CONTROL OF DR-300 SERVO USING MULTIPLE MODELS

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Abstract

The paper is concerned with the control of the nonlinear plant using multiple models. The DR-300 servo is single-input/single-output model which consists of a permanent magnet DC motor connected via clutch to a permanent magnet DC generator. The servo is connected to the PC through the Advantech multifunction card and controlled using Matlab/Simulink environment. The nonlinear dynamical system is represented by a set of locally valid sub models across the operating range. A controller is then designed for each sub model. Optimization of parameters of the validity function and local models is divided into two steps. While centers and weights of validity functions are detemined through the Johansen and Foss's algorithm, the parameters of local models are obtained using the least-squares method The control strategy is to determine the current operating conditions at every instant and activate the corresponding controller or a mixture of controllers.

1 Introduction

The technology development is constantly bringing more complex production facilities and thus rises the need for appropriate tool for engineers to help them understand and solve such systems. Fuzzy control or Expert systems, where complex problem is substituted by a simplified one, is one of the possible solutions to this kind of problems. In everyday life, the strategy how to solve complex problem is usually called *divide & conquer*. The problem is divided into simpler parts, which are solved independently and together yields the solution to the whole problem. The same strategy can be used for control of non-linear systems, where the non-linear plant is substituted by locally valid set of linear sub models.

2 Local Model Networks

Local model network (LMN) is a hybrid method which connects the properties of neural networks, fuzzy logic and conventional identification methods. Global system is substituted by finite number of local models each valid only in a part of the operating regime [1]. The output of the system is given by

$$\widehat{y}(k) = \sum_{i=1}^{N} \tilde{\rho}_i(\phi_k(k))\,\widehat{y}_i(k) \tag{1}$$

where ϕ_k is a vector of scheduling variables, $\tilde{\rho}$ is a weighting function and $\widehat{y}$ is the output of the i-model. The sum of the weighting functions has to be unity. This is provided by normalization

$$\tilde{\rho}_i(\phi) = \frac{\rho_i(\phi)}{\sum_{j=1}^{N} \rho_j(\phi)} \tag{2}$$

The Gauss function is usually used for weighting outputs of models. The Gauss function is given by

$$\rho_i(\phi) = \exp\left[-\frac{(\phi - c_i)^T (\phi - c_i)}{\sigma_i^2}\right] \tag{3}$$

where parameters c , σ defines the center and width, respectively.

3   Model Creation

The J&F algorithm suggested in [2] incorporates an outer loop for structure optimization and inner loop for parameter identification. For set of ARX models the output of the LMN is given by

$$\widehat{y}(k) = \sum_{i=1}^{N} \tilde{\rho}_i(\phi_k(k))\widehat{\theta}_i^T \varphi(k) \quad \phi \in Z \tag{4}$$

where $\varphi(k)$ is regression vector and $\widehat{\theta}_i^T$ is vector of parameters.

$$\varphi(k) = [\, y(k-1),\ldots,y(k-n_y),u(k-1),\ldots,u(k-n_u)]^T \tag{5}$$

$$\widehat{\theta}_i = [a_1,\ldots,a_{ny},b_1,\ldots,b_{nu}] $$

The scheduling variables have to be known beforehand. The J&F algorithm starts with only one model and the weighting function is unity over the whole operating d-dimensional space Z, where d is the number of scheduling variables. Using the least-squares method, the parameters estimation of the only model can be performed. The algorithm then divides the operating space into two parts. Since an infinite number of divisions are possible it is necessary to reduce the number investigated. This is done by only allowing the regime to be divided in a direction parallel to an axis of the box Z_l, and at a finite number of points along each axis. Thus for a *d*-dimensional box with s splitting points, a total of *ds* new decompositions are formed. New parameters of weighting functions are determined by the limits of each working regime

$$c_k^j = 0.5(z_k^{j\max} + z_k^{j\min}) $$
$$\sigma_k^j = 0.5\gamma(z_k^{j\max} - z_k^{j\min}) \tag{6}$$

where parameter γ influences the overlapping of Gauss function. For small values of γ the functions will not overlap and for large values the transition from one region to another will be smooth. The weights are optimized by minimizing the sum-squared error cost function:

$$J(\theta,\sigma,c) = [\, y - \widehat{y}]^T [\, y - \widehat{y}] \tag{7}$$

For fixed values of Gauss functions the output of LMN is given by

$$\widehat{y} = \begin{bmatrix} \rho_1\varphi_1^T & \rho_2\varphi_1^T & \cdots & \rho_N\varphi_1^T \end{bmatrix} \begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_N \end{bmatrix} = \mathbf{R\Theta} \tag{8}$$

which is a linear function of parameters and therefore, the minimum sum-squared error parameters are given by the linear least squares:

$$\mathbf{\Theta} = (\mathbf{R}^T\mathbf{R})^{-1}\mathbf{R}^T\mathbf{y} \tag{9}$$

For each split the value of cost function is calculated and the parameters of local models are determined. After considering all possible splits, the one with lowest cost function is then chosen and the procedure is repeated. This process continues until either a maximum number, *N*, of regimes is found or until some pre-specified modeling cost criterion is satisfied. The construction algorithms can also effectively determine which variables are required to suitably decompose the operating space. If no splits are formed over a particular axis, then the variable associated with that axis can be ignored. If the appropriate set of linear model is found, a controller for each model is designed using the pole-placement method.

