Neural Network Model Predictive Control System for Fluid Catalytic Cracking Unit

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The fluid catalytic cracking unit (FCCU) is one of the most important and complicated process in the petroleum refining industry. The catalysts performance and advanced control of the cracking catalytic plant contribute to increase the profit and gasoline production. One concept of the advanced control is represented by Neural Network Model Based Predictive Control System. The aim of this study is to develop and investigate the performance of the neural network model predictive control structure applied to the fluid cracking catalytic unit. Industrial data from a Romanian petroleum refinery was used to develop, train and validate two neural networks, for simulation and control the process. The neural networks as a process model are used to develop two neural network predictive controllers for the cracking catalytic process. In the final part will be outlined the performance that can be obtained using neural network model predictive algorithm for controlling a fluid cracking catalytic unit.

Keywords: - neuronal network predictive control, fluid catalytic cracking, dynamic simulation

The fluid catalytic cracking unit (FCCU) is the dominant conversion process in petroleum refineries, which ensure the heavy fractions oil into gasoline with high octane. This process consists of two interconnected subprocess: the subprocess riser-reactor and subprocess regenerator. In the subprocess riser-reactor take place almost all the endothermic cracking reactions and coke deposition on the catalyst occurs. In regenerator takes place the reactivation of the catalyst by burning the coke accumulated on the catalyst. The heat produced is carried by the catalyst from regenerator to reactor to assure the endothermic cracking reactions. A typically image of the cracking catalytic process is presented in figure 1.

The FCCU is difficult to control due to: i) the nonlinear properties of the process; ii) the strong interaction between the variables of the process; iii) the multivariable properties of the process; iv) a big difference between time constants of the process; v) the necessity to control system with changing operating conditions in the presence of unmeasured disturbances. For processes with these features, it is indicated the utilization of advanced control techniques, such as neural network model predictive control (NNMPC).

The control problem of the FCCU has been approached under various aspects in numerous works. Some works deal with conventional process control [1, 4] and another category of papers deal with aspect of model predictive control [3, 5, 8, 11]. A much more reduced category of works deals with aspects of the neural network model predictive control of the FCCU [7, 9, 12].

However, the NNMPC systems applied to FCCU are insufficiently treated. In these conditions, the author has focused to bring some relevant contributions on neural network model predictive control for the fluid catalytic cracking.

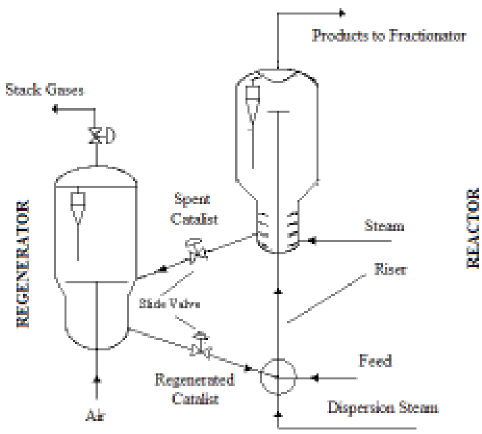

Fig. 1. The industrial fluid catalytic cracking unit

Neural network model predictive control structure of the FCCU proposed

The neuronal network model predictive control proposed by the author, is answering to the requirements of any industrial process, namely:

·safety in operation, through an adequate protection system;

·ensuring an operating regime without overshoots, using an multivariable control that can reduce the effect of the interactions;

·answer to specific quality objectives of the process, which suppose ensuring a conversion efficiency in the reactor (in riser) and a good combustion in the regenerator;

·answer to specific economic objectives, represented by maximizing of the yield gasoline in condition of the imposed research octane number.

Taking in to account requirements, the author has elaborated a control structure organized on two levels, figure 2.

