CHAPTER 2

Review and Background

In this chapter, the adaptive controller and the artificial intelligent control architectures are briefly described. Then some background on the related works are reviewed.

2.1 Adaptive Control Systems

An adaptive controller can be divided into two categories [34]: the *Model-Reference Adaptive Controller* (MRAC) and the *Self-Tuning Controller* (STC). These structures are shown on Fig. 2.1 and 2.2, respectively.

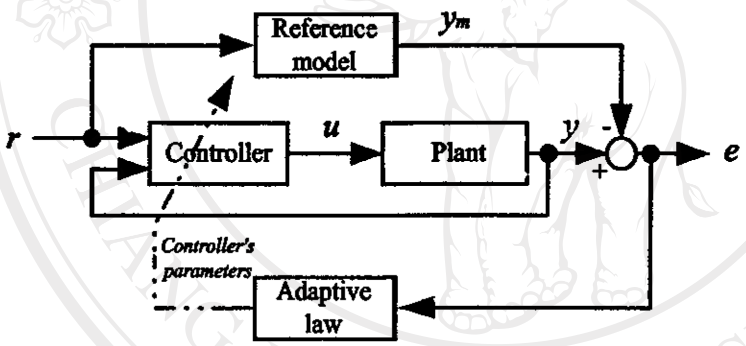

Figure 2.1: Model-Reference Adaptive Controller (MRAC) .

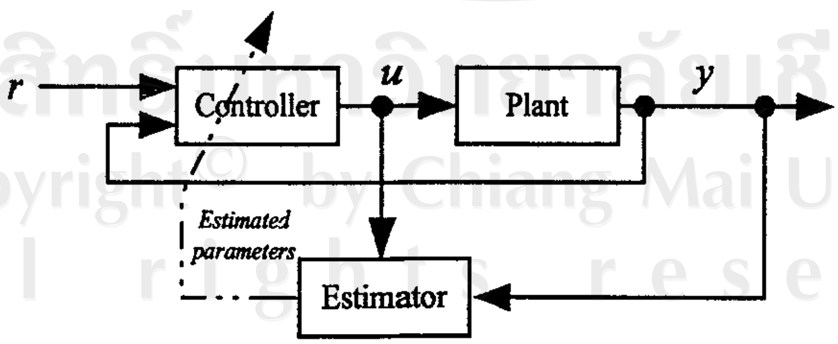

Figure 2.2: Self-Tuning Controller (STC).

In the MRAC, controller parameters are adjusted using some adaptive laws until the responses of the controlled plant and the reference model are equal. The adaptation mechanism is designed to guarantee that the control system remains stable and the tracking error eventually becomes zero. Many methods in nonlinear control theory, such as Lyapunov theory, passivity theory and hyper-stability theory can be used to design the controller. While for the STC, controller parameters are adjusted by the parameter estimator. This estimator tries to find the suitable parameters using the input and output data of the controlled plant. The performances of these controllers highly depend on the reference model and the estimator. Although the controller design becomes easier, the difficulties in obtaining appropriate reference model and estimator still remain.

2.2 Artificial Intelligent Control Systems

To avoid the problem of finding a mathematical model of the controlled plant, some artificial intelligent methods have been applied to the controller design. Examples of these intelligent control techniques are the Knowledge Based Systems (KBS), fuzzy logic and neural network.

KBS is a system based on human knowledge. It is capable of reaching decisions on the basic of incomplete, imprecise or uncertain data.

Fuzzy logic provides a system for representing the meaning of imprecise propositions in a natural language structure, through the propositions being represented as a non-crisp or fuzzification on an input variable. The rule based system is used to compute through the calculation unit called inference. Finally, the crisp output is generated by the defuzzification unit.

The design of KBS and fuzzy logic control is usually based on the input-output behavior of the controlled plant. The controller is a set of fuzzy logic units [39]: the fuzzification, the inference engine and the defuzzification. Memory requirement for fuzzy logic controller grows exponentially with the number of system variables used in the fuzzy rule base. The rule based control strategy has several weaknesses. It usually assumes that the variables used by the operator are readily measurable or quantifiable. Subtleties such as time delays between the output and the input signal can be readily articulated.

