Process performance improvement in a co-current, fixed bed biomass gasification facility by control system modifications

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ABSTRACT

Advanced control solutions are a developing technology which represent a promising approach to tackle problems related to efficiency and environmental aspects of biomass gasification process in a cost effective way. In this paper the potential of advanced control concept to improve gasification process efficiency and to reduce negative environmental effects of the process has been analysed. Advanced control solution, based on feedforward-feedback control approach has been developed using collected operation data and the effects of control concept on gasification process have been analysed using developed artificial neural network based prediction model. Measurement data for the controller and simulation model development has been extracted from a 75 MW_{th} co-current, fixed bed biomass gasification plant operated by Technical University Dresden. The effects of 6 different process improvement goals for controller algorithms development have been analysed during 20 hours of plant operation. The analysis has shown that with introduction of advanced control solutions process efficiency could be improved up to 20%, together with reduction of negative environmental aspects of the process.

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Nomenclature

Main symbols

c_{eff}	importance coefficient of process efficiency, -
c_{Hd}	importance coefficient of syngas heating value, -
c_T	importance coefficient of process temperature, -
c_{pbiom}	specific heat capacity of biomass, kJ/kgK
c_{pgases}	specific heat capacity of flue gases, kJ/kgK
$c_{psyngas}$	specific heat capacity of syngas, kJ/kgK
i	measurement number, -
Hd_{biom}	lower heating value of biomass, kJ/kg
Hd_{max}	maximum measured value of syngas heating value, kJ/kg
Hd_{syngas}	lower heating value of syngas, kJ/kg
m_{biom}	biomass mass flow, kg/s
$m_{biom-freq}$	biomass injection frequency, min
m_{gases}	flue gases mass flow, kg/s
m_{syngas}	syngas mass flow, kg/s
P_{SCORE}	process optimisation score, -
P_{th}	plant load, %
T	temperature, °C
T_{env}	environment temperature, °C
T_{max}	maximum measured value of process temperature, °C

Abbreviations

ANN	artificial neural networks
CH ₄	methane
CO	carbon monoxide
CO ₂	carbon dioxide
H ₂	hydrogen
O ₂	oxygen

Greek symbols

$\eta_{process}$	process efficiency, -
$\eta_{process_max}$	maximum measured value of process efficiency, -

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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 (H_2 , CO, CO_2 , CH_4 , light hydrocarbons, tar, char, ash and minor contaminates) called 'syngas', using gasifying agents [1]. Products of the gasification are mostly used for separately or combined heat and power generation [2] such as in dry-grind ethanol facilities [3] or in autothermal biomass gasification facilities with micro gas turbine or solid oxide fuel cells [4]. Utilisation of syngas for hydrogen production through various available thermal processes is described in [5]. Hydrogen production potential from oil palm shells through gasification has been analysed in [6]. Gasification systems integrated with methanol synthesis have potential for a cleaner methanol production [7]. Other application of gasification systems for chemical production are described in [8]. Besides chemical production, gasification systems could be utilised for building material production using gasification residues [9]. A more detailed overview of biomass gasification technologies could be found in [10]. For power generation purposes, syngas should meet some technical and environmental requirements related to a certain percentage of particular gases ($>20\%$ CO and $>10\%$ H_2) and low tar content (<100 mg Nm^{-3}) and it needs to be free of poisonous and carcinogenic gases [11].

Gasification is relatively well known technology, however, the share of gasification in meeting overall energy demand is small due to current barriers concerning biomass pre-treatment (drying, grinding and densification), gas cleaning (physical, thermal or catalytic), process efficiency and syngas quality issues [12]. Although a lot of effort has been focused to increase gasification process efficiency, to enhance energy savings and to improve environment aspects of gasification process, only some partial solutions to partial aspects have been obtained. Nevertheless, the number of projects related to small and middle-scale biomass gasification combined heat and power plants as well as syngas production plants in developed European countries [13] and especially in Germany [14] has been significantly increased in the last few years [15] as shown in Table 1. 75% of all commercial produced gasifiers are downdraft or co-current type [8] due to some advantages over updraft and fluidised bed gasifiers (such as cleaner syngas for power generation in turbines or internal combustion engines or lower investment and maintenance costs) [11]. However, in downdraft gasifiers, the temperature of oxidation process must be kept at high values and the distribution of gasifying agent must be homogenous in oxidation area [11].

