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SIMULATION AND MODEL PREDICTIVE CONTROL OF THE FLUID CATALYTIC CRACKING UNIT USING ARTIFICIAL NEURAL NETWORKS

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An Artificial Neural Network (ANN) model has been developed for an industrial Fluid Catalytic Cracking Unit (FCCU). ANN design and training are presented. Successful training procedure is proved when the prediction capability of the network is investigated on the testing set of data. The trained ANN model has been subsequently used to implement FCCU control using the Model Predictive Control (MPC) algorithm. Main process variables have been controlled in the presence of typical disturbances. Setpoint tracking and disturbance rejection show good control performance and, associated to important decrease of computation time, reveal incentives of the ANN based MPC approach for industrial implementation.

INTRODUCTION

FCC is well known to be the core process in petroleum refining and its continuous progress is strongly demonstrating this assertion.[1] FCCU performs the conversion of heavy petroleum fractions into the valuable high-octane gasoline, but also into a large range of hydrocarbon products, such as: LPG, fuel gas, lights diesel, aviation kerosene and slurry oil. Important efforts of catalytic cracking process development have been directed to the technological enhancement, catalyst improvement and to better process control. Despite its complexity, the driving force for the spectacular development of the FCC process is the large economic importance of its products with impact on a very large scale of modern society needs. Both academia and industry report research results aimed to the FCCU development, such as: chemistry of the catalytic cracking, modeling,[2,3] nonlinear dynamic behavior with steady state multiplicity and chaotic characteristics, dynamic simulation,[4] on line optimization[5,6] and advanced control.[7,8]

A special interest is devoted to find the way optimal operation can be achieved by advanced control. FCCU is difficult to control due to its multivariable, strong interacting and nonlinear features leading to a very complex dynamics. Usually, the optimum operating conditions are met where constraints are also active. As a consequence, it is important to control FCCU as close as possible to the operating and equipment constraints but without violating them. Model Predictive Control (MPC) proves to be a good candidate for performing such task but it requires a robust model of the unit. Development of an analytical mathematical model implies several simplifying assumptions. These assumptions usually refer to the need of lumping the individual components of the feed and products into groups, the simplification of complicated processes occurring on the catalytic surface during the cracking process or during coke removal from the spent catalyst and the complex heat and mass transfer phenomena describing the fluidized bed.[3] All these assumptions limit the capability of developing accurate dynamic simulators based on first principle models.

Statistical models developed by means of ANNs and using process data are promising alternatives to the traditional first principle models.[9-11] They may be also used in a mixed neural networks and first principle modeling approach. Built on the basis of a consistent set of data, ANN models are able to capture the

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complexity of the intrinsic processes featuring the global process behavior, for this reason motivating the modeling approach of the present work.

Since the modeling is the most time consuming part of the MPC design and the choice of proper modeling environment is crucial, one major challenge related to industrial MPC applications is the efficient development and identification of the control-relevant model.[12] Finding the proper balance between the accuracy of the model and computational burden is usually very challenging.[13] Typically, the model of the process used by the MPC algorithm is of first principle type. As the complexity of the first principle model increases, the computational need for solving the MPC optimization problem is becoming more and more restrictive, especially in the nonlinear case. For such situations the real time implementation may become unfeasible. The use of an ANN based model may bring the desired improvement in decreasing the computation effort, thus increasing speed of calculations, as the ANN models are generally demanding less computing power. In fact, the computation load is *partially* transferred from the *on-line* optimization calculation of the control move, when it is based on the first principle models, into the *off-line* training step needed for building the ANN model.

RESULTS AND DISCUSSION

Building the ANN Model

The FCCU of UOP (Universal Oil Products) type, for which an ANN model has been first developed and then performed the ANN based MPC control, is presented in figure 1.

