MULTI-MOTOR DRIVE NON-PARAMETRIC BLACK-BOX FUZZY MODEL

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The multi-motor drives, the typical examples of which are continuous lines (CL) for tension processing of various materials are complex and coupled MIMO higher-order nonlinear systems, which parameters are difficult to identify. The article focuses on a method for the design of a non-parametric black-box fuzzy model of a continuous production line with emphasis on minimal knowledge on the modelled system. The proposed fuzzy model structure is based on the state space representation of the dynamic system in discrete form, which only requires a suitable set of information on its input/output relations. The properties of the proposed CL fuzzy model were verified by experimental measurements on a CL laboratory model. The obtained results have confirmed the rightness and effectiveness of the fuzzy model design method that can be applied not only in the field of industry technologies with CL but also in modeling and control of nonlinear dynamic systems.

KEYWORDS

Multi-motor drive, fuzzy modeling, MIMO nonlinear systems, Black-Box fuzzy model, cluster analysis

1 INTRODUCTION

Typical examples of processes in technological practice the analytical description of which is rather complicated are combustion processes, temperature and pressure control of steam injection into power plant boilers, pressure control in injection moulding machine chambers, and also continuous technological lines for continuous processing of materials (sheet metal, foil, paper...).

However, information on the performance of these processes can often be obtained experimentally (by suitably chosen measurements or by monitoring their responses to the control activities of the operator). In these situations, fuzzy systems can always be considered as an alternative for system modeling.

The main advantage of a fuzzy logic system (FLS) is the capability of expressing nonlinear input/output relationships by a set of qualitative if-then rules. FLSs have the capability to handle both numerical data and linguistic knowledge, which is extremely difficult to quantify by means of traditional mathematics [Babuska 1997, Pedrycz 1984]. Therefore, they offer alternative solutions when the system cannot be expressed in terms of equations, i.e., when the mathematical model does not exist or is ill-defined. So far, most attention has been devoted to single-input, single-output (SISO) or multi-input, single-output (MISO) systems [Khalifa 2022, Salgado 2016]. Relatively little attention has been devoted to the identification of MIMO fuzzy models from input-output data [Babuska 1998, Salgado 2017, Kuram 2013]. It has been proved that fuzzy modeling can be recognized as one of the nonlinear black-box modeling techniques [Juditsky 1995, Sjoberg 1995]. The problem in the development of black-box fuzzy models of these systems lies in obtaining their qualitative properties on the basis of measured experimental data, having no prior knowledge on the parameters and structure of these systems. That often results in an inconsistent database, in problems with covering the entire possible space of the fuzzy system inputs, etc. [Leso 2018, Liu 2016, Johansen 1994]. The fuzzy model obtained in this way may be very inaccurate and even unusable in industry applications.

When a suitable method of data collection is used, or a suitable selection of qualitative data from the database is made, it is possible to construct a corresponding black-box fuzzy model of the unknown nonlinear dynamic system as it is shown in this paper. The functional dependencies between inputs and outputs can then be used for developing a suitable non-parametric black-box fuzzy model of the dynamic system described in state space discrete form. Proposed fuzzy model that can be applied in the design of CL control and also in the identification of CL parameters and non-measurable additive disturbances influencing the system control. The realized experimental measurements on a continuous line physical laboratory model confirmed the effectiveness and the quality of the proposed CL fuzzy model and also its applicability to MIMO nonlinear dynamic systems with as little previous knowledge as possible.

2 MODELLED SYSTEM DESCRIPTION

A typical representative of multi-motor drive is the continuous line, where the individual working machines are coupled by each other through the material. They are, e.g. lines for processing continuous flows of material (e.g. sheet metal strips, tubes, processing lines in paper mills and printing works, etc.) by material traction in the field of elastic or plastic deformation, which influences the material´s mechanical properties.

