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Neural Network Model – Based Predictive Control System for the Reactor of FCC

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Abstract

The aim of this work is to implement and evaluate the performances of neural network model-based predictive control system (NNMPC) applied to fluid catalytic cracking (FCC) reactor. The paper is structured in four parts: the presentation of the FCC reactor, neural network based predictive control overview, the proposed predictive control structure for the FCC reactor and simulation results. In the first part of this paper is analyzed the FCC reactor, where are identified the main subsystems associated to the plant and the interaction of these subsystems. In the second part are presented the theoretical aspects of the model predictive control based on neural network. In the last part are presented the performance of the neural network predictive control structure proposed for the temperature control of cracking reactor. The simulation experiments have confirmed good regulatory and tracking properties of the proposed control system. Simulation test have proved that the neural predictive control could be used in an industrial environment.

Key words: *neural network, predictive control, identification.*

Introduction

Petroleum refineries use fluid catalytic cracking (FCC) technology to convert crude oil in gasoline, diesel and heating oil. About 45% of worldwide gasoline products come from FCC process. The economic benefits of refinery could be considerably increased if proper control and optimization strategy on operating (e.g. temperatures, flow rates etc) and quality (e. g. composition) variables are implemented on FCC units [1, 5].

There have been many studies in literature addressing the problem of controlling FCC units. For instance, non-linear controllers [3, 9] and more complex mode predictive strategies [2, 10] have been proposed. Overall, these studies have shown that the FCC units are non-linear, multivariable and complex dynamic control systems. Complexity often is caused by the strong interaction existing between the control loops.

Most FCC control designs deals with the problem of stabilizing the process temperatures at a given set point. From an operating viewpoint, temperature regulation is basic control objective imposed to guarantee a safe process operation. Nevertheless, the main task in operation and control of FCC units is regulation of gasoline quality at the output riser. In practice, gasoline composition regulation is approached via indirect methodology where a specified riser outlet temperature is regulated at given set point which, in principle, corresponds to the desired composition values.

The work presents the author contribution on developing a model predictive control based on neural network for temperature regulation in reactor of FCC.

The reactor structure

The process structure of the catalytic cracking includes next subsystems: reactor, regenerator, preheating furnace [11]. The reactor represents the principal element of the catalytic cracking plant. Because the modeling of the reactor represents a difficult task, the author suggests the decomposition in three subsystems [12]. These are:

i) *The interfusion nod subsystem*, located at the de base of the riser, here the fresh gas oil is brought into contact with the hot regenerated catalyst, which leads to the vaporization of the gas oil. It assumed that the vaporization of the feed is instantaneous.

ii) *The riser subsystem* is a vertical standpipe 25-40 m in length. All cracking reactions take place in riser over a short time 2.5 s. These reactions are primarily endothermic.

iii) *The reactor-stripper subsystem*, located at the top of the reactor, a subsystem that realizes the catalyst separation from the feed stock vapors and the reaction products.

The model used for simulation of the process is developed by Popa [13]. The model is sufficiently complex to capture the major dynamic effects that occur in an actual FCCU system (multivariable, complex interacting and highly nonlinear). The model is implemented in Matlab® and was used for the study of different operating regimes induced by design changes and by changing operation strategies, but also for investigating which control strategies may be implemented.

The structure of the predictive control based on neural network

Model predictive control (MPC) is known to be a very powerful control strategy for a variety of chemical process [7].

Many chemical processes are highly nonlinear and MPC based on linear process models may results poor controller performance. There for, MPC techniques have recently been extended to nonlinear process [4, 6, 8]. An alternative to MPC for nonlinear process is neural network predictive control, which ensures high performance using identification of the process prior to implement a control strategy.

The control structure of predictive neural control is presented in figure 1. The neural network and the input have the same input u_k. The network has a supplementary input that is connected to the output of the process y_k.

