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A study on the robustness of neural network models for predicting the break size in LOCA

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ABSTRACT

The diagnosis of loss of coolant accidents in nuclear reactors has attracted a great deal of attention in condition monitoring of nuclear power plants given that the health of the cooling system is crucial to the nuclear reactor's stable operation. Many different types of neural networks have commonly been applied to loss of coolant accident diagnosis. It is important to select a suitable architecture for the neural network that delivers robust results, in that the predicted break size is deemed to be accurate even for break sizes that are not included in the training data sets. The robustness metric proposed in our previous work is applied to compare the robustness of different diagnostic models. The data used for training these models consists of a number of time-series data sets, each for a different break size, with the transient behavior of different measurable variables in the coolant system of a nuclear reactor, following a simulated loss of coolant accident in a high-fidelity simulator. Given the simulation data for different break sizes, four different neural network architectures are investigated and their properties are compared and discussed. These models include a fully-connected multilayer perceptron with one hidden layer, a multilayer perceptron with one hidden layer that is pruned using the optimal brain surgeon algorithm, a fully-connected multilayer perceptron with two hidden layers, and a group method of data handling neural network. In this paper, an interpolation pre-processing method is investigated and shown to be effective to further improve the capability of neural networks for robustly predicting the break size of a loss of coolant accident. Both linear interpolation and cubic spline interpolation are studied as alternatives for the pre-processing approach. The performance of models developed with and without interpolation pre-processing are compared with the previously proposed robustness metric. Moreover, three blind cases are introduced to evaluate and compare the performance of the diagnostic models. Finally, a combined diagnostic model is proposed based on three different architectures to obtain high prediction accuracy and good robustness.

1. Introduction

The reactor coolant system is the key part of nuclear power plants (NPPs). There is a critical part of the cooling system where 'breaks' can occur - these breaks are essentially ruptures of pipes leading to leaks of the coolant. The bigger the leak, the worse the problem is. These breaks, commonly denominated loss of coolant accidents (LOCA) may lead to serious consequences for the plant, the environment, and people's health and safety. To safely deal with such scenarios, every nuclear plant is equipped with an Emergency Core Cooling System (ECCS), which is highly reliable and operates automatically if it detects a break. It is immensely important for operators to detect breaks and understand their severity so they can take appropriate actions, in the unlikely case that the ECCS fails to operate.

The Three Mile Island accident revealed that operators may not efficiently handle voluminous information in abnormal conditions. Therefore, the timely and accurate recognition of NPP status requires automation development to guarantee safe and reliable operation (Mo et al., 2007). If a LOCA occurs in a nuclear power plant, it is quite difficult for operators to interpret the trends of measured variables because of the large volume of information from sensors and the fact that changes may occur rapidly when a plant moves from a normal state to an abnormal state (Moshkbar-Bakhshayesh and Ghofrani, 2013). Therefore, many artificial intelligence techniques including neural networks have been applied to assist the operators to detect and diagnose the break size of LOCA.

To detect and diagnose the LOCA, a great deal of attention has been paid to the monitoring of the coolant system (Mo et al., 2007;

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Moshkbar-Bakhshayesh and Ghofrani, 2013; Choi et al., 2017). Da Costa et al. (da Costa et al., 2011) developed an operator support system based on Neuro-Fuzzy approach to identify accidents, including LOCA, rapidly and accurately. Choi et al. (2017) presented a method to estimate the LOCA break size using the cascaded fuzzy neural network model. Na et al. (2004) applied probabilistic neural network to classify accidents such as LOCA, loss of feedwater station blackout, and steam generator tube rupture, and used a fuzzy neural network to identify these severe accident scenarios. Multilayer perceptrons (MLPs) with different network structures and learning algorithms are the most popular neural networks for fault diagnostics in NPPs (G. Vinod et al., 2003; Moshkbar-Bakhshayesh and Ghofrani, 2013). Radial basis function (RBF) networks were used by Renders et al. (1995) to detect incipient incidents. Probabilistic neural networks (PNNs) and learning vector quantization (LVQ) networks were used for "Don't Know" classification in (Bartal et al., 1995). Na et al. (2004) and da Costa et al. (2011) used fuzzy neural networks (FNNs) for accident classifications. Lee et al. (2011) proposed a scheme to diagnose LOCAs using support vector classification (SVC) and group method of data handling (GMDH) models. The simulation results confirmed that the proposed SVC model can discover the break location without a misclassification and the proposed GMDH models can estimate the break size accurately. To detect the cracks and leakage which may appear before LOCA, Zhang et al. applied a three-layer back propagation network and a genetic neural network to predict the leak before break (LBB) for various conditions (Zhang et al., 2017). Most current diagnostic systems focus on classification. Few of these systems were designed to predict the severity of the diagnosed scenario (Lin et al., 1995). This article focuses on the study of numerical values that measure the severity of an accident, rather than a qualitative prediction of severity.