The performance of biomass gasification processes is influenced by a large numbers of operation parameters concerning the gasifier and biomass [1] such as fuel and air flow rate, composition and moisture content of the biomass [16], geometrical configuration and the type of the gasifier [17], reaction/residence time, type of the gasifying agent, different size of biomass particles [1] derived from different feedstocks [18], gasification temperature and pressure [19]. From mentioned process parameters, process temperature is one of the most important one. It influences syngas quality, reaction rate and tar concentration. Low process temperature produces high tar content [20], low syngas quality and low cold gas efficiency [21]. However, a high process temperature causes unwanted ash melting. Therefore the process temperature should be controlled [22]. In downdraft gasifiers the gasification process is usually conducted on atmospheric pressure. Higher pressures often increase tar concentration together, decrease CO content in syngas with marginally efficiency increase [23]. Air fuel ratio should be controlled in order to maintain a minimum stoichiometric ratio of air and fuel in combustion zone and to maintain a ratio of air and fuel that is lower than stoichiometric value in gasification zone. Higher air quantities enable better oxidation and therefore reduce syngas heating value and decrease overall efficiency. Lower air quantities improve syngas heating value but increase tar yield [11]. Han et al. [24] has shown that by finding optimal operation parameters, more efficient tar decomposition and reduction could be obtained.

In order to improve efficiency, to optimise the process or to maintain constant process quality during operation, a plant operation analysis tool that enables parameter prediction in dependence of various operating conditions is needed. Large scale experiments for the purpose of syngas quality optimisation respected to different fuel and bed types [25], syngas quality improvement with process parameters changes [26] or for process performance improvement [27] could be performed. However, even with implementation of Taguchi experiment optimisation methods for minimisation of number of test [28] these experiments could often be expensive or problematic in terms of safety.

A model based optimisation is a widely used tool for various optimisation purposes. For the gasification process optimisation analysis Emun et all [29] proposed Pinch analysis to improve energy efficiency and to minimise the operation costs. Stoichiometric models could be used for analysis and optimisation of a fluidised bed gasification process [30]. For analysis of Fischer-Tropsch synthesis optimisation by changing operating conditions a non-

stoichiometric based model can be utilised [31]. Artificial neural network based models can also be used to analyse gasification process and to find optimal static operating conditions for particular optimisation function [32]. Bang-Moller et al [33] used exergy analysis to optimise gasification based energy system. For integrated plasma based waste gasification system a thermodynamic model was used to estimate process performance and to find optimal operating conditions [34]. Similar model based process analysis studies have been performed also for entrained [35] and fluidised bed gasifiers [36]. For optimisation purposes Wang et al. implemented an artificial intelligence based optimisation algorithms to optimise economic and environmental performance of a biomass gasification based system [40]. Those model based optimisation tools are applicable for unique operation point steady-state systems where only one or few process parameters are considered. However, they are not applicable for a dynamic online process control where several process parameters are controlled simultaneously.

During the past years a key issue for improving efficiency in gasification systems was integration of the gasification process dynamics and its scenario into the actual decision-making of the plant operation. The use of intelligent adaptable/evolutionary modelling and optimisation systems could lead to the development of more powerful methodologies for gasification systems analysis, control and optimisation [41]. 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. They are particularly useful in system control such as in implementing complex mappings and process identification.

