Electrical Drive Fuzzy Model Design

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Abstract: The paper deals with the methodology of designing a complete fuzzy model of an electrical drive based on a suitable database of measured input-output values. The principal requirements at the database (consistency, working space covering, ...) are presented here. This methodology covers the entire range of possible drive inputs, without requiring any information about the drive structure and parameters. The presented modeling method is verified by simulation by means of the MATLAB® software package. Obtained simulation results demonstrate that this procedure of designing a complete fuzzy model can be applied to any type of drive.y

Keywords: consistent database of measured values, fuzzy model, DC drive, AM drive

1 Introduction

Methods of applying fuzzy sets in various applications in the field of electrical drives have recently become a frequently appearing issue in specialized literature. One of the tasks involved is the development of corresponding models of the particular drives. The solution of this task can be based on analytical knowledge of the given drive type, however this approach does not introduce any advantages against conventional analytical models, neither does it exploit fuzzy system properties. The other option is to attempt setting up a model of the drive based only on the knowledge of the relevant drive inputs and outputs, without prior knowledge of the drive structure or parameters. This paper provides a description of an electrical drive fuzzy model design procedure that is based on a suitable database of measured data without any further information about the given system. The proposed algorithm has been verified by simulation on AM drive.

2 Problem Description

An electrical drive presents a dynamic system that can be generally described in state space by the following equations:

$$\dot{\boldsymbol{x}} = \boldsymbol{A}(\boldsymbol{x}, t)\,\boldsymbol{x} + \boldsymbol{B}(\boldsymbol{x}, t)\,\boldsymbol{u} \tag{1}$$

$$\boldsymbol{y} = \boldsymbol{C}\,\boldsymbol{x} \tag{2}$$

where $\boldsymbol{A}$, $\boldsymbol{B}$ are nonlinear time invariant system matrices, $\boldsymbol{x}$ is state vector of the system, $\boldsymbol{u}$ is input vector of the system and $\boldsymbol{y}$ is output vector of the system.

Suppose that the system concerned is a SISO system. In AC drives, the input is the stator frequency, while it is assumed that other inputs (e.g. stator voltage or current) have been suitably adjusted in a static inverter. The aim of the investigation is to set up a fuzzy model of the drive on basis of the measured database of inputs and their corresponding output values [1], [7]. The model is to have the common form of a set of rules of the type:

IF EVENT **X**... **THEN** ACTION **Y**... (3)

A fuzzy system (3) (further referred to as FS) can substitute with sufficient accuracy any indiscrete static nonlinear function by the application of a finite number of rules [3]. In order to enable modeling of the drive in accordance with (1) and (2), it is necessary to complement the FS by a dynamic part (DP), as common with these tasks. A complete fuzzy model of the drive may then look as shown in Fig. 1.

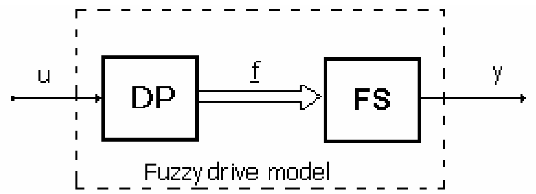

Figure 1
Proposed electrical drive fuzzy model structure

Of course, the dynamic parts of fuzzy models can also have a structure different to the one shown in the above Figure 1 [5], [6], [8].

Fuzzy model of system (1) should be built based on qualitative information about the system being modelled. These are expressed in terms of system responses to step variations in the input value; hence, the fuzzy model should be formed based on system response y to appropriately selected input step u.

For an electrical drive we suppose that:

- At step transition from one input signal value u_i to another value u_{i+1}, the drive output response value $y_{i+1}(t)$ is unambiguous and it is stabilized in a finite period of time T_{max}.
- For a constant input signal value U_i, the drive output always stabilizes at the same value Y_i during a period of time shorter than T_{max}. For example, at a specific voltage of the DC rotor the angular speed always stabilizes at the same value; at a specific asynchronous motor stator frequency the angular speed always stabilizes at the same value, etc.

A complete fuzzy model of the drive can be obtained by integration of all the transition trajectories that originate from all the transitions between all possible drive input values. If we divide the range of the input variable *u* into *n* number of levels, we will need to measure and then model *n*.(*n*-*1*) trajectories.

