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Multi-objective Optimization of an FCCU using Neuronal Network

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Abstract

The continue tide to improving the economic performance of the fluid catalytic cracking unit (FCC), was bring utilize the new model method and the new advanced control method. One of the new methods is neuronal network, which can be used for control optimizations complex process.
The main of this work is to obtain solutions for the multi-objective optimization of an industrial fluid catalytic cracking unit. The first part of this paper contains the model of the process and the optimal structure proposes by author for the fluid catalytic cracking. The second part of paper present de multi-objective of the fluid catalytic cracking. The artificial neural network (ANN) is used to obtain solution of the multi-objective optimization. The type of artificial neuronal network used and the way that training the ANN using date sets forms process is describe in the third part of paper. For development and training the ANN, author of paper used neuronal network toolbox from Matlab@. In last part of this paper the author presents the results obtain.

Key words: *neuronal network control, fluid catalytic cracking, multi-objective optimization*

Introduction

The FCC unit is one of the most importance processes in petroleum refineries due to the high commercial values of its products. Even a small benefit in this process is economically attractive. This unit offers a unique challenge to control engineers by virtue of its complex process dynamic, severe operating restrictions and because of the interaction between variables. Several studies have been reported in the literature dealing with their modeling, simulation, kinetics, multiplicity of steady state, chaotic behavior, on-line optimization and control. The modeling of the reactor – regenerator system has been studies quite extensively in [1, 2, 4, 8]. A detailed review of these several models is provided by Arbel.et.al, while their strengths and shortcomings have been reviewed critically by Elshishini and Elnashaie.

Several studies [3, 5, 10, 6] have also been reported on the multiplicity of the steady states in FCCU's as well as their bifurcation and chaotic characteristics. In marked contrast, a similar degree of activity has not been reported and the optimization studies [11, 12, 16, 17] use some kind of a profit- function as the single objective function. Most real-life system, like the FCCU, involves several objectives functions (often conflicting and non - commensurate) and constraints. Often, these objective functions cannot be accommodated meaningfully in a single objective function (e.g. cost or profit), and so one needs to carry out multi-objective function optimization. Artificial neural network (ANN) is a good solution for solves the optimization objective function.

This work focuses a three aspect: elaborating the optimal structure of the FCCU, determination the multi-objectives optimization function associated of the catalytic cracking process and development an ANN to solving the objective function optimization.

Model of the FCCU

The FCCU consists of two major units' reactor/riser and regenerator. Because the modeling of this complex process is very difficult, the author propose decomposition in four subsystems of the reactor block, modeling each unit separate and determination the interaction of these subsystems [13].The systematic analyses of the cracking catalytic plant evidencing the next subsystem: the interfusion node subsystem, the riser subsystem, the reactor - stripping subsystem, the regenerator subsystem.

The model of the interfusion node is represented by a heat balance in the steady state regime [1]. The mathematical model of the riser subsystem is structured in the next components: kinetic model, material and heat balance. The Weekman kinetic model is used. The kinetic model Weekman's describes, cracked gas oil based on a deltoid reaction scheme, the catalytic cracking of the gas oil by considering conversion gas oil of the two-order reaction. Lump group's is making by distillate limit in: base material (diesel oil); gasoline; gas and coke. The riser is modeled as a one-dimensional tubular reactor without radial and axial dispersion. Steady state model of the riser is expressed by a set of ordinal differential equations. The heat balance lengthways riser is represented by differential equation.

The mathematical model of the reactor stripper subsystem is based on the hypothesis of the perfect mixing. The dynamic model has two components: the material balance associated to the coke deposed on the catalyst and the energy balance in the strippers. For modelling the regenerator, the author adapted the model developed by Erazu, model that treats the material balance associated to the coke, the material balance associated to the oxygen and the energy balance [7].

The details of the model used, as well as the complete set of equations and model –parameters are giving by authors in [13, 15, 17].

