DC MOTOR FUZZY MODEL BASED OPTIMAL CONTROLLER

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DOI: 10.17973/MMSJ.2021_10_2021033

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This paper presents a method for the design of optimal fuzzy controller of a DC motor using a fuzzy model based approach with emphasis on minimal knowledge on the controlled system. In the first part of the paper we describe the method of the black-box fuzzy model design based only on the system´s measured input/output data without the necessity of preliminary knowledge of its internal structure and parameters. This fuzzy model is in the second part used in the design of optimal fuzzy controller based on finding the sequence of input signal values that will transfer the controlled system into the desired state in accordance with the selected optimality criterion. The realized simulation and experimental measurements performed on HIL platform have confirmed the correctness and effectiveness of the proposed design method and also its applicability to others dynamic systems with as little previous knowledge as possible.

KEYWORDS

DC motor, fuzzy systems, black-box fuzzy model, optimal fuzzy control, HIL platform

1 INTRODUCTION

DC motors are extensively used in the majority of industrial applications due to good speed regulation, wide speed range, smooth load, strong overload capability, little electromagnetic interference and low maintenance. DC motor drive systems have been used where precise speed control is required. They are controllable over a wide range with stable and linear characteristics. Conventional controllers such as PI and PID have been well developed and applied for many years, and are extensively used for industrial automation and process control today [Myo 2018], [Achanta 2017], [Tang 2017]. The main reason is due to their simplicity of design and operation, low cost of maintenance and effectiveness. On the other hand conventional controllers are applicable to a deterministic system with an accurate mathematical model and they are sensitive to variation in the motor parameters and load. Also, tuning PI or PID controller gains to eliminate and reduce the overshoot due to load disturbance is difficult [Borase 2020], [Palacky 2014]. For this reason, many researchers applied adaptive control techniques for DC motor speed control to get fast speed response and parameter insensitivity [Lafta 2020], [Bououden 2015]. However, the realization of these technics requires hardware with high computational capacity to solve optimization algorithm [Bella 2020], [Nelson 2020]. Fuzzy logic controller (FLC) can be an alternative control technique to the PID controller [Wang 2011], [Almatheel 2017], [Perez 2008], [Vo 2020]. In [Jaya 2017], [Tang 2001] the fuzzy PID controller has been used in the DC motor speed control system to get better control effect than the conventional PID controller. But the major drawback of the fuzzy controller is insufficient analytical technique design with respect to the selection of the rules and the membership functions.

FLC was originally developed as a model free control design approach, where the behaviour of the controller is modelled by linguistic control rules. However, it is not always possible to obtain the expert knowledge required for fuzzy controller design. For this reason, prevailing research efforts concerning fuzzy logic control in recent years have been devoted to systematic analysis and design of fuzzy control systems that do not demand heuristic searching for linguistic control rules [Bacik 2018], [Leso 2018], [Girovsky 2016]. In this case, it is possible to obtain information for the fuzzy system design from experimental measurements of the investigated black-box system and then use the functional dependencies between its inputs and outputs to build a suitable fuzzy model that can also be used in the design of its control [Perdukova 2017], [Fedor 2016]. It is obvious that the quality of the fuzzy model of the controlled system is of significant importance.

The problem in the development of fuzzy model lies in obtaining the description of qualitative properties from experimental data without any previous knowledge of the parameters and structure of the system being described that usually results in an inconsistent database, in the difficulty of covering the entire possible input space of the fuzzy system, etc. [Perdukova 2013], [Zeng 2000]. This issue can be resolved when a different method of data collection is used, or a suitable selection of qualitative data from the database is made.

This paper presents a method for the construction a nonparametric fuzzy model of a DC drive, which is further used in the design of its optimal control in terms of the chosen optimization criterion. The optimal fuzzy controller design methodology consists of the construction a fuzzy model of a DC drive based on the measured data of its inputs and corresponding outputs without knowledge of its structure and parameters. The obtained model is then used to design the algorithm for finding the optimal value of the input variable into the controlled system that will secure its transition from a given current state to a state that is closest to the desired final state based on the selected optimization criterion. The properties of the proposed fuzzy model and the optimal fuzzy controller of the DC drive were verified by computer simulation in MATLAB and also by experimental measurement on a new concept of hardware-in-the-loop (HIL) simulation platform based on programmable logic controller (PLC).