4 Controller Design

Pole placement is of the simpler methods of design. The idea is to find the feedback law such that the closed-loop poles have the desired location [3].The controlled system is described by the equation:

$$A(z)y(k) = B(z)u(k) + v(k)$$

(10)

RST controller with the structure on Fig. 1, is given by equation
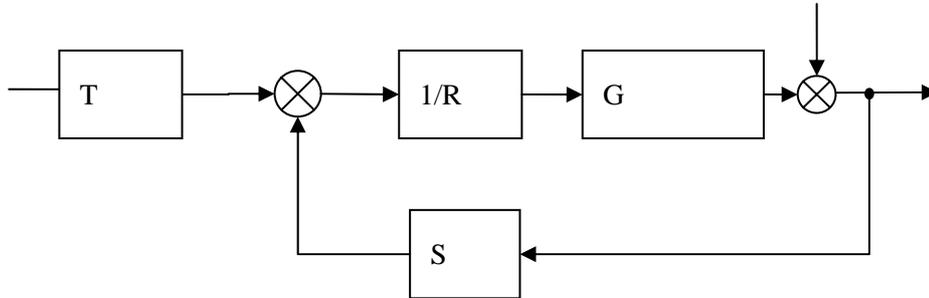
$$R(z)u(k) = T(z)w(k) + S(z)(k)$$

(11)

Figure 1: RST controller scheme

Using the Equations 10 and 11 we get the following equation for the closed-loop system:

$$(AR + BS)y = BT\,u$$

(12)

The polynomial $AR+BS$ is the characteristic polynomial of the closed-loop system. The parameters of the controller can be determined using the Diophantine equation

$$AR + BS = A_0 A_m B^+$$

(13)

where B^+ is a monic factor of B, A_0 is the observer polynomial and A_m characterizes the desired response.

5 Control of the DR300 servo

The plant is represented by a permanently exited DC-motor of which the input signal (armature current) is provided by a current control loop. The sensors for the output signal (speed) are a tacho-generator and an incremental encoder .The free end of the motor shaft is fixedly coupled to the shaft of a second identical motor which is used as a load.
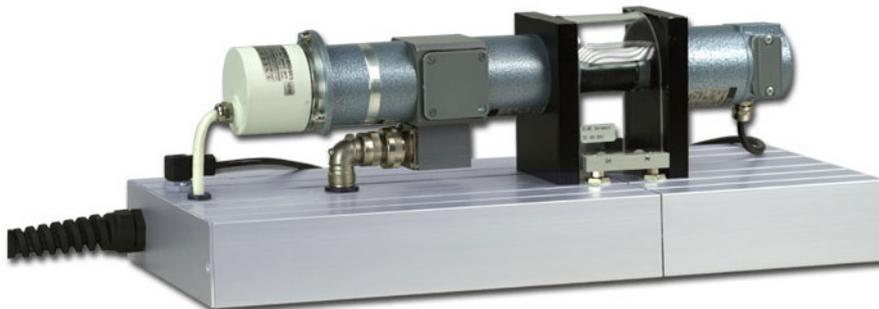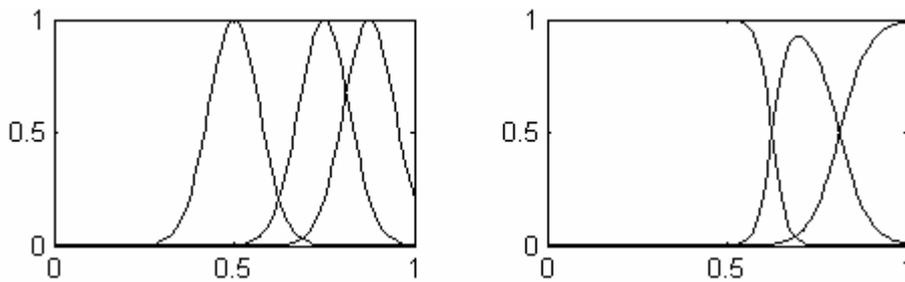

Figure 2: AMIRA DR300 Model

Figure 3: Validity functions and normalized validity functions for 3 models
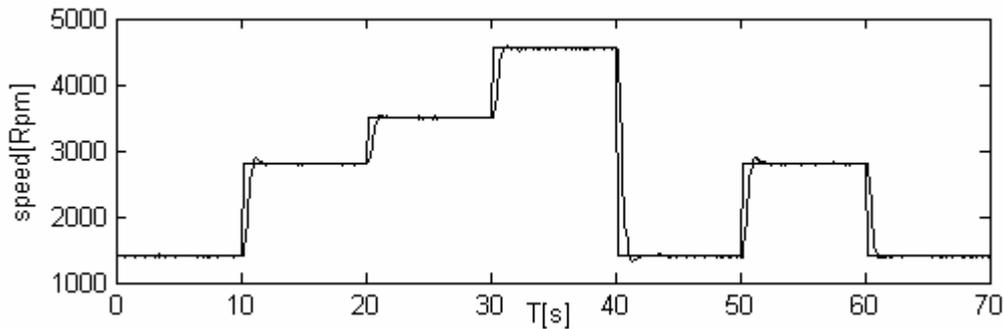

Figure 4: Control of DR300 Servo

6   Conclusion

In this paper a method to control nonlinear processes is tested on the AMIRA DR300 servo. The method is based on multiple linear models. The whole operating range is divided into local regimes where the plant can be represented by a set of linear models. The transition between is made smooth with the aid of validity function. The widths and centers of validity functions are optimized through the J&F algorithm. A local linear controller is designed for each of the models and the output is given as a weighted sum of local controllers. The effectiveness of the method is shown on the servo model.

7   Acknowledgment

References

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