Mathematical modelling of biomass gasification process in fixed bed reactors

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Sveučilište u Zagrebu

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PREFACE

Omnia mea mecum porto

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SUMMARY

The aim of the research was to develop a mathematical model that is capable to predict process parameters with reasonable speed and accuracy in different and changeable operating conditions during biomass gasification. Process parameters such as fuel and air flow rate were considered as one of the model inputs which lead to prediction of other process parameters such as syngas temperature and syngas composition. Process dynamics were modelled and simulaiton results were analysed in order to enable further development of an on-line gasification process control concept. Model was designed to predict process parameters in different and changing operating conditions. For model development purposes different equlibrium models and artificial inteligence based models were utilised and their performance was analysed. Model prediction potential was validated on measurement data from a fixed-bed type gasification facility. Developed models were able to predict process parameters such as syngas temperature with average prediction error below 10% ($R^2 > 0.82$) and syngas composition with average prediction error below 38% ($R^2 > 0.42$).Dynamic modelling approach with active prediction error estimation was developed to predict process parameters in variable operating conditions. Models were further used to develop a control strategy that could improve process efficiency by 25%.

SAŽETAK

Cilj istraživanja bio je razvoj matematičkog modela koji će predvidjeti pogonske parametre s razumnom brzinom i točnošću u različitim i promjenjivim pogonskim uvjetima tokom rasplinjavanja. Pogonski parametri poput protoka goriva i zraka uzeti su u obzir kao jedni od ulaznih parametara koji su korišteni za predviđanje pogonskih parametara kao što su temperatura i sastav sintetskog plina. Dinamika procesa je modelirana i rezultati simulacije su analizirani u svrhu budućeg razvoja regulacijskih sustava procesa rasplinjavanja. Model je u stanju predviditi pogonske parametre u različitim i promijenjivim pogonskim uvjetima. Za razvoj modela korišteni su različiti modeli temeljeni na očuvanju mase i energije kao i modeli temeljeni na umjetnoj inteligenciji te će se analizirati njihove značajke. Predikcijski potencijal modelavalidiran je na temelju mjerenih podataka prikupljenih s rasplinjača s nepomičnim slojem. Razvijeni modeli su u mogućnosti predvidjeti procesne parametre kao što je temperatura sintetskog plina s prosječnom greškom prdvuđanja ispod 10% ($R^2 > 0.82$) te sastav sintetskog plina s greškom predviđanja ispod 38% ($R^2 > 0.42$). Dinamični pristup modeliranju koji uključuje aktivnu analizu greške predviđanja korišten je za predviđanje pogonskih parametara u promjenjivim uvjetima. Razvijeni modeli su dalje korišteni za razvoj nove strategije vođenja postrojenja koja ima potencijal poboljšati efikasnost procesa za 25%.

PROŠIRENI SAŽETAK

Ključne riječi: Rasplinjavanje biomase, Numeričko modeliranje, Neuronske mreže

Proces rasplinjavanja biomase je visoko-temperaturni proces parcijalne oksidacije u kojem ugljični spojevi, pomoću raznih medija za rasplinjavanje, prelaze u plinsku mješavinu spojeva nazvanu 'sintetski plin.

Iako je rasplinjavanje tehnologija s relativno dugom tradicijom koja datira iz devetnaestog stoljeća gdje su se produkti rasplinjavanja ugljena koristili za rasvjetu i kuhanje, udio rasplinjavanja biomase u zadovoljavanju primarnih energetskih potreba na globalnoj razini danas je malen zbog prepreka koje se odnose na prikupljanje, transport, pripremu i skladištenje biomase, iskoristivost procesa te zbog problema koji su posljedica loše kvalitete sintetskog plina [15]. Produkti rasplinjavanja mogu biti korišteni u različitim energetskim procesima kao što je kombinirana ili odvojena proizvodnja električne i toplinske energije, ali i kao sirovina u procesima proizvodnje vodika, metanola ili ostalih kemijskih spojeva. Potencijal rasplinjavanja biomase u narednim desetljećima se prije svega očituje u proizvodnji kemijskih spojeva (goriva) koji će se koristiti u transportu (kamionski i zrakoplovni) kojima je prijelaz na električni pogon otežan zbog ograničenog dometa, težine i/ili sigurnosti.. Unatoč spomenutim problemima, broj novih postrojenja, kogeneracijskih postrojenja za rasplinjavanje biomase male i srednje veličine kao i postrojenja za proizvodnju sintetskog plina je u porastu u razvijenim zemljama Europske Unije, Sjedinjenih Američkih Država te Kanade [17]. Rasplinjači s nepomičnom rešetkom su najčešće korišteni tip rasplinjača prije svega zbog jednostavnosti izrade i vođenja pogona postrojenja. te se koriste u sustavima s malom snagom. Za veće sustave s koriste se rasplinjači u fluidiziranom sloju.

Na značajke procesa rasplinjavanja biomase utječu brojni pogonski čimbenici vezani za reaktor i gorivo (biomasu) kao što su protok te omjer goriva i zraka, sastav i udio vlage u biomasi, geometrija reaktora i tip rasplinjača, vrijeme zadržavanja čestica u reaktoru, tip medija za rasplinjavanje, veličina čestica biomase te temperatura i tlak rasplinjavanja [15]. Temperatura rasplinjavanja jedanje od najznačajnijih čimbenika koji utječu na rad postrojenja o kojem ovisi kvaliteta sintetskog plina, brzina kemijskih reakcija i udio smola u sintetskom plinu. Zbog toga regulacija temperature predstavlja jedan od prioriteta u vođenju postrojenja. Nadalje, pogonski

uvjeti kod rasplinjavanja se mijenjaju se tijekom dužeg pogona postrojenja zbog sinteriranja, anglomeracije i taloženja pepela na stijenkama reaktora koji kasnije mogu uzrokovati sinteriranje i očvršćivanje sloja za rasplinjavanje.

U cilju detaljnijeg uvida u proces, poboljšanja iskoristivosti procesa, optimizacije procesa i/ili održavanja potrebne kvalitete procesa tijekom pogona potreban je alat (matematički model) za analizu pogona postrojenja koji omogućuje predviđanje parametara u ovisnosti o različitim pogonskim uvjetima. Različiti eksperimenti na malim postrojenjima [22] i laboratorijskim uređajima [23] mogu se izvoditi u svrhu analize procesa ili optimizacije kvalitete sintetskog plina pomoću promjene pogonskih uvjeta ili sastava goriva. Međutim, navedeni eksperimenti su u pravilu skupi, problematični u pogledu sigurnosti te dugotrajni.

Većina dostupnih modela za opisivanje procesa rasplinjavanja temelji se na zakonima očuvanja mase i energije i minimiziranju Gibbsove energije [24], analizi primjenom računalne dinamike fluida (eng. CFD – 'computational fluid dynamics') [25] ili kinetičkih reakcija [26]. U novije vrijeme CFD-DEM (eng. DEM – 'discrete element modelling') modeli su postali vrlo koristan alat u svrhu detaljne analize rasplinjavanja u fluidiziranom sloju ili kod prisilnog strujanja. Navedeni modeli analiziraju termo-kemijske te procese dinamike fluida (temeljem dostupnih modela) koji se odvijaju unutar i oko čestica te prate kretanje pojedinih čestica kroz reaktor. Zbog nemogućnosti robusnog definiranja modelskih parametara, značajnih računalnih zahtjeva te dugog vremena računanja navedeni pristupi modeliranju još nisu praktični za predviđanje procesnih parametara u realnom vremenu. Nadalje, CFD modeli u energetskim sustavima s nepomičnom rešetkom se koriste za opisivanje procesa izgaranja ali zbog kemijske i termičke složenosti procesa rasplinjavanja navedeni pristupi još nisu implementirani za analizu rasplinjavanja biomase. Komercijalno dostupni računalni programi za analizu procesa rasplinjavanja biomase (kao što je ASPEN PLUS) su u mogućnosti predvidjeti procesne parametre s prosječnom greškom predviđanja ispod 30% [27]. Navedeni alati koriste se prvenstveno za analizu stacionarnih pogonskih uvjeta gdje sama dinamika procesa nije dio analize. Modeli temeljeni na zakonima očuvanja mase i energije i minimiziranju Gibbsove energije koriste modele kemijskih reakcija i drugog zakona termodinamike kako bi izračunali stanje kemijske i energetske ravnoteže za cjelokupni sustav. Takvi modeli su neovisni o tipu ili dizajnu rasplinjača te o specifičnim pogonskim uvjetima. Modeli temeljeni na zakonima očuvanja mase i energije su načelno jednostavni za modeliranje i simulaciju te mogu predvidjeti stacionarne procesne parametre u sustavima s nepomičnom rešetkom s relativno dobrom

točnošću. Kinetički modeli opisuju kinetičke reakcije prilikom rasplinjavanja gdje uzimaju u obzir simultane kemijske reakcije te promjene agregatnih stanja. U novije vrijeme razmatra se upotreba modela temeljenih na neuronskim mrežama kao i ostalih oblika umjetne inteligencije koje mogu predvidjeti stacionarne procesne parametre kod rasplinjača u fluidiziranom sloju. Na temelju pregleda dostupne literature može se zaključiti da dostupnih modela može predvidjeti stacionarne procesne parametre kod nepromjenjivih pogonskih uvjeta (ukoliko su parametri modela pravilno definirani) ali se navedeni modeli ne mogu koristiti kod analize procesa rasplinjavanja u sustavima s nepomičnom rešetkom gdje se razmatra dinamika procesa na satnoj bazi uz promjenjive pogonske uvjete.

Primjena evolucijskog modeliranja i optimizacijskih sustava može doprinijeti razvoju metodologija za analizu, vođenje i optimizaciju sustava rasplinjavanja. Sustavi temeljeni na tzv. umjetnoj inteligenciji (kao što su nelinearni aproksimativni matematički modeli) su široko prihvaćena tehnologija a jednom definirani sustav može predviđati i generalizirati proces u kratkom vremenu. Modeli za predviđanje parametara temeljeni na neuronskim mrežama koriste nefizikalni pristup modeliranju koji povezuje ulazne i izlazne podatke u svrhu razvoja modela za predviđanje procesnih parametara. Dinamičke neuronske mreže s unaprijednom ili povratnom 'feedforward' ili povratnom vezom se koriste za predviđanje parametara u sustavima s velikim kašnjenjem kao što su sustavi s talogom od obrade otpadnih voda [55], rashladni sustavi s vodenom parom i vodom [56], sustavi s raznim kemijskim reakcijama [57] ili kod energetskih sustava [58]. Nakon procesa učenja, neuronske mreže mogu predvidjeti procesne parametre kod rasplinjača s fluidiziranim slojem [29] ili rasplinjača u fluidiziranom sloju s vodenom parom [30]. Međutim, kvaliteta predviđanja kod neuronskih mreža uvelike zavisi od kvantitete i kvalitete dostupnih podataka iz procesa koji će se koristiti za njihovo učenje. Promjenjivi pogonski uvjeti mogu prouzročiti značajne greške u predviđanju kod modela s neuronskim mrežama ukoliko se neuronske mreže ne prilagode novonastalim pogonskim uvjetima. U svrhu minimiziranja navedenih problema s promjenjivim pogonskim uvjetima i očuvanja kvalitete predviđanja pogonskih parametara Wang i Hu [60] su predložili dinamičko predviđanje parametara pomoću korištenja genetičkih algoritama kod modela za analizu termalnih promjena u zgradarstvu. Međutim, značajke predviđanja parametara kod aproksimativnih matematičkih modela za proces rasplinjavanja biomase kod sustava s nepomičnom rešetkom još nisu analizirane.

CILJ I HIPOTEZA

Cilj istraživanja: Razviti matematički model procesa rasplinjavanja biomase u nepomičnom sloju s pogreškom predviđanja manjom od pogreške dostupnih modela tj. ispod 30% i uz trajanje predviđanja na minutnoj bazi kako bi model bio prikladan za korištenje u naprednim sustavima vođenja.

Hipoteza istraživanja glasi: Moguće je razviti funkcionalan matematički model koji će opisati složeni termokemijski proces rasplinjavanja biomase u reaktoru s nepomičnim slojem.

ZNANSTVENI DOPRINOS

Očekivani znanstveni doprinosi:

1. Novi aproksimativni matematički model procesa rasplinjavanja biomase u postrojenju s nepomičnim slojem prikladan za opis različitih pogonskih stanja
2. Analiza prednosti i ograničenja primjene razvijenog modela na različitim postrojenjima za rasplinjavanje na temelju raspoloživih pogonskih podataka s dvije lokacije
3. Ocjena mogućnosti primjene razvijenog modela u sustavu vođenja procesa te kvantifikacija učinka mogućih mjera poboljšanja

METODE I POSTUPCI

Unutar istraživanja vezanih za doktorsku disertaciju dostupni su pogonski podaci za razvoj i validaciju aproksimativnog modela s dva postrojenja za rasplinjavanje biomase koji se nalaze u sklopu istraživačke grupe na TU Dresden, Njemačka. Prvi rasplinjač je komercijalni kombinirano istostrujno - protustrujni rasplinjač toplinske snage goriva od 100 kW i nalazi se u gradu Schwarze Pumpe, Njemačka. Drugi rasplinjač biomase je laboratorijski istosmjerni rasplinjač s nepomičnim slojem, toplinske snage 75 kW i nalazi se u gradu Pirna, Njemačka. Na raspolaganju su sljedeći nizovi podataka: protok goriva (biomase) i zraka, temperatura sintetskog plina na izlazu iz rasplinjača, sastav sintetskog plina, tlak u reaktoru i temperatura zraka na ulazu. Korišteni mjereni podaci obuhvatili su višednevna ispitivanja iz 2006., 2007. i 2013. godine.

U svrhu analize značajki različitih pristupa modeliranju, pregledom literature identificirani su i analizirani glavni termokemijski procesi koji se odvijaju tijekom rasplinjavanja biomase te je objašnjen utjecaj različitih pogonskih parametara na proces. Posebna pozornost posvećena je usporedbi fizikalnih modela temeljenih na zakonu očuvanja mase i energije te aproksimativnih modela temeljenih na neuronskim mrežama. U svrhu pronalaska prikladne metode za analizu rasplinjavanja biomase u rasplinjačima s nepomičnom rešetkom analizirane su i objašnjene prednosti kao i nedostaci pojedinog pristupa modeliranju.. Implementirana su dva različita modela temeljena na zakonima očuvanja (s opisivanjem reakcije stvaranja smola i bez njih) a rezultati dobivenim simulacijom modela međusobno su uspoređeni. Razvijeni su modeli temeljeni na neuronskim mrežama i neizrazitoj logici koji su korišteni za simulaciju procesa rasplinjavanja kod različitih sustava s nepomičnom rešetkom. Različiti parametri procesa (kao što su protok goriva i zraka) definirani su kao ulaz za model pomoću kojih se predviđa temperatura i sastav sintetskog plina. Analiziran je i prezentiran utjecaj različitih ulaznih parametara modela na značajke predviđanja ostalih parametara. Nadalje, razvijene su različite strukture aproksimativnih matematičkih modela (neuronske mreže s različitim brojem skrivenih slojeva i Sugeno-tip sustava neizrazite logike) kao i modeli temeljeni na linearnoj regresiji te je analiziran njihov potencijal predviđanja procesnih parametara kod promjene pogonskih uvjeta. Kriterij za analizu značajki uključuje analizu greške pri predviđanju procesnih parametara, brzinu predviđanja, sposobnost modela za predviđanje parametara pri promjenjivim pogonskim uvjetima i potencijal modela u implementaciji na različitim konstrukcijskim izvedbama rasplinjača. Na temelju analize značajki modela objašnjena je metodologija za razvoj modela. Nakon validacije modela, rezultati dobiveni simulacijom kao i mjereni podaci iskorišteni su za analizu mogućnosti primjene modela u sustavu vođenja procesa. Predložene su mjere za poboljšanje značajki procesa. Na temelju simulacijskih rezultata kvantificiran je učinak predloženih mjera za poboljšanje procesa.

Istraživanje je izvođeno u nekoliko koraka u svrhu razvoja i validacije matematičkog modela za opis rasplinjavanja biomase u sustavima s nepomičnom rešetkom.

Prvi korak obuhvatio je pregled literature gdje su analizirane značajke dostupnih modela. Analiza je izvedena nakon identifikacije i opisivanja termokemijskih procesa tijekom rasplinjavanja. Odabrani su prikladni modeli za analizu procesa rasplinjavanja biomase u realnom vremenu za sustave s nepomičnom rešetkom u svrhu daljnje analize. Pregled literature i opis termo-kemijskih procesa u procesu rasplinjavanja biomase detaljno je opisan u ČLANKU 1 (PAPER 1).

Drugi korak uključio je provedbu mjerenja na dva različita rasplinjača. Analizirani su podaci prikupljeni tijekom rada u različitim pogonskim uvjetima. Podaci su prikupljeni na minutnoj bazi tijekom više od 100 sati rada postrojenja. Mjerenja uključuju protok goriva i zraka, tlak u procesu, temperature i mjerenja sastava sintetskog plina. Opis mjerne opreme i metodologije nalazi se u ČLANCIMA 1-3 (PAPER 1-3).

Treći korak uključio je razvoj aproksimativnog matematičkog modela u svrhu opisa procesa rasplinjavanja biomase u sustavima s nepomičnom rešetkom. Razvijeni su i implementirani različiti pristupi matematičkog modeliranja i zakonima očuvanja mase i energije. Tijekom razvoja modela analiziran je njihov potencijal predviđanja procesnih parametara te utjecaji različitih ulaznih parametara modela na značajke predviđanja. Model je validiran na temelju mjerenih podataka. Metodologija razvoja aproksimativnog matematičkom modela i analiza njegovih značajki opisana je u ČLANKU 2 (PAPER 2).

Razvoj aproksimativnog matematičkog modela u svrhu opisa procesa rasplinjavanja biomase u promjenjivim pogonskim uvjetima obuhvaćena je četvrtim korakom istraživanja. Uspoređena su dva različita pogonska uvjeta. Definiran je potencijal modela u svrhu opisivanja procesa tijekom navedenih promjena. Uspoređene su značajke razvijenog modela s predviđanjima modela s linearnom regresijom. Modeli su validirani na temelju mjerenih podataka. Opis promjene pogonskih uvjeta te metodologija razvoja dinamičkog modela za predviđanje navedenih promjena je opisana u ČLANKU 3 i 4 (PAPER 3 i PAPER 4).

Peti korak obuhvaća analizu mogućnosti primjene razvijenog modela u sustavu vođenja procesa u svrhu poboljšanju njegovih značajki. Na temelju mjerenih i simuliranih rezultata predložene su mjere za poboljšanje procesa i analiziran je njihov utjecaj na proces. Pogonski parametri kao što su protok goriva i zraka istovremeno su regulirani tijekom analize kako bi se poboljšala efikasnost postrojenja, kvaliteta sintetskog plina ili ekološki aspekti procesa.. Analiza mogućnosti primjene razvijenog modela u sustavima vođenja postrojenja je opisana u ČLANKU 5 (PAPER 5).

KEYWORDS

Biomass Gasification

Numerical modelling

Artificial Neural Networks

KLJUČNE RIJEČI

Rasplinjavanje biomase

Numeričko modeliranje

Neuronske mreže

LIST OF ABBREVIATIONS

ANFIS	Adaptive Network-based Fuzzy Inference System
ANN	Artificial Neural Network
APE	Average Prediction Error
APR	Autonomous Prediction Range
ARX	Autoregressive Exogenous
CFD	Computational Fluid Dynamics
CNC	Computer Numerical Control
EU	European Union
FIS	Fuzzy Inference System
IGCC	Integrated Gasification Combined Cycle
LHV	Lower Heating Value
MPC	Model Predictive Control
NARX	Nonlinear Autoregressive Exogenous
NNM	Neural Network Model
PLC	Programmable Logic Controller
R^2	Coefficient of Determination
TU	Technische Universitet

NOMENCLATURE

A	sphere surface, m^2
A_{geom}	sphere surface, m^2
A_p	particle surface, m^2
dt	derivative of time, s^{-1}
e	Sistem error, -
f	function of, -
G	Gibbs energy, J
g	Molar Gibbs energy, J
H	Enthalpy, J
m	Number of control steps, -
N	Prediction horizon, s
n	Molar content fraction, -
K_1	Water gas shift reaction, -
K_2	Methane reaction, -
K_3	MEthane reforming reaction, -
k	Species number, -
r	Sistem trajectory, -
S	Entropy, $J\ K^{-1}$
s	Sistem response, -
T	Temperature, K
t	Time, s
u	Input signal, -
x_{1-6}	molar fraction of syngas species, -
y	Output signal, -

Greek letters

Δ	difference , -

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1 INTRODUCTION AND STATE OF ART

1.1 Background

Biomass as a fuel for energy production has been extensively used during history for heating purposes. Biomass is considered as CO_2 neutral and renewable energy source in the sense that the CO_2 generated by biomass combustion recycles from the atmosphere to the plants that replace the fuel [1]. In the EU Commission's report was concluded that for the most common types of biomass a carbon emissions could be reduced by 55 to 98 percent compared to today's fossil fuel mix in European power generation even in situations where the biomass is transported internationally [2]. The annual usage of biomass in 2012 represented approximately 8-14% of the world's final energy consumption [3] while in 2015 the total energy demand supplied from biomass in was around 16.700 TWh with a steady growth of 2% per year since 2010 [4].

One major advantage of biomass as a fuel is that it can directly replace the usage of fossil fuels [5]. Furthermore, biomass generated power can reduce the share of intermittent power production in the overall power generation mix. Due to positive environment and technical aspects, biomass has been extensively used in the last few decades mostly for either separately heat generation or for combined heat and power generation. In the recent times biomass is used for co-firing, anaerobic digestion for methane and/or hydrogen production and for gasification purposes [6].

Today there are two main sectors of final energy consumption where renewable and biomass based energy facilities are scaled up to a commercial use: energy and power generation industry and smaller-scale heating applications. Total heat and power generation from biomass in EU is estimated to be around 1000 TWh (2010) and expected to be doubled until 2020 which would imply a reduction of fossil carbon dioxide emissions of 300 to 600 million tons annually compared to 2010 [2]. The majority of the growth potential lies in making use of agricultural and forest residues and in energy crops planted on idle or released cropland. However, the

current momentum suggests that this potential is not materializing in full potential due to lack of large investments [2]. Technical global biomass supply potential for energy production in 2020 (Figure 1.2.) is estimated to be around 19.000 TWh [4].

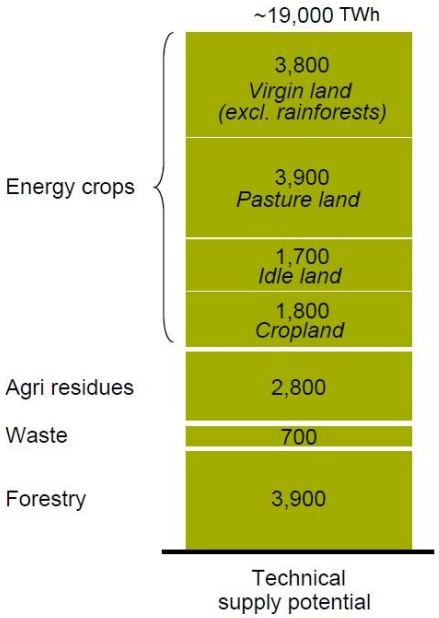

Figure 1 Technical global biomass potential for energy production in 2020 [3].

