Online Monitoring of Exhaust Gas Emissions of a Boiler with Diesel/Biodiesel Fuel Blends

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An online, low-cost, neural network based soft sensor was developed and implemented, with the aim of being compatible with the present industrial automation and control systems. The virtual sensor was designed to predict exhaust gas emission levels of an originally built diesel boiler with diesel/biodiesel mixture blends at different air ratios, using temperature, flow rates and pressure as inputs variables to the neural network model. With that purpose, experimental data were obtained for different diesel and biodiesel mixtures of fuel in the boiler, in order to validate the model. The online experimental data consisted of process variables, obtained using a SCADA system connected to fieldbus communication protocol instrumentation, and exhaust pollutant gas levels, obtained using a conventional gas analyzer. A detailed methodology was established for each phase of the study, including data collection and treatment, topology and neural training comparative studies, implementation of the neural network algorithm proposed in the SCADA system and the application of an online validation and maintenance procedure. Experimental online tests confirmed the compatibility between the exhaust gas emission levels inferred by the online soft sensor and those obtained with the analyzer. Scan acquisition intervals were six times smaller and maintenance proceedings were optimized, without demanding a large time interval. Thus, the automation solution can be used to provide pollutant monitoring, helping to achieve a more consistent operation, regarding production and environmental profits.

1. Introduction

In industrial processes the difficulties on dealing with operational disturbances are considered the main cause for productivity losses and significant changes on final product specifications. The worldwide globalization context implies that industrial process plants must have great flexibility to adapt their production line in order to obtain products within specifications, according to profitability, social and environment added value targets or even diversified raw material availability. Industrial plants depend on effective measurement devices to supervise specific process variables, allowing automatic control adjustments and diagnosis. However, online measurement instruments and analyzers are known to be expensive and unreliable solutions (Mohler et al., 2010), with large time responses. This scenario reveals that 51% of all online applications encountered in previous reviews (Hussain, 1999) are based on the artificial neural networks

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(ANN) known as multilayer perceptron models (MLP). They are the most popular ANN used in engineering applications, due to their large generalization capacity, flexibility, and reduced computational complexity (Rivera et al., 2009). This last characteristic must particularly be considered when developing an automation-integrated system, which should present low time response.

On the other hand, combustions based equipments are widely integrated in industrial environments, where fossil fuels are dominant (Drapela et al., 2009). Therefore, pollutant reduction is strongly aimed and several studies are being conducted focusing on environmental concerns (Alejo Sanches et al., 2010) and efficiency improvements (Hippinen et al., 2010). Due to international environmental policies, allied to the competitive advantages of agribusiness, the use of biodiesel as an alternative liquid fuel for industrial boilers is gradually increasing in several countries. Previous contributions also indicate MLP models as major applications for modeling and control of combustion processes (Kalogirou, 2003). This paper presents the implementation of an online virtual measuring solution for analyzing exhaust gas emissions of a boiler fueled with diesel/biodiesel blends, integrating industrial instrumentation based on fieldbus communication equipments and software, and a MLP neural network tool, specifically developed to work as a generic field device.

2. Experimental Tests

2.1 Process and automation system facilities

The pilot plant used in the current work is part of the utility facilities installed in the pilot plant of the School of chemistry, chemical department lab in Federal University of Rio de Janeiro. Basically, the plant has a feed water tank, a fuel mixture tank for preparing the blends and a semi-industrial vertical boiler (Table 1).

Table 1: Boiler specifications

Boiler Model	CV-VDM-500
Steam Production	500 kg/h
Nominal heating power	0.3 MW
Steam characteristics	Saturated
Maximum working pressure	$8.00 \mathrm{kgf/cm^2}$
Main fuel	Diesel
Fuel flow rate	~26 kg/h

The automation system has fieldbus protocol based devices for measuring continuous process variables, a dedicated PLC controller and a SCADA station to supervise the process. The continuous process variables available are: fuel temperature and feed tank level; feed water temperature, tank level, and flow rates; boiler water level; steam production flow rates and pressure; flue gas emission temperatures. Exhaust gas emission concentrations (O₂, CO, CO₂, NO, NO₂, SO₂) were continuously analyzed with a Testo 350XL flue gas analyzer. The boiler has a fixed fuel flow rate of 26kg/hr and a regulated damper allows different air flow rates adjustments. The air flow rate was initially set to 30% of excess air, to achieve the best performance when using diesel according to the

manufacturer of the boiler. Previous studies suggest that tests using biodiesel or biodiesel blends in substitution to diesel as fuel can be conducted without any modifications on the test burner (Canacki et al., 2009).

