



Modelling of Temperature and Syngas Composition in a Fixed Bed Biomass Gasifier using Nonlinear Autoregressive Networks

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ABSTRACT

To improve biomass gasification efficiency through process control, a lot of attention had been given to development of models that can predict process parameters in real time and changing operating conditions. The paper analyses the potential of a nonlinear autoregressive exogenous model to predict syngas temperature and composition during plant operation with variable operating conditions. The model has been designed and trained based on measurement data containing fuel and air flow rates, from a 75 kW_{th} fixed bed gasification plant at Technical University Dresden. Process performance changes were observed between two sets of measurements conducted in 2006 and 2013. The effect of process performance changes on the syngas temperature was predicted with prediction error under 10% without changing the model structure. It was concluded that the model could be used for short term predictions (up to 5 minutes) of syngas temperature and composition as it strongly depends on current process measurements for future predictions. For long term predictions other types of dynamic neural networks are more applicable.

KEYWORDS

Biomass gasification, Fixed bed reactor, Gasification modelling, Neural networks, Nonlinear autoregressive network with exogenous models.

INTRODUCTION

Biomass gasification is a promising technology for efficient, clean and diverse utilisation of biomass and biomass residues through production of syngas. The process of biomass gasification is a high-temperature partial oxidation process in which a solid carbon based feedstock is converted using gasification agents into what is called ‘raw syngas’ – a gaseous mixture (hydrogen, carbon monoxide, carbon dioxide, methane, light

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hydrocarbons), tar, char, ash and minor contaminants [1]. Due to the decentralized utilization of biomass, small and middle-scale biomass gasification plants for separate or combined heat and power generation [2] and trigeneration [3] have potential to become rational, efficient and economically viable way of energy conversion and power generation [4] even without governmental subsidies [5]. Syngas can be also used for hydrogen production through various available thermal processes [6], methanol synthesis [7] and for other applications [8]. Besides chemical production, biomass gasification residues could also be utilised as constituents for building material [9]. A more detailed overview of biomass gasification technologies could be found in the research done by Kirkels and Verbong [10]. Although gasification is a relatively well known technology, the share of gasification in overall energy demand is small due to current barriers concerning high investment costs, biomass pre-treatment, gas cleaning, process efficiency and syngas quality control issues [11]. Overview of process utilisation potential and process advantages (renewable generation of hydrogen and fuel flexibility) and disadvantages (low process efficiency and tar formation) can be found in a review paper written by Sikarwar *et al.* [12].

Biomass gasification is a complex thermochemical process whose performance is influenced by a large number of operational parameters. The most important ones are biomass quality (particle size, shape, chemical composition and moisture content), fuel and air flow rate, particle reaction/residence time and the type of a gasification agent [13]. Different gasifier designs will affect particle residence time and the heat exchange in the reactor. For example, fluidised bed reactors have a relatively short particle residence time where heat exchange between fuel particles and surrounding air is quite strong due to fast particle movement. Contrary to this, in fixed bed gasifiers, particle residence time is quite long and the heat exchange is relatively slow as the particles are moving very slowly through the reactor. Furthermore, gasification operating conditions have tendency to change during a long term facility operation due to ash sintering, agglomeration and deposition on reactor walls which could cause bed sintering and defluidisation [14].

To improve process efficiency or to guarantee constant process quality during operation, plant operation simulation models are needed. Those models can be used to explain, predict or simulate process behaviour and to analyse effects of different process variables on process performance in a fast and a safe way. Most of the available models for biomass gasification are based on equilibrium models for Gibbs free energy minimisation [15], Computational Fluid Dynamics (CFD) analysis [16], kinetic reactions modelling [17] or Artificial Neural Network (ANN) [18] principle. Detailed review of available models for biomass gasification process can be found in the research done by Baruah and Baruah [19]. Most of the available models are used to describe process equilibrium while taking into consideration well defined (or assumed) operating conditions. Progressive fuel quality change and bed sintering is often ignored. Therefore, they are not suitable to describe the process when operation parameters change and/or when they are not well defined. Furthermore, reactor dependable process mass and energy accumulation impose the need for a model that will take a large number of thermo-chemical interactions into account together with mass and energy accumulation while preserving high prediction speed. One of the ways to describe the process with a large number of uncertainties is by using machine learning techniques. ANN models that use a non-physical modelling approach which correlates the input and output data are universal function approximator that has ability to approximate any continuous function to an arbitrary precision even without prior knowledge on structure of the function that is approximated [20]. One of the many applications of ANN models includes estimation of solar duration [21] and irradiation [22] and estimation of wind resources for renewable energy production [23].

To describe the process of biomass gasification in changing operating conditions Mikulandric *et al.* [24] used a dynamic ANN which had to be retrained continuously to provide good prediction quality. In order to define such a model and to define the level of mass and energy accumulation, they took into account a prior knowledge regarding the process where important model input parameters were already defined. Accumulation of mass and energy has been defined through averaging fuel and air flow rate, and particle residence time has been included through fuel feeding frequency calculations. Therefore, to implement such a model into existing control system some engineering experience regarding particular process behaviour is needed. Furthermore, the model has a limited memory of previous syngas temperatures (used as model input) which could influence the prediction quality. It was hypothesized that neural networks that contain a larger amount of feedback variables (history of predicted variable as model input) could provide better prediction results.

Dynamic type of neural networks, like Nonlinear Autoregressive Network with Exogenous inputs (NARX) can be a useful tool to describe process dynamics of nonlinear chaotic systems [25]. NARX is a recurrent dynamic neural network, with feedback connections enclosing several layers of the network. NARX model is based on the linear autoregressive network with exogenous model, which is commonly used in time-series modelling. In these models, model outputs depend not only on their inputs but also on their previous values and previous values of outputs. In this way mass and energy accumulation could be described. In comparison with static (feedforward) networks (like standard ANN's) dynamic neural networks (like NARX) have feedback elements and contain parameter delays. In this way process mass and energy accumulations and particle residence time could be described. With static networks the output is calculated directly from the input through feedforward connections. One of the major drawbacks of dynamic neural networks (including NARX models) is that the modeller cannot identify the most important parameters that influence prediction performance, process dynamics and consequently process performance in general. The influence of different process parameters is defined through a complex interaction between model inputs, their delays and delays of output variable. For example, the influence of particle residence time on process behaviour cannot be clearly defined because it is already taken into consideration through delays of fuel flow rate. Similar observation can be made for syngas temperature prediction (as an output variable) where temperature derivatives are already incorporated into model structure through delays of model output. Due to the mentioned reasons, application of such models for process control purposes should be carefully analysed.