These lines usually consist of three autonomous sections [Jefteniü 2006]:

- The entry section consisting of unwinding machine is determined for accumulating a stock of material for the technological section and for reduction of traction in the strip.
- The technological section, where are carried out technological operations according to the technological formula for particular material.
- The exit section consisting of winding machine, where coiling of the strip of material takes place.

In industrial practice there exist many various typical multi-motor drive configurations [Jefteniü 2006] where the tension in the web arises due to different circumferential speeds of the work rolls, partially due to the difference of their positions. For simplicity only the coupling of two machines (central part of continuous line) is investigated but this idea can be extended to an indefinite number of machines bound by processed material. Figure 1 shows the structure of the central section of the continuous line. The structure includes DC motors powered through static transistor converters TC. The working machines of the line are driven by the motors through gearbox j; v_1, v_2 are machine rolls circumferential velocities, F_{12} is the tension in the web of material between the two machines. The main line disturbances are tensions before and after the central part of the considered line which are affecting the first and second drive (F_{01} and F_{23}). K_v are circumferential speed sensors, K_F is tension sensor, r is roll, radius, u_{v1}, u_{v2} are outputs from speed sensors and u_{F12} is the output of the tension sensor. The controlling voltages u_1, u_2 of converters present the input variables of the system. The tension in the web of material F_{12} and the web of material velocity v_2 are the output variables (let us consider $y_1=u_{F12}$ and $y_2=u_{v2}$).

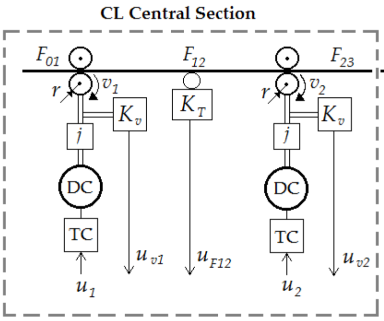

Figure 1. Structure diagram of central section of a continuous line.

The corresponding block diagram is shown in Figure 2. It is a simplified model where we assume that the static transistor converters (TC) have proportional gain and built-in fast current control loops. If the mechanical time constant of the drive is much greater than the electrical time constant of the motor, neglected can be the dynamics of the current loops. By such simplification, the current loop can be replaced with satisfactory precision by the transfer function $1/K_I$ where K_I is the current sensor gain. By such simplification the current references I_1* and I_2*present inputs into CL model.

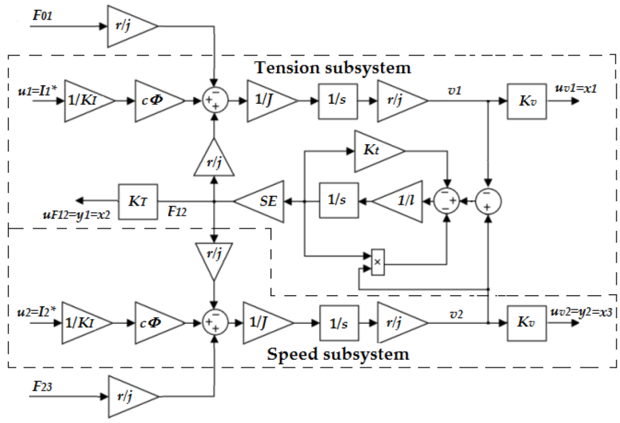

Figure 2. Block diagram of the central section of the continuous line.

The elastic coupling is modelled according to Brandenburg [Brandenburg 1973], taking into consideration variable time mechanical constant of the running elastic strip depending on the strip speed which makes the model nonlinear. In Figure 2, l is distance between the rollers of the work machines, S – the cross-section of the processed material, E represents the Young modulus of elasticity, K_t – material damping constant, J – total moment of inertia on the motor shaft (let us consider for sake of simplicity that both motors and work machines are similar) and $c\Phi$– torque constant of the motor.

The described system with the mechanical coupling of two machines presents a 3rd order nonlinear MIMO system with two inputs and two outputs (Fig.3). In the block diagram in Fig.2 the state variables were chosen as follows: $x_1= u_{v1}$, $x_2=y_1=u_{F12}$ and $x_3=y_2=u_{v2}$.