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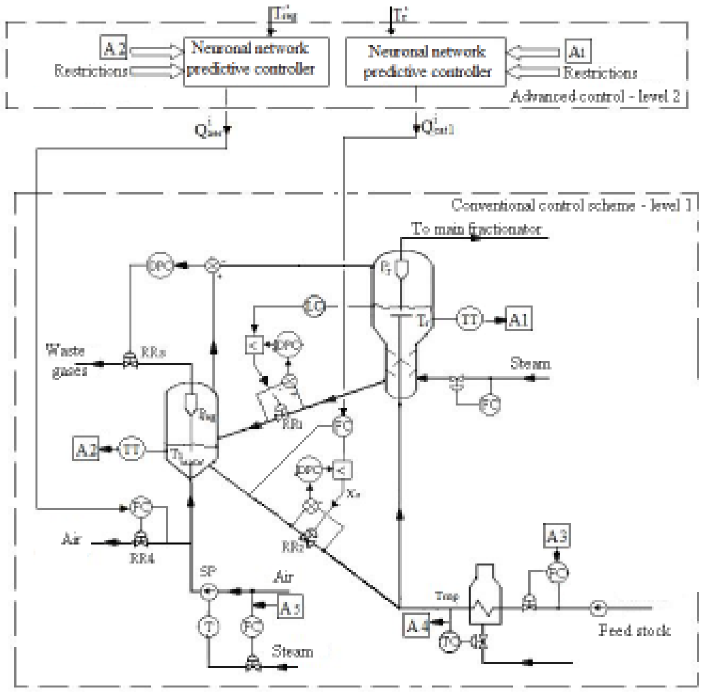

Fig. 2. The control structure of the FCC

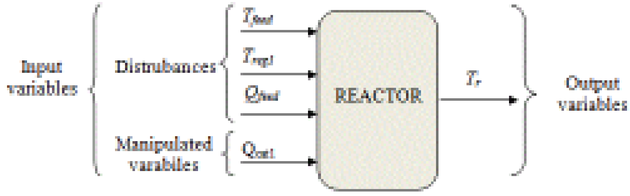

Fig. 3. The input and output variables of the reactor

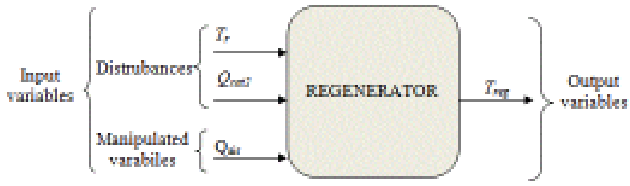

Fig. 4. The input and output variables of the regenerator

The conventional control level (level 1) contains 10 mono-variable control loops, two of these play an important role to the increasing of the performance of the process. These are the riser outlet temperature control loop (used to control the cracking conversion) and difference temperature regenerator control loop (used to control the catalyst regeneration), and were transferred to the second level.

On the second level is proposed, implemented and tested a decentralized control strategy which use two neuronal networks model predictive controllers, namely: one for riser outlet temperature control associated to the subprocess riser-reactor and one for temperature regenerator control associated to the regenerator subprocess. The figures 3 and 4 emphase a characterization of each subprocess from the point of view of automation, the input and output variables.

The input variable associated to the advanced controllers are represented by disturbance variable (feedstock flow and temperature - Q_{feed}, T_{feed} and T_{reg1} - the regenerated catalyst temperature for the subprocess riser-reactor and riser temperature -T_r, spent catalyst flow rate -Q_{cat2} for the subprocess regenerator), the setpoints that are calculated at the high level (optimal riser temperature riser – T_r^i and optimal regenerator temperature - T_{reg}^i) and reaction variable process(riser temperature – T_r respectively regenerator temperature - T_{reg}). The manipulated variables are regenerated catalyst flow rate - Q_{cat1} respectively air flow in the regenerator - Q_{air}.

The developing of the neural network model predictive controllers

The neural network predictive controller structure

Neuronal network model predictive control (NNMPC) is known as very powerful control strategy for a variety of chemical process [6]. The predictive algorithm contains two components: *a predictor* and *an optimizer*. In figure 5 is illustrated the structure of a NNMPC system. Predictive control use the neural model of the process to predict the way that the process output will evolve in the future, over a specified time horizon named prediction horizon. These predictions are used by the optimization module for calculation of the manipulated vector which can be applied to the process, over know time named control interval [13].