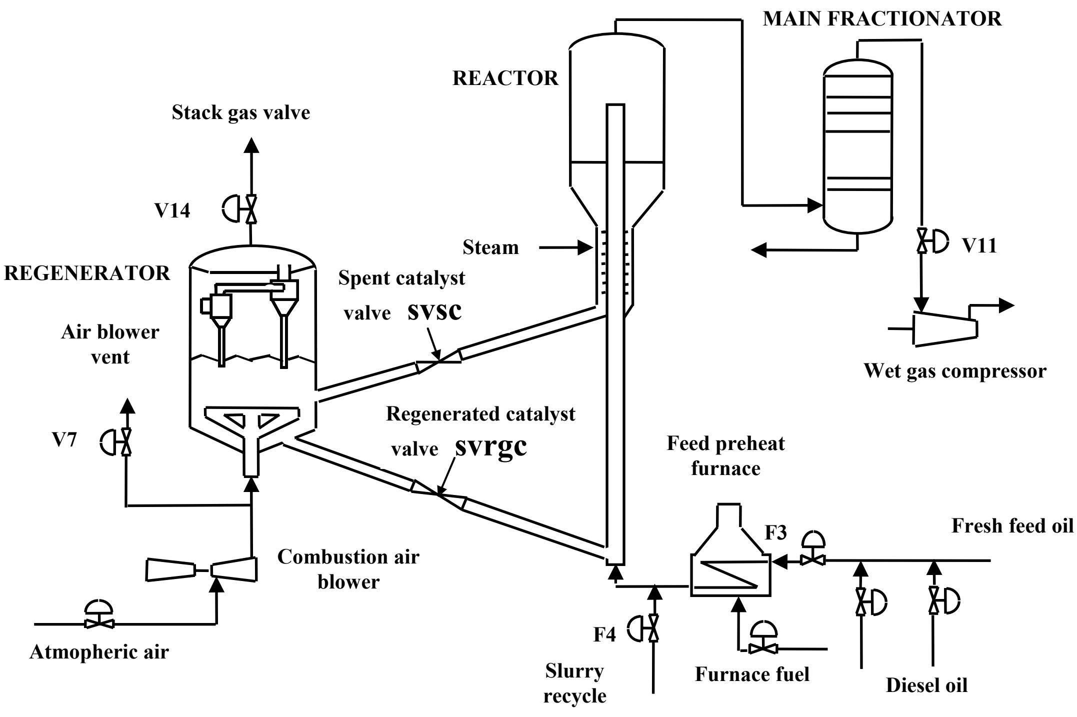

Fig. 1 – Schematic representation of the UOP Fluid Catalytic Cracking Unit.

A rather complex dynamic analytical model has been previously developed based on data from an UOP industrial FCCU working in partial combustion mode. The model describes the reactor-regenerator system consisting in its main components: feed-preheat system, reactor, regenerator, air blower, wet gas compressor, catalyst circulation lines and main fractionator, the latter included in the model by its buffer vessel effect on the flow of gaseous products produced in the reactor. Main features captured by the analytical model are revealed in the following.

Developing the analytical mathematical model for the reactor implied a thorough survey, selection and then synthesis, based on a large variety of models presented in literature. The three-pseudocomponents lump model has been considered to be adequate for the global description of the phenomena taking place in the reactor. Reactor is divided in two parts: riser and stripper. The riser model is built on the following assumptions: plug flow and very short transient time (the residence time in the riser is very short compared to other time constants, especially to the regenerator time constants). It is modeled by mass balance describing the gasoline and coke+gases production based on Weekman's triangular kinetic model.[14] The mixed system of nonlinear differential and algebraic equations also accounts for the amount of coke deposited on catalyst and for the cracking temperature dynamics. The stripper model is of CSTR type (mass and heat balance) evaluating the temperature in the stripper and the fraction of coke on spent catalyst.

The mathematical model for the regenerator has been developed in a more detailed form and higher complexity, taking into account the importance of this system in determining the dynamic behavior for the entire FCCU. The regenerator is considered divided in two zones: a dense bed zone and a zone of entrained catalyst (the disengaging zone). The dense bed zone consists of two phases: a bubble phase of gaseous reactants and products moving along the bed in plug flow and a perfectly mixed dense phase containing gases and solid catalyst. Mass transfer occurs between the two phases but at regenerator temperatures the reaction rates are controlling, rather than mass transfer between the two phases. Since the dense phase is considered perfectly mixed, the temperature is assumed uniform in the bed and the gaseous phase in equilibrium with dense phase. Catalyst is present in the zone above dense bed due to entrainment. The amount of catalyst decreases with the regenerator height. In the entrained catalyst zone the CO combustion is dominant (the amount of catalyst is diminished) and has an important role in heat generation. FCCU is operating in partial combustion mode. The regenerator model consists in mass balance equations for O_2, CO, CO_2 and coke, but also in heat balance equations for the solid and gaseous phases. These balance equations are correlated with equations describing entrained catalyst in the zone above dense bed (dependent on bed characteristics), catalyst flow and pressure in the regenerator.

For the catalyst flow in the spent and regenerated catalyst circulation lines it is assumed a steady state behavior. It is considered that dynamics of the lines is very fast compared to the time constants of other subsystems of the FCCU. Spent and regenerated catalyst circulation considers a single-phase flow, based on force balance.

The scope of the present work is to show the possibility of developing an ANN based model, able to be used for the model predictive control of the FCCU.

ANN Design

Artificial Neural Networks are founded on an idealized representation of the biological neuron. With its neurons grouped in layers and operating in parallel, the ANN behavior mainly depends on the weighted connection paths linking every two neurons from adjacent layers in such a way that the weighting structure is able to provide the overall network performance. The main benefits of the ANN approach consist in their remarkable ability for learning, generalization and robust behavior in the presence of noise. As a consequence, the ANNs may be successfully used for modeling systems in which detailed governing rules are unknown or are difficult to formalize by first principle (analytical) models.