An essential prerequisite for the replacement of any dynamic system (or its part) by the fuzzy model from Fig. 1 to be possible is the consistency of data in the database. This essentially means that for 'very close' neighbouring input points f_i there must not exist 'very different' outputs y_i for the FS part of the model.

Example 1: Let us consider a closed loop control system as shown in Fig. 2.

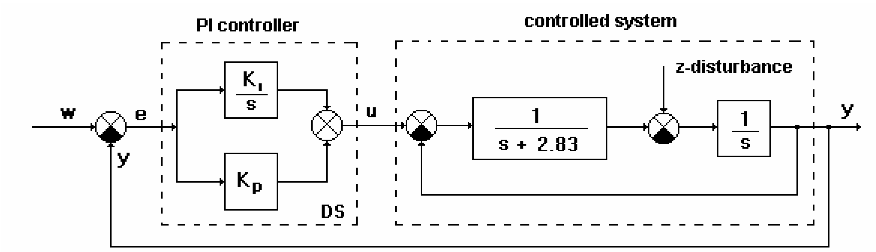

Figure 2
Closed loop control system structure

For different PI controller parameters we can generally get different types of responses of the control system, e.g. aperiodic and periodic, as shown in Fig. 3.

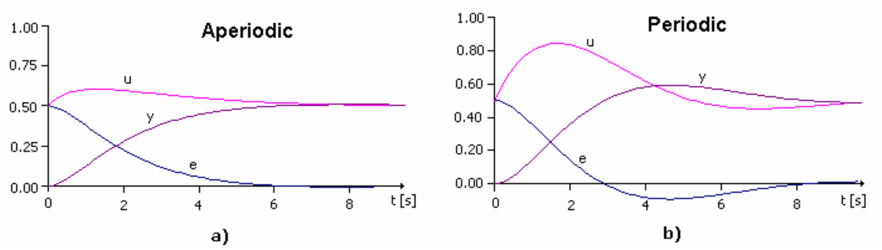

Figure 3
Aperiodic and periodic response of control circuit for different Kp and K_I

It is obvious that if the PI controller was replaced by its fuzzy equivalent, in case of the aperiodic response we would obtain a consistent database of values for the replacement (to each value of *e* there corresponds a different value of *u*), while in the case of periodic response there exist some values of *e* (e.g. e=0), for which the (3) rules require quite different values of the controller output *u*. The data measured from this response would therefore inevitably result in a nonconsistent database and thus a principally unimplementable PI controller fuzzy model from the quoted example.

Quantitatively the nonconsistency can be expressed in the following way [2]: Let the database of values for the FS design be set up from inputs x_i and their corresponding outputs y_i. Let us mark as neighbours such two items x_i , x_j from the database, the Euclidean distance of which in n-dimensional state space

$$d_{ij} = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \qquad i = 1, 2, ..., i_{max} \;,\; j = 1, 2, ..., i_{max} \tag{4}$$

is smaller than the defined closeness d_b. The nonconsistency n_{ij} of two neighbours can then be quantitatively expressed e.g. by the absolute value from the difference of their outputs.

$$n_{ij} = abs\,(\, y_i - y_j \,) \tag{5}$$

The database of values of the DS is consistent with the degree n_{ijmax}, if it is true for each item x_i of the database that the nonconsistency n_{ij} from all its neighbours is smaller than n_{ijmax} , i.e.

If $d_{ij} \le d_b$ **, then** $n_{ij} \le n_{ijmax}$ for $i = 1, 2,... , i_{max}$ $j = 1, 2,... , n$ (6)

Fig. 4 shows a graphic comparison of consistencies for the database of values obtained from aperiodic and periodic responses of the system for selected d_b=0.01 and for samples taken with sampling period T=1s.

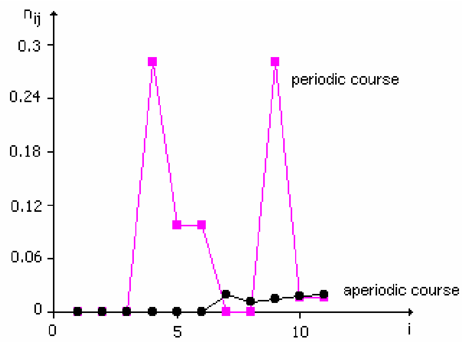

Figure 4
Comparison of nonconsistency of aperiodic and periodic courses

3 Procedure of Designing an Electrical Drive Fuzzy Model

In order to ensure the meeting of requirements from the previous chapter, let us set up a drive model according to the following algorithm:

1. Measurement of database of values for the drive. The procedure involves dividing the drive input u into n states and generating n(n-1) transient trajectories between them. The values of functions f_1, f_2, ... f_i, that represent the outputs from the dynamic part DP of the fuzzy model are recorded. It is useful to supplement this database by trajectories in non-zero steady states.
2. Reduction of the redundant items in the data database.
3. Generation of the static part of the fuzzy model FS. This involves suitable fuzzification of ranges of functions f_1, f_2, ... f_i. The FS is then set up as a set of fuzzy rules that correspond to the particular items in the reduced database.

