incremental online identification algorithm [19], [36].

Step 1. The structure of the rule base is initialized by setting all parameters of the rule antecedents in order to first contain one rule, i.e., $n_R = 1$, where n_R is the number of rules. The subtractive clustering is next applied to compute the parameters of the evolving TSK fuzzy models using the first data point $\mathbf{p}_1$ represented as a vector in $\mathfrak{R}^{n+1}$. The general expression of the data point $\mathbf{p}$ at the discrete time step k (and also the index of the current sample) is $\mathbf{p}_k$, and this point and also vector belongs to the input-output data set $\{\mathbf{p}_k \mid k = 1...D\} \subset \mathfrak{R}^{n+1}$ [19]

$$\mathbf{p}_k = [p_k^1 \ p_k^2 \ ... \ p_k^{n+1}]^T,$$
$$\mathbf{p} = [\mathbf{z}^T \ y]^T = [z_1 \ z_2 \ ... z_n \ y_l]^T = [p^1 \ p^2 \ ... p^n \ p^{n+1}]^T \in \mathfrak{R}^{n+1}, \tag{1}$$

where D is the number of input-output data points or data points or data samples or samples, $\mathbf{z}$ is the input vector, and the superscript *T* indicates matrix transposition.

The rule base of TSK fuzzy models with affine rule consequents is [19]

$$\text{Rule } i : \text{IF} z_1 \text{ IS} LT_{i1} \text{ AND} ... \text{AND} z_n \text{ IS} LT_{in} \text{ THEN} y_l^i = a_{i0} + a_{i1} z_1 + ... + a_{in} z_n, i = 1...n_R, \tag{2}$$

where $z_j, j = 1...n$, are the input (or scheduling) variables, *n* is the number of input variables, $LT_{ij}, i = 1...n_R, j = 1...n$, are the input linguistic terms, y_l^i is the output of the local model in the rule consequent of the rule $i, i = 1...n_R$, and $a_{i\chi}, i = 1...n_R, \chi = 0...n$, are the parameters in the rule consequents.

Using the notation $\boldsymbol{\pi}_i$ for the parameter vector of the rule i, $i = 1...n_R$ [19]

$$\boldsymbol{\pi}_i = [a_{i0} \ a_{i1} \ a_{i2} \ ... \ a_{in}]^T, i = 1...n_R, \tag{3}$$

the algebraic product t-norm as an AND operator in the inference engine, and the weighted average defuzzification method in TSK fuzzy model structure, the expression of TSK fuzzy model output y_l is [19]

$$y_l = \frac{\sum_{i=1}^{n_R} \tau_i y_l^i}{\sum_{i=1}^{n_R} \tau_i} = \sum_{i=1}^{n_R} \lambda_i y_l^i, \ y_l^i = [1 \ \mathbf{z}^T] \boldsymbol{\pi}_i, \ \lambda_i = \frac{\tau_i}{\sum_{i=1}^{n_R} \tau_i}, \ i = 1...n_R, \tag{4}$$

where the firing degree of the rule i and the normalized firing degree of this rule are $\tau_i(\mathbf{z})$ and λ_i, respectively. The firing degree of the rule i is [19]

4

$$\tau_i(\mathbf{z}) = \text{AND}(\mu_{i1}(z_1), \mu_{i2}(z_2), ..., \mu_{in}(z_n)) = \mu_{i1}(z_1) \cdot \mu_{i2}(z_2) \cdot ... \cdot \mu_{in}(z_n), \ i = 1...n_R. \tag{5}$$

Several parameters specific to the incremental online identification algorithm are initialized. The initialization is carried out according to the following recommendations given in [33]:

$$\hat{\boldsymbol{\theta}}_1 = [(\boldsymbol{\pi}_1^T)_1 \ (\boldsymbol{\pi}_2^T)_1 \ ... (\boldsymbol{\pi}_{n_R}^T)_1]^T = [0 \ 0 ... 0]^T, \ \mathbf{C}_1 = \Omega \mathbf{I}, \ r_s = 0.4, \ k = 1, \ n_R = 1, \ \mathbf{z}_1^* = \mathbf{z}_k, \ P_1(\mathbf{p}_1^*) = 1, \tag{6}$$

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 relatively large number, $\hat{\boldsymbol{\theta}}_k$ is an estimation of the parameter vector in the rule consequents at the discrete time moment (and also data sample index) k, and r_s, $r_s > 0$, is the spread of the Gaussian input membership functions $\mu_{ij}, i = 1...n_R, j = 1...n$, of the fuzzy sets of the input linguistic terms LT_{ij} [19]

$$\mu_{ij}(z_j) = e^{-\frac{4(z_j - z_{ij}^*)^2}{r_s^2}}, \ i = 1...n_R, \ j = 1...n, \tag{7}$$

z_{ij}^* $i = 1...n_R, j = 1...n$, 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 (2), and $P_1(\mathbf{p}_1^*)$ is the potential of $\mathbf{p}_1^*$.

