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Fuzzy Based Method For Optimal Control

Pavol Fedor
Department of Electrical Engineering and Mechatronics
FEI, Technical University of Kosice
Slovakia
pavol.fedor@tuke.sk

Daniela Perdukova
Department of Electrical Engineering and Mechatronics
FEI, Technical University of Kosice
Slovakia
daniela.perdukova@tuke.sk

***Abstract*— The paper describes the application of fuzzy logic in the procedure of designing the parameters of a controller that will secure energetically optimal control dynamics of a dynamic system with defined boundary requirements. The proposed method has been verified on a concrete example of parameter design for a PI controller of a DC drive with non-linear load. Selection of controller parameters has been done by the fuzzy model of the system obtained from the system identification of measured inputs and outputs data. The performance of the developed method has been tested and verified using simulation in MATLAB Simulink.**

Keywords—fuzzy model; optimal control; DC drive;

I. INTRODUCTION

One of the basic ways of increasing the energetic efficiency of existing or newly designed electro-energetic equipment is the optimization of its operation through the application of better ("intelligent") control technologies. The design of controllers with firmly specified parameters is not always optimal from this point of view, as the exact controlled system parameters are either not known, or they can change during the operation of the equipment (e.g. the resistance values of electric motor windings can change after warming by as much as 30%, the drive load may be non-linear, etc.) [1,2]. It is therefore advisable to identify the existing parameters of the controlled system and use these as a basis for the selection of energetically optimal controller parameter values.

For designing the parameters of a continuous dynamic system controller that is energetically optimal we used fuzzy model of controlled system generated through its identification from the measured inputs and outputs.

It has been proved that fuzzy modelling can be recognized as one of the nonlinear black-box modelling techniques [3-5]. When designing a black-box fuzzy system, it is necessary to identify its qualitative properties only on the basis of experimentally measured data, while neither its structure nor its parameters are known. That often results in problems with inconsistency of the database, problems with covering the entire space of possible inputs, etc. [6], which makes the fuzzy model unusable in practical applications. In the design of a black-box fuzzy model of a dynamic system, a suitable method for the selection of qualitative properties from the collected database always needs to be applied. The functional dependencies between inputs and outputs can then be used for developing a suitable non-parametric fuzzy model of the process that can be applied in the design of their control [7-9].

This paper presents one of the possible methods of this procedure which is based on the exploitation of fuzzy system knowledge. A brief description of the design process of the fuzzy model of the system concerned, as well as of the procedure of its exploitation in the optimisation of the PI controller parameters are provided. The applied method is tested and verified by simulations on a drive with a DC motor in MATLAB Simulink, and possible energy savings achieved through drive control are presented.

II. FUZZY MODEL DESIGN OF A DYNAMIC SYSTEM

The general form of state-space description of the dynamical system we want to control is

$$\dot{\mathbf{x}} = \mathbf{A}\dot{\mathbf{x}} + \mathbf{B}\mathbf{u} \qquad (1)$$

where **A** is system matrix, **B** is input matrix, **x** is vector of state variables and **u** is vector of system inputs.

In discrete form system (1) can be described by equation

$$x_{k+1} = x_k + \Delta x_k$$
$$\Delta x_k = f(u_{k-1}, x_{k-1}) \qquad (2)$$

This means that the state of the system in step *k* is a function (generally unknown and nonlinear) of the system state and system inputs in step (*k-1*).

Construction of the dynamic system fuzzy model consists in determining the fuzzy approximation of this function on basis of the obtained dynamic system inputs and outputs database. Numerous different dynamic system fuzzy model structures are described in literature [10-15]. Mentioned methods require at least partial information about the control system structure and parameters. Proposed methods in this article uses only experimental measured data from controlled system.

Creating of the fuzzy model for dynamic system (1) was based on its discrete form description according to equation (2). It generally applies that a change in the state of a system (1) at a given moment depends on its input and on its state in the preceding moment. Its discrete description (relation between state *x* and input

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u) can then be described by means of fuzzy rules in the following form

$$\text{IF } u_k \text{ is ... and } x_k \text{ is ... THEN } \Delta y_k \text{ is ...} \tag{3}$$

where index *k* denotes the value of the variable in the k^{th} sampling step and the terms u_k is ... , x_k is ... , Δy_k is ... represent the relevant fuzzy definition areas of the given variable. Based on the above we can set up a block diagram of the dynamic system fuzzy model (Fig. 1), where block z^{-1} represents the delay by one sampling step.

