ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 495-500

Neural networks for fault diagnosis of industrial plants at different working points

Silvio Simani† *and Ron J. Patton‡

†Dipartimento di Ingegneria, Università di Ferrara. Via Saragat, 1
44100 Ferrara - Italy. Tel: +39 0532 293844. Fax: +39 0532 768602
E-mail: ssimani@ing.unife.it

‡Department of Engineering, The University of Hull. Cottingham Road
Hull HU6 7RX, United Kingdom. E-mail: r.j.patton@hull.ac.uk

Abstract. Industrial plants often work at different operating points. However, in literature applications of neural networks for fault diagnosis usually consider only a single working condition or small changes of operating points. A standard scheme for the design of neural networks for fault diagnosis at all operating points may be impractical due to the unavailability of suitable training data for all working conditions. This paper addresses the design of a single neural network for the diagnosis of faults in the sensors of an industrial gas turbine working at different conditions. The presented results illustrate the performance of the trained neural network for sensor fault diagnosis.

1 Introduction

Industrial processes usually are complex and reliable diagnosis of faults can be therefore be a difficult task [2]. In particular, in such processes, sensor faults (e.g., bias or drift) are likely to occur. Therefore, in order to prevent machine malfunctions and to determine the machine operating state, it is essential to have a Fault Detection and Identification (FDI) system as well as a fault diagnosis method.

The industrial plants here investigated and monitored are multivariable processes for which physical relationships and process coefficients are mostly unknown [2]. Hence, a FDI scheme based on a mathematical plant description [1] can be implemented only by identifying an accurate model for the process [6]. In such a case, a reliable FDI scheme may require an high order estimated models. The difficult task of developing a fault diagnosis technique for large–scale

*Corresponding author

ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 495-500

industrial plants can be achieved efficiently by using Neural Networks (NN)s [5]. They are both pattern recognition methods as well as non–linear function approximators with arbitrary accuracy. NNs do not need a deep insight into the process, are robust to noise data and have the ability to generalise the relationship learnt to successfully diagnose learned faults as well as new fault conditions [4, 7, 8].

In this work, the classification and approximation capabilities of a NN are exploited [5]. In particular, the performances of a Multi Layer Perceptron (MLP) NNs using back–propagation learning algorithm have been compared with Radial Basis Function (RBF) ones. A basic aspect of NN design is the pre–processing of input data. Many NN applications use scaled and normalised input data before using the patterns for network training. Tools such as Principal Component Analysis (PCA) are also methods to exploit [4].

As shown in [2], most industrial plants operate at more than one operating point. It can be easier to obtain plant data for NN training during the main operating points and more difficult to acquire data from operating points which are not frequently used. Moreover, even if data from healthy conditions under different operating points can be found, data from fault conditions are nearly non-existent. Whilst the problem of the design of NNs for process FDI has received attention, the diagnosis of faults at different operating points has had little consideration.

This work describes how a NN can be successfully exploited for the diagnosis of faults on the sensors of an industrial process. Failure modes (bias or drift) can be modelled by using step and ramp functions. The process works at different operating points. Time series of real data acquired from plant sensors are available, but there was a lack of data with labelled fault classes. Due to this drawback and to the lack of a suitable and accurate mathematical model of the process, it is impossible to develop an adequate model–based fault diagnosis methodology [1]. Faulty sequences at different working conditions have to be generated using a simulated model of the monitored process. Then, the diagnosis techniques here proposed have been applied to both the real and simulated process data. The methodology involves methods to pre–process the data by statistical scaling, algorithms to reduce the NN complexity using PCA, as well as training and testing the NN. The methodologies have been initially applied to design an ANN to diagnose faults at the main operating point. The diagnosis of faults during start–up and and at the secondary operating point using the same NN was then investigated. Results are finally presented to illustrate the performance of the developed FDI scheme for the monitored plant.

1.1 FDI Method Development

The method presented has been carried out in *three stages*. The first one consisted in exploiting methods to pre–process the network input data for better classification and reduced network complexity by data scaling and PCA. The second step was the NN training and testing. Once a satisfactory network

ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 495-500

had been obtained, the third part consisted in developing methods to diagnose faults at the secondary operating point using the network trained to diagnose faults at the primary operating point.