The use of ANN models for control purposes has gained considerable attention in the field of chemical process control. They are increasingly used for system identification and controller design. The favorable opportunities offered by the ANN models consist in important savings of the computer resources. They have direct effect on the reduction of the on-line computation time for control-oriented applications, comparing with requirements of control systems based on analytical models.

The first step of the FCCU MPC system development was to build the ANN model. As an analytical model of the unit was available, it served as a rich database needed for the ANN training procedure. The analytical model parameters have been previously fitted to operating and constructive data taken from an existent industrial FCC unit. The controlled and manipulated variables have been selected having as main objective the efficient and safe operation of the unit. The selected control structure involves both reactor and regenerator variables, important for the overall dynamic behavior of the unit. In the presented study the controlled variables are the temperature of the regenerator bed and the catalyst inventory in the reactor-stripper, whereas the manipulated variables are the spent and regenerated catalyst slide valve positions (catalyst flow rates between the two units). For the control structure selection the Relative Gain Array has been also used.

The ANN has been designed such as the inputs of the network consist in the values of both controlled and manipulated variables at the four past sampling time moments: $t\text{-}\Delta t$, $t\text{-}2\Delta t$, $t\text{-}3\Delta t$ and $t\text{-}4\Delta t$, with the sampling time of $\Delta t=100\ s$. The outputs of the network (targets) are the values of the controlled variables at the next sampling time t, i.e. one step ahead prediction. This architecture of the ANN makes possible the prediction of the variables to be controlled based on the past values of manipulated and controlled variables. Applied repetitively, the ANN stands for an efficient dynamic model.

A double-layer feed-forward ANN with *tansig* and *purelin* activation function and using the back-propagation training algorithm has been used for computing the network biases and weights.[15] The input layer has *16* neurons, in the hidden layer *16* neurons have been used and the output layer consists in *2* neurons. The sixteen ANN inputs are: $T_{reg}(t\text{-}\Delta t)$, $T_{reg}(t\text{-}2\Delta t)$, $T_{reg}(t\text{-}3\Delta t)$, $T_{reg}(t\text{-}4\Delta t)$, $W_r(t\text{-}\Delta t)$, $W_r(t\text{-}2\Delta t)$, $W_r(t\text{-}3\Delta t)$, $W_r\ (t\text{-}4\Delta t)$, $svsc(t\text{-}\Delta t)$, $svsc(t\text{-}2\Delta t)$, $svsc(t\text{-}3\Delta t)$, $svsc(t\text{-}4\Delta t)$, $svrgc(t\text{-}\Delta t)$, $svrgc(t\text{-}2\Delta t)$, $svrgc(t\text{-}3\Delta t)$ and $svrgc\ (t\text{-}4\Delta t)$. The two ANN outputs are $T_{reg}(t)$ and $W_r(t)$. The number of nodes in the hidden layer has been set on the basis of a trial and error process. The quasi-Newton Levenberg-Marquardt algorithm was employed for training the ANN.[16] Overfitting has been avoided by early stopping. During the set of repeated sequence of training steps, random initial conditions have been used for the weights and biases in order to prevent convergence to undesired local minima. In order to improve the training procedure all input-output training data have been normalized using the maximum and minimum values of the input and output sets of data.

ANN Training and Testing

The entire set of input and output data has been divided into a set of data (input/target pairs) used for training the ANN and a smaller set subsequently used for testing the quality of the learning process. A set of 896 data has been presented to the ANN in order to carry out the learning procedure. The number of elements in the data set used for training has been chosen in correlation to the number of neurons in the hidden layer and covering the operating range of change of the input and output variables. Good training performance has been obtained as it is proved by the close to unity correlation coefficients between the targets and the ANN model response.

The testing set of 96 data, completely different of the training one and not yet seen by the ANN, preserves the same favorable adequacy between targets (desired) and ANN simulated outputs, demonstrating a very good generalization property of the designed and trained ANN. Results presenting the ANN model outputs versus the targets and the best linear fit are shown in fig. 2 and fig. 3, for the temperature of the regenerator bed and the catalyst inventory in the reactor-stripper.

