

Neural Modeling of Distillates Yield in Visbreaking process

Ombretta Foddi¹, Massimiliano Grosso¹, Stefania Tronci¹, Alessio Sesselego²,
Ulisse Spanu², Roberto Baratti¹

¹ Dipartimento di Ingegneria Chimica e Materiali
Piazza D'Armi, I-09123 Cagliari, Italy

² SARAS Raffinerie Sarde S.p.A.
SS Sulcitana 195, I-09018 Sarroch (Ca), Italy

An estimator which infers the distillate yields of the visbreaking plant operating at the SARAS refinery is here presented. The estimator is based on a feed forward neural network, which is trained, validated, and tested off-line by using plant data spanning an operating window of nine months. The preliminary results show a rather good agreement between the inferred yields and experimental measurements.

1. Introduction

Visbreaking is a mild liquid phase pyrolysis of atmospheric or vacuum distillation residues of crude oils. The aim of this process is to reduce the viscosity of the residues and to significantly increase the production of lighter distillates like gas, gasoline, kerosene.

First principle modelling of visbreaking processes is very complex, time consuming and difficult in view of the many operating variables affecting the product quality properties. First principle models are actually available in literature (Bozzano et al, 2005a, Bozzano et al, 2005b; Dente et al, 1995; Kataria et al., 2004), but they could not be always adequate to use for on-line applications, where simple and compact models are preferred because, generally, they have to be implemented on DCS. Within this regard, Artificial Neural Networks (ANNs) may constitute a powerful approach to develop estimators that could be used for on-line applications. ANNs are data based models, widely applied in process modelling and control (Hernandez and Arkun, 1992; Hussain, 1999; Tsen et al, 1996; Padmavathi et al., 2005), and they have demonstrated to be capable of successfully modelling non linear processes.

In this contribution, we describe the development of an ANN estimator to infer the conversion of the visbreaking unit operating at SARAS refinery located in Sarroch (Cagliari, Italy). The goal is to estimate the distillate yields as a function of operating conditions and feed characteristics. This task is not trivial, because the considered plant is characterised by frequent changes in the feedstock quality, which is formed by a mixture of heavy vacuum residues containing high concentration of sulphur compounds. Within this scenario, a strict control on the severity of the process is necessary in order to continuously obtain the maximum conversion as the feedstock quality varies and, at the same time, the stability of the visbroken residues (TAR) must be always guaranteed. In fact, the latter aspect is typically a constraint for the severity of the visbreaker being the feedstock conversion limited by the requirement to produce a stable residue. As the

feedstock is thermally cracked, the asphaltene content increases, the resin content decreases and it is possible that asphaltenes flocculate giving place to undesired mud. Furthermore, the correct management of the process should assure the optimal plant maintenance for the whole operating cycle, since it is defined as a function of the production policy and of the scheduled stops of the other plants of the refinery.

2. The industrial process and the experimental data

A schematic representation of the visbreaking plant operating at SARAS Refinery is schematically showed in Figure 1.

In this scheme, the visbreaking process takes place in two different furnaces, in parallel, which are followed by an adiabatic reactor (soaker). Each furnace is crossed by two coils that go through a radiant and a convective section. The soaker is equipped with perforated plates in order to reduce backflow and backmixing phenomena. The main purposes of the configuration “furnaces and soaker” are to increase the residence time and to reduce the average temperature of the process. In this way it is possible to decrease the fouling inside the coils and to increase the run time of the plant. The soaker is followed by a fractionating tower where the lighter fractions are separated from the residue.

Two different streams constitute the feed to the plant: the principal one directly comes at high temperature from a vacuum unit (not reported in the figure and located prior to the furnaces); the second is a cold stream, which comes from stocking vessels. Finally, the hot visbroken residue leaving the plant is usually fed to a power plant.

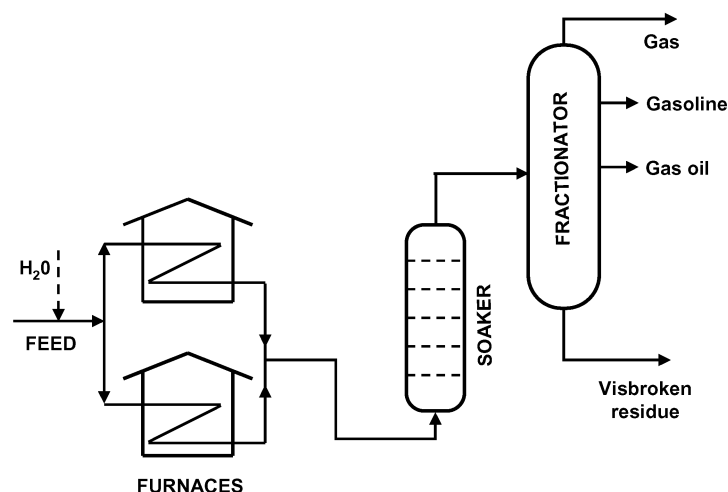


Figure 1: Scheme of the visbreaking plant

The analysis of the process was started with a thorough study of the P&ID of the visbreaking plant to get acquainted with the process. Finally, fifteen potential process variables were identified as possible inputs to the soft sensor, and they are essentially of two types: a set of variables is related to the process operating conditions (temperatures,

flowrates, etc.), while the other set concerns the feed characteristics (e.g. carbon content). These selected variables were then collected with daily frequency in about nine months of operation. Because of a confidential agreement, no detailed indications on the variables made available for the current analysis can be reported in the present paper.