The aim of the presented paper is to develop an optimal fuzzy model based control design approach with as little system information as possible and to avoid the heuristic search for a rule-based fuzzy controller.

2 DC DRIVE FUZZY MODEL DESIGN

Various possible fuzzy system structures exist, both as regards their static fuzzy subsystem (Mamdani, Sugeno ...), or their dynamic subsystems [Babuska 1998]. We will consider a fuzzy model structure based on the discrete description of a dynamic state 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.

A DC drive is a dynamic system that can be generally described in state space by the equation

$$\frac{\mathrm{d}x}{\mathrm{d}t} = \mathbf{A}\boldsymbol{x} + \mathbf{B}\boldsymbol{u} \qquad (1)$$

where **A**(nxn) is the system matrix (n- is number of states), **B** (nxp) is the input matrix (p- is number of inputs), ***x*** (nx1) is the system state vector and ***u*** (px1) is the vector of inputs into the system. The discrete description of the system (1) will have the form

$$x_{\mathrm{k}+1} = x_{\mathrm{k}} + \frac{\mathrm{d}x_{\mathrm{k}}}{\mathrm{d}t} \tag{2}$$

$$\frac{\mathrm{d}x_{\mathrm{k}}}{\mathrm{d}t} = f(u_{\mathrm{k}-1}, x_{\mathrm{k}-1}) \tag{3}$$

where *f* is the static vector function of the dynamic system, and *k* represents the sampling step. The static subsystem is represented by the static function $f(u_{\mathrm{k}-1}, x_{\mathrm{k}-1})$, which presents information of the parameters and the structure of the static subsystem. Fuzzy model construction consists of the fuzzy approximation of this function based on measured dynamic system inputs and outputs data.

A separately excited DC motor is generally a 2nd order dynamic system. If we choose the state quantity x_1 to be the DC motor angular speed ω (i.e. $x_1 = \omega$) and the state quantity x_2 the DC motor armature current ($x_2 = I_a$), then with respect to the equation (1) we obtain the known state description of the DC motor

$$\frac{\mathrm{d}x}{\mathrm{d}t} = \begin{bmatrix} 0 & \frac{c\emptyset}{J} \\ -\frac{K_a c\emptyset}{T_a} & -\frac{1}{T_a} \end{bmatrix} x + \begin{bmatrix} 0 \\ \frac{K_a}{T_a} \end{bmatrix} u =$$

$$= \begin{bmatrix} 0 & 22.22 \\ -43.75 & -100 \end{bmatrix} x + \begin{bmatrix} 0 \\ 62.5 \end{bmatrix} u \tag{4}$$

where the following parameters are considered: armature gain $K_a = 0.625\ \Omega^{-1}$, armature time constant $T_a = 0.01$ s, motor constant $c\phi = 0.7$ Vs, moment of inertia $J_N = 0.032$ kgm^2, M_N=7.8 N.

Considering the choice of DC motor input, state and output quantities the structure of the proposed DC motor fuzzy model is shown in Figure 1. (Block z^{-1} represents a delay by one sampling time *T).*

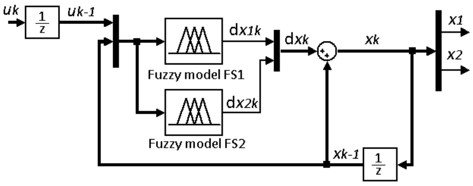


Figure 1. Structure of the discrete fuzzy model of the DC drive.