Step 2. The data sample index k is incremented, namely replaced with $k+1$, and the next data sample $\mathbf{p}_k$ that belongs to the input-output data set $\{\mathbf{p}_k \mid k = 1...D\} \subset \Re^{n+1}$ is read.

Step 3. The potential of each new data sample $P_k(\mathbf{p}_k)$ and the potentials of the centers $P_k(\mathbf{p}_\eta^*)$ of existing rules (clusters) with the index η are recursively updated according to the formulae given in [19] and [33].

Step 4. The possible modification or upgrade of the rule base structure is done using the potential of the new data (point or pair) in comparison with that of the existing rules' centers. The rule base structure is modified if certain conditions specified in [33] 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 algorithms, which can also be viewed as learning algorithms, lead to the updated vectors $\hat{\boldsymbol{\theta}}_k$ (i.e., an estimation of the parameters in the rule consequents at the discrete time step k) and $\mathbf{C}_k$, $k = 2...D$. Several details on RLS are given in [19] and [33].

Step 6. The output of the evolving Takagi-Sugeno-Kang fuzzy model at the next discrete time step $k+1$ is predicted and expressed as $\hat{y}_{k+1}$ [19]

$$\hat{y}_{k+1} = \boldsymbol{\psi}_k^T \hat{\boldsymbol{\theta}}_k, \tag{8}$$

with the general notations (applied to any element of the data set)

$$y = \boldsymbol{\psi}^T \boldsymbol{\theta}, \ \boldsymbol{\theta} = [\boldsymbol{\pi}_1^T \ \boldsymbol{\pi}_2^T \ ... \ \boldsymbol{\pi}_{n_R}^T]^T, \ \boldsymbol{\psi}^T = [\lambda_1 [1 \ \mathbf{z}^T] \ \lambda_2 [1 \ \mathbf{z}^T] \ ... \ \lambda_{n_R} [1 \ \mathbf{z}^T]]. \tag{9}$$

Step 7. The algorithm continues with step 2 until all data points of the input-output data set $\{\mathbf{p}_k \mid k = 1...D\}$ are read.

The output of all evolving TSK fuzzy models is y_k, which represents the position of the SMA wire actuators. In this regard, the generic expression of a TSK fuzzy model is

$$y_k = f(\mathbf{z}_k), \tag{10}$$

where f is the nonlinear input-output map of the TSK fuzzy model. As specified in sections 2 and 3, the input vector $\mathbf{z}_k$ of the TSK fuzzy models contains as an essential element the current signal which supplies the actuator (it flows through the wire). Additional TSK fuzzy model inputs and outputs obtained from past inputs and/or outputs are included in $\mathbf{z}_k$, thus modifying the model structures and leading to different TSK fuzzy models. In this regard, the TSK fuzzy models generally expressed in (10) can be considered as Nonlinear AutoRegressive eXogenous (NARX) models.

As shown in [C4], the first system input, namely the current signal which supplies the actuator, with the notation u_k, was generated by processing the input-output data given in [6] using a sampling period of 0.01 s. The number of input-output data pairs used in training is $D = 500$, which covers a time horizon of 5 s. The number of input-output data pairs used in validation is

5

$D = 2701$, which covers a time horizon of 27.01 s. It is supposed that these ranges of magnitudes and frequencies used in [6] actually cover and capture various process (i.e., SMA wire actuator) dynamics, which are next important in the operation of the position control system. The evolution of the system input versus time is presented in Figs. 2 and 3, which include the input data for both training and validation. The evolution of the output will be
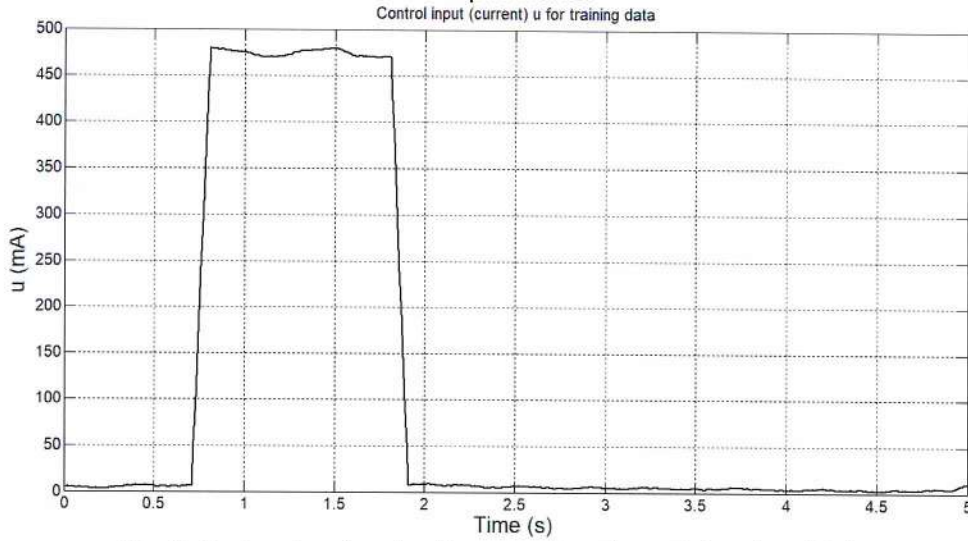

