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Neuro-Fuzzy Modelling in Petrochemical Industry

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Abstract

In the last few years, problems concerning with both air pollution and quality of products have gained a particular attention in industrial companies. A great interest in new technologies for the process of manufacturing optimisation and quality control has raised.
Mathematical models for quality control are highly nonlinear and need very expensive and sophisticated instruments. Soft-Computing, an innovative approach for constructing computationally intelligent systems, has just come into the limelight. The quintessence of designing intelligent systems of this kind is Neuro-Fuzzy computing. In this paper a Neuro-Fuzzy prediction model for the quality control of benzene is proposed.

1 Introduction

A number of new laws have imposed strict quality parameters for refined oil of the petrochemical industry. The development of a non-traditional technique in the petrochemical industry for the automatic quality control allows the realisation of reliable and cheap software clever monitoring devices.
The main target of this paper is to determine a Neuro-Fuzzy model for the prediction of the concentration of benzene in a fractionating column of a petrochemical plant.
The plant processes crude naphtha to obtain high-octane products [1]; during the last working schedule, the gained oil stokes the Splitter Benzene column (described in Section II) for the final refining and quality control.
A set of input-output data (Section III), acquired by the observation of the column in different intervals of time, have been used to create a Neuro-Fuzzy model that replaces classical on-line analyzers (chromatograph).
This intelligent system (Section IV) which is supposed to possess humanlike expertise within a specific domain, adapts itself and learns to do better in changing environment.
The results show a good agreement between the prediction of the concentration of benzene of the proposed model and the real output of the system.

2 Distillation column

2.1 The Splitter Benzene column

Data considered in this paper have been collected in a chemical plant, named ERG PETROLS set in Priolo (Sicily). After a pre-processing step the obtained oil stokes the Splitter Benzene column (see Fig.1).
The overall distillation system includes a fractionating column, a boiler in the end, and an air cooler in the head [2].

This vertical cylindrical column is physically segmented by barriers or trays holding constant volumes of liquid which falls down the column from tray to tray. The vapour forces its way up through the trays by lifting the so called 'bubble-caps' which act as non-return valves. Each tray looks like a plate that holds boiling fluid and operates like a distiller.
Vapour and liquid streams flow past one another, the streams being composed of a mixture of two components to be separated by the column.

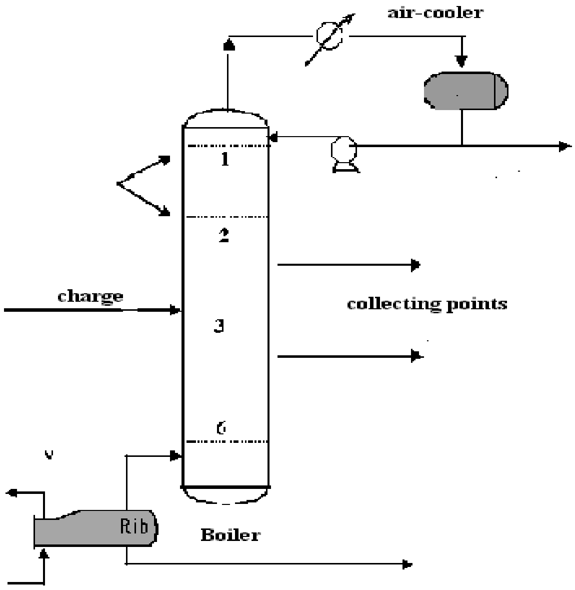


Fig.1:Distillation column

The boiling mixture is fed into the column in the bottom section, and in the mixture there is a mole fraction that is lighter than the other. Within each cell evaporation and condensation occur under adiabatic condition.
The flow that crosses from the liquid to the vapour phase ceases in situations where the neighbouring liquid and the vapour liquid and vapour mixtures are in a so-called 'thermodynamic equilibrium' with one another.

2.2 Control system

The column has three collecting points, placed at the head, the end, and the side of the plant respectively.
The quality specifications impose that the lateral collecting point is better than the others: here, the product has a concentration of benzene more than 25%; instead the others have a concentration less than 1%.
The control design aims to maximise the benzene concentration in the lateral withdrawal. The control system includes a number of PID controllers with various functions in different locations.
At the head of the column there is a temperature check, a pressure check and a capacity check; at the end, there is a temperature test and a pressure one; and at the lateral collecting point there is a capacity sensing device.
The concentration of benzene of charging column oil and of the product of the bottom collecting point is evaluated by using a reliable line analyser (NIR); instead, the side collecting point is tested every 15 minutes by using a chromatograph, which is sometimes out of order.
The changes in the concentration of benzene in the charge product cause significant variation of the product at the bottom and the lateral collecting points.

