

A Learning Linguistic Teaching Control for a Multi-Area Electric Power System

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Abstract

This paper presents a new methodology for designing a neuro-fuzzy control for complex physical systems. By developing a Neural -Fuzzy system learning with linguistic teaching signals. The advantage of this technique is that, produce a simple and well-performing system because it selects the fuzzy sets and the numerical numbers and process both numerical and linguistic information. This approach is able to process and learn numerical information as well as linguistic information. The proposed control scheme is applied to a multi-area power system with hydraulic and thermal turbines.

Keywords: Fuzzy Logic Control, Artificial Neural Network, Interconnected Power System, Load Frequency Control, Neuro-fuzzy Systems.

1. INTRODUCTION

The control engineer's knowledge of the system is based on expertise, intuition, knowledge of the system's behavior. Therefore, the main objective of the fuzzy control scheme is to replace an expert human operator with a fuzzy rule-based control system.

The fuzzy system belongs to a general class of fuzzy logic system in which fuzzy system variables are transformed into fuzzy sets "Fuzzification" and manipulated by a collection of "IF-THEN" fuzzy rules, assembled in what is known as the fuzzy inference engine.

These rules are derived from the knowledge of experts with substantial experience in the system. Then, the fuzzy sets are transformed into fuzzy variables" Defuzzification" [2, 4].

In such a system, input values are normalized and converted to fuzzy representations, the model's rule base is executed to produce a consequent fuzzy region for each solution variable, and the consequent regions are defuzzified to find the expected value of each solution variable [1, 7].

Artificial Neural networks may be employed to represent the brain activities, neural networks are attractive to the classical techniques for identification and control of complex physical systems, because of their ability to learn and approximate functions [6, 9].

The conventional control systems usually involve the development of a mathematical model of the system to derive a control law. In many of the physical systems, it may be difficult to obtain an accurate mathematical model due to the presence of structured and unstructured uncertainties. Fuzzy system and neural networks are both soft computing approaches for modeling expert behavior [7, 9]. This paper will show those combinations of neural networks with fuzzy systems, the so called neural fuzzy or neuro-fuzzy systems.

By a Neuro-fuzzy system, one understands a system which involves in some way both fuzzy systems and neural networks, or features of both, combined in a single system.

The most important reason for combining fuzzy systems with neural networks is their learning capability and such a combination should be able to learn linguistic rules and / or membership functions.

Therefore, combining neural networks with a fuzzy set could combine the advantage of symbolic and numerical processing.

Neural Networks and fuzzy systems estimate functions from sample data, it does not require a mathematical model; they are model-free estimators [6, 9]

2. FUZZY LOGIC CONTROLLER

The fuzzy logic controller comprises three stages namely fuzzifier, rule-based assignment tables and the defuzzifier. The fuzzifier is responsible for converting crisp measured data into suitable linguistic values. The fuzzy rule-base stores the empirical knowledge of the operation of the domain experts. The inference engine is the kernel of an FLC, and it has the capability of simulating human decision-making by performing approximation reasoning to achieve a desired output.

The defuzzifier is utilized to yield a nonfuzzy decision action from an inferred fuzzy system by the inference engine. The defuzzifier is responsible for converting linguistic values into crisp data [1, 7].

A typical architecture of a fuzzy logic is shown in Fig.1

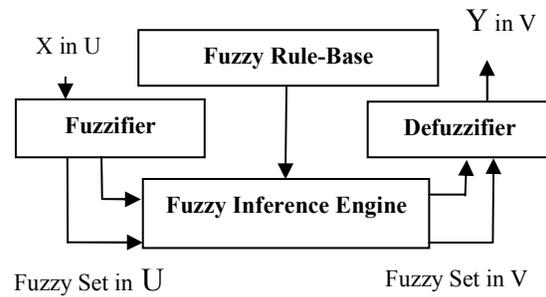


FIGURE 1: Fuzzy System Structure

The fuzzy logic system proceeds as follows to evaluate the desired output signal, as shown in Fig.2.

At First, the input variables are normalized, and the membership function of the fuzzy logic controller output signal is determined by linguistic codes

Finally, the numerical value of the adaptive fuzzy logic controller output signal corresponding to a specific linguistic code is determined.