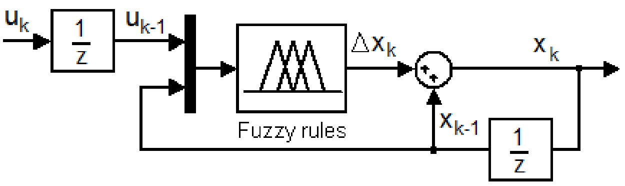

Fig.1 Block diagram of dynamic system fuzzy model

In order to set up a fuzzy model we need to accumulate a database of appropriate input/output signals from the system, e.g. in a configuration shown in Fig.2. The fuzzy model will thus be designed on basis of the measured relations between [$\mathbf{u}_{k-1}$, $\mathbf{x}_{k-1}$] → $\Delta\mathbf{x}_k$, and the particular input signal values of the system input will be such that will cover the whole range of possible inputs and by that the whole working space of possible system states.

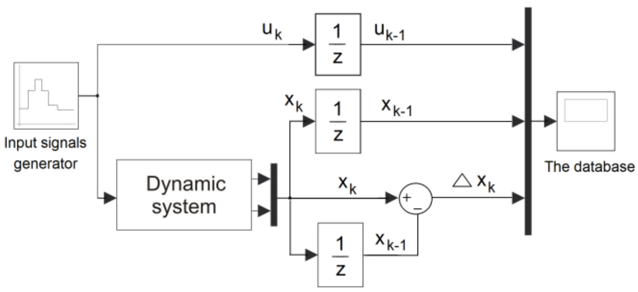

Fig.2 Creating the database for fuzzy model setup

Using the measured database, the particular fuzzy model can be designed by standardly known procedures of cluster analysis and adaptive approaches to improve the quality of modelling and reduce development time. The fundamental features of cluster analysis are reduction of the number of fuzzy rules and provision of good initial rule parameters. For our purpose from the large number of methods for adaptive fuzzy networks development we chose the adaptive neuro-fuzzy inference system (ANFIS) with subtractive clustering [16-19], which is a fast and robust data analysis method.

Let us consider a separately excited DC motor with parameters K_A=0.625 Ω^{-1} , T_A=0.01 s, cφ=0.7 Vs, J=0.03 kgm^2 as a 2nd order dynamic system. The state variables were chosen as follows: x_1=*ω* (motor angular speed) and x_2=I_A (motor armature current). Numerical values of matrices in state space description of this system are listed in the Appendix.

The first step in the design of the fuzzy model for the DC motor is the establishment of a consistent database from measured inputs and their corresponding outputs, which covers its entire assumed work space and describes the behavior of the modelled system. For establishing a consistent database we can use, for example, the method of dividing the input range into n-levels and generating n(n-1) transient trajectories between them [3, 8]. Knowledge of the structure or of the parameters of the modelled system is not required in this method. To define suitable sampling time *T* (according to the Shannon-Kotelnikov theorem) and approximate times for transitions for database measurement, we performed identification measurements considering a fan-type load torque M_z=kx_1^2 (*k*=0.0001) and input voltage U_A = 30V (Fig. 3)

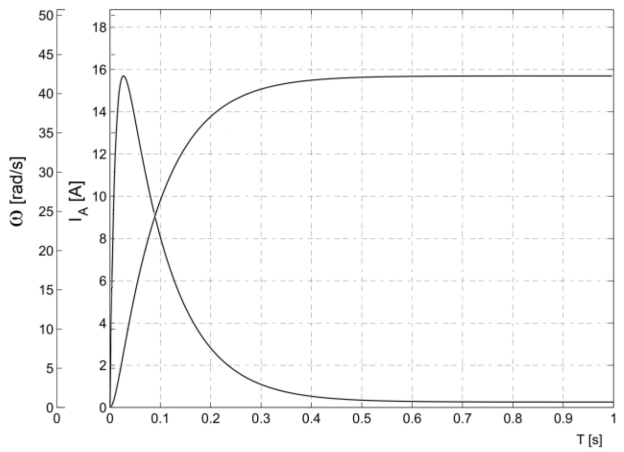

Fig.3 DC motor response to voltage jump on armature

The structure of the fuzzy model of a DC drive representing a 2nd order dynamic system is shown in Fig. 4. The fuzzy model consists of two fuzzy subsystems for the individual state variables of the drive and each fuzzy subsystem has three inputs and one output.

