Dynamic modelling of biomass gasification in a co-current fixed bed gasifier

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ABSTRACT

Existing technical issues related to biomass gasification process efficiency and environmental standards are preventing the technology to become more economically viable. In order to tackle those issues a lot of attention has been given to biomass gasification process predictive modelling. These models should be robust enough to predict process parameters during variable operating conditions. This could be accomplished either by changes of model input variables or by changes in model structure. This paper analyses the potential of neural network based modelling to predict process parameters during plant operation with variable operating conditions. Dynamic neural network based model for gasification purposes will be developed and its performance will be analysed based on measured data derived from a fixed bed biomass gasification plant operated by Technical University Dresden (TU Dresden). Dynamic neural network can predict process temperature with an average error less than 10% and in those terms performs better than multiple linear regression models. Average prediction error of syngas quality is lower than 30%. Developed model is applicable for online analysis of biomass gasification process under variable operating conditions. The model is automatically modified when new operating conditions occur.

Keywords: Biomass gasification, dynamic modelling, artificial neural networks, fixed bed gasifiers

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Nomenclature

Main symbols

m_{air}	air flow rate, m ³ /h
$m_{air_{av}}$	average air flow rate, m ³ /h
m_b	biomass flow rate, kg/h
$m_{b_{av}}$	average biomass flow rate, kg/h
$m_{b_{freq}}$	fuel injection frequency, -
$error_{av}$	average error, -
β_{1-10}	regression coefficients, -
i	measurement number, -
N	number of measurement samples, -
T	temperature, °C
t	time

Abbreviations

ANN	artificial neural networks
APE	average prediction error
CH ₄	methane
CO	carbon monoxide
CO ₂	carbon dioxide
H ₂	hydrogen
MFB	mean fractional bias
MLR	multiple linear regression
NMBF	normalised mean bias factor
NNM	neural network model
O ₂	oxygen
R ²	coefficient of determination
RMSE	root mean square error

1. INTRODUCTION

The process of biomass gasification is a high-temperature partial oxidation process in which a solid carbon based feedstock is converted into a gaseous mixture (H₂, CO, CO₂, CH₄, light hydrocarbons, tar, char, ash and minor contaminants) called ‘raw syngas’, using gasifying agents [1]. Gasification products are mostly used for separate or combined heat and power generation [2], for hydrogen production [3], methanol production [4] and production of other chemical products [5]. A more detailed overview of available biomass gasification technologies is published by Kirkels and Verbong [5].

Although, gasification is a relatively well known technology, the share of gasification in overall energy demand is small due to current barriers concerning biomass harvesting and storage [6], biomass pre-treatment (drying, grinding and densification), gas cleaning (physical, thermal or catalytic), process efficiency and syngas quality issues [7]. The performance of biomass gasification processes is influenced by a large number of operational

parameters, among them: biomass quality, fuel and air flow rate, composition and moisture content of the biomass, gasifier design, reaction/residence time, gasifying agent, biomass particle sizes, gasification temperature and pressure [8]. Process temperature is considered as one of the most important process parameters which influences syngas quality, reaction rate and tar concentration [9]. 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 [10].

To improve process efficiency or to guarantee constant process quality during operation, plant operation simulation models that enable parameter prediction as a function of various operating conditions, are needed. Large scale experiments could be used for this purpose on pilot plants [11] or laboratory scale setups [12] but they are often too expensive or problematic in terms of safety. Most of the available models for biomass gasification simulation are based on equilibrium models for Gibbs free energy minimisation [13], CFD analysis [14] or kinetic reactions [15]. A more detailed review of available models for biomass gasification process can be found in the research done by Baruah and Baruah [16] or in comparative analysis performed by Mikulandric et al. [17]. From this point of the state of the art, it can be concluded that the most of available models are well capable to describe stationary process behaviour under constant operating conditions but they are not suitable for on-line process analysis where process dynamics under changeable operating conditions is considered.