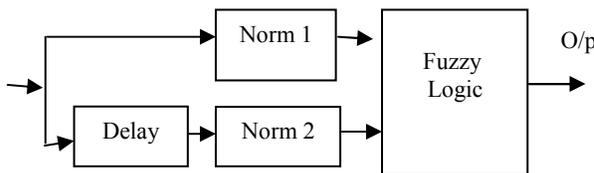


FIGURE 2: The Internal Structure of Fuzzy Logic

The error “e” and the error change “Δe” are defined as a difference between the set point value and the current output value

$$e(k) = u_r^0(k) - u_c^0(k) \quad (1)$$

$$\Delta e(k) = e(k) - e(k-1) \quad (2)$$

That is,

$$u_r^0(k) = u_r^0(k-1)$$

This assumption is also satisfied in most cases:

Case (1):

$$e(k) < 0 \quad \text{and} \quad \Delta e(k) > 0$$

$$\Rightarrow \Delta u_r^0(k) < u_c^m(k)$$

$$\text{and} \quad u_c^m(k) < u_c^m(k-1)$$

Case (2):

$$e(k) > 0 \quad \text{and} \quad \Delta e(k) < 0$$

$$\Rightarrow \Delta u_r^0(k) > u_c^m(k)$$

$$\text{and} \quad u_c^m(k) < u_c^m(k-1)$$

Where

$u_r^m(k)$: is the reference of the fuzzy logic controller at k-th sampling interval

$u_c^m(k)$: is the fuzzy logic controller signal at k-th sampling interval

$e(k)$ is the error signal

$\Delta e(k)$: is the error change signal

3. NEURAL NETWORKS

The most significant characteristic of the neural networks is their ability to approximate arbitrary nonlinear functions. This ability of the neural networks has made them useful to model nonlinear systems, which is of primary importance in the synthesis of nonlinear controllers [11]. A neuro-controller (neural network-based control system), in general, performs a specific form of a multilayer network and the adaptive parameters being defined as the adjustable weights [12].

In general, neural networks represent parallel-distributed processing structures, which make them prime candidates for use in multivariable control systems.

The neural network approach defines the problem of control as the mapping of measured signals for change into calculated controls for actions. The system shown in Fig.3 represents the neural learning and control scheme, a control system is called a learning control system, if the information pertaining to the unknown features of the system for its environment is acquired during operation, and the obtained information is used for future estimation.

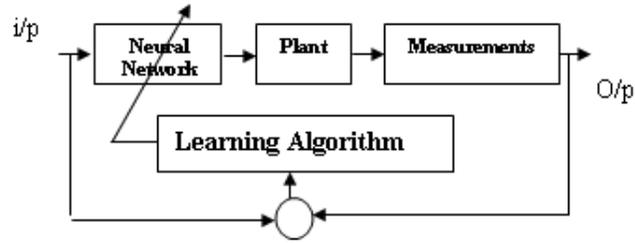


FIGURE 3: A Typical Neural Learning and Control Scheme

4. NEURO-FUZZY SYSTEMS

The neural networks and fuzzy systems solve problems by performing the function approximation. Neural networks can be used, if training data is available, and a mathematical model of the system is not needed [6-9, 11, 12]. But a fuzzy system can be used, if knowledge about the solution of the problem in the form of linguistic IF-THEN rules is available, a formal model of the system is unnecessary, and training data will not be needed.

On the other hand, if the problem of interest changes too much compared to the former training data, then the network may not be able to cope with that, there is no guarantee that resuming the training process will lead to fast adaptation to the modified problem, it may be necessary to repeat the learning again [11].

A neuro-fuzzy system, is a system which involves in some way both fuzzy systems and neural networks or features of both combined in a single system [11, 12]

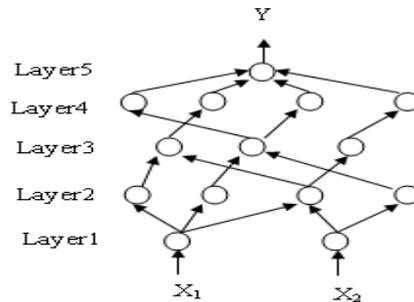


FIGURE 4: The five Layer Architecture

Fig. 4 shows the neural fuzzy system structure with five-layers. The proposed approach to develop a neuro-fuzzy logic control consists of the following five steps. At first, each node in the first layer transmits input number x_i to the next layer directly.