In the recent research done by Asgari *et al.* [26] NARX based models have been used to model gas outlet temperature dynamics during start-up of a single-shaft gas turbine using 6 different time series data sets (3 for modelling and 3 for model validation). The maximum prediction error of gas outlet temperature was 7.4%. For modelling of biomass gasification in fluidised bed reactors, NARX models were used to predict syngas temperature, flow rate and pressure in a 200 kW_{th} sorption enhanced reforming steam gasification plant [27]. NARX models seem to be a promising approach to describe non-linear systems with significant delays where accumulation of mass and energy is considered. However, their application potential for fixed bed reactors (where mass and energy accumulation is expected to be even higher) is yet to be analysed.

In this paper, a NARX model will be developed to predict syngas temperature and content of hydrogen (H₂), carbon monoxide (CO) and methane (CH₄) in a 75 kW_{th} fixed bed gasifier, operated by TU Dresden. A similar approach has been used in Salah *et al.* [27] but for fluidised bed gasifiers which usually operate at higher pressures and where process changes are much faster. Compared to the dynamic neural network model and the research done in Mikulandric *et al.* [24] the model should be able to predict syngas temperature based on raw measured data of fuel and air flow rates and without any prior

knowledge of process dynamics. It should also be able to predict process parameters under changeable operating conditions that will not be explicitly defined while keeping prediction speed appropriate for implementation in an on-line control system. Prediction quality will be quantified by coefficient of determination (R^2) and Average Prediction Error (APE). The simulation performance of NARX model will be compared with simulation results of dynamic model from Mikulandrić *et al.* [24] and standard neural-network model from Mikulandrić *et al.* [18] as they were developed by using the same set of measured data. This will give indicators which of the neural-network based models has the best performance for short and long-term process predictions of biomass gasification in fixed bed reactors.

MATERIALS AND METHODS

Development and training of NARX networks consist of 2 steps, namely, an open loop NARX model training and closed loop NARX model training. In an open loop NARX model training, a feedforward multilayer neural network is trained using backpropagation algorithms to define main structure of neural network. Afterwards, in a closed loop, NARX model training model outputs are estimated on current and previous inputs together with previously estimated outputs (making a closed loop) [27]. A detailed explanation of NARX structure can be found in Chen and Billings [28]. In order to be trained, measurement data that represent model input and output should be collected. As the goal of this research is to analyse potential of NARX models to describe process delays (resulting from mass and energy accumulation) without any prior knowledge about the process, only raw measurement data will be used.

Gasification plant and operating conditions for model training

The object of the modelling is a co-current fixed bed gasifier with thermal input of 75 kW_{th}, located in Pirna (Germany), operated by TU Dresden. Two sets of experiments (experiments 1-4 from 2006 and experiments 5-9 from 2013) were performed to analyse the process behaviour and to develop the model. Experiments were performed to measure following process parameters that will be further used for modelling purpose: biomass mass flow rate (m_b), air volume flow rate (m_{air}), syngas temperature at the exit of the gasifier, syngas composition, pressure in the reactor and temperature of inlet air. All the data was recorded on a 30 seconds base. The length of an experiment depends on gasifier initial conditions. For example, if the reactor was pre-heated due to previous utilization and the initial temperature in the reactor was relatively high (experiment 4) the time to reach stationary syngas production regime was much shorter, compared to experiment 1 where this was not the case. The goal of the experiments was to have a stable syngas production for approximately 3 hours in which the syngas composition was measured. The measurement of syngas composition started when the outlet syngas temperature was above or around 250 °C.

Biomass wood chips, distributed from a local provider, are used as fuel in the gasification process. Biomass composition has been determined by means of ultimate fuel analysis on wet basis for experiments 1-4 at TU Dresden laboratory before the start of operation and considered as constant during operation. The lower heat value of the biomass is 17.473 MJ/kg, carbon content is 47.40%, hydrogen content is 5.63%, moisture content is 7.87%, ash content is 0.55% and the content of chlorine is 0.01%. Biomass composition for the experiments 5-8 has not been determined before the start of experiments. Biomass is first fed manually in a small storage room, located in front of the valves for biomass feeding control. When the gasification bed height goes under a certain threshold (set by the control system) an alarm is activated and the operator can manually open the valves. Once the valve opens, the whole amount of biomass from the storage

room is fed into biomass shredder. The biomass is shredded and fed into gasification reactor. Air flow rate for gasification is controlled manually by setting the air valves opening and distributed by air pumps. Ash removal is also controlled manually by opening the ash valves. The facility scheme is presented in Figure 1. The list of sensors and other details regarding plant design and operation can be found in Mikulandric *et al.* [24].

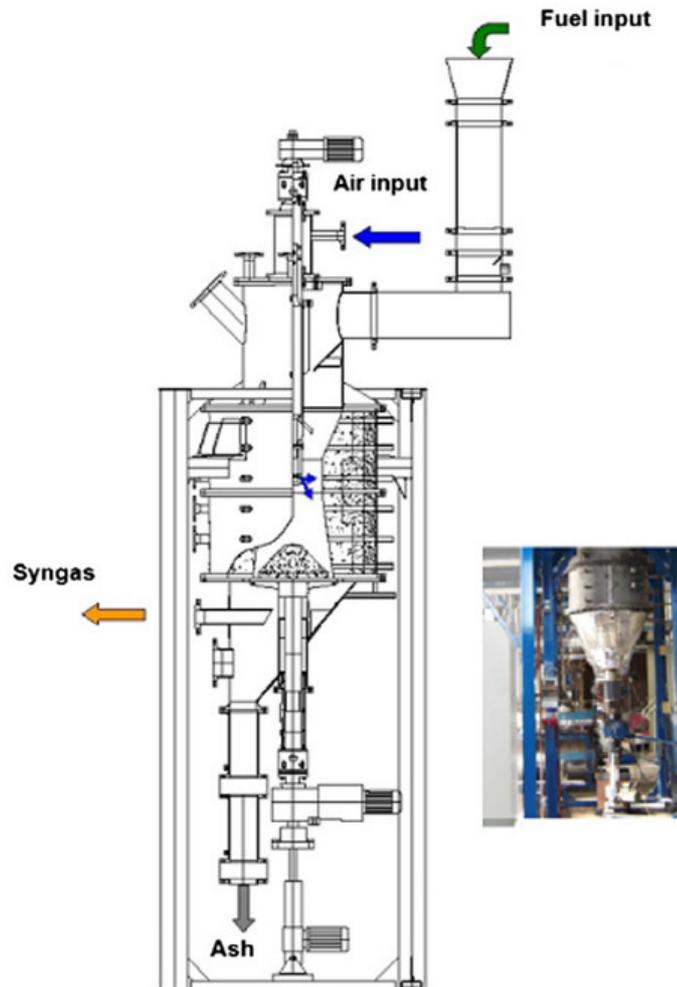


Figure 1. Co-current fixed bed biomass gasification facility operated by TU Dresden [24]