Adaptable/evolutionary models and optimisation methods have potential to become a powerful methodology for gasification systems analysis, control and optimisation [18]. Artificial intelligence systems (such as neural networks) are widely accepted as a technology that is able to deal with non-linear problems, and once trained can perform prediction and generalization at high speed. Artificial neural network (ANN) based prediction models use a non-physical modelling approach which correlates the input and output data to develop a process prediction model. ANN is a universal function approximator that has the ability to approximate any continuous function to an arbitrary precision even without a priori knowledge about the structure of the function that is approximated [19]. Dynamic neural networks with feedforward or recurrent feedback connections are used for systems with large delays like activated sludge processes [20], vapour-compression liquid chillers [21], chemical process systems [22] or energy related prediction processes [23]. Once trained ANN can predict process parameters in circulating and bubbling fluidised bed gasifiers [24], fluidised bed gasifiers with steam as gasifying agent [25] or in fixed bed gasifiers [26] with reasonable speed and accuracy. However, the prediction quality of trained ANN is

highly dependent on the quantity and quality of training data related to the process. Changing process operating conditions can cause large prediction errors if the ANN models have not been modified for those particular conditions. The importance of dynamic modelling has been elaborated for the case of flexible operation and optimisation of carbon dioxide capture plants [27]. To encounter issues related to changeable operating conditions and to obtain reasonable model prediction accuracy Wang and Hu [28] proposed a dynamic parameter estimation approach using genetic algorithms to predict thermal behaviour of buildings with changeable thermal capacitance. For prediction of the lead-acid battery state of charge during operation Fendri and Chaabene [29] proposed dynamic recursive estimation Kalman filter algorithms. However, performance of a dynamic modelling approach for changeable operating conditions in biomass gasification has still not been analysed.

In this paper a dynamic ANN based modelling approach will be utilised to describe the process behaviour in a 75kW_{th} fixed bed gasifier, operated by TU Dresden. The ANN model needs to be able to predict process parameters with reasonable speed and accuracy in a gasification process with large delays and changing operating conditions. In order to guarantee prediction accuracy for changing operating conditions a dynamic modelling approach with automatic ANN re-training sessions will be utilised and its performance will be compared with a dynamic multiple linear regression based model. Reasonable prediction speed is required in order to enable on-line parameter prediction for process analysis. Model performance has been analysed using statistical error analysis.

2. GASIFICATION PLANT AND OPERATING CONDITIONS

In order to develop a neural network based model (NNM), the neural network has to be trained using observed/measured data to predict process parameters. Neural network based models generally require a large number of measurement data to form input and output data sets for neural network training. Results from NNM could differ significant if different sets of input and output data have been used for training purposes. Due to their nature NNMs are used to describe particular processes that occur in the observed system during stable operating conditions. However, if something changes in the process due to changes in operating conditions, design changes, biomass quality or other unexpected process variables the NNM structure has to be modified (NNM has to be re-trained) to preserve prediction quality for this particular condition. For the purpose of NNM modelling 2 sets of experiments (9 experiments in total), with different operating conditions, were conducted to form a database for NNM training. The object of modelling is a co-current fixed bed gasifier with thermal input of 75 kW_{th}, located

in Pirna (Germany), operated by TU Dresden. Biomass wood chips, distributed from a local provider, are used as fuel in the gasification process. The facility scheme is presented in Fig. 1.

During facility operation the biomass is firstly injected manually in a small storage room with a manually controlled valve. Once the valve opens, the whole amount of biomass from the storage room is injected into the biomass shredder and consequently injected into the gasification reactor. Gasification air is distributed by fans and injected in the process from the upper side of the gasifier, leading to a co-current flow system. Ash is removed manually by opening ash removal valves. The biomass quality could be determined offline by dedicated laboratory tests, however it is hard to determine biomass quality for modelling purposes online due to variability between batches of distributed wood chips.

Two sets of experiments were performed to analyse the process behaviour. The first set of 4 experiments (Experiments 1-4) were performed in 2006 and resulted in more than 40 hours of operation. The second set of 5 experiments (Experiments 5-9) were performed in 2013 and resulted in more than 35 hours of operation. Experiments were performed to determine/measure following process parameters: biomass mass flow rate (mb); air volume flow rate ($mair$); syngas temperature at the exit of the gasifier; syngas composition; pressure in the reactor and temperature of inlet air. All data was recorded on a 30 seconds base in accordance with relevant international standards for this type of measurements. The measurement equipment for dedicated tests is listed in Table 1.