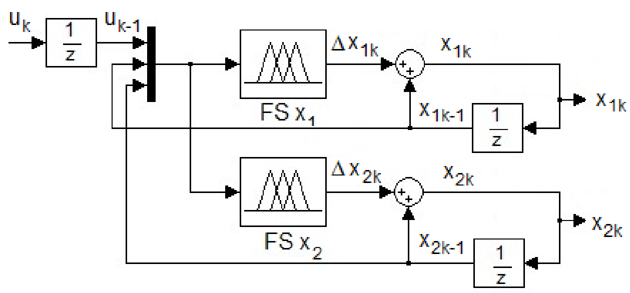

Fig.4 Fuzzy model of DC drive

It is clear that in order to create a fuzzy model for the entire operational area of the drive it is necessary to measure the relations between [u_{k-1}, x_{1k-1}, x_{2k-1}] → Δx_{1k}, and [u_{k-1}, x_{1k-1}, x_{2k-1}] → Δx_{2k}. in all of its potential states. In our case we divided the range of input voltage from 0 to 220 V into 10 levels and for the database for fuzzy model generation we measured the required values of state variables for all transitions between these values.

For creating fuzzy model we used tool ANFIS in MATLAB with subtractive clustering having the following parameters: Range of influence=0.4, Squash factor=1.25, Accept ratio=0.4, Reject ratio=0.01. Subtractive clustering determines the optimal clusters [18] in a multi-dimensional input/output space that accurately represent the data [5-6] and DC drive behaviour. The ANFIS approach uses Gaussian functions for fuzzy sets, linear functions for the rule outputs, and Sugeno's inference mechanism [15]. The results were two static Sugeno type fuzzy systems with eight rules for each output quantity as is shown in Fig.5.

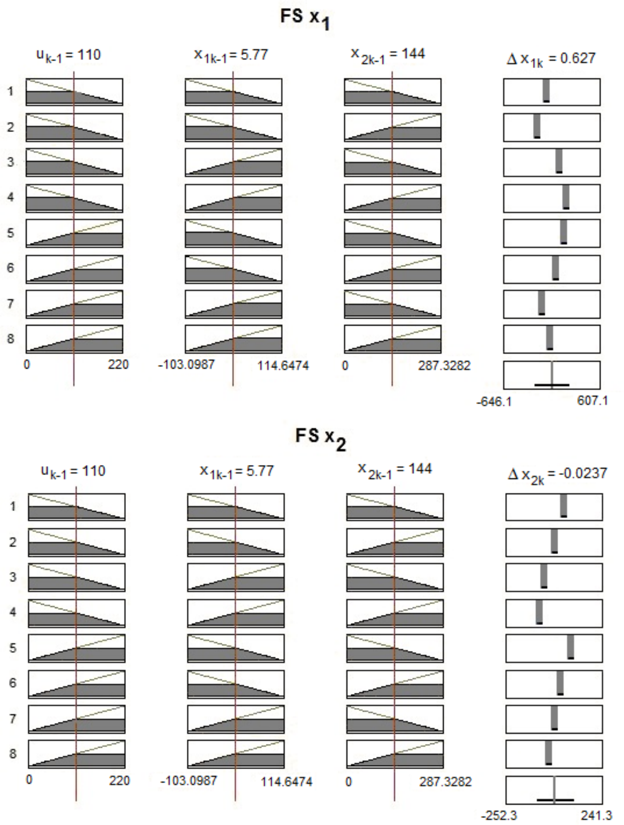

Fig.5 Structure of fuzzy subsystems FS x1 and FS x2 (fuzzification and rules)

The comparison of the DC drive and its fuzzy model responses to the chosen voltage jump U_A=50 V is presented in Fig.6. It shows a practical correspondence of the model and the drive in dynamic states.

