ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 465-470

Use of Artificial Neural Networks Process Analyzers: A Case Study

Al-Duwaish[1], H., Ghouti[2], L., Halawani[1], T., and Mohandes[1], M.

[1]Department of Electrical Engineering
[2]Department of Information and Computer Science
King Fahd University of Petroleum and Minerals
Dhahran 31261, Saudi Arabia
E-mail: hduwaish@kfupm.edu.sa

Abstract

In this paper, artificial neural networks (ANN), which are known for their ability to model nonlinear systems and their inherent noise-filtering abilities, are used as O_2 analyzer to predict O_2 contents in a boiler at SHARQ petrochemical company in Saudi Arabia. The training data has been collected over duration of one month and used to train a neural network to develop neural based oxygen analyzer. The results are very promising.

1. Introduction

Boilers are found in many industrial facilities to be used both as power source and for processsing purposes. They consist of a furnace, where air and fuel are combined and burned to produce combustion gases to a water-tube system. The tubes are connected to the steam drum, where the generated water vapor is withdrawn.

Optimization of the operation of boilers can result is large savings. One of the areas in which the optimization can be performed is through the minimization of excess air. Lowering the excess oxygen (O_2) from 1% to 0.5% will increase boiler efficiency by 0.25%, a savings of about $5000/year in a 100,000 lb/hour boiler.

O_2 measurements are obtained through O_2 analyzers. Probe-type O_2 analyzers use zirconium oxide probe. The probe should be installed close to the combustion zone but at a point where the temperature is below that of the electrically heated zirconium oxide detector. The flow should be turbulent at the sensor location to ensure that the sample is well mixed and representative of the flue gas composition.

2. Neural-Based O_2 Analyzer

The use of neural networks as process analyzers has reported in [1-14]. The main idea of the neural-based O_2 analyzer is to infer the O_2 content in the flue gas from other easily measured process variables. The data for this case study was obtained from SHARQ petrochemical company, Saudi Arabia. Four process variables, as suggested by the process engineer, were selected as the most relevant process variables which affect the O_2 contents. These variables shown in Figure 1 are fuel gas-burner pressure, outlet stem flow, combustion air flow, and fuel gas flow. The proposed neural-based O_2 analyzer is shown in Figure 2.

ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 465-470

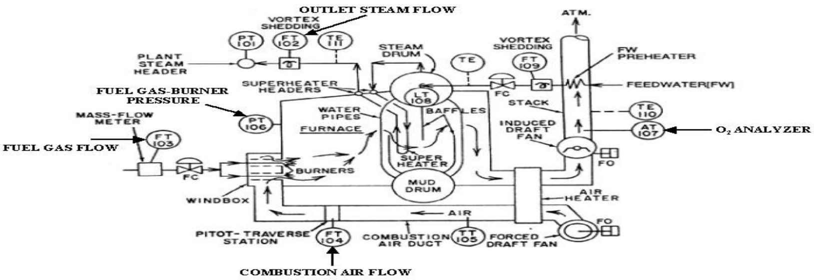

Figure 1: Boiler Schematic Diagram.

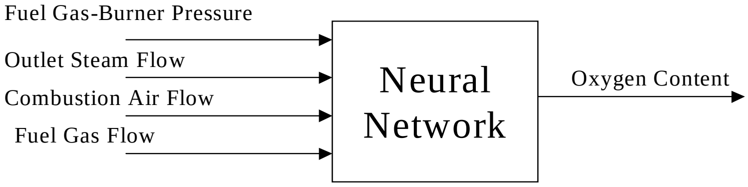

Figure 2: Proposed ANN-Based O_2 Analyzer.

3. Data Collection and Analysis

The data used for the development of the neural network was recorded by sampling the process variables and the O_2 content every 2 minutes for one month. A total of 22320 data points were gathered. Due to instrument failure during the data collection process, 4208 erroneous data points have been removed from the data set. The remaining 18112 data points were used in the development of neural based oxygen analyzer. The first 13144 data points, which constitute 62% data, were used in the training and the rest were used for testing.

Due to the large variation in magnitudes of input data, a preprocessing block is added to the neural network as shown in Figure 3. The prepocessing block performs linear transformation of the input variables such that all inputs have simillar values. To do this, each variable is treated independently, and for each input variable x_i we calculate its mean $\bar{x}_i$ and variance σ_i^2 with respect to the training set, using:

$$\bar{x}_i = \frac{1}{N}\sum_{n=1}^{N} x_i^n \tag{1}$$

$$\sigma_i^2 = \frac{1}{N-1}\sum_{n=1}^{N}(x_i^n - \bar{x}_i)^2 \tag{2}$$

Where N is the number of patterns in the training set. The transformed variables are given by:

$$\hat{x}_i^n = \frac{x_i^n - \bar{x}_i}{\sigma_i} \tag{3}$$

ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 465-470

The transformed variables will have zero mean and unit standard deviation over the transfromed training set.

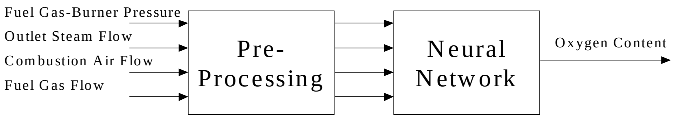

Figure 3: Proposed ANN-Based O_2 Analyzer with Pre-Processing.

