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SOFT ANALYSERS FOR A SULFUR RECOVERY UNIT

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Abstract: In this paper soft sensors for a sulfur recovery unit in the ERG PETROLI petrochemical plant located in Priolo, Italy, are designed to parallel the online analyser which is often taken off for servicing. Three strategy have been compared, namely neural networks, neuro-fuzzy networks and nonlinear LSQ techniques. The best performance has been obtained with a neural NMA model and the soft sensor is now installed on the plant for online verification. *Copyright © 2002 IFAC*

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1. INTRODUCTION

Controlling sulphur emissions from the sulphur recovery unit (SRU) in a petroleum refinery has important environmental and economic perspectives. Online analysers are used to measure concentration of both hydrogen sulphide and sulphur dioxide. In particular, the measurement of the quantity $[H_2S] - 2[SO_2]$ is performed in order to control the air-to-feed ratio to the SRU.

Online analysers which are at present installed in the SRU suffer from reliability problems and have to be frequently taken off for servicing. In these occasions, the quantity $[H_2S] - 2[SO_2]$ is evaluated through statistical techniques carried out on past stored data. This estimate offers low performance because of the nonlinearity of the process. Moreover, the estimate is performed offline and is obviously useless for control purposes. The aim of this work is to design two soft sensors able to compute the SRU tail gas composition online by using a suitable set of measurements of the input variables of the process. These soft sensors should be able to replace the traditional analyser when it is affected by a fault or taken off for servicing.

In particular, the soft sensors consist of nonlinear dynamical models, capable of predicting $[H_2S]$ and $[SO_2]$ separately. *Non Linear MA* models are considered, implemented through three different strategies, namely Artificial Neural Networks, Neuro-Fuzzy Networks, and LSQ Nonlinear Fitting.

Models have been designed on the basis of experimental data collected at ERG PETROLI ISAB REFINERY located in Priolo, Italy, where the sensors designed are now installed online.

2. THE SRU PROCESS

The SRU is an important refinery processing unit. It removes the environmental pollutant H_2S from gas streams before they are released to atmosphere. Furthermore, elemental sulphur (S) is recovered as a valuable byproduct.

The final gas stream (tail gas) from the SRU contains residual H_2S and SO_2 formed by reactions.

An SRU is made up by four units. Each of them receives acid gas rich in H_2S from the MEA plant and acid gas rich in H_2S and NH_3 from the SWS plant. Each unit is made up by a reaction furnace (F101) where air reacts with MEA gas in the heater B106.

Total combustion of the ammoniac is obtained through the heater B103. In this part of the process the stoichiometric ratio is fixed. This ratio is maintained constant during the whole process by controlling the air flows in the furnace F101.

The combustion products are let into a water-condenser (E101) that furnishes elemental sulphur (70%) and a further fraction of gas, that is let into a catalytic reactor (R101) and then into a condenser (E102). It is not possible to recover sulphur only in one solution because of the large time of reaction. In order to obtain elemental sulphur at 90% the output of the condenser E102 is then let into the second catalytic reactor (R102) and then into the second condenser (E103)

The temperatures in the reactors R101 and R102 do not affect the stoichiometric ratio.

A simplified flow diagram of the process of one unit of SRU plant is shown in Fig.1.

The reactions that occur in this process are the following:

Some combustion of H_2S occurs in the reaction furnace (F101) , according to:

$$3\,H_2S + \tfrac{1}{2}\,O_2 \rightarrow SO_2 + 2\,H_2S + H_2O \qquad (1)$$

Effluent from the reaction furnace is further converted in the downstream catalytic converters (E101, E102, E103) according to:

$$SO_2 + 2\,H_2S \rightarrow S_x + 2\,H_2O \qquad (2)$$

In the furnace (F101) the total combustion of the NH_3 contained in SWS also occurs :

$$4\,NH_3 + 3\,O_2 \rightarrow 2\,N_2 + 6\,H_2\,O \qquad (3)$$

Air, which supplies oxygen for the reaction *(1)* is an important parameter in the conversion of H_2S.

Because of the reaction stoichiometry, if there is too much air in the reaction furnace, then the tail gas will contain too much of SO_2.

If there is too little air, then the tail gas will contain too much of H_2S.

