AIDIC *Conference Series*, Vol. 10, 2011
Editor Sauro Pierucci
DOI: 10.3303/ACOS1110039

ISBN 978-88-95608-58-7 ISSN 2036-5969

A SYSTEMATIC METHODOLOGY ON DEVELOPING AN ONLINE SOFT SENSOR BASED ON NEURAL NETWORKS FOR MONITORING BOILER GAS EMISSIONS

Andrea Valdman*, Maurício Bezerra de Souza Jr., Rossana Folly, Belkis Valdman

School of Chemistry, Chemical Engineering Department, Federal University of Rio de Janeiro, Brazil
Av.Horacio Macedo, 149 - Centro de Tecnologia - Bloco E/sl. E-209 - Rio de Janeiro - 21941-909 – Brazil
*avaldman@eq.ufrj.br

Automation and control systems are inherent to all industrial process plants, introducing high computational capabilities and processing flexibility to improve availability of process variables. Although true efforts are achieved on monitoring, supervision and control tasks with fieldbus transmitters and SCADA systems, online sensor implementations for measuring and quantifying chemical and biochemical components are still limited by their high cost hardware, complicated maintenance procedures and low time response. Nevertheless, several important and immeasurable process variables have been successfully predicted and implemented in advanced control strategies by using soft-sensors applications. In order to present a real time solution capable of minimizing the constraints and maximize the capabilities of this scenario, a systematic methodology is established and detailed to allow the development of an online, low-cost, neural network based soft sensor, with the aim of being compatible with the present industrial automation and control systems. Following this methodology, an online virtual sensor application was designed to perform online predictions of the 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 input 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. The main steps of the study include 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. Soft-sensor applications in chemical industrial processes have been worldwide studied, consolidating two basic methods: model-based approaches and historical data approaches (Fortuna et al., 2006). Basically, the data driven

Please cite this article as: Valdman A., De Souza Jr. M., Folly R. and Valdman B., (2011), A systematic methodology on developing an online soft sensor based on neural networks for monitoring boiler gas emissions, AIDIC Conference Series, 10, 353-362 DOI: 10.3303/ACOS1110039

methods apply mathematical heuristic methods or neural networks and multivariable statistic methods on data provided by plant instruments to provide qualitative or quantitative diagnoses (Jamsa-Jounela, 2007).
Hussain (1999) revealed that 51% of all online applications encountered in previous reviews were based on the artificial neural networks (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 methodology that was successfully developed and established for 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.

2. SOFT-SENSOR DEVELOPMENT METHODOLOGY FOR ONLINE PREDICTION

Based on an extensive overview of methodologies applied on soft sensor development for batch and continuous process (Fortuna et al., 2006, Salvatore et al., 2009, Kadlec et al., 2009), the present work defined a systematic methodology approach on developing an online soft sensor based on neural networks, as shown on Fig. 1. The present procedure combines the capabilities of a modern integrated automation system with historical data quantitative methods to develop a soft-sensor that works as a generic field device. The main steps of the method are the analysis, validation and implementation of the neural network model, including specific online steps, such as collecting data, online implementation, validation, maintenance and diagnosis.

2.1 Historical data acquisition and preliminary data analysis

The experimental tests are the core concern when developing a data driven soft-sensor based on experimental data. All the operational procedures must be previously specified and normalized in order to allow a comparative analysis of the results and produce a set of experimental data that represents the full scope of the analyzed process variables. The automation system must be reliable, especially the instrumentation sensors and calibration curves used in all the tests to avoid corrupted data that could hardly be pointed as outliers. Supervision Control and Data Acquisition (SCADA) systems are constantly used in industrial process plants and can be specified to score historical data of any digital instrument available on the field. In addition, fieldbus technology presents intelligent instruments that can provide, along with the measurement value, other important information for plant diagnosis, such as signal self-diagnosis details. Parameters such as engineering units, zero, span, time interval acquisition and numeric precision are important to be registered in order to improve data information. This step provides a preliminary data matrix, specifying individual groups of measurement data, acquisition time and signal diagnosis for each process variable preliminary considered in the soft-sensor analysis.