Transportation (especially shipping and aviation), as the third large sector of final energy consumption, is still relying on primary on conventional liquid fuels. This imposes the need for renewable and sustainable biofuels production in the future. The production of biofuels for these transport segments is therefore likely to become a top priority [2].

The negative sides of a large-scale usage of biomass are often connected to major environmental and social risks like potential lack of biodiversity or a shift from food driven to energy driven land usage. Therefore, world's growing population and necessity for rational usage of agricultural land imposes need for more efficient usage of biomass.

1.2 Biomass gasification status

Due to biomass decentralized utilization, small and middle-scale biomass gasification plants for separate or combined heat and power generation [7] have potential to become rational, efficient and economically viable way of energy conversion and power generation [8]. Biomass gasification products can be also used for hydrogen production through various available thermal processes [9], methanol synthesis [10] and for other applications [11]. Besides chemical production, biomass gasification systems could be utilised for building material production using gasification residues [12]. A more detailed overview of biomass gasification technologies could be found in [13]. For power generation purposes, syngas (product of biomass gasification) 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 [14].

Although gasification is relatively well known technology 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 [15]. 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 [16] and especially in Germany [17] has been significantly increased in the last few years as shown in Table 1.1. The total installed biomass gasification thermal capacity in EU countries in 2016 is around 360 MWth while total installed power capacity is more than 105 MW_{el} [18]. There are 9 projects in EU, involving biomass gasification, currently planned or under construction.

Table 1 Status of biomass gasification in 2011 and 2016.

Country	Biomass gasification facilities in operation (2011)	Biomass gasification facilities in operation (2016)	Planned/under construction biomass gasification facilities (2022)
Germany	70 MW_{th} + 24 MW_{el}	156 MW_{th} + 25 MW_{el}	5 (1.6 MW_{th} + 0.4 MW_{el})
Austria	19 MW_{th} + 6 MW_{el}	19 MW_{th} + 10 MW_{el}	0
Finland	137 MW_{th} + 1,8 MW_{el}	141 MW_{th} + 50 MW_{el}	0
Denmark	12 MW_{th} + 1,4 MW_{el}	30 MW_{th} + 7 MW_{el}	1 (6 MW_{th})
Other EU countries	31 MW_{th}	15 MW_{th} + 13 MW_{el}	4 (10 MW_{th} + 6.8 MW_{el})

75% of all commercial produced gasifiers worldwide [11] and more than 40% of commercially operating gasifiers in EU [16] in 2016 were downdraft or co-current type gasifiers 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 [14]. However, due to their relative small power output their share in overall installed power capacity was 7,5% and 5% in overall biomass gasification thermal capacity.

As mentioned before, process efficiency and syngas quality control represents one of the biggest barriers for gasification technology [15]. Process control and optimisation of such systems is very difficult due to process complexity [15]. 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 [19]. Therefore, process control is often conducted based on operator experience or with in-house developed control systems (developed for the particular gasifier) that require sensitive adjustments to have adequate control response [20]. The lack of adequate process control often results into sub-optimal operation regimes and low process efficiency.

1.3 State of art in biomass gasification modelling

Biomass gasification is a complex thermochemical process which performance 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 [15]. 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 [21]. To improve process efficiency or to guarantee constant process quality during operation through process control, plant operation simulation models are needed. Those models can be used to explain, predict or simulate the process behaviour and to analyse effects of different process variables on process performance. Large scale experiments could be used for this purpose on pilot plants [22] or laboratory scale setups [23] 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 [24], computational fluid dynamics (CFD) analysis [25], kinetic reactions [26] or artificial neural networks. Comparative analysis of available

models has been summarised in Table 2 and explained in detail in PAPER 1. Based on the analysis it was concluded that thermodynamic equilibrium models based on Gibbs free energy minimisation are useful to predict unique stationary operating point. Their potential to predict multiple process operating points is yet to be analysed. Commercially available software for biomass gasification process analysis like ASPEN PLUS are also based on Gibbs free energy minimisation and can predict process temperature with an average prediction error under 30% [27]. CFD and models with kinetic reactions are very useful in terms of delivered information about the process but their sensitivity in terms of model parameter estimation and computational intensiveness makes them inappropriate for on-line process control.

Contrary to mentioned models, artificial neural network (ANN) models use a non-physical modelling approach which correlates the input and output data to develop a prediction model. ANN is an universal function approximator that has ability to approximate any continuous function to an arbitrary precision even without apriori knowledge on structure of the function that is approximated [28].This means that for biomass gasification modelling, ANN modelling approach needs less knowledge about the real process and does not give an analytic solution but rather a numerical result. Therefore, it depends on large quantity of experimental data and many idealised assumptions. Once trained ANN can predict process parameters in circulating and bubbling fluidised bed gasifiers [29] and fluidised bed gasifiers with steam as gasifying agent [30]. However, the prediction quality of trained ANN highly dependents on the quantity and quality of training data related to the process. Furthermore, changing process operating conditions could cause large prediction errors if the ANN models have not been modified for those particular conditions. Hybrid neural network models can also be used for process parameter prediction. This modelling approach incorporates a partial first principles model which describes some parts of process and artificial neural network that serves as an estimator of unmeasured process parameters that are difficult to model from first principles [30].

Table 2 Comparative analysis of different modelling approaches of biomass gasification.

Mathematical model approach		Advantages	Disadvantages
Kinetic models		Realistic process description Extensive information regarding process operation Appropriate for gasifier design and improvement purposes	All possible process reactions are not considered Different model reaction coefficients and kinetics constants Dependable on the gasifier design Impractical for online process control
CFD models		Realistic and detailed process description Extensive information regarding process operation Appropriate for gasifier design and stationary process improvement purposes	Computational intensive Complex model reaction coefficients and kinetics constants Impractical for online process control
Equilib-rium models		Independent from gasifier type and design or specific range of operating conditions Useful in prediction of stationary gasifier performance with various operational parameters Easy to implement Fast convergence	Describe only stationary gasification process Do not offer insight in gasification process
	Stoichio-metric models	Applicable for describing complex reactions in general	Only some reactions are taken into consideration Reaction mechanisms must be clearly defined Equilibrium constants are highly dependable on specific range of process parameters
	Non-stoichio-metric models	Simplicity of input data Used to predict the composition of syngas	Describe gasification process only in general Lack of detailed process information
	Pseudo-equilibri-um models	More realistic equilibrium models	Estimation of methane, carbon and tar in outlet steam is necessity Model is dependable on site specific measurements and type of the gasifier.
Artificial neural networks models		Do not need extensive knowledge regarding process	Depends on large quantity of experimental data Many idealised assumptions
	Hybrid neural network model	Physical relations and reactions are partially included	Knowledge regarding process is needed

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1.4 State of art in biomass gasification control and optimisation

Many authors give special attention to model based optimisation of downdraft fixed bed biomass gasifiers as there are many gasifiers of such type in operation. Most of the optimisation is based on predictions from equilibrium models [31, 32, 33]. The main drawback of the proposed method is that equilibrium models can be used only for analysis in stationary conditions and their prediction quality has been validated only on a unique operating point. Their potential for optimisation on different operating regimes is yet to be analysed.

For control of an updraft gasifiers Paes [34] reported a dynamic gasification model that can be used for online process control of a simple laboratory gasifier. First, static gasification model is developed in order to model static reaction equations and estimate all unknown values for his model. The model is one-dimensional and consists of number of horizontal segments in which species concentrations and gasification temperature is calculated in time. Segments are assumed to be perfectly mixed and all the elements behave identically. Integral conversion laws have been used for calculation of species concentration, mass flow and gasification temperatures. The static model is then shifted into a dynamic model by reduction of segment height due to solid material reactions. The static and dynamic models have been modelled in Simulink. The aim was to control the syngas temperature at the exit of a gasifier together with temperature inside of a reactor. Cascade controller (one controller sets a setpoint for acting controller) has been further used to control mass-flow of the syngas by controlling air flow while remaining a desired temperature in the reactor. It has been noticed that due to inadequate pyrolysis model structure and related chemical reaction coefficients pyrolysis process cannot be described with a reasonable accuracy which produces relatively high prediction errors of the overall model. However, adjusting a static model into dynamic (for example from static neural network to a dynamic neural network model) and variable control setpoints seems to be a promising approach for efficient biomass gasification control.

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 [19]. 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.

[35]. Al Seyab et al. [36] 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. [37] 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. [38] 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 [39] 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. It seems that for biomass gasification control a linear model based control is not sufficient for an efficient process control and a non-linear model type (like neural networks) should be used instead. Such control systems should be also adaptive to be efficient on various operating regimes.

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. Potential of equilibrium based models to predict process parameters for an on-line process control and optimisation in changeable operating regimes is yet to be analysed. Neural network based modelling of a gasification process has shown to be a promising approach to tackle high process nonlinearity and could be further used in process control and optimisation. Control and optimisation strategies should be adaptive to be efficient on various operating regimes.

1.5 Objective and hypothesis of the research

Objective of research is to develop a mathematical model that will describe biomass gasification in fixed bed gasifiers with prediction error under 30% (better than in currently available models) and prediction time under one minute so the model could be further utilised in advanced process control systems.

Hypothesis of research is stated as follows: It is possible to develop a functional mathematical model that can be used to describe a complex thermochemical process of biomass gasification in a fixed bed biomass gasification facility.

Expected scientific contribution:

1. A new approximate mathematical model for description of biomass gasification in fixed bed reactors and various process conditions (defined by changeable process variables)
2. Analysis of model advantages and limitations based on measurement data from two different biomass gasification facilities
3. Analysis of model implementation potential for process control purposes and quantification of potential process improvements

2 EQUILIBRIUM MODELLING OF BIOMASS GASIFICATION

As concluded in Chapter 1.3 equilibrium models have proven their potential to predict process temperature and syngas composition for a unique operating point and a steady state conditions. However, their prediction quality for multiple operating points is yet to be analysed. To do so, 2 equilibrium based models will be developed and their prediction results will be compared with results derived from from Jarungthammachote and Dutta model [40] and experimental results done by Jayah et al.[41].

2.1 Constitutive models for equilibrium-based biomass gasification modelling

One of modelling approaches that can be used to describe overall biomass gasification process behaviour is equilibrium modelling approach. Those model types do not solve particular processes and chemical reactions in the gasifier and instead consist of overall mass and heat balances for the entire gasifier. Equilibrium models are generally based on chemical reaction equilibrium and take into account the Gibbs free energy (Eq.2.1) minimisation (sum of molar Gibbs energy for all phases and their fractions) and the second law of thermodynamics for the entire gasification process (observed reactor system) (Eq. 2.2).

$$G = \sum_{k=1}^{np} n^k g^k \quad \text{(Eq. 2.1)}$$

$$\Delta G = \Delta H_{system} - T\Delta S_{system} \quad \text{(Eq. 2.2)}$$

Equilibrium models are usually used to describe process behaviour for unique stationary process conditions. However, potential of these kinds of models to predict process performance for various stationary operating conditions (changes in biomass composition, changes in process due to ash agglomeration etc.) that could occur during the gasifier operation has not been analysed in details. To analyse the potential of equilibrium models to describe gasification

process in different stationary operating conditions using an unique set of model parameters two different equilibrium modelling approaches have been devised.

The equilibrium model without tar calculations was developed on methodology presented in research done by Babu and Seth [42] while the equilibrium model with tar calculations is based on the methodology presented in research done by Barman et al [43]. Both models are based on energy and mass conservation laws as well as equilibrium chemical balances calculations. Equilibrium chemical balances (kinetic constants) of the water gas shift reaction (K_1), methane reaction (K_2) and methane reforming reaction (K_3) have been taken into consideration. An iterative approach is imposed to solve the set of process equations because chemical reaction coefficients are temperature dependent and resulting chemical reactions have influence on stationary process temperature. Input parameters of both models are biomass composition, biomass moisture content and air quantity. Model outputs are syngas composition and process temperature. The syngas is assumed to consist of fractions such as H_2, CO, CO_2, H_2O (vapour), CH_4, N_2 gases and tar. In the equilibrium model with tar calculation, the chemical compound "Acenaphthene" ($CH_{0.83}$) has been used to represent tar in model calculations. The energy that is released or consumed during particular process reactions is taken from [44, 45] while reaction rates and activation energies have been taken from [42] and [43]. Constitutive equations for both models are presented in EQ 2.3 till 2.11 and other modelling details are presented in PAPER 2, Chapter 3.

	Equilibrium model without tar calculations	**Equilibrium model with tar calculations**
Mass balance	$CH_xO_y + wH_2O + mO_2 + 3.76mN_2 = x_1H_2 + x_2CO + x_3CO_2 + x_4H_2O + x_5CH_4 + 3.76N_2$ (Eq. 2.3)	$CH_xO_y + wH_2O + mO_2 + 3.76mN_2 = x_1H_2 + x_2CO + x_3CO_2 + x_4H_2O + x_5CH_4 + 3.76N_2 + x_6CH_{0.83}$ (Eq. 2.4)
Chemical balance	$K_1 = f(temp) = \frac{H_2 \cdot CO_2}{CO \cdot H_2O}$ (Eq. 2.5) $K_2 = f(temp) = \frac{CH_4}{(H_2)^2}$ (Eq. 2.6)	$K_1 = f(temp) = \frac{H_2 \cdot CO_2}{CO \cdot H_2O}$ (Eq. 2.7) $K_2 = f(temp) = \frac{CH_4}{(H_2)^2}$ (Eq. 2.8) $K_3 = f(temp) = \frac{CO \cdot (H_2)^3}{CH_4 \cdot H_2O}$ (Eq. 2.9)
Energy balance	$Q_{in} + LHV_{biomass} = Q_{reactions} + LHV_{syngas}$ (Eq. 2.10)	$Q_{in} + LHV_{biomass} = Q_{reactions} + LHV_{syngas}$ (Eq. 2.11)

For model validation experiment data from Jayah et al. [41] and simulation results from Jarungthammachote et al. [40] have been considered. In the experiments biomass composition has been defied as $CH_{1.54}O_{0.622}N_{0.0017}$ with 0.16 kmol of moisture per kmol of biomass. For

gasification purposes 0.33 kmol of air per kmol of biomass has been used. Resulting syngas contained 17.0% H_2, 18,4% CO, 1.3% CH_4, 10.6% CO_2 and 52.7% N_2 of mol fractions.

2.2 Model validation of equilibrium-based biomass gasification modelling

Results derived from the equilibrium model with tar calculations for specific operating conditions is in good correlation with the simulation results of Jarungthammachote and Dutta model [40] and experiments described in [41]. Difference between predicted temperature and measured temperature is 30°C (prediction error of 4.62 %). Prediction error of model with tar calculations for H_2 and CO volume contents are 18.92 % and -7.69 %. Results derived from model without tar calculation show a great difference between simulated and experimental results for the same operating conditions. Prediction error for process temperature is -10.77 % while for H_2 and CO volume contents are 13.51 % and -10.26 %. All presented models generally overestimate a volume fraction of H_2 component in syngas composition while underestimating volume fraction of CO. The difference in simulated results can be explained by specific chemical reactions and related kinetic constant values that were taken for modelling purpose which do not present realistic process behaviour. Therefore, it can be concluded that for equilibrium modelling all relevant chemical reactions should be taken into consideration. This will lead to increased model complexity and problems related to definition of chemical reaction rates for all considered chemical reactions. Simulation results are presented in Figure 2.

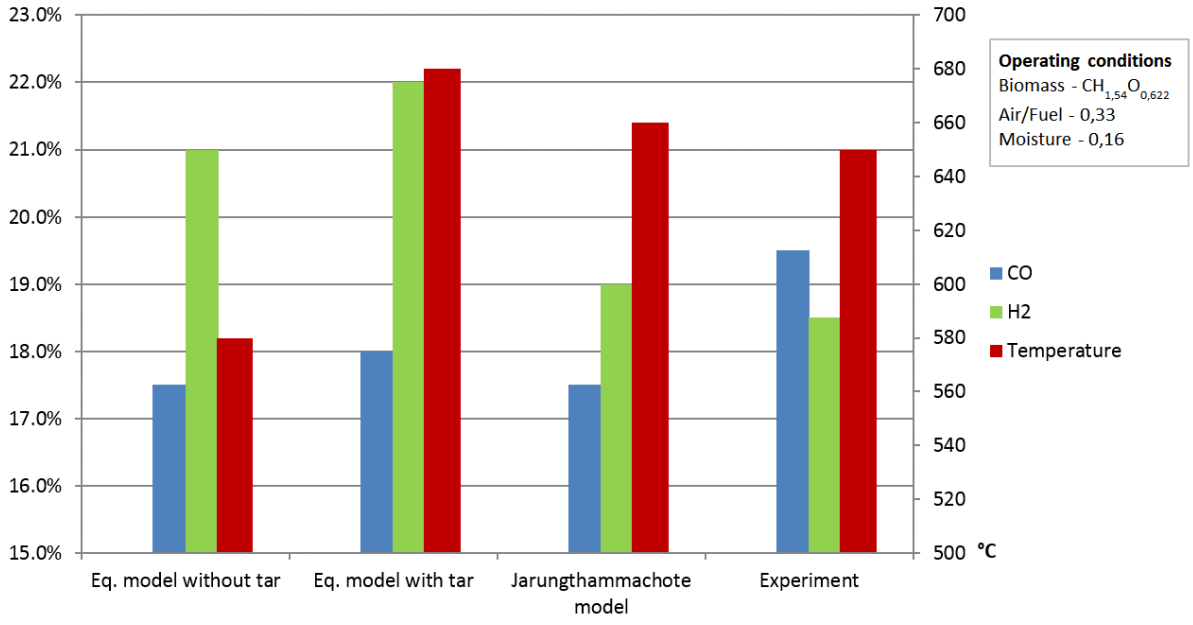

Figure 2 Comparison of results derived from different equilibrium-based models and experiments

To analyse effect of different operating conditions a sensitivity analysis with different model inputs has been performed. Moisture content has been varied from 0.15 to 0.3 kmol/kmol while air content has been varied from 0.1 to 0.3 kmol/kmol.

Results derived from the equilibrium model without tar calculations are presented in Figure 3. The results show that with an increase of the moisture content in the biomass together with an increase of the air flow, the process temperature decreases. This is something that can be expected because with moisture increase a part of energy is consumed for moisture evaporation. Similar to this, with excessive use of air the content of non-reactive nitrogen is increased which results in overall temperature decrease. With the moisture and air flow increase H_2 and CO values decrease. This is explained by temperature dependence of different chemical reactions that contribute to H_2 and CO formation [15]. The water/vapour values firstly decrease with the air flow and moisture content increase but after some point they start to increase. Temperature values around 0°C (273.15 K) that occur on high air flow and moisture contents are not physically explainable and they are result of model calculations.

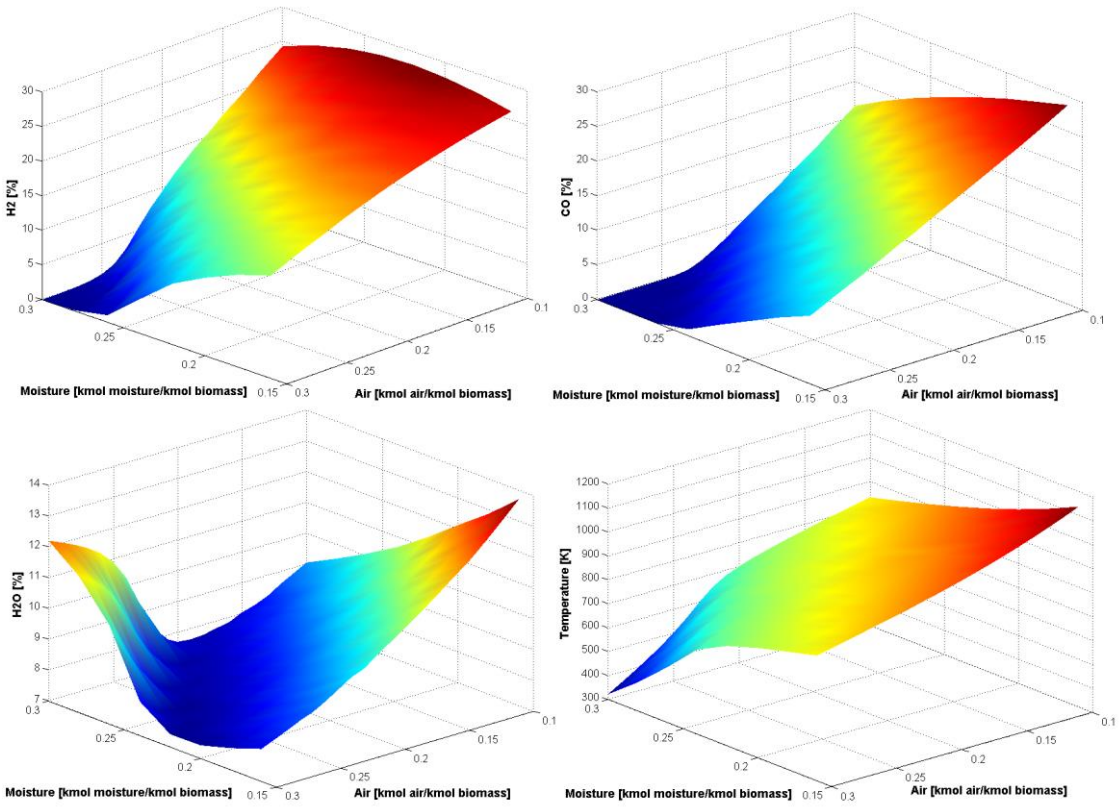

Figure 3 Results of the equilibrium model without tar calculation

Results from equilibrium model with tar calculations (Figure 4.) show that the temperature increases with the moisture content while with different air flows it remains relative constant. CO values follow the tendency of temperature changes due to strong dependence of chemical reactions for CO formation with process temperature. These results differ from the results derived from model without tar calculations due to additional temperature dependable correlation (methane reforming reaction) that has been introduced in the model. Tar calculations show that the tar is increased with moisture content in biomass and with air flow decrease. This could be due to lower overall process temperature decrease. Negative tar values are not physically explainable. They are result of modelling approach (equations that define the equilibrium gasification model).