The Structure of the Control FCCU

In general all control structures develop for the FCC are focuses to improving product selectivity. This thing supposes:

- Maximization of the yield of gasoline - for a given feedstock, the control of the gasoline yield is realized by conversion. The conversion depends on catalyst regenerator temperature – T_{car_reg}, catalyst–to-oil ration- *a,* feedstock temperature- $T_{mp,}$ and research octane number – *COR*. The objective function for maximization of yield gasoline (Q_{ben}) is described by :

$$\max f_1\left(T_{mp}, a, T_{reg}, COR\right) = gasoline\ yield \tag{1}$$

- Obtain a superior gasoline quality (highest COR) – in practice the control of the gasoline quality is make using the riser temperature- T_{ris}. The COR is in direct correlation whit reactor temperature, that can be described by relation (2). Reza S. and Stratiev was determined that each 10% increase in riser temperature leads to increase of COR by one point.

$$f_2(T_{ris}) = COR \tag{2}$$

- Minimization of the coke formed on the catalyst during cracking reaction – is known that coke on regenerated catalyst has influence on the catalyst selectivity and activity. In consequence other problem that is appearing in unit operating is to making a good regeneration of the catalyst (quality of teh regeneration). This thing is making by control regenerator temperature (T_{reg}) using the flow air – $Q_{air.}$ The function objective is:

$$\min f_3\left(Q_{aer,} T_{reg}\right) = \%coke \tag{3}$$

Figure 1 show the control structure proposed by author for FCCU. The control structure is hierarchical and consists of three layers: the instrumentation layer, the predictive controller and on-line optimization control.

The instrumentation layer consists of devices for acquiring data (sensor and transmitters), field display devices for displaying process variables. The devices at this level sense the process variables and transmit the data to the computer control system running the plant. The instrumentation layer reports the data to the regulatory layer, which is implemented using model predictive control. The function of the model predictive control is to maintain the process variables at their prescribed set point in spite of local disturbance that are occurring at a time scale of second to minutes. The details of the MPC and the manner elaboration of this is found in [17].

The function of the optimization layer is to keep the process operating near optimum efficiency by constantly adjusting the set points of the MPC. The optimum set point of the MPC can be found solve the relations (1), (2), (3). Solving this multi-objective optimization function is very heave and difficult to programming. Form this reason the author proposed utilization of the artificial neural network. By training process the ANN can be found o correlation between in input date and output date.

The Artificial Neuronal Network

Artificial neural network (ANN) is formatted by processor element, called neurons or nodes, arranged in layers linking the input to output variables. The way the nodes are connected and their structure determine the architecture of the neural network.

In the present study, the network is configured as a fully connected feed-forward, with one hidden layer. The first layer was formed by six variables: T_{mp}, a, COR, Q_{ben}, Q_{air}, coke, T_{cat_reg}. The output layer was format by two neurons that represented by T_{reg} and T_{ris}. The number of nodes in hidden layer (H) is obtained from trial-and error procedure.
Mathematically, the behavior of the neuron in a generic layer can by represented by

$$\lambda_{pj,k+1} = \left[\sum_{i=1}^{n_k} w_{jik} S_{pi,k}\right] + \theta_{j,k+1} \quad , \tag{4}$$

where λ_p represents the outputs of the neuron 'j', in the layer ,*'k+1'*, *S* corresponds to the outputs or activations of all neurons of the layer 'k', *w* is the connection weigh and θ is the internal limit of action of the corresponding neuron 'j' (bias).