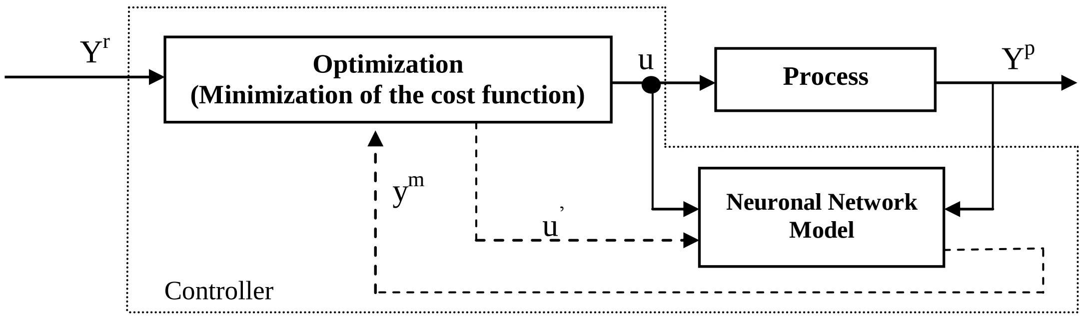


Fig. 1. The scheme of predictive neural control system.

NNMPC for the reactor of the FCC

Figure 2 presents a characterization of the cracking process form the point of view of automation, the input and output variables.

The *controlled variables* have been selected to provide, through control, a safe and economic operation. The controller variable is reactor temperature T_r, this variable has to be maintained at certain level to a desired maximum conversion of the feed oil. The *manipulated variables* are Q_{cat} – regenerated catalyst flow rate. The *disturbances variables* are Q_{mp}, T_{mp} – raw material flow and temperature.

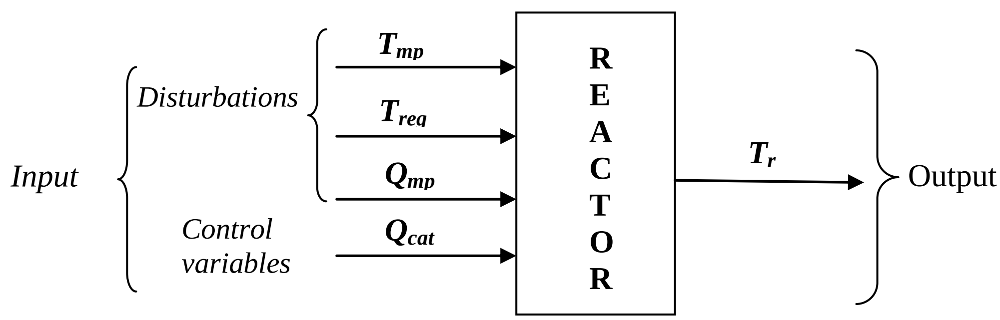


Fig. 2. The input-output of the reactor.

The implementation of the predictive control involves the process identification and control design. The NN Predictive Controller used to implement is from Network Toolbox from Matlab®.

Because a neural network is a universal estimator, in the identification phase; the process dynamic is copied in the neural network structure. When the process is characterized by mathematical relation the training of the NN can be done offline by correlating the inputs applied to the process with outputs delivered by the process. After the training procedure the NN is representing a replica of the physical process.

As excitation for the system a Pseudo-random Multilevel Signal (PRMS) is used, where the amplitude is changed at each N-th sampling instant or at random instance. An example of PRMS is presented in the figure 3.

Practical experience has shown that the best model performance will be achieved by the duration of change (or hold time) in amplitude and the sampling interval. The holding duration must be long enough to cause an effect in the output but limited in order to cover just the dynamic of the system. If the sampling interval is too large the data will contain poor information about the high frequency response, and if the sampling interval is too small, the disturbances may have a relatively large influence by causing an excess of poles. For the current experiment the sampling interval was chosen to be 10-20% of the settling time of the step response of the system.

