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RULE-BASED CONTROL – DESIGN AND PERFORMANCE

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Abstract

This paper deals with some aspects of the rule-based control. The rule-based controller design methods are discussed and compared. New simulation results, obtained on the basis of the data from real-time experiments, carried out with a robust pre-production type of the magnetoreological (MR) shock damper and its controlled behavior by implementing both – the Adaptive Neuro-Fuzzy Logic Controller and adjusted by GA-FLC, are presented.

Keywords: Rule-Based Control, Fuzzy Logic Controller, Adaptive-Network-Based Fuzzy Logic Controller (ANB-FLC), self-learning ANB-FLC, ANB-FLC architecture optimization

1 INTRODUCTION

Conventional control techniques require mathematical models, which often have a complicated structure, derived from a deep understanding of a system. Moreover, achievement of an exact system description by adequate system of equations and precise numeric values is troublesome. Implementation of fuzzy logic control schemes, which are rule-based systems, shows its efficiency in modeling and control of unwell-studied complex systems. A set of fuzzy rules as one of main components of fuzzy system represents a control decision mechanism to adjust the effects of certain causes, arising in the controlled system [9, 11, 15, 17, 19].

Employing fuzzy logic control a process can be controlled without the knowledge of its underlying dynamics and the operator can simply express the control strategy, learned through experience, by a set of rules.

Fuzzy rules describe the controller behavior by using linguistic terms or controller implicates the proper control action from fuzzy rule base, which plays the role of the human operator. Because the control strategy mimics the human way of thinking, the experience of a human operator can be implemented through an automatic control method.

Main idea of fuzzy logic is to relate the numeric variables to linguistic variables, because dealing with the linguistic variables is closer to the human perception. Each linguistic variable represents a fuzzy subset, which owns a membership function that defines how a certain measurement belongs to the related linguistic variable.

Basic configuration of a fuzzy logic controller (FLC), as shown in Figure 1, comprises four principal components: a fuzzyfication module, FM, a rule base, RB, an inference mechanism, IM, and a defuzzification module DFM. Simplicity of fuzzy logic concept makes it easy to implement and much faster to develop efficient tool to deal with complicated non-linear and ill-defined systems.

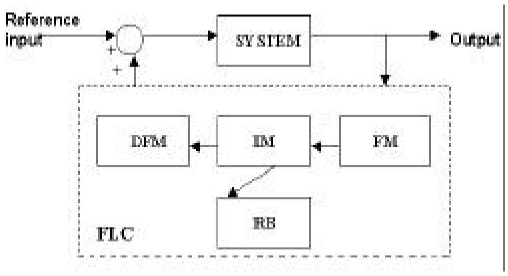


Figure 1: Basic configuration of a fuzzy logic controller (FLC)

Rule-based or fuzzy logic control most attractive features are the following. This method does not require the exact mathematical model of the system and the model is possible to construct by using small number of experimental data. Fuzzy logic offers ways to implement simple but robust solutions that cover a wide range of system parameters and can cope with major disturbances. The simplicity of the fuzzy logic concept requires writing less software code.

Disadvantage of rule-based or fuzzy control concept follows from the drawback of controller parameter tuning. Proper decision rules cannot easily be derived by expertise for more complex MIMO systems. Some significant operation conditions, as well as disturbances or parameter changes may be outside the expert's experience, which makes fine-tuning and achieving the optimal FLC a difficult task.

Above mentioned disadvantages of rule-based controllers design can overcome by implementing artificial neural network learning methods or genetic algorithms-based parameter optimization [8, 10, 16, 17].

2 ADAPTIVE-NETWORK BASED FUZZY LOGIC CONTROLLER

A hybrid neuro-fuzzy design approach takes advantages of the positive features of both fuzzy logic and neural networks for FLC design [1, 2, 4 - 7, 14]. The most important advantage of such a design technique is the automatic determination of an appropriate set of rules and membership functions [4, 16, 19].

Architecture

Considering the functional form of the neuro-fuzzy logic controller, (Figure 1), it becomes unquestionable that the fuzzy system can be transformed into a layered feedforward network, as is depicted in Figure 2. Such a connectionist network representation of the fuzzy logic system allows implementing the back propagation algorithm or a similar method for adjusting the membership functions and inference rules parameters.

Each layer in Figure 2 corresponds to one specific function, with the node functions in each layer being of the same type.

