COMPUTATIONAL INTELLIGENCE BASED CONTROL OF SENSORLESS DC DRIVE AT LOW SPEEDS

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Abstract

The paper deals with applicability of computational intelligence techniques in the design of a speed controller for electric drives. A medium-sized speed-sensorless drive system is considered. Control structure consists of a state observer based on three ANNs and a speed controller based on self-organizing Takagi-Sugeno rule-based model. The controller is developed and tested for a plant comprising a separately excited DC motor, operated at low speed. A comparison is made with respect to the drive performance obtained with a conventional PI controller that was optimized for every considered transient duty cycle. A simulation study indicates that the self-organizing Takagi-Sugeno controller offers very good performance, better than optimal PI controller.

1 Introduction

The last decade has seen an increasing interest in computational intelligence (CI) applications in control of various dynamic systems, including electric motor drives [1, 2, 5, 7]. Most frequently used CI methods, artificial neural networks (ANN) and fuzzy logic (FL), are widely utilised in areas of modeling, identification, diagnostics and control. Control structures based on CI appear to be an advantageous solution for control of the wide range of dynamic processes.

ANNs are suitable when the knowledge, contained within the available data sets, need to be generalized. Their main drawback is that they act in a ‘black box’ manner. On the other hand, fuzzy logic deals with problems as a human mind, trying to handle vagueness, imprecision and uncertainty in a robust manner. However, the pure fuzzy logic systems have a disadvantage of being extremely difficult to tune for high performance. Fortunately, ANNs and FL are complementary techniques; hence shortcomings of one technique can be overcome by advantages of the other. When ANNs are combined with FL, neuro-fuzzy systems with learning capability are obtained [3, 11]. Such systems are capable of acquiring and storing new knowledge about the process on the basis of representative numerical training samples.

This paper deals with the use of neuro-fuzzy combination for control of a speed-sensorless medium-power separately excited DC motor drive. The main part of the proposed control structure is a speed controller, based on a self-organizing first-order Takagi-Sugeno (TS) fuzzy rule-based model that relies on the product space clustering. The input-output space is partitioned using Gustafson-Kessel (GK) clustering algorithm [10]. The control system structure includes a state observer, whose role is to provide the CI-based speed controller with the information about the estimated load torque, the estimated speed and the predicted speed. The state observer is designed using three separate ANN structures.

In order to provide a thorough and unbiased comparison, a conventional optimized PI controller is designed and its performance is compared with self-organized TS based controller. Detailed consideration of a number of different transient operating regimes of the drive shows that self-organizing TS speed controller offers better performance than optimal PI controller, with respect to the behaviour in both transients and steady states. It should be noted that the TS controller is especially advantageous as it is characterized with a relatively quick training process, low computational requirements and a simple knowledge base.

The paper is organized as follows. Section 2 provides a short description of the self-organizing Takagi-Sugeno rule based model considered in the design of the speed controller. The control structure of the DC drive, with three ANN-based components of the state observer and the design of the TS-based speed controller, are presented in Section 3. Simulation results, contained in Section 4, compare the performance of the DC drive obtained using self-organizing TS and the optimized PI speed controller. Conclusions of the paper are summarized in Section 5.

2 Speed controller design: self-organizing Takagi-Sugeno rule based model

The goal is to construct a TS fuzzy model of the first order that relies on the product space clustering [10]. This means that when K clusters are formed, the corresponding TS fuzzy model contains K rules of the following form

\[
R_i : \text{If } x_1 \text{ is } A_{i_1} \text{ and } x_2 \text{ is } A_{i_2} \text{ and } \ldots \text{ and } x_n \text{ is } A_{i_n} \quad \text{Then } y_i = x a_i + b_i, \quad i = 1, 2, \ldots K, \tag{1}
\]

where \(R_i\) is the \(i^{th}\) rule, \(x=[x_1, x_2, \ldots, x_n]\) is the input variable vector, \(A_{i_1}, A_{i_2}, \ldots, A_{i_n}\) are the fuzzy sets assigned to the input variables, \(y_i\) is the value of the output of the \(i^{th}\) rule, and \(a_i\) and \(b_i\) are parameters of the consequent function.
The procedure consists of two phases. The first phase identifies the structure of the rule base. During this phase, partition of the input-output space by means of GK clustering method takes place. The training data that contain N input-output samples \( z_k = [x_k; y_k]^T \); \( k = 1 \ldots N \), are used. Each resulting cluster represents a certain operating region of the system, where the input-output data are highly concentrated. These information clusters are interpreted as rules. The crucial part of the GK clustering algorithm [10] represents calculation of the distance from the sample under consideration to the center of a cluster. This distance is calculated in the given \( i \) iteration of the GK algorithm using

\[
d^2_{ik} = [z_k - v_i^{(l)}]^T \left[ \frac{1}{\det(F_i)+1} \right] [z_k - v_i^{(l)}],
\]

\( i = 1, 2, \ldots, N; \quad k = 1, 2, \ldots, N, \)

where \( F_i \) is covariance matrix for the \( i^{th} \) cluster, and \( v_i \) is the centre of the \( i^{th} \) cluster. Completion of the GK clustering process yields fuzzy partition matrix \( U \). This matrix contains values that give a measure of the levels of belonging of all the samples to the appropriate clusters.