Fig. 2. System input u_k (mA) versus time for training data [C4].
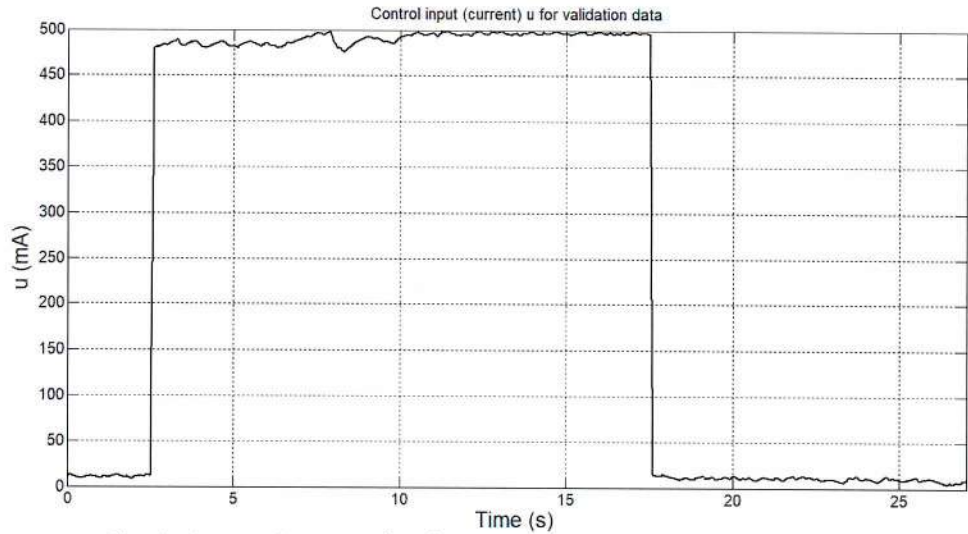

Fig. 3. System input u_k (mA) versus time for validation data [C4].

The graphs presented in Figs. 2 and 3 illustrate the nature of the input values. They illustrate the noisy nature of the signals, which require and justify nonlinear models, and also the fact that the simplification of the models can be achieved. The real system output values will be presented as follows along with the model output.

The past input and output values were actually obtained by shifting the training and validation data samples. Several fuzzy models were tested in this regard but the two ones are described as follows because they are the simplest ones as far as their numbers of parameters are concerned. The first TSK fuzzy model operates with the input vector [C4]

$$\mathbf{z}_k = [u_k \quad u_{k-1} \quad u_{k-2} \quad y_{k-1}]^T, \tag{11}$$

and the second TSK fuzzy model operates with the input vector [C4]

$$\mathbf{z}_k = [u_k \quad u_{k-1} \quad y_{k-1} \quad y_{k-2}]^T. \tag{12}$$

The application of the online identification algorithm presented in the previous section with the RLS algorithm involved in step 5 gave the following results [C4]: the first TSK fuzzy model evolved to $n_R = 9$ rules and the number of evolved parameters is 117; the second TSK fuzzy model

evolved to $n_R = 1$ rule and the number of evolved parameters is 13.

As expected and shown in [19] for a different nonlinear system, the TSK fuzzy models and their performance depend on the number of input variables. Different model structures, i.e., different numbers of rules resulting in different number of evolved (or identified parameters) are obtained for different input variables.