After measurements, the data was analysed in order to define a set of input and output datasets for NNM training after which the data was pre-processed. For the process temperature prediction the average biomass fuel flow rate was averaged on 25 minutes basis, together with the air flow rate (Eq 1 and 2). Injection frequency (the time from the last fuel injection) was also calculated to incorporate the dynamic behaviour (delays) of the process (instead of using a dynamic neural network modelling approach). A detailed description of the data analysis and motivation for this particular data analysis approach are presented in [26]. Results of data analysis for fuel flow rate, air flow rate and fuel injection frequency for Experiments 1-4 (2006) and 5-8 (2013) are presented in Figures 2, 3 and 4.

$$mb_{av} = \int_{t=i-25}^{t=i} mb \, dt \quad (\text{Eq. 1})$$

$$mair_{av} = \int_{t=i-25}^{t=i} mair \, dt \quad (\text{Eq. 2})$$

During Experiments 1-4 the amount of the injected biomass (fuel) is in general less than during Experiments 5-8. This could be due to different biomass quality, plant ageing, ash agglomeration or due to some other unwanted changes in the gasifier. Furthermore, the profile of the fuel flow rate has been changed. While in Experiments 1-4 the fuel injection rate is quite constant (can be seen from time without fuel injection diagrams) in Experiments 5-8 the fuel injection rate is more scattered during gasifier operation and can reach up to 20 minutes without fuel injection (while in Experiments 1-4 the time without fuel injection is generally less than 7 minutes). Generally, more fuel in a more dispersed way has been injected during Experiments 5-8 in comparison to Experiments 1-4. Air injection rate profiles are rather constant in all experiments and range between 10 and 15 m³/h. It is reasonable to assume that due to changes in fuel flow rate and fuel injection frequency the process will behave in a different way which will result in different temperature profiles (together with other process parameters).

3. MODELLING METHODS

For modelling purposes data collected from Experiments 1-9 has been used to form a database for NNM training. For artificial neural-network (ANN) based prediction models the adaptive network-based fuzzy inference system (ANFIS) with Sugeno type of fuzzy model and hybrid learning algorithms with 27 nodes (together with membership functions) in structure layers were used. The individual Multi Input Single Output system comprises of 4 inputs (fuel flow rate, fuel injection frequency, air flow rate and current temperature of syngas at outlet) and one output which represents the temperature change. A simple analysis for different number of iterations for NNM training has been performed with 10, 25, 50 and 100 iterations. The prediction quality after 50 iterations did not improve considerably so due to a shorter computational time and to reduce the risk of NNM overfitting the NNM model with 50 iterations has been chosen. The change in syngas outlet temperature (to be considered as process temperature in the further text) was set as model output. Syngas temperature was then determined by integration of predicted temperature changes. With this approach the process dynamics related to process temperature can be described in a qualitative way [26]. Dynamic neural network models with feedforward or recurrent feedback connections could be used for the same purpose but due to limitations of this approach in terms of automatic on-line analysis in MATLAB software, a general scheme that is presented in Figure 5 has been used.

The NNM model was initially trained on data derived from Experiments 1-4. Detailed training results can be found in [26]. For the trained cases, the ANN temperature prediction model shows good correlation with measured data

[26]. After the model was initially developed based on data from Experiments 1-4 it has been applied to predict process temperature for Experiments 5-9. As discussed in the previous section, the process conditions in Experiments 5-9 have changed considerably in comparison with the conditions from Experiments 1-4 due to unknown reasons. Therefore it is shown later in the paper that the developed NNM has larger prediction errors than in the cases from Experiments 1-4.

A similar methodology has been applied to predict gas composition (H_2 , CH_4 and CO) during operation. The combination of fuel flow rate, fuel injection frequency, air flow rate and current temperature of syngas at outlet as input for NNM provided the best prediction results in the previous study [26] and therefore those inputs were considered again for the development of a dynamic model for syngas composition prediction.

