FUZZY ACTIVATED NEURAL MODELS FOR PRODUCT QUALITY MONITORING IN REFINERIES

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Abstract**:** In the paper the problem of estimating the octane number of powerformed gasoline produced in a refinery is addressed. The model is designed in order to replace the existing measurement device during maintenance operation guaranteeing the continuity of product quality monitoring and control. Linear and nonlinear Moving Average models based on MLP neural networks have been designed to take into account the two different working points of the process and different strategies are compared. The models obtained are presently implemented on line in the refinery to be tested over a long period.

Keywords: Neural networks, products industry, quality control, nonlinear models, fuzzy models, identification algorithms

1. INTRODUCTION

In the last few decades ever-growing interest has been shown in production quality standards and pollution phenomena in industrial environments. Government laws enforce hard limits on pollutant and product specifications. Increasingly efficient monitoring and control policies are therefore required. The refinery community has recognised the importance of the optimisation of production process because of the benefits in terms of both profitability and tight control on product quality. To this aim a huge number of variables might be monitored by using adequate measuring devices. A possible alternative, which allows a remarkable reduction of monitoring and control costs, is to use 'soft sensor', i.e. mathematical models designed to estimate the desired variable on the basis of available measured variables.

Soft sensors for industrial plants are usually designed by using the ability of neural networks to extract a nonlinear model exploiting the information contained in the plant data base (Arena, *et al.,* 1995; Bozzanca *et al.,* 1999; Matsumura, *et al.,* 1998; Park and Han, 2000; Tham, *et al.,* 1991; Willings, *et al.,* 1992; Assis and Filho, 2000; James, *et al.,* 2002; Park and Han, 2000; Su, *et al.,* 1998). They allow also to easily implement fault detection strategies (Rizzo and Xibilia, 2002), (Buceti 2002) and to obtain real time estimation in those cases when the measuring devices, e.g. gas-chromatographs, introduce large-delay (Bozzanca *et al.,* 1999; Tham, *et al.,* 1989).

In this paper the possibility to monitor product quality in refinery by using soft sensor is

investigated, in particular the estimation of the research octane number (RON) in gasoline produced by a powerformer unit is considered.
The estimation is required from the plant technologists in order to replace on line measuring devices during planned maintenance actions.
The performance of different methodologies that represent the state of the art for soft sensing applications in industrial plants, i.e linear Moving Average Models, derived with a LMS approach, and nonlinear neural networks based models are compared with a novel hierarchical nonlinear structure.
In more details the hierarchical structure has been introduced in order to take into account two different working conditions of the powerformer plant. Both a neural network trained on the whole set of data and two different neural networks coupled with switching algorithms have been developed.
Data used to derive the models were collected by measuring devices installed in a large refinery settled in Priolo Gargallo, Syracuse, Italy, during a period lasting about 45 days with a sampling period of 3 min.
In Section two a brief description of the plant is reported. The performance of the different models are in deep described in Sections 3 and 4, by using the Experimental Data Analysis (NIST/SEMATHEC, 2002) approach. Also Subsection 4.3 is dedicated to the analytical comparison of the different models obtained.

2. THE POWERFORMER UNIT

The *Powerformer* U*nit,* represented in Fig. 1, receives as input the *Heavy Virgin Naphtha* (HVN) flow coming from the *Naphtha Splitter* bottom*.* Its output flow, that feeds the Deetanizer and Debutanizer distillation columns, is a liquid high in octane number (RON) which contains aromatic composites, hydrogen, oil gas, and liquefied petroleum gas (LPG).
The RON value of the powerformed gasoline is used to monitor the product quality and to control the powerforming process.
Based on process experts' knowledge the following variables that influence the RON value were selected:

- reactors temperature (u_1=t001, u_2=t002, u_3=t003, u_4=t004)
- input flow (u_5=f002)
- pressure value at the top of the Debutanizer (u_6=p023)

The powerformer output flow is required to satisfy two different targets for the RON value of the produced gasoline, depending on two different working conditions, given by the input flow (u_5) values. When the RON value is lower than the desired level adequate control actions on process temperature profile are taken.
In the next sections, linear and non linear strategy to predict the RON value of powerformed gasoline on the basis of the selected input variables are described and their performance are compared.