The real-time experimental results on the training data set are presented in Fig. 4 for the first TSK fuzzy model and Fig. 5 for the second TSK fuzzy model. The real-time experimental results on the validation data set are presented in Fig. 6 for the first TSK fuzzy model and Fig. 7 for the second TSK fuzzy model. The results in Figs. 4 to 7 are given as responses of y versus time of the TSK fuzzy models and the real-world system, i.e., the SMA wire actuator). The additional subscript d is inserted to the output value in order to highlight the desired value, i.e., the real-world system output y_d and to differentiate it from the model output y.
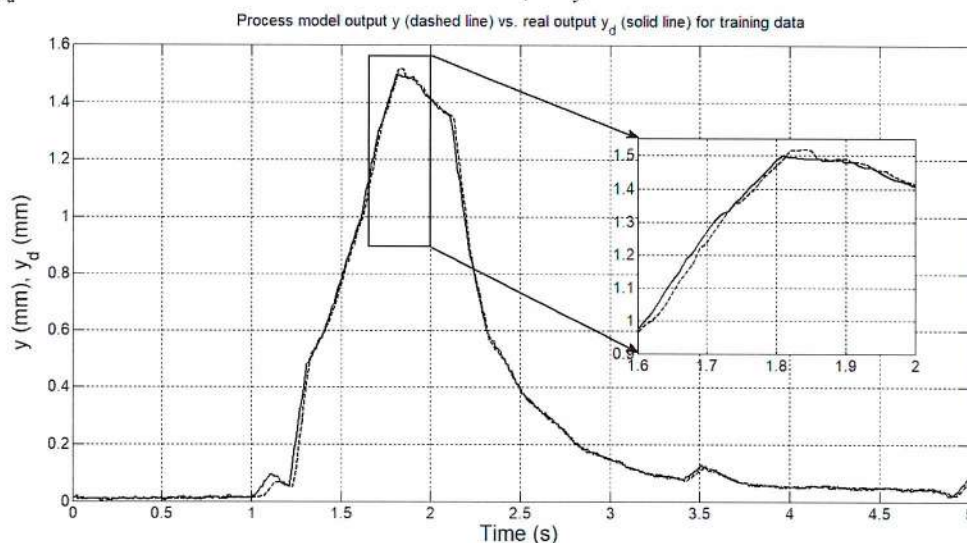

Fig. 4. SMA position versus time of first TSK fuzzy model (dashed line), y_k (mm) and real-world system (solid line). y_{kd} (mm), on training data set [C4].
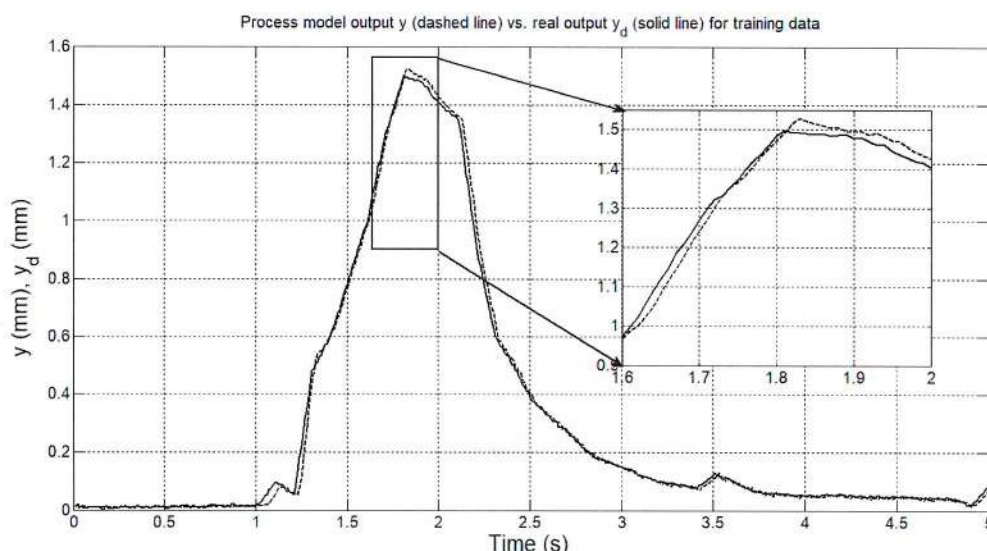