2.2 Data processing

The first data filter applied to the process variables obtained from the preliminary data matrix can be achieved considering specific operational process characteristics, such as over sizing valves and bombs. This kind of know-how is obtained from specialized supervisors and operators that work for many years at the process plant. This analysis eliminates unreliable variables and defines the maximum number of neurons in the first layer. Considering a continuous process, steady state periods must be identified, in order to provide consistent groups of training and validation patterns, used by the neural network to acquire enough knowledge to predict the process behavior. During this step, initial and final transient dynamics and noise (outliers) are eliminated. In addition, the input variables are normalized, providing a set of data processed patterns to be fed as information to the soft sensor and allowing preliminary definition of topology and neural network performance tests.

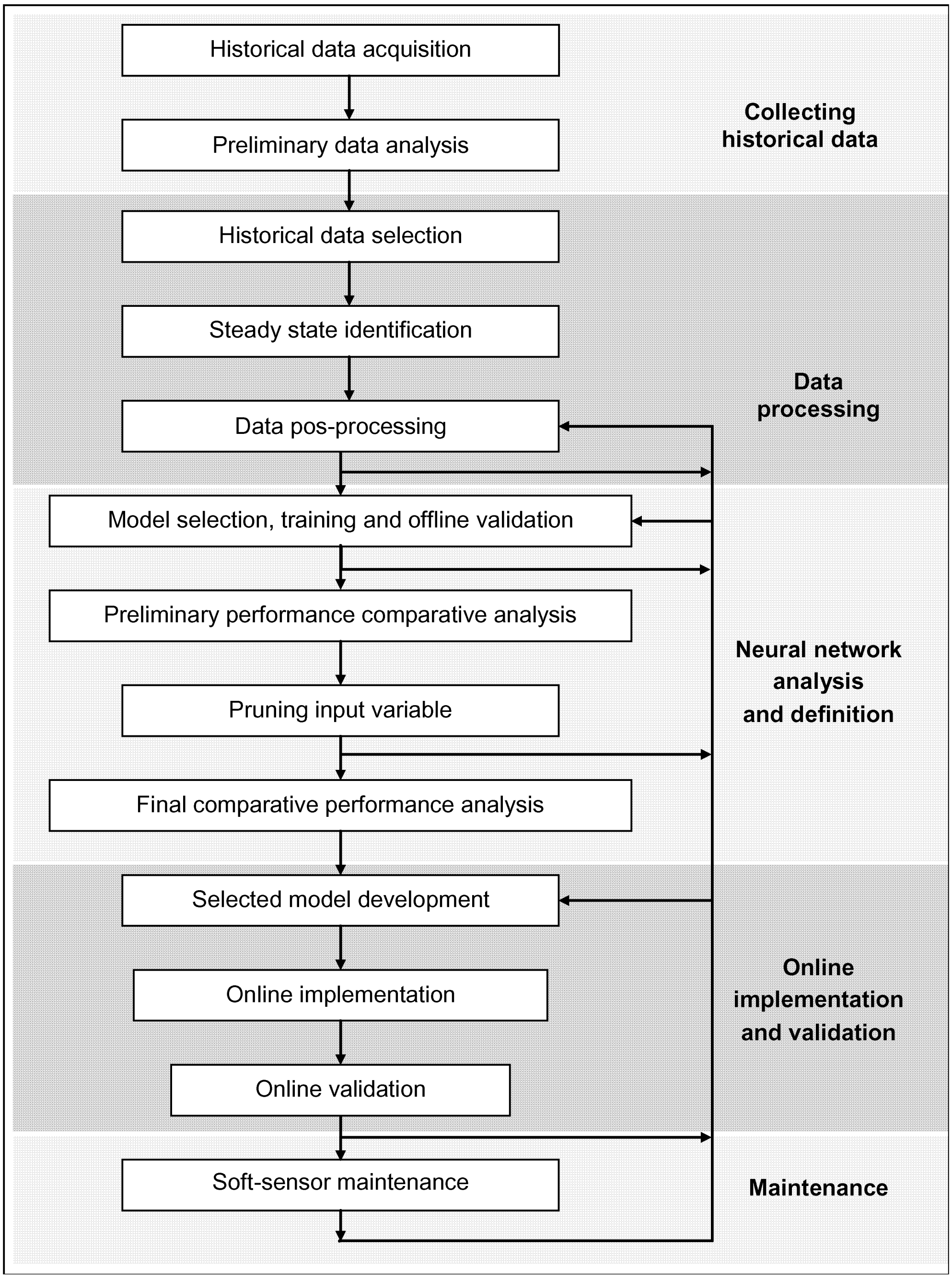

Fig. 1: Soft-Sensor development methodology for online prediction

2.3 Neural network analysis and definition

In sequence, the experimental processed data are treated and studied to achieve the best MLP neural network model for predicting gas emission concentrations. At this point neural network topology is optimized, including number of layers and neurons in each layer, and different networks are compared in order to achieve optimum prediction results. The best neural network models are selected, trained and validated offline, using part of the processed data matrix obtained previously. Nevertheless, preliminary performance results are compared to obtain a first set of possible models that could be implemented as a soft sensor. Considering that processing time and mathematical complexity are core concerns in online implementations, sensibility tests can be performed on the input variables to reduce the number of neurons in the input layer. This elimination is performed in the preliminary data matrix and not in the processed data matrix, because patterns that are removed from the original matrix due to outlier detection in the removed variable must be reconsidered. After eliminating the less relevant variables, the final data matrix is processed and a new analysis of the neural network models obtained is performed. The definition of the soft sensor model to be integrated in the automation system is based on the analysis of all the neural networks obtained (original and reduced), including prediction performance and computational complexity.

2.4 Online development and validation - Integrating the soft sensor to the available automation system