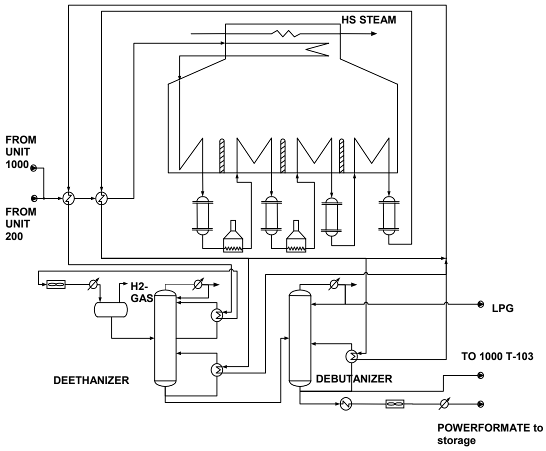

Fig. 1 The Powerformer Unit

3. THE LINEAR MODEL FOR RON ESTIMATION

As a first attempt, two separate linear models have been considered, each of them corresponding to a working condition. Taking into account the necessity to estimate the model output in (temporary) absence of any measuring device for the RON, MA models will be considered in the following. The structure of the models was chosen on the basis of both expert knowledge and input-output correlation analysis. Also, a trial and error approach was used to select the best model among possible candidates.
The following linear model gave the best results for both working conditions:

$$\begin{aligned} RON(k) = {} & a_1 u_1(k)+a_2 u_1(k-3)+a_3 u_1(k-5)+ b_1 u_2(k)+ \\ & +b_2 u_2(k-5)+ c_1 u_3(k)+c_2 u_3(k-4)+c_3 u_3(k-5) \\ & +d_1u_4(k)+d_2u_4(k-5)+ e_1u_5(k)+e_2u_5(k-1)+ \\ & +f_1u_6(k)+f_2u_6(k-1)+K \end{aligned} \tag{1}$$

the coefficients were obtained by using the LMS approach.
In Figs. 2 and 3 the performance of the linear model in processing data corresponding to one of the two working conditions is shown. Simulations are run on a data set different from that used to determine the model coefficients.

In particular in Fig. 2 the acquired RON values are compared with the linear model estimations. In Fig.3 the 4-plot analysis of the model residuals is reported (NIST/SEMATHEC, 2002).
Though the linear model follows the trend of measured data, the model accuracy was considered not satisfactory from the plant technologists.

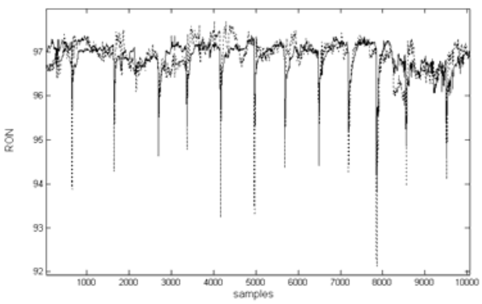

Fig. 2:Acquired RON values (dotted line) and their linear estimation (solid line) – scaled units

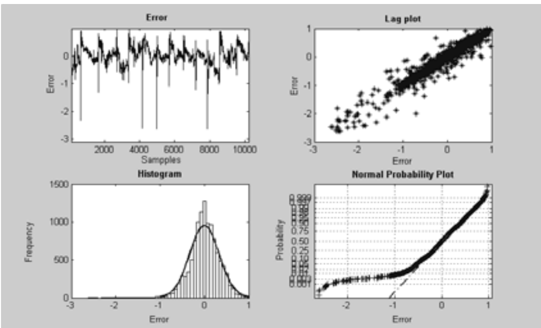

Fig. 3: 4- plot of the residual of the linear model (residual trend, histogram, normal probability plot and its dispersion).

Comparing performance were obtained in the processing of data referring to the second working point. In next sections nonlinear models developed to improve prediction capabilities are described.