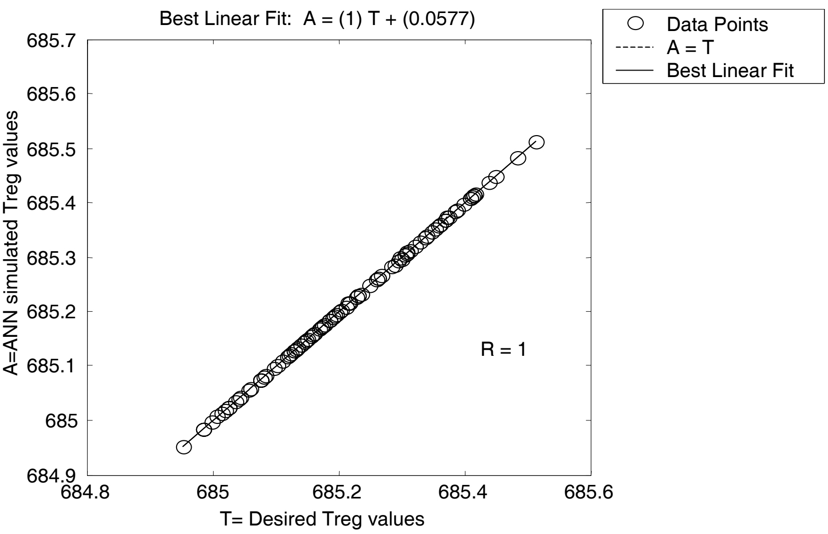

Fig. 2 – Results of the regression analysis between the ANN model response and the corresponding targets, for the temperature of the regenerator bed variable T_{reg} (testing set of data).

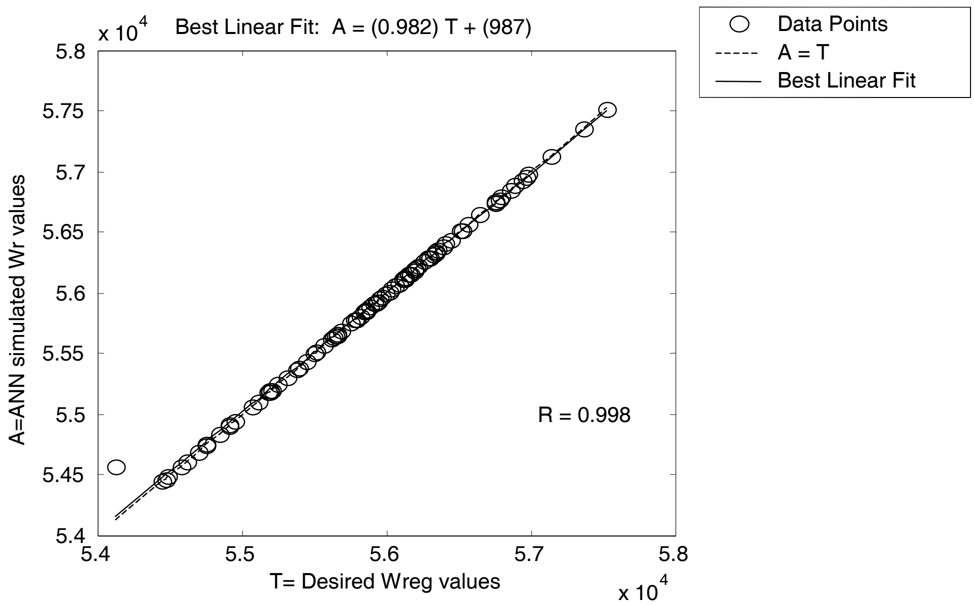

Fig. 3 – Results of the regression analysis between the ANN model response and the corresponding targets, for the catalyst inventory in the reactor variable W_r (testing set of data).

As a second, more comprehensive test, a random amplitude sequence has been generated for both considered input (manipulated) variables: spent and regenerated catalyst slide valve position, having random changes equally distributed in time at multiples of one thousand seconds. Figure 4 and Figure 5 present the dynamic simulation results of the FCCU analytical model, compared to the already trained ANN model, for the two considered output variables of interest: catalyst inventory in the reactor W_r and the regenerator temperature T_{reg}.

As shown in figures 4 and 5, it may be concluded that the developed ANN model has good dynamic performance. Able to capture the time evolution of the two considered FCCU output variables, the ANN model will be further considered for performing the MPC control. This approach has the incentives of being based only on measured process values and preventing error accumulation.