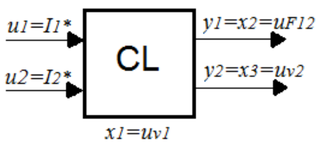

Figure 3. The central section of the continuous line as MIMO system.

For the design and verification of the continuous line fuzzy model we used experimental measurements taken from its physical model built at the Department of Electrical Drives and Mechatronics of the Faculty of Electrical Engineering and Informatics, Technical university of Kosice.

3 PHYSICAL MODEL OF THE CONTINUOUS LINE

The physical model of the continuous line represents a functional model of multiple-motor drive technology coupled by a strip of material. The physical model includes a strip unwinder and winder and three transfer rolls over which the strip of material passes (magnetic tape 0.03 m wide). Between the unwinder, the work rolls and the winder the material creates a loop in which it is tensioned by a movable tension roll (Fig. 4).

It is obvious from Fig. 2 that the continuous line roll drives are "coupled" together through the strip of material. From the physical analysis of the continuous line model [Jefteniü 2006, Brandenburg 1973] it follows that the system contains a fast (tension) subsystem and a slow (speed) subsystem. The parameters of the system change depending on the mechanical properties of the material and on the speed of its motion.

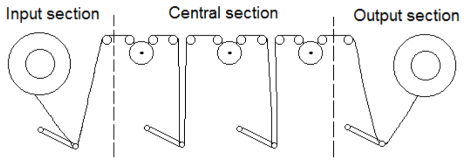

Figure 4. Structure of the physical model of continuous line.

As a result, the strip tension corresponds to the position of the tension roll. The model is driven by 5 DC disc motors powered by Allen Bradley DC converters 1386 DC Servo Drive System with PWM modulation. The control system is based on programmable controller PLC S7-400 with technological card FM458. CFC language was used for control program development. The physical model inputs are the control voltages for converters in the range of ± 10V, and the outputs are the velocities of the individual drives and the tensions in the sections between the work rolls. Incremental sensors (IRC) which generate 4000 increments per revolution were used for measuring the revolutions of all the motors. Sensing of the tensile force is carried out indirectly, by monitoring the position of the tension rolls with a potentiometric sensor, where it is changed to voltage and is brought directly onto the analogue inputs of the control system.

Speeds and tensions of individual drives from position sensors are output variables of the physical model. Elastic material properties are simulated by mechanical changing spring, which causes the elongation of the web of magnetic tape.

The physical model of the continuous line is shown in Figure5.

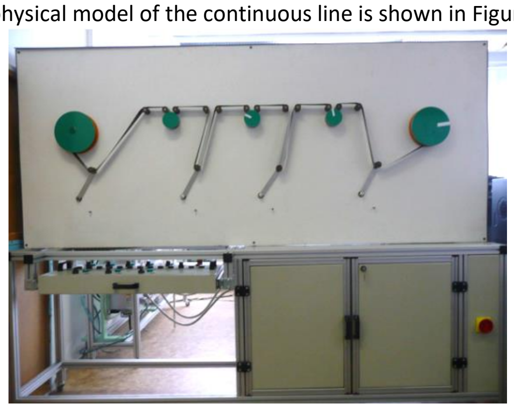

Figure 5. The physical model of the continuous line.

To determine basic properties of CL, experimental identification measurements were performed on the physical model of the CL for current pulses applied sequentially to each input of the model. In Figure 6 the reference signals of I_1^* – the first motor current and I_2^* – the second one are shown. The measurements were performed with a sampling time of 1 ms, and the outputs are illustrated in Fig.7.