4. NON LINEAR MODELS

In this section two different nonlinear modelling strategies are considered. They are designed in order to improve prediction accuracy and to cope with the two different working points with a single model. Both approaches are based on Nonlinear Moving Average structures, implemented by Multi-Layer Perceptron Neural Networks (MLPs).
The first approach, based on traditional solutions suggested in literature, consists in training a single MLP with data covering both working points.

In the second approach two different MLPs are trained to cope with each working point, they are then coupled with a fuzzy selection algorithm which allows a smooth transition between the different working conditions.
Nonlinear MA models considered in this section are based one hidden layer MLPs (Chen and Billings, 1989; Cybenko, 1989; Fortuna, *et al.,* 2001) trained by using the Levenberg-Marquardt algorithm with early stopping strategy to avoid overlearning. The lagged input structure reported in (1) was adopted also in this case, while the number of units in the hidden layer was determined by using a growing strategy.

4.1 The single nonlinear model

In the first case one MLP was trained merging data corresponding to the two working points. Performance obtained is reported in Figs. 4 and 5.
The results reported have been obtained with a network with 12 hidden neurons. As it can be observed, model performance is improved with respect to linear models, moreover a single model cover both working points overcoming the possible difficulty to select a crisp threshold to assign data to each working point.

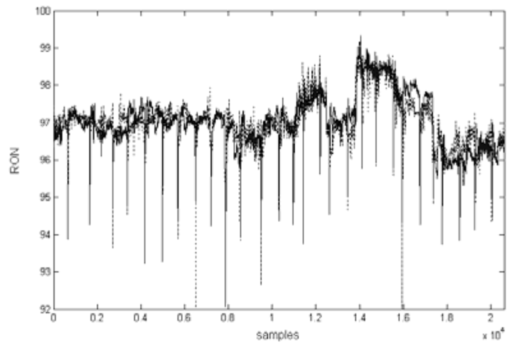

Fig. 4: Acquired RON values (dotted line) and their nonlinear estimation (solid line) – scaled units, two working points.

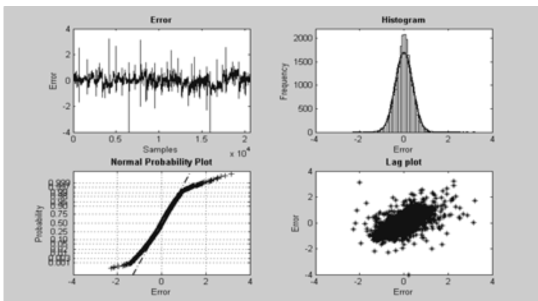

Fig.5: 4 - plot of the residual of the nonlinear model, two working points

4.2 The fuzzy switched nonlinear model

A different strategy was also used to obtain a model that can face separately the two different working conditions, taking into account that transitions between the working points occur frequently. A typical trend of the input flow rate values, ruling the transition between one working point and the other one, is reported in Fig. 6
The approach proposed requires as a first step to train two separate neural models to cope with the different working points. To this aim the same pattern used to obtain the linear models were considered.

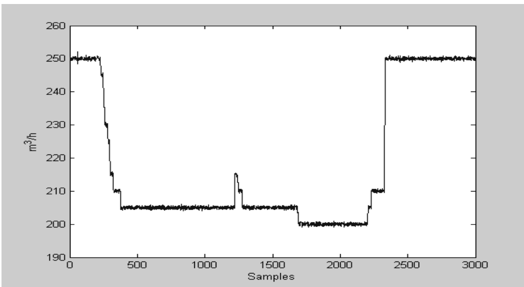

Fig. 6 Input flow rate, scaled units.

In Fig. 7 and 8 the performance of the obtained 14-11-1 MLP in processing a set of checking data of the first working point is shown.
In particular in Fig. 7 the acquired RON values are compared with the nonlinear model estimations. In Fig. 8 the 4-plot analysis of the model residuals is reported. It is possible to observe that this nonlinear model behaves much better than the linear one both as regards residual range and distribution.
Similar results were obtained for the second working point.
The two different neural models were then coupled by using a fuzzy algorithm composed of the following fuzzy rules:

- *if input_flow is input_flow_low then RON=y(model_1);*
- *if input_flow is input_flow_ high then RON=y(model_2);*

where the fuzzy set membership functions for the scaled input flow are reported in Fig. 9.
The defuzzyfied output is computed as:

$$RON = \frac{y(model\_1)*\mu 1 + y(model\_2)*\mu 2}{\mu 1 + \mu 2} \qquad (2)$$

where μ_1 and μ_2 are the activation levels of the two fuzzy sets.