Based on the above considerations, let us choose the DP of the model in such a way that it would contain the following functions:

$$f_1(kT) = \begin{cases} u_{k\text{-}1} & \text{if } u_k - u_{k\text{-}1} \neq 0 \\ f_1 & \text{if } u_k - u_{k\text{-}1} = 0 \end{cases} \tag{7}$$

$$f_2(kT) = u_k \tag{8}$$

$$f_3(kT) = \begin{cases} -\int \mathrm{d}t + 1 & \text{if } f_3 > 0 \quad \text{or} \quad u_k - u_{k\text{-}1} \neq 0 \\ 0 & \text{if } f_3 = 0 \end{cases} \tag{9}$$

Fig. 5 shows the course of functions f_1, f_2, f_3 which will provide the consistent database of values used for designing the fuzzy model of the dynamic system.

Function f_3 in fact represents linearly decreasing values of a relative time axis which is started off at the start of an individual trajectory.

Equation (7) defines the starting point of an individual trajectory, equation (8) its ending point. The individual trajectories are explicitly distinguished from one another by their starting and ending points, represented by the respective pair of function f_1 and f_2 values. Projections of individual trajectories into f_1-f_2, f_1-f_3, f_2-f_3 planes will be represented by parallel lines, which will enable fuzzification of their points with the membership function widths up to the immediate neighbours along the given axis. This will cover the entire range of input values and, at the same time, the requirement for congruence of the FS output with the database values in selected points will be satisfied.

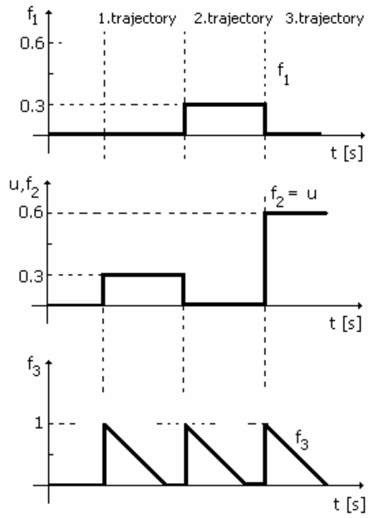

Figure 5
The course of function f_1, f_2, f_3 for creating the consistent database of values

Example 2: An AM drive fuzzy model

Let us investigate the fuzzy model of an AM drive for the entire range of u, which represents the motor stator frequency [4], [9]. For the sake of simplicity, suppose that the input u may adopt 3 different states, i.e. u_1=0, u_2=0.3 and u_3=0.6. To design the model, six different trajectories T_1 to T_6 have to be measured, as shown in Fig. 6.

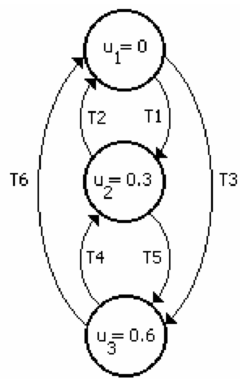

Figure 6
Six different transitions T_1 to T_6 between three different input states

The structure for creating a suitable database and measured responses of the motor moment for the entire range of input frequency u are shown in Fig. 7 and Fig. 8.