1. The magnitudes of measured process variables can span a wide range. Data conditioning is achieved by scaling the data using standard statistical normalisation methods. Time series of data are divided by the corresponding standard deviation and the mean values were subtracted. This gives all variables the same variance, brings them to comparable range. The mean and the standard deviation values used are those of the healthy condition at each operating point.

2. Since the plant is often a multivariable process, all the variables are to be used as inputs to the NN and this will result in a very complex network topology with a large number of hidden nodes. In order to reduce the input space of the NN, the well-known PCA statistical method can be used. Therefore, the number of highly correlated variables in a multivariable data set can be reduced to a smaller one of uncorrelated variables without any loss of information. Selection was carried out using methods proposed in [3].

3. The data conditioned are used as inputs to the NNs. The NN training has been performed using the *Neural Network* Toolbox for *MATLAB*®. Tests have been initially carried out on both MLP and RBF networks to compare their performances in the classification of faults.

Once the network had been trained to diagnose faults at both the primary and the secondary operating point satisfactorily, using the *simulated* process model, the next part of the study consists in developing a methodology to use this network to diagnose faults occurring under the secondary operating point of the *real* plant.

Simulated turbine data has to be statistically scaled, converted into principal component variables using PCA and are therefore used to train the networks. The results of the presented fault diagnosis methodology are shown in the following.

2 Multiple Working Condition FDI using NNs

The process under investigation is the single–shaft industrial gas turbine [7, 8, 5]. As stated previously, the monitored process operates mainly at steady state and several (8) noisy process measurements ($u(t)$ and $y(t)$), including temperatures, flow rates, pressures, control signals, turbine speed and torque can be acquired.

In this application study, data for two fault cases and the healthy conditions were extracted from measurements and were used to obtain the results. Although other two faults were present in the available data, they were non included in this work.

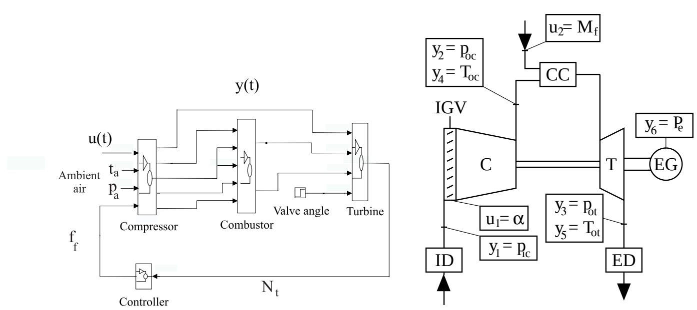
- *Fault 1.* **Pressure sensor bias**: incipient (drift) fault on the p_{ot} pressure sensor signal.
- *Fault 2.* **Actuator failure**: incipient (drift) fault on the $\alpha(t)$ actuator signal.

Several amount of process data from the gas turbine was available for investigation. The data sets have an average length of 1000 samples acquired every 0.1s. for the 8 input and output variables. This included some data sets that were not suitable for these investigation, due to the turbine start–up and shut–down during that period. Data acquired at two working conditions were available, both for analysis and for the development of the NN fault diagnosis scheme.

There was considerably more data from the primary operating point (shaft speed $2 \times 10^4 \frac{rad}{s}$) than data from the secondary condition (shaft speed $1 \times 10^4 \frac{rad}{s}$). The data available from the secondary operating point consisted mainly of healthy operating conditions, with little fault data.

For the method development it was necessary to obtain enough labelled fault data during the different working conditions. Therefore, it was decided to use a simulated gas turbine non–linear model (1(a)) in *SIMULINK®* environment to generate sufficient fault data under different operating points, to develop and test the FDI methods.

When the network had been trained to diagnose faults at both the primary and the secondary operating point satisfactorily, using the *simulated* turbine model, the next part of the work consisted in developing a methodology to use this network to diagnose faults occurring under the secondary operating point of the *real* plant (1(b)).



(a) (b)

Figure 1: (a) The simulated process and (b) the real plant.