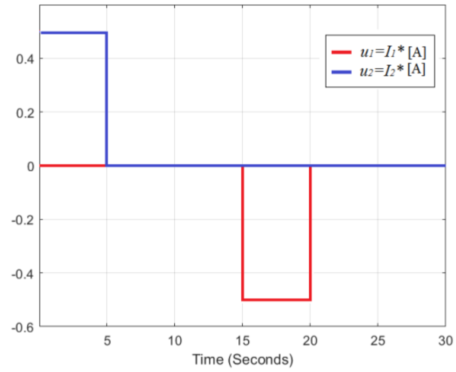

Figure 6. Input signals $u_1=I_1^*$and $u_2=I_2^*$ for identification measurements

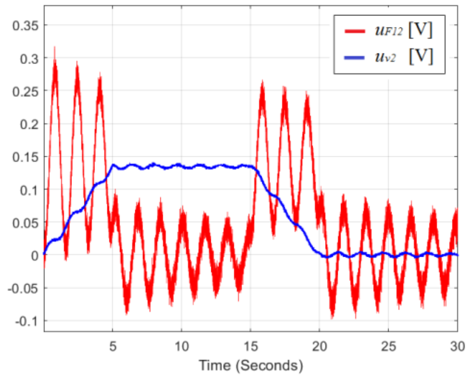

Figure 7. Time responses of the subsystems: the tension $y_1 = u_{F12}$ and the speed $y_1 = u_{v2}$ to the input pulses illustrated in Fig.6.

From time courses in Fig. 7 it is seen that the system contains a fast (tension) subsystem with oscillating response and a slow (speed) subsystem. They are coupled and mutually interact. In such MIMO system a strong interaction between the transfer channels of the tension and of the speed leads to worsening of the strip quality, even can lead to destruction of the processed strip.

Defining precise parameters of such nonlinear system analytically presents a rather demanding task, and therefore it is suitable to use for its description a fuzzy model obtained only on basis of its measured input/output data.

The parameters of the CL physical model are specified in the Appendix.

4 CONTINUOUS LINE CENTRAL SECTION FUZZY MODEL DESIGN

Various possible fuzzy system structures exist, both as regards their static fuzzy subsystem (Mamdani, Sugeno ...), or their dynamic subsystems. From this point on we shall consider a fuzzy model structure based on the state concept of a discrete dynamic system, according to which the state of a system in a particular step depends on its state in the previous step and on the increment in state between these steps, which is a function of the preceding inputs and states. This concept can be expressed mathematically by the following equations

$$x_k = x_{k-1} + dx_k$$

$$dx_k = f(u_{k-1}, x_{k-1}) \qquad (1)$$

where $\boldsymbol{u}$ is the model´s input quantities vector, $\boldsymbol{x}$ is the state quantities vector, f is the searched for static vector function of the modelled system, and k represents the sampling step.

The static subsystem is in this case is represented by the static function $f(\mathbf{u}_{k-1}, \mathbf{x}_{k-1})$, which comprises information on the structure and the parameters of the given subsystem.

Construction of the CL fuzzy model consists in determining the fuzzy approximation of this function on basis of the obtained CL inputs and outputs database.

Considering the choice of CL input, state and output quantities presented in Fig. 3, the structure of the proposed CL fuzzy model is shown in Fig. 8.

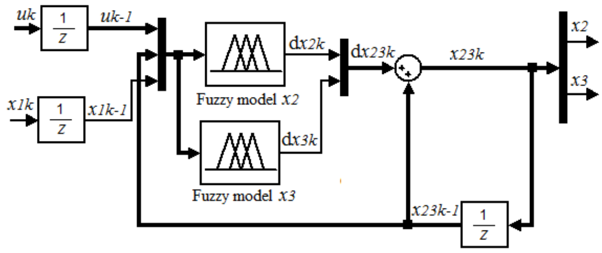

Figure 8. Structure of the discrete CL fuzzy model.