It should be noted that a reliable feedstock characterization is not available and this fact is one of the main difficulties when modeling the actual process. Within this regard, these variables were derived by daily global mass balances combined with analysis (TBP curves) of the crude oils processed in the refinery.

The selected inputs were used to infer one important index of the plant performance, which is the distillate yield Y . This variable is not directly measured in the plant, but it is attained through the measurements of the mass flowrate of the products (gas, Q_g ; gasoline, Q_{BZ} ; and gasoil, Q_{GO}) and the feedstock flowrate, Q_F , according to the following relation:

$$Y = \frac{(Q_g + Q_{BZ} + Q_{GO})}{Q_F} \quad (1)$$

Incidentally, it is worth noting that flowrate measurements are affected by an error which depends on the instrument precision. At the Saras visbreaking plant, flowrates are measured by obstruction flow-meters. Generally this kind of sensors is characterized by small rangeability (3:1) and limited accuracy (3-5 %). The measurement error was thus calculated by considering that each flow rate is affected by an error $\delta Q/Q$ estimated equal to 4% circa. Resorting to consolidate formulas for the error propagation, one ends up with an error estimation on the experimental measure for the distillate yield equal to $\delta Y/Y=8\%$.

3. Software sensor

In order to continuously monitor the distillate yield obtained in the visbreaking plant, a soft sensor based on neural models was developed. The aim is to estimate the product yields through indirect measurements easily accessible. The estimated yields may be used either to obtain the unit performances for a feedstock change, or support the operator to take a proper and prompt action when the yield quality is not at the desired value. Soft sensors are required to be as simple and compact as possible, since they are devoted to on-line applications, and they usually have to be implemented on DCS.

The selection of the inputs for the neural soft sensor is not a trivial task. In fact, measurements with high level of noise or with significant time delays should be not considered. Moreover, a proper selection of the inputs variables will allow reducing the number of inputs and will help the soft sensor design. The input selection was accomplished by means of a knowledge-based approach exploiting the knowledge of the physical and chemical steps governing the process. Incidentally, it is mandatory to select out, among all the potential variables, the actual variables carrying out enough information to detect variations of the process status. Redundancy should be avoided and, quite often, lumping (grouping) more variables may improve the neural model performance.

Another important issue, when developing neural models, is the selection of the number of hidden layers and neurons in each hidden layer. This problem was here approached by a trial and error procedure, with the final goal to obtain the simplest structure as possible. The subsequent calibration of the ANN model was accomplished in two different steps: model training and off-line validation.

The model calibration was accomplished by searching the minimum of the cost function mean square error giving the distance among the experimental values y_i and the ones predicted by the model, y_{pi} . The minimization of the cost function is always performed by means of the Levenberg-Marquardt algorithm.

The capability of the neural model to reconstruct the distillate yields is evaluated by considering the Pearson correlation coefficient and the determination coefficient R^2 as performance indexes. The determination coefficient is given by eq. (2)

$$R^2 = 1 - \frac{\sum (y_i - y_{pi})^2}{\sum (y_i - \bar{y})^2} \quad (2)$$

where \bar{y} is the average value of the data. The determination coefficient R^2 represents the percentage of the data fluctuations explained by the model.

The Pearson correlation coefficient is given by eq. 3

$$\sigma = \frac{\sum (y_{pi} - \bar{y})(y_i - \bar{y})}{\sqrt{\sum (y_{pi} - \bar{y})^2} \sqrt{\sum (y_i - \bar{y})^2}} \quad (3)$$

Values of σ close to one mean a good agreement between prediction and observation.

4. Results and discussion

The total available data (233 daily averaged values) were split into a training data set (200 points) and a test data set (the remaining 33 points). Potential outliers had been removed from the data.

The neural model was based on a feed-forward neural network with one hidden layer and one output neuron. The neurons for each layer were activated by means of a sigmoidal function.