The second step is called matching, each node in the 2nd layer has exactly one input from some input linguistic nodes and feeds its output to rule node, and the weight is fuzzy number w . the third step.

The input and output of a node in the 3rd layer are numerically calculated to find the minimum matching of fuzzy logic rules. The fourth step, finds the maximum value for the 3rd layer, and the nodes in the 4th layer should be fuzzy OR. Finally, Merging and Defuzzification of each node has a fuzzy weight w_{Y_i} .

All previous steps can be governed by the following equations

$$O_i^1 = U(O_{i1}^1 - O_{i2}^1) = X_i \quad (3)$$

$$f_{ij}^2 = 0.5 \sum (w \times X_{ij1} - u_{ij}(t))^2 + \sum (w \times X_{ij1} - u_{ij}(t))^2 \quad (4)$$

$$O_1^3 = \min(u_1^3, \dots, u_k^3) \quad (5)$$

$$O_1^3 = \max(u_1^4, \dots, u_k^4) \quad (6)$$

$$O_5 = U(O_1^5, O_2^5) = Y = \frac{\sum u_1^5 w y}{\sum u_1^5} \quad (7)$$

5. ELECTRIC POWER SYSTEM

It is reasonable to study in considerable details the megawatt frequency control problem for multi-area electric power system. Load Frequency Control “LFC” is a very important factor in power system operation. It aims at controlling the output power of each generator to minimize the transient errors in the frequency and tie-line power deviations and to ensure its zero steady state errors [15, 16].

Load frequency control “LFC” sometimes, called Automatic Generation Control “AGC” is a very important aspect in power system operation and control for supplying sufficient and reliable electric power with the desired quality [13, 14].

Load frequency control generally involves several designed power areas within an integrated power grid with each area responsible for controlling its area control error ‘ACE’

A two area interconnected power system model is developed. The load frequency control “LFC” of interconnected power system “IPS” relies on an operating schedule that is usually prepared all day. In advance, this schedule indicates the expected demand profile of the area as well as, the area commitment to its adjacent areas. The problem of the LFC of an IPS can be expressed mathematically as follows

$$X = [X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8] \\ = [\Delta F_1, \Delta X_{g1}, \Delta P_{g1}, \Delta F_2, \Delta X_{g2}, \Delta H_{g2}, \Delta P_{g2}, \Delta P_{tie2}] \quad (8)$$

$$U = [U_1, U_2, U_3, U_4] = [\Delta P_{c1}, \Delta P_{d1}, \Delta P_{c2}, \Delta P_{d2}] \quad (9)$$

The commitment is the tie-line power interchange which should be maintained at a certain point in time. This value is fed to the other area. The functional block diagram of Hydro-Thermal interconnected power system is shown in Fig.5. Power deficits may be purely active, purely reactive, or combined. Any of these deficits affects the frequency of the system either directly.

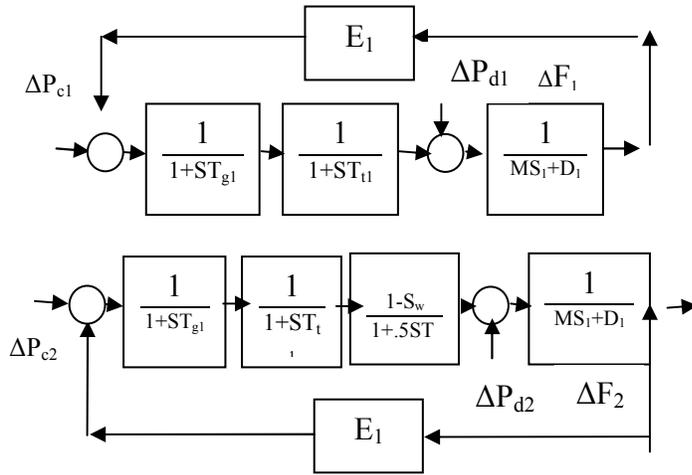


FIGURE 5: Block diagram of Hydro-Thermal Interconnected power system

Due to active power unbalance, or indirectly, through change in system demand due to changes in voltage caused by reactive power unbalance.

