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Nonlinear predictive control based on artificial neural network model for pilot reformer plant: Approach for ratio control

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The reformer box is an important operation unit in many refineries such as petrochemical, oil refineries and DRI (direct reduction of iron) production plants for producing syngas from different hydrocarbons. As the heart of a DRI production plant in MIDREX technology, it is very crucial to control the syngas composition in desired condition, especially hydrogen to carbon monoxide ratio which should be kept in a limited range of 1.6-2 to achieve the most proper reducing gas for converting the iron pellets to sponge iron with best percentage of carbon. In operation, this process package is difficult to handle from control stand point due to its nonlinear behavior, multivariable interaction and existence of constraints on its different reaction conditions. Neural network techniques have been increasingly used for a wide variety of applications where statistical methods have been traditionally employed. In this work we proposed a multi input multi output (MIMO) feed foreward neural network based multivariable control strategy to simultaneously control the inlet gas composition and reaction temperature, to control the outflow gas composition in desired condition. Modeling and controlling were investigated by use of data collected from a methane reforming pilot plant using CO_2 and steam, in process conditions near to those in a MIDREX reforming plant in sponge iron production. Different reaction temperatures from 700 to 1100 ˚C with different values of gases were randomly selected and used to generate around 5000 data sets of input- output data structure. Gas conversions and H_2/CO ratio were considered as the set points and tracking results of each showed the effective performance of the neural network- model predictive control (NN-MPC) strategy in this application.

Key words: Neural network, model predictive control, reformer, DRI plant

INTRODUCTION

Model predictive control (MPC) is now the most widely implemented advanced process for the control of technology. Control algorithms use an explicit process model to predict the future performance of a plant and the term “model predictive control” came from this definition. The most important section of MPC is choosing the model as it can simplify and accelerate the controller if selected properly. Although plants normally operate in a nonlinear manner, most of the MPC techniques implemented are based on linear models, which is mainly for their easier implementation, stability and general robustness in comparison to nonlinear ones which are relatively more complex. Generally, nonlinear modeling methods can be divided in two main groups: fundamental and empirical. The first group includes theorical and mathematical relations focused on mass, energy, momentum balance and kinetics of reactions. Such methods are very useful in case of availability of mechanistic information. These methods have been widely used in MPC for some processes that exhibit highly nonlinear behavior, as well as large operating regions, such as different reactors for oil and gas production [3-5]. The second one includes data from driven models which can relate the input- output data in a dynamic mode *via* black box estimators. One of these methods is the neural network, which has become an attractive tool in developing models for various types of complex non-linear systems [6,7]. A neural network-based predictive controller usually will be designed for non-linear systems with an iterative multilayer network prediction model in a predictive strategy. Moreover, addition of different constraints in MPC is a feature that makes this method prominent to other control strategies.

One of the process systems, which is full of nonlinearities, is the reformer package which converts hydrocarbons, mainly methane, to syngas using steam and carbon dioxide. The reaction takes place in a tubular reactor filled of mostly nickel alloy catalyst at around 900-1100 ˚C *via* an extremely endothermic reaction. Besides desired reactions, probability for occurrence of some undesirable reactions like production of coke will be high if the process parameters are not fixed at optimum, which can lead to formation of hot spot and rupture of reforming tubes [8]. One of the main controlling set points in reforming tubes is H_2/CO ratio in outflow gases which desired value varies with its application. For example, in DRI plant using MIDREX technology which is reviewed in this study, the ratio should be 1.5-2 in order to be most efficient in its usage.

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As some examples of NN-MPC applied in the literature, in the following some of recent studies are presented: Ruano *et al.* applied neural network based MPC for controlling HVAC system in order to maintain thermal comfort and simultaneously minimize the energy spent in both winter and summer time. Their report showed that their feasible and robust approach is able to achieve energy savings greater than 50%, under normal building occupation [9]. In another work done by Shi Li a NMPC was applied for an intensified continuous reactor working in high pressure and temperature conditions and designed to replace the traditional batch reactor for a hydrogenation process. The performances of nonlinear and linear MPC were compared with satisfactory performance for NMPC and failure of LMPC due to high nonlinearities of the process [10] was found. A parallel-structured model using NN (GNN) for incorporation into a general NMPC structure to an experimental distillation column control was proposed by Jing Ou. The experimental results demonstrated the effectiveness of the approach for a nonlinear process subject to a variety of constraints and environmental effects [11]. Paisan *et al.* used a multi-layer feed forward neural network model based predictive control scheme for a multivariable nonlinear steel pickling process. The results of this study were reported as better performance in the control of the system over the conventional PI controller in all cases [12]. In another paper, a nonlinear predictive control strategy was developed and applied to an industrial crystallization process simulator by Damour *et al.* The control scheme comprised an artificial neural network predictive controller and a more suitable manipulated variable. Simulation results showed the efficiency of the proposed control strategy to improve the process control [13].