A side collection concentration model can be useful for different reasons:

1) the benzene rate could be evaluated in real time,
2) the benzene rate could be estimated when the chromatograph is out of order,
3) in future this model could be used to realise an overall intelligent control of the column.

3 The data set

The considered system is a very complex one and a huge set of parameters should be taken into account when trying to estimate the concentration of benzene in the side collecting point. Moreover the plant is a dynamic system, therefore, its output (y), i.e. the benzene concentration at the side collecting point depends on values, at a suitable number of previous sampling times, both of the same parameter and of the input quantities. A NARMAX model of the system has been, therefore, searched for :

$$y(t) = f(\underline{U}(t), \underline{U}(t-1), \ldots \underline{U}(t-n), , y(t-1), y(t-2), \ldots, y(t-n)) \qquad (1)$$

Being:

- $f(\bullet)$ a suitable function to be determined, based on experimentally acquired data.
- $\underline{U}(i)$ a vector collecting the considered input quantities.
- n is the model order, to be found by using a trial and error approach.

From the knowledge of the system experts it is apparent that the significant parameters for the process description are:

1) the charge capacity (u_1)
2) the benzene concentration in the charge product (u_2)
3) the temperature value in the bottom of the column (u_3)
4) the temperature value in the lateral collecting point (u_4)
5) the capacity value in the lateral collecting point (u_5).

After a careful observation of the system, the charge capacity has been neglected while, on the contrary, the value of the concentration of benzene in the charging product has been considered an important parameter and two different samples of its value have been considered. For each of the remaining parameters in the previous list, one sample has been taken into account.
As regards the samples of the output quantity to be taken into account, i.e. the system order, it has been found that 3 previous samples of the benzene concentration are necessary to obtain suitable performance of the model. The final model assumes therefore the following structure:

$$y(t) = f(u_2(t-2), u_2(t-1), u_3(t-1), u_4(t-1), u_5(t-1), y(t-3), y(t-2), y(t-1)) \qquad (2)$$

Based on the previous consideration, data to be used to experimentally identify the system model have been arranged in vectors, composed of eight input variables and one output quantity, as follows:

$$[\underbrace{u_2(t-2), u_2(t-1), u_3(t-1), u_4(t-1), u_5(t-1), y(t-3), y(t-2), y(t-1)}_{\text{input vector}} \;|\; \underbrace{y(t)}_{\text{target}}]$$

Data have been collected during two different periods spanning from March to April 1998 and from August to September 1998.

4 Soft-Computing for quality control

Soft-Computing consists of several computing paradigms, including neural-networks, fuzzy set theory, and derivate-free optimisation methods such as genetic algorithms and simulated annealing [3]. The synergism of all these paradigms allows Soft-Computing to incorporate human knowledge effectively, to deal with imprecision and uncertainty, and to learn to adapt itself to unknown or changing environment for a better performance. The realised Neuro–Fuzzy system is an adaptive network, functionally equivalent to a fuzzy model [4].

4.1 The Neuro-Fuzzy system

The identification target is to predict the output value $y(t)$ (see. Eqn. 2, reported above) by using a suitable 3*rd* order model by a Sugeno fuzzy algorithm [5].
The fuzzy algorithm is based on a number of fuzzy rules whose structure is as follows:

Rule i:

If $u_2(t-2)$ is A_i and $u_2(t-1)$ is B_i and $u_3(t-1)$ is C_i and $u_4(t-1)$ is D_i and $u_5(t-1)$ is E_i and $y(t-3)$ is F_i and $y(t-2)$ is G_i and $y(t-1)$ is H_i then

$$f_i=p_i\, u_2(t-2)+ q_i\, u_2(t-1)+ r_i\, u_3(t-1)+ t_i\, u_4(t-1)+ v_i\, u_5(t-1)+ x_i\, y(t-3)+ k_i\, y(t-2)+ z_i\, y(t-1)$$

A_i, B_i, C_i, D_i, E_i, F_i, G_i, H_i: are the membership functions of the fuzzy sets for the input variables used in the *ith*-rule.
$p_i, q_i, r_i, t_i, v_i, x_i, k_i, z_{i:}$: are the linear parameters of the output function in the *ith*-rule.