In order to mitigate the effects of changing operating conditions on the NNM prediction performance a dynamic modelling approach is proposed. First, the NNM is trained on existing data from Experiments 1-4. The same model is initially applied to predict the process temperature in different process conditions (Experiments 5-9). Prediction error (defined by Eq. 3) is continuously analysed (error value can range between -1 and $+\infty$) in order to preserve prediction quality of the model. When the average error (defined by Eq.4) between predicted and measured values in the last 50 minutes exceeds the defined average error tolerance threshold (in the presented case the defined average error tolerance threshold is set to be 10%) then the trigger for re-modelling is turned on. The trigger enables re-training of the NNM based on a newly formed database (old database extended with new measurements up to that moment). After re-training, the error tolerance is temporary increased to $\pm 100\%$ for the next 3 minutes in order to prevent fast trigger resetting after NNM re-modelling (constant re-training will result in extensive time loss). After re-training the predicted temperature is set to the last measured value. This modelling methodology is presented in Figure 6.

$$error = \frac{T_{predicted} - T_{measured}}{T_{measured}} \quad (Eq. 3)$$

$$error_{av} = \frac{\int_{t=i-50}^{t=i} |error| dt}{50} \quad (Eq. 4)$$

For additional model performance analysis, temperature predictions from developed NNM have been compared to temperature predictions of Multiple Linear Regression (MLR) models. 2 different MLR models have been utilised for analysis. General form of first (MLR1) model is given in Eq. 5 while general form of second (MLR2)

model is given in Eq. 6. During analysis MLR models will follow the same procedure for model re-training as for NNMs. Similar analysis approach can be found in the research performed by Vlachogianni et al [30].

$$\Delta T = \beta_0 + \beta_1 \cdot mb_{av} + \beta_2 \cdot mair_{av} + \beta_3 \cdot mb_{freq} + \beta_4 \cdot T \quad (\text{Eq. 5})$$

$$\Delta T = \beta_0 + \beta_1 \cdot mb_{av}^2 + \beta_2 \cdot mair_{av}^2 + \beta_3 \cdot mb_{freq}^2 + \beta_4 \cdot T^2 + \beta_5 \cdot mb_{av} \cdot mair_{av} + \beta_6 \cdot mb_{av} \cdot mb_{freq} + \beta_7 \cdot mb_{av} \cdot T + \beta_8 \cdot mair_{av} \cdot mb_{freq} + \beta_9 \cdot mair_{av} \cdot T + \beta_{10} \cdot mb_{freq} \cdot T \quad (\text{Eq. 6})$$

To analyse models performance in terms of error metrics the coefficient of determination (R^2), root mean square error (RMSE), average prediction error (APE), mean fractional bias (MFB) and the normalised mean bias factor (NMBF) metrics have been calculated. Coefficient of determination is the most commonly used technique to evaluate model fitting performance. However, it is used for linear models and it does not provide the information related to an average prediction error. In order to quantify average model prediction error the root mean square error and user defined average prediction error analysis has been performed. User defined average prediction error derived from Eq 3 presents prediction error in a way that can be easily interpreted by plant operator during plant operation. In order to analyse model prediction bias the mean fractional bias and normalised mean bias factors have been calculated. Although mean fractional bias has been commonly used [31], the normalised mean bias factor metrics can evaluate model over- and under-prediction more proportionally [31]. Related equations (Eq. 6- Eq.10) for statistical analysis of temperature prediction model are following:

$$R^2 = 1 - \frac{\sum_{t=0}^{t=i} (T_{measured} - T_{predicted})^2}{\sum_{t=0}^{t=i} (T_{measured} - T_{mean})^2} \quad (\text{Eq. 6})$$

$$RMSE = \sqrt{\frac{\sum_{t=0}^{t=i} (T_{measured} - T_{predicted})^2}{N}} \quad (\text{Eq. 7})$$

$$APE = \frac{\sum_{t=0}^{t=i} \left| \frac{T_{predicted} - T_{measured}}{T_{measured}} \right|}{N} \quad (\text{Eq. 8})$$