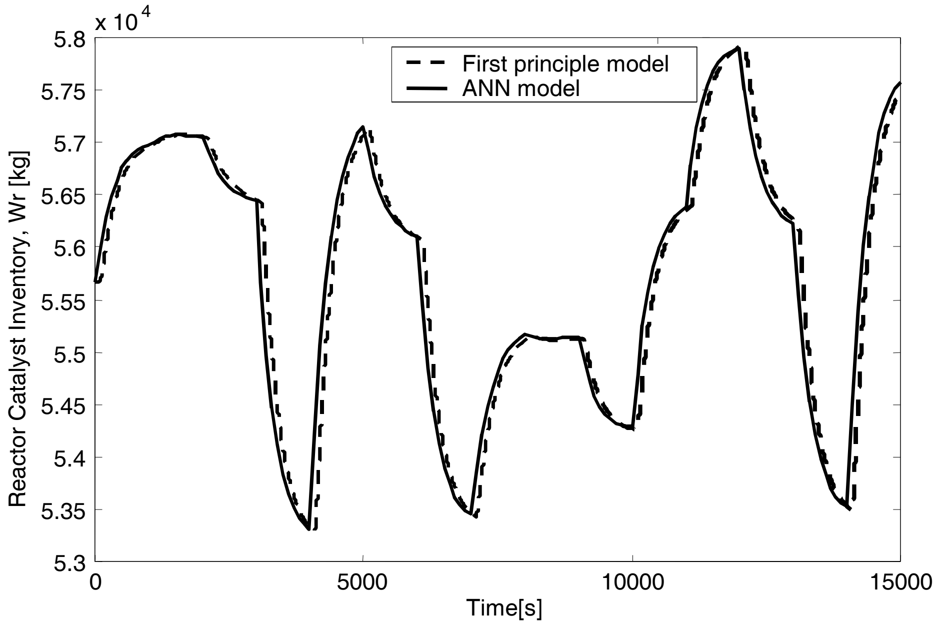

Fig. 4 – Comparative simulation results of ANN and first principle models, presenting the catalyst inventory simulated (target) variable, W_r.

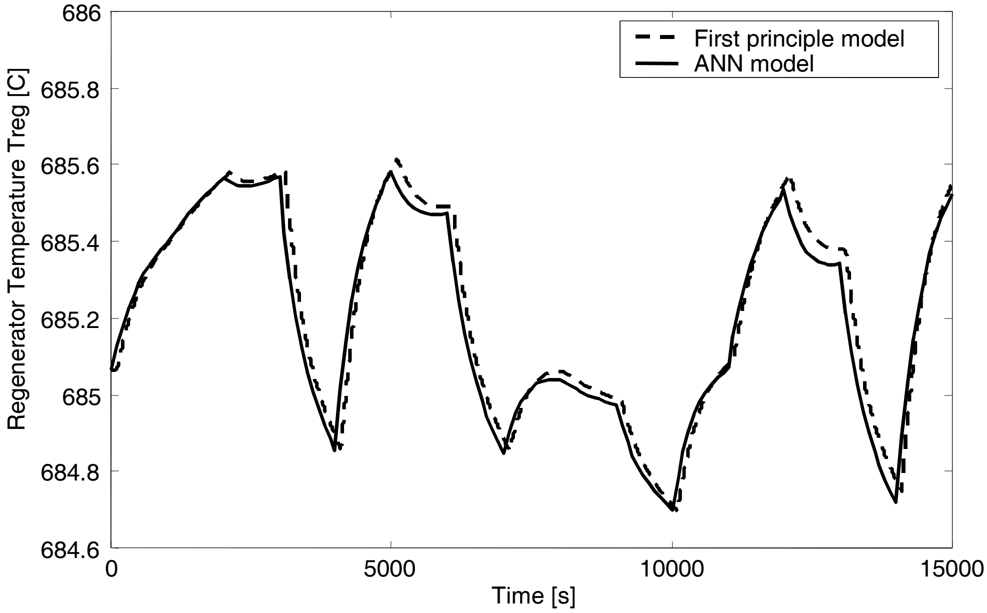

Fig. 5 – Comparative simulation results of ANN and first principle models, presenting the regenerator temperature simulated (target), T_{reg}.

The computation time for the dynamic simulation, using both analytical and ANN based models, has been measured and subsequently compared. It may be reported a reduction in the computation time of the ANN model compared to the analytical model, by a ratio of *1* to *9*. Model Predictive Control of FCCU can take advantage of this substantial computation time saving.

Model Predictive Control using the ANN model

A large part of processes in chemical engineering, as FCCU also does, present challenging control problems such as: nonlinear dynamic behavior, multivariable interactions between controlled variables, unmeasured state variables, unmeasured and frequent disturbances, high-order and distributed parameters, uncertain and (variable) dead-time on inputs and measurements. A distinct part of model based approaches and control algorithms have been developed to handle the aforementioned process characteristics and have spread out in the recent years.[17,18]

Model Predictive Control, also referred as moving (receding) horizon control, is an attractive control strategy especially for linear but also for nonlinear systems subject to input, state and output constraints. MPC is basically formulated as an open loop optimal control with finite horizons subject to the system dynamics and to input or state constraints. Based on the current time measurements and on the model of the process, the model predictive controller makes a prediction of the future behavior over an output prediction time horizon. The manipulated variable sequence (over an input horizon) is computed in order to minimize an objective performance function (usually, the square error between setpoint and prediction). Only the first value of the computed manipulated variable sequence is implemented up to the next time step when a new set of measurements becomes available. Prediction and optimization are repeated again for a new manipulated variable sequence computation, with input and output time horizons shifted one step into the future. It results a discrete feedback control with an implicit control law (for the general nonlinear case), and manipulated variables are calculated by solving the on-line optimization problem at each sampling time. The incentives of MPC algorithm, compared to traditional control algorithms, are associated to the need the process usually has for satisfying input, state or output constraints. These constraints put limitations on the achievable control performance, task that is systematically managed by the MPC optimization objective (with associated constraints), compared with the ad-hoc solutions frequently used in conventional PID control.