For gasification control purposes, advanced control concepts have been implemented on several small-scale gasifiers. Due to high process nonlinearity a non-adaptive fuzzy controller has shown better performance over conventional PID controllers for biomass downdraft gasifier control purposes in the research done by Sanjeevi Gandhi et al. [42]. Al Seyab et al. [43] proposed a nonlinear model predictive control based on Wiener model that has been developed and used to control an ALSTOM gasifier. The approach has shown control performance improvement when compared with pure linear model based predictive control. In the field of adaptive control algorithms for coal gasification control, Nobakhti et al. [44] proposes a self-adaptive differential evolution algorithm for control parameter modifications where steam, limestone air and coal flow were controlled. Similar work has been performed by Taylor et al. [45] where proportional-integral-plus controller has been tested. However, the

control algorithms have been implemented and tested only for 3 different loads using linearized models. For temperature control on various operating regimes in a coal water slurry gasification process Wei and Liu [46] developed adaptive programming algorithms. Neural network based models were used to predict process output and adaptive dynamic programming was used to find optimal coal slurry flow to keep gasification temperature at a certain level. Other process parameters such as process efficiency or syngas quality have not been considered as the optimisation goal.

Fuzzy neural network based modelling and control of a gasification process has shown to be a promising approach to tackle high process nonlinearity. However, a fuzzy based process optimisation and control should also be able to adapt to changing operating conditions during gasification plant operation on various syngas production loads and be able to control multiple process parameters simultaneously. Available adaptive optimisation solutions have a limited capabilities in terms of optimisation goal flexibility or range of operating conditions. The goal of the research is to analyse the potential of an on-line process parameter tuning control concept to improve performance of a co-current fixed bed gasification plant for different plant syngas production loads by changing several operating parameters simultaneously. The novelty of the research is stated by developed user-defined process performance improvement approach that comprises of a combined feedforward/feedback control system for multiple process parameters on various plant operation regimes with an adaptive control map that represents a simplified model for feedforward control (to be referred as ‘advanced control system’ in further text). Adaptive control map is generated by developed heuristic based algorithms for process parameter tuning and on-line process analysis. Particular goals for process improvement are defined by users.

2. BIOMASS GASIFICATION FACILITY AND MODEL FOR PROCESS ANALYSIS

The object of process improvement through advanced process control is a Co-current fixed bed gasifier with thermal input of 75 kW_{th} , located in Pirna (Germany), operated by TU Dresden. The facility scheme is presented in Fig. 1. Biomass wood chips, distributed from local provider, are used as a fuel in gasification process. Biomass composition

has been determined at TU Dresden laboratory before start of the operation. Biomass composition has been considered as constant for measurement campaigns. The lower heat capacity value of the fuel 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 chlor is 0.01 %.

Current process control diagram has been described in Fig. 2. The operation of the system is ensured by a conventional PLC controller. Significant manipulated variable is the negative pressure in the gasifier, which is maintained by a frequency converter on induced draft fan. Safety chains (for emergency stops or shutdowns) are also incorporated. Biomass is injected manually in a small storage room that is located in front of valves for biomass flow control. Biomass flow is controlled manually by opening and closing the valves. Current control system that is provided by manufacturer only gives indication to the plant operator when the reactor is running low on biomass. Once the valve opens, the whole amount of biomass from the storage room is injected into biomass shredder. The biomass is shredded and injected into gasification reactor. Air for gasification is distributed by air pumps and air valves, located before reactor. Air flow is controlled manually either from central control system (computer) or with manual control over air valves. Ash removal is also controlled manually by opening the ash valves. Current automation and control systems gives an on-line information to process operator related to value of process parameters such as gasification temperature in different parts of the gasifier, syngas heating value, syngas flow and ash flow.

For biomass gasification process analysis and further process improvement purposes, an artificial neural network based model has been developed. Artificial neural networks (ANN) models use a non-physical modelling approach which correlates the input and output data to form a process prediction model. ANN is a universal function approximator that has ability to approximate any continuous function to an arbitrary precision even without a priori knowledge on structure of the function that is approximated. ANN models have proven their potential in prediction of process parameters in numerous thermo-energy related processes like Stirling cycle [47] or biomass gasification process [48]. The detailed description of the ANN model that has been used for process analysis can be found in [49]. Data for model development and validation has been collected from gasification facility in Pirna. For artificial neural-network based (ANN) prediction model 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 system comprises of 3 inputs (fuel flow, fuel injection frequency and air flow for temperature prediction and temperature, fuel and air flow for syngas composition prediction) and one output. Overall model outputs are process temperature and syngas composition (H_2 , CO_2 , CO , CH_4 , O_2 and N_2 values). Developed neural network prediction model has proven its potential to predict biomass gasification process parameters on different facility loads and syngas production loads in a fast way and with reasonable accuracy [49]. Developed model has been used as a simulation tool to analyse the influence of different process variables: fuel and air flow together with fuel injection frequency on process performance. General influence of fuel injection frequency and fuel and air flow on process temperature and syngas composition changes during particular process operation are presented in [49].