Measurements on the gasification plant

Measurements of fuel flow rate are presented in Figure 2 and air flow rate in Figure 3. As it can be seen from Figure 2 there is an obvious difference between experiments 1-4 (conducted in 2006) and experiments 5-8. Experiment 9 is not presented due to practical reasons (better visual comparison between 2 set of experiments) as it is relatively short and will be used only for validation of temperature model. In experiments 1-4 fuel flow rate is relatively constant and ranges between 50 and 150 kg/h while in experiments 5-8 (and 9) fuel flow rate is generally higher and usually ranges between 50 and 250 kg/h. Air flow rate in experiments 1-4 is slightly higher than in experiments 5-8. This change indicates a shift from enhanced complete fuel combustion regime (experiments 1-4) towards incomplete fuel combustion regime (experiments 5-8) which results in lower process temperatures in experiments 5-8. As fuel flow rate control system (related to bed height alarm system) has not been changed (the system is described in Mikulandric *et al.* [24]) this shift represents a change in operating conditions that can be due to changes in fuel quality, amount of ash sintering or due to some other unknown reason.

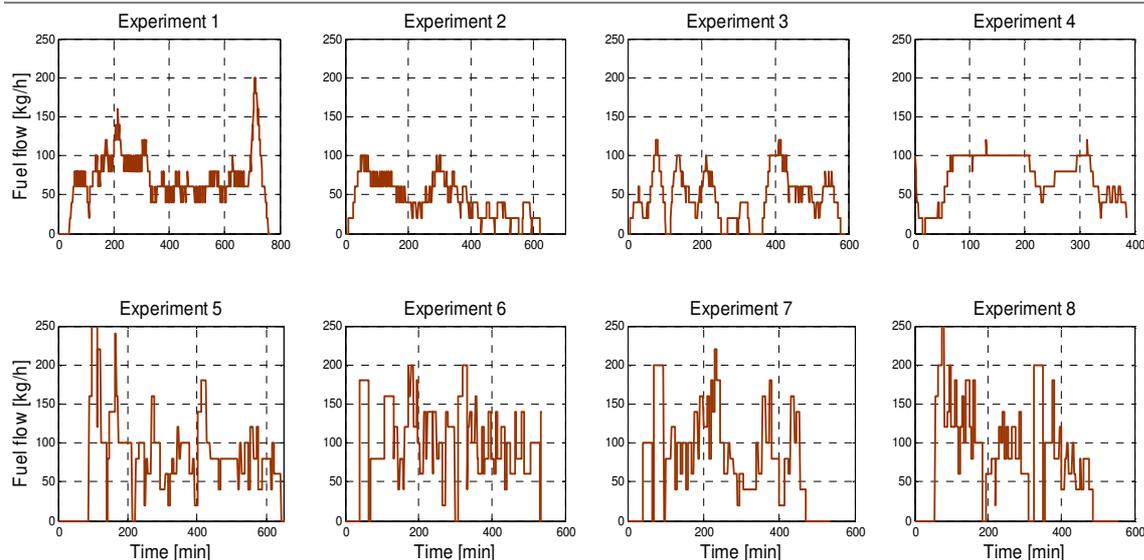


Figure 2. Fuel flow rate for experiments 1-8 [24]

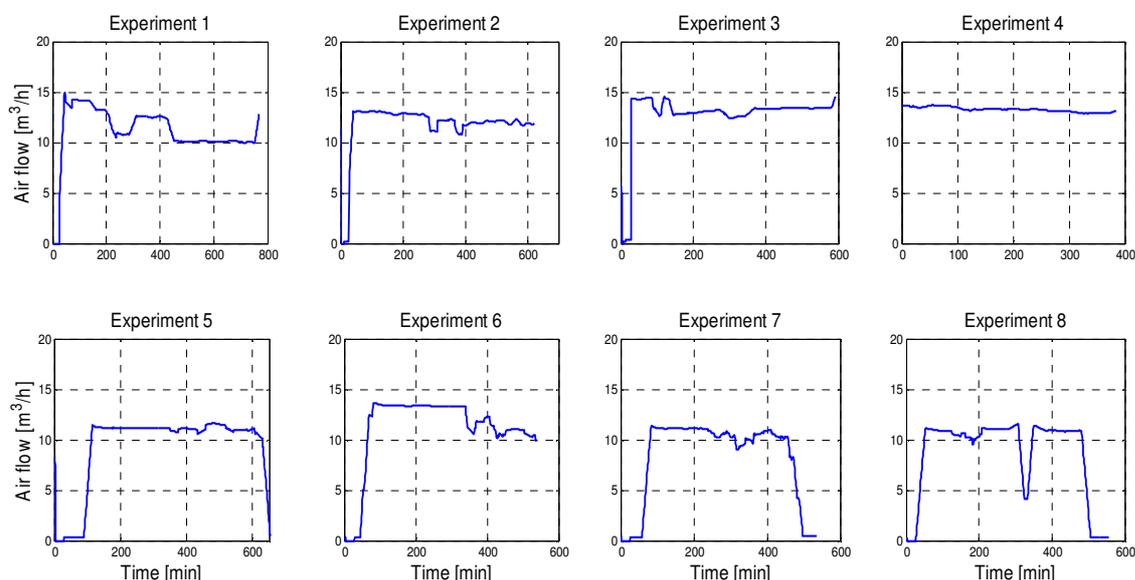


Figure 3. Air flow rate for experiments 1-8 [24]

Nonlinear autoregressive exogenous model

Syngas temperature and syngas composition of presented gasification system is predicted through sub-models that are defined with non-linear functions. They include current and past fuel and air flow rates together with previous values of the output (syngas temperature and H₂, CO and CH₄ content) itself. Each sub-model can be represented as a nonlinear time series with following equation [29]:

$$y(t) = f[y(t - 1), \dots, y(t - d_y), u(t - 1), \dots, u(t - d_u)] + e(t) \quad (1)$$

where $y(t)$ represents model output for the time t , $u(t)$ model input for the time t , d_y , d_u corresponding number of lags (delays) for output and input, and $e(t)$ error or noise for time t . For a detailed explanation of NARX structure authors refer to the research done by Chen and Billings [28]. By interaction of different non-linear sub-models (which could represent sub-processes during gasification) an effect of different input parameters on final gasification variables (syngas temperature and composition) can be defined.