$$MFB = \frac{1}{N} \sum_{t=0}^{t=i} \frac{T_{predicted} - T_{measured}}{\frac{T_{predicted} + T_{measured}}{2}} \quad (\text{Eq. 9})$$

$$NMBF = \frac{\sum_{t=0}^{t=i} T_{predicted} - \sum_{t=0}^{t=i} T_{measured}}{|\sum_{t=0}^{t=i} T_{predicted} - \sum_{t=0}^{t=i} T_{measured}|} \left[\exp \left(\left| \ln \frac{\sum_{t=0}^{t=i} T_{predicted}}{\sum_{t=0}^{t=i} T_{measured}} \right| \right) - 1 \right] \quad (\text{Eq. 10})$$

RESULTS AND DISCUSSION

The performance of the developed dynamic modelling approach has been analysed using 9 different experiments. The first 4 experiments (conducted in 2006) were utilised as initial data for the NNM development. Experiments 5-9 were used to simulate a real-time plant operation after a change in the plant's operating conditions due to unknown reasons. Measurements from Experiments 5-9 have been added sequentially to the database so that the algorithm for the ANN model training and re-training can use only data collected prior to model re-training (NNM re-training algorithms do not have prior knowledge of other experiments). Online model performance has been evaluated and monitored using Eq. 3.

Results derived from the NNM that has been trained only with the initial database from Experiments 1-4 are presented in Figure 7. Some values are missing due to practical reasons (they are too large to be fitted in a graph). The Figure shows that the NNM that has been trained only with the initial database has no ability to predict process temperatures during Experiments 5-9 (after process conditions have been changed). For Experiments 5 and 8 the model predicted temperature is unrealistically high so the prediction error is more than 150%. The calculated prediction error is higher than 100% due to nature of equation that has been used for online model prediction error estimation (Eq. 3). In some cases the prediction error (difference between predicted and measured value) is larger than the measured temperature itself which results in prediction errors that are larger than 100%. For experiment 7 predicted temperatures are much lower than measured values. Measured temperatures in Experiments 5, 8 and 9 are lower than temperatures in Experiments 1-4 due to unknown changes in process operating conditions so the predicted temperature values in Experiments 5, 8 and 9 with the NNM structure from Experiments 1-4 are generally higher. Even in Experiments 6 and 9 where predicted temperatures are more or less realistic the absolute prediction error is mostly above 50%. One way to reduce the prediction error could be to continuously change NNM model structure (type of neural network or the number of hidden layers) in order to have a better prediction quality for all experiments. However, a changing NNM structure would result in a large engineering effort during plant operation. Therefore, this approach would be unpractical for on-line process analysis. Approach that has been proposed in 'Modelling methods' section (that uses an automatic approach to adjust the prediction model) should be able to modify the model in a way that is more appropriate for on-line process analysis.

After the initial analysis with the NNM that has been trained with the original database only, the developed dynamic modelling methodology is applied to analyse its performance. As in the previous case, the NNM was initially trained with the existing database from Experiments 1-4 in order to have a base for prediction purposes. After initial training the model is utilised to predict the process temperature (syngas outlet temperature) after a change in operating conditions (starting from Experiment 5). The same database as in the previous case is used to analyse the potential of the dynamic ANN modelling approach. Different average prediction error tolerances are used to analyse the sensitivity (in terms of prediction quality and speed) of the modelling approach. It is clear that higher error tolerance threshold enables faster parameter prediction due to smaller number of re-training sessions but reduces prediction quality. Results of the sensitivity analysis are presented in Table 2.

Results derived from the developed dynamic NNM approach with an average error tolerance threshold of 50% are presented in Figure 8. Although the prediction potential of the developed dynamic NNM is improved compared to the previous case, the prediction error is still very high (around $\pm 30\%$ on average). The largest prediction error appears in Experiment 6. Although the prediction error is high, due to a large error tolerance threshold (50%) the re-training session is triggered only 200 minutes after last re-training session. Nevertheless, the predicted values differ significantly from the measured ones. The sensitivity analysis suggests that the error tolerance threshold should be significantly reduced in order to improve prediction quality.