The motivation behind this paper was also training an NN-predictive control network for setting the conversions and the outflow gas ratios specially hydrogen and carbon monoxide. The neural network was trained by use of around 5000 input-output samples extracted from a reformer pilot plant in randomly sufficient numbers to cover the whole operating range. 6 inputs were CH_4, CO, CO_2, H_2O and H_2 volumetric flowrate and reaction temperature and 5 output parameter were for gas compositions. All the implementations for ANN and MPC were done in MATLAB/SIMULINK environment. After the network was designed and trained the controller performance was investigated in terms of set point tracking and system forward movement and its arrangement to provide the required changes.

METHODOLOGY

Data generation

A pilot plant was built specifically to evaluate experimental data gathering of methane reforming with steam and carbon dioxide. The basic design of this pilot plant was scaled down from an industrial unit of DRI production using MIDREX technology. It essentially consists of a tubular reactor with 2” diameter and 2 m height, filled with three levels of catalysts (inert, semi-active and active) with different percentage of nickel oxide. The reactor was fixed in a cubic electrical heater designed to reach to 1400 ˚C with three heating zones. Five temperature sensors (TT) were implemented on inlet, outlet and three sections of heater to accurately control the reaction temperature. Five mass flow controllers (Alicat- MCR) for gas cylinder lines and one vortex flow meter (Yokogawa-DY015) on the steam line were used to accurately control the reactant flow rates. The plant is schematically shown in Figure 1.

Methane, steam, carbon dioxide, carbon monoxide, hydrogen and nitrogen were mixed and preheated up to around 500 ˚C through electrical heaters, and then the mixture flowed to the reactor on three levels of catalysts. The reaction occured at 900-1100 ˚C and produced syngas was then cooled *via* a water condenser and was subjected to composition analysis through online gas chromatography. The typical reaction conditions, and catalyst properties used in MIDREX plant used in operation of the pilot are listed in table 1.

Application of artificial neural network

One of the main features of the neural network is parallel processing of databank for capturing the dynamics of a complex and multivariable system. In case of enough and informative dataset in hand, a good network of neurons, layers and connections in its various types, like multilayer perceptron, radial basis function, recurrent neural network, etc., can predict the behavior of an unknown system and consequently can keep the system optimized and in desired position when used in a predictive control strategy. In this study, a multilayer perceptron feed forward neural network with back-propagation algorithms was used to predict the reformer behavior and syngas produced.

The model had 6 inputs, 4 hidden layers with 5 neurons in each one and 5 neurons in the output layer. The considered learning rule and training function are Levenberg Marquardt (LM) and trainlm, respectively.

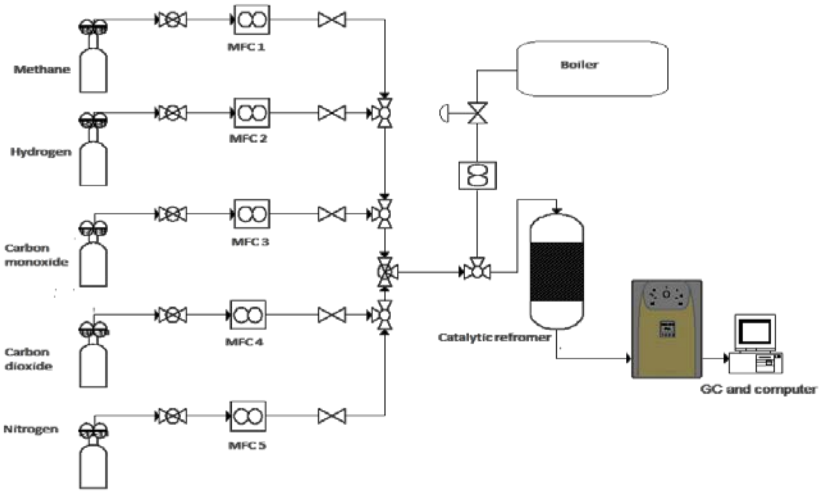

Fig. 1. Schematic diagram of the experimental system

Table 1. Reaction conditions in a MIDREX reformer

Catalyst parameters			
Type	Particle size (mm)	Porosity	Sphericity
Raschig ring	16×6×1	0.52	0.656
Tortuosity	Loose density(kg/m^3)	Bed density (kg/m^3)	
2.74	2390	1362	
Reaction conditions			
Pressure (bar)	Temperature (˚C)	CO_2 %	CO%
2	900-1100	15.21	17.4
H_2 %	H_2O %	N_2 %	CH_4 %
31.09	13.94	1.5-2	19.73