3. METHODOLOGY FOR PROCESS PERFORMANCE

IMPROVEMENT

Sets of different measurements from selected downdraft gasifier in Pirna have been used to develop algorithms for process parameter tuning purposes and to generate an adaptive control map that together with feedback PI controller enables on-line process control. Process temperature, syngas composition and flow and process efficiency for different operating regimes have been collected/calculated and analysed. Process efficiency (as one of the main optimisation parameters) has been calculated based on Eq. 1. Due to a high mass and energy accumulation during process operation and constant changes in particular biomass quality the efficiency has been averaged on hourly basis to mitigate effects of various transient regimes during that period. Different kind of averaging could produce different results. Therefore, the averaging should be performed in the light of particular process dynamics. Sum of syngas mass flow and flue gases from the process are comparable to the sum of mass flow of biomass and air that have been injected in the process (Eq. 2.). The methodology has been performed for nominal operating conditions where syngas can be produced in a safe way (on the measured gasification temperatures above 250 °C). Transient regimes that are necessary to reach those conditions (or after them) have not been considered. However, due to changes in syngas quality caused by various chemical reactions on different temperature and changes in process temperature caused by oxidation process the particular gasifier syngas production load can vary. Therefore, for the

calculation of process performance the gasifier's syngas production load has been defined by the quality and the amount of produced syngas (Eq.3). Therefore, the particular syngas production load can differ from nominal thermal gasifier load. For example, the same syngas production load can be reached by a high syngas quality and low syngas flow or by low syngas quality and a high syngas flow while maintaining the same thermal output of the gasifier. Furthermore, due to mentioned reasons various syngas production loads can be reached during steady-state nominal gasifier thermal loads. Nominal gasifier loads for syngas production have been defined on temperatures above 250°C and relatively small process temperature changes have been defined as a condition to determine steady-state conditions.

$$\eta_{\text{process}} = \frac{m_{\text{syngas}} \cdot [\text{Hd}_{\text{syngas}} + \text{Cp}_{\text{syngas}} \cdot (T - T_{\text{env}})] + m_{\text{gases}} \cdot \text{Cp}_{\text{gases}} \cdot (T - T_{\text{env}})}{m_{\text{biom}} \cdot \text{Hd}_{\text{biom}}} \quad (\text{Eq.1.})$$

$$m_{\text{syngas}} + m_{\text{gases}} \approx m_{\text{biom}} + m_{\text{air}} \quad (\text{Eq.2.})$$

$$P_{\text{th}} = \frac{m_{\text{syngas}} \cdot [\text{Hd}_{\text{syngas}} + \text{Cp}_{\text{syngas}} \cdot (T - T_{\text{env}})] + m_{\text{gases}} \cdot \text{Cp}_{\text{gases}} \cdot (T - T_{\text{env}})}{75} \quad (\text{Eq.3.})$$

For particular syngas production output (load - P_{th}) and corresponding biomass heating value (LHV), process temperature, syngas composition and flow, process efficiency and all other process input variables (fuel and air input, fuel injection frequency and fuel heating value) are collected and compared to find process parameter values settings (fuel flow, air flow and fuel injection frequency) that show good results in terms of process performance. Three different process variables (process efficiency, syngas heating value and process temperature) were considered to calculate process performance and to form user-defined goals for process improvement. Process temperature has been considered due to process environmental aspects. With higher process temperature, the tar decomposition process is more efficient and tar emissions are lower [24].