For prediction of syngas temperature and quality a NARX model that consists of 2 layer network with 2-delay feedback with one hidden layer of 5 neurons has been proposed. Tan-sigmoid transfer function is used between hidden layers (as it provides a good trade-off between the calculation speed of sigmoid functions and prediction flexibility of tanh functions) and linear transfer function for output layer. After changing the number of training epochs to define the case with the best prediction quality it has been concluded that 600 training epochs provides the best prediction quality for considered system. More training epochs could lead to model overfitting. Fuel and air flow rates have been chosen as model inputs while syngas temperature is chosen as model output. Simplified model scheme is presented in Figure 4.

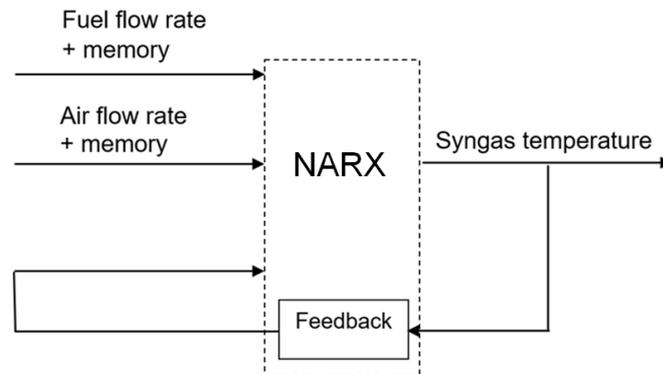


Figure 4. General scheme of NARX temperature prediction model (for model training)

To analyse the effect of training data quantity on prediction performance, 10 different cases with different training data quantities have been defined (Table 1). For example in CASE 1, first 60 minutes have been used as training data for NARX model. The rest of the process (second part of experiment 1 and experiments 2-9) has been used for model validation (validation set of data). For model validation, syngas temperature and composition were predicted based on developed model and measured model inputs. In CASE 2 the data from the first 120 minutes of the process has been used for model training and the rest has been used for validation. In CASE 3 data from whole first experiment (first 800 minutes of the process) has been used for NARX training. Experiments 2-9 were used for model validation and prediction potential analysis. Later on (cases 4-10), the number of training data was increased until the data from experiments 1-8 was used as training data and only experiment 9 was used for model validation.

Table 1. Model performance analysis for different training data sets

CASE	Training experiments	Validation experiments	Prediction error for training data set [%]	Prediction R^2 [-]	APE [%]
1	1 (first 60 min)	1-9	0.7435	0.90	46.96
2	1 (first 120 min)	1-9	0.3766	0.95	1.4017
3	1 (whole)	2-9	0.3137	0.98	0.6165
4	1-2	3-9	0.4989	0.98	0.6064
5	1-3	4-9	0.4471	0.98	0.6769
6	1-4	5-9	0.3906	0.97	1.1885
7	1-5	6-9	0.2756	0.98	0.7372
8	1-6	7-9	0.4863	0.98	0.9858
9	1-7	8-9	0.9563	0.98	0.9464
10	1-8	9	0.5109	0.97	1.0969

Furthermore, the number of model input delays has been varied from 1 to 20 in order to investigate the influence of model delays on temperature prediction performance. Model input delays are used during model training procedure as process history/memory data (feedback temperature loop and corresponding air and fuel flows for that moment). Higher number of model input delays means that during the training procedure more history data will be taken in consideration for prediction of future values. Each simulation delay represents an actual time delay of 30 seconds. Therefore, time delays for model inputs will range from 30 s to 10 minutes.

Continuous model prediction error will be analysed using eq. (2) and eq. (3) for syngas temperature (T) and volume fractions of constitutive gases (φ) while overall model prediction performance will be defined by using coefficient of determination (R^2). APE represents time averaged absolute values of prediction errors.

$$\text{error}(T) = \frac{T_{\text{predicted}} - T_{\text{measured}}}{T_{\text{measured}}} \quad (2)$$

$$\text{error}(\text{syngas composition}) = \frac{\varphi_{\text{predicted}} - \varphi_{\text{measured}}}{\varphi_{\text{measured}}} \quad (3)$$

RESULTS AND DISCUSSION

The performance of the developed NARX modelling approach has been analysed using 9 different experiments. The first 4 experiments were performed in 2006 and present process behaviour before changes in operating conditions. Experiments 5-9 were performed in 2013 and represent process behaviour after changes in operating conditions. The process changes (changes in fuel flow which resulted in different temperature distributions) could be due to changes in fuel quality, amount of ash sintering or due to some other unknown reason.

Data size for syngas temperature model training

Model prediction performance and model validation has been performed based on methods described in previous sections. First, a different size of training data sets has been used to analyse the influence of training data set size on prediction performance. Number of delays has been set to 2. Afterwards, the number of delays for model input has been varied in order to analyse the effect of model delays on prediction performance.

In the first case (Figure 5) first 60 minutes of experiment 1 have been used as training data set for NARX model. The rest of the process (experiment 1 from 60th till 800th minute and experiments 2-9) has been predicted based on developed NARX model (blue line) and measured model inputs. Simulation results show that the first 60 minutes (training data) of the experiment 1 has been described with very low prediction error (between $\pm 10\%$). For comparison, simulation prediction error of commercial state-of-art software like ASPEN-PLUS on a different set of data and for fluidised bed reactor type is in the range of $\pm 30\%$ [30]. This is understandable because this data set was used as training data for model development. However, the rest of the process (part of the process data not used for the training) has not been described in a quality way. The prediction error that is well above 50% suggests that used training data size is generally not sufficient for modelling purpose. Negative prediction error values suggest that the syngas temperature is underestimated while positive prediction error values suggest that the syngas temperature has been overestimated. Resulting coefficient of determination (R^2) has been defined at the end of performed simulation (presented in Table 1, CASE 1).