Nodes in layer 1 perform the membership function, and every node in layer 2 represents the firing strength of the rule.

The normalized firing strength of each rule is calculated by nodes in layer 3, and the output of each node in layer 4 is the weighted consequent part of the rule table.

The single node in layer 5 sums all incoming signals to determine the overall crisp output of the system [4].

The links between the nodes from one layer to the next layer in this network only indicate the direction of flow signals, and part or all of the nodes involve the adjustable parameters. These parameters are specified by the learning algorithm and are updated to achieve the desired input/output mapping.

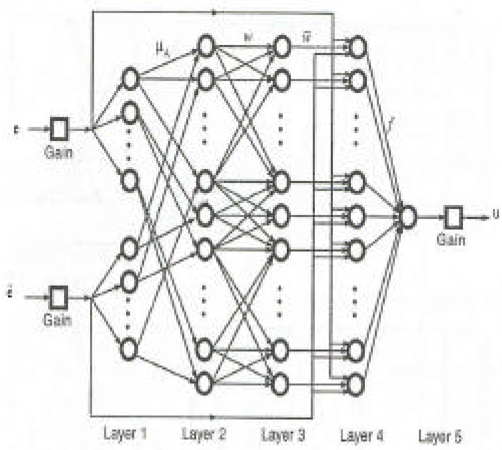


Figure 2: Adaptive- Network Based Fuzzy Logic Controller

As it was shown, the transformed in the NN FLC owns learning capability. In order to achieve a desired input/output mapping, its parameters are updated according to given training data and a gradient-descent-based learning procedure. It can be considered and implemented as an identifier for non-linear dynamic systems or as a non-linear controller with adjustable parameters.

Training and performance

Learning procedure is based on the processing of the control error data. In order to adjust the membership functions and fuzzy rules for a better controller performance, the error can be evaluated by comparing the output of the neuro-fuzzy controller and a desired controller.
The training procedure is performed as usual over a wide range of operating conditions, which include various types of causes and disturbances in the system.
The number of membership functions of each input variable is determined by the complexity of the training data and by trial and error, similar to choosing the number of neurons in the hidden layers of the artificial neural network (ANN).
The number of rules depends on the number of input variables and its linguistic presentation with a certain number of fuzzy membership functions.
Experimental studies with the Adaptive Network-Based Fuzzy Logic Controller (ANB-FLC) show a good performance over a wide operating range and can significantly improve the dynamic performance of different MIMO system [9, 10,11, 12, 13, 16, 17, 18].

3 SELF-LEARNING APPROACH FOR ADAPTIVE–NETWORK–BASED FLC DESIGN

As it was shown in previous section, the Adaptive-Network-Based FLC is designed on the basis of the data obtained from a desired, usually conventional, controller. In the case when the desired controller is missing, the neuro-fuzzy controller can be trained using a self-learning approach [8].
Firstly a separate neuro-fuzzy identifier is trained to behave like the plant. This plant identifier computes the derivative of the plant's output with respect to the plant's input by means of the back propagation process. The final output error of the controlled plant is back propagated

through the neuro-fuzzy identifier in order to obtain the equivalent error for the controller output. This scheme uses two neuro-fuzzy systems, as shown on the block diagram in Figure 3. The first one play role of the controller and the second is acting as the plant identifier. The dashed line in Figure 3 depicts the back propagation process, which passes through the forward identifier and continues back through the neuro-fuzzy controller that uses it to learn the control rule.

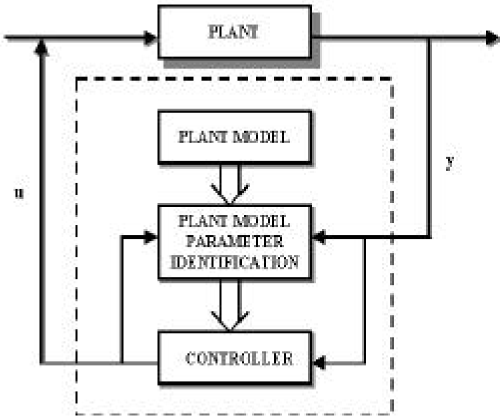


Figure 3: Self-learning Adaptive-Network-Based Fuzzy Logic Controller – block diagram

The self-learning neuro-fuzzy controller is trained for both the controller and the plant model (identifier) over a wide range of operating conditions and a wide spectrum of possible disturbances.