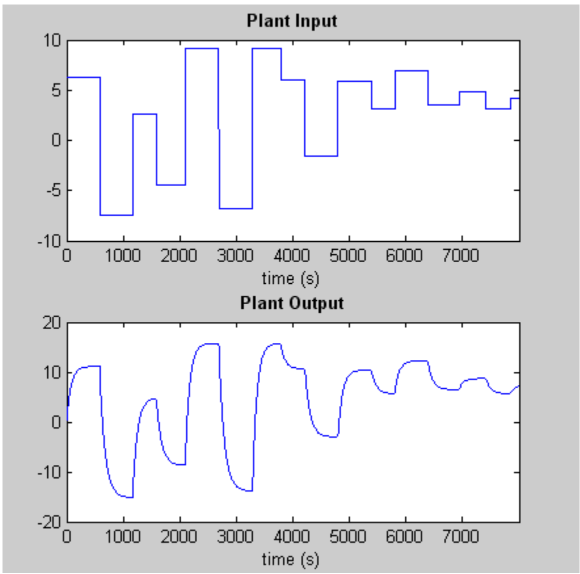
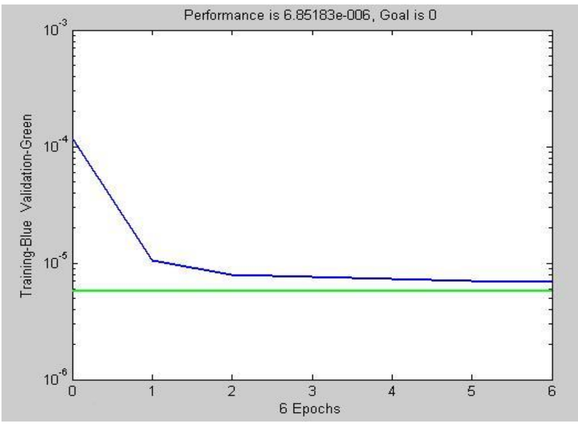


Fig. 3. The PRMS training signal and system response.

After identification procedure, the neural network is trained whit this data. The performance of the neural network is presented in figure 4, and the validation is presented in figure 5. The optimal number of the nodes in the hidden layer found by author is seven.



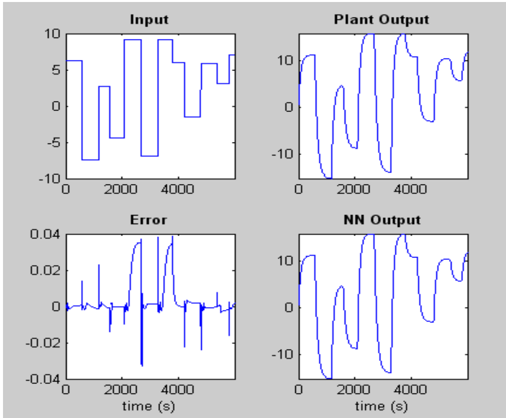


Fig. 4. The neural network performance. **Fig. 5.** The neural network validation.

The controller design of MPC involves the replica of the plant model and an optimization algorithm to select the control inputs over a finite time horizon. By having the process embedded in the NN, the controller is generating offline more candidate commands to NN structure and is recording the NN outputs. Using a cost function based on the mean-squared error the controller is selecting the appropriate command for the process evolution. This generic procedure is used just for SISO systems.

The simulation results

The control structure of temperature from reactor is presented in figure 6. For the performances evaluation of the MPC based on neural network on temperature control of the cracking reactor were tested two scenarios:

- **Test A** which consists in step change the controller reference - the temperature of the reactor T_r;
- **Test B** which consists in step change of a disturbance, for example raw material temperature - T_{mp};

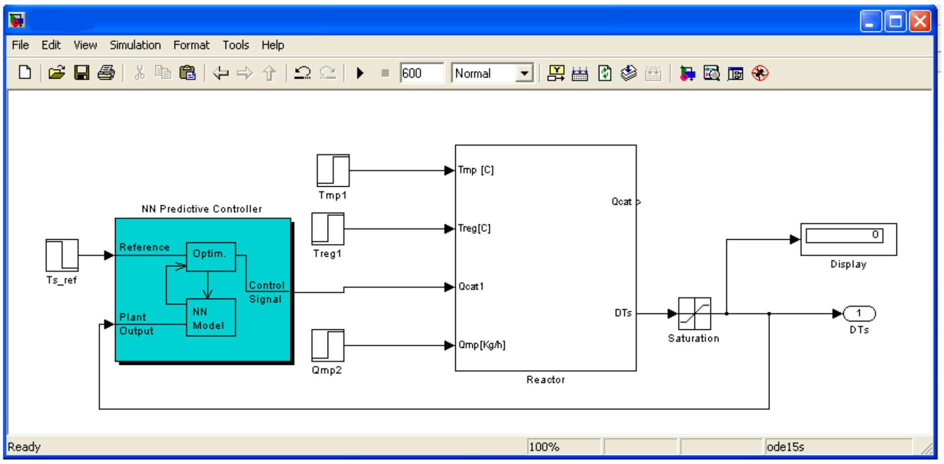


Fig. 6. The reactor temperature control structure.