The first step in the design of the fuzzy model for the central section of the continuous line is the establishment of a consistent database from measured inputs and their corresponding outputs, which covers its entire assumed work space. In a consistent database, the database does not contain different output values for the same input values [Fedor 2013]. This can basically be achieved either by exciting the system by a suitable statistic input signal $u(t)$ [Babuska 1997], or by an input signal which evenly divides the entire input space [Yan 2014]. Using a random input signal is suitable for existing systems with which it is not possible (e.g. for operational reasons) to enforce predetermined inputs to the system. Such a database can be obtained also in the course of normal operation of the modelled system which is controlled by an operator who is the "generator" of input signals. In principal, no previous information on the characteristics and the structure of the modelled system is required in this case. Typical examples would be continuous technological lines for material processing, temperature control in power plant units, chemical technological processes, etc.

Assume the operation range of input u_2 for line velocity tuning is [-3, 3] and of input u_1 for strip tension tuning [-1, 1]. Then for generating the database for CL fuzzy model construction we can apply a systematic transition over the operation range e.g. by applying step change of line velocity u_2 every 12s and then in 1s intervals exciting the faster oscillating part of the system to both sides by input u_1. The performance of the generated inputs for CL is illustrated in Fig. 9. Time responses of corresponding outputs $y_1=u_{F12}$ and $y_2=u_{v2}$ are shown in Fig. 10.

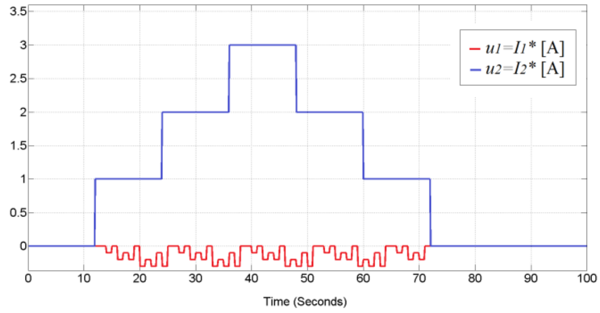

Figure 9. Input generator for collection of database for fuzzy model.

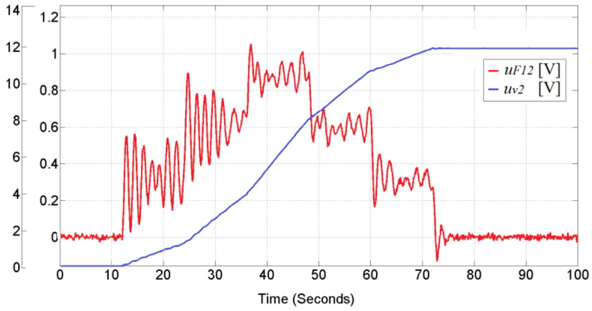

Figure 10. Time waveform of the tension u_{F12} and the speed u_{v2} in CL for the inputs illustrated in Fig.9.

The database for CL fuzzy model was generated as demonstrated in Fig. 11. The state quantity $x_1=u_{v1}$ also needs to be entered into the database. With sampling time T=0.1s we obtained a database with 1000 samples. A sampling time T was determined based on Shannon-Kotelnikov theorem from measured transient responses in Fig.7.

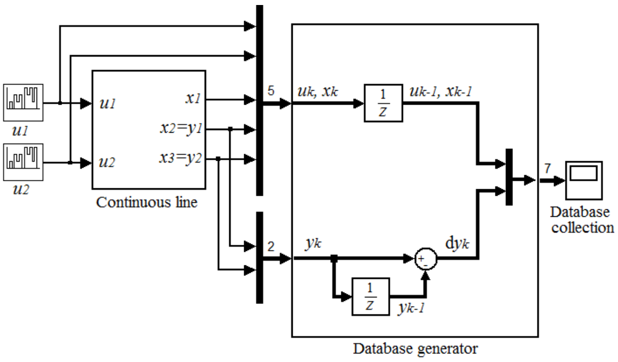

Figure 11. Database generator for CL fuzzy model.

This measured database can be used for serching two FIS structures of the given nonlinear system which best describe the measured relations between [u_{1k-1}, u_{2k-1}, x_{1k-1}, x_{2k-1}, x_{3k-1}] → dy_{1k}, and [u_{1k-1}, u_{2k-1}, x_{1k-1}, x_{2k-1}, x_{3k-1}] → dy_{2k}.