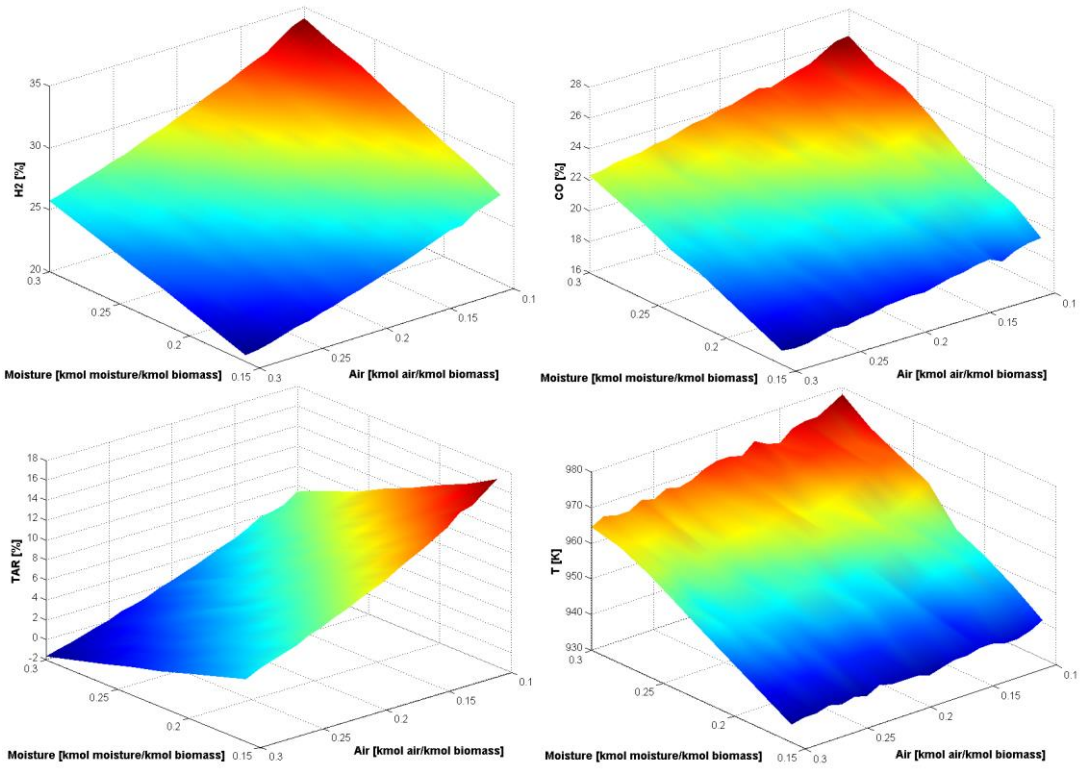

Figure 4 Results of the equilibrium model with tar calculations

Results derived from two different equilibrium modelling approaches (for various operating conditions) show different results and cannot be compared or explained in some cases. This leads to conclusion that equilibrium models are fitted to give a realistic prediction for one operating point and if those operating conditions are changed predictions derived from those models could lead to wrong conclusions.

2.3 Conclusion

Equilibrium based models cannot be used to predict process parameters for various operating conditions because they are highly sensitive to definition of model structure (chemical reactions taken into consideration) and values of kinetic constants for chemical reactions. One way to solve those issues is to use models that do not solve particular chemical reactions in gasifier system but rather predict overall process behaviour directly from input variables. Therefore, models based on neural networks seem to be a promising approach to predict process parameters in biomass gasification process for fixed bed reactors.

3 GASIFICATION PLANTS

To develop artificial neural network model it has to be trained on measured data. To define training data and to validate model performance dedicated measurements on two biomass gasification facilities have been performed. To analyse if the modelling approach is applicable for different fixed bed reactor designs the measurements have been performed on a commercial Combined counter- and co-current gasifier (Combi-gasifier) and Co-current fixed bed gasifier. Both of gasifiers use biomass as their feedstock.

3.1 Combi-gasifier and Co-current fixed bed gasifier

One of the biomass gasifiers for analysis, the combined counter- and co-current gasifier (Combi-gasifier) with a two-step gasification reactor, has a thermal input of 100 kW_{th} and it is located in Schwarze Pumpe, Germany. This gasifier is a commercial type of reactor (Nagel Ingenieurbau Ltd.) and it is used to produce a high quality syngas. In 2006 the gasifier has been used to process 200,000 tons of a solid waste and 50,000 tons of liquid waste (oil, glycerine and paints). This feedstock has been used to produce more than 80,000 tons of methanol and to generate electrical power [46]. Thermal output of the gasifier is 100 kW_{th} which enables production of 50 Nm^3/h of syngas with an average biomass flow rate of 25 kg/h and air flow rate of 18-23 Nm^3/h.

In the reactor whose simplified scheme is presented in Figure 5., the fuel (brown and black lines) is introduced through top opening. In the first step the fuel reaches Counter-current zone where it is partialy gasified with air that is flowing in a counter stream. Resulting syngas (red lines) that contains some parts of unreacted fuel is transferred to Co-current zone where it is finally gasified in a co-current stream of air. The rest of the fuel slowly moves towards Co-current zone where it is gasified in a co-current stream of air. Resulting unreacted particles (ash) are removed at the bottom of the reactor. After gasification, syngas is cleaned through non-catalytic partial oxidation with regenerative heat recovery. Syngas is cooled after cleaning and

converted into electricity and heat by using a gas engine In order to increase the energetic balance of the overall process, the resulting waste heat is redirected into the overall process at suitable points [47].

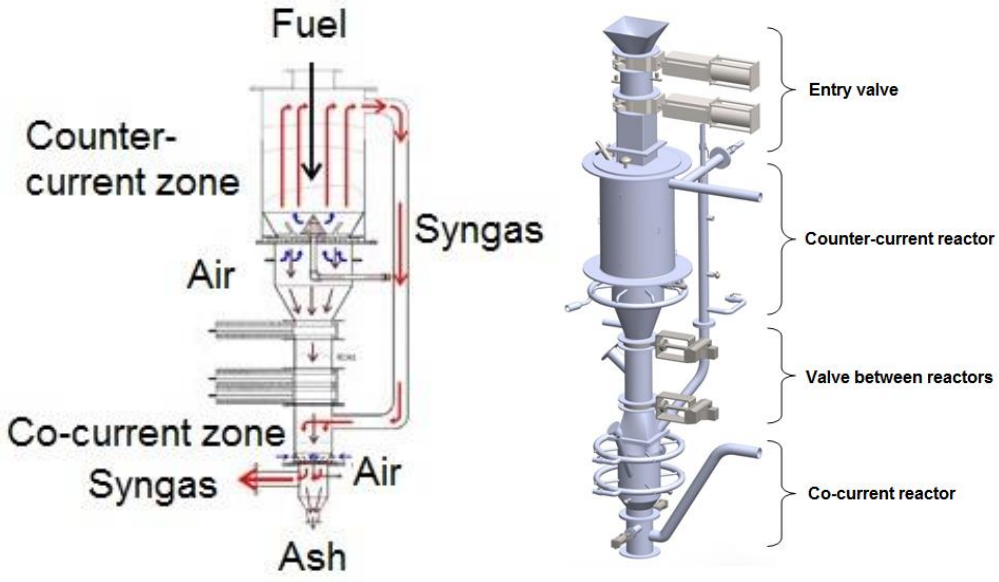

Figure 5 A simplified scheme of Combined counter- and co-current gasifier (Combi-gasifier)

Second gasifier, which will be investigated in more details, is a laboratory Co-current fixed bed gasifier with thermal input of 75 kW_{th}, located in Pirna (Germany), operated by TU Dresden. The gasifier is used to produce syngas which is further used to produce combined heat and power (CHP) in internal combustion engine or as a fuel for conventional gas burner. During operation the biomass is firstly injected manually in a small storage room with a manually controlled valve. Once the operator gives a signal the valve opens and 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 pumps and 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. Produced syngas is then distributed towards a CHP unit or conventional gas burner. If the syngas is used in CHP unit it first goes through a cleaning unit where it is cleaned through various catalytic reactions. Reaction temperature is controlled by a water cooling system. After cleaning the syngas is introduced into a CHP unit and resulting flue gases are cooled down and introduced to atmosphere. For calorific value and combustion properties analysis the syngas is used in combustion chamber. The combustion chamber is preheated by natural gas. Resulting flue gases are cooled down by a water cooling

system and introduced to atmosphere through a chimney. Detailed facility scheme is presented in Figure 6.

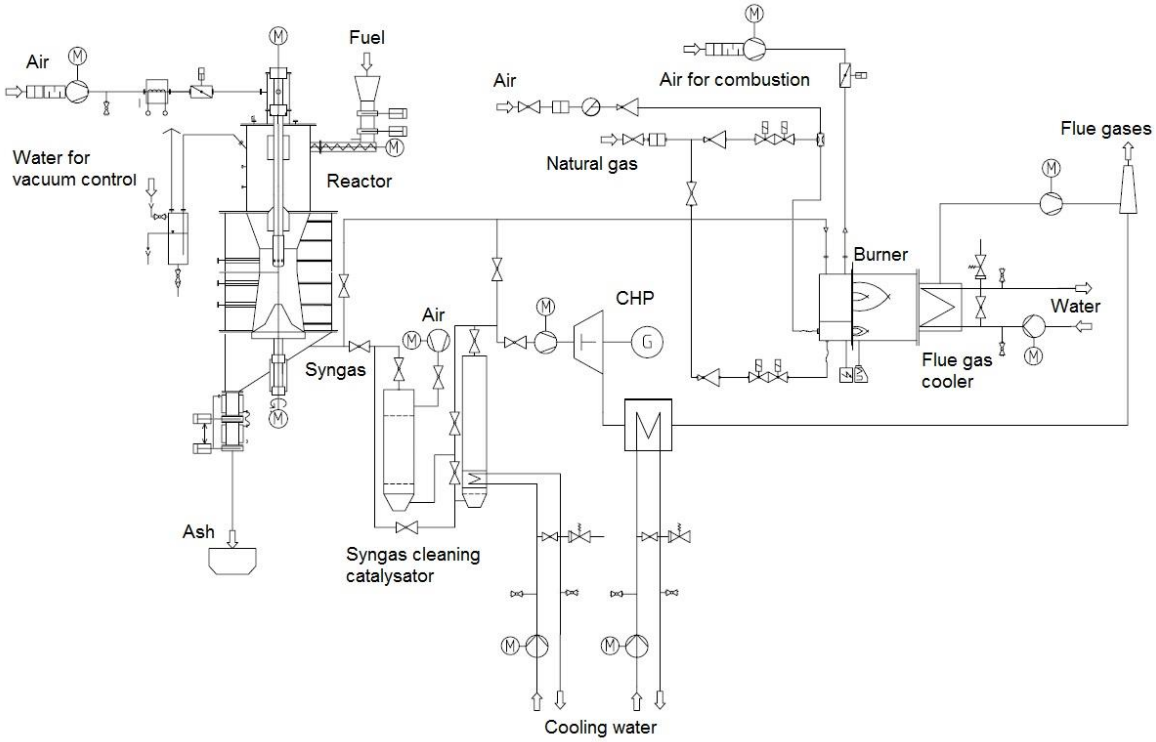

Figure 6 A detailed scheme of Co-current fixed bed gasifier facility

The operation control of the reactor is ensured by a conventional PLC controller. Major manipulated variable is the negative pressure in the gasifier, which is maintained by a frequency converter or 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 upstream of the reactor. Air flow is controlled manually either from central control system 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.

3.2 Measurement equipment and acquired measurement data

Measurements on commercial 100KW_{th} Combined counter- and co-current gasifier (Combi-gasifier) have been performed in 2007. Biomass mass flow rate, air volume flow rate and syngas temperature at the exit of the reactor were measured on a minute based frequency. One of available experiments that resulted in more than 9 hours of gasifier operation has been used for modelling and neural network training. In the case of Combi-gasifier biomass mass flow rate has been measured automatically through dedicated measurement system. No syngas or biomass quality measurements have been obtained during the experiment. Due to limited amount of available data only the temperature measurements from Combi-gasifier will be used to analyse if the proposed modelling approach can be used for different gasifier designs.

Data for model development and detailed model validation was collected in several measuring campaigns on Co-current fixed bed gasifier (75kW_{th}) in 2006 and 2013 comprising following measurements/analyses: biomass mass flow rate; air volume flow rate; syngas temperature at the exit of the gasifier; syngas composition (CO, CO_2, CH_4, O_2 and H_2) and flow rate; pressure in the reactor; temperature and flow rate of inlet air; rotation speed of the reactor bed; temperature in combustion chamber and system time. Most of data (except biomass flow rate) were recorded on a 30 second base in a correspondence with relevant international standards for this type of measurements. Biomass flow rate was measured manually with a frequency time of 3 minutes. Biomass flow rate was not measured with lower frequency due to nature of the system operation. To insert biomass into the reactor, operator has to travel from the bottom of the reactor (where a computer for system control is placed) till the top of the reactor and then manually insert biomass into reactor. Equipment used for measurements is listed in PAPER 2, Table 4.

Two sets of experiments were performed to analyse the process behaviour. The first set of 5 experiments (Experiments 1-4 and validation experiment) 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 gasifier operation. Between 2006 and 2013 the system was operating on sporadically and it was used only for short, one

day experiments. After measurements, the data was analysed and pre-processed in order to define a set of input and output datasets for model development and validation. Details regarding data pre-processing are described in PAPER 3, Chapter 2.

Collected data from biomass mass flow rate measurements are presented in Figure 7. In experiments 1-4 the average biomass mass flow rate usually ranged between 50 and 300 kg/h during gasifier operation. In experiments 5-8 the biomass mass flow rate ranged between 50 and 500 kg/h of biomass.

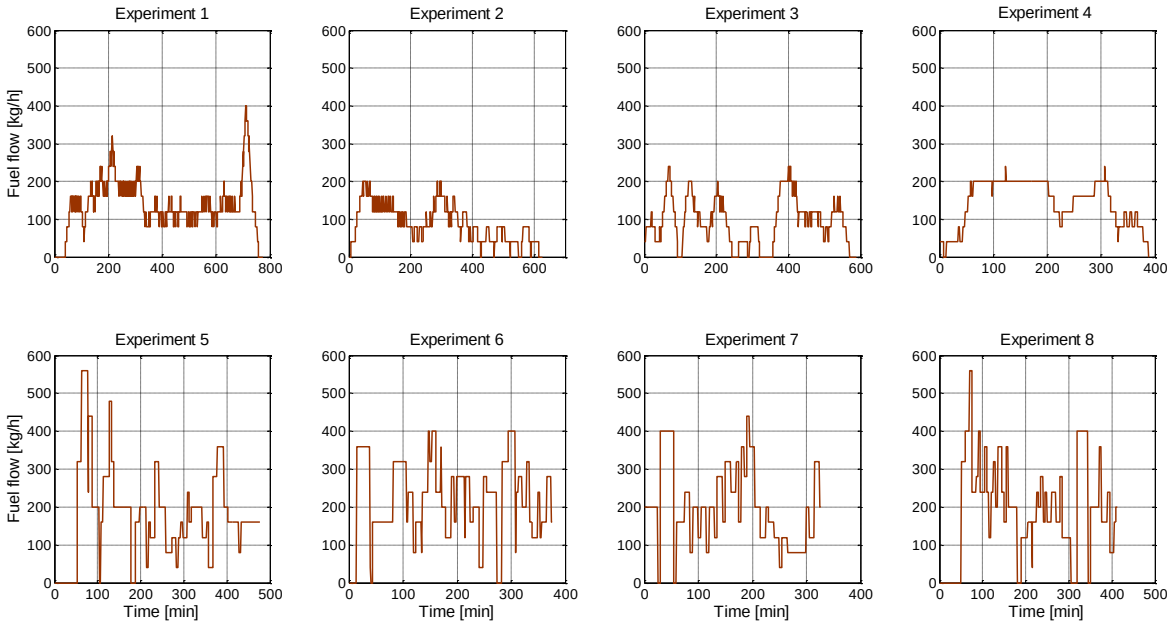

Figure 7 Average fuel flow rate for experiments 1-8

Obtained data from air volume flow rate measurements are presented in Figure 8. In Experiments 1-4 the average air volume flow rate usually ranged between 10 and 15 Nm^3/h with very small changes during plant operation. This is due to a manual air flow control. When compared to Experiments 1-4 it can be seen that the average air flow in Experiments 5-8 is lower. When this is combined with higher fuel flow rate from Experiments 5-8 it can be concluded that the air/fuel ratio has decreased which should lead to enhanced incomplete combustion and lower process temperatures [15].

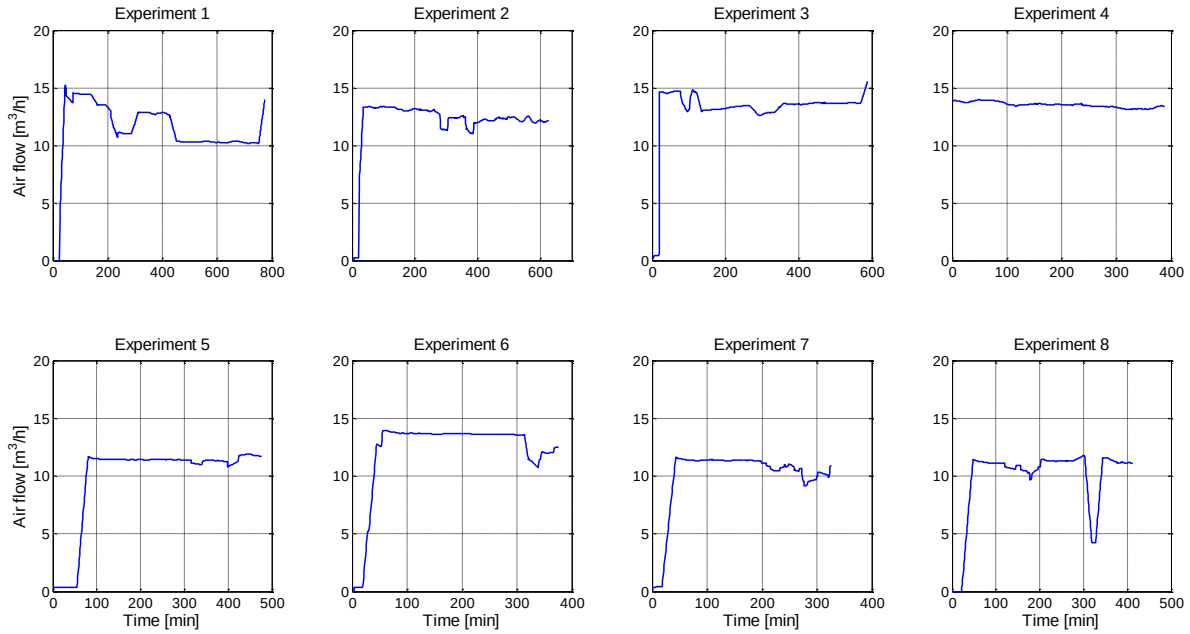

Figure 8 Average air flow rate for experiments 1-8

Time passed without fuel injection has been added in post-analysis of the measurement as one of the process parameters. This has been done to incorporate and to quantify dynamic behaviour of the system that will be used afterwards for model development. This variable is related to residence time in reactor (average period for which the biomass particles remain inside the reactor) as it is defined by signals derived from fuel control system which indicates if the reactor is running low on biomass. Residence time is an important process parameter that defines which chemical reactions took place in the reactor. For some chemical reactions to take place the residence time should be long enough [15]. As the time without fuel injection increases the residence time increases accordingly. Time passed without fuel injection for Experiments 1-4 (2006) and 5-8 (2013) is presented in Figure 9. During experiments 1-4 the operator had inserted fuel with quite high frequency. The fuel was inserted into the reactor once during time period of 3 to 5 minutes. In the Experiments 5-8 the fuel was usually inserted once in 7 to 10 minutes. This means that the control system that gives indication to the plant operator when the reactor is running low on biomass had a lower triggering frequency during Experiments 5-8. This leads to conclusion that the residence time in Experiments 5-8 was longer than in experiments 1-5 which should result into higher yield of H_2 and CO [48]. The changes between operating conditions in 2007 and 2013 could be explained by ash sintering, agglomeration and deposition on reactor walls which could cause bed sintering and defluidisation [21] or simply by biomass quality change.

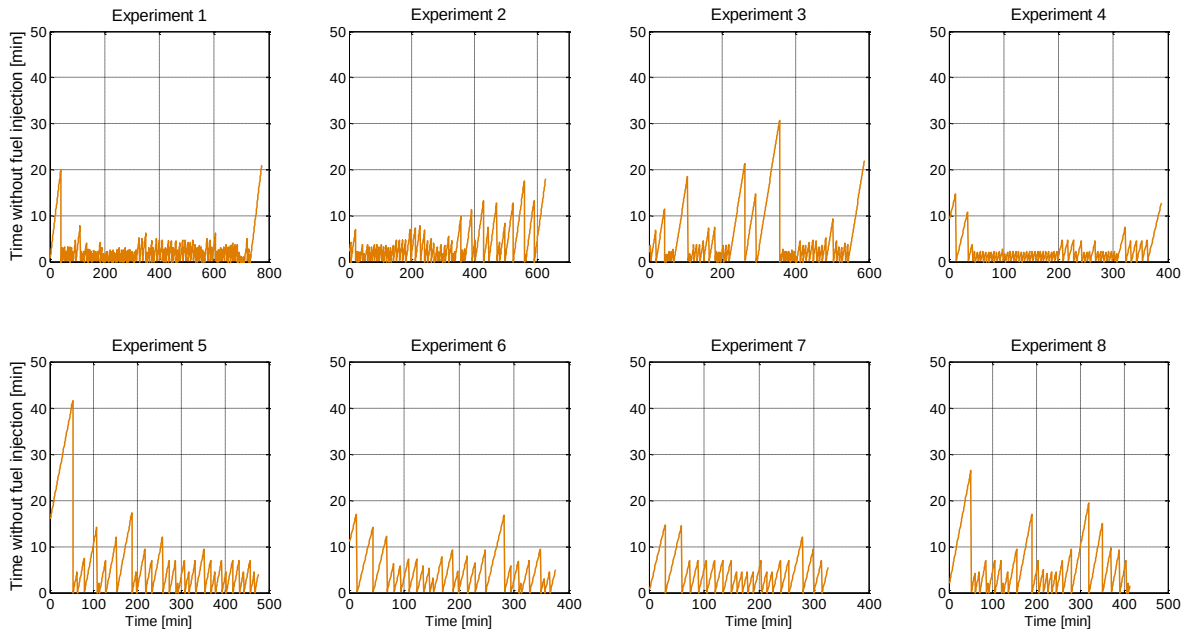

Figure 9 Time without fuel injection for experiments 1-8

Biomass wood chips, distributed from local provider, are used as a fuel in gasification process during Experiments 1-9. The biomass quality has been 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. Biomass composition for experiments conducted in 2007 has been determined at TU Dresden laboratory before start of the gasifier operation. Biomass composition has been considered as constant for measurement campaigns in 2007. 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 %.

3.3 Conclusion

Based on measurements from Co-current fixed bed gasifier from 2007 and 2013 it was concluded that the operating parameters like air/fuel ratio and particle residence time have changed between those two experimental years. This effect could be explained by ash sintering, agglomeration and deposition on reactor walls during period between 2007 and 2013 or by fuel quality change. Therefore, besides good prediction quality, the model that describes the process

should be adaptable to consider changing operating conditions that could occur during plant operation. For equilibrium, kinetic and CFD based models this could be done by re-fitting (adjusting) model parameters related to chemical reaction kinetics and by gasifier model changes. This would require a lot of additional time for new sets of measurements for model parameter estimation and model adjustments. Artificial neural network based models seem to be more flexible from that point of view as they do not take specific chemical reactions into consideration but rather overall process behaviour. However, to prove that such models are adaptable to changing operating conditions a prediction quality analysis and model validation should be first performed on one set of measurements where changes in operating conditions do not occur.