Because the system (2) is a discrete system, we have to search a sampling time *T* according to the Shannon-Kotelnikov theorem. Given that we have to define the frequency band width of the modelled system from the dynamic transitions. The number of dynamic transitions affects the complexity of data processing. The system order of the modelled system (i.e. the number of state variables) is very important information for fuzzy model design. If we propose the fuzzy model of a lower order than that of the modelled system, it can cause inconsistency of the fuzzy model rules and can reduce the quality of the designed fuzzy model [Tao 2005].

In order to determine the sampling time, identification measurement for input voltage step $u = 1$ V was carried out, (Fig. 2). We can see that the responses of the DC drive discrete model are practically identical to its continuous model. The Shannon-Kotelnikov theorem was used to determine sampling time $T = 0.01$ s.

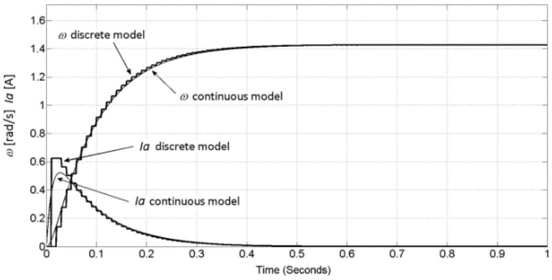


Figure 2. Responses of the continuous and discrete models of DC motor to voltage step $u = 1$V

In this step of the fuzzy model design, it is necessary to measure a consistent data of the modelled dynamic system between its inputs and outputs for the entire workspace.

This can be achieved principally by application of a suitable input signal that divides the entire input workspace [Chiu 1994]. In principle, no prior information about the modelled system structure is required in this method.

For the systematic data generation first, it is needed to define the ranges of the modelled system inputs and outputs. Then it is possible to divide the workspace into a given number of levels. The selected input signals are applied to the input of the modelled system and the corresponding data are measured from these dynamic transitions.

If input signal *u* range is divided into *m* levels, then the transitions number between them is represented by the second-class variations from *m* elements

$$V_2(m) = \frac{m!}{(m-2)!} = m\,(m-1) \tag{5}$$

If we consider that the inputs and outputs of the DC motor are in normalized quantities, then for a system with single input *u* that would be divided in the range <0-1> into 6 levels [0, 0.2, 0.4, 0.6, 0.8, 1] there will be 30 transitions, as illustrated in Fig. 3 where value 1 on the vertical axis represents the maximum of the assumed range and does not have a physical meaning.

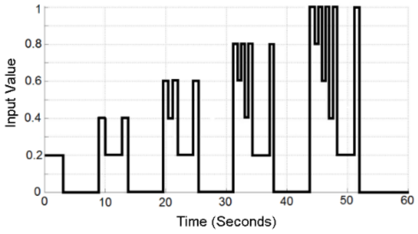


Figure 3. Generator of inputs for obtaining inconsistent database for the controlled system fuzzy model.

Data collection for DC fuzzy model design is shown in Fig. 4.

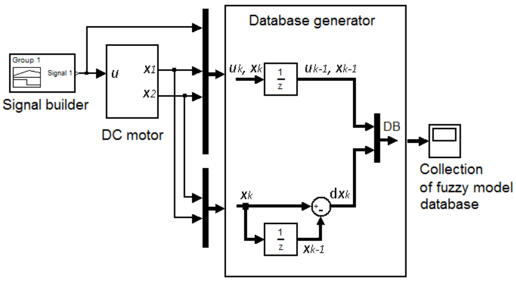


Figure 4. The database generation for DC motor.

The obtained database can be used for searching two fuzzy inference structures (FIS) of the modelled dynamic system describing the measured relations between [u_{k-1}, x_{1k-1}, x_{2k-1}] → dx_{1k}, and [u_{k-1}, x_{1k-1}, x_{2k-1}] → dx_{2k}.

Using the measured database, the particular fuzzy models FS1 and FS2 (see Fig.1) 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 adjustment of good initial rule parameters. For our purpose, subtractive clustering [26], which is a fast and robust data analysis method, was used, having the following parameters: Range of influence = 0.4, Squash factor = 1.25, Accept ratio = 0.4, Reject ratio = 0.01.