Fig. 5. SMA position versus time of second TSK fuzzy model (dashed line), y_k (mm) and real-world system (solid line). y_{kd} (mm), on training data set [C4].
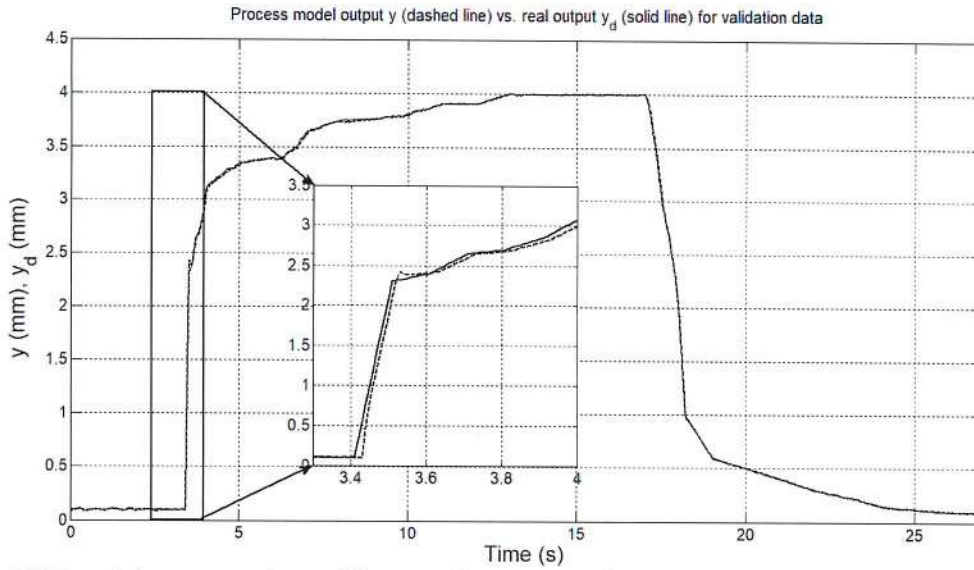
Fig. 6. SMA position versus time of first TSK fuzzy model (dashed line), y_k (mm) and real-world system (solid line). y_{k_d} (mm), on validation data set [C4].
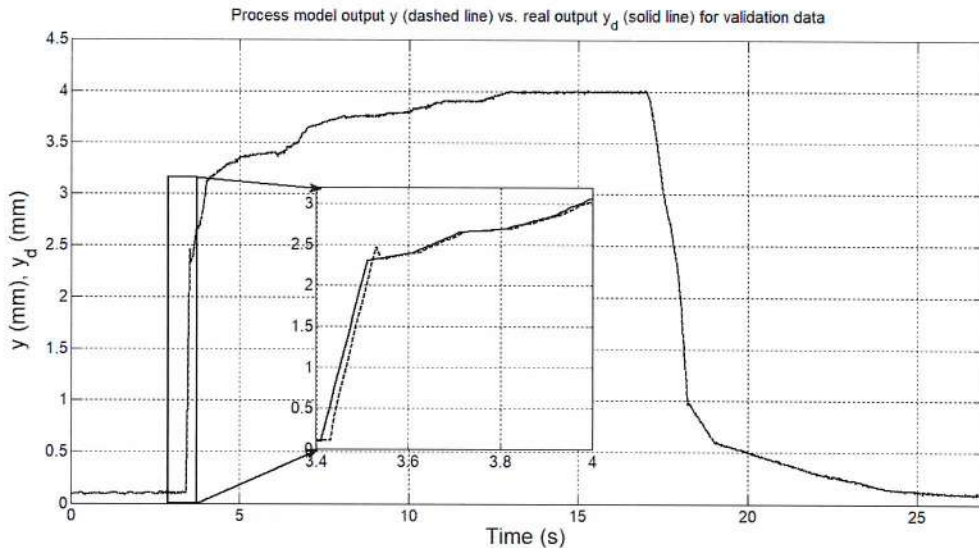

Fig. 7. SMA position versus time of second TSK fuzzy model (dashed line), y_k (mm) and real-world system (solid line). y_{k_d} (mm), on validation data set [C4].

Figs. 4 to 7 show that the validation performance is consistent with the training one. In addition, since no numerical performance comparison is carried out, the visual comparison shows that the first model exhibits overall better performance compared to the second one. That is expected as the number of parameters of the first model is higher compared to the second one. The performance can be further improved if the number of inputs is increased. However, as outlined in [19], a trade-off to performance and model complexity should be targeted. The systematic performance assessment and comparison can be done in terms of using adequate performance indices as, for example, those applied in authors' recent paper [37].

The paper [C4] gives results on training and validation data. As highlighted in [19], this could be a methodological issue because the performance of the models is checked and illustrated on validation data. But these models were selected as the best ones for modeling this validation data considering an as reduced as possible number of inputs resulting in a reasonable number of parameters to be trained (or identified). The model performance should be ideally checked in new unseen test data.

The experiments conducted on the challenging process analyzed in [C4] show that the RLS algorithm involved in step 5 of the online identification algorithm ensures better performance

compared to the wRLS algorithm. However, this is not valid at all system inputs. Moreover, as pointed out in [C4] and authors' recent papers on evolving fuzzy modeling and tensor product-based modeling, the conclusions drawn in this paper cannot be generalized to other processes.

The paper [C4] suggested two TSK fuzzy models to describe the dynamics specific to the position of SMA wire actuators as a representative and challenging SISO system considered as a controlled process. The structures and the parameters of TSK fuzzy models were evolved by an incremental online identification algorithm.

The experimental results given in [C4] illustrate that past outputs and inputs improve the model performance. Adding mode inputs would definitely further improve the model performance, but attention should be paid to the trade-off to performance and model complexity because model-based fuzzy control is one of the future research directions.

These TSK fuzzy models are important because they were built using the data reported in [6], which was collected manually. Therefore, the models suggested here are useful in the digital simulation of the behaviors of SMA wire actuators and allow the convenient testing of various position control system structures.

Bibliografie aferentă capitolului B

[1]   BOJAN-DRAGOS C.-A., *Fuzzy controllers for shape memory alloys systems (FuzzySMA)*, http://www.aut.upt.ro/~claudia.dragos/TE2019.html, accessed: July 5, 2021.

