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Neural networks for modelling and fault detection of the inter-stand strip tension of a cold tandem mill

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ABSTRACT

This paper deals with the multilayered approach of the high-order neural network applied in a robust fault detection scheme. To introduce dynamic properties in these networks, a dynamic high-order neural unit is presented. It is shown that these networks can approximate any function with less parameters than in the case of multi-layer perceptron neural network. Such networks have good modelling properties, which make them useful for designing residuals in fault detection of dynamic processes. A method of computing a variable threshold derived from the confidence interval prediction is applied in order to obtain robustness in the fault detection process. Application of these networks for system identification and robust fault detection of the inter-stand strip tension of a continuous five stands cold mill is presented in the final part.

1. Introduction

Artificial Neural Networks (ANNs) can be used to solve practical problems in engineering, e.g. to build models, especially when dealing with nonlinear processes. The importance of models in many domains has led to a strong demand for advanced modelling and identification schemes. Models are useful for system analysis, prediction or simulation of system behaviour, design of controllers, optimization, supervision and also for fault detection and diagnosis (Korbicz, Kościelny, Kowalczuk, & Cholewa, 2004; Narendra & Parthasarathy, 1990). The area of process fault diagnosis has drawn a lot of attention due to the necessity of maintaining a high level of safety, performance and reliability in controlled processes. For this, it is important that system errors, component faults and abnormal system operations are promptly detected and that the source and severity of each malfunction is diagnosed so that corrective action can be taken. Briefly, the task of fault diagnosis consists of determining the type, size, location and appearance time of a fault. There are different types of diagnosis methods like hardware redundancy methods, knowledge based and signal processing methods or model-based approaches (Isermann, 2006; Patton, Frank, & Clark, 2000; Samy, Postlethwaite, & Da-Wei, 2011).

A common approach to fault diagnosis is the analytical redundancy, also referred to as the model-based approach, which makes use of a mathematical model of the diagnosed system. However, a complete mathematical model of a physical system is hard to obtain (Chen & Patton, 1999; Patton et al., 2000). When dealing with nonlinear dynamic processes, analytical models are in some cases difficult to obtain. The ANN, as an optimal approximation tool for handling nonlinear problems, can be used to overcome difficulties found in conventional techniques when dealing with nonlinearity. If sufficient data is available, then there is enough information to build and train an ANN. In such a case the problem and its solution are described giving examples and ANN is mapping these examples and tries to learn and to generalize the phenomena connected with the presented problem.

High-Order Neural Network (HONN) (Kosmatopoulos, Polycarpou, Christodoulou, & Ioannou, 1995; Pao, 1989) has better approximation properties than the Multi-Layer Perceptron (MLP) network. HONNs are capable of dealing with pattern classification problems by capturing the nonlinear properties of the input pattern space. Such networks with a single hidden layer have been successfully used in engineering applications for nonlinear system identification (Kosmatopoulos et al., 1995) or nonlinear surface fitting (Taylor & Coombes, 1993). In the case of Multilayered High-Order Neural Network (MLHONN), an increase in structure complexity may become intolerable. The number of weights increases exponentially

Abbreviation: ANN, Artificial Neural Networks; DD, detection decision; DHONU, Dynamic High-Order Neural Unit; FDI, Fault Detection and Isolation; IIR, Infinite Impulse Response; GMDH, Group Method of Data Handling; HONN, High-Order Neural Network; HONU, High-Order Neural Unit; MIA, Multi-Layer Iterative Algorithm; MLDHONN, Multi-Layer Dynamic High-Order Neural Network; MLHONN, Multi-Layer High-Order Neural Network; MLP, Multi-Layer Perceptron

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with the number of inputs and the number of layers. Thus, a pruning action is required. There are many ways to introduce dynamics in neural networks (Gupta, Jin, & Homma, 2003). Adding a filter module to the neuron, the obtained Multilayered Dynamic High-Order Neural Network (MLDHONN) can be used to deal with dynamic processes.

The objective of this paper is to investigate the design of dynamic multi-layer high-order neural networks with automatically adjustable structure and to create a robust fault detection scheme that can be used for detection of faults in nonlinear dynamic processes. First, in Section 2, the structure of Dynamic High-Order Neural Unit (DHONU) is presented. The combinatorial algorithm used for the development and selection of the network structure as well as the approximation properties of these networks are also described in this section. For estimating the network's accuracy as a modelling tool, a confidence interval as a prediction of the model's output range where the actual value exists is computed. A variable threshold is derived from this confidence interval. Passive robustness in the fault detection process is achieved using the obtained threshold— Section 3. In Section 4, MLDHONNs are applied off-line for modelling and fault detection of the inter-stand strip tension of a cold tandem mill using real data collected from a continuous cold mill. The final Section presents conclusions.

2. Dynamic high-order neural network

2.1. Dynamic high-order neural unit structure

The neuron described in this section is used in the hidden layers of the network. This neuron is derived from the functional link net (Pao, 1989). It can be seen as a combination of N-Adaline neuron (Pham & Xing, 1995) (adaptive linear element with a nonlinear preprocessor) and a perceptron with a nonlinear activation function. The main feature of this neuron is that its inputs are nonlinearly preprocessed. Such a neuron is known as High-Order Neural Unit (HONU).

