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Survey on Neuro-Fuzzy systems and their applications in technical diagnostics and measurement

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ABSTRACT

Both fuzzy logic, as the basis of many inference systems, and Neural Networks, as a powerful computational model for classification and estimation, have been used in many application fields since their birth. These two techniques are somewhat supplementary to each other in a way that what one is lacking of the other can provide. This led to the creation of Neuro-Fuzzy systems which utilize fuzzy logic to construct a complex model by extending the capabilities of Artificial Neural Networks. Generally speaking all type of systems that integrate these two techniques can be called Neuro-Fuzzy systems. Key feature of these systems is that they use input–output patterns to adjust the fuzzy sets and rules inside the model. The paper reviews the principles of a Neuro-Fuzzy system and the key methods presented in this field, furthermore provides survey on their applications for technical diagnostics and measurement.

1. Introduction

As two important techniques of artificial intelligence, Fuzzy Systems (FS) and Artificial Neural Networks (ANNs) have many applications in various fields such as production, control systems, diagnostic and supervision. They evolved and improved throughout the years to adapt arising needs and technological advancements. As ANNs and Fuzzy Systems had been often applied together the concept of a fusion between them started to take shape. Neuro-Fuzzy systems were born which utilize the advantages of both techniques: they have learning and generalization capabilities and at the same time they reveal the functionality stored in the model. To reach this behavior they are able to learn and tune their parameters based on input–output patterns (learning phase) and then they work like a fuzzy logic system (execution phase), too. These combined features make this type of systems useful when solving complex problems also for technical diagnostic and measurement assignments.

The paper contains seven sections. After the introduction the second section presents Neuro-Fuzzy applications of the last two decades in technical diagnostics and measurement. The third section describes the two main components of a Neuro-Fuzzy system followed by the forth one reviewing the progression of the Neuro-Fuzzy systems and the modern solutions used today. The last three sections are conclusions, acknowledgments and references.

2. Application of Neuro-Fuzzy systems to technical diagnostics and measurement

This section gives a survey on Neuro-Fuzzy system applications in the field of technical diagnostics and measurement. Different Neuro-Fuzzy architectures are named here, their history and a more detailed description are presented in the next sections. At the end of this section a table is also presented which gives a comprehensive overview of these applications and their fields categorically.

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2.1. 90s

In the early 90s Neuro-Fuzzy was still a new concept to be shaped by different implementations and applications. In these years a relatively small amount of Neuro-Fuzzy application was published and naturally these were unique approaches rather than utilization of existing solutions. For example among the pioneers, Ayoubi presented a structure that models the fuzzy inference mechanism based on neural units [1]. He tested the system on two real-world problems: monitoring the state of a turbocharger and supervision of air pressure in vehicle wheels. The implemented model proved to be efficient when the problem space is low-dimensional; however, when it had significantly more dimensions, Multi-Layer Perceptron (MLP) performed far better than the fuzzy inference mechanism.

Zhang and Morris also used a Neuro-Fuzzy solution for fault diagnosis of continuous stirred tank reactor process [2]. The chosen test problem is well known about its highly nonlinear dynamics which is a result of the phenomenon that process gain changes drastically with any operating condition modification. The network applied for this problem consists of 4 layers: an input layer, a fuzzification layer, a hidden layer and an output layer. The input layer has 14 neurons, because the system has 14 measured signal values, the fuzzification layer has 3 neurons for each input neuron, because each input information is ordered to 3 individual fuzzy membership function, the hidden layer has 10 neurons representing 10 fuzzy rules and the output layer has 11 neurons, each corresponding to a particular fault. They achieved much better performance than with a conventional feed forward neural network while the system also provided a more interpretable structure.

2.2. 2000s

Neuro-Fuzzy systems became more widespread in the 2000s especially in technical diagnostics and measurement. For example Mahapatra et al. built such systems for adaptive filtering of oscillatory signals [3]. The used model proved to be more efficient than other alternative fuzzy adaptive systems; moreover, it can be used for online monitoring of signals, independently whether they are described by linguistic variables or crisp variables.

Frey et al. used a Neuro-Fuzzy model to control a rotary hammer drill [4]. For solving this problem the authors had to find the optimal settings of rotational speed and strike rate to achieve optimal drill penetration. A self-learning Neuro-Fuzzy model was developed to intelligently control these two variables during the drilling process to achieve optimal performance.

Detecting the onset of damage in gear systems was the goal of Wang et al., for which they developed a Neuro-Fuzzy based diagnostic system [5]. The diagnosis of the gear system is conducted gear-by-gear, which means that for every gear there is a separated Neuro-Fuzzy model. Each model has three inputs and one output: the inputs are reference functions that reduce the feature dimensions, i.e. they aggregate multiple features of the real system to one variable; the output is the condition of the gear, which can be normal or damaged. To train the implemented model they proposed a constrained–gradient–reliability algorithm which can effectively update the membership function parameters and set the rule weights.

Evsukoff and Gentil created a recurrent Neuro-Fuzzy system for fault detection and isolation in nuclear reactors [6]. In their model a fuzzification module is linked to a neural network based inference module which was adapted to recognize related faults based on the process variables.

One of the first and probably most widespread Neuro-Fuzzy architecture is the Adaptive-Network-based Fuzzy Inference System (ANFIS) which has similar accuracy as the Multi-Layer Perceptron (MLP) which makes it ideal for function approximation. This architecture was used for mechanical fault diagnostics of induction motors with variable speed drives by Sadeghian and Wu [7]. The authors managed to significantly reduce the system complexity and learning duration of the network by using multiple ANFIS units in their model.

Fig. 1 shows the multiple ANFIS units where each one is responsible for detecting a specific fault type as these fault types have different feature coefficients. This modular structure provides an easy way to make extensions for detecting other fault types and also has the advantage that the units can be easily trained due to their simplicity. In another application Lei et al. used multiple ANFIS combination with genetic algorithm for fault diagnostics of rotating machinery [8]. They implemented a classifier system where the features describing the problem were divided into six predetermined and separated groups and individual Neuro-Fuzzy classifiers were constructed for each group. The final classification result of the system is the weighted average of the individual groups. During training, genetic algorithm was applied for optimizing these weights. This method can yield better classification result than the member classifiers individually.

Amaral et al. applied a diagnostic technique based on the identification of a specified current pattern for detection of motor stator fault and used a Neuro-Fuzzy model for an image feature extraction based identification [9]. They used the Neuro-Fuzzy strategy to get a better linguistic knowledge about the underlying fault detection and diagnosis process.

Machinery malfunctions often reduce productivity and increase maintenance costs in various industrial fields. Zio and Gole proposed a Neuro-Fuzzy approach to solve fault diagnosis of rotating machinery by pattern classification while obtaining a model which remained easily interpretable [10].

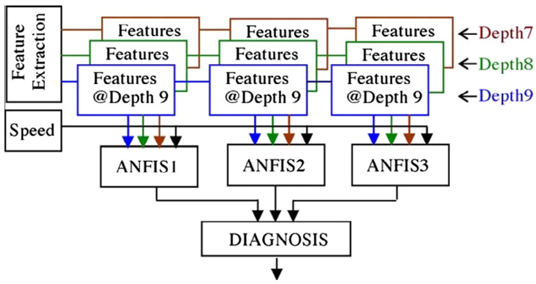

Fig. 1. Multiple ANFIS units for multiple fault diagnostics [7].