The algorithm is an iterative technique that locates the minimum of a function that is expressed as the sum of squares of non-linear functions [8]. A number of 3461 data were utilized during training session and 742 data were used for testing the structure. Among structures and configurations tested, four hidden layers predicted the best and nearest results to the actual ones. The log sigmoid function was employed as an activation function and 872 numbers of epochs considered to overcome over and under fitting of data. The prediction error between the plant and network outputs was used as the training signal. So NN plant model which uses plant inputs and outputs in its history to predict future values of the plant output will be used in the NN-based model predictive controller and will calculate the predicted control input that will optimize plant performance over a specified future time horizon. The NN-MPC structure is shown in Fig. 2. As depicted, the structure is composed of two neural networks, one which mimics the plant behavior (yellow block) and the other the model in MPC controller. For a desired time horizon, the controller will optimize the plant output using the neural network plant model for calculating controller moves and predicting plant output. Neural network controller was trained in order to produce the correct controller moves generated by the optimization algorithm [14].

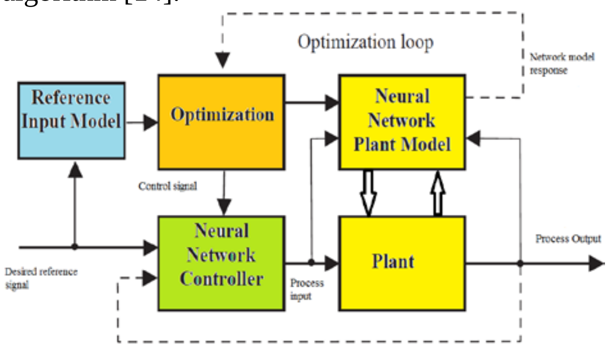

Fig 2. NN-MPC basic structure

RESULTS AND DISCUSSION

ANN model with the above description was developed with the aim of estimation of the output parameters for the catalytic reformer, from input parameters. Around 70 % of the datasets were used for training of the neural network. The performance indicators related to the train, test and validation of the ANN model including the R^2 and MSE are listed in Table 2.

Table 2. Performance of the developed ANN network

	No. of data	MSE	R^2
Train	3461	7.19e^{-5}	9.99e^{-1}
Validation	742	1.83e^{-4}	9.97e^{-1}
Test	742	5.43e^{-5}	9.99e^{-1}

A comparison between the real experimental and predicted data separately is presented in Figures 3, 4, 5, 6, and 7 for CH_4, CO, CO_2, H_2 and H_2O, respectively.

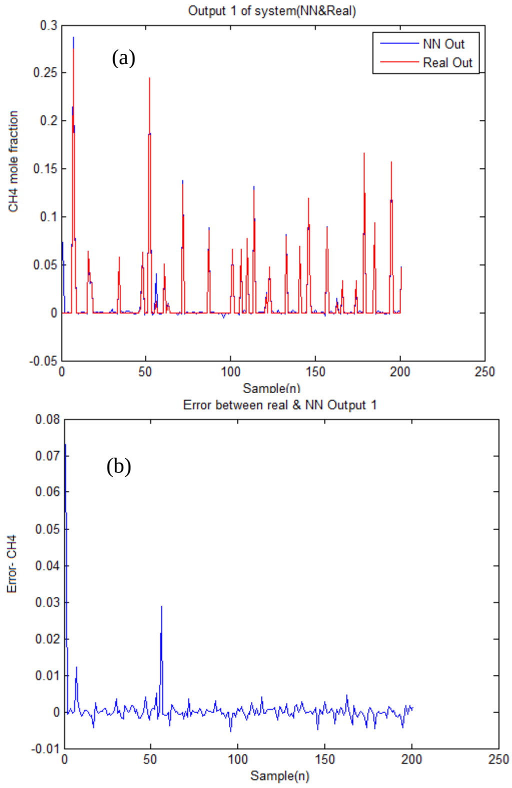

Fig. 3: (a) Comparison of model output and real data (b) and related Error for outlet CH_4 composition