Test A: In figure 7 are presented the evolution of temperature T_r and the evolution of the Q_{cat} at the change of reference. From figure it can be seen that the adjustment automatically succeed to bring the temperature to the prescribed value with no stationary error. The prediction horizon used is 7.

Test B: Figure 8 presents the evolution of temperature in the reactor T_r and the flow catalyst regenerate - Q_{cat} for a disturbance change (raw material temperature- T_{mp}).

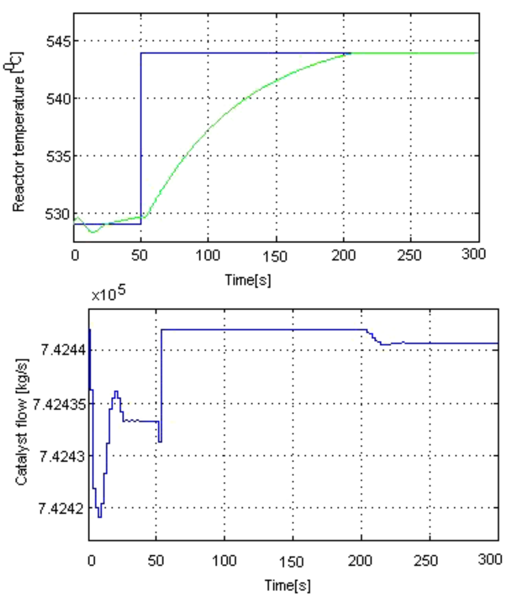


Fig.7. Evolution of the reactor temperature and catalyst flow for a reference step change.

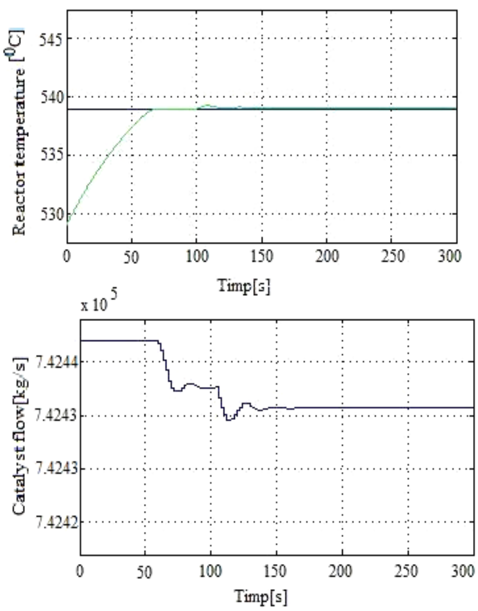


Fig. 8. Evolution of the reactor temperature and catalyst flow for a disturbance step.

Conclusions

In this work are discussed aspects of the implementation of a controller based on predictive neural networks to adjust the temperature of the cracking reactor. The main author contributions in this paper are:

- development of a neural network that is able to capture the dynamic of the cracking reactor;
- elaboration of the control structures for the cracking reactor that includes the neural networks;
- in the final part of the paper the performance of the control structures proposed for the reactor is demonstrated by simulation.

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Sistem de reglare predictiv bazat pe reţele neuronale pentru reactorul instalaţiei de cracare catalitică

Rezumat

Obiectivele acestei lucrări sunt implementarea şi evaluarea performanţelor unui regulator predictiv bazat pe reţele neuronale aplicat reactorului din cadrul instalaţiei de cracare catalitică. Lucrarea este structurată în patru părţi: structura procesului, aspecte ale reglării predictive bazată pe reţele neuronale, structura de reglare predictivă bazată pe reţele neuronale utilizată pentru reglarea temperaturii în reactorul de cracare şi rezultatele simulărilor. În prima parte a lucrării este analizat reactorul instalaţiei de cracare catalitică, unde sunt identificate subsistemele asociate reactorului şi interacţiunile între acestea. În partea a doua a lucrării sunt prezentate aspectele teoretice ale unui regulator predictiv bazat pe reţele neuronale. Lucrarea se continuă cu prezentarea performanţelor structurii de reglare predictivă bazată pe reţele neuronale, propusă pentru reglarea temperaturii în rectorul de cracare. Rezultatele simulărilor au evidenţiat faptul că sistemul de reglare propus reuşeşte să aducă într-un timp relativ scurt ieşirea procesului la valoarea prescrisă. În această situaţie se poate spune că reglatorul predictiv bazat pe reţele neuronale poate fi utilizat cu succes într-un mediu industrial.