Using the measured database, the particular fuzzy models can be designed by standardly known procedures of cluster analysis and adaptive approaches. The fundamental features of cluster analysis are reduction of the number of fuzzy rules and setting of good initial rule parameters. For our purpose from the numbers of methods for adaptive fuzzy systems development [Vo 2020, Ferreira 2015, Salgado 2017, Schafer 2015] we chose the adaptive neuro-fuzzy inference system (ANFIS) with subtractive clustering [Fedor 2016, Vu 2012]. The ANFIS approach uses Gaussian functions for fuzzy sets, linear functions for the rule outputs, and Sugeno's inference mechanism [Liao 2005, Zuo 2017]. Subtractive clustering determines the optimal clusters in a multi-dimensional input/output space that accurately represent the data [Rani 2012], in our case CL behavior. Subtractive clustering was running with the following parameters: Range of influence=0.4, Squash factor=1.25, Accept ratio=0.4, Reject ratio=0.01. The results were two static Sugeno type fuzzy systems with two rules for each output quantity as is shown in Figure 12a. Fuzzification of inputs of this fuzzy system is illustrated in Figure 12b. These obtained fuzzy systems were implemented into the final continuous line fuzzy model structure, as illustrated in Figure 8.

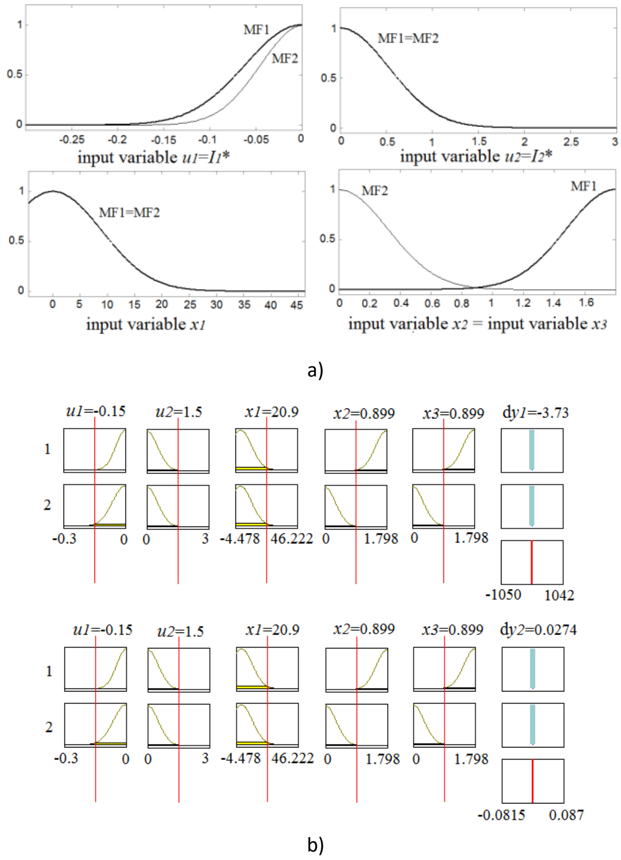

Figure 12. a) Fuzzyfication of CL fuzzy model inputs (MF=membership function), b) SUGENO type fuzzy system with 2 rules.

The properties of the designed CL fuzzy model were verified by experimental measurements on the physical laboratory model described in Chapter 3.

The CL fuzzy model verification was firstly carried out for input values, on basis of which the database for fuzzy model design was measured. The responses of the CL fuzzy model for these identification inputs are illustrated in Fig.13 and Fig.14.

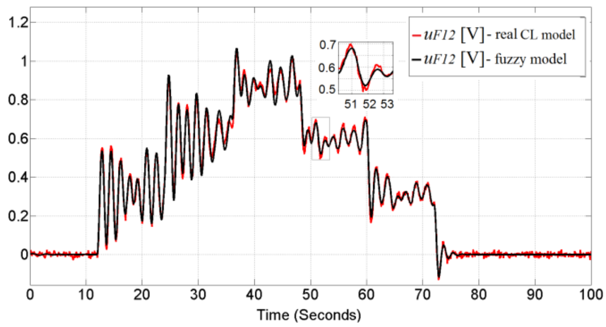

Figure 13. Comparison of fuzzy model and real physical model output $u_{F12}=y_1$ for a continuous line.

