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Software Sensor for Sulphur Recovery Unit Control

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This paper elaborates methods of soft sensor development for dynamic model identification and process control of Sulphur Recovery Unit (SRU) in refinery production. Experimental data are acquired from refinery unit and include available on-line measured variables and on-line analysis.

The results are soft sensor models for optimal control of SRU with aim to minimize SO_2 and H_2S emissions. The soft sensors were developed conducting multiple linear regression analysis and using neural network-based and fuzzy logic models. From a variety of different model structures the best results were achieved with multi-layer perceptrons and neuro-fuzzy soft sensor models.

1. Introduction

Control systems and optimization procedures require regular and reliable measurements at the appropriate frequency. At the same time, legislation dictates strict product quality specifications and refinery emissions. As a result, greater number of process variables need to be measured and new expensive process analyzers need to be installed to achieve efficient process control. The quality measure may only be available as a laboratory analysis or very infrequent on-line measurement. (Martin, 1997)

The application of soft sensors for estimating hard-to-measure process values is extremely interesting in the process industry, where there are usually a large number of values measured continuously and quickly, and they may serve as input signals for the soft sensor (Bolf *et al.*, 2007). They can work in parallel with real sensors, allowing fault detection schemes devote to the sensor's status analysis to be implemented. Also, they can take the place of sensors which have been taken off for maintenance, to keep control loops working properly and to guarantee product specification without undertaking conservative production policies, which are usually too expensive (Fortuna *et al.*, 2007).

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In developing soft sensors, any modelling paradigm may be employed. In many cases, only data based modelling methods are involved (Quek *et al*. 2000). Using artificial neural network and fuzzy logic paradigms it is possible to capture non-linear process characteristics. If sufficiently accurate, the inferred primary output states may then be used as a feedback for automatic control and optimization.

2. Sulphur Recovery Unit

SRU removes environmental pollutants from acid gas streams previous they are released into the atmosphere. Furthermore, elemental sulphur is recovered as a valuable by-product (Fortuna *et al*., 2003).

The SRU in INA-Refinery Sisak is shown on Figure 1. The inlet streams are MEA gas, rich in H_2S, which comes from the gas washing plants; the SWS gas, rich in H_2S and NH_3, which comes from the Sour Water Stripping (SWS) plant; the air inlet stream in Claus section and hydrogen which enters TGT section. Acid gases are burnt in reactors, where H_2S is transformed into pure sulphur via a partial oxidation reaction with air. Gaseous combustion products coming from furnaces are cooled, causing the generation of liquid sulphur, which is collected, then passed through high temperature converters, where a further reaction leads to the formation of water vapour and sulphur. The remaining, nonconverted gas (less than 5%), is fed to the TGT section for a final conversion phase. The tail gas stream from the SRU contains residual H_2S and SO_2.

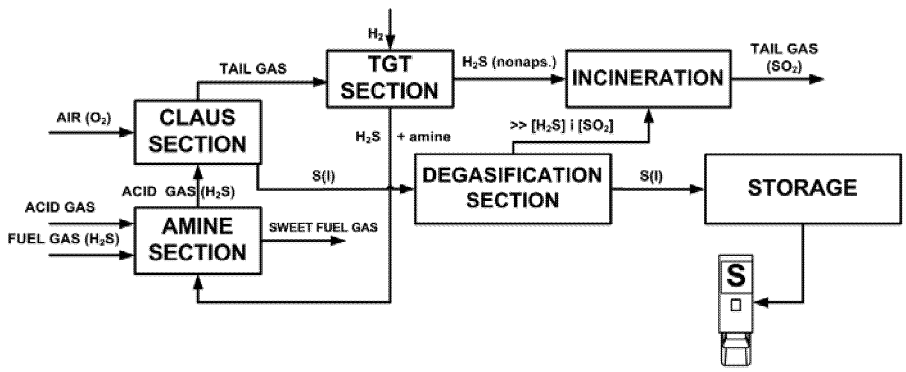

***Figure 1** Simplified process flow diagram of SRU in INA-Refinery Sisak*

Claus section consists of furnace and thermal reactor, two catalytic reactors, three condensers and basins for elementary liquid sulphur, Figure 2. The main air stream is kept in ration with acid gas stream, and a trim stream is adjusted by feedback control with on-line H_2S and SO_2 analyzer as controlled variable. Conversion of H_2S occurs in the reaction furnace according to:

$3H_2S + 3/2O_2 \rightarrow 2H_2S + SO_2 + H_2O$ oxidation (1)

Effluent from the reaction furnace is further converted in the downstream catalytic converters according to:

$2H_2S + SO_2 \leftrightarrow 3/2S_2 \text{ (or } 3S) + 2H_2O$ conversion (2)

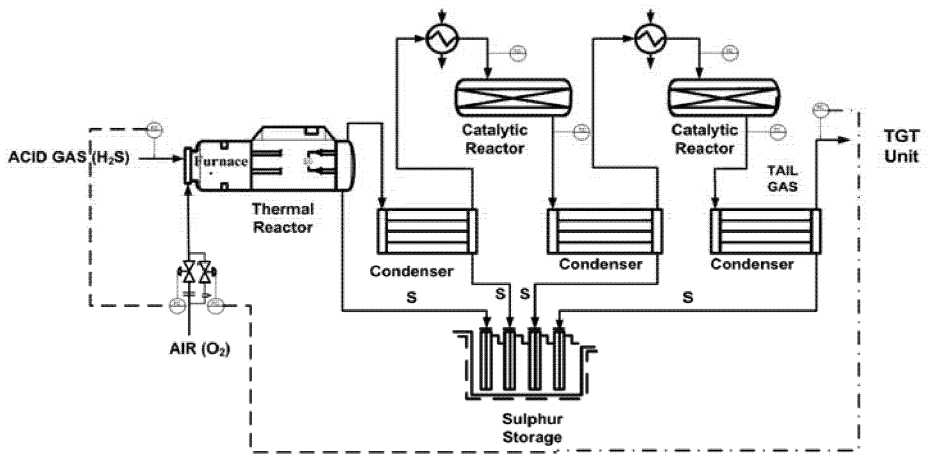

Figure 2 *Process flow diagram of Claus section*

3. Soft sensor model for SRU

Air, which supplies oxygen for the reaction, is an important parameter in the conversion of H_2S. In particular, an excessive air flow tends to increase the concentration of SO_2 with respect to H_2S, whereas a low air flow leads to the opposite situation. The analyzers are able to measure the quantity $[H_2S]–2[SO_2]$ in order to monitor the performance of the conversion process to optimal control the air-to-feed ration to the SRU. The desired value of the $[H_2S]–2[SO_2]$ difference is zero, which implies that these pollutants are either absent in the tail gas, or that the reactants in reaction are in stoichiometric proportion. Since traditional analyzers require frequent servicing and are not reliable, a viable option is installing a "soft-sensor", using readily available process variables to predict $[H_2S]$-$2[SO_2]$ concentration (Quek *et al.*, 2000).

The structure of proposed soft sensor model is shown on Figure 3. Four relevant process variables which influence the controlled variable are acid gas flow, air flow into the furnace, the temperature difference at the first and at the second catalytic reactors. Data on these variables during normal operating condition were collected from DCS historical database.

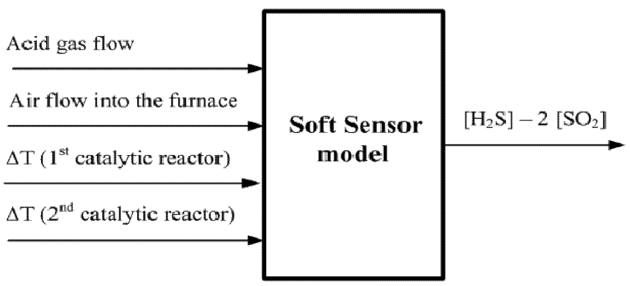

Figure 3 *Structure of proposed soft sensor*

4. Results and discussion

Linear and nonlinear models were identified using Matlab (System Identification, Neural Networks and Fuzzy Logic toolboxes). Sensitivity analysis was shown that model output, $[H_2S]$-$2[SO_2]$, is mainly influenced by acid gas flow and air flow into furnace. The temperature differences in catalytic reactors have relatively small influence on model output. For model development purpose 2500 historic data were taken from refinery database for estimating purpose, and 2500 data for additional validation with a sampling time of 1 min. The number of model structures were tried altering regression vectors, time delays and number of inputs. Model validation was performed based on the following criterion:

$$FIT = \left(1 - \frac{\left|y - \hat{y}\right|}{y - \bar{y}}\right) \times 100 \tag{3}$$

where y stand for measured output, $\hat{y}$ for output predicted by model, and $\bar{y}$ is mean value of measured output.

4.1 Linear models

The number of structures has been tested, and the best has achieved with the ARX model. The ARX model with the best validation performance has structure of 4 past outputs, 4 past inputs and the time delays of 2 min with FIT = 18.87.

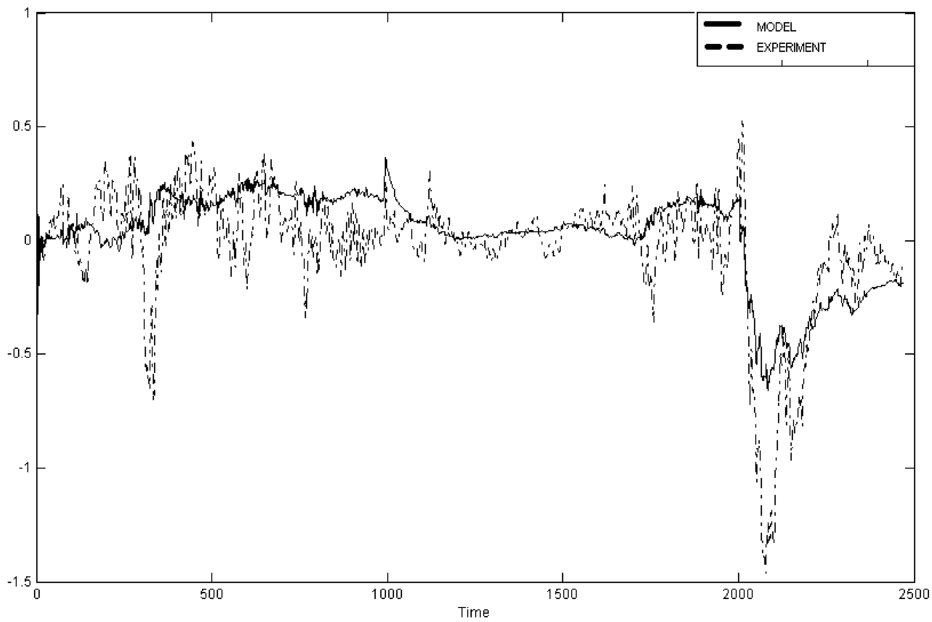

***Figure 4** Comparison between measured and estimated data for linear ARX model*

The mismatching between linear model and real-plant data for validation data on Figure 4 can be explained by process nonlinearities and complexity.

4.2 Nonlinear models

In the case of nonlinear modelling the best results have been achieved with the nonlinear ARX model (NARX) and FIT = 20.44. The estimated data follows real-plant trends, but deviations still persist especially with capturing of high-frequency variations, shown on Figure 5 also for validation data.