[2]   SOOTHER D.K., DAUDPOTO J., CHOWDHRY B.S., *Challenges for practical applications of shape memory alloy actuators*, Materials Research Express, **7**(7), 073001, 2020.

[3]   KIM H.-J., SONG S.-H., AHN S.-H., *A turtle-like swimming robot using a Smart Soft Composite (SSC) structure*, Smart Materials and Structures, **22**(1), 014007, 2013.

[4]   LAGOUDAS D.C. (Ed.), Shape Memory Alloys: Modeling and Engineering Applications, Springer-Verlag, New York, NY, 2008.

[5]   JANI J.M., LEARY M., SUBIC A., GIBSON M.A., *A review of shape memory alloy research, applications and opportunities*, Materials & Design, **56**, pp. 1078–1113, 2014.

[6]   DOMINIK I., *Type-2 fuzzy logic controller for position control of shape memory alloy wire actuator*, Journal of Intelligent Material Systems and Structures, 27(14), pp. 1–10, 2016.

[7]   ZHANG B., ZHAO X.-G., LI X.-G., ZHANG D.-H., *Robust indirect adaptive control for a class of nonlinear systems and its application to shape memory alloy actuators*, IEEE Access, **6**, pp. 35809–35823, 2018.

[8]   MITULETU I.-C., BIZAU V.I., CHIONCEL C.P., GILLICH G.R., *The design of a test stand for the shape memory alloys control at high current and low voltage*, Proceedings of XIth International Symposium on Advanced Topics in Electrical Engineering, Bucharest, Romania, pp. 1–6, 2019.

[9]   HULEA M., *Bioinspired control method based on spiking neural networks and SMA actuator wires for LASER spot tracking*, in Nature-Inspired Computing for Control Systems, ESPINOSA H.E.P. (Ed.), Studies in Systems, Decision and Control, Springer, Cham, **40**, pp. 13–38, 2015.

[10]   ALSAYED Y.M., ABOUELSOUD A.A., AHMED M.R. BAB F.E., *Fuzzy logic-based PI controller design and implementation of shape memory alloy actuator*, International Journal of Automation and Control, **12**(3), pp. 427–448, 2018.

[11]   SUHEL K., SAI Y., MANI PRABU S.S., PALANI I.A., AMOD C.U., SINGH P., *Active control of smart shape memory alloy composite flapper for aerodynamic applications*, Procedia Computer Science, **133**, pp. 134–140, 2018.

[12]   ENEMARK S., SANTOS I.F., SAVI M.A., *Shape memory alloys applied to improve rotor-bearing system dynamics-an experimental investigation*, Proceedings of 17th International Symposium on Dynamic Problems of Mechanics, Natal, RN, Brazil, pp. 1–10, 2015.

[13]   MATSUMORI H., DENG M.-C., NOGE Y., *An operator-based nonlinear vibration control system using a flexible arm with shape memory alloy*, International Journal of Automation and Control, **17**(1), pp. 139–150, 2020.

[14]   LI X., ZHANG D., ZHANG B., ZHAO X., *Sliding mode control of a SMA actuator based on unscented Kalman filter*, Proceedings of 2018 IEEE International Conference on Robotics and Biomimetics, Kuala Lumpur, Malaysia, pp. 1431–1436, 2018.

[15] YANG H., XU M., LI W., ZHANG S., *Design and implementation of a soft robotic arm driven by SMA coils*, IEEE Transactions on Industrial Electronics, **66**(8), pp. 6108–6116, 2019.

[16] ANDRIANESIS K., TZES A., *Development and control of a multifunctional prosthetic hand with shape memory alloy actuators*, Journal of Intelligent and Robotic Systems, **78**(2), pp. 257–289, 2014.

[17] KIM Y., JANG T., GURUNG H., MANSOUR N.A., RYU B., SHIN B., *Bidirectional rotating actuators using shape memory alloy wires*, Sensors and Actuators A: Physical, 295, pp.512–522, 2019.

[18] KESHTKAR N., RÖBENACK K., FRITZSCHE K., *Position control of textile-reinforced composites by shape memory alloys*, Proceedings of 2019 23rd International Conference on System Theory, Control and Computing, Sinaia, Romania, pp. 442–447, 2019.

[19] PRECUP R.-E., TEBAN T.-A., ALBU A., SZEDLAK-STINEAN A.-I., BOJAN-DRAGOS C.-A., *Experiments in incremental online identification of fuzzy models of finger dynamics*, Romanian Journal of Information Science and Technology, **21**(4), pp. 358–376, 2018.

[20] ANGELOV P., BUSWELL R.A., WRIGHT J.A., LOVEDAY D.L., *Evolving rules-based control*, Proceedings of EUNITE 2001 Symposium, Tenerife, Spain, pp. 36–41, 2001.