4 FLC ARCHITECTURE OPTIMIZATION

Adaptive fuzzy system offers a potential solution to the knowledge extraction problem; in the case of known in advance structure of the fuzzy system [3, 5, 6, 10, 14].
The structure, expressed in terms of the number of linguistic terms (membership functions) and the number of inference rules, is usually derived on the basis of experimental study and trial and error.
The number of inference rules has to be determined from the standpoint of overall learning capability and generalization capability.
The adjustment of membership functions and rule parameters can be resolved by employing also a genetic algorithm (GA) [17].
Implementing both genetic algorithm and adaptive neuro-fuzzy approach can optimize the membership functions parameters at the same time. Such an optimization consists of two major processes: determination of the optimal number of rules and membership functions shapes by exploiting a GA; training the NN to determine the consequent parts of the rule base by the gradient descent algorithm. However, GA implementation has certain limitations because it can fall into a local optimum point if the parameters are improperly selected [3, 9, 10, 11].

5 APPLICATIONS AND DISCUSSION

Conventional dampers are sufficient for most applications. For transportation of dangerous or vibration-sensitive goods, innovative dampers with a controlled behavior are required. Recent solutions in the controller damper development are magnetoreological fluids-based dampers. Due to their feedback control, disturbances like temperature and friction do not influence the desired behavior of these intelligent dampers.

Dampers based on magnetorheological fluids (MRF) generate damping forces, which are modifiable quickly and continuously by a magnetic field in a wide range [12, 13].

The MRF-based shock damper consists of two interconnected cylinders filled with MRF and uses the flow mode (Figure 4). Due to an external force F_{ext} the pistons are moving with the velocity v. A non-contact sensor measures the displacement s. At the interconnecting channel with a cross section of 4 x 20 mm^2 acts a magnetic flux density B, induced by an electromagnet. Thereby a damping force $F_D(B)$ is generated. In consequence of this the velocity v is controllable between zero and the maximal velocity v_0 at $B = 0$. An electric power of some watts only is required to provide a damping force of about 1 kN.

The approximate type of relevant transfer function between the output velocity v and the input current I_{set} is shown in [12]. It is explained that gain and time constant depend on the construction features of the damper. Main part of the time delay is due to the inertia forces of the moved masses. Our previous investigations with one kind of MRF-based shock damper [12] show satisfactory results, which have been reached with conventional PI, predictive by Smith PI-controller and a PI-FLC, designed by Mamdani [12, 13].

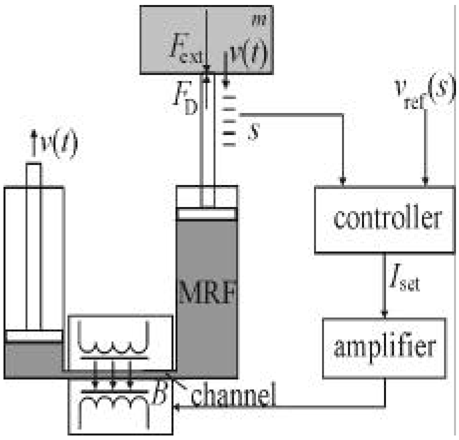


Figure 4: Scheme of a magnetoreological shock damper

In this paper are presented simulation results, obtained on the basis of the data from real-time experiments, carried out with a new robust pre-production type (Figure 5) of the shock magnetoreological (MR) damper and its controlled behavior by implementing both – the Adaptive Neuro-Fuzzy Logic Controller and adjusted by GA-FLC.

Figure 5: Robust pre-production type of MRF-based shock damper

A total of 6,000 input-output data pairs were obtained for training the adaptive neuro-fuzzy controller. Selected instances of the real-time experiments are show in Figure 6.