For the adaptive approach, a hybrid arrangement that uses a fuzzy inference engine in conjunction with a neural network was employed [Aicha 2015]. From the large number of methods for adaptive fuzzy networks development [Guldemır 2006] we chose the adaptive neuro-fuzzy inference system (ANFIS) structure and optimization process due to its accuracy [Fan 2014], [Velmurugan 2014]. As a result, we obtain two static Sugeno type fuzzy systems (FS1, FS2) with three rules for each output quantity, as shown in Fig. 5.

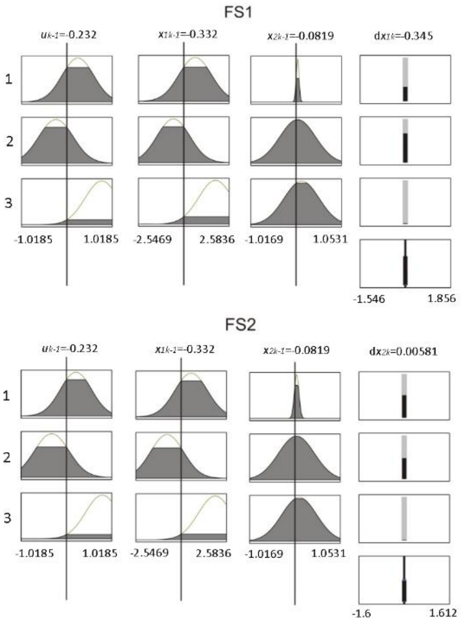
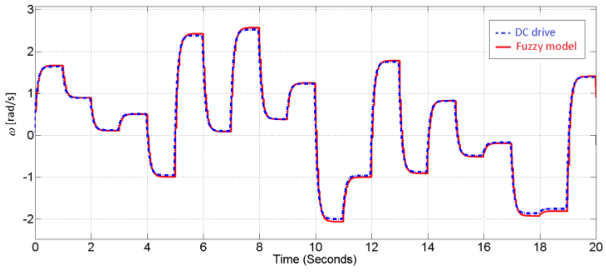
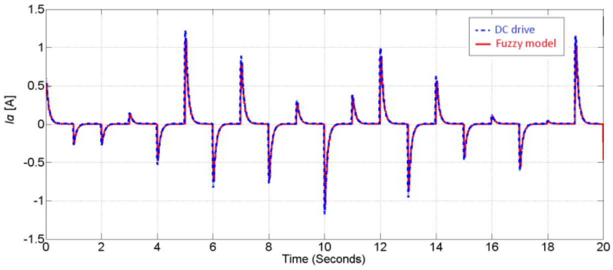


Figure 5. DC motor fuzzy model – SUGENO type with 2 rules.

The properties of the proposed fuzzy model were verified by simulation in MATLAB/Simulink program. Figure 6 shows the comparison of responses of the DC motor and of its fuzzy model for several steps of input voltage *u* within the range <0, 1V>. The obtained results confirm the quality of the proposed DC motor fuzzy model.



a)



b)

Figure 6. Comparison of responses of the fuzzy model and the modelled system to various steps of input voltage u: a) DC motor angular speed, b) DC motor armature current

3 DESIGN OF DC MOTOR FUZZY OPTIMAL CONTROLLER

The proposed DC motor fuzzy model will further be used in the design of its fuzzy controller that will be optimal in terms of the chosen optimization criterion.

The aim of the proposed fuzzy controller will be, based on the current values of the system states, to generate such an optimal input into the controlled system that will ensure transition of this system from a given actual state into a state that is closest to its desired final state.

The principle of finding the optimum values of input variable *u* for a given initial state (point X_0) and for the desired final state of the controlled system (point W) is explained in Fig. 7. The fuzzy model of the controlled system (Fig.1) will be used for determining the point in state space into which for a given input *u* and given state X_i [x_{1i}, x_{2i}] controlled system will get during the next step defined by the sampling time *T*. If the control goal is to get the controlled system to reference state W [x_{1W}, 0], then in state X_i it is necessary to choose from the set of possible inputs ***u*** such value that will be optimal in terms of the selected criterion.