[21] ANGELOV P., BUSWELL R.A., *Identification of evolving fuzzy rule-based models*, IEEE Transactions on Fuzzy Systems, **10**(5), pp. 667–677, 2002.

[22] ANGELOV P., *Evolving Rule-Based Models: A Tool for Design of Flexible Adaptive Systems*, Springer-Verlag, Physica-Verlag, Heidelberg, 2002.

[23] ANGELOV P., FILEV D., *Flexible models with evolving structure*, Proceedings of 2002 First International IEEE Symposium on Intelligent Systems, Varna, Bulgaria, pp. 28–33, 2002.

[24] ANGELOV P., FILEV D., *On-line design of Takagi-Sugeno models*, in: T. Bilgiç, B. De Baets, O. Kaynak, Eds., *Fuzzy Sets and Systems - IFSA 2003*, Springer-Verlag, Berlin, Heidelberg, Lecture Notes in Computer Science, vol. 2715, pp. 576–584, 2003.

[25] SADEGHI-TEHRAN P., CARA A.B., ANGELOV P., POMARES H., ROJAS I., PRIETO A., *Self-evolving parameter-free rule-based controller*, Proceedings of 2012 World Congress on Computational Intelligence, Brisbane, Australia, pp. 754–761, 2012.

[26] ANGELOV P., ŠKRJANC I., BLAŽIČ S., *Robust evolving cloud-based controller for a hydraulic plant*, Proceedings of 2013 IEEE Conference on Evolving and Adaptive Systems, Singapore, pp. 1–8, 2013.

[27] BLAŽIČ S., ŠKRJANC I., MATKO D., *A robust fuzzy adaptive law for evolving control systems*, Evolving Systems, **5**(1), pp. 3–10, 2014.

[28] FERDAUS M.M., PRATAMA M., ANAVATTI S.G., GARRATT M.A., LUGHOFER E., *PAC: A novel self-adaptive neuro-fuzzy controller for micro aerial vehicles*, Information Sciences, **512**, pp. 481–505, 2020.

[29] DE CAMPOS SOUZA P.V., LUGHOFER E., *Evolving fuzzy neural hydrocarbon networks: A model based on organic compounds*, Knowledge-Based Systems, **203**, 106099, 2020.

[30] PRECUP R.-E., TEBAN T.-A., ALVES DE OLIVEIRA T.E., PETRIU E.M., *Evolving fuzzy models for myoelectric-based control of a prosthetic hand*, Proceedings of 2016 IEEE International Conference on Fuzzy Systems, Vancouver, BC, Canada, pp. 72–77, 2016.

[31] PRECUP R.-E., TEBAN T.-A., PETRIU E.M., ALBU A., MITULETU I.-C., *Structure and evolving fuzzy models for prosthetic hand myoelectric-based control systems*, Proceedings of 26th Mediterranean Conference on Control and Automation, Zadar, Croatia, pp. 625–630, 2018.

[32] PRECUP R.-E., TEBAN T.-A., ALBU A., BORLEA A.-B., ZAMFIRACHE I.A., PETRIU E.M., *Evolving fuzzy models for prosthetic hand myoelectric-based control*, IEEE Transactions on Instrumentation and Measurement, **69**(7), pp. 4625–4636, 2020.

[33] ANGELOV P., FILEV D., *An approach to online identification of Takagi-Sugeno fuzzy models*, IEEE Transactions on Systems, Man, and Cybernetics – Part B: Cybernetics, **34**(1), pp. 484–498, 2004.

[34] RAMOS J.V., DOURADO A., *On line interpretability by rule base simplification and reduction*, Proceedings of European Symposium on Intelligent Technologies, Hybrid Systems and Their Implementation on Smart Adaptive Systems, Aachen, Germany, pp. 1–6, 2004.

[35]   AIRES L., ARAÚJO J., DOURADO A., *Industrial monitoring by evolving fuzzy systems*, Proceedings of Joint 2009 IFSA World Congress and 2009 EUSFLAT Conference, Lisbon, Portugal, pp. 1358–1363, 2009.

[36]   PRECUP R.-E., PREITL S., BOJAN-DRAGOS C.-A., RADAC M.-B., SZEDLAK-STINEAN A.-I., HEDREA E.-L., ROMAN R.-C., *Automotive applications of evolving Takagi-Sugeno-Kang fuzzy models*, Facta Universitatis, Series: Mechanical Engineering, **15**(2), pp. 231–244, 2017.

[37]   HEDREA E.-L., PRECUP R.-E., ROMAN R.-C., PETRIU E.M., BOJAN-DRAGOS C.-A., HEDREA C., *Tensor product-based model transformation technique applied to servo systems modeling*, Proceedings of 30th International Symposium on Industrial Electronics, Kyoto, Japan, pp. 1–6, 2021.