The online analysers on the tail gas stream measure the concentrations of H_2S and SO_2. The desired value of the difference $[H_2S]\text{-}2[SO_2]$ is zero, which implies that these pollutants are either absent in the tail gas or that the reactants in the second reaction are in stoichiometric proportion: this is an optimal condition for the total removal of the sulphur compounds in the catalytic converters.

The value of the difference $[H_2S]\text{-}2[SO_2]$ is used as the process variable for the feedback control of air-to-feed ratio.

In order to predict the concentrations of the pollutants H_2S and SO_2 in the gas stream in the case of a fault occurring in the on line analyser, a soft sensor has been designed.

3. DATA ANALYSIS.

In order to predict the concentration of H_2S and SO_2 in the tail gas of an SRU, data were collected from the historical database of the plant.

Five relevant variables, have been selected, driven by the experts knowledge of the system:

- the gas flow in MEA zone (MEA GAS)
- the air flow in MEA zone 1(AIR MEA1)
- the air flow in MEA zone (AIR MEA 2)
- the air flow in SWS zone (AIR SWS)
- the gas flow in SWS zone (SWS GAS)

The temperatures in the furnaces have been neglected because of their slight variations during the process.

As a design guideline, only nonlinear MA models (which do not require to feed the model with delayed output samples) have been considered to satisfy the requirement made by the system operator to be able

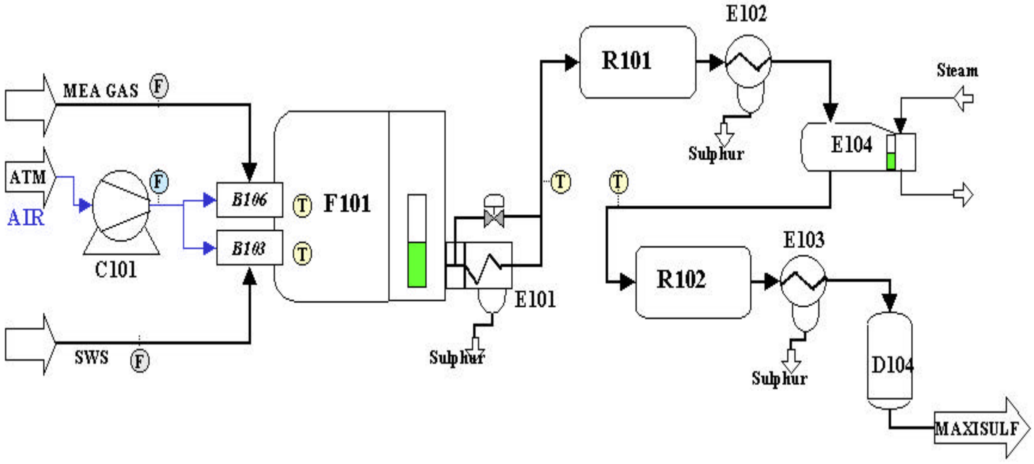

Fig. 1. Simplified scheme of a SRU.

to substitute a faulty analyser. Some experiment with NARX models have been carried out by feeding the network with delayed samples of the predicted output, achieving poor performance.
As stated in the introduction, models have been obtained through three strategies: Artificial Neural Networks, Neuro-Fuzzy Networks and LSQ Nonlinear Fitting. The learning set includes 500 samples, whereas the checking set includes 4000 samples, with a sampling time of 1min.
The whole set of variables is illustrated in Fig. 2.a-e.