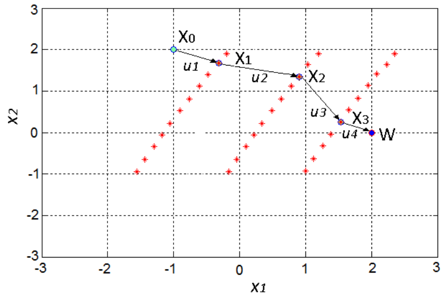


Figure 7. Finding uopt for the subsequent step from point X_0 to final point W.

The described method enables us to choose various optimality criteria or their combinations according to the demands of the particular technology.

In our case the chosen optimality criterion is the minimum Euclidean distance between the reference state W and all the system states that were reached from state X_0 after applying values of possible inputs ***u***.

The optimality criterion can be described by the equation

$$J = \min \sum_{i=1}^{n} \sqrt{(x_{1w} - x_{1i}) + (x_{2w} - x_{2i})} \tag{5}$$

where *n* is the number of input values ***u*** that are being applied into the controlled system.

In this way it is possible to gradually generate a sequence of optimal input values ***u*** which will get the controlled system from initial state X_0 through states X_1, X_2 … X_n up to the reference state W.

The block diagram for finding the optimal input vector $\boldsymbol{u}_t$ for concrete reference value w (state W[x_{1w}, 0]) is shown in Fig. 8.

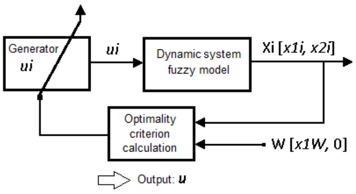


Figure 8. Finding the optimal input vector $\boldsymbol{u}$ for selected optimality criterion J.

In the design of the concrete DC motor fuzzy controller, the fuzzy model of which is shown in Fig. 1, we considered the range of reference values of angular speed ω and of input u from the interval <-2.5, 2.5>, the range of states x_1 and x_2 from the interval <-4, 4>, and the sampling time $T = 0.01$s. Hence for the set of all possible system states and the set of the desired final states of the system we will apply the approach described above to determine the set of optimal system inputs that will always get the system to the state that is closest to the desired final state.

To find an optimal input vector for the desired final state of the controlled system we must repeatedly apply various inputs to the previously constructed fuzzy model and then evaluate criterion (5) for each one of them. However, if there is a fuzzy model of the controlled system available, the whole process of finding the optimal input vector can be fully algorithmized by means of m-file in the MATLAB program. The result of this procedure is a database that can be used for constructing a fuzzy controller described by the relation [X_i [x_{1i}, x_{2i}], W [x_{1W}, 0]] → u_i which expresses the relationship between the actual system state (point X_i), the desired value of system state (point W), and the value of input u_i which will optimally transfer the system in the given step to the state that is closest to the desired final state of the system.

Using this database, the fuzzy controller can be designed by standardly known procedures of clustering the data into significant clusters and their description by rules, e.g., by means of the ANFIS Editor tool in the MATLAB/Simulink program. The method used for the fuzzy system generation was the subclustering method, having the following parameters: Range of influence = 0.3, Squash factor = 1.25, Accept ratio = 0.3, Reject ratio = 0. The proposed fuzzy controller is represented by Sugeno type fuzzy system with 22 rules. The structure of the proposed fuzzy controller is shown in Fig. 9.