4 ANFIS MODELLING OF BIOMASS GASIFICATION

For utilizing a neural network based model, the model has to learn/to be trained from observed/measured data. Data for neural network training were extracted from a database attached to two biomass gasification facilities operated by the TU Dresden, Germany, presented in Chapter 3. It is expected that with various sets of input and output data as well as different training procedures, results from the model will differ. Influence of different input and output data on prediction performance will be analysed. For this purpose, data from Co-current fixed bed gasifier will be used. Furthermore, network based models are often dependable on site specific measurements and, therefore, the proposed modelling approach will be validated on second set of data derived from Combi-gasifier.

4.1 ANFIS modelling method

Although some non-linear processes can be modelled using neural network based models (where multilayer networks represent static nonlinear maps) [49] in cases where prediction of fast responses in non-linear systems with large uncertainties (high complexity) is needed neural networks become inadequate [50]. The reasons are that the neural networks are based on the gradient method which cannot guarantee that the prediction error converges to zero and therefore, when a system have large uncertainties a good robustness cannot be obtained (neural networks do not have a built-in capability to predict process/system changes) [50]. In the other hand, adaptive network-based fuzzy inference system (ANFIS) is based on a combination of neural networks and fuzzy systems which can describe complex and non-linear systems with large uncertainties. Advantages of ANFIS structure in comparison with neural networks is analysed on the case of thermal expansion process on CNC machine tools [51]. Furthermore, ANFIS based models have proven their usefulness in predicting parameters in a highly complex process (with a strong nonlinearity between inputs and outputs) of anaerobic digestion in upflow anaerobic sludge bed reactor [52]. Dynamic neural network models with feedforward

or recurrent feedback connections could be also used to describe dynamic nonlinear process behaviour and their potential will be analysed later in the text.

For artificial neural-network based prediction model the ANFIS with Suggeno type of fuzzy model and hybrid learning algorithms with 27 nodes (together with membership functions) in structure layers were used. A fuzzy inference system (FIS) is a system that uses a set of fuzzy (*if-then*) rules to define relationships between inputs and to define outputs. Sugeno type of FIS defines a set of fuzzy rules of inputs, adjusts the inputs based on membership functions, defines a rule strength between adjusted inputs, determines the result of the rule by the rule strength and the output membership function and finally combines results to get an output distribution. However, it does not use output membership function to determine the result of fuzzy rules. In adaptive network-based fuzzy inference system (ANFIS) neural network learning approach is combined with FIS to determine the set of fuzzy rules and to determine membership functions in order to generate input-output relations. A detailed explanation of ANFIS structure is presented in [53].

The inputs for the model were defined based on comparative analysis with different input and output data sets derived from Co-current fixed bed gasifier in Pirna. For different cases, it has been assumed that the process temperature is influenced by different process parameters. Different time periods for averaging fuel and air flow rate have been analysed (fuel and air supplied in the last 1, 5, 10, 15, 20, 25, 30, 40 and 60 minutes). It has been assumed that different time periods for fuel and air averaging will result in different model response due to a specific accumulation of mass and energy in reactors. In this way, process dynamics for a specific reactor can be modelled. Simulation results from models with different time periods for averaging fuel and air flow rate have been used to find prediction model with the lowest prediction error. It was concluded for Co-current gasifier in Pirna that the best temperature prediction results are obtained when the fuel and air flow rate in the last 25 minutes is considered. It was also concluded that, together with fuel and air flow rate, time without fuel injection and current process temperature should be included as one of model inputs. To avoid ANFIS model overfitting a simple analysis with different number (10, 25, 50 and 100) of iterations for ANFIS training has been performed. The prediction quality after 50 iterations did not improve considerably so to reduce the risk of ANFIS overfitting the ANFIS model with 50 iterations has been chosen. Details related to the analysis are presented in PAPER 2, Chapter 4.

Similar approach has been used to predict process temperature on Combi-gasifier in Schwarze Pumpe. Knowledge related to model structure gathered from the case of Co-current fixed bed gasifier in Pirna has been applied to develop model structure of Combi-gasifier in Schwarze Pumpe. Due to fact that those two gasifiers are different in design and size it has been assumed that they will have a different specific accumulation of mass and energy in the process. Therefore, it has been expected that time periods for averaging fuel and air flow rate would change in case of Co-current gasifier (Pirna). It has also been assumed that important process parameters for modelling will not change due to similar nature of the process. Applying same model inputs (with different time averaging periods) which would result in a good prediction quality for both gasifiers would prove hypothesis that proposed methodology is suitable for different gasifier designs. Simulation results (PAPER 2, Chapter 4) have shown minimum prediction error could be obtained with averaging fuel and air flow for the last 10 minutes in the case of Combi-gasifier in Schwartze Pumpe and 25 minutes in the case of Co-current fixed bed gasifier in Pirna. This leads to conclusion that mass and energy accumulation in Schwartze Pumpe Combi-gasifier might be lower than in Co-current fixed bed gasifier in Pirna.

The individual Multi Input Single Output system comprises of 4 inputs (fuel flow rate, time without fuel injection, air flow rate and current temperature of syngas at gasifier outlet) and one output which represents derivative of syngas temperature. The change in syngas outlet temperature was set as model output. Syngas temperature was then determined by integration of predicted temperature changes. With this approach it has been assumed that process dynamics related to process temperature could be described in a qualitative way. This approach is similar to model structure that is used in dynamic neural networks where history of the output value is used as input for future calculations. Scheme of the model is presented in Figure 4.1.

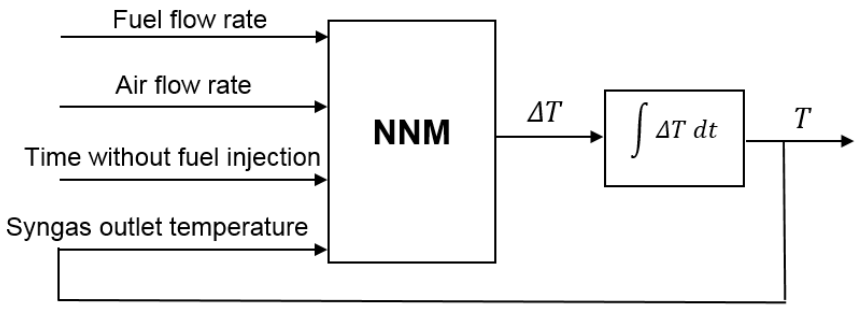

Figure 10 General scheme of neural network based (ANFIS) temperature prediction model

Similar type of input data sets (described in temperature prediction model) has been used to devise neural network prediction model for the syngas composition. Due to measurement characteristics, the syngas composition prediction model has been devised for the outgoing syngas temperature between 250 and 430 °C. The summary of proposed model structure (input and output parameters) for temperature and syngas composition models is presented in Table 3.

For ANFIS model training a set of 4 experiments (from 2006) has been used. 5th experiment (from 2006) has been used for validation. Cross-validation has been conducted where all 5 experiments have been considered as validation experiment and other 4 experiments were used to train neural network model. The usefulness of a cross-validation method has been explained in [54].

Table 3 Summary of temperature and syngas composition prediction neural network models for gasifier in Pirna

Model inputs		
	Syngas temperature (gasifier exit)	**Syngas composition (CO, CO_2, CH_4, H_2 and O_2 values)**
Fuel flow	Fuel supplied in the last 25 min [kg]	Fuel supplied in the last 60 min [kg]
Air flow	Air injected in the last 25 min [m^3]	Air injected in the last 60 min [m^3]
Related time	Time passed from the last fuel supply [min]	Time passed from the last fuel supply [min]
Temperature	Current syngas temperature	Current syngas temperature
Number of daily experiments used for NNM training	4	4
Neural network training method	Gaussian curve membership function	Gaussian curve membership function
Model boundaries	Modelled syngas temperature: 20 - 450 °C	For syngas temperature (gasifier exit): 250 - 430 °C
Model outputs		
Model output	Temperature derivative/ Syngas temperature [°C/min]/ [°C]	Syngas composition[%]

4.2 ANFIS modelling simulation results and model validation

Performance of ANFIS model prediction potential has been analysed on 5 different experiments (4 experiments for training and 1 experiment for model validation). Input data for model training was extracted from Experiments 1-4, presented in Chapter 3.2. Experimental conditions differ from experiment to experiment. In Experiment 3 and the validation experiment the gasifier operation starts from non-preheated conditions (cold start). The operation in Experiments 2 and 4 starts from preheated conditions while in Experiment 1 the gasifier operation starts from highly-preheated condition (hot-start). The biomass composition is considered as constant because the biomass from the same delivery has been used. The environment temperature has been considered as constant.

For simulation performance analysis the fuel and the air flows (as model inputs) have been varied according to measured data. The ANFIS prediction model shows good results for the syngas temperature prediction (Figure. 11.). The error between measured and calculated values is mostly between ±10 % which represents a good prediction of the syngas temperature during the plant operation. In some marginal cases the error can reach up to ±25 %. ANFIS prediction model shows good prediction possibilities in terms of the syngas temperature progression prediction during the plant operation with different operating starting points (“cold” start and “warm/preheated” start). It can be concluded that devised model for temperature prediction is suitable for syngas temperature prediction between 20 °C which represents a “cold” start and 450 °C which represents typical conditions when the gasifier is at full load.

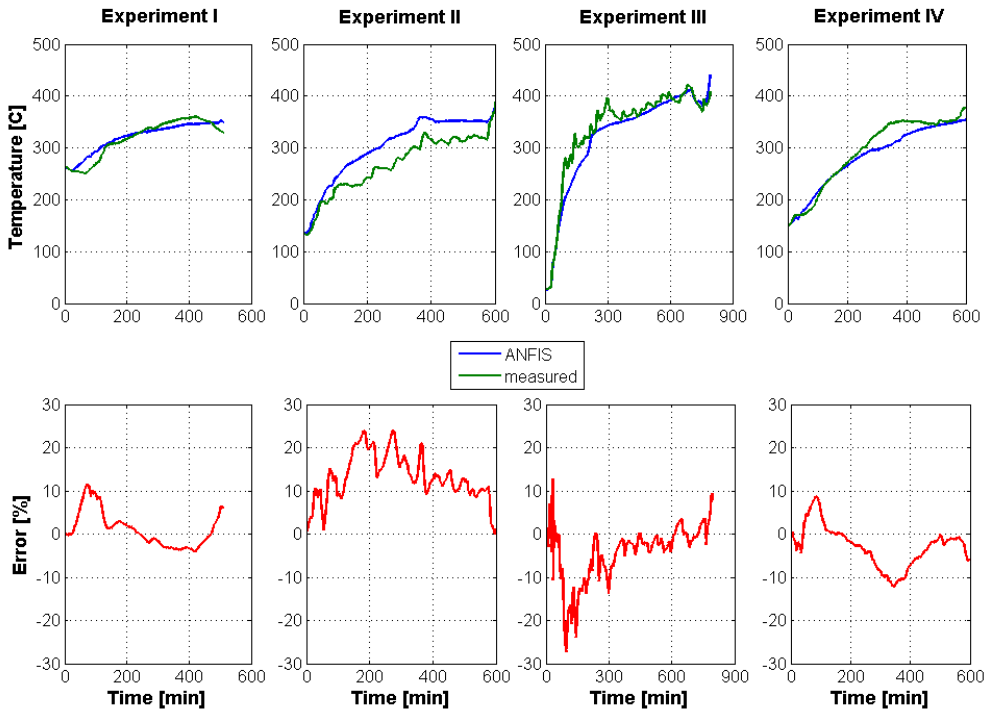

Figure 11 Results of the neural network model for syngas temperature production – Pirna gasifier

Developed model was validated on a new set of measurement data from Pirna gasifier (for the syngas temperature range between 25 °C and 425 °C) as presented in Figure 12. The prediction error is mostly between ±10 % and in some marginally cases it reaches -25 %.

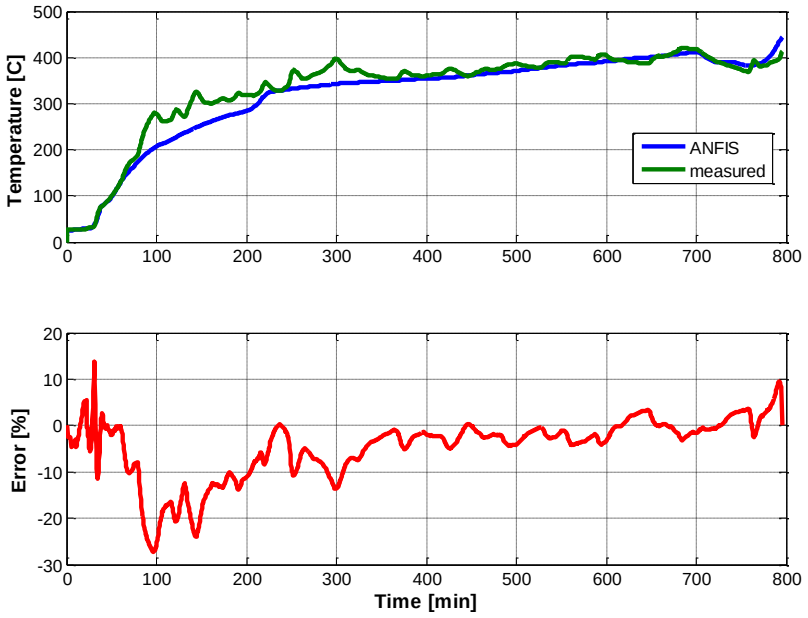

Figure 12 Neural network model validation for syngas temperature prediction – Pirna gasifier

The same validation procedure has been performed for model cross-validation where different Experiments were used for model training and validation. 4 experiments were used for model training and one of the experiment has been used for model validation. In all cases the average prediction error was under 20% as presented in Table 4.

Table 4 Results of cross-validation for temperature prediction

Experiment for model validation	Average prediction error [%]
Experiment 1	5.71
Experiment 2	19.72
Experiment 3	7.09
Experiment 4	18.84
Experiment 5	7.07

Similar to the syngas temperature prediction model, the syngas composition prediction model performance was also analysed. The prediction performance of H_2 ANFIS model for 4 different experimental sets/measurement campaigns is presented in Figure 13. The predicted H_2 values and progression of these values during the plant operation is in good correlation with the measured data. During the plant operation, H_2 values are mostly between 5-10 % of total volume gas composition, with maximum value of 11 %.

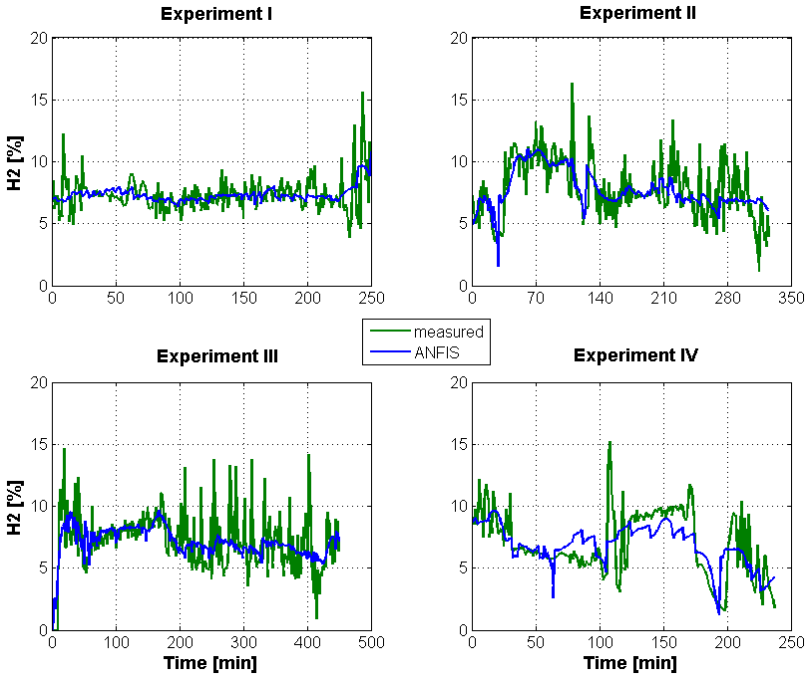

Figure 13 Neural network model validation test for syngas temperature prediction – Pirna gasifier

The syngas composition prediction model has been verified on the new set of measured data (Figure 14.). Although measured H_2 values range significant from minute to minute, neural network model predicts average H_2 values and their progression tendency with reasonable accuracy.

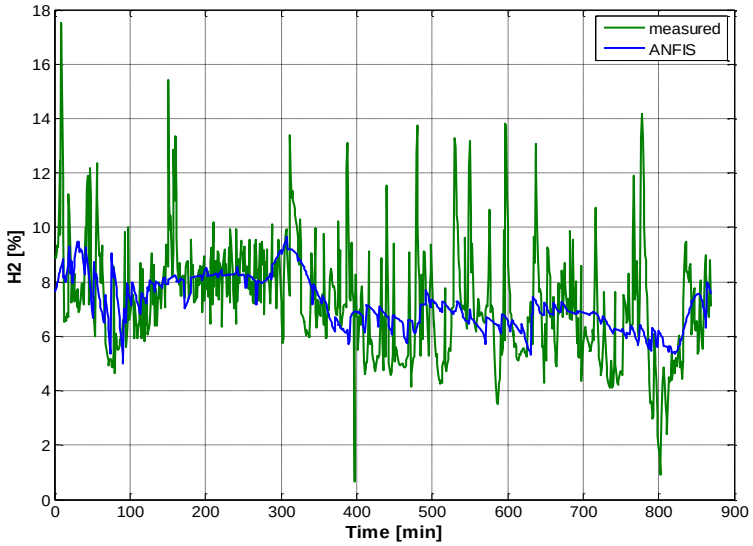

Figure 14 Neural network model validation test for syngas composition prediction (H_2) – Pirna gasifier

Due to measurement equipment sensitivity which resulted in significant differences between minute based measurements of syngas components, potential of prediction model to predict averaged syngas composition values has been analysed. Similar analysis has been performed for other syngas components namely; CH_4, CO, CO_2 and O_2. It was concluded that ANFIS prediction model enables good approximation of syngas composition during the gasifier operation. Details of the analysis are presented in PAPER 2, Chapter 5.

Performance of temperature prediction ANFIS model for the gasifier in Schwarze Pumpe (Combi-gasifier) is presented on Figure 15. The prediction error percentage has been calculated by division of prediction error (the difference between simulated and measured values) with exact measured values. The prediction error is mostly between ±20 % but in some cases can reach up to 100% due to division of relative small temperature prediction error with small temperature values in the denominator. This occurs only during initial stages of gasifier

"cold" start, which represents marginal timeframe in total gasifier operation. ANFIS prediction model for the gasifier in Schwarze Pumpe has shown good correlation with the measured data for different operating points during the gasifier operation (from start-up till reaching stationary operation). Based on this analysis and results from Co-current gasifier in Pirna it can be concluded that proposed modelling method is appropriate for prediction of process temperature during gasifier operation for different gasifier types.

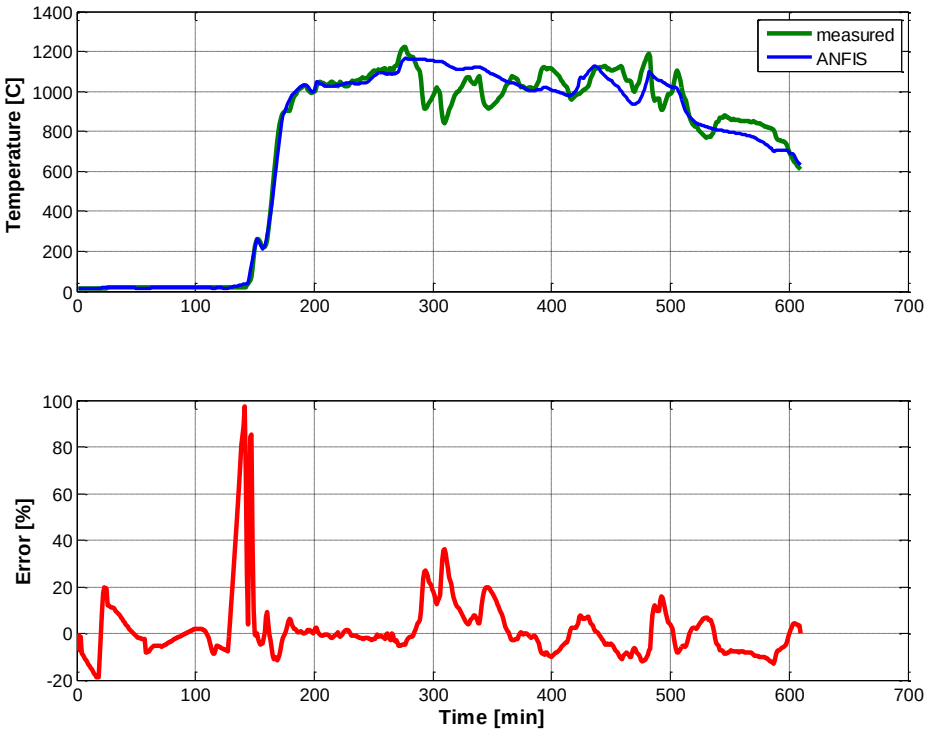

Figure 15 Results of the ANFIS model for syngas temperature prediction – Schwarze Pumpe gasifier

After model validation on Experiments 1-4, developed model was used to predict process temperature for Experiments 5-8 (after changes in operating condition). Results derived from the simulation are presented in Figure 16. Some values are missing due to practical reasons (they are too large to be fitted in a graph). It should be noted that the syngas temperature in Experiment 5-9 are significantly lower than in Experiments 1-4. This can be explained by lower air/fuel ratio and higher rate of incomplete combustion (presented in Chapter 3.2). From the Figure it can be concluded that the ANFIS model that has been trained only with the initial database (Experiments 1-4) 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. More details regarding simulation results can be found in PAPER 3, Chapter 4.