2.3 Adaptive Networks

In this section, the typical adaptive network and other fuzzy neural integrated systems are introduced. An adaptive network is a network structure consisting of nodes and directional links which connect the nodes together [31]. The linking weights can be automatically adjusted by some basic learning algorithms based on the steepest descent and the chain rule [49].

2.3.1 Typical Adaptive Networks

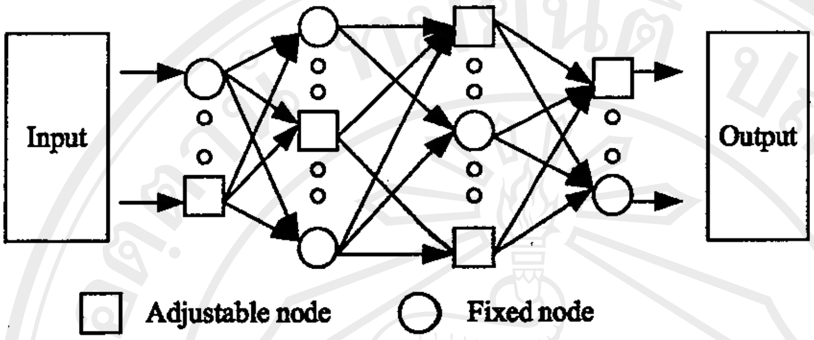

Figure 2.3: Typical adaptive network architecture.

The typical structure of an adaptive network is shown in Fig. 2.3. Nodes in the adaptive network can be divided into two types as following:

Fixed nodes In this type, node function parameters are fixed. No learning algorithm is applied.

Adjustable nodes In this type, the learning algorithm is applied to adjust node function parameters. The direction of this adaptation is done to follow the negative gradient of the cost function with respect to the adjusted parameters.

The links of each node between the previous and the next layers have the parameters called weights or linking weights. They can be adjusted by many algorithms such as the conventional back propagation. The numbers of the input and the output nodes are determined by the application of this network. However, the numbers of nodes in the hidden layers are usually determined by trial and error. In the conventional neural network, all nodes are fixed nodes and only the linking weights are adjusted.

2.3.2 Neuro-Fuzzy Network

The combination between the human knowledge as IF-THEN rules and the neural network has been proposed and are widely applied in many fields [8,29,43]. The aim of this combination is to combine both the operations expressed as linguistic fuzzy expressions and the learning schemes used to tune up the system. Recently, the neuro-fuzzy systems can be divided into two main categories [4]. The first type is based on the parallel structures and learning algorithms as in neural networks. The fuzzy inferences are implemented for every fuzzy rule using the neural networks. The reader can refer to [28, 29] and the references therein for more details. In the other appoarch, the fuzzy inference are directly incorporated into the neural network [46, 57, 66].

In order to get some idea about the neuro-fuzzy networks, two well-known fuzzy-neural networks are briefly presented here.

SONFIN

The *Self-cOnstructing Neural Fuzzy Inference Network* (SONFIN) is proposed by Juang and Lin in [2]. This network contains 6 layers and realizes the traditional TSK model.

The structure of SONFIN is shown in Fig. 2.4. To enchance the knowledge representation capability of SONFIN, the input variables are incorporated through human-defined membership functions, and the linear transformation is automatically adjusted during the parameter learning phase. The drawbacks of this network are its complex structrue and a large number of adjustable parameters. Furthermore, the learning algorithm for this network is not suitable with the direct control system application.

ANFIS

The *Adaptive-Network-based Fuzzy Inference System* (ANFIS) has been proposed by Jang in [28] and [29]. It can be shown that this network which is based on the TSK model is functional equivalent to the radial basis function network. ANFIS has been applied in many research areas such as system indentifications, control system applications.