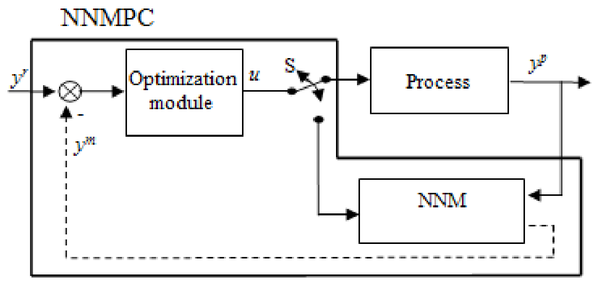

Fig. 5. The structure of the neuronal network model predictive controller.y^r – set point; u - manipulation; y^p – output process; y^m- predictive output.

Neural network models for the predictive controllers

To determine the neural network models for each subprocess, the author proposes the identification scheme presented in the figure 6. This identification method is based on the simulator developed by authors in SIMULINK and presented in the paper [11]. The mathematical model was validated by author using industrial data [10].

The steps involved in every effort to build a functional neural network model of an industrial process are:

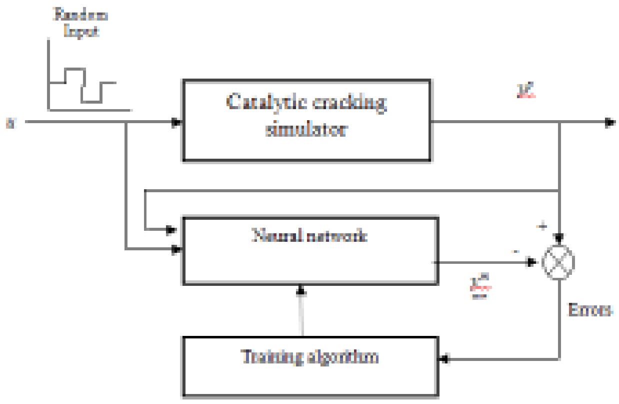

Fig. 6. The identification scheme

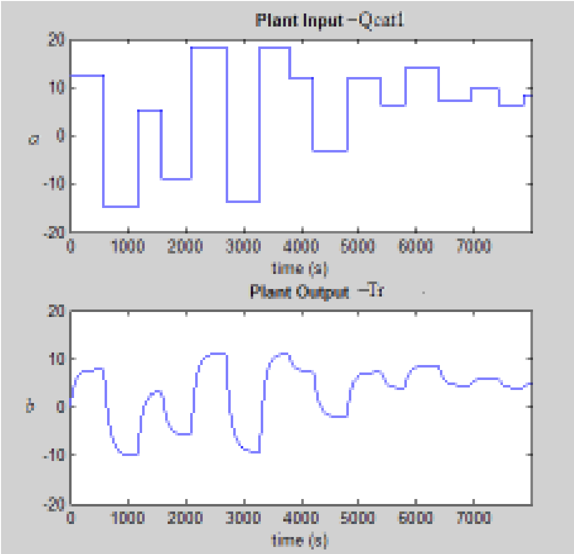

Fig. 7. Data for training neural network associated to the controller of the riser sub-process: a- random signal, b- output process.

The recorded data for training both the plant's neural network model and controller were obtained from dynamic simulations using the simulator. The data is obtained by applying the process inlet, represented by the simulator, of a random signal with variable amplitude and frequency. The data for training is presented in figure 7 and 8, respectively.