4. Neural Network Design

The adopted neural network used is a multilayer feedforward network with four inputs, one hidden layer, and one output trained using backpropagation algorithm [15]. After many trials, it has been found that 10 neurons in the hidden layer give an acceptable compromise between network estimation accuracy and network complexity. The behavior of the sum of square errors between the actual and predicted oxygen contents during training is shown in Figure 4. The O_2 contents from the existing process analyzer and from the neural network are shown in Figure 5 and Figure 6 respectively. The two figures clearly show that the neural network was able to closely predict the O_2 contents. The mean of the estimation error for the training data is 0.00054 with standard deviation of 0.1982. The distribution of the oxygen contents estimation error indicates that 92% of the errors are within the range of ±0.35.

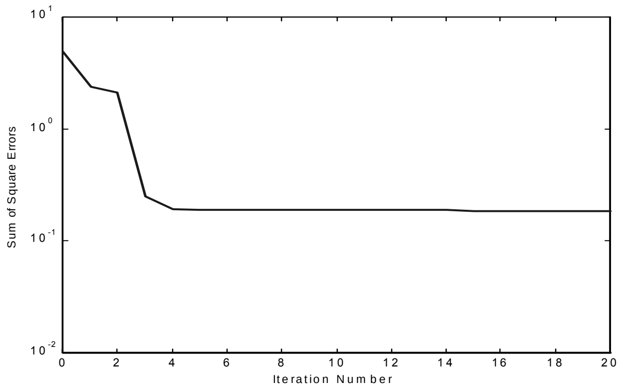

Figure 4: Sum of Squared Errors.

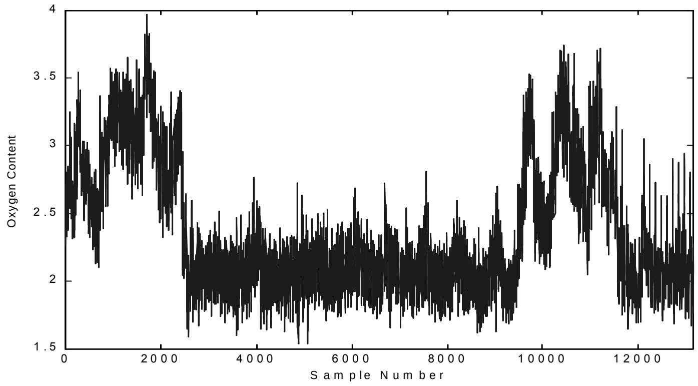

Figure 5: O_2 Contents from the O_2 Analyzer (Training Data).

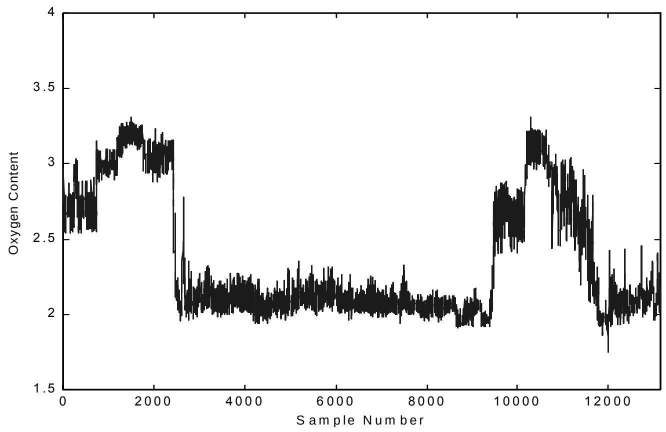

Figure 6: O_2 Contents from the ANN-Based Analyzer (Training Data).

The testing data has been used to investigate generalization capabilities of the developed neural network. The O_2 contents from the existing process analyzer and from the neural network are shown in Figure 7 and Figure 8 respectively. The mean of testing data is 0.0104 and the standard deviation is 0.1362. The distribution of the oxygen contents estimation error indicates that 92% of the errors are within the range of ±0.35.

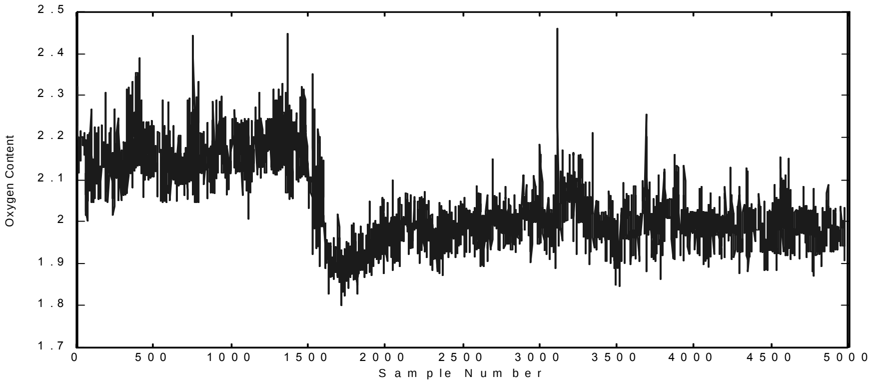

Figure 7: O_2 Contents from the O_2 Analyzer (Testing Data).