After developing the mathematical model, the soft sensor itself is integrated in one of the automation system elements. All instances of the available plant automation system are analyzed in order to determine the best location to implement the algorithm itself, including the fieldbus instruments and the SCADA system. Even though fieldbus instrumentation devices have built-in mathematical functions, they still have few generalization aspects due to the limited international standard specification on the subject (IEC, 2006). Since the main objective of the developed tool is to allow the implementation in as many as possible industrial facilities, the SCADA system was selected as the online development platform in this study (Fig. 2).

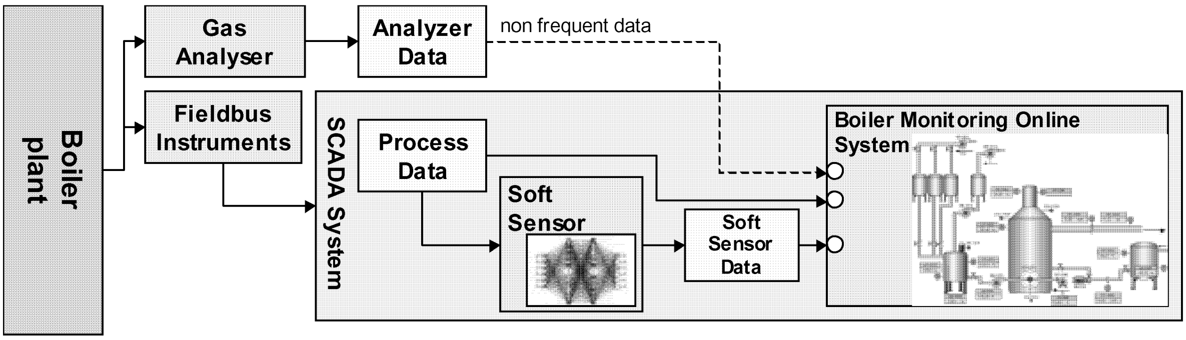

Fig. 2: Integration of the automation equipments and the soft sensor

The developed soft sensor model is implemented in the SCADA system, using application tools provided by each supplier. Nowadays, many SCADA systems are Windows based softwares and use Visual Basic for Applications as an integrated programming language tool. After developing the program code, the process variables are connected to the neurons of the input layer in order to supply process information to the neural network, according to the developed model previously defined. The predicted variables are created in the SCADA database as regular process variables and connected to the output neurons that are continuously updated in a time basis cycle. The neural network profile, hidden layer parameters, activation functions, as well as pos and pre treatment parameters are created with customized configuration flexibility, regarding maintenance facilities. Special attention regards the optimum acquisition time basis, considering the sensor and transmitter time constants of the input process variables and computational processing of the mathematical model itself.
An online soft sensor validation is determined in two sequential experimental tests. The first test relies on the validation of the SCADA tool itself and the second test relies on the validation including plant communication interface layers. During the offline validation test, the data matrix with the processed patterns inputs used in the performance validation is fed on a time basis interval to the SCADA database. The developed application predictions are compared with those achieved by the same neural network model when using reference neural network toolboxes, such as Matlab and Statistica. Performance results of the SCADA sensor integration and the reliability on the input and output neuron connections are confirmed, along with a preliminary analysis of the

computational processing time. The last validation test is realized to integrate the plant communication layer with the developed soft sensor. On this step, the input process variables are acquired from plant instrumentation, the output process variables are obtained from a reference analyzer or lab analysis and the calculated output variables are predicted through the soft sensor. The online validation performance compares the resulted predictions with the output variables obtained by conventional analysis methods.