Active power deficits may take place in power systems as a result of forced outage of generating units and / or loaded tie lines, or due to the switching on of appreciable loads.

The interlinking of the various areas in case of a two-area system is through the tie-line power exchange. Changes in tie-line power flows affected the power balance in corresponding areas as shown in Fig.6.

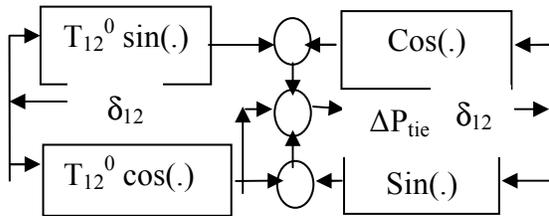


FIGURE 6: Tie -Line Power Exchange

The incremental tie-line power is

$$\begin{aligned} \Delta P_{tie2} &= T_{12}^0 \sin(\delta_1^0 - \delta_2^0) \cos(\delta_1^0 - \delta_2^0) \\ &\quad - T_{12}^0 \sin(\delta_1^0 - \delta_2^0) + T_{12}^0 \cos(\delta_1^0 - \delta_2^0) \sin(\delta_1^0 - \delta_2^0) \end{aligned} \quad (10)$$

6. NUMERICAL DATA

As a numerical example, a two area load frequency control system was studied. The numerical data has shown:

Thermal-area

$$M=0.04, G=0.01, T_g=0.5, T_t=0.5, E=0.03$$

Hydro-area

$$M=0.03, G=0.08, T_g=0.5, T_t=0.5, E=0.013, T_w=0.5$$

Tie-line power

$$T_{12}=0.02701$$

In this section, the development of a Neuro-fuzzy system, learning with linguistic teaching signals is shown.

This system is able to process and learn numerical information as well as linguistic information. It can be used as an adaptive fuzzy controller by using the reinforcement learning proposed in [12]. The proposed Neuro-fuzzy techniques confirmed the effectiveness of the human operator in the presence of system nonlinearities. The results are shown in Fig.7, indicates the closed loop response of the Neuro-fuzzy control.

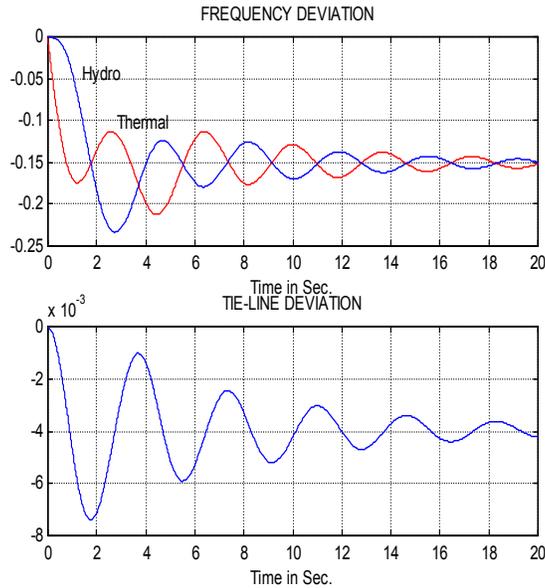


FIGURE 7: the System Response with Neuro-Fuzzy Control

6. CONCLUSION

This paper proposed combining a neural network with a fuzzy set; It could combine the advantage of symbolic and numerical processing. Neural Networks and fuzzy systems estimate functions from sample data, it does not require a mathematical model; they are model-free estimators a Neural-Fuzzy system that process both numerical and linguistic information. The proposed system has some characteristics and advantages, the inputs and outputs are fuzzy numbers or numerical numbers, the weights of the proposed Neural-fuzzy system are fuzzy weights, owing to the representation forms of the fuzzy weights, the fuzzy inputs and fuzzy outputs can be fuzzy number of any shape, and except the input-output layers, numerical numbers are propagated through the whole Neural-fuzzy system. The proposed Neuro-fuzzy techniques confirmed the effectiveness of the human operator in the presence of system nonlinearities. This controller does not require the system model, this model is a complex model, and needed to leanirezed to design a controller, but our controller require only the observation of input-output. The response of Hydro-Thermal plant has an error less than the conventional controller used, and it is an adaptive controller.

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