In order to characterise each fuzzy set it is important to choose the kind of membership functions (MFs). Gaussian MFs have been used; a Gaussian MF is characterised by two parameters: c (centre) and σ (width).
In a second step, it is required to choose the number of rules and to evaluate the suitable values for both the parameters in the output linear relation and in Gaussian functions for every fuzzy set. The suitable number of rules has been determined by using a subtractive clustering.
Given a set of input and output data, this technique extracts a set of rules that models the data behaviour. The rule extraction method estimates the cluster centres in a set of data by using subtractive clustering method. This method assumes that each data point is a potential cluster centre and calculates a measure of the potential of each data point, based on the density of surrounding data points. An important parameter is the cluster radius for each input variable. It specifies a cluster range of influence in each of the data dimensions, assuming that the data fall within a unit hyperbox.
Both the number of rules and the antecedent membership functions have been determined by clustering technique; instead the architecture and learning rules of adaptive networks have been used to estimate the linear parameters in the consequent equations of each rule.
In the network architecture the nodes of the same layer have similar functions and the different layers have different functions. The network has five layers; the number of nodes in each hidden layer is the same of the fuzzy rules; the nodes in the first layer are as many as the total number of MFs.

4.2 Numerical Results

Many simulations have been executed by setting different radii clustering values; the best result has been obtained with *radium*=0.23. The obtained Neuro-Fuzzy model is composed of 12 MFs for each variable and 12 rules. The total number of fitting parameters is 300, including 192 premise(nonlinear)parameters and 108 consequent (linear) parameters.

The value of the root mean square error between the real set of training data and the predicted one has been estimated to be about $err = 6{,}5\cdot 10^{-4}$, instead the error between a set of checking data and the predicted values has been valued about $err = 4{,}4\cdot 10^{-4}$.
The comparison between the real set of training values of the concentration of benzene in lateral collecting point and the predicted values in one step and five steps has been displayed in Figs.2-4. In Figs.5-7 another comparison between a real set of checking data and the predicted values, in one step and five step has been shown. The error between the real sets of training and checking data and the predicted values has displayed in Figs.3-6. In both the comparison a good agreement between the real dynamics, determined by the set training data and the checking one, and the predict values has been obtained.

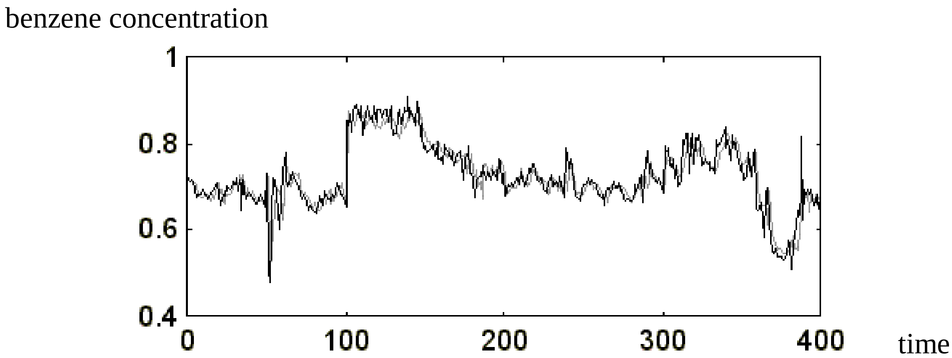


Fig.2: Comparison between the real training values of the concentration of benzene in lateral collecting point (black line) and the predict values in one step (grey line)

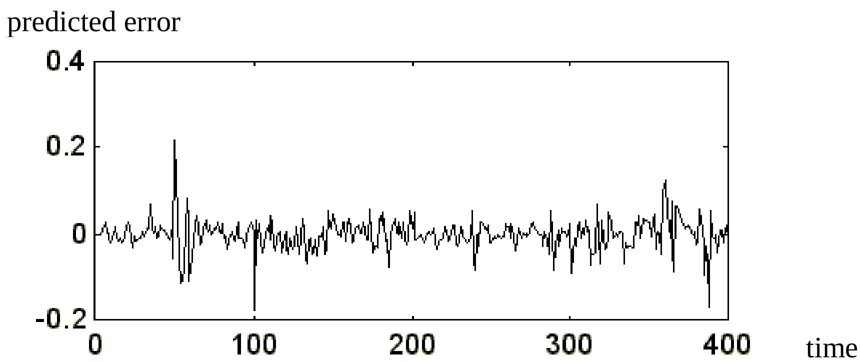


Fig.3: The error between the real training values of the concentration of benzene in lateral collecting point and the predict values