In order to prove the incentives of this ANN approach the MPC case of the two previously mentioned controlled variables, i.e. catalyst inventory in the reactor-stripper and temperature of the regenerator bed, has been investigated considering as manipulated variables the regenerated *svrgc* and spent *svsc* catalyst slide valve position.

The control performance of the MPC based on ANN model has been investigated in the presence of two representative disturbances. The considered disturbances have been chosen according to typical practice encountered cases. They consist in step changes for the intensity of catalyst coking, and for the reactor-main fractionator pressure drop ΔP_{frac}. The first considered disturbance is the step change of the intensity of catalyst coking (*3.2 %* step increase) and has been applied at time *t=500 s* from the beginning of the simulation. This type of disturbance simulates changes in properties of the feed oil residing in the increase of the amount of coke deposited on the catalyst. The second considered disturbance is the step change of the reactor-main fractionator pressure drop ΔP_{frac} (*+37%* step increase) and has been also selected to act at time *t=500 s*. This latter disturbance reveals the effect of upsets in main fractionator operation, acting on the reactor-regenerator system. Such main fractionator pressure upsets may appear when: vapor flow is changed as a result of suction flowrate change of wet gas compressor, internal liquid-vapor traffic of the main fractionator is changed due to reboiler, condenser load upset or by pressure changes induced from the downstream gas recovery unit.

The setpoint value of W_r= *55675 t* for catalyst inventory in the reactor stripper and the value of $T_{reg}=685.06^0$ *C* for regenerator bed temperature have been considered in the simulation. Simulation results, showing the two controlled variables, are presented in figures 6 and 7 for the case of the intensity of catalyst coking disturbance and in figures 8 and 9 for the ΔP_{frac} disturbance, both disturbances acting stepwise. The MPC tuning was performed by choosing the output and input weights based on the maximum allowable deviation of the corresponding variables, followed by a trial and error refining step.

The simulation results presented in figures 6 to 9 show good disturbance rejection capability of the ANN model based MPC. MPC brings the controlled variables at the desired setpoints with low overshoot and reduced settling time. This behavior is important for keeping the FCCU variables closed to the optimum operating point. When using the ANN model the real-time implementation of the MPC algorithm is supported by the important reduction of the computation time.

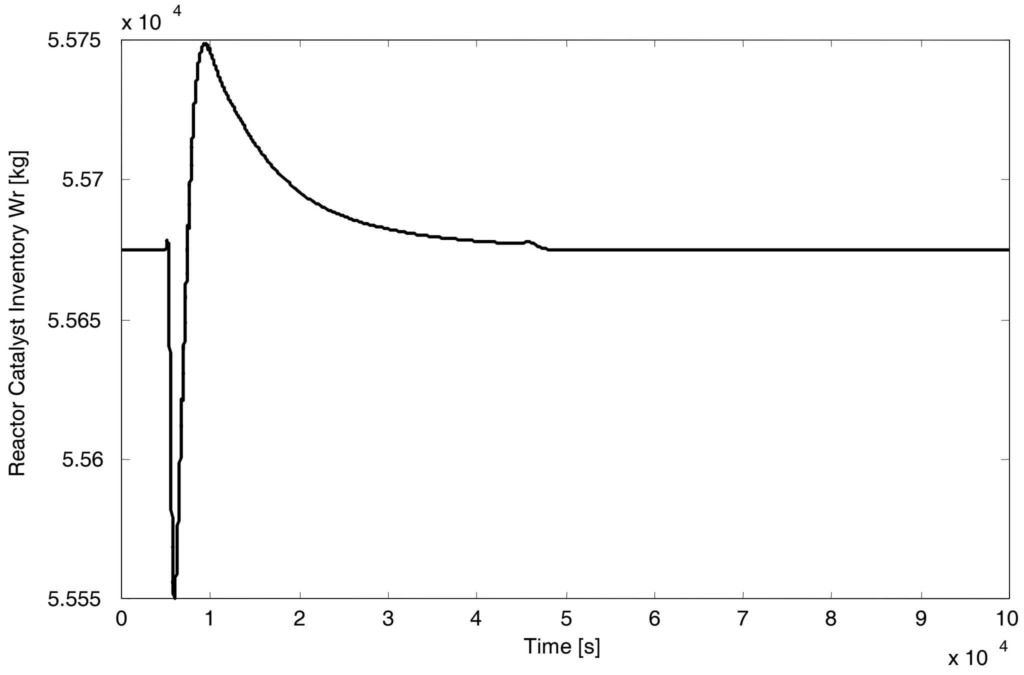

Fig. 6 – ANN based MPC of the catalyst inventory W_r in the reactor, in the presence of the intensity of catalyst coking disturbance.