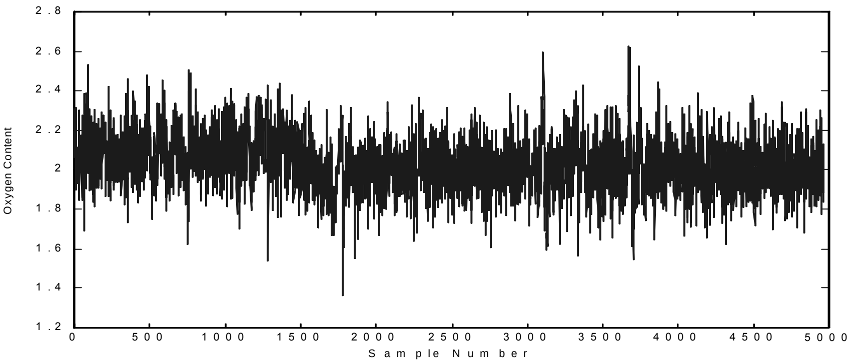

Figure 8: O_2 Contents from the ANN-Based Analyzer (Testing Data).

The results obtained from actual plant data show excellent estimation reliability and the resulting model is considered accurate enough for oxygen online estimation use. The resulting neural model represents savings of time and effort as it does not require complex modeling skills and can be retrained when operating conditions change. When implemented online, the neural network based analyzer offers a cost-effective, reliable alternative to existing analyzer.

5. Conclusion

This paper describes the use of multilayer feedforward neural networks as process analyzer for a case study of O_2 analyzer. Data for the O_2 contents and relevant process variables has been collected and used in the training of the neural network. The trained neural network has been tested with new data and the results obtained are very promosing.

6. Acknowledgments

The authors acknowledge the support of King Fahd University of Petroleum and Minerals and King Abdulaziz City for Science and Technology under grant No. AR 18-16.

7. References

[1] Bhat, N. V., P. A. Minderman, T. J. McAvoy, and N. Wang, 1990. "Modeling Chemical Process Systems via Neural Computation," *IEEE Control Systems Magazine,* pp. 24-30.

[2] Lambert, J. M. and R. Hecht-Nielsen, 1991. "Application of Feedforward and Recurrent Neural Networks to Chemical Plant Predictive Modeling," *IJCNN-91-Seattle International Joint Conference on Neural Networks,* pp. 373-378.

[3] Bulsari, A. B., and H. Saxen, 1991. "A feed-forward Artificial Neural Network as A Simulator for A Chemical," *Proceedings of the Twenty Fourth Annual Hawaii International Conference on System Sciences,* pp. 500-506.

[4] Broten, G. S., and H. C. Wood, 1992. "A Neural Network Approach to Analyzing Multi Component Mixtures," *IJCNN-92 Proceeding*, vol. 2, pp. 957-962.

[5] Crowe, E. R., and C. A. Vassiliadis, 1995. "Artificial Intelligance: Starting to Realize Its Practical Promise," *Chemical Engineering Progress*, pp. 22-30.

[6] Boger, Z., 1995. "Experience in Developing Models of Industrial Plants by Large Scale Artificial Neural Networks," *Proceedings of the Second New Zealand International Two Stream Conference on Artificial Neural Networks and Expert Systems,* pp. 326-329.

[7] Al-Duwaish, H. N., A. O. Al-Khowaiter, and H. S. Al-Hajj, 1996. "Inferentail Prediction of Distillation Properties Using Neural Networks," *Saudi Aramco Journal of Technology,* pp. 58-64.

[8] Qin, S.J., 1997. "Neural Networks for Intelligent Sensors and Control – Practical Issues and Some Solutions," in O. Omidvar and D. L. Elliott, eds, Chapter 8, Academic Press.

[9] Mukesh, D., 1997. "Hate Statistics? Try Neural Networks," *Chemical Engineering Progress,* pp. 96-104.

[10] Yang,Y., and T. Chai, 1997. "Designing a Soft Sensor for a Distillation Column with Fuzzy Distributed Radial Basis Function Neural Network," *Proceedings of the American Control Conference*, New Mexico.

[11] Yang, Y., and T. Chai T., 1997. "Experience of Neural Networks for Inferential Estimation in Industrial Process Control," *Proceedings of the American Control Conference,* New Mexico.

[12] Yang,Y., and T. Chai, 1997. "Soft Sensing Based On Artificial Neural Network," *Proceedings of the American Control Conference,* New Mexico.

[13] González, G. D., 1999. "Soft Sensors for Processing Plants," *Proceedings of the second International Conference on Intelligent Processing and Manufacturing of Materials (IPMM-99),* pp. 59-69.

[14] Neelakantan, R., 1999. "Implementation of non-linear inferential sensors," *Proceedings of the American Control Conference,* San Diego.

[15] Haykin, S., 1994. Neural Networks: A Comprehensive Foundation. Upper River Sadler, NJ: Prentice-Hall.