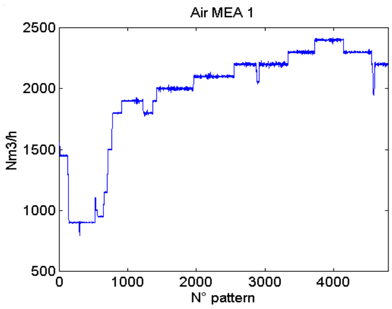

Fig. 2.a - AIR MEA 1

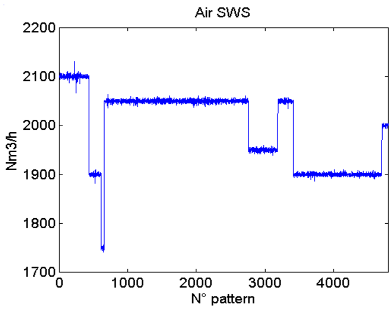

Fig. 2.b. AIR SWS

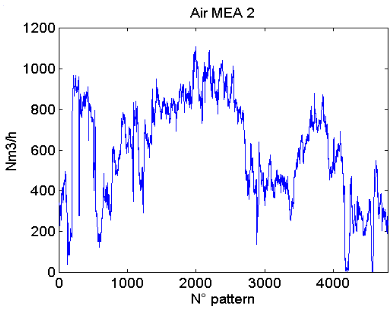

Fig. 2.c. AIR MEA 2

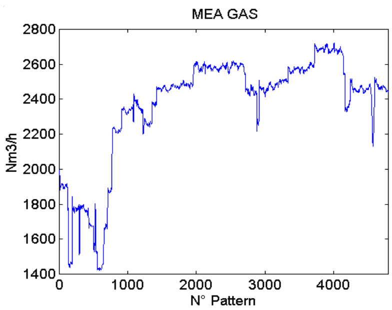

Fig. 2.d. MEA GAS

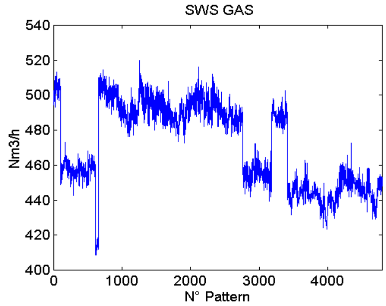

Fig. 2.e. SWS GAS

The step trend of the variables AIR MEA 1 and AIR SWS is justified by the fact that these two variables are set manually by the plant operators to guarantee the reaction *(2)* to occur in stoichiometric proportion. The variable AIR MEA 2 is controlled by an automatic feedback loop.
The output variables, which are illustrated in Fig. 3.a-b. present isolated peaks that are the critical data set that should be predicted.

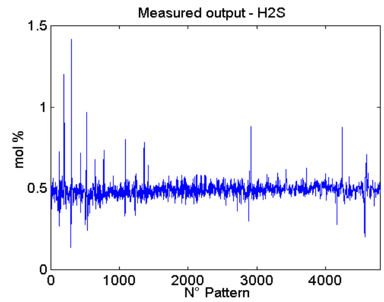

Fig. 3.a. Measured output H_2S

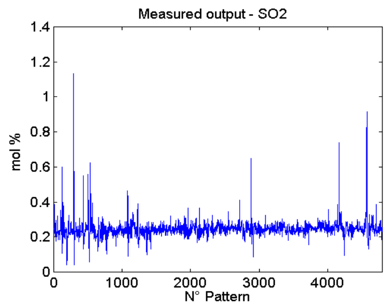

Fig. 3.b. Measured output SO_2

4. NEURAL MODELS.

Several neural models have been trained by using a MLP structure trained with the *Levenberg-Marquardt Back Propagation* algorithm (Hagan *et al.*, 1994) in order to find the correct number of both the delayed samples (Chen *et al.*, 1990) and the hidden neurons. All input variables have been normalised between the values 0 and 3, which correspond to the output range.
Best results have been obtained with the models:

$$[H_2S](k) = f_1\,(x_1(k), x_1(k\text{-}5), x_1(k\text{-}7), x_1(k\text{-}9),.., x_5(k), x_5(k\text{-}5), x_5(k\text{-}7), x_5(k\text{-}9))$$

$$[SO_2](k) = f_2\,(x_1(k), x_1(k\text{-}5), x_1(k\text{-}7), x_1(k\text{-}9),.., x_5(k), x_5(k\text{-}5), x_5(k\text{-}7), x_5(k\text{-}9))$$

each implemented by a 20-8-1 MLPs. The results obtained are illustrated in Figs.4-5 on a subset of the checking data set, in order to show more clearly the accuracy of the modelling in correspondence of the peak values.

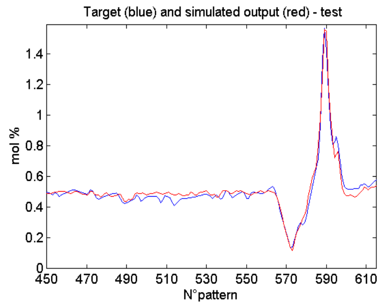

Fig. 4. Comparison between target and predicted output – test H_2S

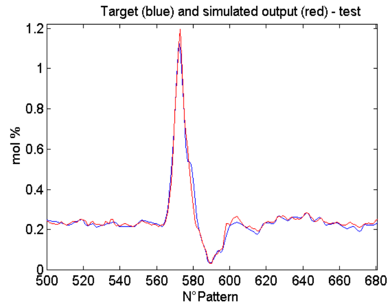

Fig. 5. Comparison between target and predicted output – test SO_2

Fig. 6 shows a comparison between the predicted and measured process variables *$[H_2S] - 2[SO_2]$* used for feedback control of the air-to-feed ratio to the SRU.