Once the structure of the fuzzy model is defined, the second phase, parameter identification, is initiated. This phase enables calculation of the parameters that are present in the antecedent and consequent parts of the TS fuzzy rules. One-dimensional fuzzy sets in antecedent part of the \( i \) rule \( A_i \) are obtained from multidimensional fuzzy clusters, on the basis of matrix \( U \), by point-wise projection onto the space of the input variable \( x_k \). In order to determine parameters of the consequent function, it is necessary to calculate normalized firing strength \( \xi_i \) of each rule for all the input samples. By forming the matrix composition of normalized firing strengths, it is possible to determine the consequent parameters using least-squares method [3].

The functional dependence between the input and output of the system is established once when the parameters \( a_i \) and \( b_i \) of each \( i^{th} \) rule are calculated. It is possible now to calculate the aggregated output of the model as the weighted average of the rule consequents

\[
y_k = \frac{\sum_{i=1}^{K} \xi_i(x_k) (x_i a_i + b_i)}{\sum_{i=1}^{K} \xi_i(x_k)}. \tag{3}
\]

3 Description of the drive control structure

Two control structures of a speed-sensorless separately excited DC motor drive are discussed. The first one is regarded as the reference control structure and it is introduced for the sake of comparative analysis. The reference control structure, shown in Figure 1, utilises the conventional PI speed controller (drive \( D_{PI} \)). The PI speed controller is initially designed using the symmetrical optimum criterion [6], and subsequently optimized for each transient operating regime using the static Nelder-Mead (simplex) method [8], as will be explained in the next section. The block ‘Actuator’ in Figure 1 denotes the power supply of the motor. Motor’s angular speed is estimated from the sampled armature voltage and current, as shown in Figure 1, so that a speed-sensorless drive is under consideration.

The second drive control structure (drive \( D_{TS} \)), Figure 2, consists of a state observer and a self-organized TS-based speed controller. The state observer contains three components [9]: a speed estimator, a speed predictor, and a motor torque estimator. The speed predictor is essentially the model of the control object, whose role is to predict the motor speed. The torque estimator, designed on the basis of the mechanical motion equation of the motor model, dynamically estimates the load torque both in transient and steady state operation. The outputs of the three state observer components are the inputs of the TS speed controller.

The state observer components are realized by means of ANNs, trained using error back-propagation method [3]. The data used in the training and testing of the neural networks were obtained on random, using the discrete DC motor model and accounting for the stated limits. The training set consisted of 800 samples, while the test set contained 100 samples. The training and testing sets are different, but the values of individual variables belong to the same intervals (all variables are normalized and belong to the set [-1,1]).

The TS-based speed controller has been chosen to have four inputs and one output. The output is the reference voltage \( u_{ref} \) while the inputs are the reference speed at the \( k^{th} \) instant, the difference between predicted and estimated speed at instant \( k \) \( (\Delta \omega(k) = \omega_{ref}(k) - \omega_{est}(k-1)) \) and the estimated load torque at both instants \( k \) and \( k-1 \). Hence the input vector is :

\[
x = [ \omega_{ref}(k) \quad \Delta \omega(k) \quad T_{nest}(k) \quad T_{nest}(k-1) ]. \tag{4}
\]

With such choice of the input/output variables, the controller parameters become :

\[
a_k = [ 0.9518 \quad 0.1524 \quad 0.0593 \quad -0.0059 ] \tag{5}
\]

while the parameter \( b_k \) is -2.27x10^{-10}. Therefore the TS-based control law is a relatively simple analytical expression:

\[
u_{ref} = 0.9518(\omega_{ref}(k) + 0.1524\Delta \omega(k) + 0.0593T_{nest}(k) - 0.0059T_{nest}(k-1) - 2.27E-10. \tag{6}
\]

The antecedent part of the rule base is contained in the partition matrix \( U \). Number of samples and number of clusters determine dimensions of the partition matrix. A large memory space is therefore required if a large number of samples is used. This shortcoming is eliminated by using an ANN as the approximator of the membership functions of all the samples to the given fuzzy cluster. An additional ANN, with one hidden layer and the number of outputs equal to the number of clusters in the model, is formed in this way. Utilization of the memory space is therefore greatly improved, without any adverse effect on the accuracy of the TS model operation.
4 Simulation results

The standard second-order DC motor model, for operation with constant excitation flux, is utilized [4]. Motor data are given in the Appendix A. Speed controller structures described above are elaborated in simulation. Two different transient operating regimes (duty cycles) are presented here:

1. Response to a small-step speed command ($w_{ref}(t) = 0.1\text{[p.u.]}$) with the constant rated load torque ($T_m(t) = 1\text{[p.u.]}$).