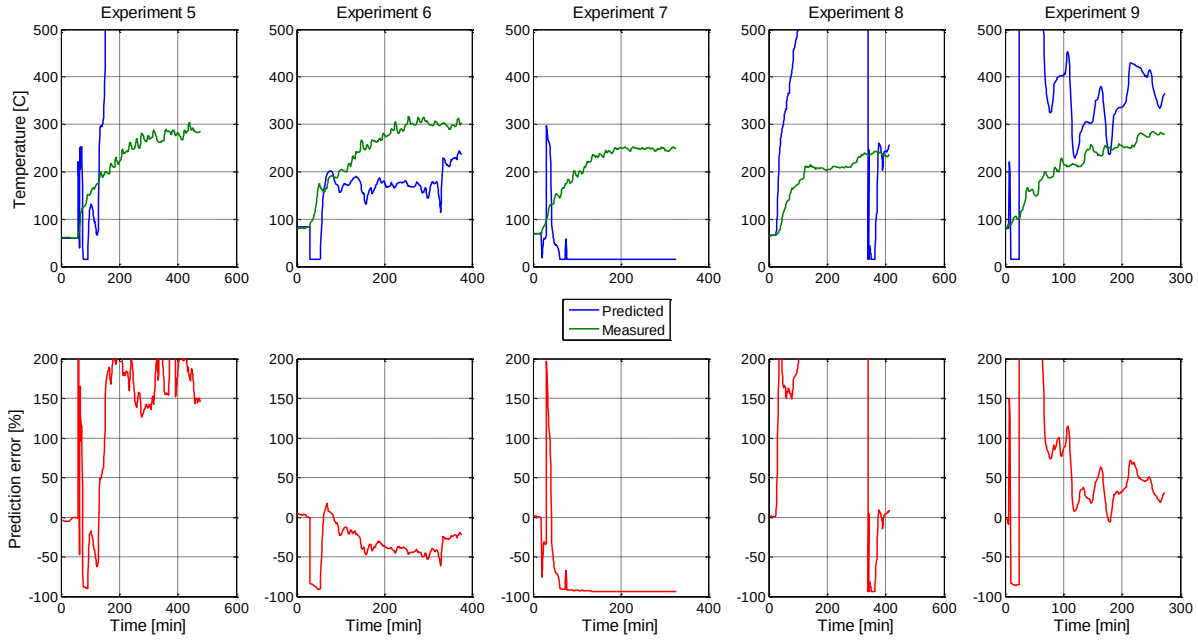

Figure 16 Simulation results for Experiments 5-9 with initial training database from Experiments 1-4

4.3 Conclusion

Similar model inputs and model structure has been used to predict process temperature in two different gasifier types. Due to their differences in design and operation a different accumulation of mass and energy can be expected. This accumulation can be described by using different time averaging of fuel and air flow rate quantities. Different averaging periods will have to be defined for different gasifier designs to obtain reasonable model prediction quality. However, it has been shown that by using a unique set of input parameters and by changing only time periods for their averaging the biomass gasification process dynamics and stationary regime can be described with an average prediction error under 10%. Therefore, proposed modelling method is appropriate to predict process parameters for different gasifier designs. When the model was applied to predict process temperature after operating conditions have changed the prediction quality became unacceptable. It leads to conclusion that the model should be adapted to capture process behaviour in new operating conditions.

5 DYNAMIC ANFIS MODEL FOR BIOMASS GASIFICATION

It was hypothesised that one way to reduce the prediction error of developed ANFIS model (that occurs when operating conditions change) could be to continuously change 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 model structure would result in a large engineering effort during plant operation. Therefore, this approach would be impractical for on-line process analysis. Different approach, that includes on-line prediction error analysis, will be proposed so the model can be modified in a way that is more appropriate for on-line process analysis.

5.1 Dynamic ANFIS modelling

Standard static neural networks with feedforward or recurrent feedback connections can be used to describe process dynamics in systems with large delays like activated sludge processes [55], vapour-compression liquid chillers [56], chemical process systems [57] or other energy related processes [58]. Once trained, artificial networks can also predict process parameters in circulating and bubbling fluidised bed gasifiers [29] or fluidised bed gasifiers with steam as gasifying agent [30] 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 [59]. To encounter issues related to changeable operating conditions and to obtain reasonable model prediction accuracy Wang and Hu [60] 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 [61] 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.

To mitigate effects of changing operating conditions on the model prediction performance a dynamic modelling approach is proposed. The approach consists of standard ANFIS training procedure (described in Chapter 4.1) and active prediction error estimation that triggers/activates model re-training. The combination of fuel flow rate, time without fuel injection, air flow rate and current temperature of syngas at outlet has been defined as an input for model training and derivative of the temperature has been used as model output. First, ANFIS 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 is continuously analysed (error value can range between -100% and $+\infty$) in order to preserve prediction quality of the model. When the average error 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/re-training is turned on. Tolerance threshold was varied to analyse its influence on simulation speed. Lower tolerance threshold should produce higher prediction quality but will result into larger number of model re-trainings. The trigger enables re-training of the ANFIS model on a newly formed database (old database extended with new measurements up to that moment). Training data size was also varied to analyse simulation performance. After re-training, the error tolerance is temporary increased to ±100% for the next 3 minutes in order to prevent fast trigger resetting after model re-training (constant re-training will result in extensive time loss). After re-training the predicted temperature is set to the last measured value. Details related to prediction error calculation and modelling flow is presented in PAPER 3, Chapter 3.

5.2 Simulation results of dynamic ANFIS model

Results derived from the dynamic ANFIS model with error tolerance threshold of 10% where all the data has been used for re-training purposes are presented in Figure 17. With the proposed dynamic modelling approach the prediction error has been reduced significantly. The prediction error is mostly within ±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 model 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.

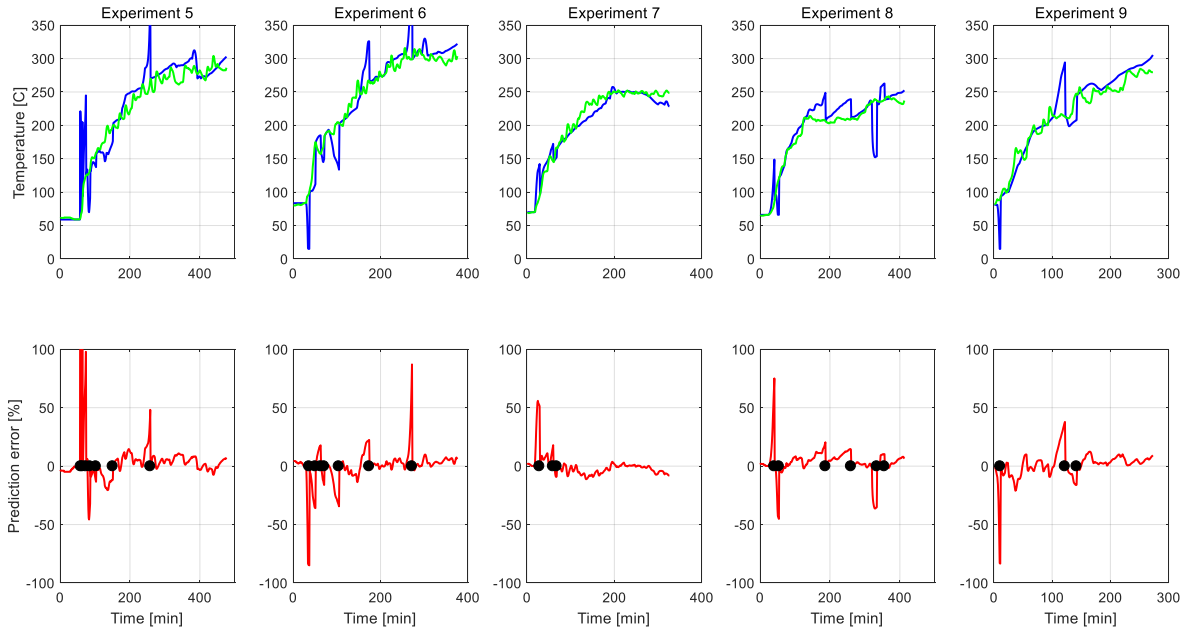

Figure 17 Temperature predictions of dynamic ANFIS model

Re-training sessions are marked with a black dot 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 old ANFIS model structure and training data that is inappropriate for these particular operating conditions. Therefore, the algorithms try to find an appropriate ANFIS model structure by using

a high frequency of re-training sessions in the first minutes of operation. However, due to insufficient data quantity 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 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 model 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.

Based on the proposed methods, predictions of syngas composition components have 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 some constitutive gases (CH_4) prediction error is above 30% which is higher than the desired value specified in the research objectives. However, it should be mentioned that CH_4 represents only 1-6% (vol) of total syngas composition while for the major syngas components (H_2 and CO) prediction error is below 30%. For a more detailed analysis of syngas composition model prediction potential, measurements with more accurate measurement equipment should be obtained. Simulation performance of the syngas composition models is presented in PAPER 3, Chapter 4 and the overall performance summary is presented in Table 5.

Table 5 Simulation performance summary of the dynamic ANFIS model for temperature and syngas composition prediction

Prediction parameters	Average prediction error [%]	Number of re-training sessions [-]	Total time for re-training [sec]
Temperature (Experiments 5-9)	7.06	26	410
H_2 (Experiments 5-8)	26.4	102	780
CO	29.9	88	760

(Experiments 5-8)			
CH_4 (Experiments 5-8)	38.3	105	810

For the dynamic ANFIS model development and simulation 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 using a tolerance threshold of 10% (26 re-training sessions in total). Around 10 seconds are necessary for one re-training session and 20 seconds for initial training. For syngas composition prediction one re-training session lasts around 8 seconds due smaller amount of training data. This configuration and modelling approach enables re-training between 2 measurements (measurement sampling frequency is 30 seconds). Therefore, the proposed approach can be used for on-line process parameters prediction in a dynamic environment where operating conditions change with time.

5.3 Conclusion

Proposed method that comprises of an ANFIS model with active prediction error analysis and model re-training can be used to predict process temperature and syngas composition in changing operating conditions. Commercially available computers are suitable for process simulation as the required time for model re-training and parameter prediction is well under 30 seconds. Therefore, proposed modelling method could be used for on-line process analysis and control. For on-line process analysis active measurement of process parameters is needed. Performance of such model to be used as constitutive model in control systems is yet to be analysed. Although developed ANFIS models have a good prediction quality some engineering knowledge is needed to identify proper model structure in terms of input training data. Such models should be trained and the input data should be modified for each gasifier separately. To avoid that, a model that does not require any data pre-processing for training purpose (uses raw measurement data for model training) should be developed.

6 NARX MODELLINF OF BIOMASS GASIFICATION

As discussed in Chapter 5, some data pre-processing is needed to develop ANFIS model for particular gasifier. However, expertise needed for such activities is not always available and, therefore, a simpler modelling approach is needed. Prediction model should be able to predict process temperature and syngas composition without any prior knowledge about the process and by using only raw measurement data for model training. In this chapter potential of a nonlinear autoregressive exogenous (NARX) model to predict syngas temperature and composition during plant operation with variable operating conditions will be analysed. Raw measurement data from Co-current fixed bed reactor in Pirna will be used for model training.

6.1 NARX modelling

The nonlinear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic neural network, with feedback connections enclosing several layers of the network. The NARX model is based on the linear ARX 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 comparison with dynamic neural networks (like NARX), static (feedforward) networks have no feedback elements and contain no delays therefore the output is calculated directly from the input through feedforward connections. Training of NARX networks consist of 2 steps namely: an open loop NARX model training and closed loop NARX model training. In open loop NARX model training a feedforward multilayer neural network is trained using backpropagation algorithms to define main structure of neural network. Afterwards, in closed loop NARX model training model outputs are estimated on current and previous inputs together with previously estimated outputs (making a closed loop) [62]. A detailed explanation of NARX structure can be found in [63]. Model

outputs are predicted through sub-models that are defined with a non-linear function that consist of all inputs and their previous values, together with the previous values of the output itself.

Dynamic type of neural networks can be useful tool to describe process dynamics of nonlinear chaotic systems [64]. In the recent research done by Asgari et al. [65] NARX based models have been used to model 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). Maximal 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 200kW$_{th}$ sorption enhanced reforming steam gasification plant [62]. NARX models seems to be a promising technology to describe non-linear systems with large delays but their application potential for fixed bed reactors in biomass gasification systems is yet to be analysed.

One of major drawbacks of dynamic neural networks (including NARX models) is that 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 instance (in terms of biomass gasification), the influence of a time without fuel injection (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.

For prediction of syngas temperature and syngas composition 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 and linear transfer function for output layer. After analysis of optimal number of training epochs it has been observed that training length is 600 epochs provides the best prediction quality. As model input variables fuel and air flow rates have been chosen (Figure 18). Model outputs are syngas temperature and syngas components (H_2, CO, CH_4 and CO_2). NARX model structure is presented in details in PAPER 4, Chapter 2.

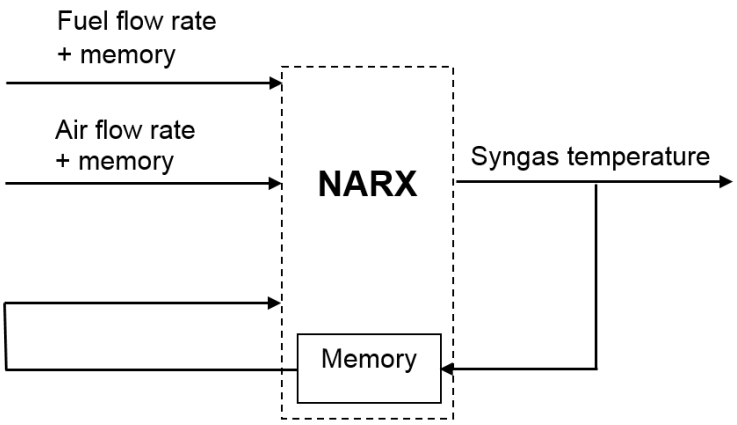

Figure 18 Temperature predictions of dynamic ANFIS model

To analyse the effect of training data quantity on prediction performance 8 different cases with different training and validation data quantity have been tested. It was concluded that training data from Experiment 1 is sufficient to have a good prediction quality of process temperature for Experiments 1-9. After the training data size has been defined, the number of model delays was varied to analyse the case with the best prediction performance. It was concluded that the model structure with 2 delays (which represents a time delay of 1,5 minute) has the highest prediction performance. With increasing 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. The second potential reason is that the model is very dependable on temperature values (as model inputs) and as the number of delays is increasing the temperatures that are not relevant for the prediction of the temperature in next increment are taken into consideration. Simulation performance analysis for model development is presented in PAPER 4, Chapter 3. With similar analysis for syngas composition predictions it was concluded that dataset derived from Experiment 1 was not sufficient enough to quality describe the process. It must be emphasized that datasets 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 been 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.

Validation of NARX models can be performed in 2 ways due to the nature of feedback loop of predicted value. First validation case is performed by using measured history to predict future value. Second validation case can be performed by using model predictions (and its history) as an input for a feedback loop. This case resembles the way how a standard and dynamic ANFIS model has been developed and validated.

6.2 Simulation results of NARX model

As discussed in Chapter 6.1 data from the whole first experiment has been used as training data set and syngas temperature from Experiments 2-9 was predicted based on developed model and model inputs. Simulation results show that for this training data set (Experiment 1) model prediction error is usually below ±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 ±8%. After changes in operating conditions (Experiment 5-9) the prediction error generally rises but remains under ±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. However, a prediction error under ±10% suggests that training data set from Experiment 1 is still sufficient for general NARX model. Model performance for NARX temperature prediction model with Experiment 1 as training data set is presented in Figure 19.

The overall training and prediction time of developed NARX model for Experiments 1-9 is 16 seconds which represents an adequate speed for on-line parameter prediction models. Together with prediction error under ±10 % it can be concluded that developed NARX model can be used to predict syngas temperature in changeable operating conditions.

Model predictions of volumetric content of H_2 are presented in Figure 20. Based on simulations of H_2, CH_4 and CO content it was concluded that, in general, syngas composition prediction follow measured values with a good accuracy. R^2 of prediction is above 0.73 in all cases. The highest prediction error occurs in Experiment 7 and during some periods in Experiment 8.

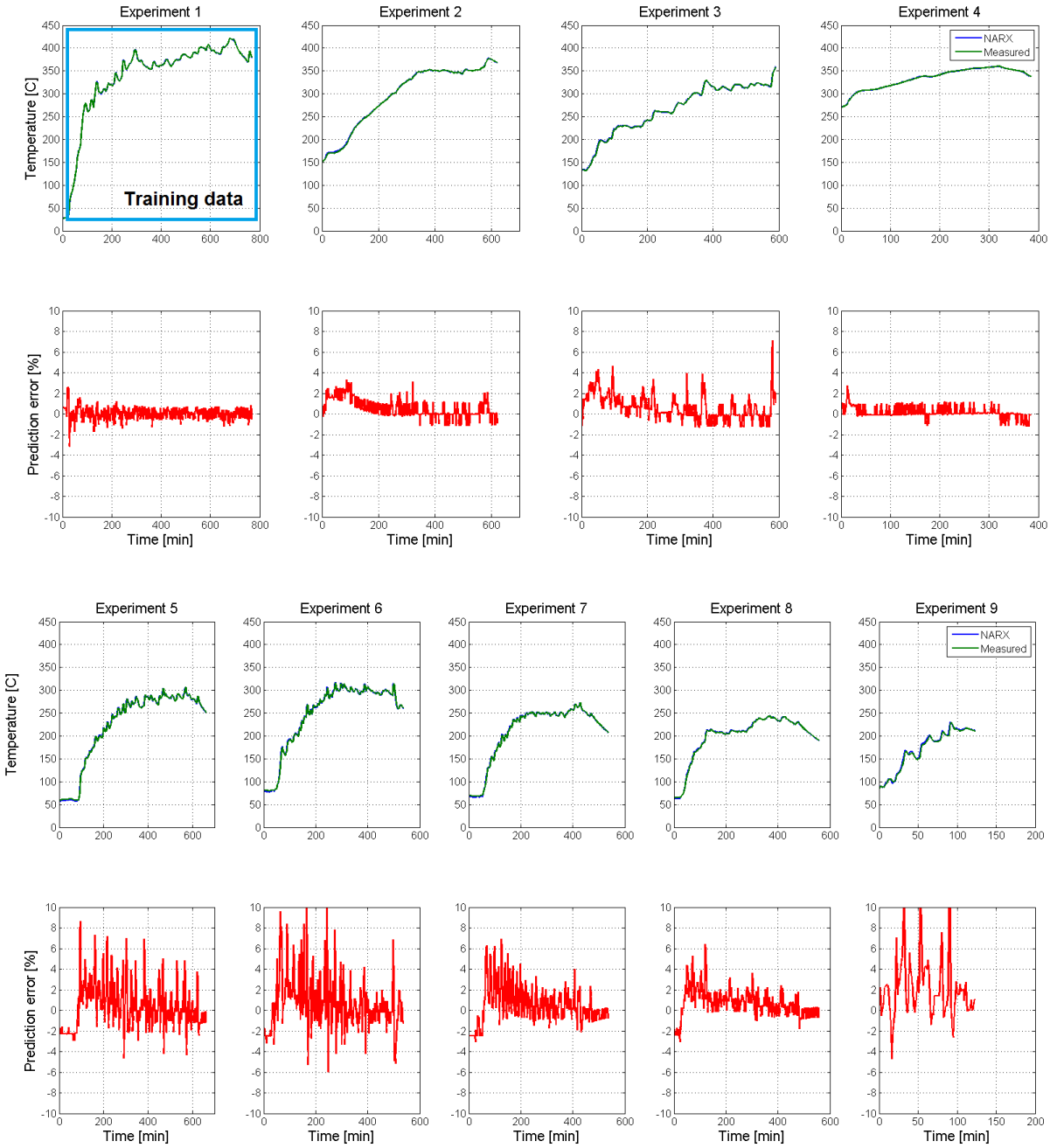

Figure 19 Model performance with Experiment 1 as training data set

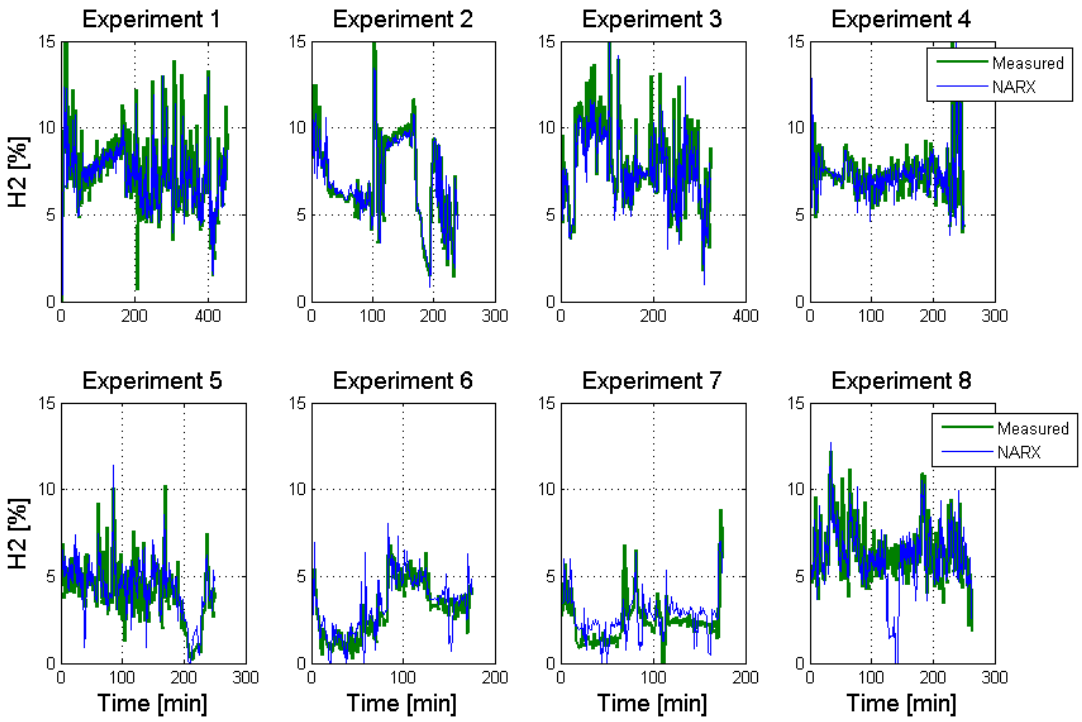

Figure 20 NARX model prediction performance for H_2 syngas composition predictions

Prediction potential of NARX model for a long-term temperature prediction without active temperature updates is analysed based on second validation case. It can be seen on Figure 21. 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 relative small prediction error. However, when algorithms start to use output of NARX model as history (in 4th minute) the model becomes unstable. 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 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. Similar case was observed for syngas composition predictions.

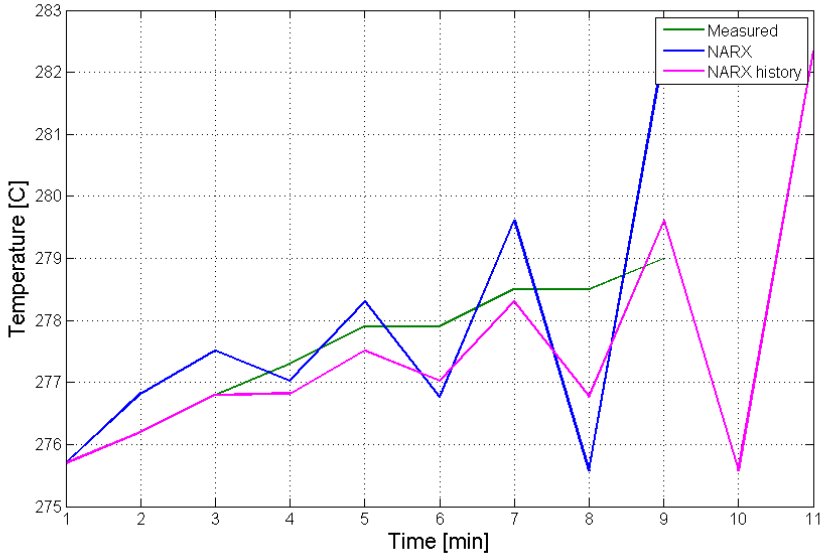

Figure 21 NARX model (temperature) prediction performance for second validation case

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. To analyse which of proposed models (dynamic ANFIS or NARX) are appropriate to use in on-line process analysis and for control purposes a comparative analysis has been performed.