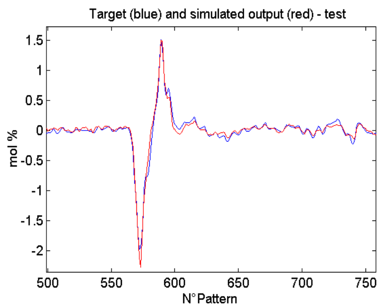

Fig. 6. Comparison between target and predicted output – test $[H_2S] - 2[SO_2]$

Although the results achieved are satisfactory, different modelling strategies have been implemented for comparison purposes.

5. NEURO-FUZZY MODELS

In order to design a Neuro-Fuzzy model the ANFIS (Adaptive Neuro Fuzzy Inference System) has been used by considering the same number of delayed input variables (L. Fortuna *et al.*, 2001).
The best configuration of the FIS model is composed by 6 rules and 6 membership functions per input both for the H_2S and the SO_2 models.
The results are illustrated in Figs. 7-9.

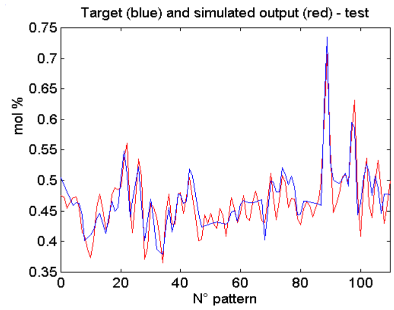

Fig. 7. Comparison between target and predicted output – test H_2S

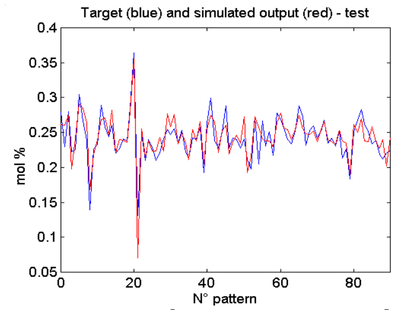

Fig. 8. Comparison between target and predicted output – test SO_2

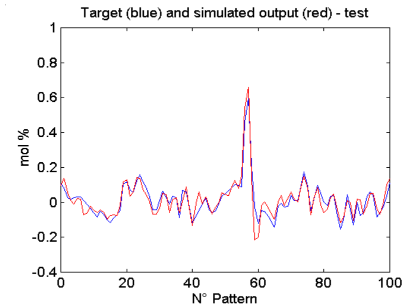

Fig. 9. Comparison between target and predicted output – test $[H_2S] - 2[SO_2]$

Comparing the results obtained with those obtained by neural models, no improvement is observed. Moreover, due to the computing power required by the fuzzy inference system when a dedicated fuzzy processor is not used, the fuzzy model has not been implemented online.

6. LSQ NONLINEAR FITTING .

A further comparison has been made by using a nonlinear multivariable rational function, like that used in (Quek *et al.*, 2001) on a similar plant. In this work, a second order function has been adopted, in the form:

$$y = \frac{a_0 + a_{11} x_1 + a_{12} x_1^2 + \dots\dots\dots\dots + a_{n1} x_n + a_{n2} x_n^2}{1 + b_0 + b_{11} x_1 + b_{12} x_1^2 + \dots\dots\dots\dots + b_{n1} x_n + b_{n2} x_n^2}$$

where n is the number of the inputs.
The coefficients have been computed by using a nonlinear least square data fitting algorithm (Ponton *et al.*, 1993). The results are illustrated in Fig. 10-12. The results are slightly worse than those obtained by neural modelling. However, due to their simplicity, both neural models and nonlinear LSQ models have been implemented online for a long on-field testing period. During this period, neural models showed best performance. In Fig. 13 the trend of a short portion of the online prediction performed during this period is illustrated, showing the successful performance of the soft sensor.