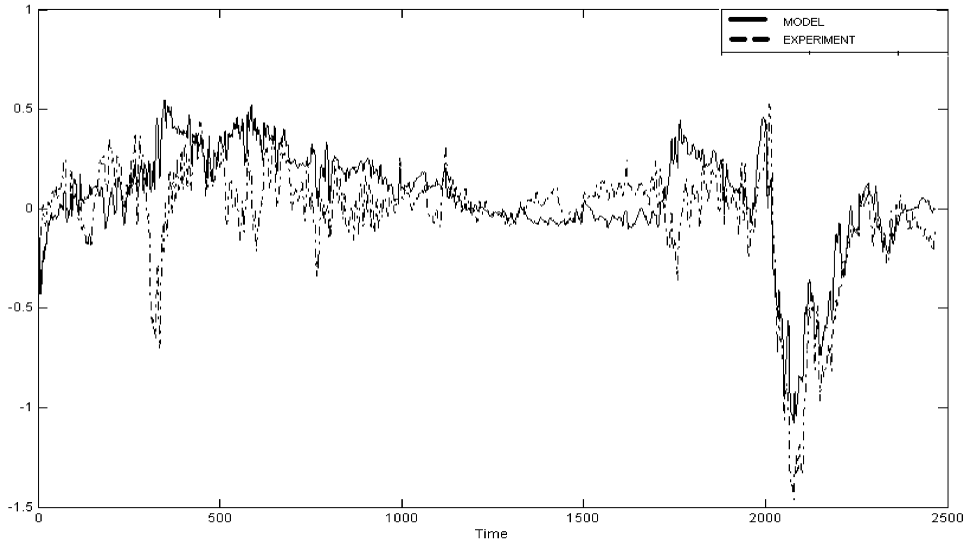

Figure 5 *Comparison between measured and estimated data for NARX model*

4.3 Neuro-fuzzy models

In order to design a neuro-fuzzy model the ANFIS (Adaptive Neuro Fuzzy Inference System) is used (Sugeno, 1985). In the first stage fuzzy inference system is generated using fuzzy subtractive clustering and accomplishes by extracting a set of rules that models the data behaviour. Second stage then uses linear least squares estimation to determine each rule's consequent equations. Tuning of parameters is performed using hybrid learning algorithm. For the consequent parameters training, the least squares method is used, because the output of the ANFIS is a linear combination of the consequent parameters.

The ANFIS structure has first order Sugeno model structure. Gaussian membership functions with product inference rule are use at the fuzzyfication level. Each of four network inputs is defined with seven membership functions. The results obtained by neuro-fuzzy network is shown on Figure 6 with FIT= 34.02 which is remarkably improvement.

5. Conclusion

The developed linear and nonlinear soft sensors are not suitable at the moment for real plant implementation. Neuro-fuzzy soft sensor is potentially applicable, especially when additional plant data will be available to refine the soft sensor models. Since this unit started one year ago there will be place for further improvements.

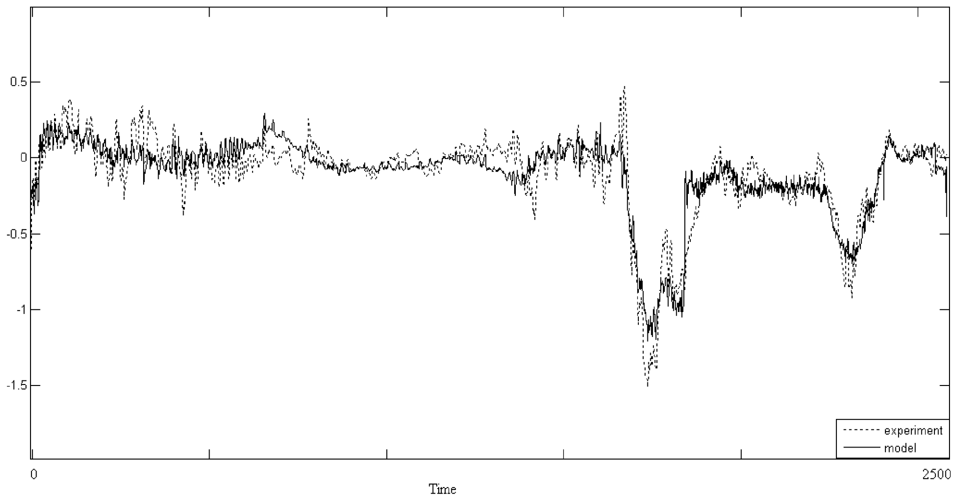

Figure 6 *Comparison between measured and estimated data for neuro-fuzzy model*

The developing process requires a careful attention during data selection, design phase to assure that relevant dynamics are not missed. The purpose of developed soft sensors are to warn about problems in operation and malfunctions of analyzer, to replace the analyzer during repair time and servicing, and, at the same time, allow for continuously monitoring of sulphur compound emissions.

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