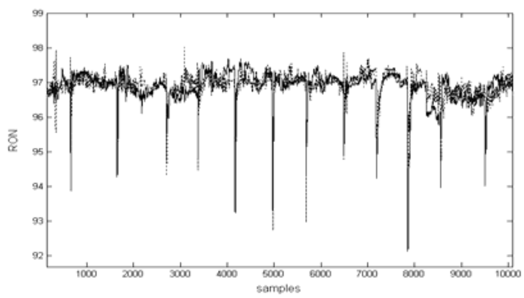

Fig. 7: Acquired RON values (dotted line) and their nonlinear estimation (solid line) – scaled units, one working point.

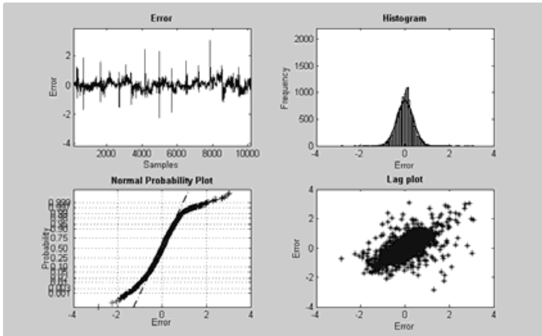

Fig. 8: 4 - plot of the residual of the nonlinear model, one working point.

Performance obtained in this case is reported in Fig. 10 and 11.

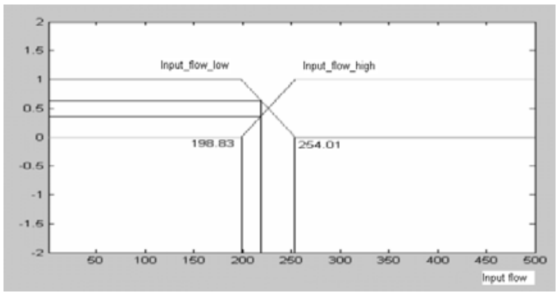

Fig. 9: membership functions for the variable *input_flow* - scaled values

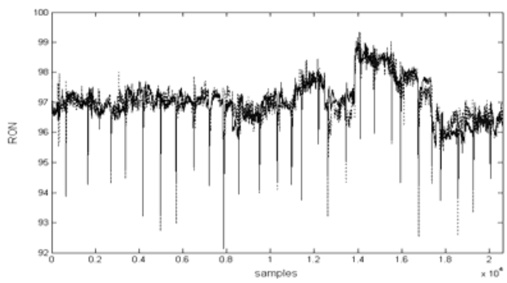

Fig. 10: Acquired RON values (dotted line) and their nonlinear estimation (solid line) – scaled units, two working points.

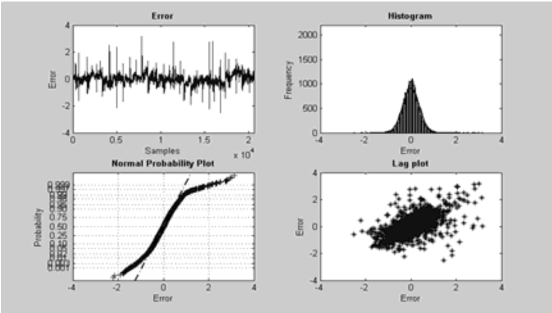

Fig. 11: 4 - plot of the residual of the nonlinear model, two working points.

The performance of all considered models will be reported in next sub-section.
Performance obtained with the non linear neural models seems comparable, these models have been therefore implemented in the refinery hardware for their on-line validation.