2.5 Maintenance

Analogous to all the commercial instrumentation sensors, an online soft sensor requires periodic maintenance to guarantee the reliability of the provided information. In comparison to the calibration curves presented to update non linear sensors, a soft sensor based on neural network requires that the predicted values have to be regularly checked to guarantee the performance of the soft sensor. After implementing the soft sensor itself, preventive maintenance procedures are established by regularly comparing the predicted values with commercial calibrated analyzers and the operational diagnosis of the plant is used as an indicator that the soft sensors parameters might be out of date. The calibration is realized as an offline procedure without need to stop the industrial plant by introducing a new set of historical patterns to the data processing step. This offline intervention aggregates updated process knowledge to the neural network, allowing the mathematical model to be re-trained and a new analysis to be performed. Considering that the first prediction analyses defined the number of input and output neurons as well as the neural network model as a MLP network, the new calibration information can include new activation functions, new low and high process variable operational limits, and new biases and thresholds values. This new set of parameters is immediately provided to the soft sensor analyzer without need to shut down the plant or modify the programming code. Since industrial process plants are subject to a great number of disturbances, some of them unknown and not initially predicted, the maintenance facilities offered by the soft-sensor interface can be crucial to define the sensors lifetime and the flexibility of their industrial applications.

3. EXHAUST EMISSION SOFT-SENSOR APPLICATION

3.1 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 Engineering 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 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, PLC controllers to control and guarantee the security levels of the plant and a SCADA station to supervise the process. The SCADA system is configured to collected data in a 1 minute base frequency and 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 (O_2, CO, CO_2, NO, NO_2, SO_2) were continuously analyzed with a Testo 350XL flue gas analyzer, in a 1 minute base frequency, although the equipment demands an automatic operational purging cycle every 7 minutes. The boiler has a fixed fuel flow rate of 26kg/h 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).

3.2 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/h 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.

4. RESULTS AND DISCUSSION

4.1 Soft sensor development

Initially, the experimental data were treated to select the measured process variables that most influenced the gas emission concentrations. As discussed in Section 2, 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 (Fig. 3). This MLP presented a R^2 coefficient of 0.95 and a mean square error of 0.01, both for training and validation data, indicating that over-fitting was not present.

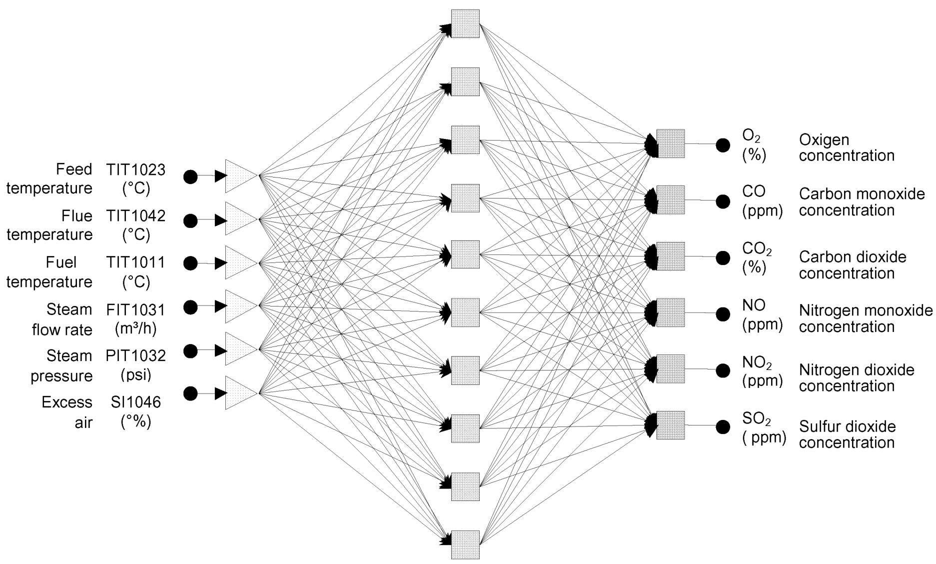

Fig. 3. Soft sensor neural network topology

4.2 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 using VBA (Visual Basic Application) language and integrated in the industrial SCADA system 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).