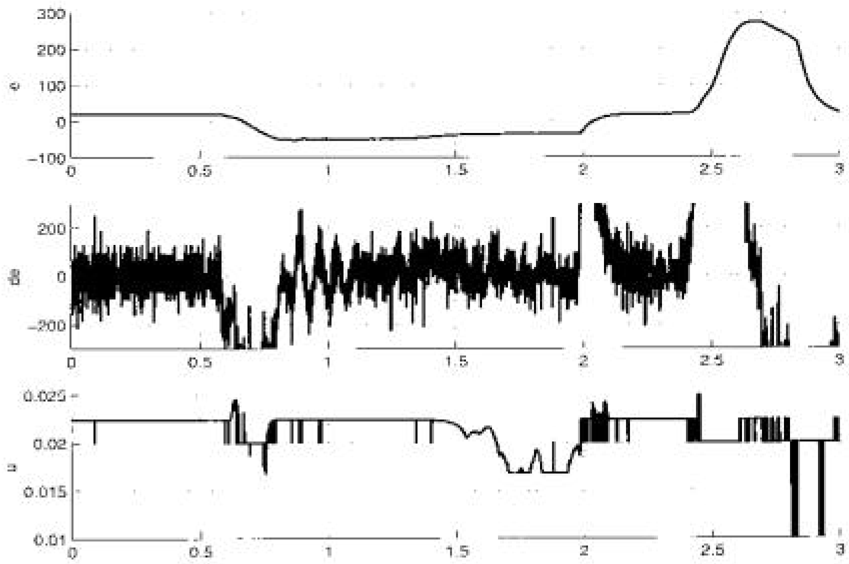
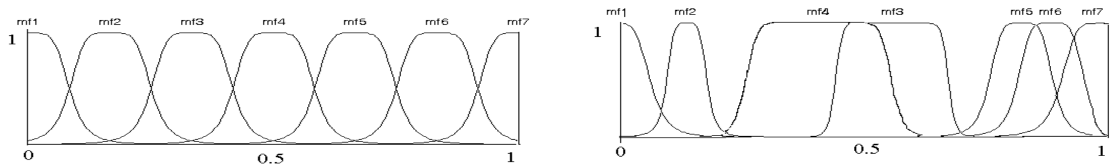


Figure 6: Selected instances of the real-time experiments

Based on earlier experience, seven linguistic variables (Bellman shaped membership functions) were used for each input variable to get the desired performance, thus the controller rule base consist of 49 fuzzy rules.

The membership functions for the input variable e before and after training are shown in Figure 7.



a) before training b) after training

Figure 7: Membership functions adjustment

The universe of discourse for both input and output variables is normalized and the gain parameters are chosen based on the input-output space.

Controller performance is presented in [12, 13] by the simulation results, which shows a smoothed transient response of ANB-FLC, compared with the previously designed by optimal module approach conventional PI controller.

Genetic algorithms-based controller optimization is carried out in two ways: parameter optimization of a conventional PI-controller as is described in [17] and GA- optimization on fuzzy paradigms [10]. Implemented there GA operates on a number of controller (membership function) parameters, called population. GA operating with very small population of approximately 10 or less individuals, is a micro GA (as is in the parameter optimization of conventional PI-controller), with a restrictive reproduction and replacement

strategy. The most commonly used representation of real-valued genes in the GA can be implemented for the FLC-membership functions optimization [18].
Simulation results obtained by implementing GA-optimized PI-controller are shown in Figure 8.

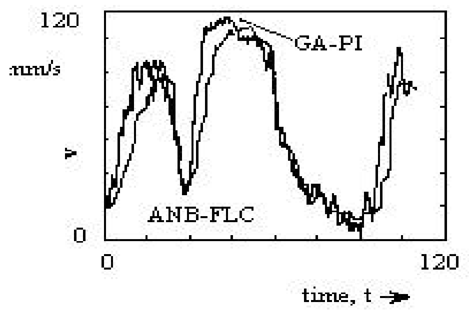


Figure 8: Simulation performance of GA-optimized PI and FLC controller

Comparison of the simulation results in Figure 8 shows good performance of GA-optimized controller, which claims the efficiency of GA algorithms for controller parameter adjustment. The GA-PI-controller is faster in comparison with the conventional and ANB-FLC controllers, designed for magnetoreological damper control.
As it was mentioned, FLC design requires deep expert's skill and experience. Such a problem is very sufficiently overcome implementing rule-based or adaptive NN-learning techniques and optimization power of genetic algorithms.
The rule-based control advantages and disadvantages were discussed theoretically and by simulative research on a new robust pre-production type of the magnetoreological (MR) shock damper. Our future planes are in implementing the rule-based design techniques on the other MR systems. It arises from the recent trends in advanced technology, which continue to move away from an industrial-based economy to economies based in large part on the new, AI-based technologies: Neural Networks Techniques, Fuzzy Systems Theory, Knowledge Based Systems Techniques, and Expert Systems Techniques.

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