Process complexity does not enable definition of optimisation goal for process improvement in a clear way. There is no simple mathematical model that can describe the process (for this purpose ANN modelling approach has been used) and therefore it is hard to formulate optimisation equality and inequality constraints that define process behaviour in a clear and conventional way. The list of inequality constraints is listed in Table 2. Goals for process performance improvement were set to maximise process performance score derived from equations that are presented in Eq. 4 and 5. In Eq. 4 process efficiency, process temperature and syngas heating values represent semi-

controllable variables. Semi-controllable variables are result of process performance and will be influenced by fuel flow, air flow and fuel injection frequency which represent controllable variables. Controllable parameters are process performance weight coefficients in Eq. 5 which are defined by user. Due to fact that the same plant load could be reached either by a high syngas quality and low syngas flow or vice a versa, the user can define a compromise between these two parameters, respected to his particular needs, by changing weight coefficients for syngas quality. The list of process improvement variables and parameters are presented in Table 2.

$$P_{\text{SCORE}} = c_{\text{eff}} \cdot \frac{\eta_{\text{process}}}{\eta_{\text{process_max}}} + c_T \cdot \frac{T}{T_{\text{max}}} + c_{\text{Hd}} \cdot \frac{\text{Hd}}{\text{Hd}_{\text{max}}} \quad (\text{Eq. 4.})$$

$$c_{\text{eff}} + c_T + c_{\text{Hd}} = 1 \quad (\text{Eq. 5.})$$

For process performance improvement purposes a heuristic based approach has been used to develop algorithms for process parameters tuning. Tuned process parameters are used to develop an adaptive control map in a feedforward/feedback control system. The best available process parameters values settings for operating conditions that occurred during 20 h of plant operation have been extracted from existing database to form an adaptive control map. However, better process performance, together with related process parameter settings can occur during plant operation if the process is operated under different conditions (from operating regime that are still not in database). New process settings could be found by process simulation or simply during plant operation. When a “better” process parameter settings are found (from the standpoint of the process performance goals) than algorithm automatically sets these new settings as currently the best and adapts control map for these particular operating conditions. This process can be called “controller training”. In Fig 3. the flow chart for parameter tuning has been described. Initially, the process parameters (syngas quality and flow, airflow, biomass flow and injection frequency and process temperature) are collected from measurement system. Averaged process efficiency and syngas production load are calculated based on equations 2 and 3. Process performance for is calculated based on equations 4 and 5. Algorithms are then used to initialise/extract current process settings (process parameters) for specific syngas production load (syngas production load was divided in 10 segments and each segment has individual optimised process settings). Newly calculated values in terms of process performance are compared with current/existing ones and if they are higher than in current case then the current ones are replaced with the new ones. The process is repeated for each time step (minute based) during plant operation. Proposed methodology has been

conducted in MATLAB® programming tool. Biomass composition and its lower heating value is defined by laboratory at TU Dresden. Biomass lower heating value has been taken as constant during plant operation.

In order to meet particular syngas production load set by plant operator, additional PI controller for fuel and air flow has been introduced into advanced control system while fuel injection frequency can be adjusted manually. Additional PI controller can correct proposed values derived/suggested from control map up to $\pm 15\%$ in order to meet particular syngas production load demand due to process changes. The changes can be result of changing operating conditions that cannot be controlled or easily monitored (like biomass quality). PI controller terms for air and fuel flow control were tuned by Ziegler-Nichols method. Gain values are 0.225 for air controller and 0.9 for fuel flow controller. Integral gain of the controller is 0.0007 for air flow control and 0.011 for fuel flow control which suggests very slow response time of the system (reset time for air flow PI controller is 1430 s and 90 s for fuel flow PI controller).

As mentioned before, for creating advanced control system with adaptive control map that enables on-line plant process improvement all related operating parameters from gasifier's operation are collected, analysed, compared and the process performance through process performance calculation has been done and compared with previous calculations. Data from 4 different experiments that resulted in over 20 hours of gasifier operation have been collected to develop described control system. Operating regimes with the highest calculated process performance values (red squares) related to facility load (blue squares) are presented on Fig. 4. From these operating regimes, all operating parameter data settings have been extrapolated. These operating settings will be used as reference to create an adaptive process control map for currently optimal plant operation on different syngas production loads. For particular syngas production operating point, parameters such as fuel flow, air flow and fuel injection frequency are extrapolated and presented to plant operator. Tuned process parameters derived from developed algorithms for different syngas production loads are presented on Fig. 5. These tuned ('optimal') operation parameters will be used to form a process control map of the particular system. Developed performance improvement methodology could also be used by plant operator as an expert system tool for plant operation and process optimisation purposes (through on-line suggestions how to operate the process) or simply for facility operation training purposes. Advanced control system scheme is presented on Fig. 6