4.3 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 Fig. 4.

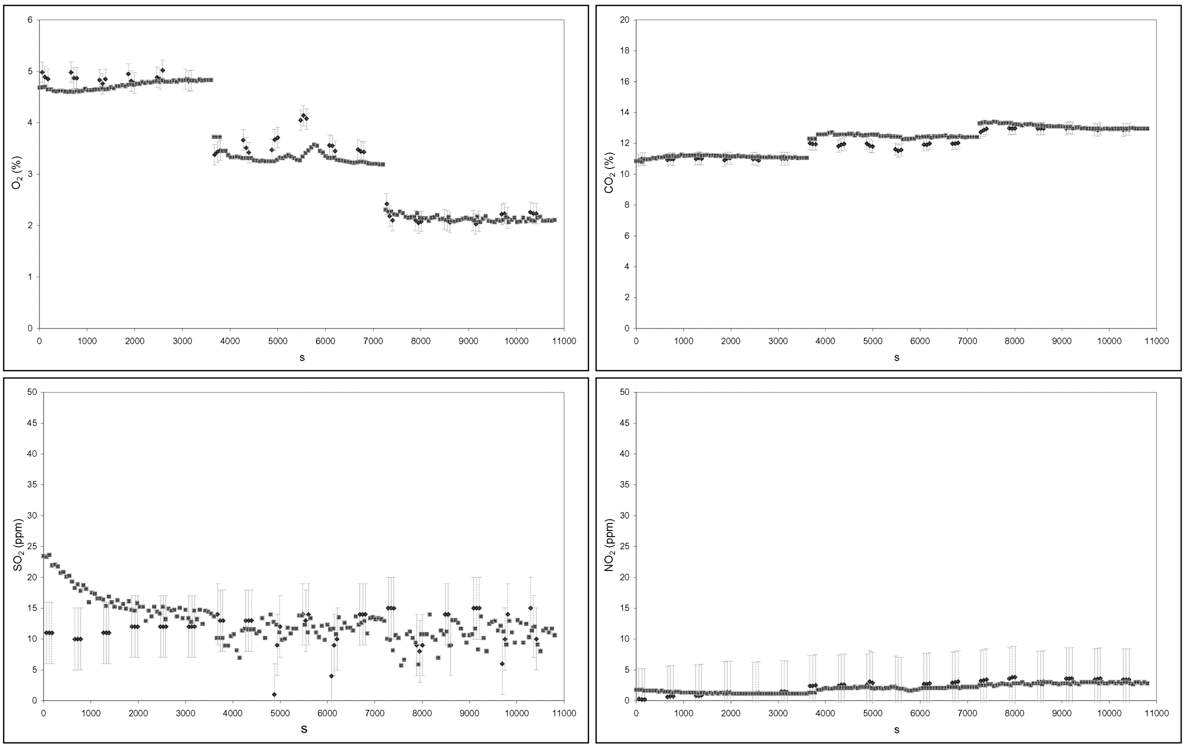

Fig. 4. Online experimental validation data comparing soft sensor (■) and gas analyzer (◆) results

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 sulfur 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.

5. CONCLUSIONS

The methodology proposed in this study introduces a new approach for the development of online neural network based soft sensors. It includes several steps from data acquisition and processing to training, validation, online implementation and maintenance.

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.

6. 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.

Fortuna L., Graziani S., Rizzo A., Xibilia M.G., 2006, Soft sensors for monitoring and control of industrial processes, Springer, London.

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.

IEC, 2006, Function blocks (FB) for process control – Part 2: Specification of FB concept, International Standard IEC 61804-2, International Electrotechnical Commission, 2nd Edition.

Jamsa-jounela, S.L., 2007, Future Trends in process automation, Annual Reviews in Control: 31:2, 211-220.

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.
Salvatore L., De Souza Jr. M.B., Campos M.C.M.M., 2009, Design and implementation of a neural network based soft sensor to infer sulfur content in a brazilian based diesel hydrotreating unit, Chemical Engineering Transactions, 17, 1389-1394.
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).