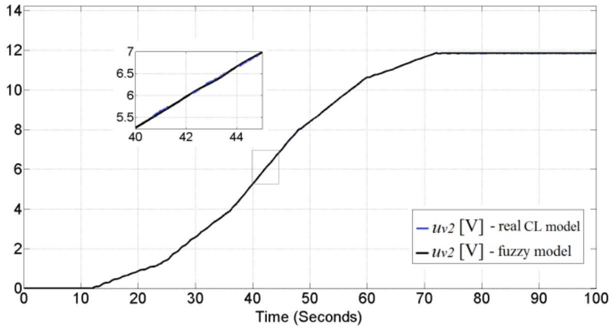

Figure 14. Comparison of fuzzy model and physical model output $u_{v2}=y_2$. for a continuous line.

To verify the correctness of the CL fuzzy model, randomly generated signals u_1 and u_2 were applied to its input, as demonstrated in Fig. 15.

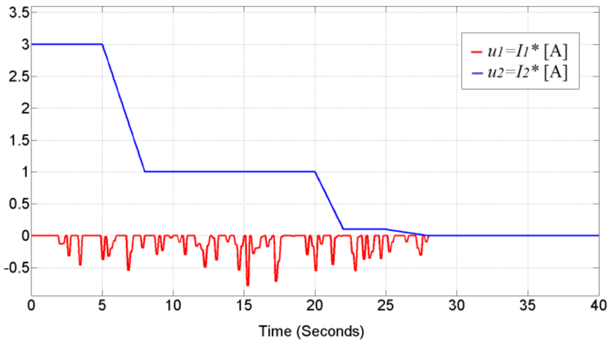

Figure 15. Rrandomly generated input signals u_1 and u_2.

The comparison of the fuzzy model outputs and CL physical model outputs for these inputs is shown in Fig. 16 and Fig.17.

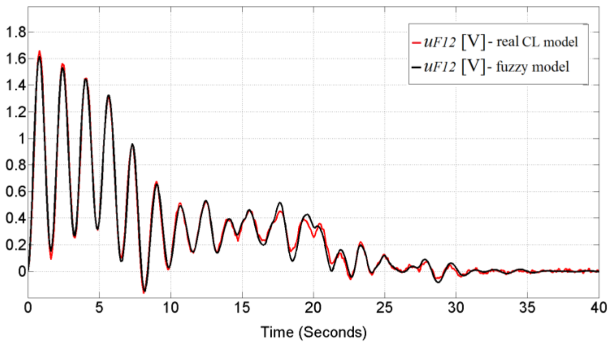

Figure 16. CL fuzzy model output y_1 performance for randomly generated inputs u_1 and u_2.

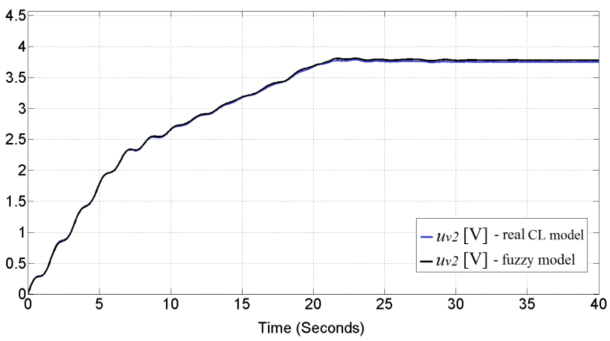

Figure 17. CL fuzzy model output y_2 performance for randomly generated inputs u_1 and u_2.

The obtained results confirm that the proposed fuzzy model very precisely approximates the performance of the continuous line physical model for identification inputs and also for randomly generated inputs.