2. Response to the small-step speed command ($w_{ref}(t) = 0.1\text{[p.u.]}$) without any load, followed by the step application of the rated load torque and subsequent removal of the load.

Both drive structures, $D_{PI}$ and $D_{TS}$, are simulated for these two transients. For a fair comparison, the conventional PI speed controller of the $D_{PI}$ drive is optimized individually for each duty cycle. Optimization of P and I gains is performed by static Nelder-Mead (Simplex) method [8], minimizing a performance index, here defined as:

$$I = \sum_{i=1}^{T} e_i^2 + 20 \sum_{i=T}^{\infty} e_i^2,$$

where $T$ is the time instant when the speed response reaches 90% of the demanded step, while $e_i$ is the speed error. The selected performance index has weighing of 20 for the cumulative error occurring after time $T$, thus placing a larger emphasis on the steady-state accuracy. This has proved to be a good way to reduce both the overshoot and the duration of transient process when optimizing the PI controller.

An illustration of the simulation results is given in Figures 3 and 4, describing the performance during duty cycles No.1 and No.2, respectively. Figures 3a and 4a show behaviour of the speed, Figures 3b&4b behaviour of voltage and Figures 3c&4c traces of current for both drives, $D_{PI}$ and $D_{TS}$.

It can be seen that the $D_{TS}$ drive offers better tracking in both transients. Values of the performance index, Table 1, also confirm that the $D_{TS}$ drive achieves better performance than the $D_{PI}$ drive with optimally tuned PI controller.

<table>
<thead>
<tr>
<th>Duty cycle</th>
<th>$D_{PI}$</th>
<th>$D_{TS}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0744</td>
<td>0.0344</td>
</tr>
<tr>
<td>2</td>
<td>1.4125</td>
<td>0.8085</td>
</tr>
</tbody>
</table>

Table 1: Performance index values for the considered duty cycles.
Figure 3. Speed, voltage and current traces for DC drives with PI and TS speed controllers for duty cycle No 1.

Figure 4. Speed, voltage and current traces for DC drives with PI and TS speed controllers for duty cycle No 2.
5 Conclusion

The paper analyses performance of a sensorless low-speed DC motor drive with a self-organized Takagi-Sugeno speed controller. Controller design is described, as well as the design of the additional components of the control system, such as the speed estimator, the speed predictor and the load torque estimator. Outputs of the additional components, which are based on the artificial neural networks, serve as the inputs into the TS-based speed controller.

For a better insight into achievable performance with the self-organized TS-based speed controller, a control system with a conventional PI speed controller is designed as well. Numerous simulations of both drive structures have been performed and two different low-speed transient duty cycles are shown here. In both duty cycles the reference speed was only 10% of nominal speed, which is a difficult operating point for an electrical drive without a speed sensor. The load torque profile was different – constant nominal value in the first duty cycle, but varied between zero and nominal value during the second duty cycle.

The reference control system is an optimized conventional PI controller, characterized by a simple design procedure and a simple structure. The accuracy shown in simulation is very good, since the parameters of the PI controller were individually optimized for each considered duty cycle. The optimized PI controller therefore to some extent corresponds to an ‘adaptive’ PI controller. Special tuning of the PI controller for each possible duty cycle would represent a computationnally complex solution that would eliminate the major advantage of a PI controller, its simplicity. Needless to say, had a constant parameter PI controller been considered, with its parameters obtained for a single operating regime (typically nominal speed and nominal torque), the performance of the PI control for any other duty cycle would have been significantly worse.

The performance of such specially tuned PI controller is still inferior to the self-organized Takagi-Sugeno controller. The results of the analysis justify the application of the computational-intelligence-based control techniques in electric motor drives. Although the work described here is related to a separately excited DC motor drive, the results are directly applicable to vector-controlled AC motor drives. This generalisation is possible since the application of vector control principles in AC motor drives in essence converts an AC machine into its DC machine equivalent. Thus, from the point of view of the speed controller, it becomes irrelevant whether the electric drive under consideration utilizes an AC or a DC motor.

The main conclusions of this research are believed to be directly applicable to the control of a wider class of industrial processes in the working regimes with low inputs. Detailed expert knowledge about the process is not required. The self-organising TS fuzzy model based approach enable grouping of samples in clusters, which may represent individual operating regimes. Combination of such individual regimes, represented by appropriate control rules, facilitates an adequate description of the complex dynamics of the system under consideration.

References


Appendix A

Motor data: \( U_{\mu}=260V; \; R_p=0.75\Omega; \; I_{\mu}=1.76A; \; L_{\mu}=3.32mH; \; n=3370rpm; \; \psi_{\mu}=0.7Wb; \; \omega_0=352.9rad/s; \; J=0.018kgm^2; \; P=3.9kW; \; I_{\mu}=0.56A; \; K_w=0.0012Nm/(rad/s). \)