4.3 Analytical comparison of RON estimation models

In this sub-section the behaviour of the various models are evaluated by using some performance parameters.
In particular the following models have been considered:

a) one linear model working on the whole data set;
b) two linear models activated by using a fuzzy selection algorithm;
c) one neural model working on the whole data set;
d) two neural models activated by using a fuzzy selection algorithm;

In particular both experimental mean value and variance of model errors on the set of testing data are reported along with the correlation coefficient between actual data and their estimations.

Tab I: Analytical comparison of different models for the estimation of RON

Index / **Model**	**Residual mean value**	**Residual variance**	**Correlation coefficient**
a)	$3.38\ 10^{-4}$	0,2234	0,7742
b)	$-216\ 10^{-4}$	0,2041	0,7977
c)	$-8{,}87\ 10^{-4}$	0,1518	0,8541
d)	$6{,}2\ \ 10^{-4}$	0,1294	0,8772

The analysis of results reported in Tab. I confirms the superiority of nonlinear models with respect to linear LMS model. Also, among non linear models, the switched models behave better than the single NN based model.

Further comparison of nonlinear models has been based on their line performance. Taking into account a long period of on-line monitoring, it has been decided by plant technologist that the fuzzy approach gives better results.
As an example, in Fig. 12 a comparison between actual data, the prediction obtained with the single neural model and the prediction obtained with the fuzzy switched model on data collected 3 months after on-line implementation is reported (only a subset of data is shown in the figure to emphasize the different model behaviour). The corresponding residual trends and histograms are reported in Fig. 13.

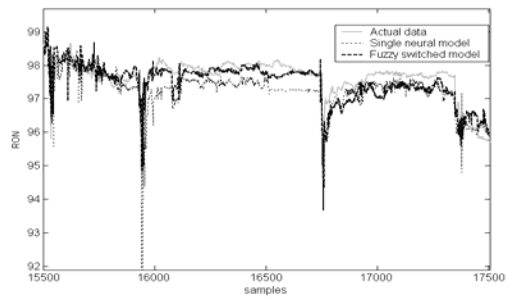

Fig. 12: On-line behaviour of the single neural model and the fuzzy switched model (on a subset of data).

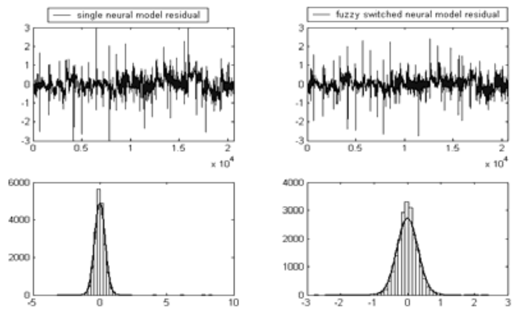

Fig. 13: On-line behaviour of the single neural model and the fuzzy switched model: residual trends and histograms.

5. CONCLUSION

In the paper the problem of designing a soft sensor to predict the RON of powerformed gasoline in a refinery is addressed. It is designed in order to guarantee the continuity of process monitoring and control during the periodical maintenance of the measuring devices. Data used to model the system were collected in a refinery located in Italy, where the designed soft sensor is currently implemented on line. In the paper different modelling strategies are compared, in particular linear and nonlinear

Moving Average models implemented by using Multi- Layer Perceptrons are considered.

In order to take into account that the process shows two different working conditions, depending on the level of one of the input variables, two linear models were designed. Their performance are however not satisfactory.

Two different non linear modelling strategies have been also implemented. The first approach simply consists in training a single MLP with data belonging to all the possible system working conditions. The second approach is based on a fuzzy switching algorithm that activates two different MLP-based models, each designed on a single working point. Form a first comparison made on a large set of checking data, both approaches give comparable results, they have been therefore both implemented on-line in the refinery. The comparison of on-line performance in a long period has shown that the fuzzy switched nonlinear model guarantees best performance.

Though the results are obtained by a structure that requires more computing resources than traditional algorithms, it should be taken into account that the proposed application is used for the monitoring of a large industrial plant. As a matter of fact computation resources in such a plant is largely available and the increase in the computation requirements is not to be considered a problem.

Also, the proposed hierarchical solution needs more computation time to estimate the system outputs. Anyway the system dynamic is slow enough with respect to the algorithm computation time that the time constraints are largely respected.

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