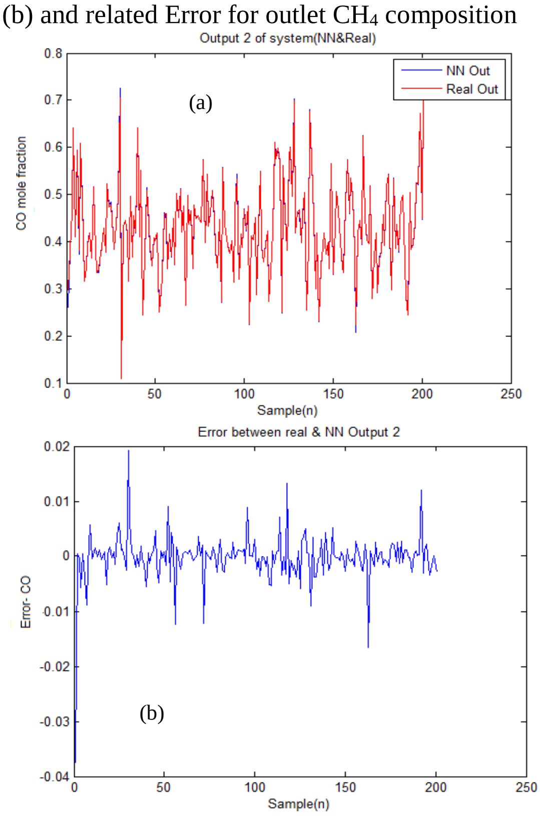

Fig. 4. (a) Comparison of model output and real data (b) and related error for outlet CO composition

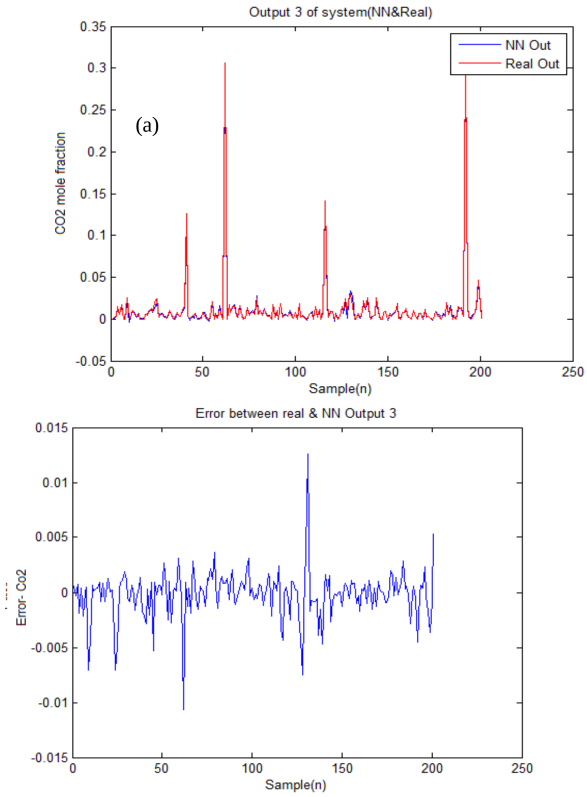

Fig. 5. (a) Comparison of model output and real data (b) and related error for outlet CO_2 composition

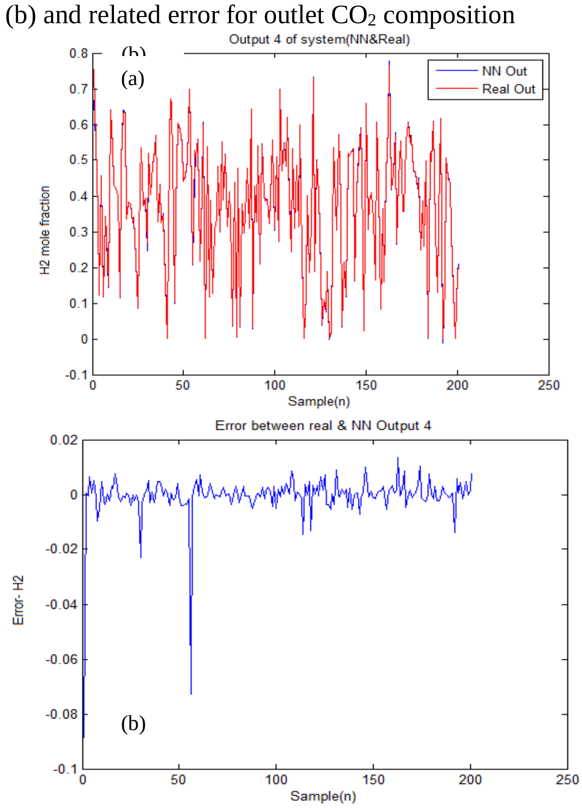

Fig. 6: (a) Comparison of model output and real data (b) and related error for outlet H_2 composition