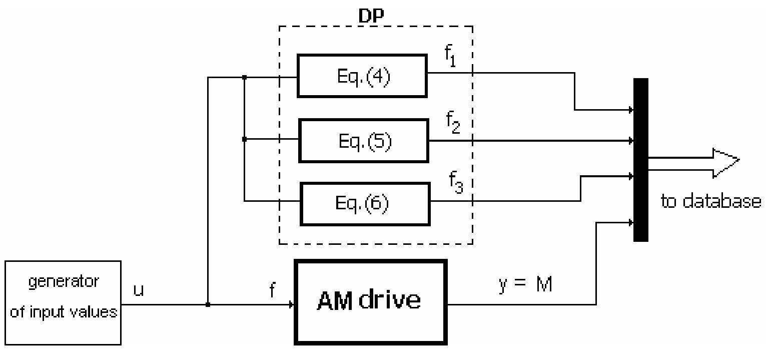

Figure 7
The structure for creating the database

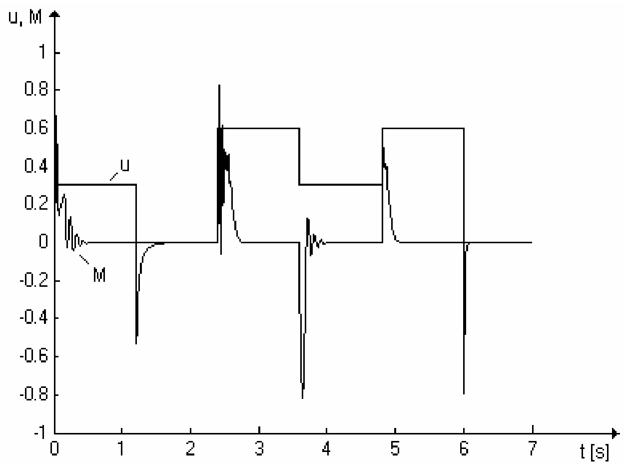

Figure 8
Measured responses of the motor moment for the entire range of input frequency *u*

The Mandani type fuzzy model of the asynchronous motor for dividing the input space f_1 – 3 bands, f_2 – 3 bands, f_3 – 100 bands contains 90 rules. Its structure is shown in Fig. 9.

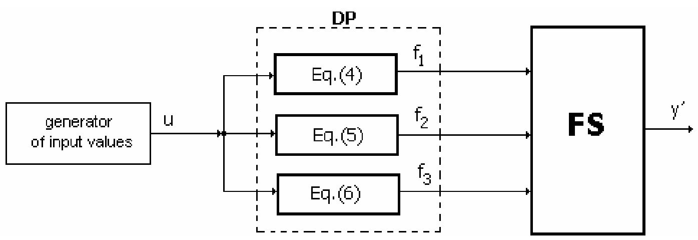

Figure 9
The structure for the fuzzy model of the AM drive

Responses of the model to paradigmatic input trajectories are practically identical with data obtained from a real motor, as shown in Fig. 10. Comparison of the asynchronous motor responses for randomly selected input values *u* is shown in Fig. 11.

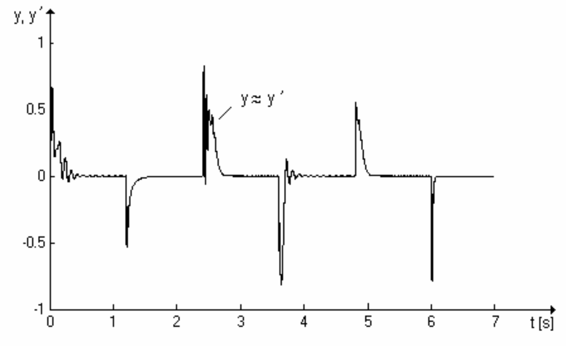

Figure 10
Comparison of the asynchronous motor responses for paradigmatic trajectories

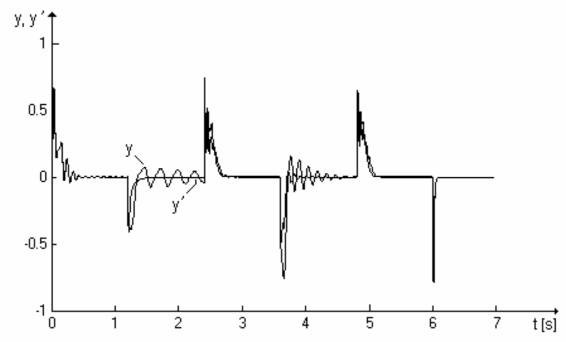

Figure 11
Comparison of the asynchronous motor responses for randomly selected input values *u*

We can see that even for such a complicated nonlinear system as the asynchronous motor drive is the fuzzy model approximates practically accurately a real drive for paradigmatic trajectories and with sufficient degree of precision also for trajectories from within the considered range of inputs, as it is shown in Figs. 10 and 11.