There are many ways to introduce internal or external dynamics into neural networks (Campolucci, Uncini, Piazza, & Rao, 1999; Fransconi, Gori, & Soda, 1992). To create a neuron which has dynamic properties, an Infinite Impulse Response (IIR) filter module is added to HONU before the activation module. Thus, locally recurrent activation feedback (Campolucci et al., 1999) is obtained. Internal dynamics are introduced into the network by each neuron. Different learning algorithms, approximation and stability properties for networks with similar neural units has been developed and analysed (Gupta et al., 2003; Kosmatopoulos et al., 1995).

Fig. 1 presents DHONU structure. The neuron has p inputs $\mathbf{x}^n_{(k)} = [x^n_{1(k)}, x^n_{2(k)}, \ldots, x^n_{p(k)}]$, where k is the discrete time and n is the neuron number. The neuron's inputs are the inputs for the nonlinear preprocessor block where the products $\prod_{j\in I_i} x^{n,d_{j(k)}}_{j(k)}$ are calculated (see Eq. (1)). The outputs of the nonlinear preprocessor block are weighted and summed up in the sum block which gives a signal described by the relation

$$z_{(k)} = w_0 + \sum_{i=1}^{L} w_i \prod_{j\in I_i} x^{n,d_{j(k)}}_{j(k)}, \tag{1}$$

where $\{I_1, I_2, \ldots, I_L\}$ is a collection of L not-ordered subsets of $\{1,2,\ldots,p\}$, w_i are the weights of the neuron and $d_{j(k)} \le n_o$ non-negative integers with n_o the neuron order.

The filter block is described by the following equation:

$$\tilde{z}_{(k)} = \frac{\sum_{i=0}^{n_b} b_i q^{-i}}{1-\sum_{j=1}^{n_a} a_j q^{-j}} z_{(k)} = \frac{B(q)}{A(q)} z_{(k)}, \tag{2}$$

where q denotes the forward shift operator, $\tilde{z}$ is the state of the neuron, a_j are the feedback weights and b_i are the feedforward weights. For simplicity, the filter is a first or second order IIR (the order of the filter $n_a \in \{1,2\}$).

The output filter module is fed as input of the activation function ϕ (the last module). The neuron output is given by $y^n_{(k)} = \phi(\tilde{z}_{(k)})$. The function $\phi(\cdot)$ is a monotone increasing differentiable sigmoidal function. The logistic and hyperbolic tangent functions are most frequently used in neural networks applications (Gupta et al., 2003) as activation functions.

2.2. Network's structure

Several DHONUs can be connected to an output neuron to form a DHONN with one hidden layer. Multiple hidden layers make the network much more powerful and complex. It is obviously that the number of parameters will increase with the number of layers and the order of the neuron. Thus, a pruning action is required. To reduce the size of the network, a pruning algorithm for the MLDHONN similar to the development of Group Method of Data Handling (GMDH) neural networks is proposed (Farlow, 1984).

The target of the network is denoted with $\mathbf{y}$ and the inputs $\mathbf{u} = [u_1, u_2, \ldots, u_m]$, with m being the size of available network inputs. The set of data observation with N samples, $D = \{\mathbf{u}_{(k)}, y_{(k)}\}_{k=1}^{N}$ is divided into the training set $D_A = \{\mathbf{u}_{(i)}, y_{(i)}\}_{i=1}^{N_A}$ and the validation set $D_B = \{\mathbf{u}_{(j)}, y_{(j)}\}_{j=1}^{N_B}$, with $N_A + N_B = N$.

2.3. Network development algorithm

DHONUs of order n with p inputs are used in the construction of hidden layers. The algorithm applied to determine the structure of the network is based on GMDH Multilayered Iterative Algorithm (MIA) (Farlow, 1984).

The network development procedure is depicted in Fig. 2 and has the following steps:

1. Create different DHONUs from all input combinations. The number of neurons will be C^p_m for the first layer or $C^p_{m_{j-1}}$ for the $\{j\}$th layer, with $m > p$ being the size of network input,

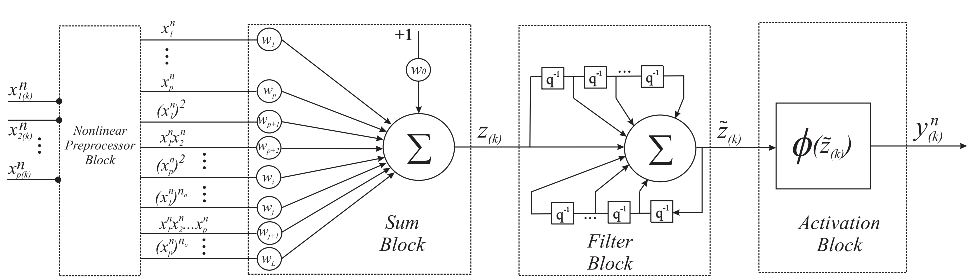

Fig. 1. DHONU structure.