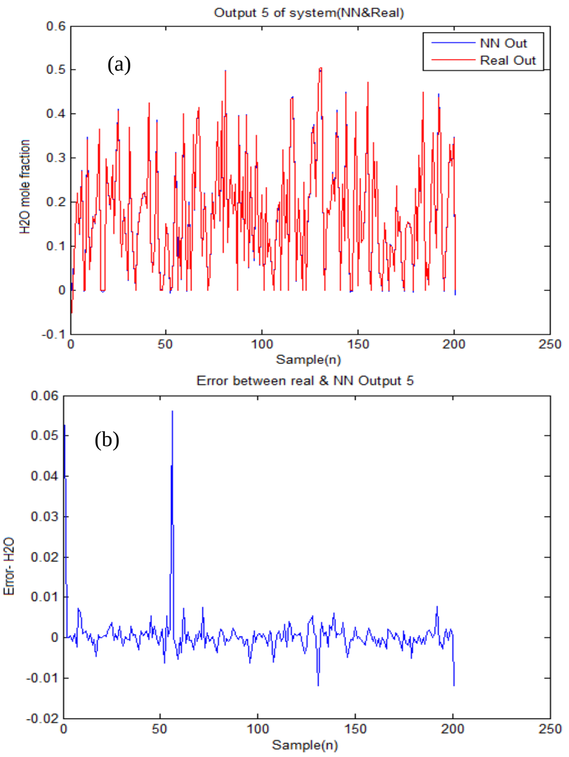

Fig. 7: (a) Comparison of model output and real data (b) and related error for outlet H_2O composition

As can be seen, there is excellent agreement between the predicted results by ANN and the real datasets from experimental setup, it is so obvious that the neural network fits and follows the real data diagram in a consistent way.

Also the error plot, as can be defined the difference between the modeled and real experimental data shows the deviation more clearly, however there are some steep differences in some data which can be due to some outlying experimental data, all of them are in an acceptable range. It should be noted that in order to have a clearer plot, 200 sets of data are used in each graph which can be generalized to all datasets.

General mechanistic model mentioned in section 2, was coded in MATLAB/SIMULINK environment. The system was composed of 6 input variables (CH_4, CO, CO_2, H_2O, H_2 volumetric flow rate, and reaction temperature) and 5 output variables (outflow composition of each above gases). The schematic views of structured neural network MPC in Simulink is shown in Fig. 8.

There are two main blocks, as system NN model, which is the plant model and MPC control which includes NN controller and optimizer. One of the MPC strategies in this study was to use the gas conversions as the measured variable while the flowrate of the inlet gas and temperature was the manipulated variable. The predictive controller was implemented using prediction horizon of 4 and control horizon of 3.