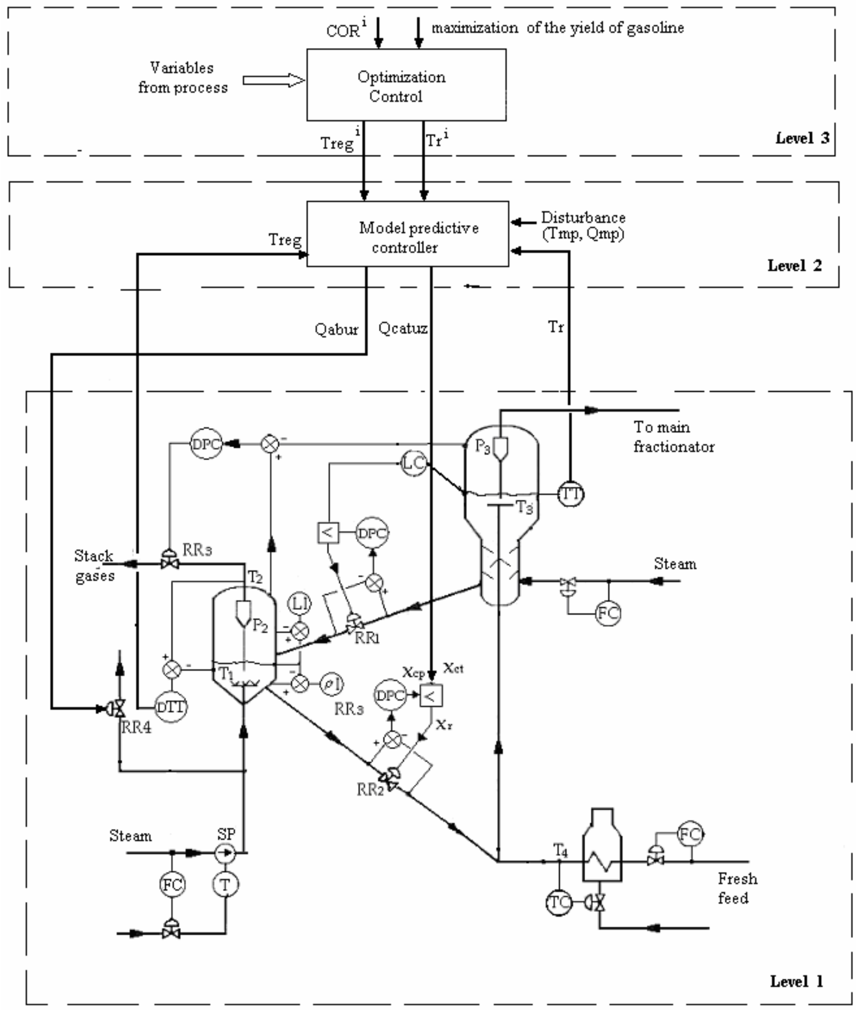

Fig. 1. The control structure of the FCCU

In the present work, the activation function *f*, applied to λ_p is sigmoid

$$f(\lambda_{pj,k+1}) = [1 + \exp(-\lambda_{pj,k+1})]^{-1} \ . \tag{5}$$

The industrial data set using for training the ANN are presented in table 1. This data are presented to network in a process where the weights and biases are modified though predefined rules, in our case the backpropagation training algorithm. In this optimization process, the strategy of the steepest descendent is used. Adjustments in weights and bias are performed as follows:

$$\Delta w_{p,k+1} = \Delta w_k + \eta \nabla E(w_k) S_{p,k} \ , \tag{6}$$

where E is the error function between actual and desired network outputs, η the learning rate. The algorithm is available in references [17].

A few training set for the ANN see in table 1. After training, the network validation was performed with test data.

Table 1. Date for training ANN

Inputs date								Output date	
T_{mp} [^{0}C]	Qmp	Qcat	T_{cat_reg} [^{0}C]	COR	Q_{gasoil} [kg/h]	Q_{aer} [kg/h]	%cocs	T_{ris} [^{0}C]	T_{reg} [^{0}C]
195	161750	742432	709	92.3	76509	65000	0.073	528	722
205	161750	742432	709	92.04	76408	65000	0.75	531	724
195	177925	742432	709	91.84	83794	65000	0,057	711	712
195	161750	113648	709	91.84	71896	65000	0.093	709	780
195	161750	742432	739	92.16	72740	65000	0.111	744	743

Figure 2 show a comparison for COR between set date training and response of the ANN. A relative error between the results of set of training and the results of the network is 1% and is considered sufficient for acceptance of the training procedure.