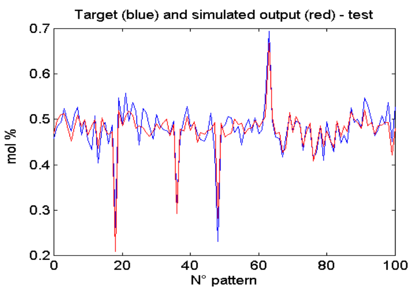

Fig. 10. Comparison between target and predicted output – test H_2S

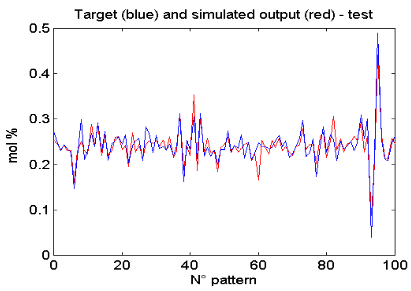

Fig. 11. Comparison between target and predicted output – test SO_2

Referring to Fig. 13, it can be noticed that performance remains comparable to that obtained off-line, considering also that the online results reported concern an operational period corresponding to six months later than the collection of training data. Moreover, the detriment of the performance occur only far from the relevant peaks, which are the significant data to be predicted. This online results are therefore considered by the plant operators as fully satisfactory

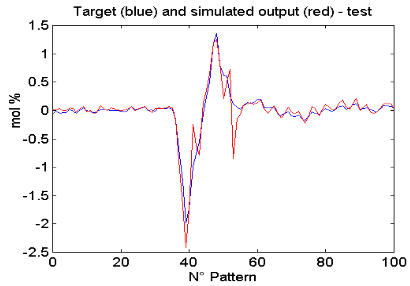

Fig. 12. Comparison between target and predicted output – test $[H_2S] – 2[SO_2]$

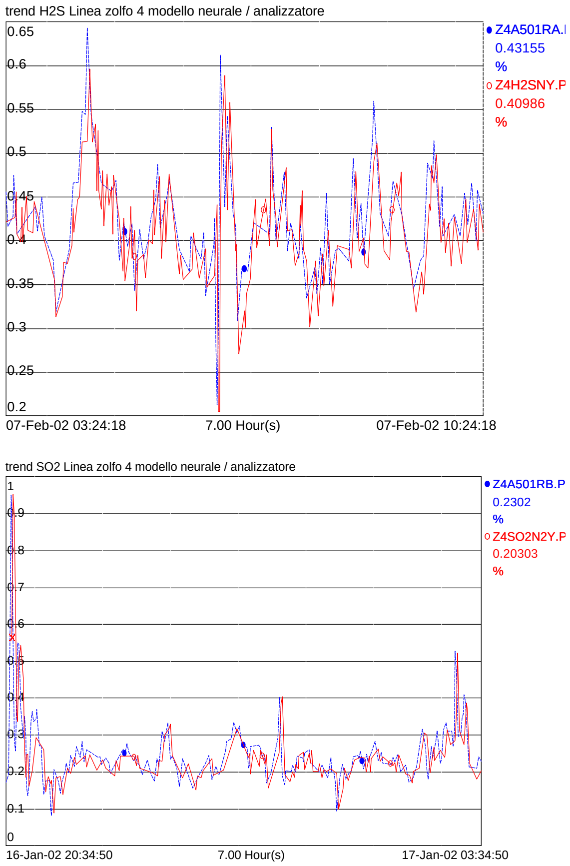

Fig. 13. Online prediction performance for H_2S and SO_2 respectively.

7. CONCLUSIONS.

In this work a *soft sensor* able either to parallel an analyser in an sulfur recovering unit or to replace it during its servicing periods has been designed and implemented through three different strategies: Artificial Neural Networks, Fuzzy Logic and LSQ Nonlinear Fitting.
The soft sensor has been designed and installed on a petrochemical plant located in Priolo (SR), Italy.
All the three techniques adopted lead to satisfactory offline results. Thanks to their computational

simplicity, only the neural and nonlinear LSQ models have been implemented on the plant to be tested online. During the online testing, the neural model has shown the best performance.
The satisfactory performance of the model allows us to maintain the control action on the SRU even when the analyser is taken off for servicing, thus improving the overall performance of the system.

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