5 DISCUSSION AND CONCLUSION

The paper presents a method for the construction of a fuzzy model of a continuous processing line. The model is designed only on basis of suitably measured relations between the system´s inputs and outputs, without the necessity of preliminary knowledge of its internal structure and parameters. In terms of the available information the modelled system may be considered as a typical Black Box system. The database for the construction of such model should be consistent. In order to achieve this goal, it is necessary to generate suitable input signals at the input of the modeled system (Fig. 9) to collect data into the database, which regularly cover its entire working range. A systematic procedure aimed at meeting this condition is presented in the paper.

The sampling time T is also important for creating a database, because the number of measured samples for the database grows as T becomes shorter and similarly the number of transitions influences the complexity of further database processing. In our case, the sampling time was chosen based on the Shanon-Kotelnik theorem (T=0.1s), which was sufficient for the design of a high-quality and simple fuzzy model (Fig. 12).

The fuzzy model design is based on the basic idea of dynamic system description in state space. The number of state quantities of the modelled system (i.e. the order of the system) represents important information. If we choose a smaller order of the fuzzy model than that of the modelled system, it will result in ambiguity and inconsistency of the fuzzy model rules, which reduces its quality. To derive the fuzzy rules, subtractive cluster analysis is applied. For the adaptive approach, a hybrid arrangement that uses a fuzzy inference engine in connection with a neural network was used (ANFIS tool). The result was two simple fuzzy models with two Sugeno-type rules for tension and speed subsystem of continuous line (Fig. 12).

The proposed fuzzy modeling method was verified by experimental measurements on a real physical model. The designed CL fuzzy model properties have been demonstrated by comparing its outputs with those of the physical model for identification (Fig. 9) and randomly (Fig. 15) chosen input signals into the individual drives of the line. The obtained results have confirmed that the fuzzy model designed in this way can be very simple and at the same time can very well approximate the performance of a continuous line as a nonlinear system with multiple inputs and outputs (Figs. 13-14, Figs. 16-17). With this method no principal limitations for the modelled system´s nonlinearities are defined.

Considering the quality of the proposed fuzzy model this fuzzy modeling method can be used to design various fuzzy model based control structures for controlling MIMO nonlinear systems, systems with transfer lag, complex systems, etc., the analytical model of which would be very difficult to describe, or the concrete parameters of which would be hard to obtain by analysis in practice. In mentioned control applications, a detailed analysis of the internal structure and parameters of such systems is often substituted by estimation of their performance on basis of an experimentally obtained fuzzy model. Described fuzzy model method could also be used in the identification of non-measurable additive disturbances influencing the MIMO system, principally in real time.

The proposed method of fuzzy model design for a Black-Box nonlinear dynamic system for which only external information is available can be considered as an enhancement to the wide range of fuzzy modeling methods. Regarding to its simplicity and high-quality this method could find wide use in multi-motor drives in steel industry, paper-making, printing and textile industries, in the production of synthetic fibres and foils in the chemical industry and in other industries.

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APPENDIX

Parameters of the physical model:

DC motors:

U_N = 24 V	n_N = 3650 rpm-s
R_a = 0.7 Ω	I_N = 8.5 A
P_N = 140 W	L_a = 0.1 mH
M_N = 0.39 Nm	J = 0.002 kgm^2
j = 24	$c\phi$ = 0.043 Vs
F_N = 250 N	I_{max} = 20 A

Converters:

T_{TM} = 0.1 ms

Sensors:

Current sensor K_I = 2V/A

Velocity sensor K_v = 6.6 V/ms^{-1}

Tension sensor K_F = 0.022 V/N

Working rolls:

r = 0.04 m, v_{max} = 1.5 ms^{-1}

Processed material:

b = 0,03 m, h = 0,5·10^{-3} m, $S = bh$ = 15 10^{-6} m^2, E = 1,8·10^9 Nm^{-2}, SE = 27 10^3 N

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