6.3 Comparative analysis of dynamic ANFIS and NARX model for biomass gasification

The overall model prediction performance of developed models is presented in Table 6. NARX model performance has been compared with dynamic ANFIS model (developed and described in Chapter 5). It can be seen that NARX model requires a significant smaller training database for a higher prediction performance. This also results into a faster prediction speed. The highest improvement can be seen on prediction of syngas composition quality where R^2 of NARX model is ranging between 0.73 and 0.97 while R^2 of ANFIS model is ranging between 0.45 and 0.83. Similar conclusion can be derived from average prediction error (APE) analysis where the APE of NARX model is under 0.25 (25 %) while for a dynamic ANFIS model it can reach up to 0.38 (38 %). It has been concluded that NARX model shows a better model

prediction performance than developed dynamic ANFIS model. However, it should be noted 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 history of syngas temperatures. By this, prediction horizon of NARX model without active temperature measurements is quite limited (in this case it is 3 minutes). To compare performance indicators of NARX and dynamic ANFIS model for a longer-term predictions, autonomous prediction range (APR) has been calculated. APR is an average time without active temperature measurement update in which model has a good prediction performance. For dynamic ANFIS model this is the average time between 2 re-training sessions and it is calculated based on Table 5.1 in Chapter 5.2. As mentioned before, NARX model needs an active temperature update every 3 minutes to have a good prediction quality. This leads to conclusion that in its structure is strongly dependable to parameter history values that are used for future predictions. Compared to NARX, dynamic ANFIS model has a larger autonomous prediction range that extends up to 77 minutes in case of temperature predictions. This means that dynamic ANFIS model is valid (without retraining or knowledge of current process parameters) for predictions up to 9 minutes for syngas composition or 77 minutes in case of temperature predictions. This prediction horizon makes it a better candidate for implementation in model based control systems as prediction speed for both models is under 30 seconds.

Table 6 Overall model prediction performance of NARX and dynamic ANFIS model

Model	Datasets for training	R^2	APE	APR [min]
NARX - CH_4	2 experiments	0.82	0.15	3
NARX - H_2	2 experiments	0.73	0.25	3
NARX - CO	3 experiments	0.97	0.18	3
NARX - Temperature	1 experiment	0.98	0.01	3
Dynamic ANFIS - CH_4	4 experiments + re-training	0.45	0.38	9
Dynamic ANFIS - H_2	4 experiments + re-training	0.47	0.30	9
Dynamic ANFIS – CO	4 experiments + re-training	0.83	0.26	10
Dynamic ANFIS – Temperature	4 experiments + re-training	0.82	0.07	77

6.4 Conclusion

Based on performed comparative analysis of 2 neural network based modelling approaches 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 (needed for longer-term predictions in control systems) the model becomes unstable and produces high prediction errors. This leads to conclusion that NARX models are very useful tool for a short-term predictions. However, if such models are decoupled from real time measurements, they can produce a significant prediction error. For a case of Co-current fixed bed gasifier NARX models can predict with a good accuracy only several minutes ahead if measured data is available. Dynamic ANFIS model is able to predict process parameters with a smaller prediction accuracy (still sufficient for on-line process analysis) compared to NARX model. However, prediction horizon of dynamic ANFIS model where no parameter measurements updates are needed is much longer. Therefore, for a long-term process predictions, as needed in control systems, ANFIS model should be used. This makes it a good candidate for implementation as a constitutive model in a model based control system for Co-current fixed bed reactors. Prediction horizon of such system should be limited to 9 minutes in case of syngas quality control and 70 minutes in case of temperature control to assure good prediction quality.

7 MODEL PREDICTIVE CONTROL FOR FIXED BED GASIFIERS

Model predictive control (MPC) is established control strategy because it can successfully control multivariable systems with constraints. In this chapter a model predictive controller for biomass gasification in fixed bed reactors will be developed. Control system will be validated on measured data. Afterwards, the effect of the controller on gasification plant start-up will be analysed in details. Potential of model predictive control to improve process performance will be elaborated.

7.1 Model predictive controller

The basic control strategy of MPC is to follow desired output trajectory by changing input variables and by minimization of control cost function over a prediction horizon with desirable length. Such model requires an accurate internal model that can describe process nonlinearities with good accuracy [36]. For control of coal gasifier Seyab [36] et al. have proposed a combination of linear and nonlinear model predictive control based on Wiener model. Linear model has been used to control fuel gas calorific value, bed mass and fuel gas temperature while a nonlinear model has been used to control fuel gas pressure. However, the proposed method is useful if only a part of the system exhibits in a strong nonlinearity. In the work done by [66] an Aspen model has been used as internal model that has been combined with Matlab MPC design to control air separation unit of IGCC gasifier.

For analysed system developed ANFIS model has been used as internal model for model predictive controller to control syngas temperature at the exit of a gasifier. This was done as ANFIS model has better long-term prediction capabilities that do not need updates on current process values. For performance analysis no changes in operating conditions were assumed. Therefore, the ANFIS model has been developed based on measured data from Experiments 1-

4 (Chapter 4.). The goal of MPC is to keep syngas temperature in desired range and to suggest corresponding fuel and air flow rate together with fuel injection frequency (manipulated variables). Fuel flow rate is controlled in steps of 25 kg/h (6.25% of maximum fuel flow rate) and air flow rate in steps of 1m^3/h (6.25% of maximum air flow rate). Fuel injection has 2 states: 'on' or 'off'. Afterwards, time from previous injection ('on' case) is calculated. Input process parameters (fuel and air flow) were optimized (to reach desired syngas temperature) for the control horizon of 2.5 minutes with 5 control steps in between. After each control step input parameters were modified for the upcoming control horizon according to the plant output (represented by NARX model). . This was done because dedicated tests on the real plant were not possible. NARX model was updated with syngas temperature predictions from ANFIS model to make process parameter predictions more accurate. Proposed control system is presented in Figure 22.

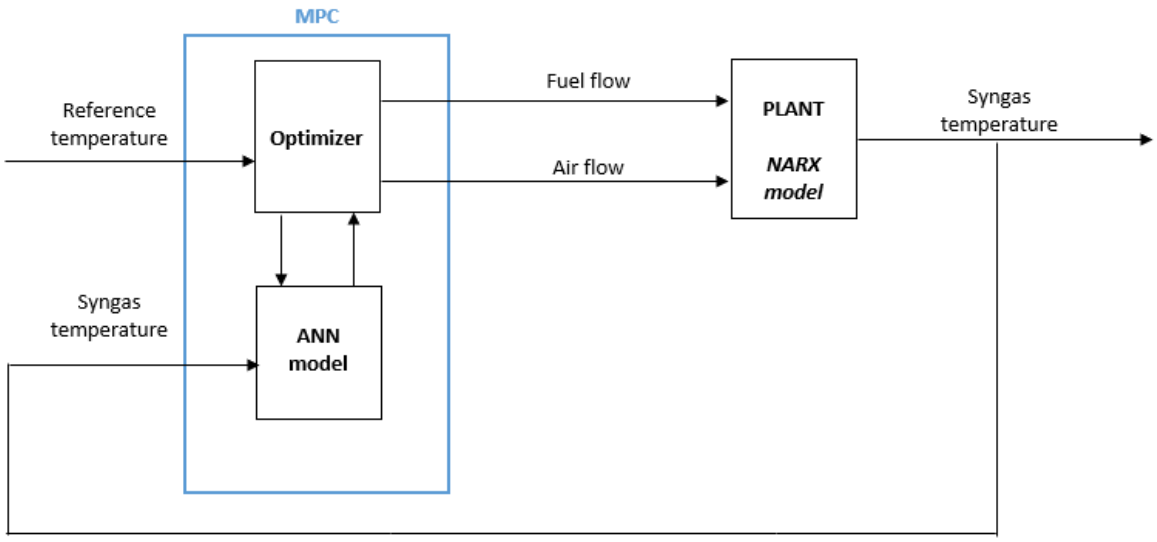

Figure 22 Model predictive control system for biomass gasification

The system is represented as a discrete-time t, nonlinear system with input signal $u(t)$, output signal $y(t)$, system response $s(t)$, signal trajectory $r(t)$, system error $e(t)$, number of control steps m and prediction horizon N.

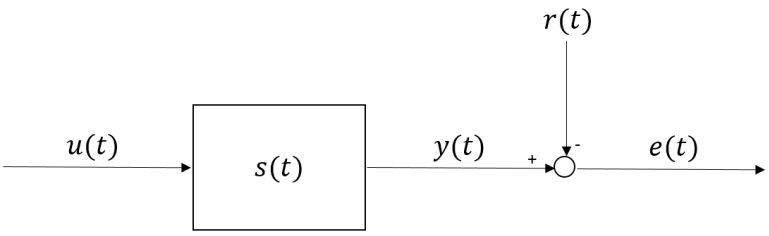

Figure 23 Proposed MPC model scheme

For proposed gasification control system input signal represents combination of fuel and air flow rate together with fuel injection frequency. System response is defined by developed ANFIS model. Output signal is syngas temperature at the exit of the gasifier which is defied by desired temperature trajectory (or measured values in validation cases). In proposed system response is defined as:

$$s(t) = f_{ANFIS}(u(t)) \quad \text{(Eq. 7.1)}$$

Based on such defined model output signal can be defined as:

$$y(t + \Delta t) = \sum_{m=1}^{5} s(m)u(t + \Delta t - m|t) \quad \text{(Eq. 7.2)}$$

In order to minimise output error $e(t) = y(t) - r(t)$ the performance index has been defined as:

$$\min_u J(u, t) = \min_u \sum_{\Delta t=1}^{N} e(t + \Delta t|t) \quad \text{(Eq. 7.3)}$$

As the system is highly nonlinear it is difficult to define optimisation algorithms to minimise output error. For nonlinear systems those goal functions are usually solved by sequential quadratic programming or nonlinear interior point methods [67]. In presented case a standard grid search algorithms (among input signals) have been used to minimise output error. Standard grid search approach is very computational and time intensive approach as it goes through all possible scenarios for each control step. With proposed approach (12 fuel and air flow rate steps and 2 fuel injection steps) it would result into 2 x 10^{12} calculations that should be performed in 2,5 minutes. As this is not possible with current computational power the size of grid has been reduced. Constant fuel and air flow rate was consider constant for each of 5 control steps. In this way the number of calculations that should be performed in 2,5 minutes has been reduced to 1440. This, however, reduces system control quality.

As a first validation step the MPC has been used to suggest adequate fuel and air flow (based on developed ANFIS model) to control syngas temperature. Syngas temperature trajectory has been taken from measurements and the role of MPC is to follow measured syngas temperature progress. Average fuel and air flow rates have been compared in order to check if simulated case follows mass and energy conversion behaviour from measurements. After validation, proposed MPC system will be used to follow one-step and multiple steps plant start-up strategies. The syngas temperature will be increased and MPC will be used to estimate necessary fuel and air flow rate and fuel injection frequency.

7.2 Model predictive controller system validation

Based on simulation results presented in Figure 24. it can be observed that MPC is well capable to follow desired (measured) syngas temperature setpoint (trajectory) from Experiment 1. However, MPC suggest different (than measured) fuel and air flows, together with different injection frequency. Due to complexity of the process and process dynamics it is possible that different combination of fuel and air flow rates could give similar effect on process temperature (but different in syngas yield). Furthermore, ANFIS model was trained to represent process behaviour for all 4 experiments. Therefore, the overall mass and air quantities during Experiments 1-4 should be compared to check if the same or similar amount of mass and energy has been introduced to reach the same effect on the process temperature. Results of the analysis are presented in Table 7.1.

Table 7 Validation of proposed MPC system

	Average fuel flow rate [kg/h]		**Average air flow rate [m^3/h]**	
	MPC	Measured	MPC	Measured
Experiment 1	119.22	184.73	11.47	12.75
Experiment 2	163.99	113.17	11.09	12.83
Experiment 3	154.02	168.77	11.49	11.18
Experiment 4	140.21	106.59	12.33	11.69
Experiment 1-4	145.95	143.02	11.61	12.01

Based on MPC validation analysis it can be concluded that developed system proposes higher fuel consumption in Experiments 2 and 4 and higher air consumption in Experiments 3 and 4. This is due to structure of ANFIS model that has been trained to describe the process in general. However, when looking at average process behaviour during Experiments 1-4 (the one that ANFIS model has been trained for) the MPC system proposes similar fuel and air consumption during syngas temperature control. This leads to conclusion that developed MPC system, in general, describes process behaviour with good accuracy.

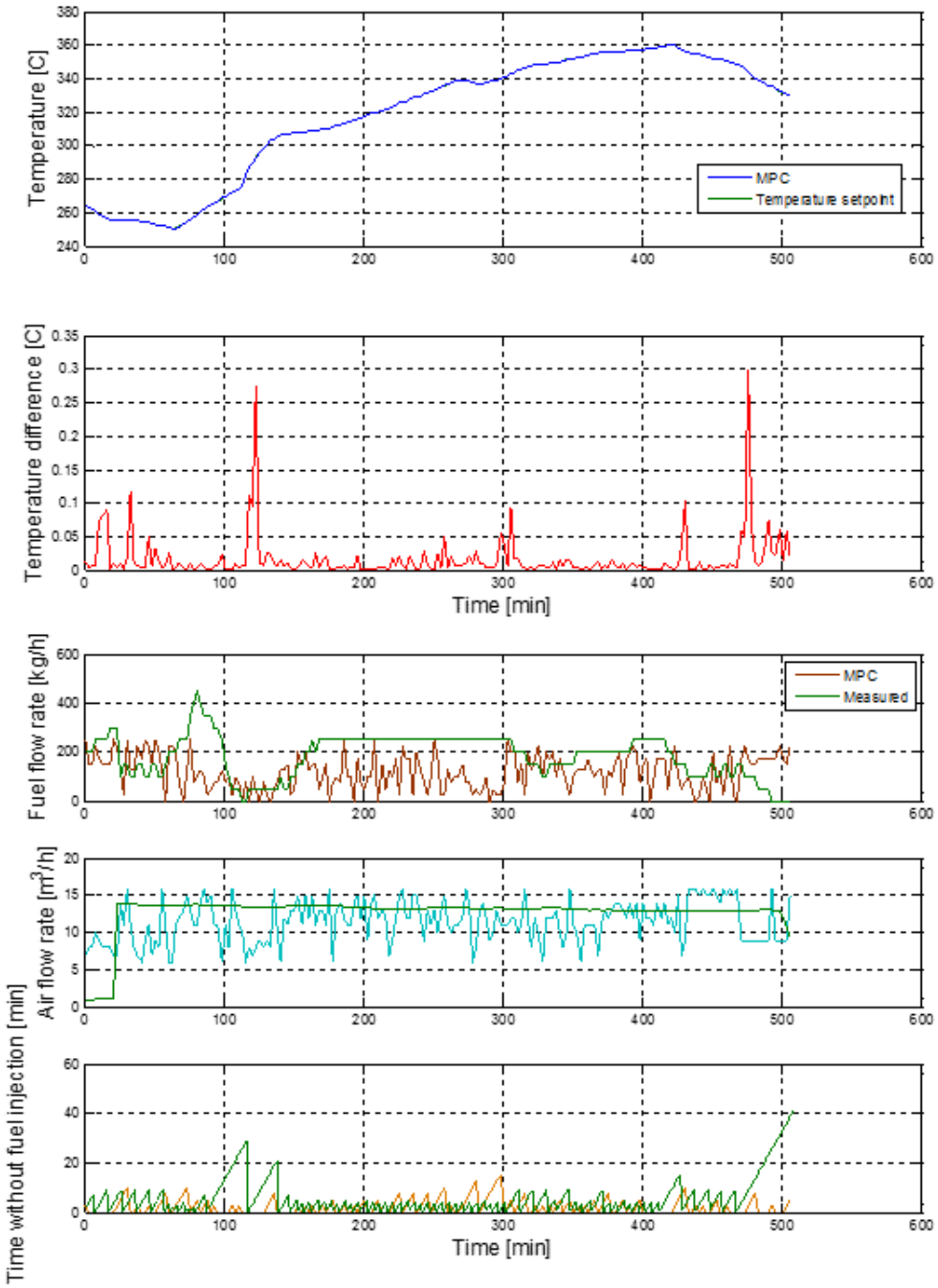

Figure 24 MPC temperature control for Experiment 1

7.3 System start-up strategy

After it has been concluded that developed MPC controller with ANFIS model can be used for syngas temperature control the analysis of system start-up (warming up) has been performed. The temperature was increased in 4 steps of 55 °C during 2 hours of plant operation, starting from 100 °C. First, the desired temperature trajectory was followed with changes in fuel flow only (air flow remained constant at $16m^3/h$ and injection frequency was set to 0 minutes – continuous fuel flow). Simulation results from the analysis are presented in Figure 25. It can be seen that appropriate temperature control cannot be obtained with only fuel flow rate control. Using similar analysis it was also concluded that appropriate temperature control cannot be obtained with only air flow rate control. Therefore, combination of fuel and air flow rate, together with fuel injection frequency should be controlled.

System response of MPC with 3 controllable variables (fuel and air flow rate and fuel injection frequency) is presented in Figure 26. Compared with previous case the desired syngas temperature trajectory was followed with reasonable accuracy. System response to trajectory changes is slower at temperatures up to 220 °C while on higher temperatures the system response is faster. This can be explained by faster chemical reaction rates at higher process temperatures and lower particle residence time [15].

After it has been concluded that proposed MPC system can be used for gasifier start-up control 2 different start-up control strategies will be compared in terms of fuel and air consumption. Simulation results will be used to analyse potential of the MPC to improve process performance.

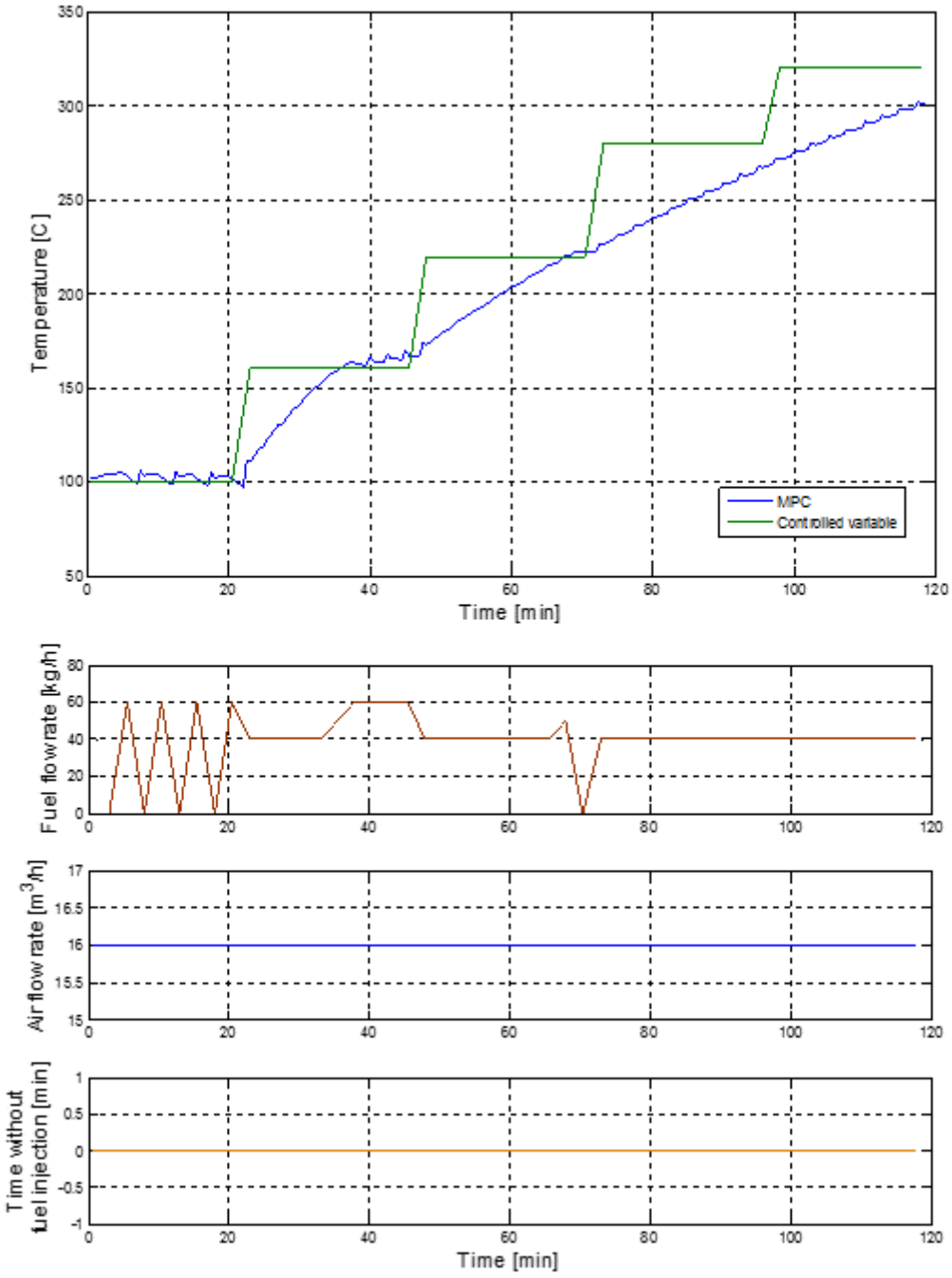

Figure 25 System start-up with fuel flow control

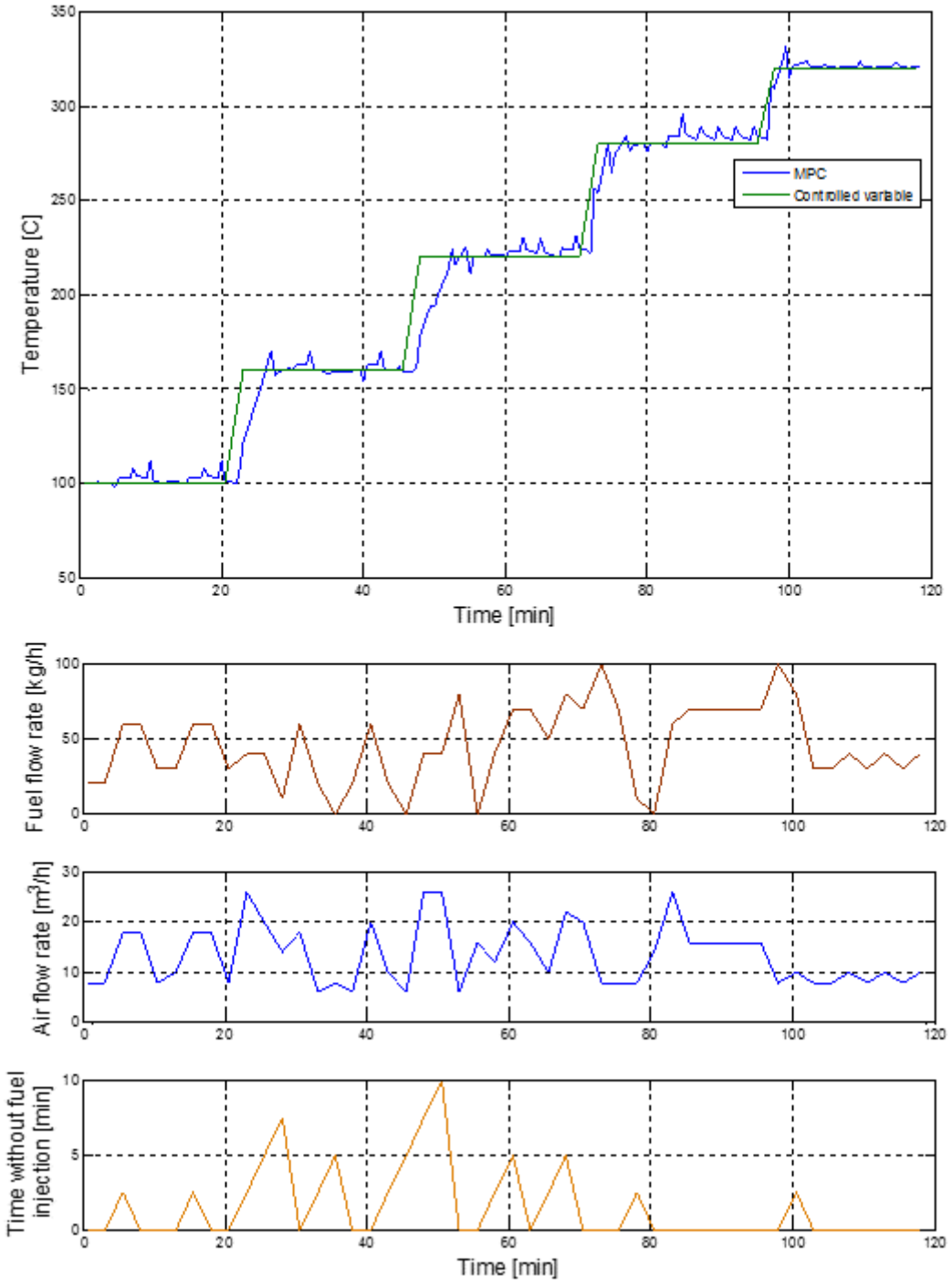

Figure 26 System start-up with multiple variable control

7.4 Improvement of process start-up performance with model predictive control

To analyse potential of MPC to improve process performance 2 start-up control strategies have been proposed and the performance has been analysed using developed models for process parameter prediction. One is the stepwise (multiple steps) start-up strategy from Chapter 7.3 and the other is a one-step start-up strategy. In multiple step start-up strategy a temperature increase of 55 °C during 120 minutes has been proposed. In the other strategy one step with temperature increase from 100 to 320 °C will be considered. Trajectory lines were set so that both strategies reach 320 °C at similar times. Simulation results are presented in Figure 7.4. It can be seen that both strategies are identical in terms of fuel and air consumption in the first 20 minutes. Afterwards, the air flow rate is increased and fuel flow rate decreased in strategy with multiple temperature steps. This leads to conclusion that complete combustion is enhanced to raise syngas temperature. After 50 minutes both fuel and air flow rate are increased to introduce more energy into the system while keeping similar air/fuel ratio. After 75 minutes the fuel flow rate has reached its maximum value so the air flow rate is increased to enhance complete combustion of fuel and to further increase syngas temperature. In the case of start-up strategy with one step temperature increase the fuel flow remained at initial values while air flow was increased to reach desired syngas temperature by enhancing complete combustion of fuel. Total fuel consumption and average air flow rate for both start-up strategies are presented in Table 8.