Due to a high prediction error from the first simulation case the training data set has been increased. In CASE 3 data from the whole experiment 1 has been used as training

data set and syngas temperature from experiments 2-9 was predicted based on developed model and model inputs (experiments 2-9 are validation data). Simulation results show that for this training data set (experiment 1) model prediction error is usually below $\pm 4\%$. For experiments 2-4 which are based on the same operating conditions but were not used for model training model prediction error is below $\pm 8\%$. After changes in operating conditions (experiment 5-9) the prediction error generally rises but remains under $\pm 10\%$. This general increase in model prediction error for experiments 5-9 is due to changes in operating conditions which current NARX model structure is not able to describe in a very precise way. Those changes in operating conditions could be due to use of different biomass quality or due to changes in the reactor (ash sintering). Use of different biomass compositions (moisture content or lower heat value) results in different syngas compositions but also in different temperature distributions in the reactor. Ash sintering could change the heat transfer between the reactor and environment which will result in different temperature distribution and consequently in different syngas composition. However, a prediction error under $\pm 10\%$ suggests that training data set from experiment 1 is still sufficient for general NARX model. Model performance for NARX model with experiment 1 as training data set is presented in Figure 6.

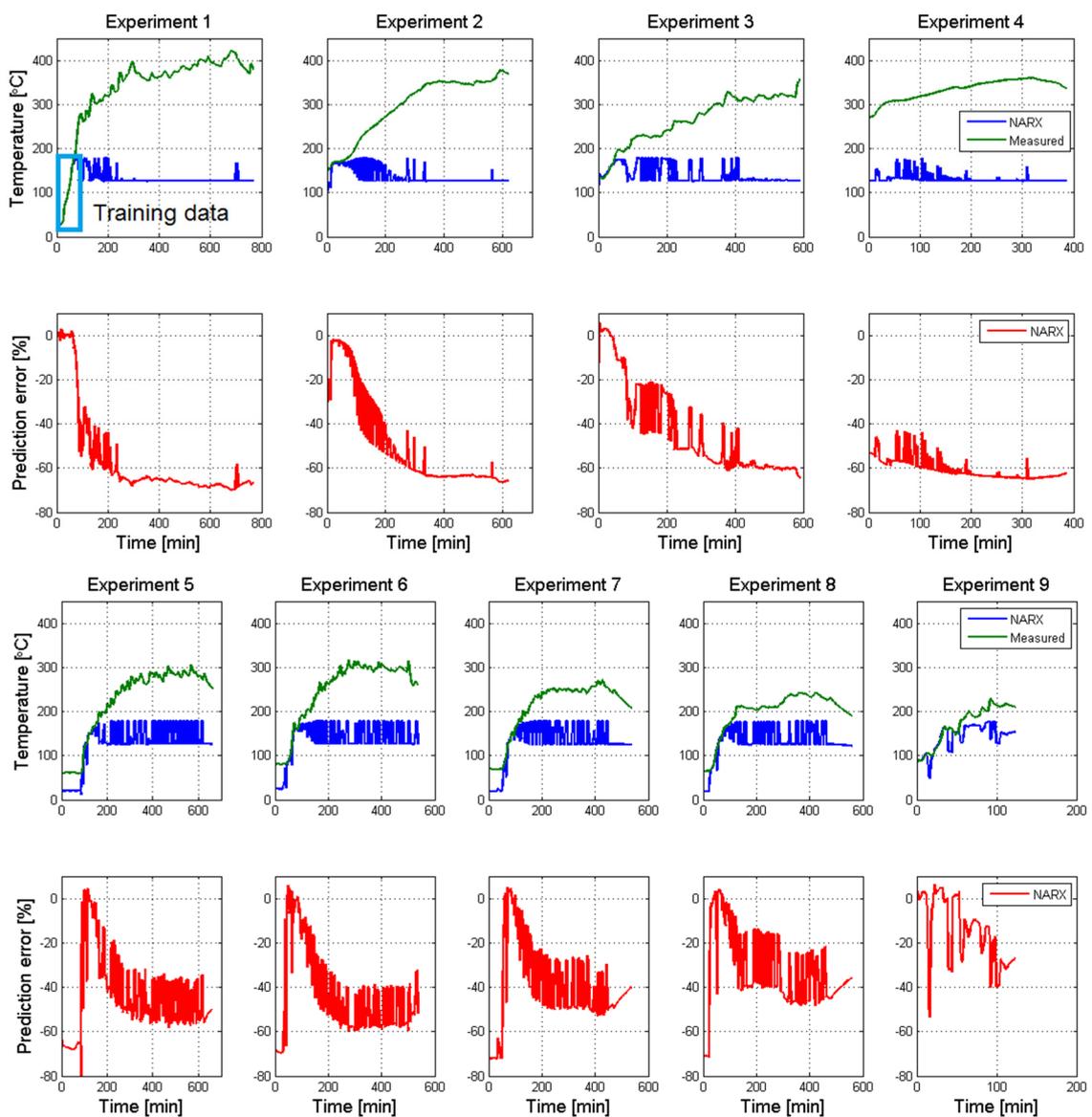


Figure 5. Model performance with 60 minutes of training data set (CASE 1)