The structure of the neural network needs to be specified. This step supposes the specification of number of hidden layers and the number of nodes in each hidden layer. The type of neural network used in generally for process control is known as a feed-forward network, figure 9 [12]. The output from the last layer represents the network predicted outputs, and it is calculated with the relation

$$y^m(t) = \sum_{j=1}^{nh} w_j \cdot f_j\left(net_j(t)\right), \qquad (1)$$

$$net_j(t) = \sum_{i=1}^{nu} w_{j,i+1} \cdot u(t-i) + \sum_{i=1}^{ny} w_{j,nu+i+1} \cdot y(t-i) \qquad (2)$$

where $y^m(t)$ denotes network output; $f_j(.)$ – output function of j node from hidden layer; $net_j(t)$ – output activation function of the associate j node of the hidden layer; nh – neurons number of the hidden layer; nu – neurons number associate with input $u(.)$; ny – neurons number associate with output $y(.)$; w_j – weight for the connection from the j hidden node and output node; $w_{j,i}$ – weight for the connection from the i input node and j output node; $y(t-i)$ – delay output process; $u(k-i)$ - input network .

In this case for the neural network hidden layer associated to riser – reactor sub-process are designed seven neurons, and five hidden neurons for the neural network associated to the controller of the regenerator sub-process.

Training and validation the neural networks. From recording data for training the neural networks, only 80% of the records data are used for train, the remainder being necessary to validate the neural network. The training algorithm used in this study is Leverberg-Marquart algorithm. In figure 10 and 11 is shown the graphic of validation of neural network.

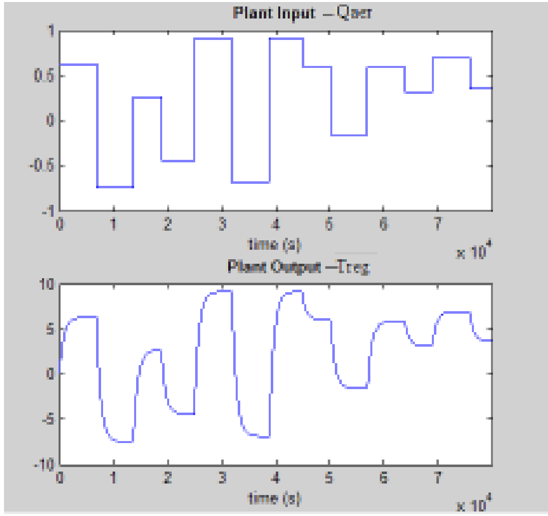

Fig. 8. Data for training neural network associated to the controller of the regenerator sub-process: a- random signal, b- process output

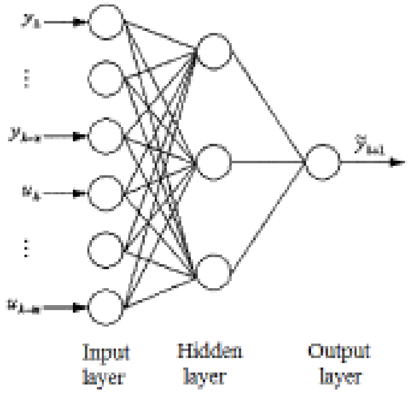

Fig. 9. The basic architecture of a feed-forward neural network with a single hidden layer

As conclusion of the figures 10-c and 11-c results that the error is small enough (of the 10^{-3} order, 10^{-2} respectively), this conferring the fact that the two neural networks model development is adequate for their use in the catalytic cracking process control, the errors being totally insignificant. The model shows a good performance after training.

Investigation of NNMPC dynamic performance

The performance investigation of the NNMPC system consist of modifying the setpoint (outlet riser temperature T_r the regenerator temperature T_{reg}) and the disturbances which appears in the process (the spent catalyst flow Q_{cat2}, and the regenerated catalyst temperature T_{reg1}).

The first test consists in modifying the controllers references (outlet riser temperature T_r, the regenerator temperature T_{reg1}) in step variations. In figures 12 and 13 are presented the dynamics of those variables, together with the associated manipulated variables (Q_{cat1} and Q_{air}). As it can be seen from the above trends, the two control systems successfully brings the output values to the setpoint values, without steady error.