C. BIBLIOGRAFIE PROPRIE

[C1]   R.-E. Precup, R.-C. David, R.-C. Roman, A.-I. Szedlak-Stînean and E. M. Petriu, Optimal tuning of interval type-2 fuzzy controllers for nonlinear servo systems using slime mould algorithm, International Journal of Systems Science (Taylor and Francis), DOI: 10.1080/00207721.2021.1927236, pp. 1-16, 2021, impact factor (IF) = 2.281, IF according to 2020 Journal Citation Reports (JCR) released by Clarivate Analytics in 2021 = 2.281.

[C2]   A. Topîrceanu and R.-E. Precup, A novel geo-hierarchical population mobility model for spatial spreading of resurgent epidemics, Scientific Reports (Nature), vol. 11, paper 14341, pp. 1-12, 2021, impact factor (IF) = 4.379, IF according to 2020 Journal Citation Reports (JCR) released by Clarivate Analytics in 2021 = 4.379.

[C3]   I. A. Zamfirache, R.-E. Precup, R.-C. Roman and E. M. Petriu, Reinforcement Learning-based Control Using Q-learning and Gravitational Search Algorithm with Experimental Validation on a Nonlinear Servo System, Information Sciences (Elsevier), accepted, impact factor (IF) = 6.795, IF according to 2020 Journal Citation Reports (JCR) released by Clarivate Analytics in 2021 = 6.795.

[C4]   R.-E. Precup, C.-A. Bojan-Dragoş, E.-L. Hedrea, R.-C Roman and E. M. Petriu, Evolving Fuzzy Models of Shape Memory Alloy Wire Actuators, Romanian Journal of Information Science and Technology (Romanian Academy, Section for Information Science and Technology), accepted, to be published in vol. 24, no. 4, pp. 1-13, 2021, impact factor (IF) = 0.643, IF according to 2020 Journal Citation Reports (JCR) released by Clarivate Analytics in 2021 = 0.643.

[C5]   C.-V. Pop, R.-E. Precup and L. I. Cădariu-Brăiloiu, Analysis of Monetary Policy Decisions of the National Bank of Romania with Text Mining Techniques, Proceedings of 2021 IEEE 15th International Symposium on Applied Computational Intelligence and Informatics SACI 2021, Timisoara, Romania, pp. 21-26, 2021, indexed in Clarivate Analytics Web of Science.

[C6]   C.-A. Bojan-Dragoş, R.-E. Precup, S. Preitl, R.-C. Roman, E.-L. Hedrea and A.-I. Szedlak-Stînean, GWO-Based Optimal Tuning of Type-1 and Type-2 Fuzzy Controllers for Electromagnetic Actuated Clutch Systems, Proceedings of 4th IFAC Conference on Embedded Systems, Computational Intelligence and Telematics in Control CESCIT 2021, Valenciennes, France, 2021, IFAC-PapersOnLine, vol. 54, no. 4, pp. 189-194, 2021, indexed in Scopus.

[C7]   E.-L. Hedrea, R.-E. Precup, R.-C. Roman, E. M. Petriu, C.-A. Bojan-Dragoş and C. Hedrea, Tensor Product-Based Model Transformation Technique Applied to Servo Systems Modeling, Proceedings of 30th International Symposium on Industrial Electronics ISIE 2021, Kyoto, Japan, 2021, pp. 1-6, to be published in ieeexplore.

[C8]   I.-D. Borlea, R.-E. Precup and A.-B. Borlea, Improvement of K-means Cluster Quality by Post Processing Resulted Clusters, Proceedings of 8th International Conference on Information Technology and Quantitative Management ITQM 2020 & 2021, Chengu, China, pp. 1-8, 2021, to be published in Procedia Computer Science (Elsevier).

[C9]   R.-C. Roman, R.-E. Precup, E.-L. Hedrea, S. Preitl, I. A. Zamfirache, C.-A. Bojan-Dragoş and E. M. Petriu, Iterative Feedback Tuning Algorithm for Tower Crane Systems, Proceedings of 8th International Conference on Information Technology and Quantitative Management ITQM

2020 & 2021, Chengu, China, pp. 1-8, 2021, to be published in Procedia Computer Science (Elsevier).

[C10]   R.-E. Precup, E.-I. Voişan, R.-C. David, E.-L. Hedrea, E. M. Petriu, R.-C. Roman and A.-I. Szedlak-Stînean, Nature-inspired optimization algorithms for path planning and fuzzy tracking control of mobile robots, in: Applied Optimization and Swarm Intelligence, E. Osaba and X.-S. Yang, Eds., Springer Tracts in Nature-Inspired Computing, Springer, Singapore, pp. 129-148, 2021.

Director proiect,

Prof.dr.ing. Radu-Emil Precup