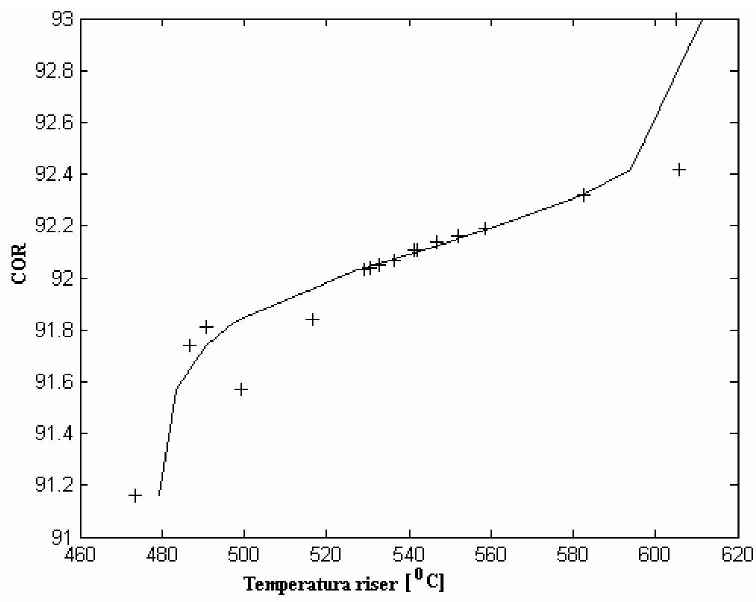

Fig.2. Compare between results simulation and date real

Conclusion

The structure control proposes by author is focuses to improving the product selectivity. This thing supposes fulfill the next objective functions: maximization of the yield of gasoline, obtain a superior gasoline quality (highest COR) and minimization of the coke formed on the catalyst during cranking reaction. The control structure is hierarchical structure and consists of three layers: the instrumentation layer, the predictive controller and on-line optimization control.

This paper describes a procedure for solution of the multiobjective function associates of the FCCU. A fully connected multilayer feedforward network was used. The structure of the ANN is: in the first layer contains eight neurons, the second layer contains neurons, and the last layer two neurons. The results of simulation confirmed a good optimal control based on ANN for the FCC.

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Optimizarea multi-obiectiv a procesului de cracare catalitică bazat pe model utilizǎnd rețele neuronale artificiale

Rezumat

Tendința de îmbunătățire continuă a performanțelor economice ale instalației de cracare catalitică a determinat utilizarea unor noi tehnici de optimizare a performanțelor proceselor complexe. Rețele neuronale artificiale reprezintă una dintre aceste tehnici ce poate fi aplicată în conducerea optimală a procesului de cracare catalitică.

Principalul obiectiv al acestei lucrări îl reprezintă utilizarea rețelelor neuronale artificiale în rezolvarea funcțiilor obiectiv (optimizarea) ale procesului de cracare catalitică. In prima parte a lucrării se va realiza o prezentare sumară atât a modelului procesului cât şi a structurii optimale propuse de către autoare. In cea de-a doua parte a lucrării sunt determinate funcțiile obiectiv ale procesului. Pentru găsirea soluțiilor funcțiilor obiectiv propuse, se utilizează o rețea neuronală artificială. Tipul de rețea neuronală utilizată şi modul de instruire a acesteia, utilizând date din proces, se vor descrie în cea de-a treia parte a lucrării. Pentru dezvoltarea rețelei neuronale şi instruirea acesteia, autoarea a utilizat neuronal network toolbox from Matlab$^{@}$*. Lucrarea se încheie cu interpretarea soluțiilor obținute.*