The second test consists in modifying the disturbances of each subsystem. In figure 14 and 15 are presented the dynamic of the riser outlet temperature T_r, regenerator temperature T_{reg} and the manipulated variable associated when the disturbances (regenerate catalyst temperature T_{reg1} for the controller associated subprocess riser – reactor and spent catalyst flow Q_{cat2} for the controller associated the subprocess regenerator) are changed.

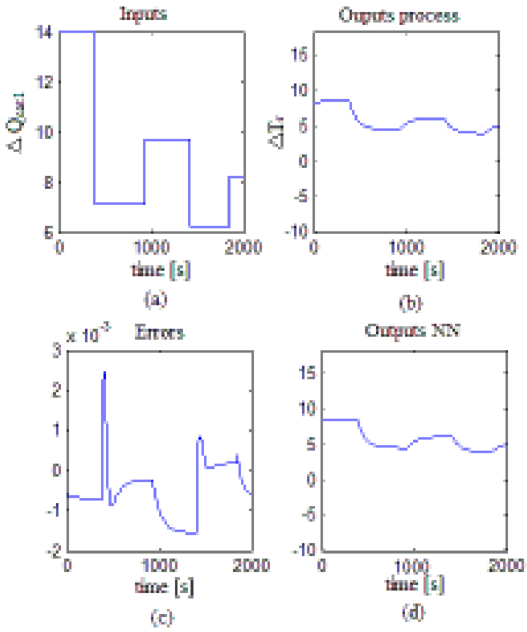

Fig. 10. The graphics associated to the validation of the neuronal network for the controller of the riser sub-process: a) catalytic flow rate; b) riser outlet temperature; c) errors between the output process and output neuronal network; d) neural network output

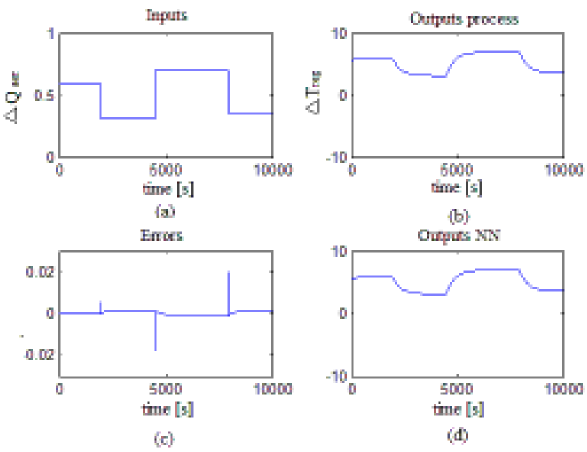

Fig. 11. The set of graphics associated to the validation of the neuronal network for the controller of the regenerator sub-process: a) air flow rate; b) regenerator outlet temperature; c) errors between the output process and output neural network; d) output neural network

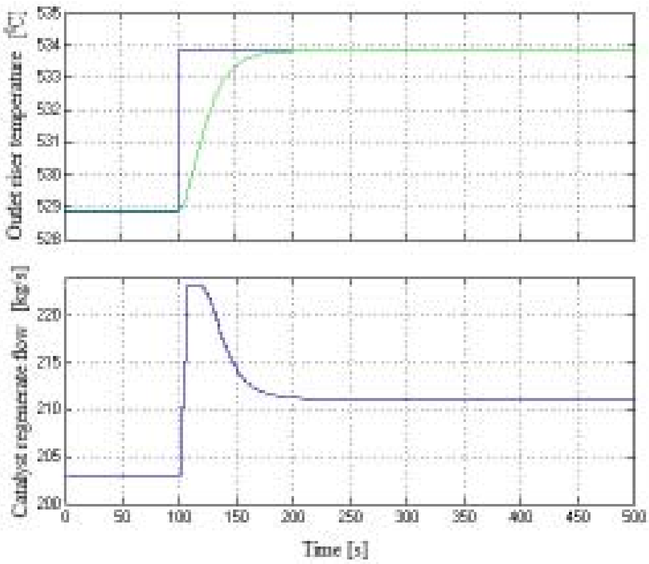

Fig. 12. The dynamic evolution of the riser outlet temperature and regenerated catalyst flow when the riser temperature controller setpoint increases from 529 to 534^{0}C

