Neural Networks for Fault Detection and Isolation of a Nonlinear Dynamic System

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Abstract: The proper and timely fault detection and isolation of industrial plant is of premier importance to guarantee the safe and reliable operation of industrial plants. The paper presents application of a neural networks-based scheme for fault detection and isolation, for the pressurizer of a PWR nuclear power plant. The scheme is constituted by two components: residual generation and fault isolation. The first component generates residuals via the discrepancy between measurements coming from the plant and a nominal model. The neural network estimator is trained with healthy data collected from a full-scale simulator. For the second component detection thresholds are used to encode the residuals as bipolar vectors which represent fault patterns. These patterns are stored in an associative memory based on a recurrent neural network. The proposed fault diagnosis tool is evaluated on-line via a full-scale simulator to detect and isolate the main faults appearing in the pressurizer of a PWR.

Keywords: Neural Networks, Fault Detection and Isolation, Nonlinear Dynamic System, Pressurizer.

1. Introduction

Fault diagnosis is usually performed by a three steps algorithm [1]. One or several signals are generated which reflect faults in the process behavior. These signals are called residuals. On the second step, the residuals are evaluated. A decision, regarding time and location of possible faults, is obtained from the residuals. Finally, the nature and the cause of the fault is analyzed by the relations between the symptoms and their possible causes. In order to describe the fault free behavior of the process under supervision, a mathematical model is employed; due to this fact, the term model-based fault diagnosis is used. Model-based approaches have dominated the fault diagnosis research for many years [2, 3].

The main disadvantage of this method is that, being based on a mathematical model; it can be very sensitive to modelling errors, parameter variations, noise and disturbances. The success of the model-based method is heavily dependent on the quality of the models; accurate modelling for a complex nonlinear system is very difficult to achieve in practice. Different applications of fault diagnosis to industrial processes, which include conventional and artificial intelligence techniques are reported in [4]. However, for the second type of techniques, most of the power plant applications use a combination of analytical and/or computational intelligence tools [5]. Using adequate data base and methods for on-line and/or on-line training, neural networks are able to reproduce the dynamics of complex nonlinear systems; after training, they can estimate quite precisely the output of nonlinear systems [6, 7]. Employing measurements of the process under normal operation, if possible, or with the help of a realistic simulator, a suitable neural network can be trained to learn the process input-output behavior. The residuals generated using a neural network estimator can be evaluated via thresholds to obtain fault patterns. The fault pattern recognition can be done by means other neural network, which allows isolating different faults.

This paper presents a neural network scheme for fault diagnosis. It uses for residual generation an estimator, which consists of a bank of recurrent
multilayer perceptron neural network models. Fault classification is carried out by an associative memory, which is based on a recurrent neural network (RNN). The scheme is evaluated on-line using a full-scale simulator to diagnose the main faults appearing in nuclear power plants.

2. Problem Description

A nuclear power plant is a complex system which has more than one variable that influences its dynamic behavior. Deviation in any variable, as a result of normal or abnormal events, will almost simultaneously initiate a change in most of the other variables. This occurs due to the strong and fast coupling among system process variables, especially in the nuclear system. Fault diagnosis for nuclear power plants is a task carried out by human operators, who recognize typical faults via supervision of key variables evolution. Adequate fault detection and diagnosis aids will help the human operator in order to take the right decisions to maintain the required energy production, avoiding failures and even accident risky to humans and the environment.

2.1. Plant Description

The main faults can be clustered as: faults related to temperature control of the pressurizer, faults related to water level control. In order to understand the faults, it is helpful to briefly describe the PWR plant and pressurizer system. A simplified scheme is presented in Figure 1, which illustrates the main components of a typical power plant and pressurizer system.