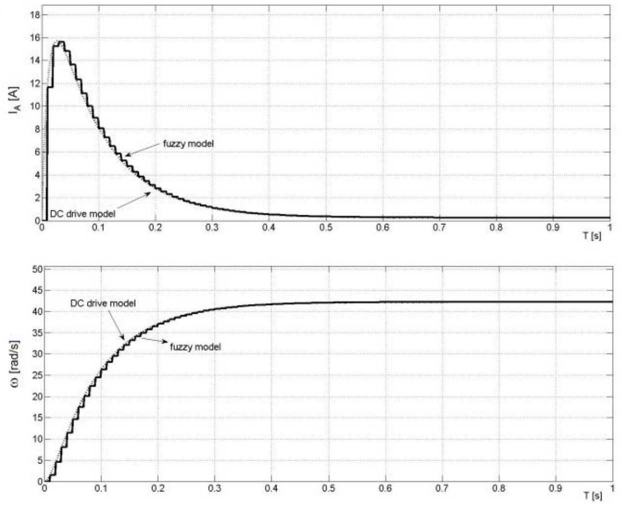

Fig.6 Comparison of the dynamics of the DC drive and its fuzzy model

III. PI CONTROLLER PARAMETERS OPTIMIZATION

Proposed and verified fuzzy model for the system´s operational space can be used for establishing the optimal parameters of the selected controller, most often of the PI type.

First we must define the space for the range of controller parameters. One of the ways, in case we have analytical knowledge of the system, is to calculate them in the standard manner and thus obtain information on their initial values, around which we then define their range. For thus calculated controller parameters we then define the energetic consumption of the system motion, with special attention on whether there are also other controller parameters that would be energetically optimal. For this purpose we have to scan the defined set of parameters in cycles and for each given concrete pair of parameters and concrete required input value calculate the energetic consumption of the motion of the system. The data that do not meet the determined boundary conditions are then excluded, and, at the same time, the parameters at which the motion is least energetically demanding are selected. The said algorithm can be implemented for example by means of an m-file created in MATLAB.

For the mentioned DC drive we defined the following boundary conditions for the dynamics of its motion

- Start-up time ±10 % of desired start-up time (0.5 s),
- Speed in start-up time ±10 % of desired angular speed,
- Maximum current at start-up must not exceed double the nominal current $2*I_n$.

The criterion for the selection of optimal parameters for the PI controller was minimum energy consumption, according to the formula

$$E = \int_0^t U_A I_A dt \quad (4)$$

where t is the simulation time.

First, we calculated the DC drive PI controller parameters without considering the load in the standard manner, according to the optimal module criterion (K_P=3.15 a K_I=35.01). These values were useful in the definition of the range of values of controller parameters (K_P=1:0.05:4, K_I=10:1:50). Within the thus defined space, for each concrete input value we then searched for such pair of parameters that would satisfy the criterion for minimum consumed energy according to criterion in equation (4) as well as boundary conditions for the dynamics of the system under consideration.

Results of the optimisation m-file are shown in Table I.

TABLE I. OPTIMAL PARAMETERS OF THE PI CONTROLLER WITHIN ITS OPERATIONAL SPACE

ω_D[rads^{-1}]	K_P	K_I	E_{opt} [J]	E[J]	Saving
20	1.4	11	30.48	38.79	21.42 %
40	1.45	12	44.20	58.41	24.32 %
60	1.55	12	77.62	93.66	17.12 %
80	1.6	12	118.34	147.00	19.49 %
100	1.6	12	153.34	192.71	20.42 %
120	1.65	13	229.24	278.46	17.67 %
140	1.55	13	354.52	408.20	13.10 %
160	1.5	14	467.81	566.12	17.36 %
180	1.55	13	656.04	770.20	14.82 %
200	1.55	14	879.72	1006.51	12.59 %
220	1.5	14	1128.08	1347.23	16.26 %

From the table above it follows that PI controller parameters K_P, K_I (with regard to the fact that this is a system with non-linear load) have to be adjusted according to the magnitude of the desired drive angular speed value. On basis of the measured relations between $\omega_D \rightarrow K_P$ and $\omega_D \rightarrow K_I$ in Table I, using the Anfisedit tool in MATLAB, we can create two simple static Sugeno type fuzzy systems (FS K_P and FS K_I), the structure of which (number of rules, fuzzification method and membership functions shape) are shown in Fig. 7.