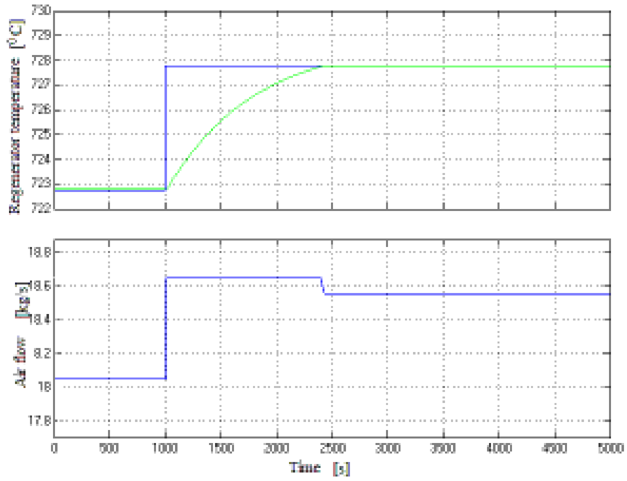

Fig. 13. The dynamic evolution of the regenerator temperature and air flow rate when regenerator temperature controller setpoint increases from 722 to 732 ^{0}C.

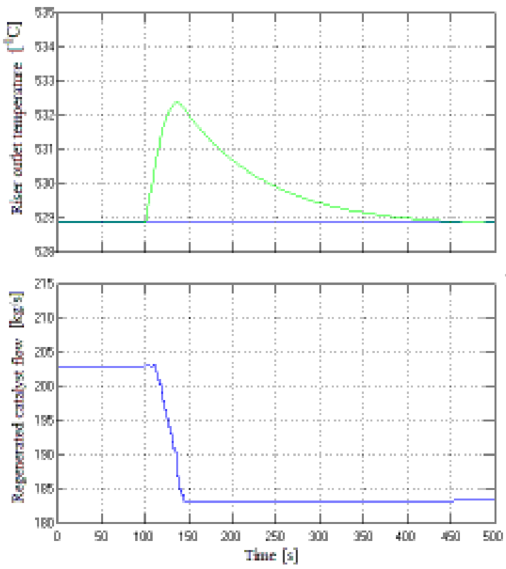

Fig. 14. The dynamic evolution of the riser outlet temperature and regenerated catalyst flow when the regenerated catalyst temperature increases from 709 to 729 ^{0}C

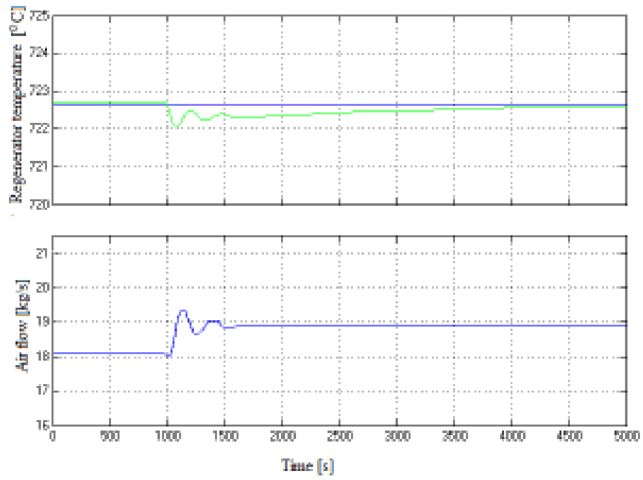

Fig. 15. The dynamic of the regenerator temperature and air flow rate when the spent catalyst flow increases from 206kg/s to 211 kg/s

From second test it can be observed that the two control systems eliminate the effect of the main process disturbances.