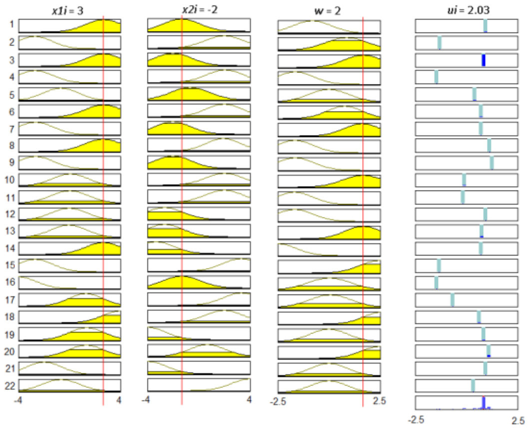


Figure 9. Fuzzification and rules of optimal DC motor fuzzy controller.

The block diagram of the control circuit including the proposed fuzzy controller is shown in Fig. 10.

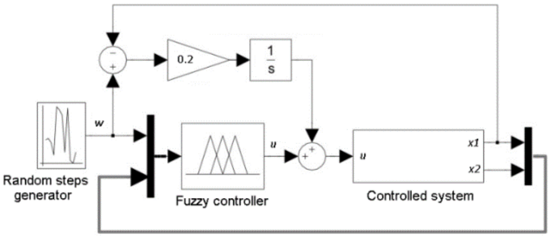


Fig. 10 Block diagram of control circuit with fuzzy controller.

The fuzzy controller is of proportional character, so in case when zero control deviation is required in steady state, it can be supplemented with an integration component as shown in Fig. 10.

4 VERIFICATION OF PROPOSED OPTIMAL FUZZY CONTROLLER

Verification of the fuzzy control structure properties was carried out for the DC drive basic operating states by computer simulation in MATLAB software environment and also by experimental measurements on HIL simulation platform based on PLC.

The operation cycle of the DC drive consists of three phases - starting the DC drive, running at constant speed and stopping the DC drive.

The dynamic course (obtained by simulation in MATLAB) of the output-controlled variable – the angular speed ω for the considered working cycle for various randomly generated reference values within the interval <-2.5, 2.5> is shown in Fig. 11. It is obvious that time courses confirm the quality of the proposed fuzzy controller which is able to provide the desired dynamics of the DC drive angular speed without overshoot.

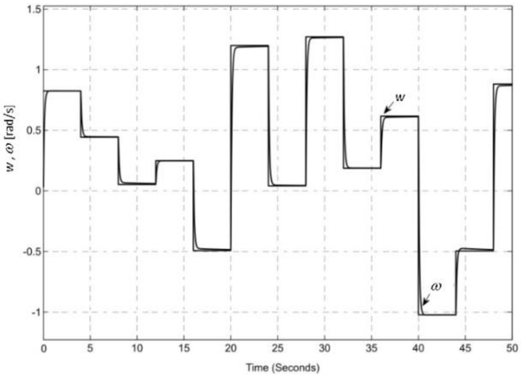


Figure 11. Dynamic course of output variable of the controlled system with fuzzy controller for various reference values of ω.

The invariance and robustness of the proposed fuzzy controller were verified by experimental measurements on a new concept of HIL simulation platform (Fig.12).

The workplace consists of two standard PLCs and one standard PC. Communication between these devices is via standardized Ethernet interface. The first PLC, equipped with an operator display, is used for modelling the controlled technological process. The operator display enables independent animation of the process model and also external modelling of various process situations (change of drive load torque). The second PLC is used as the control member of the system and enables testing of various controller options. Interface of control and information signals between the controller and the process model is implemented by standardized electric signals.

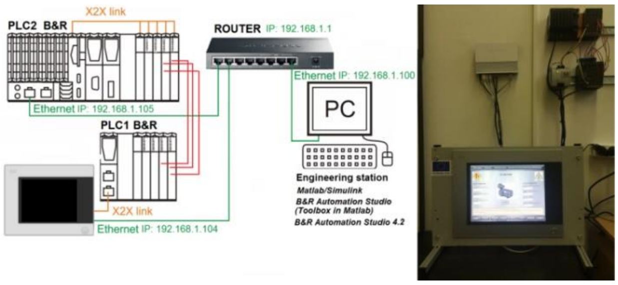


Figure 12. HIL simulation platform

A standard PC with Windows operating system enables programming of both the control PLC and the PLC for technological process simulation. For this purpose, it has to be provided with a program package from the manufacturer of the PLCs being used, and possibly also software for dynamic systems modelling. As in this particular case PLCs from B@R were used, for their programming the program package B@R Automation Studio 4.2. was installed on the PC. The MATLAB package with the relevant tools was installed for modelling purposes.