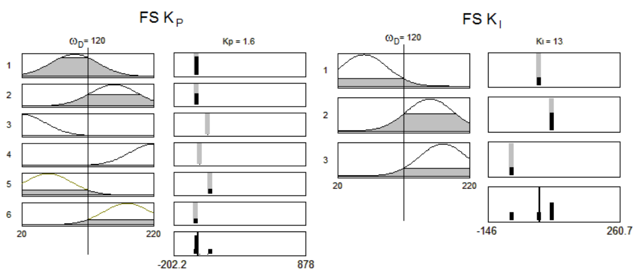

Fig.7 Structure of fuzzy systems FS K_P and FS K_I

The resulting block diagram of an energetically optimal controller for a DC drive with non-linear load is shown in Fig. 8, where the FS K_P and FS K_I fuzzy systems provide for the selection of PI controller parameters based on the desired angular speed value in such a way as to render the system optimal in terms of consumed power in line with criterion (4) and at the same time to make it meet the required boundary criteria.

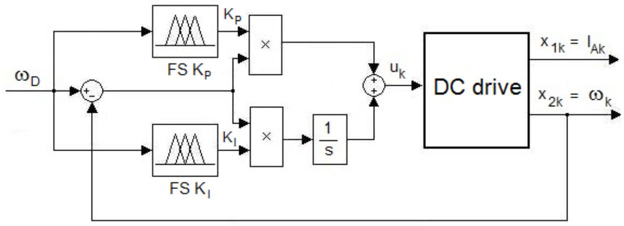

Fig.8 Optimal fuzzy controller of DC drive with non-linear load

The responses of a standard PI controller designed in accordance with the optimal module criterion from the drive parameters without considering any load, and the PI controller with optimized parameters for voltage jump on motor armature U_A=30V, are shown in Fig. 9. The comparison of both transient actions in terms of power consumption shows that in this particular case saving approx. 17.68 % of the drive´s electric power input is possible.

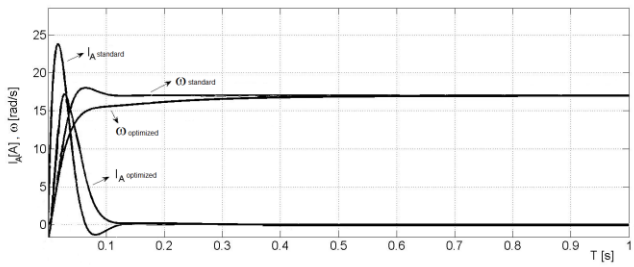

Fig.9 Responses of a drive with standard and optimized PI controller for voltage jump on motor armature U_A=30V

IV. CONCLUSION

The paper deals with the application of fuzzy logic in the method of designing the parameters of a continuous dynamic system controller that is energetically optimal and at the same time meets the desired dynamic control parameters. The suitable controller parameters are established on the basis of a fuzzy model of the system, generated through its identification from the measured inputs and outputs. The proposed method has been verified by simulations on an example of parameter design for a PI controller of a DC drive with non-linear load. In comparison with a standardly designed PI controller with constant parameters for the whole operational space of the drive, in the concrete example presented it is possible to save as much as 17.68 % of electric power at each dynamic motion of the drive.

This dynamic system controller design method will therefore be suitable mainly for drives with frequent changes of operational points, e.g. for drives of manufacturing line manipulators, of electro mobiles, etc. The procedure is of course also applicable in position control in drives, or in drives with other types of motors.

APPENDIX

Numerical values of matrices in state space description of DC drive

$$\mathbf{A} = \begin{bmatrix} 0 & 22.22 \\ -43.75 & -100 \end{bmatrix} \quad \mathbf{B} = \begin{bmatrix} 0 \\ 62.5 \end{bmatrix}$$

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