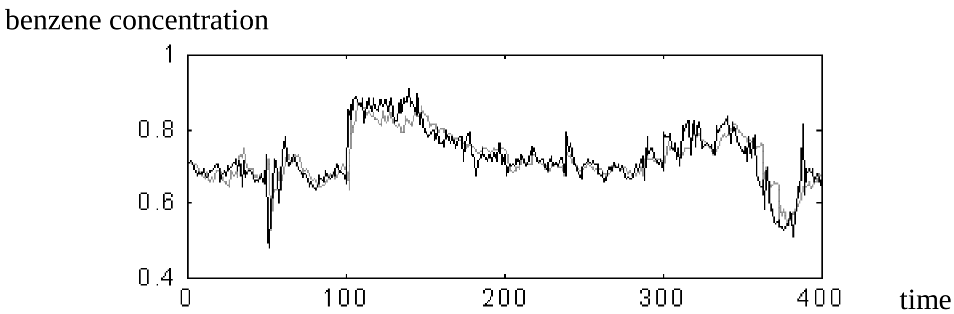
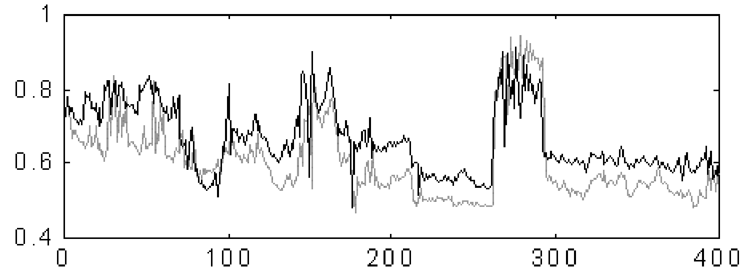


Fig.4: Comparison between the real training set of values of the concentration of benzene in lateral collecting point (black line) and the predict values in five steps (grey line)

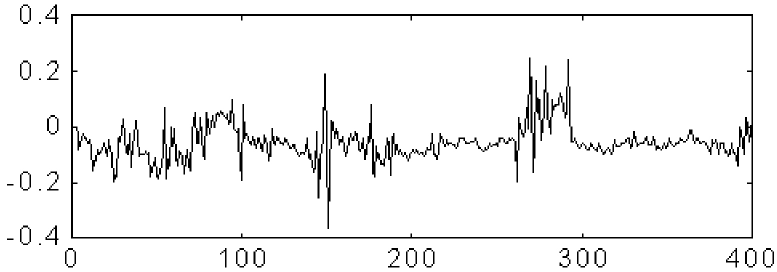
benzene concentration



time

Fig.5: Comparison between the real checking set of values of the concentration of benzene in lateral collecting point (black line) and the predict values in one step (grey line)

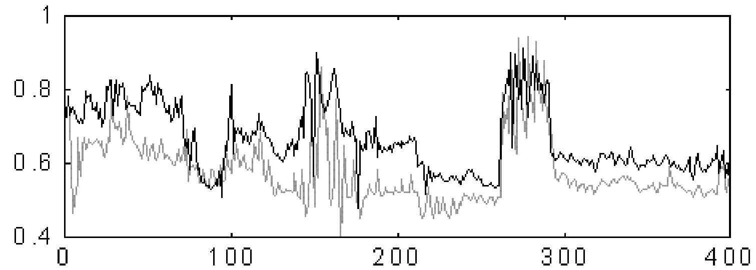
predicted error



time

Fig.6: The error between the real checking set of values of the concentration of benzene in lateral collecting point and the predict values

benzene concentration



time

Fig.7: Comparison between the real checking set of values of the concentration of benzene in lateral collecting point (black line) and the predict values in five steps (grey line)

5 Conclusion

In this paper Neuro-Fuzzy modelling is used for the quality control of a Splitter Benzene column in petrochemical plant. In particular, a model to predict the concentration of the benzene in the distillation column has been realised and has been shown that a Neuro-Fuzzy software system can take the place of a classical on-line analyser.

Data considered in the paper were collected in a large petrochemical plant, named ERG PETROLS, set in Priolo (Sicily).

A number of numeric simulations has been performed and results have been compared with the corresponding acquired data. Satisfactory results have been obtained in terms of model prediction capability, it has been shown that the use of the proposed approach allows the realisation of a more flexible, reliable and cheaper predictive model.

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