2.2 Fuel blends and test procedures

All the blends were prepared before each test with metropolitan diesel and dende palm biodiesel, and followed an experimental schedule, including mixture blends of 20%, 30%, 40%, 50%, 60% and 100% of palm biodiesel. After heating the boiler up to the working pressure level, the steam flow rate was fixed on 450 kg/hr and the air flow rates were maintained at different levels of excess air (10%, 20% and 30%) during an hour each. The experimental procedure was conducted continuously along all the proceeding steps and, after each test, the process data was gathered from the SCADA system and the gas analyzer. In sequence, the experimental data were treated and studied to achieve the best MLP neural network model for predicting gas emission concentrations.

3. Results and Discussion

3.1 Integrating the soft sensor to the available automation system

Before developing the soft sensor, all instances of the available automation system were analyzed in order to determine the best location to implement the algorithm itself, including the fieldbus instruments and the SCADA system. Since the main objective of the developed tool was to allow the implementation in as many as possible industrial facilities, the SCADA system was selected as the development platform (Figure 1).

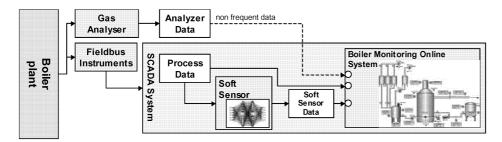


Figure 1. Integration of the automation equipments and the soft sensor

3.2 Soft sensor development

Initially, the experimental data were treated to select the measured process variables that most influenced the gas emission concentrations. This step of development was based on the phenomenological analysis of the boiler operation, elimination of possible outliers and consideration of steady state conditions.

In this study both input and output data were normalized to the range [0, 1]. A total of 502 input-output patterns were available, being 80 % of them used for training and 20 % for validation of the ANN. The number of neurons on the hidden layer varied from 4 to 13, where hyperbolic tangent, sin, exponential and identity functions were tested as

activation functions. Different networks were trained, validated and analyzed according to the prediction performance limits of standard deviation ratio and mean square error.

Considering that the soft sensor was to be implemented as an inherent part of the automation system and that the computational effort of the model is a determinant part of its performance, sensitivity studies were carried out, in order to reduce the number of input variables. Only input variables whose withdraw at least doubled the prediction error of the MLP were kept (Valdman, 2010).

The best model was composed of 6 linear input neurons, 1 hidden layer with 10 hyperbolic tangent neurons and 6 linear output neurons (Figure 2). This MLP presented a R² coefficient of 0.95 and a mean square error of 0.01, both for training and validation data, indicating that overfitting was not present

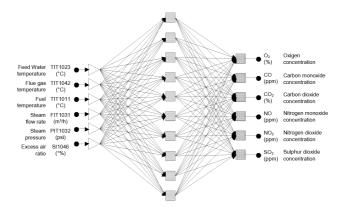


Figure 2. Soft sensor neural network topology

3.3 Online automation system development

Controlling optimal ratios of reduced pollutant gas emissions and energy gains require efficient monitoring tasks with reliable sensors to control the settings of the industrial process (Rivera et al., 2009).

In order to provide industrial applications, a generic MLP neural network tool was developed in the present study, using VBA (Visual Basic Application) language and integrated in an industrial SCADA system such as iFix Proficy.

After informing the input variables, the weights, biases and activation functions of the model, and the output variables of the neural network model, a real-time online soft sensor for the boiler gas emission predictions was achieved. On automatic cycle basis, the soft sensor receives the 6 specified measured process variables (input variables to the soft sensor), processes the neural network model and predicts the 6 gas emission concentrations released through the chimney (output variables of the soft sensor).

3.4 Online validation

After validating the automated application itself, a new experimental test was conducted for online confirmation (validation) of the developed soft sensor. The blend consisted of 31% of biodiesel and 69% of diesel as the boiler fuel and the results for O_2 , CO_2 , SO_2 and NO_2 are presented on Figure 3.