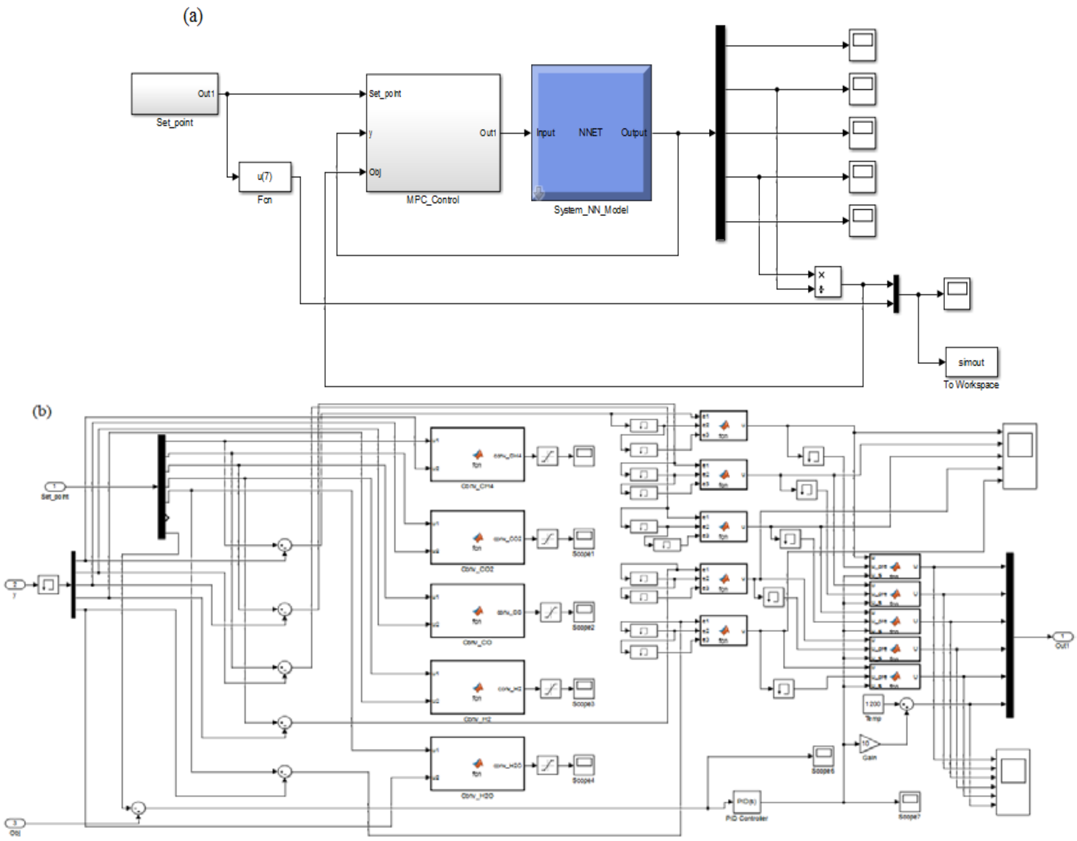

Fig. 8 (a) General view of the NNMPC structure; (b) Detailed structure of the MPC controller