4. RESULTS

Effects of advanced control implementation into existing control system on gasification process performance have been analysed using developed neural network process parameter prediction model. Simulation of gasification process for gasifier in Pirna has been conducted in MATLAB/Simulink[®] simulation tool. Simulation results from 4 different experiments that resulted in more than 20 hours of gasifier operation are presented on Fig. 7. Process values of current process control are presented by red lines and process values from advanced process control are presented with green lines.

The process efficiency is improved during the most of the observed/simulated time of gasifier operation. In some cases during short periods of operation the efficiency is decreased with introduction of advanced control. This is result of efficiency averaging during process performance analysis. However, during 20 hours of gasifier operation the average process efficiency has been improved by 24.27%. The highest efficiency improvement can be seen during gasifier operation on syngas production partial loads (50-70%). This means that on partial production loads the conventional control system that is currently used has not been calibrated to provide the best process efficiency. In addition to that, the existing knowledge of operator regarding the process is not sufficient to make necessary corrections to improve process performance. Therefore the control map (defined by adaptive optimisation algorithms) provides a suggestions for operator/control system how to operate the process in a more effective way.

Advanced control system follows planned production load with very good accuracy. This is a result of PI controller which corrects the process parameters derived from control map to meet specific load. The averaged difference between planned gasifier load and the load that has been delivered with advanced control system is 7,5% but can reach up to $\pm 10\%$.

Results of process simulation show that advanced controller generally decreases biomass fuel input. Less fuel is needed to generate the same output (Fig. 8). Control map generally suggests that the fuel input should be reduced 50-60%. In order to meet desired syngas production load, fuel input values do not differ significantly from suggested values derived from control maps. Greater influence on gasifier's load has air flow input. In order to meet desired syngas production load, air quantitates that are currently introduced into the process differ significantly from

suggested values. Although fuel input is significantly decreased with advanced control implementation, the air flow has not been decreased accordingly. The air flow in some cases is even increased during some operating regimes. Air flow differences are mostly between $\pm 30\%$. This implies that with current (conventional) control system much more fuel than needed is introduced into process. By this, the oxidation process that is essential for the reduction process (in terms of delivered energy) is reduced and other unwanted process effects regarding hydrogen and carbon monoxide formation rate could occur. This results in a low syngas quality and suggests that with current process control the emphasis is on the quantity of produced syngas to satisfy particular demand.

With introduction of the advanced control system the gasifier generally operates on higher nominal process temperatures for syngas production (Fig. 9) due to enhanced oxidation process. A higher process temperature together with lower fuel flow implies that the energy that has derived from the fuel has been utilised in a more efficient way. Higher process temperatures provide better CO, CH₄ and H₂ formation rate which results in higher syngas heating value. Syngas heating value with advanced control system is ranging between 3-5 MJ/m³ while with conventional control system it is ranging between 2,8-4,5 MJ/m³. Higher temperatures also provide more efficient tar decomposition [24] which implies that the tar formation has also been reduced. Syngas composition prediction through advanced control system are presented on Fig. 10. H₂ values are ranging between 4-14 %vol. while CO values are ranging between 8-25% vol.

Described process improvement process has been conducted in order to find the best available process control for process efficiency. In another analysis, the values of particular process parameters (Eq. 5.) in process performance calculation (Eq. 4.) have been varied in order to analyse effects of those parameters on process performance. Several different cases that are described in Table 3. have been analysed. For example, in Case 1 the main process performance improvement goal is to improve overall process efficiency. In Case 2 the main process performance improvement goal is to improve the heating value of syngas. In Case 5 the main goal is to improve process efficiency with a slight improvement of syngas heating value.