![Figure 1. Schematic of PWR Nuclear Power Plant](image)

Most of the light-water reactors now operating or under construction are Pressurised-Water Reactors. The fundamental characteristic of PWRs is that the primary coolant is heated to very high temperatures under extremely high pressures in the reactor core. The primary coolant, driven by the primary pump raises steam in a heat exchanger called steam generator. In the secondary coolant system, steam is transported from the steam generators out of the containment to drive the turbo-generator system. Condensate returns to steam generators. In a PWR nuclear power plant, the pressurizer is attached at the reactor outlet hot leg and acts as a surge tank in maintaining primary loop pressure. At steady state, the fluid in the pressurizer is approximately two-thirds saturated water and one-third saturated steam at a constant pressure. When the primary coolant temperature increases the expanding fluid flows into the pressurizer through the surge line, increasing the liquid mass, compressing the vapor region, and increasing pressure. Conversely, a temperature decrease results in an outsurge and corresponding pressure drop. Additional pressure control is provided by a cold water spray and relief valves (to avoid overpressurization) and electric heaters (to increase pressure). In the model developed here, steam and water in the pressurizer are assumed to be in a homogeneous saturated mixture. For this system, the main automatic control loops are the pressurizer heater control and the spray control.

A detailed nonlinear model for a typical PWR system has been considered for the development of a PWR simulator. Each component in the PWR system has been represented by appropriate nonlinear differential equations which are solved simultaneously [8]. Then, the overall PWR power plant model is constructed by connecting individual components to each other. The primary side components are the reactor core, pressurizer and steam generator. The secondary side components are steam turbine, moisture separator, reheater, condenser, feed-water pump and heaters.

The validity of models for each components and overall system has been verified. Simulation results are compared with reported results from similar studies [9].

Faults are applied to the simulation via step changes in some variables. The simulation is run for 800 seconds. Locations of the critical plant parameters
and symptoms used for this study are summarized in Figure 1.

2.2 Fault in the Pressurizer Heater Control

To simulate this fault using the pressurizer heater control system, the cycling heater set point was changed from (1545 Pa) to (1550 Pa) and, similarly, the backup heater set point from (1540 Pa) to (1545 Pa), with the threshold of the switch control set at (1550 Pa). So if the pressurizer pressure is equal to this value, the cycling heater switch will turn from on to off; in turn, the backup heater switch is switched over when the pressurizer pressure is (1545 Pa). The resulting symptoms of the fault are the increase in pressurizer pressure and the increase in pressurizer water level.

2.3 Fault in the Pressurizer Spray Control

To simulate a fault in the pressurizer spray control during normal operation, the pressurizer spray flow is set to the (ON) position when the pressurizer pressure is (1550 Pa). When the set point value is changed from (1550 to 1545 Pa), the pressurizer water spray rate is decreased. To generate this fault by using a switch, its threshold is changed from (1550 to 1545 Pa). That is, when the pressurizer pressure equals this value, the pressurizer spray rate switch is switched over from off to on. This fault has just one symptom, which is the increase in pressurizer water level.

3 Scheme for Fault Diagnosis

The scheme proposed in this paper has two components: residual generation and fault isolation. The scheme is displayed in Figure 2. The first component is based on comparison between the measurements coming from the plant and the predicted values generated by a neural network estimator. The estimator is based on neural network models which are trained using healthy data from the plant. In this paper, the plant is represented by a full-scale simulator.

The differences between these two values, named as residuals, constitute a good indicator for fault detection. The residuals are calculated as:

\[ r_i(k) = x_i(k) - \hat{x}_i(k), \quad i = 1, \ldots, n \]  

(1)

Where \( x_i(k) \) are the plant measures and \( \hat{x}_i(k) \) are the predictions. The residuals should be independent of the system operating state under nominal plant operation conditions. In absence of faults, the residuals are only due to noise and disturbance. When a fault occurs in the system, the residuals deviate from zero in characteristic ways [10].

For the second component, residuals are encoded in bipolar vectors using thresholds to obtain fault patterns. These fault patterns are used to train an associative memory-based on a RNN [11], which is employed to carry out the fault diagnosis.
3.1 Residual Generation

For residual generation purposes the neural network model replaces the analytical one describing the process under normal operation. The estimator is obtained using system identification theory via neural network modelling with nonlinear structures [12]. To achieve the identification is necessary to collect experimental data, which are obtained from a full-scale simulator. The recurrent neural networks (RNNs) training are done using the series-parallel scheme. After finishing the training, the nominal model (recurrent neural networks) can be applied for residual generation (Figure 3); its weights are fixed and it is used as a parallel scheme to carry out predictions. The neural network estimator is designed using ten neural network models, which are trained via the Levenberg-Marquardt Learning Algorithm. Each neural network is a recurrent multilayer perceptron. The networks have one hidden layer with hyperbolic tangent or linear activation functions and a single neuron with a linear activation function as the output layer. The neural network models are obtained employing the toolbox NNSYSID for MATLAB, [13].