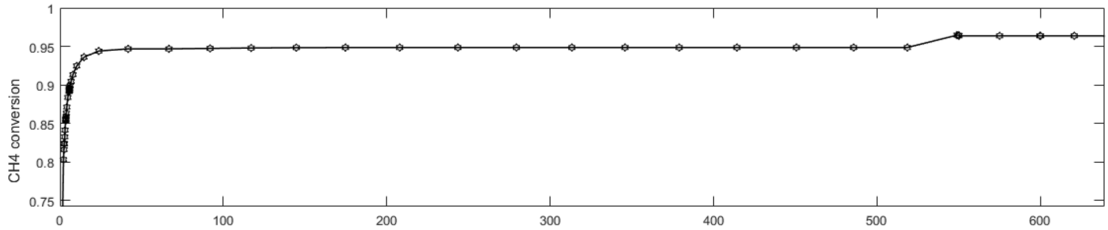

Fig. 9. Control output-CH_4 conversion

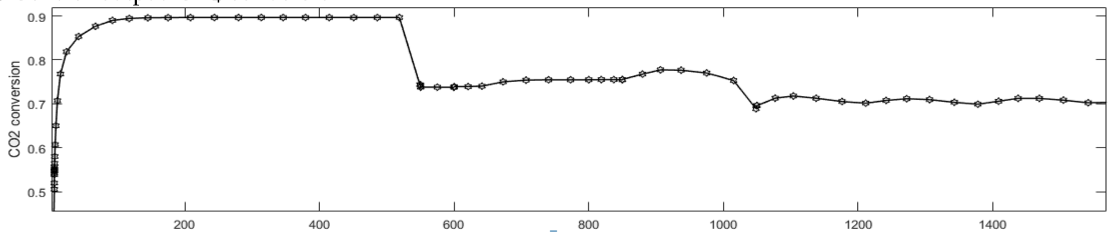

Fig. 10. Control output-CO_2 conversion

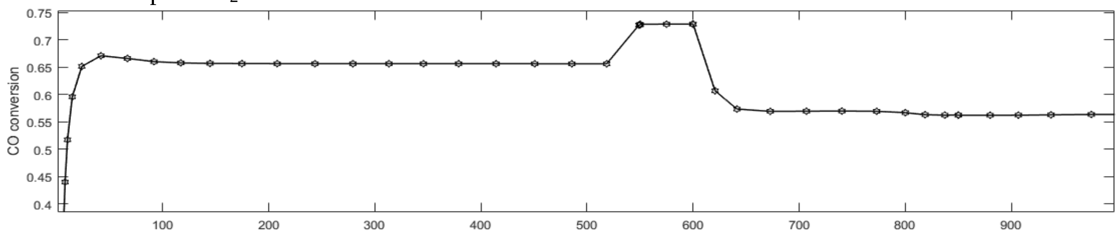

Fig. 11. Control output-CO conversion

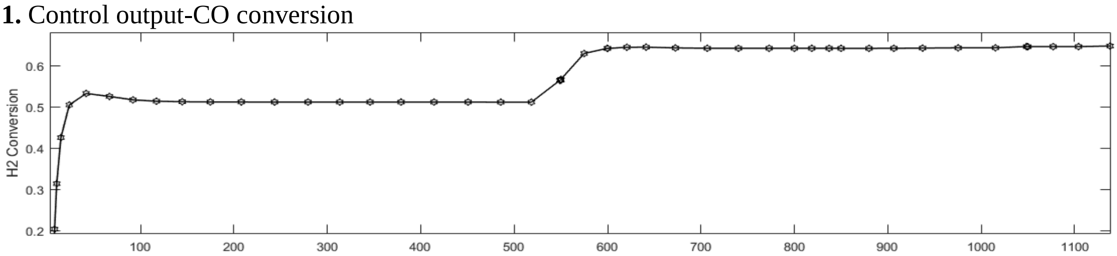

Fig. 12. Control output-H_2 conversion

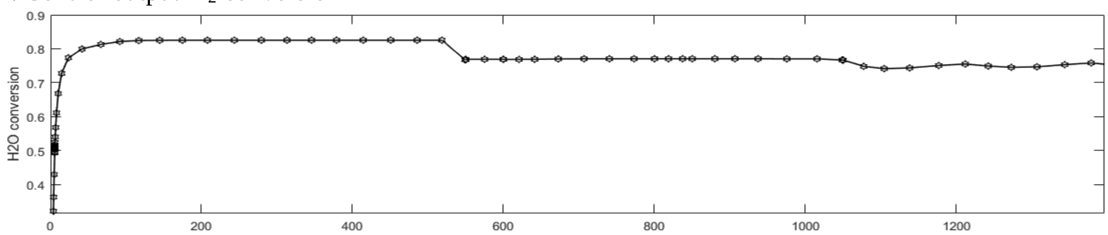

Fig. 13. Control output-H_2O conversion

Figure 9 shows the methane conversion obtained when the reference set point was 0.94. The process was observed to overshoot before attaining steady state after about 20 sec.

Figures 10, 11, 12 and 13 depict the conversion of CO, CO_2, H_2 and H_2O, respectively. As it can be seen in each of the graphs, the system has got its stability after around 20 sec at the optimum desired conversion.

As the other MPC strategy used in this study, was the H_2/CO ratio which as mentioned above should be between 1.5- 2.

By considering this range as our set point and also by manipulating this value, the inputs arrangement were change to produce required control signal.

Figure 14 shows the control object change bychanging in desired ratio from 1.6 to 1.8 and 2. It can be seen in figures 15 (a-e) that in order to track the reference signal how each input variable would change. The performance obtained with the neural network plant model in the predictive control scheme was indeed