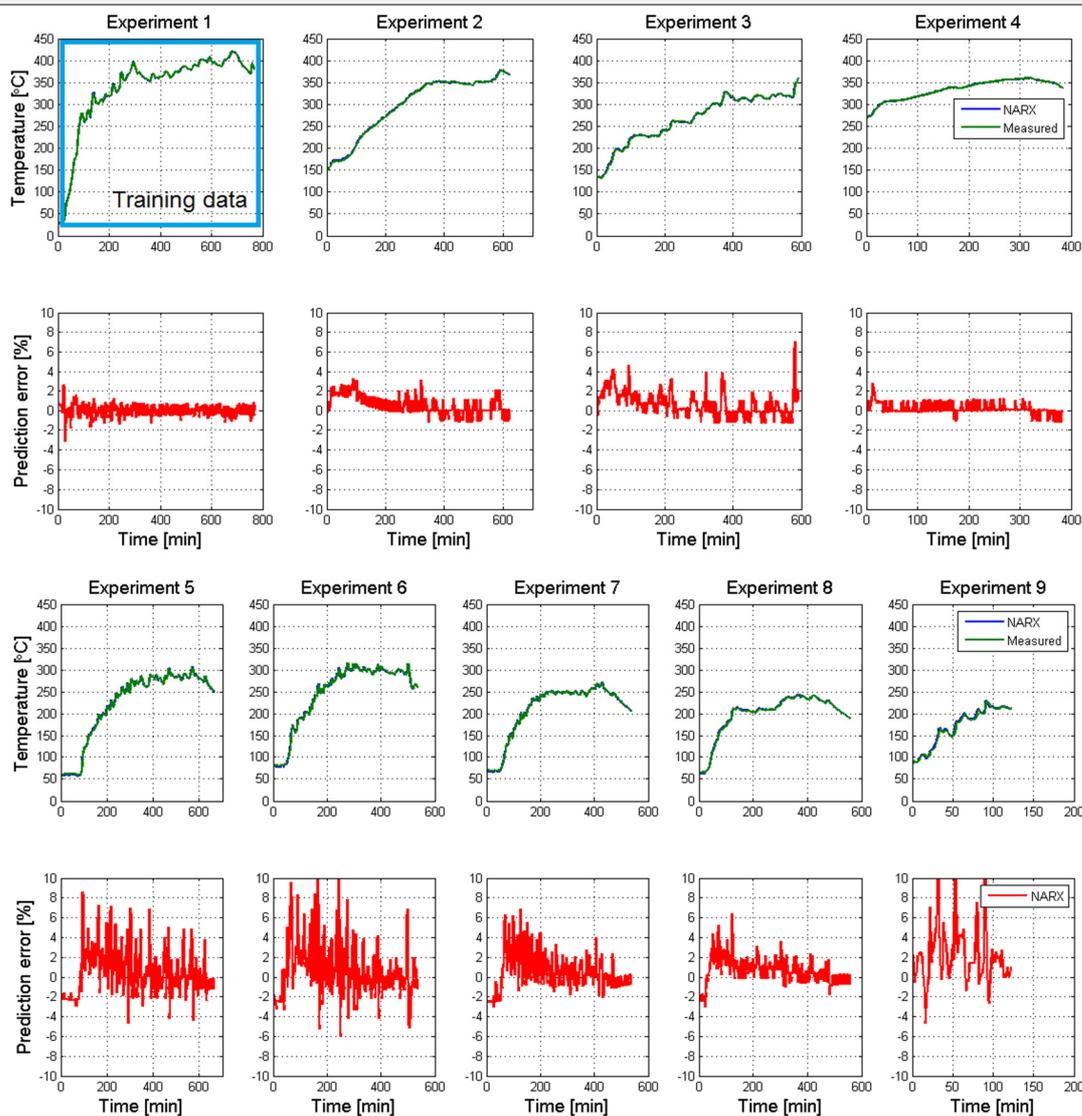


Figure 6. Model performance with experiment 1 as training data set (CASE 3)

Different training data sizes have been used to analyse model prediction performance. Summary of the analysis is presented in Table 1. For example, in CASE 1 first 60 minutes of experiment 1 was used for model training. In CASE 2 first 120 minutes of experiment 1 was used for model training. In CASE 4, data from experiment 1 and 2 was used for model training. In CASE 10 data from experiment 1-8 was used for model training and experiment 9 was used for validation purpose. First 60 minutes as a data set for model training is not sufficient to develop a NARX model with reasonable prediction accuracy (prediction error under 30%). Average prediction error is above 40% and R^2 is 0.9. With increasing training data size the model prediction performance improves. However, with increase of a training data size beyond data from experiment 1 the model prediction performance does not increase significantly and in some cases it even declines. This leads to conclusion that increasing data size (after including data from experiment 1) leads to over-fitting of the model and does not contribute to increase of model prediction accuracy.

Output memory size for syngas temperature model training

After the size of model training data has been determined (the whole experiment 1 has been used as training data set) a different number of model input delays and model output feedback delays have been used to analyse model prediction performance. With 2 delays

of input and output variables (which represents a time delay of 1.5 minutes) the NARX model has the highest prediction performance. With increasing the number of delays prediction performance of temperature prediction model decreases. This can be due to a slow response of the model with a high number of delays. In the case of large number of delays a parameter history that is no longer relevant to the process is taken into consideration to predict future values. Furthermore, the number of delays gives the indication of particle residence time in the reactor. It implies that the residence time of particles close to oxidation zone is around 90 seconds. The summary of model prediction performance for different number of time delays is presented in Table 2.

Table 2. Model performance analysis for different time delays of input and output model variables

Number of delays	Temperature prediction model (R^2 [-])	Temperature prediction model (APE [%])
1	0.96	0.8765
2	0.98	0.6165
3	0.92	2.7462
4	0.95	1.0042
5	0.97	0.7903
10	0.95	2.5122
20	0.90	6.0452

Model prediction speed

The overall training and prediction time of developed NARX model for experiments 1-8 is 16 seconds which represents an adequate speed for on-line parameter prediction models. Together with model R^2 of 0.98 it can be concluded that developed NARX model can be used to predict syngas temperature in changeable operating conditions.

Data size for syngas composition model training

A similar modelling method has been used to predict volumetric content of H_2 , CO and CH_4 in syngas. Model prediction performance for syngas composition predictions is presented in Figure 7 (H_2), Figure 8 (CH_4) and Figure 9 (CO). For prediction of syngas composition, the training dataset derived from experiment 1 was not of sufficient to quality describe the process. It must be emphasized that dataset of syngas composition is smaller than a dataset for process temperature as it was measured when temperatures reached 250 °C. Therefore, the training dataset had to be expanded to datasets from experiment 1 and 2 for H_2 and CH_4 values and datasets from experiments 1, 2 and 3 for CO values. In general, syngas composition predictions follow measured values with a good accuracy, with R^2 of prediction above 0.73 in all cases. The highest prediction error occurs in experiment 7 and during some parts in experiment 8 and 9.