Optimisation process analysis shows that process performance improvement goal parameters from cases 1 and 5 give good base for process improvement (Fig. 11). In Case 1 efficiency improvement is the largest while in Case 5

the efficiency increase is smaller for 5% but average syngas heating value has been increased in comparison with other cases. In Case 2, the heating value is indeed enhanced, together with average process temperature but the efficiency of the process has been decreased significantly. In Case 3, the temperature of the process is on the highest value but the values of other process parameters (efficiency and syngas heating value) are decreased because they are not considered as relevant by algorithms. Result analysis suggests that this set of operation parameters is contra effective.

Proposed process improvement methodology has proven potential to improve process performance by giving suggestions to plant operator or facility control system (through adaptive control map) how to control several process parameters (fuel flow, air flow and fuel injection frequency) for different syngas production loads. By changing optimisation factors for optimisation algorithm development proposed methodology also enables flexibility in terms of particular optimisation needs.

5. CONCLUSION

The paper analyses the potential of proposed advanced control system to improve biomass gasification facility performance. Data collected during gasifier operation were used to develop a feedforward-feedback control approach with an adaptive control map that represents a simplified model for control purposes. Advanced control system allows on-line plant process improvement for different syngas production loads. Effects of advanced controller implementation on process performance have been analysed with the results derived from process simulation. The simulation result shows that by introducing developed feedforward/ feedback control system for multiple process parameters with adaptive control map the average process efficiency could be improved up to 25%, together with syngas quality. This is mainly result of suggested changes in air and fuel distribution on partial syngas production loads and improvement of syngas quality. Implementation of developed advanced control system for biomass gasification process improvement also shows potential in terms of improvement of process environmental aspects and flexibility in terms of process improvement. However, in order to make further conclusions this kind of controller should be tested during the real time plant operation.

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Table 1.

The number of operational/planned/under construction biomass gasification facilities in Europe in 2013.

Country	Biomass gasification facilities in operation	Planned/under construction biomass gasification facilities
Germany	160 ($>70 \text{ MW}_{\text{th}} + 24 \text{ MW}_{\text{el}}$)	150
Austria	6 ($19 \text{ MW}_{\text{th}} + 6 \text{ MW}_{\text{el}}$)	2
Finland	3 ($137 \text{ MW}_{\text{th}} + 1,8 \text{ MW}_{\text{el}}$)	2
Denmark	8 ($12 \text{ MW}_{\text{th}} + 1,4 \text{ MW}_{\text{el}}$)	2
Other EU countries	31	15

Table 2.
Performance analysis inequality constrains, goal variables and parameters

	Variable
Controllable variables	Fuel flow
	Air flow
	Fuel injection frequency
Semi-controllable variables	Process efficiency
	Process temperature
	Syngas heating value
Controllable parameters	Optimisation weight factors
Inequality constrains for controllable variables	$m_{\text{biom}} \geq 0$
	$m_{\text{air}} \geq 0$
	$m_{\text{biom}} - \text{freq} \geq 0$
Inequality constrains for semi-controllable variables	$\eta_{\text{process}} \geq 0$
	$T \geq 0$
	$Hd \geq 0$

Table 3.
Process performance goal sensitivity analysis

Parameter importance	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Efficiency [%]	100	0	0	50	75	33
Heating value [%]	0	100	0	50	25	33
Temperature [%]	0	0	100	0	0	33

Fig 1. Scheme of biomass gasification facility operated by TU Dresden

Fig 2. Process diagram of biomass gasification facility with existing control block diagram for fuel flow control

Fig 3. Flow chart of algorithms for adaptive control map development

Fig 4. Analysis of operating points for the best available process performance

Fig 5. Process parameters for different syngas production loads derived from developed algorithms for process performance improvement

Fig 6. Advanced control scheme for biomass gasification process

Fig 7. Effects of process control modifications on gasification process

Fig 8. Simulation results of fuel and air flows with and without advanced control system

Fig 9. Simulation results of temperature and syngas heating values with and without advanced control system

Fig 10. Simulation results of syngas composition with advanced control system

Fig 11. Process performance quality analysis