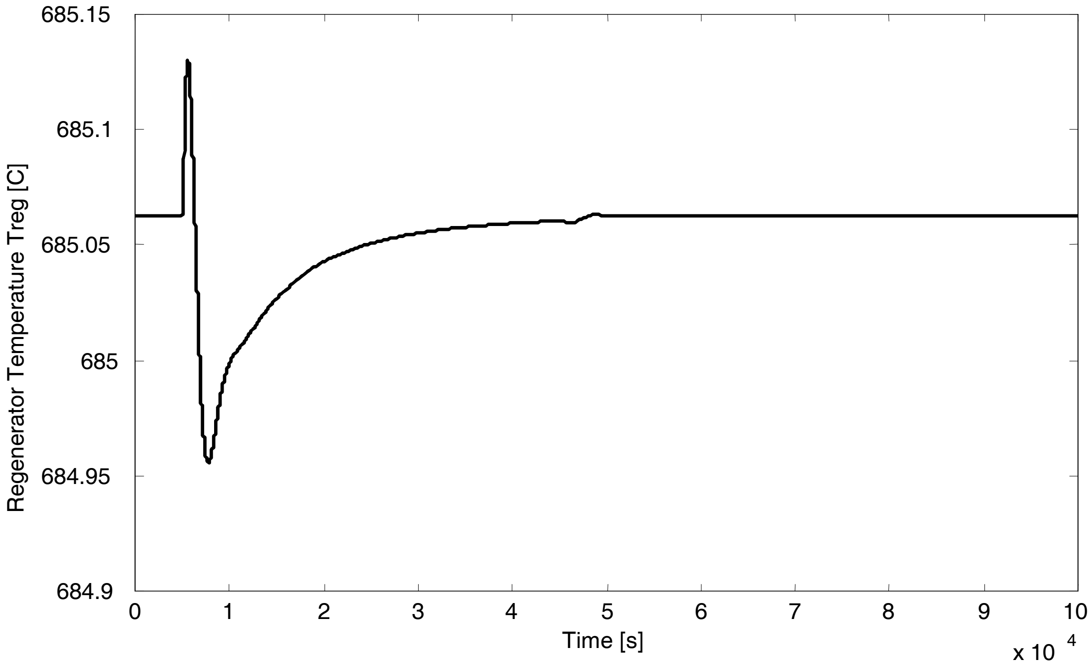

Fig. 7 – ANN based MPC of the regenerator temperature T_{reg} in the presence of the intensity of catalyst coking disturbance.

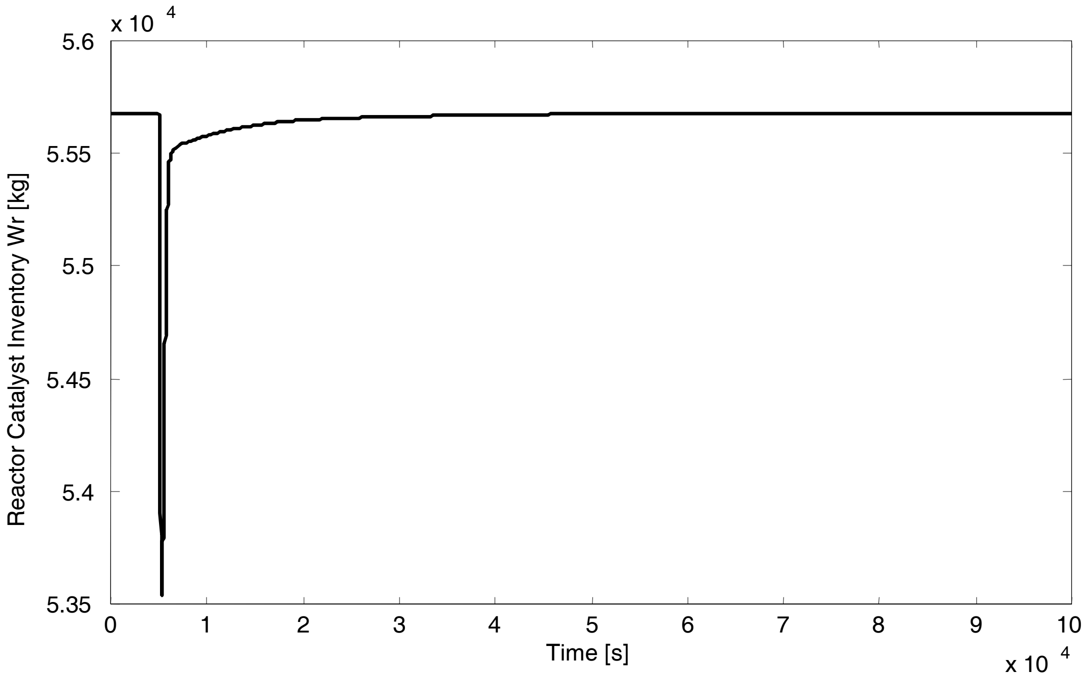

Fig. 8 – ANN based MPC of the catalyst inventory W_r in the reactor, in the presence of ΔP_{frac} disturbance.