Table 8 Fuel and air consumption for 2 start-up strategies

	One step start-up	Multiple steps start-up
Fuel consumed [kg]	211.46	204.16
Average air flow rate [Nm^3/h]	11.32	13.42

Based on fuel and air flow rate comparisons it can be concluded that multiple step start-up strategy is more efficient in terms of fuel consumed. However, higher average air flow rate suggests that the controlled temperature increase was the results of higher air/fuel ratio which leads to complete combustion of the fuel. Complete combustion of fuel and higher process temperatures will benefit to syngas temperature increase but it will also decrease calorific value of syngas by reducing CO and H_2 formation [15]. In the other hand, lower process temperature leads to lower char conversion and higher tar concentration [15]. It is obvious that there is a high dependence and a trade-off between process efficiency, syngas quality, plant thermal load and its environmental aspects. This imposes the need for multiple variable control.

Furthermore, it is not clear if proposed temperature trajectory for multi-step start-up strategy represents the optimal start-up strategy. Other temperature trajectories for gasifier start-up could give even higher fuel savings. Therefore, the optimal syngas temperature trajectory should be first defined to improve process performance. The temperature trajectory should be also put into perspective with other process operation parameters like plant load and syngas quality that define process performance.

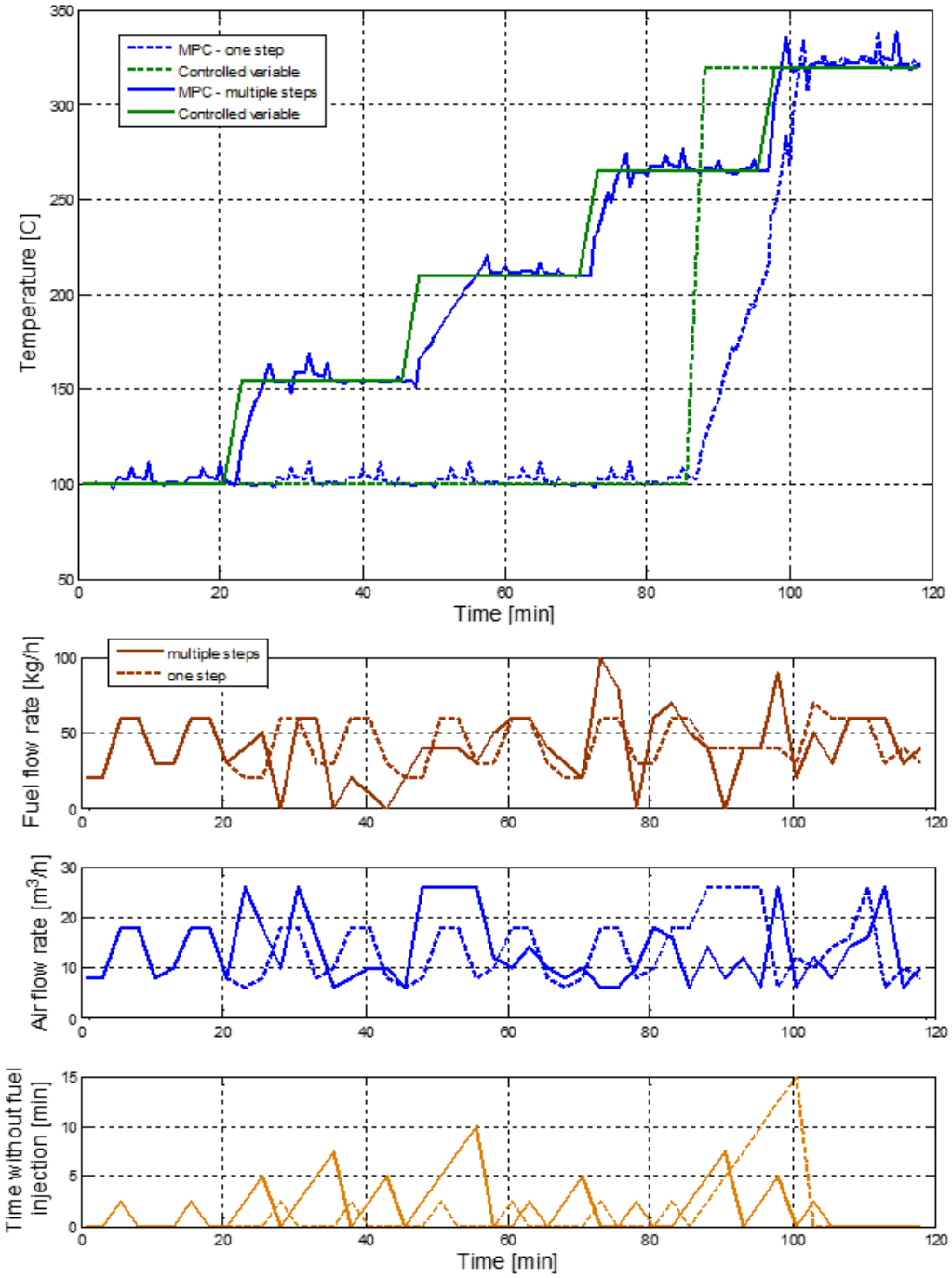

Figure 27 System start-up with multiple variable control

7.5 Conclusion

Developed model predictive control system with ANFIS model can be used for temperature process control as the system response follows desired trajectory with reasonable performance and resulting fuel and air flow rate values are in expected range. To improve control system performance advanced algorithms for non-linear optimisation should be used in control optimiser instead of proposed standard grid search algorithms. To effectively control process temperature, fuel and air flow together with fuel injection frequency should be controller simultaneously. Different air to fuel ratio will increase (or decrease) complete or incomplete fuel combustion which will lead do process temperature changes. However, with process temperature changes the plant load, quality of syngas, system efficiency and tar formation are expected to change. There is a trade-off between those process variables. Therefore, control of process temperature is only one of variables that should be controlled. On example of gasifier start-up strategy it was shown that different temperature control trajectories could result into different process performance. This leads to conclusion that for an efficient process control adequate control trajectories for plant load, syngas quality and syngas temperature should be defined. As those operation parameters are interconnected their combined influence on process performance should be taken into account.

8 PROCESS PARFORMANCE IMPROVEMENT IN FIXED BED GASIFIERS

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 Chapter 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. Advanced control concept performance has been analysed using developed ANFIS model.

8.1 Method for process performance improvement

For gasification control purposes, advanced control concepts have been implemented on several small-scale gasifiers. State of the art cases are presented in Chapter 1.4. Based on state-of-art analysis it was concluded that available adaptive optimisation solutions have a limited capabilities in terms of optimisation goal flexibility, number of controllable variables or range of operating conditions. The goal of the research within the Chapter will be 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 (fuel and air flow rate, together with fuel injection frequency) simultaneously. Fuel and air flow rate, together with fuel injection frequency should be controlled simultaneal and independently to reach desired plant outputs (e.g. syngas temperature) as explained in Chapter 7.3.

Current process control is explained in Chapter 3.1.. To analyse system performance ANFIS model (trained on Experiments 1-4) will be used. 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. Control map will be used to give optimal values for fuel and air flow rate for a desired process performance strategy. As discussed in Chapter 7.4. and Chapter 7.5. the combined effect of plant load, syngas quality and syngas temperature should be taken into consideration for an efficient plant control. For this purpose process temperature, syngas composition and flow and process efficiency for different operating regimes have been collected/calculated and analysed. Equations for efficiency and load calculation are presented in PAPER 5, Chapter 3. The methodology has been performed for nominal operating conditions where syngas can be produced with controllable syngas quality (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. 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 as different fuel/air flow ratios would contribute to more complete or incomplete combustion which would consequently have effect on syngas temperature, quality and total mass flow. Due to mentioned reasons various syngas quality can be reached during steady-state nominal gasifier thermal loads. The goal of the system optimisation is to follow a desired plant load while keeping high process efficiency, syngas quality and high environmental aspects.

For particular syngas production output (load) 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 performance was calculated based on equations presented in PAPER 5, Chapter 3. Process temperature has been considered due to its effect on process environmental aspects. With higher process temperature, the tar decomposition process is more efficient and tar emissions are lower [24].

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, if the plant is operated manually or without the help of developed control system by using different process parameter settings, new process conditions might occur which could lead to improved process performance. 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 the best and adapts control map accordingly. This process can be called "controller training" or "control map training". Flow chart of parameter tuning is presented in PAPER 5, Figure 3. In order to meet particular syngas production load set by plant operator, 2 additional PI controllers for fuel and air flow have been introduced into advanced control system. Fuel injection frequency can be adjusted manually. Additional PI controllers can correct proposed values derived/suggested from control map up to ±15% in order to meet particular syngas production load demand due to process changes. 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. . System scheme is presented in Figure 28.

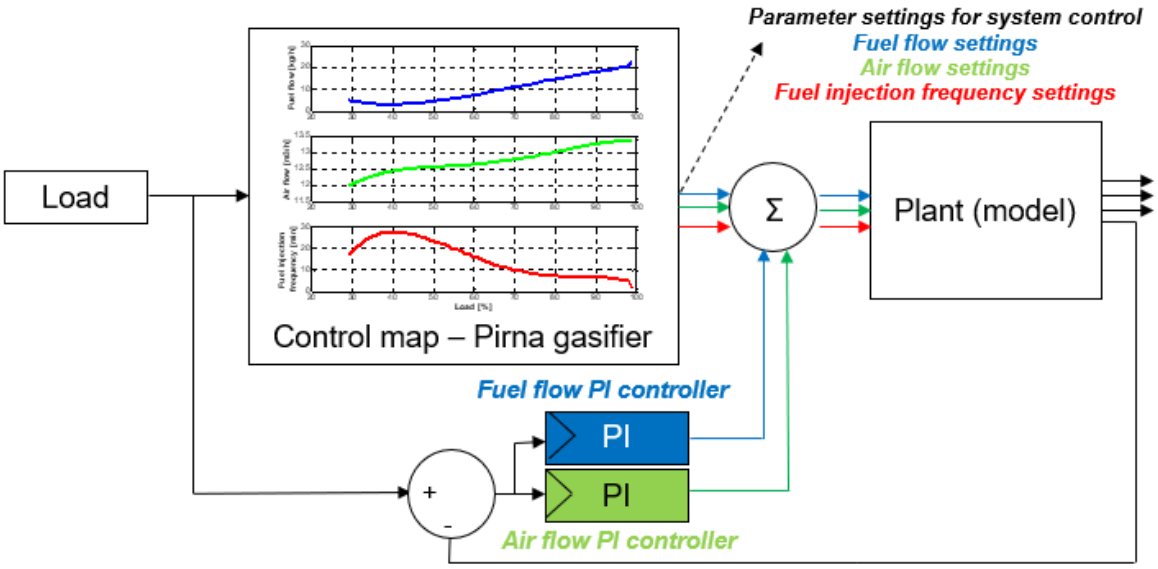

Figure 28 System start-up with multiple variable control

8.2 Impact of advanced control system on process performance

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 results from 4 different experiments that resulted in more than 20 hours of gasifier operation are presented on Figure 29. Process values of current process control are presented by red lines and process values from advanced process control are presented with green lines.

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 ±10%. 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. With introduction of the advanced control system the gasifier generally operates on higher nominal process temperatures for syngas production 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, CH_4 and H_2 formation rate which results in higher syngas heating value. Syngas heating value with advanced control system is ranging between 3-5 MJ/m^3 while with conventional control system it is ranging between 2,8-4,5 MJ/m^3. Higher temperatures also provide more efficient tar decomposition [24] which implies that the tar formation has also been reduced. Details regarding advanced control system performance is presented in PAPER 5, Chapter 4.

As there is a trade-off between process thermal efficiency, syngas quality and syngas temperature different optimisation goals have been proposed. In some cases the goal was to maximise syngas quality while in the other case the goal was to maximise syngas temperature

in order to improve process environmental aspects. Combination of optimisation goals was also analysed. Based on the analysis it was concluded that the main emphasis during control system development should be given to process thermal efficiency increase which would lead to combined syngas quality increase and the improvement of environmental aspects. Results of the analysis are presented in PAPER 5, Chapter 4.

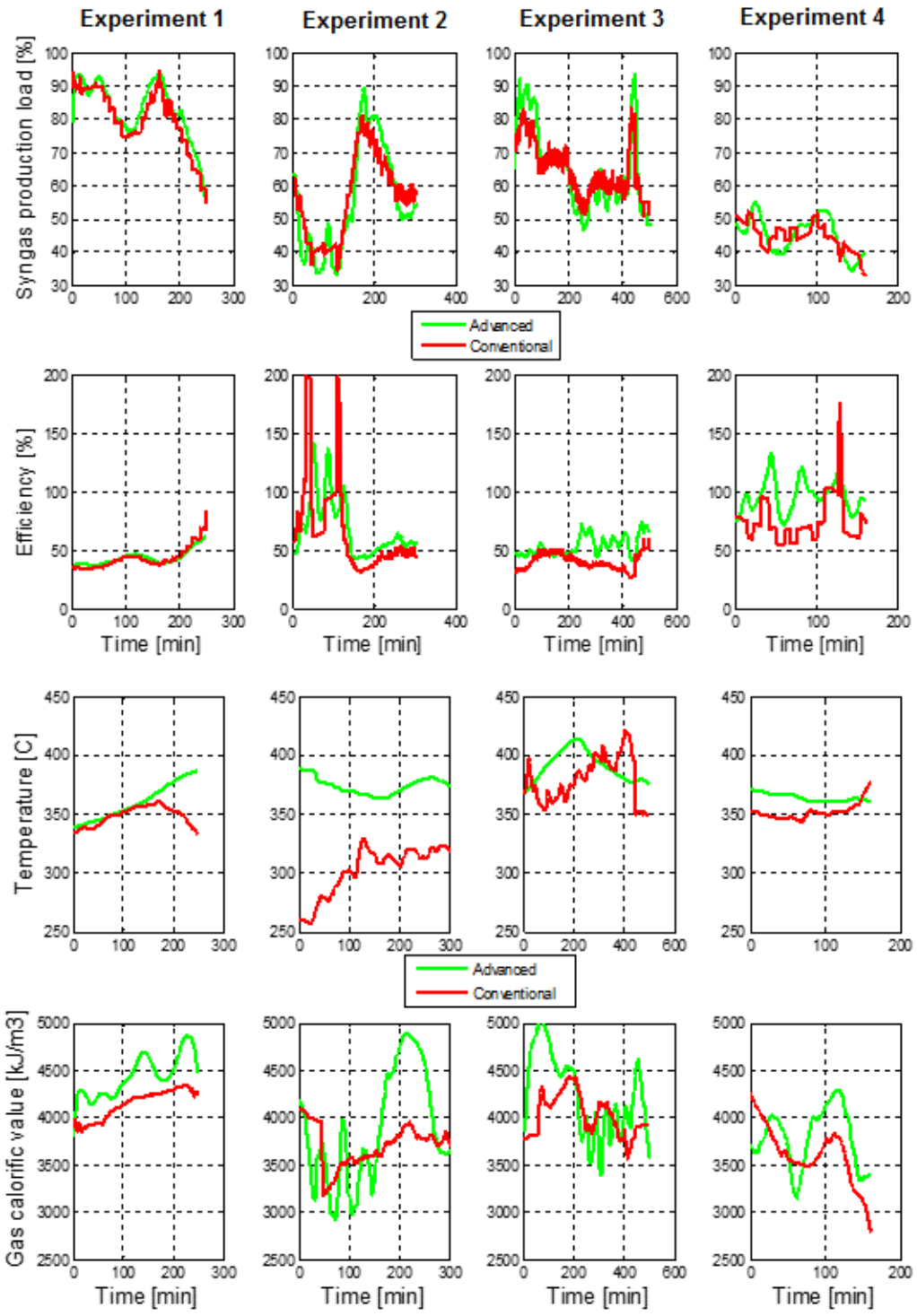

Figure 29 Performance changes with advanced control system

8.3 Conclusion

Proposed advanced control system enables efficient on-line plant process improvement for different plant loads. 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. The structure of the control system might be improved by replacing standard PI controller with model predictive controller proposed in Chapter 7. However, in order to make further conclusions the proposed control system should be tested during the real time plant operation.

9 CONCLUSIONS AND FUTURE WORK

Biomass gasification is a promising technology for renewable energy and fuel production. Gasification products can be used for heat and power generation, production of various chemicals or as a transport fuel. Issues related to syngas quality control and high investment costs are preventing utilisation of the technology on a larger scale. Biomass gasification is a complex thermo-chemical process which is influenced by large number of parameters. Due to this reason a lot of attention is given to modelling and control of the process to analyse it and consequently to improve gasification performance.

Available equilibrium models can be used to describe the process in unique operation point. However, due to their sensitivity to model structure and constitutive equations that have been taken for modelling they are often not appropriate for simulation in different operating points. Furthermore, they can be used to simulate only stationary operating regimes. For transient operating regimes kinetic models or CFD models could be applied. However, due to their computational intensity and sensitivity to model parameters they are still impractical for on-line process analysis and control. With development of computational technology they could be incorporated in control systems in the future. More emphasis should be also given to measurement of model parameters in different operating conditions.

To describe the gasification process in co-current fixed bed reactor artificial neural network models can be used. To develop such models some engineering experience knowledge regarding the process is needed to incorporate relevant process parameters like fuel and air flow rate into model structure. Afterwards, they could be easily adapted to simulate different types of gasifiers. Artificial neural network-based models have a fast prediction performance and good prediction quality. Due to these reasons, they could be incorporated into control systems or for on-line process analysis. However, their performance should be actively monitored to assure prediction quality during long-term gasifier operation where some changes in operating conditions are expected. Dynamic neural networks can be used to describe the process by using raw measurement data. Their prediction performance should be carefully analysed to define

their autonomous prediction range. With improvement of computational and mathematical science new algorithms for efficient machine learning based models are expected.

Developed neural network-based models can be used as a constitutive model in model predictive control systems. For better control performance new optimisation routine should be developed and implemented. Other advanced control systems like fuzzy-logic control should be analysed. Gasification control system should be able to control several operating parameters simultaneously. Interconnected effects of process temperature, syngas quality and syngas yield should be considered during process control and optimisation. Advanced control system based on adaptive control map has a potential to improve process performance and process environmental aspects.. To prove potential of developed control system it should be implemented into existing gasification plant and the plant performance should be analysed.

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11 CURRICULUM VITAE

Dr. ROBERT MIKULANDRIĆ, mag.ing.mech. was born on the 24th of September 1986 in Zagreb, Croatia. In 2005 he finished High School "XV. Gimnazija" in Zagreb and started his studies on the Faculty of Mechanical Engineering and Naval Architecture (FMENA), University of Zagreb. In 2010 he finishes his Master studies in mechanical engineering and starts to work as a research assistant at Faculty of Mechanical Engineering and Naval Architecture, University of Zagreb, at the Department of Power Engineering, Energy and Environment. During his studies he was awarded City of Zagreb reward for exceptional achievement in field of physics (2005), two 'Davorin Bazijanac' awards for excellence in Mechanical Engineering (2009 and 2010) and Faculty Medal for Academic Achievement (2010). During his stay at FMENA he was working on 2 European projects (SEE-ERA.NET PLUS and 4DH). In 2013 he receives 'Deutsche Bundesstiftung Umwelt' scholarship to do the research on biomass gasification at TU Dresden. From 2014 he starts to work as a research assistant at Faculty of Bioscience Engineering, KU Leuven, Belgium on industrial project with Case New Holland (MoCoBa) to improve performance of industrial balers. In 2018 he obtains PhD in the field of Bioscience Engineering. Since 2018 he works as Technology Developer for Atlas Copco Belgium on R&D projects for compressor technique. He is author of 6 scientific articles published in scientific journals (SCI), author of many conference papers and he is holder of 2 international patents. From sports he plays curling and he is multiple national champion and winner of silver medal at European Curling Championship – C Group from Erzurum, Turkey. He is married and has one child. From languages he speaks Croatian, English, Dutch, and German

12 SUMMARY OF PAPERS

PAPER 1

Mikulandrić Robert, Lončar Dražen, Boehning Dorith, Boehme Rene. *Biomass gasification modelling aspects.* Proceedings of the International Conference on Polygeneration Strategies 2013; 319-333.