Conclusions

The drive fuzzy model design algorithm presented in this paper can be summarized into the following steps:

1 Measurement of the drive database values. The procedure involves dividing the drive input *u* into *n* states and generating *n*.(*n-1*) transient trajectories

between them. Values of functions f_1, f_2, f_3, which make up the dynamic part DP of the fuzzy model, are taken down (see e.g. Fig. 6). It is advisable to complement the database by trajectories corresponding to the non-zero steady states.

2 Reduction of redundant items in the database of values.

3 Generation of the fuzzy model FS static part. This is achieved by fuzzification of the function f_1, f_2, f_3 ranges, which, when they are selected according to (4) to (6), is trivial. The FS is then set up as a set of fuzzy rules that will correspond with all the individual items of the reduced database.

The principal properties of a fuzzy model designed in the described manner are as follows:

- It covers the entire state space of the drive.
- Depending on the required degree of precision, the density of dividing *u* into individual states can be selected.
- For a number of selected input levels *n*, the number of FS rules will always be *n.n.p*, where *p* is the number of points selected for an individual trajectory (at complemented trajectories for steady states).
- The dynamic part of the model will be identical for each drive, and it will be compiled on basis of equations (7) to (9).
- The fuzzification of the nonlinear static part of the FS model is very simple and it ensures coverage of the entire state space of the drive.
- Principal consistency of the measured database values is ensured.
- No knowledge of the drive type, structure or parameters is required.

With regard to the properties outlined above it can be assumed that the presented manner of modeling can be applied to any type of drive.

Acknowledgement

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References

[1] P. Brandštetter: AC Control Drives. Modern Control Methods. VŠB TU, Ostrava, 1999

[2] P. Fedor, D. Perduková: Dynamic System Substitution with Fuzzy System. Automatizace, 46/7(2003), pp. 430-434

[3] L. T. Kóczy: Fuzzy If … Then Rule Models and their Transformation into One Another. IEEE Transactions on Systems, Man, and Cybernetics, 26 (1996), pp. 621-637

[4] V. Mostýn, J. Skařupa: Dynamic Models of Drives in CAD Systems. Proceedings of the 4th International Conference Robtep 99. SjF TU, Košice, 1999, pp. 183-186

[5] M. Setnes, R. Babuška, H. B. Verbruggen: Complexity Reduction in Fuzzy Modeling. IMACS Journal Mathematics and Computers in Simulation, 46 (1998), pp. 507-516

[6] T. Takagi, M. Sugeno: Fuzzy Identification of Systems and its Application to Modeling and Control. IEEE Trans. Systems, Man and Cybernetics, 15 (1985), pp. 116-132

[7] V. Vysoký: Fuzzy Control. ČVUT Publishing House, Prague, 1996

[8] L. X. Wang, J. M. Mendel: Generating Fuzzy Rules by Learning from Examples. IEEE Trans. Systems, Man and Cybernetics, 22 (1992), pp. 1414-1427

[9] Vittek, J.: Shaft Sensorless Forced Dynamics Control of AC Drives for Applications with Moderate Precision. In: Proc. of Int. Conf. Electrical Drives and Power Electronics EDPE´03, The High Tatras, Slovakia, 2003, pp. 13-21, ISBN 80-89061-77-X

Appendix:

Simulation parameters:

$P_N = 15$ kW	$M_N = 98{,}8$ Nm	
$U_{1N} = 220$ V	$J = 0{,}11$ kgm^2	
$I_{1N} = 29{,}5$ A	Stator phase resistance	$r_1 = 0{,}267\ \Omega$
$n_N = 1450$ rev/min	Rotor phase resistance	$r_2 = 0{,}54\ \Omega$
$n_p = 2$	Main inductance	$L_h = 96$ mH

$M = 0{,}064$ H
Leakage inductace $L_{S1} = L_{S2} = 2{,}75$ mH
$R_1 = 0{,}178\ \Omega$
$R_2 = 0{,}36\ \Omega$
$K_{11} = 277{,}08\ H^{-1}$
$K_{12} = -269\ H^{-1}$ $\omega_2 = \omega_1 - \omega_g$ - slip angular speed
$\omega_0 = K_{11}\,(R_1 + (M^2/L_2).\omega_g) = 143{,}33\ s^{-1}$
$\omega_g = 5{,}46\ s^{-1}$
ω_m - the motor mechanical angular speed
ω_1 - angular frequency of the stator voltage
$np = 2$ - number of pole pairs