The results derived from the dynamic NNM with error tolerance threshold of 10% are presented in Figure 9. With the proposed dynamic modelling approach the prediction error has been reduced significantly. The prediction error is mostly within $\pm 20\%$ but can reach up to 80% for the time periods just before re-training. After re-training the prediction error is generally reduced for the time periods close to re-training points, which is the result of setting the prediction temperature to the last measured value after re-training but it is also due to a new NNM structure that has been re-trained with the newly extended database. In most cases, the tendency of error increase after re-training is lower than before re-training.

Re-training sessions are marked with a black line in the prediction error graphs. After the changes in operating conditions have occurred (at the beginning of Experiment 5) the error tolerance threshold is triggered very often in the first 200 minutes of plant operation. This is due to large prediction errors that occur in the first 200 minutes of plant operation. High prediction errors result from changes in operating process conditions in combination with an NNM structure that is inappropriate for these particular operating conditions. Therefore, the algorithms try to

find an appropriate NNM structure by using a high frequency of re-training sessions in the first minutes of operation. However, due to insufficient data quantity for a qualitative NNM structure, the prediction error is still high and re-training sessions occur quite often in that period. After the model has been trained with sufficient data, that is relevant to the current process, the prediction error is reduced together with the frequency of re-training sessions. The same effect can be seen at the beginning of Experiment 6. Retraining sessions occur frequently in the beginning but after 200min (when sufficient model training data related to the current process has been collected) the frequency of re-training is reduced. In experiment 7 the developed NNM is able to predict temperatures with reasonably good accuracy so the number of retraining sessions is significantly reduced. A similar behaviour can be seen in Experiment 9.

Additional analysis allows investigating the influence of the amount of data for each re-training session on the prediction performance of the dynamic model. 5 different cases were analysed. In the first case the data from the last 1000 minutes has been used for model re-training. In the other cases the data from the last 1500, 2000 and 2350 minutes as well as all the available data has been used. Analysis has been performed based on 30% error threshold. With a larger dataset the average prediction error can be decreased together with the number of required re-training sessions. Although a larger amount of data for re-training will require more computational power and time for each individual re-training session the reduced number of required re-training sessions could reduce overall time for model development. Analysis results are presented in Table 3.

For the dynamic ANN model development a computer configuration that comprises of an i7-3820 processor with 3.60 GHz and 64 GB of RAM memory has been used. 4 minutes are necessary to predict the process temperature for Experiments 5-9 with the dynamic NNM approach in the way that is presented in this paper using a tolerance threshold of 10% (26 re-training sessions in total). Around 10 seconds are necessary for one re-training session. That enables re-training between 2 measurements (measurement sampling frequency is 30 seconds). Therefore, the proposed approach can be used for on-line process temperature prediction in a dynamic environment where operating conditions change due to unknown reasons.

After it has been concluded that developed NNM is well capable to predict process temperature with required speed and reasonable accuracy the temperature prediction results were compared with developed dynamic MLR models. For the analysis the threshold has been set to 10% and all the data has been utilised for model re-training

sessions. Performance analysis results have been summarised in Table 3. Dynamic MLR1 has a higher prediction error than MLR2 model. However, dynamic NNM has the smallest prediction error of temperature prediction for an observed case. The number of re-training sessions is the smallest in the case of MLR2 model while the highest in the case of NNM. Dynamic MLR models are much faster in terms of process temperature prediction and re-training time but due to fact that the prediction speed and the time for a re-training session of NNM is below sampling time the advantage has been given to prediction accuracy. A detailed performance analysis of developed models has been presented in Figure 10.

Based on the proposed methodology for NNM development dynamic syngas composition models (H_2 , CH_4 and CO) have been developed and their potential has been analysed based on Experiments 1-8. The data from Experiment 9 does not include syngas composition measurements and therefore this experiment will not be considered. In general dynamic models for estimation of syngas composition require much more retraining sessions than dynamic models for temperature prediction to obtain reasonable prediction quality. This is due to a more complex processes related to syngas production but also due to the sensitivity of measurement equipment and measurement error. For a more detailed analysis of syngas composition model prediction potential, measurements with more accurate measurement equipment should be obtained.