An important problem of the NNMPC is represented by the tuning of the controllers. The author achieved a special

Table 1
THE CONTROLLER PARAMETERS OF THE NNMPC

Parameters	Reactor controller	Regenerator controller	MU
Prediction horizon	100	110	control intervals
Control share	0.5	0.25	h
Control horizon	2	2	control intervals

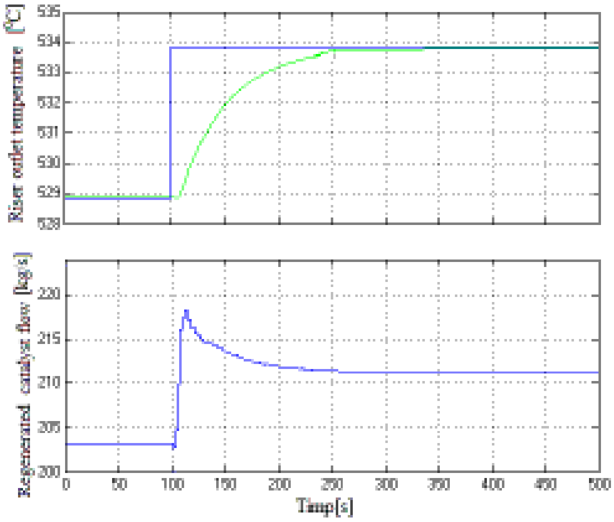

Fig. 16. The dynamic evolution of the riser outlet temperature and regenerated catalyst flow when the riser temperature controller setpoint increases from 529 to 534°C when the prediction horizon has 150 intervals

test which consists in modifying the tuning controller parameters. The tuning parameters of the neural network controllers are: prediction horizon, control share and control horizon. The author has simulated the NNMPC with different values of the tuning controller parameters. In table 1 are presented the best controller parameters obtained from numerical simulations.

In case when the prediction horizon increases (from 100 to 150 for the riser – regenerator subsystem and 110 to 200 for the regenerator subsystem), the transient time of the riser outlet temperature controller increases (from 250 to 350 s respectively from 2500s to 3000 s), (figs. 16, 17).

Conclusions

In this paper there are presented aspects of modeling the catalytic cracking fluid process using neural network used to develop neural network model predictive control structure for process. It was develop two neural networks, one for modeling the subproces riser-regenerator and one for the modeling the regenerator subprocesess.

The efficiency of NNMPC control is sustained by ability of rejection disturbance and output process tracks the setpoint variable with the best dynamic performance. As

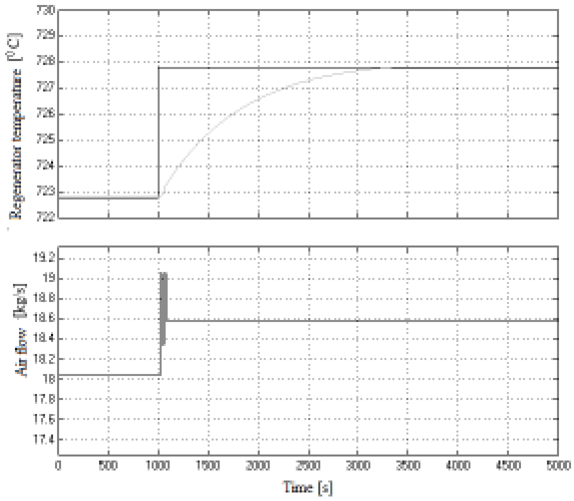

Fig. 17. The dynamic evolution of the regenerator temperature and air flow rate when regenerator temperature controller setpoint increases from 722 to 732°C when the prediction horizon has 150 intervals

there can be seen from the above trends, the behavior of the process and control system was studied for different values of turning parameters, observing that an increase of the control interval can lead to an increase of the transient time.

As a final remark neural network is a promising control technique and can be effectively used for improved process control of the FCCU and other units in the petroleum refinery production processes.

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