The whole process of implementation of the specified task in the HIL simulation workplace is executed in four basic steps.

In the first step, the DC drive fuzzy control (Fig. 10) was computer modelled in MATLAB environment using Simulink.

In the second step it is necessary to build a hardware configuration for the process simulation PLC1 (PP500) and for the control PLC2 (X20 CP 1484-1.

In the third step it is necessary to transform from MATLAB the DC drive fuzzy model (Fig. 1) into the source code for PLC1 for process simulation and the controller structures (Fig. 10) into the source code for the control PLC2. It was implemented by using the B&R Automation Studio toolbox in MATLAB for automatic generation of the code for PLCs according to the Simulink block diagram created in the first step.

In the fourth step we verify the correctness of the fuzzy controller design.

When verifying the properties of the proposed fuzzy control, we have assumed external (additive) disturbance in DC drive, namely load torque T_L = 80% T_N in time t = 2 s.

The dynamical performance of the output-controlled variable for the operation cycle and the reference value ω = 2 [rad/s] is shown in Fig. 13. It is evident that the time course of angular speed of the DC drive has required dynamics during the whole operation cycle, even during the considered step disturbance T_L settled with an adequate dynamic. This verifies the invariance of the proposed control against the additive disturbances.

The robustness of the proposed control structure has been verified against the change of one most important parameter of the controlled system that significantly affects its properties, namely: the moment of inertia J of the DC motor.

In many applications of electric drives (e.g. in robotics, transportation, winding machines in plants, etc.), the moment of inertia J applied to the motor shaft significantly changes its value during the operation cycle. As shown in Fig. 14 and Fig. 15, the reduction/increase of the moment of inertia to a half/or double of the DC motor nominal moment of inertia does have not any influence to the control dynamics.

Simulation and experimental measurements have confirmed that the proposed controller is able to meet the basic control objectives, i.e., the desired optimal dynamics and invariance to external disturbances, robustness against changes of important parameter (moment of inertia). Thus, it ensures a high-quality angular speed control of the DC motor during the entire operation cycle (including the transient states).

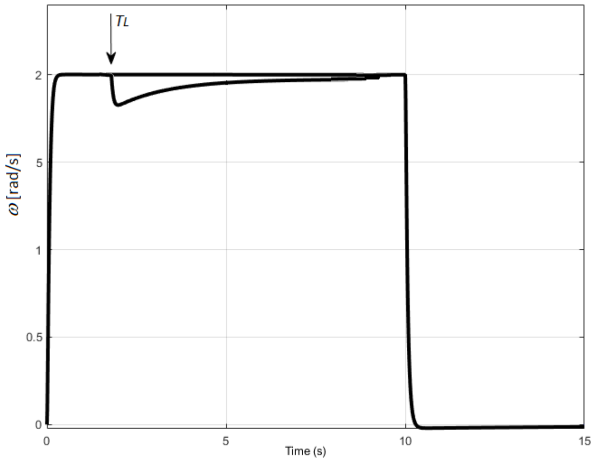


Figure13. Time course for DC motor angular speed at occurrence of external disturbances T_L= 80% T_N

