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# COMPARISON OF LEARNING ALGORITHMS FOR FUZZY NEURAL NETWORKS (FNN) USED FOR NONLINEAR SYSTEMS MODELING

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**Abstract.** In this research, we focus on making a comparative study between different learning algorithms that have been proposed to train fuzzy neural networks, which has attracted a lot of attention for nonlinear system modeling. Thus, an analyzing of recent training algorithms and methods for FNNs is presented regarding their main structures, advantages, shortcomings, computational complexity, and training time for convergence. Moreover, an elaborated study of fixed structure or self-organized fuzzy neural networks is carried out as step toward using FNN in nonlinear system modeling.

**Introduction.** Nonlinear system modeling has been successfully employed in many areas, such as control, process monitoring, and so on. However, nonlinear system modeling is a complex problem: generation of appropriate models requires the consideration of both the aims of task specification and user preferences [1]. Moreover, due to the high dimensionality and complexity of nonlinear systems, this problem becomes more difficult. Even though that, the modeling approaches based on conventional mathematics are widely used, those approaches fail to maintain good performance when the dynamic process of the system imposes complicated characteristics in terms of strong nonlinearities, multivariable coupling, variations of operation conditions together with unknown model structure and parameters [2]. Recently, FNN method for nonlinear system modeling has received huge interest from the scientific community because it provides the advantages of both neural networks and fuzzy systems, i.e., adaptability, high accuracy, and quick convergence [3], [4]. Thus, conducting a comparative study for existing FNN learning algorithms, considering their applicability in nonlinear system modeling, is a justified step toward developing an efficient technique for modeling nonlinear systems.

**Main part.** Many different learning algorithms have been proposed for FNN, and the Backpropagation (BP) method is probably the most frequently used technique. But the primary shortcoming of BP method is the uncertainty that is associated with taking a global minimum of the error function and the excessively long training time for convergence [5]. To overcome the aforementioned problems, there has been much research proposed to improve this algorithm. In this regard, there are two main types of training algorithms that we are analyzing in this work:

- The first type of training method only focuses on the learning phase of the parameters, which is determined using supervised or unsupervised learning algorithms. The structures of these FNNs are fixed in advance, so they are somewhat subjective [4]–[7].
- The second type of training method has a training phase of structure design of FNNs in addition to the training phase of the parameters. Those training methods are called self-organized FNNs [8]–[13].

**Conclusion.** The comparison between the different training algorithms for FNNs shows that self-organizing FNNs learning methods are more adequate than the ones with fixed structure in nonlinear system modeling. However, based on our analyzing, the computation time and testing error of the self-organizing FNNs can be improved for more efficient performance and better accuracy. Thus, a combination of the different learning algorithms for FNNs is a promising solution for improving the computation time and accuracy of nonlinear system identification.

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