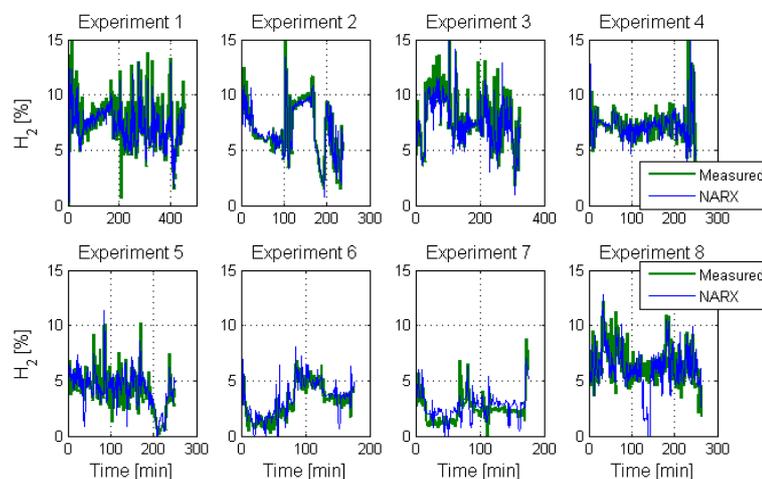


Figure 7. NARX model prediction performance for H_2 predictions

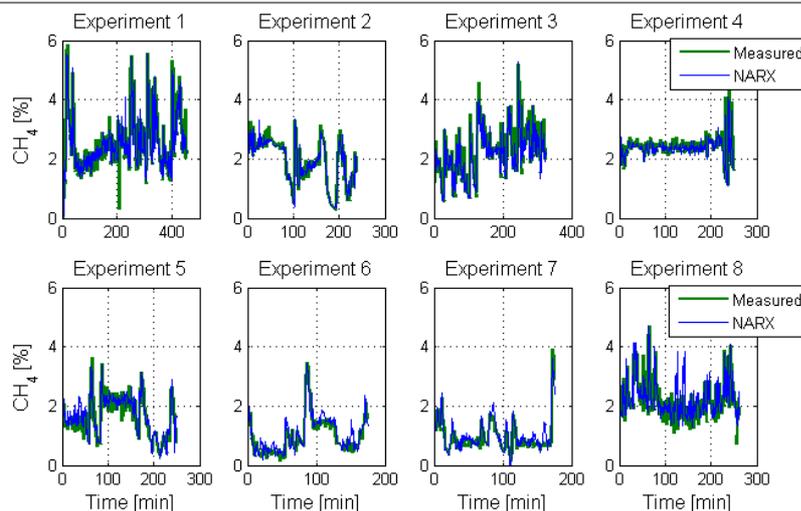


Figure 8. NARX model prediction performance for CH₄ prediction

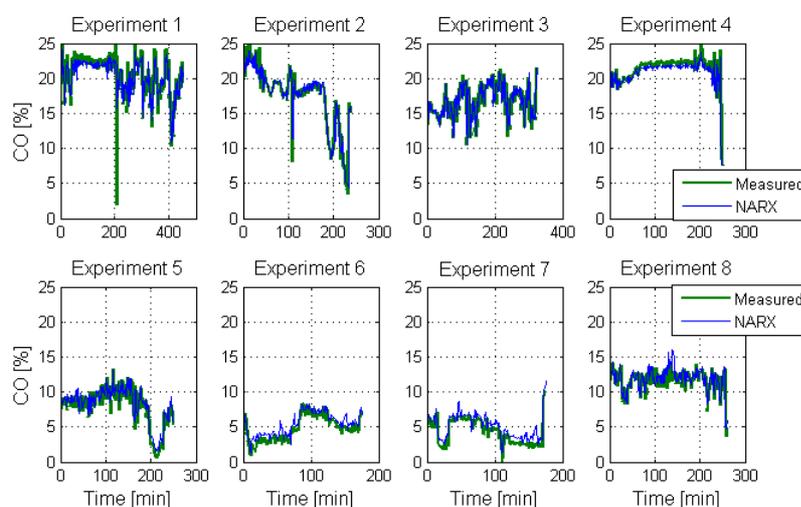


Figure 9. NARX model prediction performance for CO predictions

Model prediction performance analysis

The prediction performance of NARX models is summarised in Table 3. From the table it can be seen that the maximum temperature prediction deviation is 13.52 °C while the average temperature prediction deviation is 1.21 °C. For syngas composition in some sporadic time periods the model is not able to predict syngas composition values (example – Figure 7, H₂ prediction, experiment 8, 140-145 s). However, the average prediction deviation for syngas composition is below 1% vol. Resulting R^2 is 0.98 for temperature, 0.82 for CH₄, 0.73 for H₂ and 0.97 for CO.

Table 3. NARX prediction deviation for different process variables

Model	Unit	Max.	Average	Min.	R^2 [-]
Temperature	[°C]	13.52	1.21	0.00007	0.98
CH ₄	[% vol.]	2.41	0.25	0.00015	0.82
H ₂	[% vol.]	9.92	0.92	0.00024	0.73
CO	[% vol.]	19.42	0.78	0.00041	0.97

The overall model prediction performance of developed models is presented in Table 4. NARX model performance has been compared with dynamic Adaptive Neuro Fuzzy Inference System (ANFIS) model, described and reported in Mikulandrić *et al.*

[24] and standard ANFIS model developed, described and reported in Mikulandrić *et al.* [18] as the model training was performed on the same set of data. Compared to the training of NARX model the training of ANFIS model requires more data pre-processing and the feedback history of model input is very limited (only one delay is implemented). It can be seen that NARX model requires a significant smaller training database for a higher prediction performance. This also results in a faster prediction speed. The highest improvement can be seen in prediction of syngas composition quality where R^2 of NARX model ranges between 0.73 and 0.97 while R^2 of dynamic ANFIS model ranges between 0.45 and 0.83. Compared to standard ANFIS model, NARX model has a much better prediction performance for syngas temperature (1% of prediction error of NARX model compared to 7% of prediction error of standard ANFIS). Furthermore, standard ANFIS model is proven not to be appropriate as a simulation tool in changing operating conditions [24]. It has been concluded that NARX model shows a better model prediction performance than developed dynamic and standard ANFIS models. However, it should be noticed that in this kind of a comparison NARX model uses history of measured output data (temperature and syngas composition) in order to predict their future values. This means that NARX model should be constantly updated with measured past values of syngas temperatures. By this, prediction horizon of NARX model without active temperature measurements is quite limited. To compare performance indicators of NARX and dynamic ANFIS model for a longer-term predictions without active temperature measurements and history updates NARX model outputs/predictions were taken to update model output history (instead of measured temperatures).