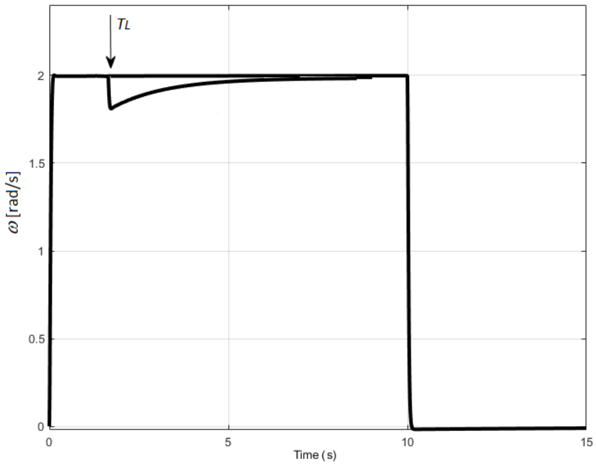


Figure 14. The effect of change of moment of inertia to the value J = J_N/2 and at load torque T_L = 80% T_N on DC motor control dynamics during the operation cycle

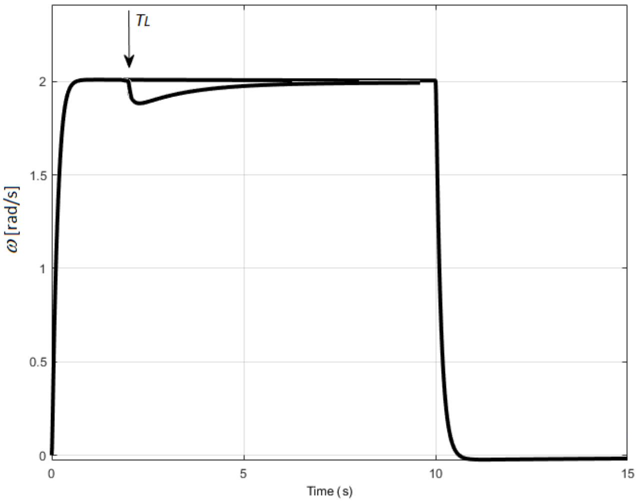


Figure 15. The effect of change of moment of inertia to the value J = 2 J_N and at load torque T_L = 80% T_N on DC motor control dynamics during the operation cycle.

5 CONCLUSION

The paper describes the procedure of designing a fuzzy controller that guarantees optimal control dynamics in terms of the selected criterion, for system described only by input/output relations. The proposed method has been verified by computer simulation in MATLAB and experimental measurements on HIL simulation platform based on PLC.

Simulation and experimental results have confirmed the correctness of the described method of fuzzy model based fuzzy controller design and its applicability to dynamic systems, such as DC motor with as little previous knowledge as possible and without the heuristic search for a rule-based controller. The quality of the control structure based on a fuzzy model is strongly dependent on good-quality of the dynamic system fuzzy model. The database for its construction should be consistent and it should cover the entire assumed workspace of input quantities entering the controlled system. The fuzzy model of the controlled system is defined on basis of its inputs/outputs data by means of fuzzy clustering. Similarly, the fuzzy controller also has a simple structure, and its parameters are determined by means of simulation of the found optimal vector for the concrete desired quantity. The described method enables us to choose various optimality criteria or their combinations according to the demands of the particular technology, which is a major advantage from the practical point of view. For example, the selection of a suitable energetic optimality criterion can bring marked energy savings.

The achieved simulation and experimental results performed for basic operating conditions of the DC motor have confirmed that the proposed controller is able to meet the desired optimal dynamical properties of the control performance while ensuring the DC motor invariance and robustness.

Comparing fuzzy to conventional modelling and control it must be stressed that in some cases the achieved results are better and in other cases they are not. It depends on the system or the problem to be solved which methods fits best. In this spirit the proposed method of designing a fuzzy controller of a dynamic system for which only external information is available (i.e. the measured dependencies between the inputs and outputs) has to be understood as an enhancement of the wide range of fuzzy modelling and control methods.

With this method no principal limitations for the investigated dynamic system are defined, and therefore there is a good reason to assume that the presented method can be also applicable to other types of dynamic systems of similar structures. For example in the area of electrical drives for asynchronous and synchronous motors control, for robotic systems control, for various types of electromechanical systems control and also for control multi-motor drive systems.

ACKNOWLEDGEMENTS

This work was supported by the Slovak Research and Development Agency under the Contract no. APVV-19-0210.

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