Simulation results are presented in Figure 11 (H_2), Figure 12 (CH_4) and Figure 13 (CO). Error prediction threshold has been set to 30% in order to reduce the frequency of re-trainings and to make representation of results more practical. Although the prediction error during Experiments 5-8 is relatively high (26.4% for H_2 , 38.3% for CH_4 and 29.9% for CO) the re-training frequency is decreasing during plant operation together with the average prediction error. This is the result of a new NNM structure that has been developed during plant operation using re-training sessions. It must be noted that the number of available data for syngas prediction model training is much smaller (900 minutes of available data) than in the case for temperature prediction model (2300 minutes of available data) and it does not cover all temperature ranges (only between 200°C and 300°C). An increase of the number of available data will definitely contribute to a better model performance. Furthermore, a decrease of error prediction threshold would improve prediction quality but also the required re-training time. Although a large number of re-trainings were needed for an online dynamic modelling (around 100 for 900 minutes of operation) the total re-training time lasts less than 15 minutes in total. One re-training session takes around 7.5 seconds which

enables model modification between two measurements. The summary of the dynamic model performance (related to syngas composition prediction) for the applied prediction error threshold of 30% is presented in Table 5.

The summary of statistical model prediction performance analysis is presented in Table 6. The best result is obtained in the case where the temperature prediction model has been developed with a 10% error tolerance threshold with all the data for model training. The model has the lowest root mean square error and average prediction error. Furthermore, the model results in a low (in absolute terms) and positive bias which means that the model predictions are generally close to the correct value with a slight over-prediction. With reducing error tolerance threshold the root mean square error, the average prediction error and model bias factor decrease. With improving the size of database for re-training model's root mean square error and average prediction error decrease but there is no general conclusion related to model bias.

Both developed models (the one for temperature and the one for syngas composition) have potential to be implemented in the proposed system with measurement frequency of 30 seconds. The time between 2 measurements is enough for the algorithms to collect the data, to analyse the data and to modify the existing model. Temperature prediction error can be kept around 10% with the proposed methodology while syngas prediction error can be kept around 30% on average. Therefore, the model is well capable of predicting syngas temperature and syngas composition with reasonable accuracy and under changing operating conditions. The proposed methodology seems to be a promising approach to model gasification process for different biomass types or different gasification fuels (coal or sludge). However, a related research should be performed in order to analyse the performance of those model types. For a more detailed analysis of the proposed methodology to predict syngas quality a more robust and accurate measurements set-up is needed.

4. CONCLUSION

For the purpose of temperature and syngas composition prediction in a 75kW_{th} gasification plant a dynamic artificial neural network modelling approach has been applied. Artificial neural networks have a good potential to approximate process parameters in a highly nonlinear processes but they are sensitive to the quality and the quantity of training data that is available. If the training data for neural network model development does not correspond to current process behaviour the prediction error of the model will be high. Therefore, progressive

modifications in the neural network model structure are needed during plant operation. The proposed approach for dynamic artificial neural network modelling comprises of an on-line prediction error analysis that enables on-line neural network re-training in order to preserve parameter prediction quality. Developed dynamic neural network model is able to predict process temperature and syngas composition with reasonable accuracy and speed that allows on-line analysis in changeable operating conditions. It performs better in terms of temperature prediction accuracy than multiple linear regression models. The average process temperature prediction error of the proposed dynamic artificial neural network model is 7.06% during more than 70 hours of plant operation while the syngas composition prediction error is around 30%. The associated neural network re-training time of 10 seconds enables on-line prediction quality analysis and neural network model structure modifications. Proposed methodology seems to be a promising approach to model particular gasification process for different fuel types under changeable operating conditions.