The corresponding equivalence of two-input ANFIS architecture is illustrated in Fig. 2.5. In this network, the human knowledge can be included through the membership functions and rule definiteness. Many parameter adaptive techniques such as the back-propagation, the steepest descent, and the least squares estimation are applied to tune up both linear parameters in the consequent part and nonlinear parameters in the membership functions. Unfortunately, linear consequent parameters are not easy to set in human senses and these parameter are

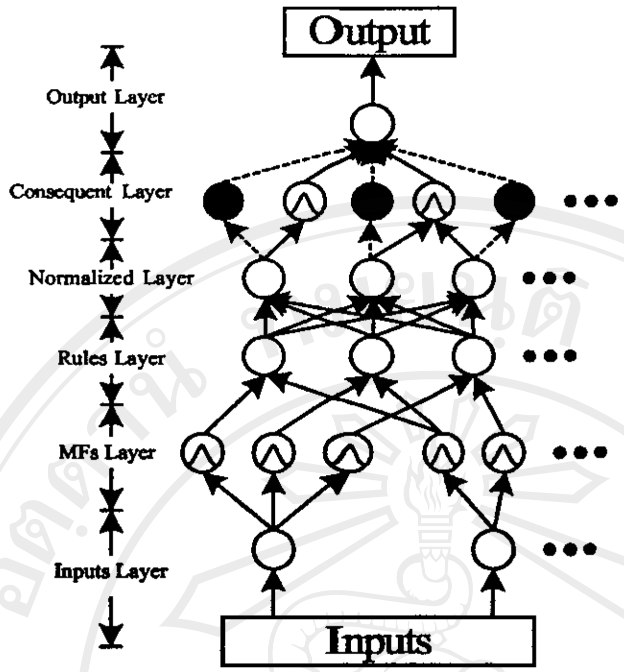

Figure 2.4: Structure of SONFIN.

normally set to small random values. Moreover, the computation on this network is quite complicated during the parameter adaptation phase.

Notice that both SONFIN and ANFIS have rather complicated structures and adaptive algorithms. As a result, how to select the initial setting of network parameters is not clearly defined. In general, they are set by small random values. [6, 28, 38].

Characteristics of some neural fuzzy inference systems are summarized in Table 2.1. Although these neuro-fuzzy techniques have been successfully applied in many engineering fields such as nonlinear control systems, the lack of stability analysis is one of the important problems [2, 5–7].

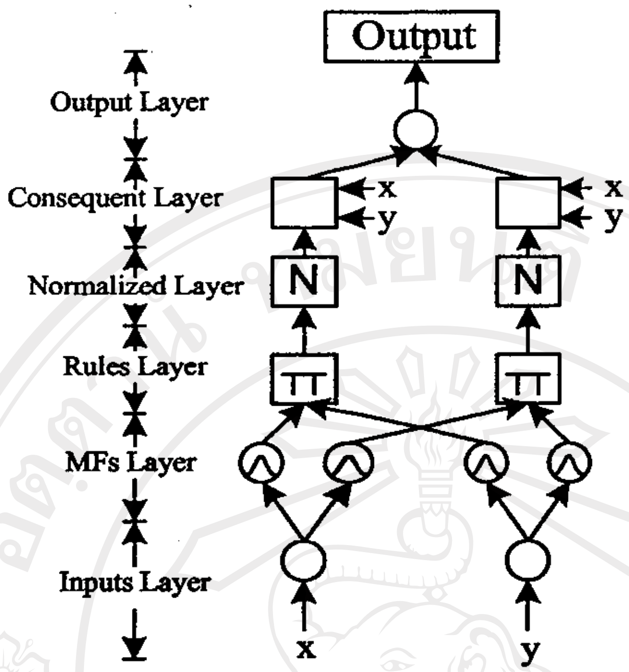

Figure 2.5: Structure of ANFIS.

Table 2.1: Examples of neural fuzzy inference systems

Researcher(s)	Antecedent MFs	Rule operations	Consequent MFs	Defuzzification
Lin [6]	Bell	AND/product	Bell	WA, COA
Berenji [22]	Triangular	AND/soft-min	Triangular	LMOM
Nie [27]	Bell	AND/product	Singleton	WA
Jang [29]	Bell	AND/product	Singleton	WA
Vuorima [48]	Triangular	AND/min	Singleton	WA
Horikawa [56]	Bell	AND/product	Singleton	WA,TSK

Note that MF, WA, COA, LMOM, and TSK denote the membership function, the weight average, the center of area, the localized mean of maximum and the Tsukamoto defuzzification [56, 60] respectively. Bell, Triangular and Singleton are the types of membership functions. Product, soft-min and min are fuzzy set operations. Interested readers can refer to [4], [28] and references therein for more detail.