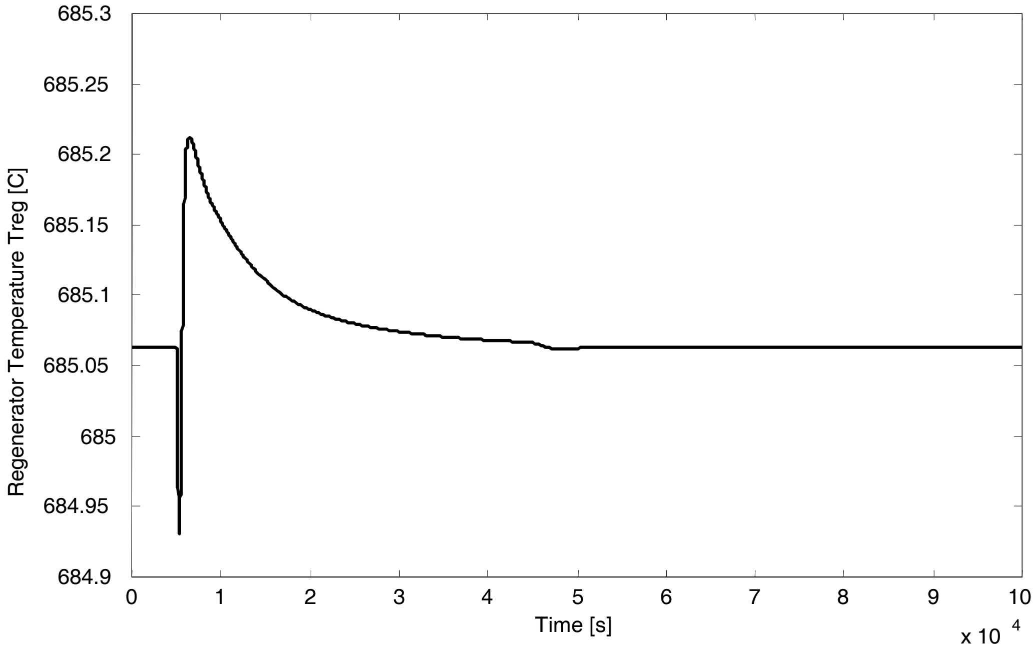

Fig. 9 – ANN based MPC of the regenerator temperature T_{reg} in the presence of ΔP_{frac} disturbance.

CONCLUSIONS

The present work first presents a successful approach for modeling the dynamic behavior of the FCC unit, using ANNs. An analytical model, validated with construction and operation data, has been used for producing a comprehensive input-target set of training data. The ANN architecture and training algorithm used by the ANN are efficient and this is proved by the results obtained during the testing steps performed both on sets of input-target data not met during the training procedure (close to unity correlation coefficients) and on the comparison between dynamic simulation results emerged from the ANN versus first principle modeling using randomly varying inputs. The reduction of the computation time is about one order of magnitude when the simulation is performed using the ANN model, compared to the use of the analytical model. The trained ANN model has been successfully used, as inherent model, for the MPC of two important FCCU variables. The efficiency of the ANN model based MPC control is sustained by the disturbance rejection ability. Both control performance requirements, setpoint tracking and disturbance rejection, are fulfilled and show short settling time, reduced overshoot and zero offset. Incentives of the ANN based control technique have several motivations. The first one is the possibility to embed in the ANN model the complex dynamic behavior of the FCCU intrinsic concurrent processes, alternatively described by first principle models based on simplifying assumptions. The second one is the robustness of the ANN model showing a good tolerance to the noise effect. The third one is the gain in reducing the computation effort having direct effect on the feasibility of the real time implementation. The presented results show the incentives and benefits for the industrial implementation of the MPC based on the ANN.

NOMENCLATURE

CSRT - Continuous Stirred Tank Reactor
FCCU - Fluid Catalytic Cracking Unit
F_3 - feed flowrate [kg/s]
F_4 - slurry recycle flowrate [kg/s]
LPG - Liquefied Petroleum Gas
MPC - Model Predictive Control
ANN - Artificial Neural Networks
svsc - spent catalyst slide valve position [0-1]
svrgc - regenerated catalyst slide valve position [0-1]
t - time (s)
T_{reg} - temperature of regenerator bed [°C]
UOP - Universal Oil Products
V_7 - position of the air vent valve [0-1]
V_{11} - position of the wet gas compressor suction valve [0-1]
V_{14} - position of the stack gas valve [0-1]
W_r - inventory of catalyst in the reactor-stripper [kg]

ΔP_{frac} - pressure drop across reactor-main fractionator [Pa]

Δt - sampling time [s]

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