Table 4. Overall model prediction performance of NARX and dynamic ANFIS models

Model	Datasets for training	R^2 [-]	APE [%]
NARX – CH ₄	2 experiments	0.82	0.15
NARX – H ₂	2 experiments	0.73	0.25
NARX – CO	3 experiments	0.97	0.18
NARX – Temperature	1 experiment	0.98	0.01
Dynamic ANFIS – CH ₄ [24]	4 experiments + re-training	0.45	0.38
Dynamic ANFIS – H ₂ [24]	4 experiments + re-training	0.47	0.30
Dynamic ANFIS – CO [24]	4 experiments + re-training	0.83	0.26
Dynamic ANFIS – Temperature [24]	4 experiments + re-training	0.82	0.07

Model performance analysis for long-term predictions

Prediction potential of NARX model for a long-term temperature prediction is presented in Figure 10. By term ‘long-term’ is considered a time period between plant start-up and the point when the stationary operating conditions have been reached. It usually takes around 100 to 300 minutes for the plant to reach stationary regime from the start-up (Figure 6). For model performance analysis, 175th minute of experiment 1 has been chosen as a starting point for the analysis. This point represents a middle point between process start-up and a moment where stationary operating condition has been achieved. Therefore, it was tested if the model can predict future values (in the time-span of 10 minutes) from 175th minute of experiment 1 without using measurements as model input. It can be seen that NARX model cannot predict future temperature values in a quality way if it uses history of its own output as an input. In the first 3 minutes NARX model has history (2 delays) that equals to measured values. Based on that history the model can produce prediction with a relatively small prediction error. However, when algorithms start to use output of NARX model as history (in 4th minute) the model soon becomes unstable and the prediction error reaches 1% in 9th minute (5th minute after the NARX model is disconnected from measurements). This is due to accumulation of prediction error that occurs in NARX model predictions. In the 3rd minute (3rd minute of

real time represents 5th minute of history) model history suggests that predicted temperature from NARX model is higher than measured one. Based on such suggestion and measured fuel and air flow rate the model decides to decrease predicted temperature. However, in the next time increment, the model history suggests that this value is too low (based on previous temperature and fuel and air flow rates) which results in a significant temperature prediction increase. In this way the model soon becomes unstable. A similar case was observed for syngas composition predictions.

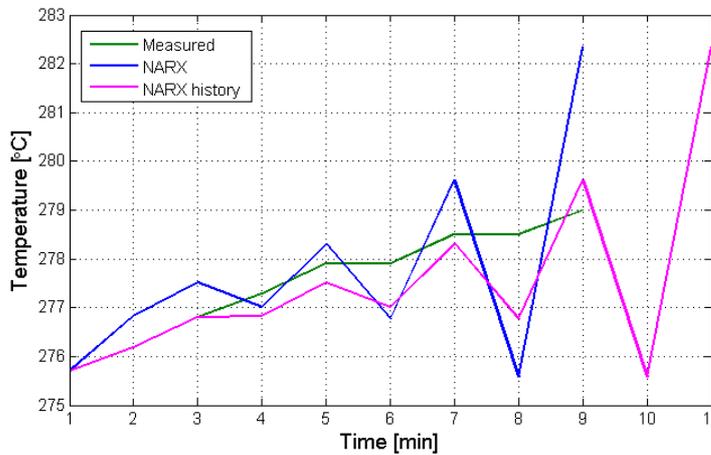


Figure 10. NARX model (temperature) prediction performance for second validation case

It can be concluded that NARX model can produce quality parameter prediction if measured values are used as history for model input. However, if model predictions are used as history for model input (like in long-term predictions) the model becomes unstable and produces high prediction errors. This leads to the conclusion that NARX models are very useful tool for a short term predictions (up to 5 minutes) and, therefore, could be used for short-term control loops. However, if such model is decoupled from real time measurements they can produce a significant prediction error. In comparison with dynamic ANFIS model which works on similar principle (if the prediction error is too high after some time it resets predicted value to measured one) NARX models seem to have a much lower autonomy in process prediction. Summarised comparison between developed NARX model, dynamic ANFIS model from Mikulandric *et al.* [24] and standard ANFIS model [18] for prediction of syngas temperature is presented in Table 5.

Table 5. Comparison of general prediction performance for standard ANFIS, dynamic ANFIS and NARX model

	Standard ANFIS	Dynamic ANFIS	NARX
General prediction performance	Moderate	Moderate	High
Prediction performance in changeable operating conditions	Very low	Moderate	High
Long term process prediction quality	High	Moderate	Very low
Prediction speed	High	Moderate	Very high

CONCLUSION

In order to predict syngas temperature and syngas composition in a 75 kW_{th} fixed bed biomass gasification plant a NARX model has been developed. Taking current and past values of model inputs and output into consideration specific system time delays caused by the accumulation of mass and energy and particle residence time can be modelled. Therefore, to model process dynamics it is important to define the right size of data history (time delays) for model training and development. Furthermore, the prediction quality of such models strongly depends on the quality and the quantity of training data

that has been applied. Developed NARX model is robust enough to predict syngas temperature under changeable operating conditions. It requires a relatively small amount of data for training and can predict syngas temperatures in changing operating conditions. In comparison with other state-of-art cases NARX models do not require any prior knowledge regarding the process to be developed and thus can be trained based on raw measurement data of fuel and air flow rate. The average temperature prediction error of developed NARX model is below 1% with R^2 of 0.98. Average prediction errors of syngas composition are below 25% with R^2 equal or higher than 0.73. Prediction quality of the syngas composition could be improved by more accurate measurements and larger data size for model training. Due to fast prediction speed such models are applicable for on-line process analysis of fixed bed biomass gasification systems. However, for a quality model prediction, history values of NARX models should be constantly updated with measured values. This makes them a good prediction tool only for a short term time horizons. In the case of developed NARX model, the prediction horizon was 5 minutes. For long-term predictions dynamic ANFIS models are more appropriate. To improve the prediction autonomy of NARX models it is suggested to develop sub-models for different reactor regions, to perform related measurements for data collection and to improve the number of delays in model training.

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