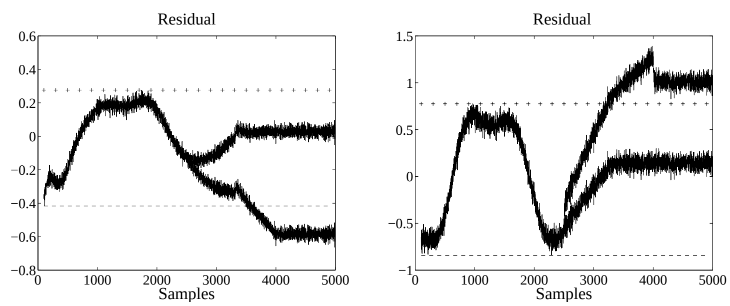
Again, turbine data was statistically scaled, converted into principal component variables using PCA and used to train the networks.

ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 495-500

3 Simulation Results

The simulated process was run at the primary and secondary points, and steady state data was collected from 8 variables, for the healthy condition and two faults. This data was used to develop the FDI techniques previously mentioned, involving data scaling, input reduction and NN training. In order to reduce the dimensionality of the data set, it was decided to use the first 4 principal components that accounted for a variance of 95% of the data set. This resulted in a reduction of dimensionality, form 8 process variables to 4 principal component variables.

RBF networks were trained with the principal component converted data as inputs, and the final network was selected for the simulated process with 4 inputs, one for each principal component, 8 centres and 3 outputs, one for a healthy condition and one for each fault. The root mean square (RMS) value for the network output error on the data set was 0.001. Figures (2(a)) and (2(b)) show the faulty residuals compared with fault–free ones. For the fault detection task, thresholds were fixed under fault–free conditions.



(a) (b)

Figure 2: (a) $\alpha(t)$ and (b) $p_{ot}(t)$ fault signals.

In this case, residual was defined as the difference between the measured output and its estimate, given by the NN. A successful classification from simulated data was obtained and no information was lost reducing the input dimensions using PCA.

The trained network was then applied to fault classification of the real plant sensor and actuator. The RMS error of the network output applied to real data was 0.06. The output nodes correctly classified faults occurring on the sensor and actuator of the real plant at both the primary and the secondary working point. The classification results demonstrate that for the secondary (and primary) operating points for the real process, these two faults can be diagnosed successfully using the same NN trained to diagnose faults at the primary and secondary operating point of the corresponding simulated model.

ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 495-500

4 Conclusion

Fault diagnosis of a real single–shaft industrial gas turbine processing under two different operating points has been investigated. It has been shown, in simulation and with real industrial data, that one NN trained with simulated data from both the working points can be successfully used to diagnose faults at secondary (and primary) operating point using the data from the real industrial process. Although successful for real and simulated industrial gas turbine process, general application of the developed method still needs further investigation. Further work on the simulated model is planned to extend the tests to cover the whole operating space.

References

[1] J. Chen and R. J. Patton. *Robust Model–Based Fault Diagnosis for Dynamic Systems*. Kluwer Academic, 1999.

[2] J. Gertler. *Fault Detection and Diagnosis in Engineering Systems*. Marcel Dekker, New York, 1998.

[3] J. E. Jackson. *A user's guide to principal components*. Wiley-Interscience, N.J., 1991.

[4] T Marcu and L. Mirea. Robust detection and isolation of process faults using neural networks. *IEEE Control System Magazine*, pages 72–79, Oct 1997.

[5] S. Simani. Fault Diagnosis of a Power Plant at Different Operating Points using Neural Networks. In *SAFEPROCESS2000*, volume 1, pages 192–196, Budapest, Hungary, 14-16 June 2000. 4th Symposium on Fault Detection Supervision and Safety for Technical Processes. Invited session.

[6] S. Simani, C. Fantuzzi, and S. Beghelli. Diagnosis techniques for sensor faults of indistrial processes. *IEEE Transactions on Control Systems Technology*, 8(5):848–855, September 2000.

[7] S. Simani, C. Fantuzzi, and P. R. Spina. Application of a neural network in gas turbine control sensor fault detection. In *CCA'98*, volume 1, pages 182–186, Trieste, Italy, September, 1-4 1998. 1998 IEEE Conference on Control Applications.

[8] S. Simani, F. Marangon, and C. Fantuzzi. Fault diagnosis in a power plant using artificial neural networks: analysis and comparison. In *ECC'99*, pages 1–6, Karlsruhe, Germany, 31. August - 3. September 1999. European Control Conference 1999.