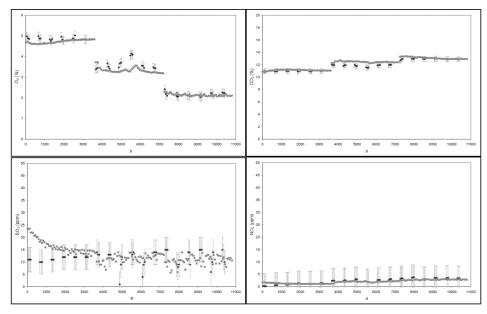


Figure 3. Online experimental validation data comparing soft sensor (a) and gas analyzer (4) results

The results obtained for oxygen concentration indicate that the trends are consistent with the process behavior, revealing the three different steps of air excess. The results predicted by the soft sensor were within the error measurement presented by the gas analyzer, except for the sulphur dioxide concentrations during the first hour of the run. Considering that the experimental blend in this new test used a different biodiesel concentration, not contemplated on the experimental data set used during training and validation, the online soft sensor presents good interpolation results. Another important aspect of the results is the lower acquisition time interval achieved by the online soft sensor in comparison with the online gas analyzer, including the maintenance of gas concentration predictions during the cleaning purge period of the equipment. In comparison with the online equipment, maintenance procedures are much easier to be performed and an adjusted (actualized) model can be achieved only a few minutes after any experimental test.

4. Conclusions

The application developed in this study introduces a new approach of the usefulness of online model-based sensors. The integration of these concepts within an automation system increases the opportunities of successful industrial solutions, especially when critical process variables are not available online. The availability of dynamic process information enlarges the possibilities of improvement on control and optimization strategies and operational diagnosis. Based on these facts, the main conclusions are:

i.A soft sensor, based on MLP, was developed to predict gas emission concentrations of the residual gases expelled in result of fuel combustion in a boiler;

- ii.An online open solution was developed, integrating a generic MLP neural network with one hidden layer, within an industrial automation SCADA system;
- iii.The SCADA application was customized according to the model characteristics of the developed soft sensor for gas emission analyses predictions, obtaining an online sensor analogous to any other measured process variable.
- iv. The validation online results present that the developed solution achieves low acquisition time intervals and prediction results similar to those obtained with a commercial gas analyzer;
- v. The timing and performance results obtained show that the online soft sensor application can be efficiently used for process monitoring, improving the implementation of control and optimization strategies and operational diagnosis.

References

- Alejo Sanches D., Morales Perez M.C., Alfonso G., Rosa Dominguez E., Herrera I., Nunez, V., 2010, Diagnosis of the air quality in a zone affected by combustion gases sources, Chemical Engineering Transactions, 21, 199-204.
- Canacki M., Ozsezen A.N., Arcaklioglu E., Erdil A., 2009, Prediction of performance and exhaust emissions of a diesel engine fueled with biodiesel produced from waste frying palm oil. Expert Systems with Applications, 36, 9268-9280.
- Drapela T., Pavlas M., Popela P., Boran J., Stehlik P., 2009, Energy conception of an integrated system I. Analysis of available data and its processing, Chemical Engineering Transactions, 18, 635-640.
- Hippinen I., Ruohonen P., Sivill L., Federley J., Hakala J., Manninen J., Ahtila P., 2010, Methods for industry to measure and improve the energy efficiency of utility systems, Chemical Engineering Transactions, 21, 349-354.
- Hussain M.A., 1999, Review of applications of neural network in chemical process control Simulation and online implementation, Artificial Intelligence in Engineering, 13, 55-68.
- Kalogirou S.A., 2003, Artificial intelligence for the modelling and control of combustion processes: a review, Progress in Energy and Combustion Science, 29, 515-566.
- Mohler I., Hölbling N., Galinec G., Bolf N., 2010, Soft sensors for diesel fuel property estimation, Chemical Engineering Transactions, 21, 1477-1482.
- Rivera E.A.C., Farias F.J., Atala D.I.P., Ramos R.D.A., Carvalho A.D.A., Maciel Filho R., 2009, Development and implementation of a automated monitoring system for improved bioethanol production, Chemical Engineering Transactions, 18, 451-456.
- Valdman A., 2010, Sistema de Automação para Monitoramento Online de Gases Residuais e Diagnóstico de uma Caldeira Operada com Misturas Diesel/Biodiesel, M.Sc. Dissertation, Federal University of Rio de Janeiro (in Portuguese).