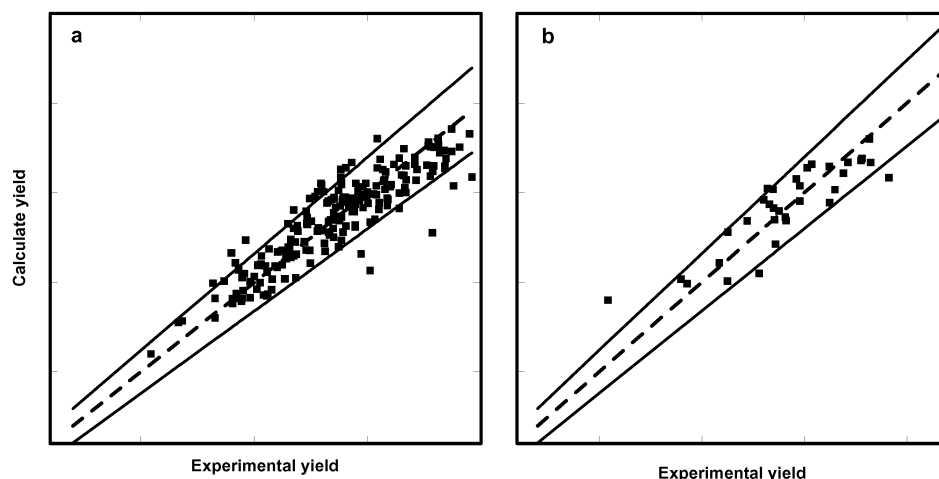


Figure 2: Comparison of the predicted distillate yields with measured ones for the training set (Figure a) and for the test set (Figure b).

The selection of the model inputs was first carried out by using a knowledge based approach, aimed to find out the set of process variables leading to the best description of the process. Starting from the fifteen candidate inputs obtained by the preliminary study of the P&ID of the plant, a thorough analysis led to the selection of eight inputs. Because of the confidential agreement, no detailed indications on the selected variables can be reported in the present paper. The selected inputs variables collect information both on the operating conditions and on the feed characteristics. With the aim of obtaining a parsimonious model, the number of hidden neurons leading to a good compromise between complexity and performance of the model was found to be two.

Figure 2a shows the comparison of the ANN predicted distillate yields with the measured yields for training data set. The determination coefficient R^2 is 0.80 and the Pearson correlation coefficient is 0.81. Figure 2b shows the comparison of the predicted yields with the measured experimental ones for test data set. In this case, the Pearson correlation coefficient is 0.78 and $R^2=0.64$. For confidential reasons all the figures do not report the values of the distillate yield. The figures show good agreement with an average error comparable to that of the measured yields. The two solid lines in the figures indicate the error of $\pm 8\%$ (estimated experimental error) on the measured values. It is evident that the prediction error is under the experimental one for the most of situations, hence the results are surely satisfactory.

Although not reported, data redundancy was also compressed by resorting to multivariate statistical analysis. In more detail the Principal Component Analysis was carried out and it was found that the total available data can be described in terms of only seven latent variables (that are the projections of the input data on the selected principal components). On the other hand, ANN models trained with data preprocessed with PCA do not demonstrate a better performance with respect to the knowledge-based approach.

5. Conclusions and future work

A neural-based sensor software has been developed to allow a preliminary characterization of the measured distillate yield with respect to the main operating conditions and feed characteristics collected in a visbreaking plant. Two different approaches were used to find the proper neural network inputs: a knowledge-based approach and an input selection based on a multivariate statistical analysis (PCA). The results show that the first method seems to be preferable.

The current analysis provided useful insights to evaluate the better approach for the development of a neural model to infer the product quality of the SARAS visbreaking plant. The promising results suggest the possibility to use this methodology to obtain an on-line monitoring of the distillate yield, by means of real time data. Furthermore, the prediction of another important index of the process performance, that is the stability of TAR, will be tackled in the future. The prediction of the visbroken residue stability can be extremely useful in determining the proper operating conditions in order to prevent the occurrence of precipitation phenomena and to assure the maximum conversion.

6. References

- Bozzano G., Dente M., Sinatra M., Conti G.. 2005a, Chem. Eng. Trans. 7, 255
 Bozzano, G., Dente, M., Carlucci, F. Comp. and Chem. Eng. 2005b. 29 (6 SPEC. ISS.), 1439-1446.
 Dente M., Bozzano G., Bussani G., Comp. and Chem. Eng., 1995, 19, Suppl. S205-S210.
 Hernandez, E. and Arkun Y., Comp. and Chem. Eng., 1992, 16, 227-240
 Hussain M.A., Artificial Intelligence in Engineering, 1999, 13, 55-68
 Kataria K.L., Kulkarni R.P., Pandit A.B., Joshi J.B. and Kumar M., Ind. and Eng. Chem. Res. 2004, 43, 1373-1387.
 Padmavathi G., Mandan M.G., Mitra S.P. and Chaudhuri K.K., Comp. and Chem. Eng., 2005, 29, 1677-1685
 Tsen A.Y.D., Jang S.S., Wong D.S.H., Joseph B., AIChE J. 1996, 42(2), 455-465