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Table 1

Measurement methodology and equipment

Process parameter	Measurement methodology and equipment
Biomass mass flow rate	Manual weight measurement
Air volume flow rate	Pressure difference based methodology (orifice plate)
Syngas temperature at the exit of the gasifier	Measurement based on thermoelectric effect (thermocouple type K)
Syngas composition	CO, CH ₄ , CO ₂ - Non Dispersive Infrared Absorption methodology H ₂ - Thermal conductivity methodology O ₂ - Electrochemical process (Emerson - MLT 2 Multi-Component Gas Analyzer)
Temperature of inlet air	Measurement based on platinum resistance effect (Pt 100)
Pressure in the reactor	Wheatstone bridge circuit based measurement methodology (Piezoresistive strain gauge)

Table 2

Average prediction error tolerance sensitivity analysis

Error tolerance threshold	Average prediction error for Experiments 1-9 [%]	Number of re-training sessions [-]	Total time for re-training [sec]
50%	12.90	7	140
40%	11.66	8	150
30%	10.61	12	190
20%	8.38	20	315
10%	7.06	26	410

Table 3

Average prediction error tolerance analysis for different datasets sizes

Data available for retraining [min]	Average prediction error for Experiments 1-9 [%]	Number of re-training sessions [-]	Total time for re-training [sec]
1000	12.06	19	115
1500	11.85	18	125
2000	11.52	17	165
2350	11.02	16	180
All data	10.61	12	190

Table 4

Average prediction error tolerance analysis for different datasets sizes

Model type	Average prediction error for Experiments 1-9 [%]	Number of re-training sessions [-]	Total time for re-training [sec]
MLR1	9.93	13	9
MLR2	9.56	22	10
NNM	7.06	26	410

Table 5

Performance summary of the dynamic model for syngas composition prediction

Prediction parameters [%]	Average prediction error for Experiments 5-8 [%]	Number of re-training sessions [-]	Total time for re-training [sec]
H ₂	26.4	102	780
CO	29.9	88	760
CH ₄	38.3	105	810

Table 6

Statistical model performance analysis

Model	R ²	RMSE	APE	MFB	MMBF
Error tolerance threshold - 50%	0.74	45.07	0.13	0.0047	-0.0204
Error tolerance threshold - 40%	0.78	41.71	0.12	0.0009	-0.0136
Error tolerance threshold - 30%	0.80	39.47	0.11	0.0146	0.0023
Error tolerance threshold - 20%	0.87	31.13	0.08	0.0042	-0.0098
Error tolerance threshold - 10%	0.82	24.79	0.07	0.0044	0.0029
Data available for retraining - 1000	0.78	41.37	0.12	0.0104	0.0016
Data available for retraining - 1500	0.79	40.52	0.12	0.0045	-0.0072
Data available for retraining - 2000	0.80	39.80	0.12	0.0031	-0.0039
Data available for retraining - 2350	0.83	39.77	0.11	0.0094	-0.0194
Data available for retraining - All data	0.82	39.46	0.11	0.0146	0.0023
MLR 1	0.81	38.39	0.10	0.0126	0.0067
MLR 2	0.80	39.64	0.10	0.0191	-0.0191
H ₂	0.47	195.37	0.26	0.0085	-0.0323
CO	0.83	276.83	0.30	-0.004	-0.0294
CH ₄	0.45	133.47	0.38	0.0194	-0.0339

Fig 1. Scheme of co-current fixed bed biomass gasification facility operated by TU Dresden

Figure 2. Average fuel flow rate for experiments 1-8

Figure 3. Average air flow rate for experiments 1-8

Figure 4. Time without fuel injection for experiments 1-8

Figure 5. General scheme of artificial network based temperature prediction model

Figure 6. NNM modelling scheme with 10% of error tolerance threshold

Figure 7. NNM prediction result with initial database from Experiments 1-4

Figure 8. Dynamic NNM prediction result with 50% of error tolerance threshold

Figure 9. Dynamic NNM prediction results with 10% of error tolerance threshold

Figure 10. Detailed performance analysis of different dynamic modelling approaches

Figure 11. Dynamic NNM performance for H_2 predictions (Experiments 5-8)

Figure 12. Dynamic NNM performance for CH_4 predictions (Experiments 5-8)

Figure 13. Dynamic NNM performance for CO predictions (Experiments 5-8)