Dynamic neural networks have been commonly applied for time series prediction. However, in this work, a static neural network with constant weights is used to map the instantaneous values of the set of input variables to the predicted break size. Normally, to train a dynamical model the training data is required to capture how the output of the system changes with the changes in the input. In our case, the available input-output data is not suitable to train dynamical models, as the training output is a constant for each break size. Therefore, dynamic neural networks are not suitable for predicting the break size in LOCA.

MLPs may have difficulties with generalization when the training data is limited (Hagan and Menhaj, 1994). It is important to select an optimal architecture for the neural network that delivers robust results. To achieve this purpose, different attempts have been made to automate the architecture selection. One common strategy is to start with a fully-connected network architecture which (in principle) is large enough to describe the system, then weights are eliminated one at a time according to well defined criteria, until an architecture that is optimal in some sense has been reached. An example of this approach is the use of the optimal brain surgeon (OBS) algorithm (Hassibi and Stork, 1993). Other strategies go in the opposite direction by starting with small network architecture and then gradually growing it, such as a GMDH approach.

In our previous work (Tian et al., 2017), we have presented a robustness measure for designing robust neural networks for LOCA break size predictions. Based on this robustness measure, this paper introduces interpolation approaches for data processing as a way to improve the robustness of the models. Moreover, blind cases are used for evaluating the developed models. The paper is organized as follows: Section 2 introduces the neural network structures that are investigated in this paper. Section 3 details the data description, modelling and testing process, along with the proposed robustness measure. Section 4 shows the data processing results and discussion. Section 5 presents the validation of the diagnostic models and proposes a robust combined diagnostic model, followed by conclusions in Section 6.

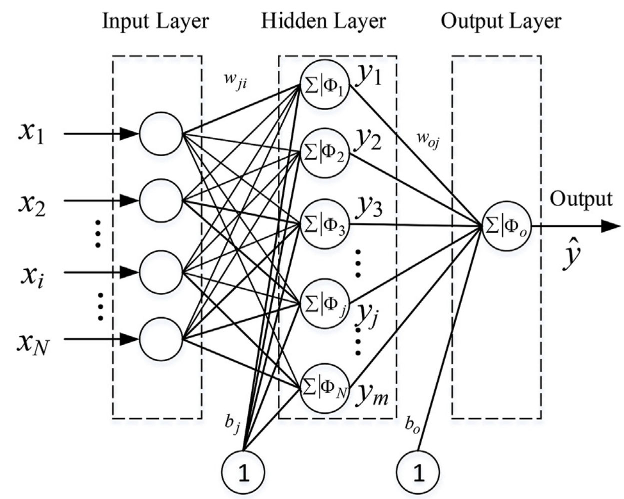

Fig. 1. One hidden layer MLP with one output.

2. Methodology

This section introduces the working principles of the neural networks that are investigated in this paper.

2.1. Multilayer perceptron

MLP is a kind of feedforward artificial neural network (Haykin, 1999) where a large number of processing elements (called neurons) are interconnected in a directed graph to create a functional mapping from an input data space to an output target space after training. A basic MLP contains three layers (input layer, hidden layer, and output layer) as shown in Fig. 1. Except for the input layer, all neurons in the other layers contain activation functions which are either linear or non-linear.

The output of the hidden neuron j can be written as

$$y_j = \Phi_j(\mathbf{w}_j^T\mathbf{x} + b_j) = \Phi_j\left(\sum_{i=1}^{N} w_{ji}x_i + b_j\right) \tag{1}$$

Here, the input vector to the neural network is $\mathbf{x} = [x_1, x_2, \cdots, x_N]^T$, $\mathbf{w}_j = [w_{j1}, w_{j2}, \cdots, w_{jN}]^T$ denotes the weight vector between the hidden neuron j and the inputs, b_j is the bias, and Φ_j is the activation function which is normally taken as a non-linear function, such as a sigmoid function. The output of the neural network is given by Eq. (2) (Laurene, 1994; Simon, 1998).

$$\hat{y} = \Phi_o\left(\sum_{j=1}^{M} w_{oj}y_j + b_o\right) \tag{2}$$

Here, Φ_o is the activation function of the output neuron which is normally taken as a linear function, $\widehat{y}$ is the final output of the MLP network, b_o is the bias value of the output neuron o, and w_{oj} is the synaptic weight value from the hidden neuron j to the output neuron o.

A MLP is often trained with the widely used backpropagation algorithm. The algorithm consists of two steps. In the forward pass, the predicted outputs are calculated corresponding to the given inputs. In the backward pass, partial derivatives of the cost function with respect to the different parameters are propagated back through the network. The network weights can then be adapted using any gradient-based optimisation algorithm. The whole process is iterated until the weights have converged (Laurene, 1994) or a given stopping criterion is satisfied.

In this paper, the Levenberg-Marquardt algorithm is used for training because it is the fastest method for moderate-sized feedforward neural networks (up to several hundred weights). The application of the