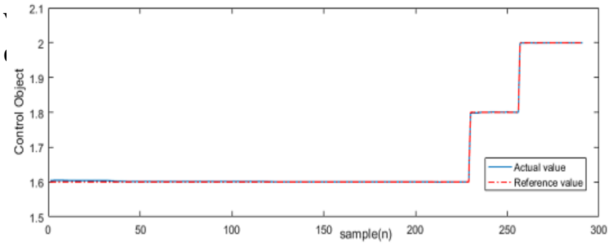

Fig. 14 Set point tracking diagram

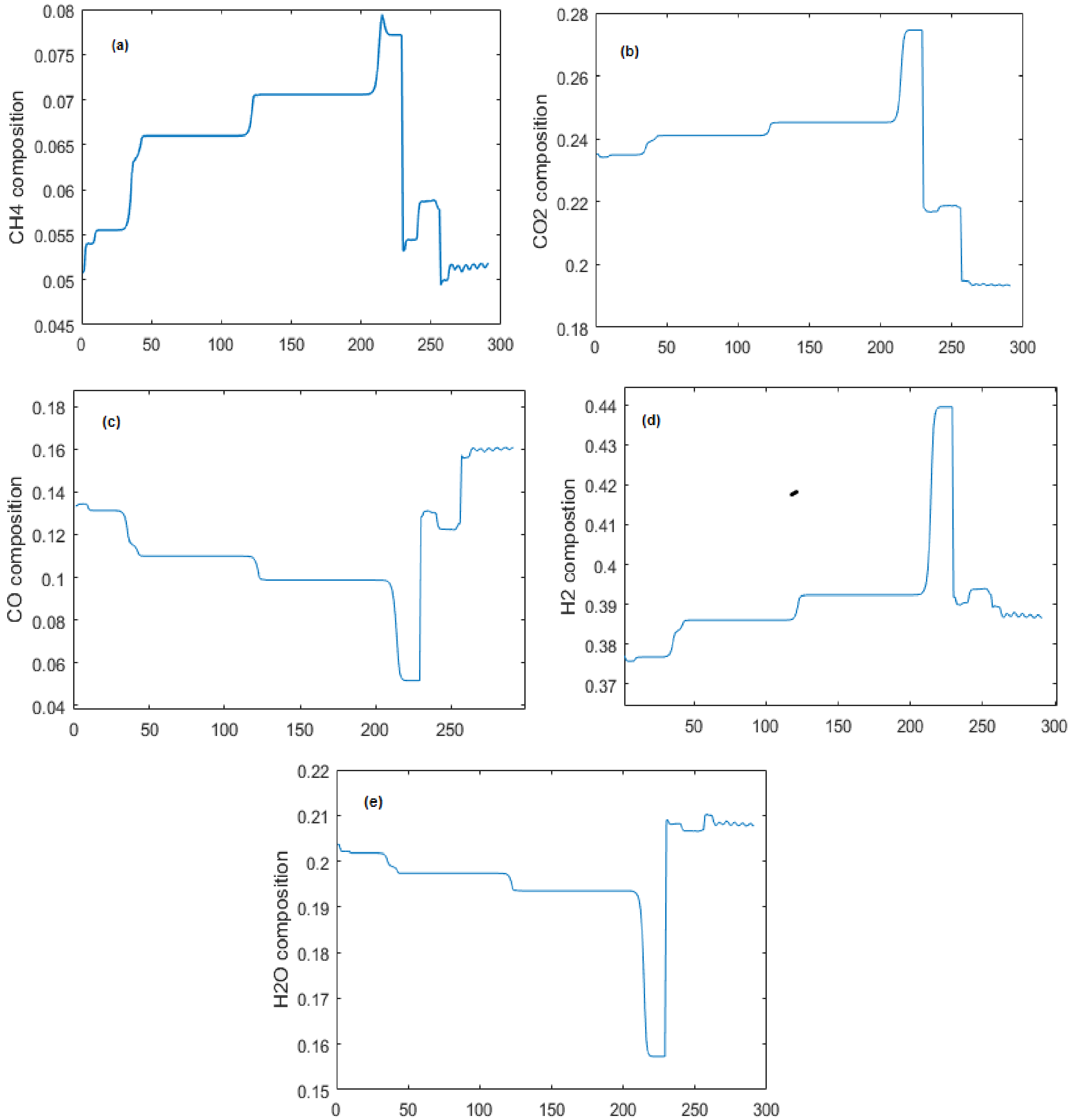

Fig.15. Gas composition arrangement with changing the set point (a) CH_4 (b) CO_2 (c) CO (d) H_2 (e) H_2O

CONCLUSION

An optimal neural network based on predictive control of constrained nonlinear systems was studied. The neural network controller was designed by minimizing an MPC type cost function off-line for a set of training data got from a reformer pilot plant. The neural network designed as plant model predicted the plant behavior with a very good accuracy. Implementation of the NN-MPC controller for the set point tracking case revealed that this controller was able to force process output variables follow their target values smoothly and with a good and logical margin.

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НЕЛИНЕЕН ПРЕДСКАЗВАЩ КОНТРОЛ НА ОСНОВАТА НА ИЗКУСТВЕН МОДЕЛ НА НЕВРОННА МРЕЖА ЗА ПИЛОТНА УСТАНОВКА: ПОДХОД ЗА КОНТРОЛ НА СЪОТНОШЕНИЯТА

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(Резюме)

Реформерът е важна операционна единица в много рафинерии, например, за нефт и масло, както и в заводи за директна редукция на желязо, за производство на синтетичен газ от различни въглеводороди. Като централна част от завод за директна редукция на желязо чрез MIDREX технология, е много важно да се контролира съставът на синтетичния газ в желани съотношения, особено съотношението водород:въглерод, което трябва да е в интервала от 1.6-2 за да се получи най-подходящият редуциращ газ за конвертиране на железните пелети в гъбесто желязо с най-добро процентно съдържание на въглерод. Този процес се управлява трудно поради нелинейното отнасяне, многостранното взаимодействие и наличието на ограничения върху реакционните условия. Техниките на невралните мрежи се използват все повече за голям брой приложения, където традиционно се използват статистически методи. В настоящата статия се предлага неврална мрежа с много входове и изходи за многостранен едновременен контрол на състава на входящия газ, реакционната температура и състава на изходящия газ. Моделирането и контролът са изследвани върху база данни, събрани от пилотна установка за реформинг на метан с използване на CO_2 и пара при условия близки до тези в MIDREX реформинг завод за производство на гъбесто желязо. Реакционни температури от 700 до 1100 ˚C с различни произволно избрани стойности на газовете са използвани за генериране на структура от около 5000 набора от входящи-изходящи данни. Конверсията на газа и съотношението H_2/CO са зададени параметри и резултатите от проследяването им показват ефективността на модела за предсказващ контрол с използване на неврални мрежи.