Each model has eight input variables and one output variable with a NNARX (Neural Network AutoRegressive, eXternal input) structure as:

\[
x_j(k) = F_j \left[ \left( W_j \cdot u_1(k), \ldots, u_8(k) \right) \right]
\]

Where \( j = 1, \ldots, 10 \) and the input variables are \( u_1(k), \ldots, u_8(k) \), the output variables are \( x_1(k), \ldots, x_{10}(k) \). \( W_j \) represents the weights for each neural network model. The lag structure of each neural network model \((n_a, n_b)\) is determined using the same criterion as in [13], which is based on Lipschitz quotients. The residual generation scheme is implemented for two faults. In this paper, due to space limitations, for explaining the process to generate residuals and fault patterns, only fault 1 is considered. The residuals are close to zero before fault inception. After that (i.e. fault injection at 200 second), residuals deviate from zero in different ways (see Figures 4 and 5).

Figure 4. Residual of Pressurizer Pressure for fault 1

Figure 5. Residual of Pressurizer Water Level for fault 1
3.2 Fault Isolation

Figure 6 presents a scheme which illustrates the fault isolation procedure. The previous stage generates a residual vector with ten elements, which are evaluated by fault detection thresholds ($\tau_i$). Detection thresholds are presented in Table 1. This evaluation provides a set of residuals encoded as bipolar vectors $[s_1(k), s_2(k), \ldots, s_{10}(k)]^T$, where:

$$s_j(k) = \begin{cases} 
-1 & \text{if } |r_j(k)| < \tau_j \\
1 & \text{if } |r_j(k)| \geq \tau_j 
\end{cases} \quad i=1,2,\ldots,10$$

For fault diagnosis, these encoded residuals are fed as input bipolar vectors to an associative memory. Once residuals are encoded, it is necessary to analyze them to select the fault patterns to be stored in the associative memory. This selection is done in order to discriminate adequately every fault, to reduce false alarms and to isolate faults as soon as possible. The patterns obtained are used, based on the synthesis algorithm proposed in [11], to train the recurrent neural network and to design the respective associative memory as a way to isolate faults. Fault patterns for faults previously mentioned, are displayed in Table 2, where $\alpha^0$ indicates normal operation.

An associative memory based on a recurrent neural network is designed for fault classification. The recurrent neural network considered in the present paper is given by:

$$\dot{x} = -Ax + Tsat(x) + I$$

$$y = sat(x)$$  \hspace{1cm} (3)

In this equation $x \in R^n$ is the state vector, $\dot{x}$ denotes the derivative of $x$ with respect to time $t$, and $y \in D^n = \{x \in R^n : -1 \leq x_i \leq 1, i=1,\ldots,n \}$ is the output vector, $A = \text{diag}[a_1, \ldots, a_n]$ with $a_i > 0$ for $i=1,\ldots,n$, $T=[T_y] \in R^n$ is a connection matrix, $I=[I_1] \in R^n$ is a bias vector, and $sat(x)=[\text{sat}(x_1), \ldots, \text{sat}(x_n)]^T$ represents the activation function, where:

<table>
<thead>
<tr>
<th>Variable</th>
<th>$\tau_i$</th>
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<tbody>
<tr>
<td>Coolant Average Temperature</td>
<td>± 1 °C</td>
</tr>
<tr>
<td>Pressurizer Pressure</td>
<td>± 69 KPa</td>
</tr>
<tr>
<td>Pressurizer Water Level</td>
<td>± 38 mm</td>
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<tr>
<td>Steam Generator Pressure</td>
<td>± 15.5 KPa</td>
</tr>
<tr>
<td>Steam Generator Steam Flow</td>
<td>± 4.5 kg/s</td>
</tr>
<tr>
<td>Steam Generator water Level</td>
<td>± 255 mm</td>
</tr>
<tr>
<td>Condenser Water Level</td>
<td>± 76 mm</td>
</tr>
<tr>
<td>Feedwater Pressure</td>
<td>± 20.68KPa</td>
</tr>
<tr>
<td>Feedwater Flow</td>
<td>± 4.5 kg/s</td>
</tr>
<tr>
<td>Feedwater Temperature</td>
<td>± 0.55 °C</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$\alpha^0$</th>
<th>$\alpha^1$</th>
<th>$\alpha^2$</th>
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<tr>
<td>-1</td>
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Table 1: Detection thresholds for variables in the PWR model

Table 2: Fault Patterns
\[ sat(x_i) = \begin{cases} 1 & \text{if } x_i > 1 \\ x_i & \text{if } -1 \leq x_i \leq 1 \\ -1 & \text{if } x_i < -1 \end{cases} \]

It is assumed that the initial states of equation (3) satisfy \( |x_i(0)| \leq 1 \) for \( i = 1, \ldots, n \). System equation (3) is a variant of the analog Hopfield model with activation function \( sat(\cdot) \).

The following synthesis problem concerns the design of Equation (3) for associative memories [11]. Given \( m+1 \) vectors \( \alpha^0, \ldots, \alpha^m \) in the set of \( n \)-dimensional bipolar vectors, \( B^n \), choose \( \{A,T,I\} \) in such a manner that:

1- \( \alpha^0, \ldots, \alpha^m \) are stable memory vectors of system with equation (3).
2- The system has no oscillatory and chaotic solutions.
3- The total number of spurious memory vectors (i.e., memory vectors which are not desired) is as small as possible, and the domain (or basin) of attraction of each desired memory vectors is as large as possible.

The previous synthesis problem can be solved by applying the perceptron training algorithm proposed in [11]. This algorithm consists of obtaining \( n \) perceptrons \( W_i = [w^i_1, w^i_2, \ldots, w^i_{n+1}] \), \( i=1,2,\ldots,n \) such that:

\[
\begin{align*}
W_i\alpha^{-k} &\geq 0 & \text{if } & \alpha^k_i = 1 \\
W_i\alpha^{-k} &< 0 & \text{if } & \alpha^k_i = -1 
\end{align*}
\]

for \( k = 0, 1, 2, \ldots, m \), where

\[ \alpha^{-k} = \begin{pmatrix} \alpha^k \\ \vdots \\ 1 \end{pmatrix} \]

Choose \( A = diag[a_1, \ldots, a_n] \) with \( a_i > 0 \). For \( i,j = 1,2, \ldots, n \) choose \( \bar{T}_{ij} = w^i_j \) if \( i \neq j \), \( T_{ij} = w^i_j + a_i \mu_j \) with \( \mu_j > 1 \), and \( I_i = w^i_{n+1} \). The synthesis algorithm is programmed in Matlab to train the recurrent neural network such that fault patterns are stored as stable memory vectors. A learning rate \( \eta = 0.1 \) and initial weights of negative values with magnitude smaller than 1 are used. The number of neurons is \( n = 10 \) and the patterns are \( m+1 = 3 \). The associative memory is evaluated, with the matrices fixed using encoded residuals as input bipolar vectors. When any fault evolves, fault patterns which are retrieved by the associative memory can correspond to a wrong pattern; this fact is mainly due to input transient bipolar vectors which force the associative memory to converge to wrong fault patterns. However, during this interval the encoded residuals do not correspond to true fault pattern and this fact is taken into account to carry out an efficient diagnosis. Taking into account this fact, information to operator is presented as in Figure 7, for fault 1.

![Figure 7. Fault Type Indication for Fault 1](image)

4. Conclusion

The results demonstrate that the neural network estimator proposed in this paper is a feasible alternative for the residual generation. The detection thresholds allow to obtain fault patterns to train an associative memory based on a recurrent neural network. The associative memory is designed and applied for FDI tasks in the pressurizer of a PWR.

References


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