In developed European countries the number of small and middle-scale biomass gasification power plants as well as syngas production plants has been significantly increased in the last decade mostly due to extensive incentives. Existing issues regarding syngas quality, process efficiency, emissions and environmental standards are preventing biomass gasification technology to become more economically viable. With technology and plant design development, mathematical models which can contribute to emission and syngas generation prediction and biomass gasification process control are being developed and constantly improved. Nowadays, complexity of biomass gasification mathematical models can range from three-dimensional models, that take fluid dynamics (CFD models) and chemical reactions into consideration, to simpler models where mass and energy balances are considered over entire gasifier to predict gas composition. Three-dimensional models are very useful in terms of delivered process information and understanding but due to their complexity these models require very extensive computational resources which are usually impractical for online control. The complexity of detailed models initiates research of simpler models, either based on first principles or neural networks, which will be applicable for process parameter prediction and control. The work presents different biomass gasification modelling aspects as a preparation for more extensive modelling research to be performed during 2013. After a related literature review, different biomass gasification modelling approaches for process control and possibilities of neural networks to predict process parameters with high speed and accuracy will be analysed.

In this paper the literature review was done by Mikulandrić. Lončar was responsible for technical guidance, review and project financial support. Boehning contributed with providing relevant literature and Boehme contributed during the internal review with his personal experience on modelling.

PAPER 2

Mikulandrić Robert, Lončar Dražen, Boehning Dorith, Boehme Rene, Beckmann Michael. *Artificial neural network modelling approach for a biomass gasification process in fixed bed gasifiers*. Energy Conversion and Management 2014;87:1210-1233.

The number of the small and middle-scale biomass gasification combined heat and power plants as well as syngas production plants has been significantly increased in the last decade mostly due to extensive incentives. However, existing issues regarding syngas quality, process efficiency, emissions and environmental standards are preventing biomass gasification technology to become more economically viable. To encounter these issues, special attention is given to the development of mathematical models which can be used for a process analysis or plant control purposes. The presented paper analyses possibilities of neural networks to predict process parameters with high speed and accuracy. After a related literature review and measurement data analysis, different modelling approaches for the process parameter prediction that can be used for an on-line process control were developed and their performance were analysed. Neural network models showed good capability to predict biomass gasification process parameters with reasonable accuracy and speed. Measurement data for the model development, verification and performance analysis were derived from biomass gasification plant operated by Technical University Dresden.

In this paper modelling and simulations were done by Mikulandrić. Boehning was responsible for measurements and data collection. Boehme was responsible for gasifier operation. The paper was written by Mikulandrić and reviewed by Lončar, Boehning and Beckmann.

PAPER 3

Mikulandrić Robert, Lončar Dražen, Boehning Dorith, Boehme Rene, Helsen Lieve, Beckmann Michael. *Dynamic modelling of biomass gasification in a co-current fixed bed gasifier.* Energy Conversion and Management 2016;125:264-276

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.

In this paper modelling and simulations were done by Mikulandrić. Boehning was responsible for measurements and data collection. Boehme was responsible for gasifier operation. Lončar and Helsen contributed with ideas on model development. The paper was written by Mikulandrić and reviewed by Lončar, Helsen and Beckmann.

PAPER 4

Mikulandrić Robert, Boehning Dorith, Lončar Dražen. *Temperature prediction in a fixed bed biomass gasifier using NARX modelling.* Journal of Sustainable Development of Energy, Water and Environment Systems 2020;1:976-1,976-10

Biomass gasification is a promising technology for efficient, clean and diverse utilisation of biomass and biomass residues through production of syngas. It is a complex thermo-chemical process where specific mass and energy accumulation plays an important role in overall process performance. To improve process efficiency through process control and to tackle existing technical issues related to the process a lot of attention has been given to development of models that can predict process parameters in real time and changing operating conditions. Therefore, biomass gasification models for process improvement and control should be able to describe such a complex and site dependent system while keeping high prediction speed and accuracy. The paper analyses the potential of a nonlinear autoregressive exogenous (NARX) model to predict syngas temperature during plant operation with variable operating conditions. The model has been designed and trained based on measurement data from 100kWth fixed bed gasification plant operated by Technical University Dresden. Developed model is able to predict syngas temperature under changeable operating conditions with coefficient of determination (R2) of 0.98.

In this paper modelling and simulations were done by Mikulandrić. Boehning was responsible for measurements and data collection. The paper was written by Mikulandrić and reviewed by Lončar.

PAPER 5

Mikulandrić Robert, Lončar Dražen, Boehning Dorith, Boehme Rene, Beckmann Michael. *Process performance improvement in a co-current, fixed bed biomass gasification facility by control system modifications.* Energy Conversion and Management 2015;104:135-146

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 MWth 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 h 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.

In this paper modelling, control system development and simulations were done by Mikulandrić. Boehning was responsible for measurements and data collection. Boehme was responsible for initial gasifier operation. Lončar contributed with discussions on control system design. Beckmann was responsible for financial support. The paper was written by Mikulandrić and reviewed by Lončar and Beckmann

PAPER 1

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Biomass gasification modelling aspects

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Abstract:

In developed European countries the number of small and middle-scale biomass gasification power plants as well as syngas production plants has been significantly increased in the last decade mostly due to extensive incentives. Existing issues regarding syngas quality, process efficiency, emissions and environmental standards are preventing biomass gasification technology to become more economically viable.

With technology and plant design development, mathematical models which can contribute to emission and syngas generation prediction and biomass gasification process control are being developed and constantly improved. Nowadays, complexity of biomass gasification mathematical models can range from three-dimensional models, that take fluid dynamics (CFD models) and chemical reactions into consideration, to simpler models where mass and energy balances are considered over entire gasifier to predict gas composition.

Three-dimensional models are very useful in terms of delivered process information and understanding but due to their complexity these models require very extensive computational resources which are usually impractical for on-line control. The complexity of detailed models initiates research of simpler models, either based on first principles or neural networks, which will be applicable for process parameter prediction and control.

The work presents different biomass gasification modelling aspects as a preparation for more extensive modelling research to be performed during 2013. After a related literature review, different biomass gasification modelling approaches for process control and possibilities of neural networks to predict process parameters with high speed and accuracy will be analysed.

1. Introduction:

Gasification of biomass 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 contaminates) called "syngas", using gasifying agents [1]. As the most important process products of gasification, H2 and CO contain only around 50% of the energy in the gas while the remained energy is contained in CH4 and higher (aromatic) hydrocarbons [2]. As gasifying agents, air, pure oxygen, steam, carbon dioxide, nitrogen or their mixtures could be used. The utilisation of different gasifing agents results in different gasification process characteristics (gas quality, gas production rate, char and tar production and gas lower heating value). The lower heating value (LHV) of syngas that is produced by using air as gasifing agent is 4-7 MJ/Nm3 while with oxygen and steam produced gas has a LHV of 10-18

MJ/Nm3 [1]. Comparison of gasification process with different gasification agent usage is given in Table 1.

Gasifying agent	LHV [MJ/Nm3]	Process characteristics
Air [1,3]	4 - 7	H2 content: 8-14 vol.% High nitrogen content
Steam [1,3]	10 - 20	H2 content: 30-60 vol.% Low reaction temperature causes usage of additional energy Higher carbon conversation efficiency and improved gas yield
Oxygen [1,3]	10 - 18	High production costs due to additional equipment for O2 production

Table 1: Comparison of gasification process with different gasification agent usage

Gasification process could be divided into three main stages: drying (100-200 °C), pyrolysis (200–500 °C) and gasification (500–1000 °C) [1,2]. In the drying process the moisture from biomass evaporates and biomass becomes dry. In the pyrolysis stage of the process, the volatile components from biomass are vaporised through various complex reactions. By-products of the pyrolysis stage are char and other inert components that have not been vaporised. In the gasification process, the char is gasified through reactions with the gasifing agent and products of pyrolysis (H2 and CO).

The energy that is needed for this process is produced from combustion of part of the fuel, char and gases. The main reactions during the biomass gasification process [4,5] are shown in Table 2.

Reaction	Chemical reactions	ΔH [kJ/mol]
Primary devolatilisation (pyrolysis)	Biomass → H_2O, CO, CO_2, CH_4, C_2H_4 and C	
Tar cracking and reforming	Primary tar → Secondary tar + H_2, CO, CO_2, CH_4, C_2H_4	
Homogenous gas-phase	Secondary tars → C, CO, H_2 $H_2 + 0{,}5\ O_2 \rightarrow H_2O$ $CO + 0{,}5\ O_2 \rightarrow CO_2$ $CH_4 + 0{,}5\ O_2 \rightarrow CO + 2\ H_2$ $CH_4 + CO_2 \rightarrow 2\ CO + 2\ H_2$ $CH_4 + H_2O \rightarrow CO + 3\ H_2$ $CO + H_2O \rightarrow CO_2 + H_2$	- 242 - 283 - 110 +247 +206 - 40,9
Heterogeneous	$C + O_2 \rightarrow CO_2$ $C + 0{,}5\ O_2 \rightarrow CO$ $C + CO_2 \rightarrow 2\ CO$ $C + H_2O \rightarrow CO + H_2$ $C + 2\ H_2 \rightarrow CH_4$	- 393,5 - 123,1 + 159,9 + 118,5 - 87,5

Table 2: Main reactions during biomass gasification process

The performance of biomass gasification processes is influenced by large numbers of operation parameters concerning the gasifier and biomass [1], such as fuel and gasification agent flow rate, composition and moisture content of the biomass, geometrical configuration of the gasifier, reaction/residence time, type of gasifying agent, different size of biomass particles (typically from 0.1-0.4 mm for entrained flow gasifiers [1], 0.4-1.5 mm for fluidised bed gasifiers [6] and 5-100 mm for fixed bed gasifiers [7]), gasification temperature (750-1000°C [2, 6]), pressure (1 – 20 bar [6]) and the gasifying agent/biomass ratio. The gasification temperature affects the syngas heating value and composition. High gasification temperatures improve syngas quality but cause higher process heat losses and ash melting (depends on type of biomass). Small particle sizes increase overall energy process efficiency due to lower devolatilisation time but this increases biomass pre-treatment costs. Equivalence ratio (actual air to biomass weight ratio divided by stoichiometric air to biomass weight ratio needed for complete

combustion [3]) is one of the most important parameters in biomass gasification process with air as gasifing agent. Higher equivalence ratio causes combustion of char and by that reduces syngas LHV. A smaller equivalence ratio causes lower gasification temperatures. The equivalence ratio typically ranges between 0,2 - 0,45 [6] (dependable on type of gasifier). Gasifiers can be mainly classified as autothermal or allothermal gasifiers [8]. In autothermal gasifiers the reactions of combustion and gasification are performed simultaneously in one single reactor while in allothermal gasifiers, part of reactor that is used for gasification reactions is indirectly heated. Three types of gasifier are used for biomass gasification purposes: fluidised bed; fixed bed; and entrained flow gasifiers (Figure 1.). Fixed bed gasifiers are generally characterised by simple design with comparatively low syngas production and investment costs, flexible fuel input, high tar content and relatively low efficiency [2,3,9,10,11]. Fixed bed gasifier can be further divided (depending on the direction of the gasification agent flow) into downdraft, updraft, cross-flow and multistage [12] gasifiers. Fluidised bed gasifiers are characterised by high syngas quality, good mixing and heat exchange process, uniform and controllable temperature distribution in the gasification zone, low tar content, flexible fuel input, high carbon conversion rate, high content of particles in syngas and risk of equipment erosion [2,3,9,10]. Fluidised bed gasifier can be further divided into circulating, bubbling, twin-bed and multistage gasifiers [13]. These gasifiers differ in fluidising velocity as well as gas path [1]. General descriptions of different types of gasifiers can be found in Table 3.

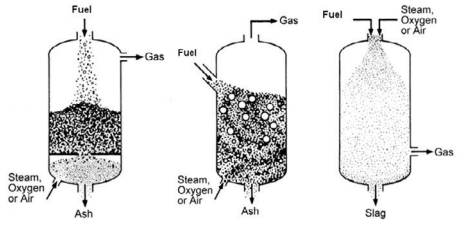

Figure 1. Simplified scheme of fixed bed (left), fluidised bed (middle) and entrained flow (right) gasifier [14]

The downdraft type of gasifiers are the most manufactured (75%) types of gasifiers in Europe, United States of America and Canada. 20% of all produced gasifiers are fluidised bed gasifiers and the remaining 5% are updraft and other types of gasifiers [15]. Products of gasification are mostly used for separately or combined heat and power generation, hydrogen production, liquid fuels production and methanol and chemical production. Biomass gasification seems to have promising potential for electricity and heat cogeneration through conventional or fuel cells based technology. Types of gasifier type for different scales are shown on Figure 2.

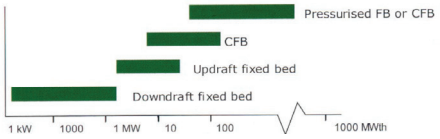

Figure 2. Types of gasifier type for different scales [16]

Type of gasifier	Process characterisation	Advantages	Disadvantages
Updraft fixed bed	Gasifying agents flow in counter-current from fuel flow	Economical for small scale application Flexible to fuel input quality Simple and proven technology Low exit gas temperature High thermal efficiency	Environmental issues (high tar and ash content) Extensive syngas cleaning needed Limited scale-up potential
Downdraft fixed bed	Gasifying agents flow in co-current with fuel flow	Economical for small scale application Low tar content in syngas Simple and low cost process	Requires low moisture content in biomass High exit syngas temperature Limited scale-up potential
Cross-flow fixed bed	Gasifying agents flow from one side of the fuel flow	Lower exit syngas temperature	Low overall efficiency High tar content
Circulating fluidised bed	High fluidizati-on velocity – turbulent flow	Economical for large scale application Fuel flexibility High heat and mass transfer High conversion flexibility Good process temperature control Low content of tar and unconverted carbon Flexible load	High velocities result in equipment erosion Heat exchange less efficient than bubbling fluidized-bed
Bubbling fluidised bed	Gasifying agents are forced through the inert particles	Simplest and cost-effective concept for continuous biomass gasification High fuel flexibility High heat transfer rate Uniform temperature through the reactor Low content of tar	Gas bypasses through the bed Moderate syngas LHV
Twin fluidised bed		Economical for large scale application Good particle mixing Good scale-up potential	Complex construction and operation Gas cleaning required Low efficiency
Multistage fixed and fluidised bed	Multista-ge processes	High flexibility Higher efficiency	More complex construction
Entrained flow	Gasifying agents flow co-current with fuel flow	Low feedstock inventory High conversion efficiency Good syngas quality Low tar content Good scale-up potential	Needed additional equipment to reach high pressure condition and small biomass particle sizes Complex construction and operation

Table 3: General descriptions of different types of gasifiers

2. Mathematical models for biomass gasification

Mathematical models can be used to explain, predict or simulate the process behaviour and to analyse effects of different process variables on process performance. Experiments for these purposes could often be very expensive. Mathematical models are essential for process optimisation and control because they can be used to analyse effects of various different operating parameters on process behaviour in reasonable time and with reasonable costs. Nowadays, special attention is given to the biomass gasification process modelling [17] which can contribute to more efficient plant design, emission and syngas generation prediction or plant control in order to optimise the gasification process.

Mathematical modelling is mostly based on the conservation laws of mass, energy and momentum. The complexity of models can range from complex three-dimensional models that take fluid dynamics (CFD models) and chemical reactions into consideration to simpler black-box models where mass and energy balances are considered over the entire gasifier to predict the gas composition. A comparison of different modelling approaches is described in Table 1.

Kinetic models

Kinetic models are used to describe kinetic mechanisms of biomass gasification. They take into consideration various chemical reactions that are often simultaneous and transfer phenomena among phases [1]. Common ground for all kinetic models are conservation laws for solids and gasses as well as energy balances for all phases. Equations for momentum conservation law and specific chemical reactions for pyrolysis,

combustion of char and gas, gasification of char and other equilibrium reactions may vary from model to model. Rate laws, Arrhenius equation [1,18], kinetic parameters and hydrodynamic equations for the gasifier represent the basics for construction of such models. Kinetic models are more realistic in terms of process description and can provide extensive information regarding the gasification process (composition of syngas under various conditions, gasification temperatures and particle kinetics). However, applicability of these models is limited due to several constraints. All possible reactions are not taken into account (almost all models assume pyrolysis and sub-stoichometric combustion as instantaneous because these processes are much faster than the gasification process [19]). The literature often offers different reaction coefficients, kinetics constants and model parameters that are often related to the design of a gasifier [20]. Any error in parameter calculation or estimation could lead to errors in process parameter prediction results. Kinetic models are very useful in describing biomass conversion during the gasification process, for gasifier design and improvement purposes, but due to their computationally intensiveness and long computational time they are still impractical for online process control.

For example, Corella [21] offers one-dimensional stationary model for an atmospheric circulating fluidized bed biomass gasifier with a sub-model for the tar generation. The model is based on the kinetic equations (supported by literature and site-based corrective factors) and mass and heat balances with several hydrodynamic considerations. Twelve different reactions have been taken in consideration. Liu [22] describes a circulating fluidized bed biomass gasification model that consists of sub-models for devolatilisation, tar cracking and nitrogen formation. Fiaschi [20] describes one-dimensional kinetic model for bubbling fluidised bed biomass gasifier that consists of two phases (a bubble and a dense phase). His model is capable of predicting temperature and concentration gradients along the reactor axis. Optimisation regarding ER, pressure, bed height and gas velocity has been performed. Gerber [23] offers a similar model that is based on an Eulerian modelling approach [24] where the solid phase in the reactor is modelled as three continuous phases. Fletcher [25] developed a kinetic model for an entrained flow biomass gasifier with non-equilibrium chemistry. Sommariva [26] has developed a general mathematical steady state model for updraft gasifier. He takes into consideration heat and mass transport resistances and chemical kinetics at reactor and particle scale. Literature offers more than 12 kinetic models for fluidised bed gasifiers as well as 7 kinetic models for fixed bed biomass gasifiers [1]

Equilibrium models

Models that do not solve particular processes and chemical reactions in the gasifier and instead consist of overall mass and heat balances for the entire gasifier are called the Black-box models (BBM) [17]. In development of such models many assumptions must be taken into account. One type of BBM is the equilibrium model. Equilibrium models are generally based on chemical reaction equilibrium and take into account the second law of thermodynamics for the entire gasification process [1]. This means that these models describe only stationary gasification process without a deep-in-analysis of processes inside gasifier. Equilibrium models are based on equations for Gibbs free energy

minimisation [27] and equations for mass and heat transfer. These models are independent from gasifier type, gasifier design or specific range of operating conditions. In some cases the gasifier is divided into black-box regions where specific processes are assumed to be dominant and different models, based on equilibrium or kinetics, are applied [17]. They are useful in prediction of the gasifier performance under various different operational conditions and therefore are often used for preliminary design and optimisation purposes. Generally, these models are suitable as a simulation tool for processes either whose duration is usually quite long with respect to the reaction time scale or for processes with gasification temperature that is higher than 800 °C. Equilibrium models are relatively easy implementable with fast convergence [1]. Equilibrium models can be subdivided into stoichiometric and non-stoichiometric models.

Stoichiometric equilibrium models are models based on equilibrium constants with clearly defined independent set of reactions which can be associated with Gibbs free energy minimisation approach [17]. In those models, only reactions and species that are present in larger amounts are taken into consideration in their equilibrium contents. For these reactions, mechanisms that incorporate all chemical reactions and species must be clearly defined. These models are applicable for describing complex reactions in general. The equilibrium constants for the most of equilibrium reactions could be found in literature but they are highly dependable on specific range of process parameters and their accessibility could be limited in some cases [19].

Non-stoichiometric equilibrium models do not take any particular reaction mechanisms or species into consideration. They are based on minimising Gibbs free energy for the system without specifying the possible reactions taking place [1,19]. They are used to predict the equilibrium composition of the species from gasification process. The only input they need is biomass composition (and gasification medium) which can be obtained from ultimate analysis data [10]. These models are mostly used to predict the composition of syngas without deep-in-analysis of gasification process. The temperature inside gasifier could be calculated only with the estimation of heat losses.

Pseudo-equilibrium models aim at making the equilibrium calculations more realistic by supporting the equilibrium models with empirical relations [17]. In these models, carbon, methane and tar are considered to be contained in the outlet gas and the corresponding quantities of carbon and hydrogen are discounted from the input fuel and the remaining fuel elements as well as the gasification agent react to attain equilibrium [17]. For utilisation of pseudo-equilibrium models estimation of methane, carbon and tar in outlet steam is necessary. This makes the model are dependable on site specific measurements and type of the gasifier.

Artificial neural networks models

Artificial neural networks (ANN) models use a mathematical modelling approach which correlates the input and output data to form a mathematical prediction model. ANN is an universal function approximator that has ability to approximate any continuous function to an arbitrary precision even without apriori knowledge on structure of the function that is approximated [10].This means that for biomass gasification modelling, ANN modelling approach needs less knowledge about the real process. Therefore it depends on large quantity of experimental data and many idealised assumptions. Due to these reasons, not many works on

neural networks model development have been reported [1]. ANN biomass gasification modelling approach has shown good results in syngas composition prediction in research conducted by Guo [28].

Hybrid neural network models can also be used for process parameter prediction. This modelling approach incorporates a partial first principles model which describes some parts of process and artificial neural network that serves as an estimator of unmeasured process parameters that are difficult to model from first principles [28].

Mathematical model approach		Advantages	Disadvantages
Kinetic models		Realistic process description Extensive information regarding process operation Good for gasifier design and improvement purposes	All possible process reactions are not considered Different model reaction coefficients and kinetics constants Dependable on the gasifier design Impractical for online process control
Equilib-rium models		Independent from gasifier type and design or specific range of operating conditions Useful in prediction of gasifier performance under various different operational parameters Easy to implement Fast convergence	Describe only stationary gasification process Do not offer insight in gasification process
	Stoichio-metric models	Applicable for describing complex reactions in general	Only some reactions are taken into consideration Reaction mechanisms must be clearly defined Equilibrium constants are highly dependable on specific range of process parameters
	Non-stoichio-metric models	Simplicity of input data Used to predict the composition of syngas	Describe gasification process only in general Lack of detailed process information
	Pseudo-equilib-rium models	More realistic equilibrium models	Estimation of methane, carbon and tar in outlet steam is necessity Model is dependable on site specific measurements and type of the gasifier.
Artificial neural networks models		Do not need extensive knowledge regarding process	Depends on large quantity of experimental data Many idealised assumptions
	Hybrid neural network model		Knowledge regarding process is needed

Table 4. Comparison of different modelling approaches

3. Models for biomass gasification process control

Comprehensive models for biomass gasification process control

The literature offers several comprehensive gasification models that could be used for biomass gasification process control and optimisation. These are mostly equilibrium based models and offer only static process analysis and optimisation.

Buragohain [19] offers a non-stoichometric equilibrium model called SOLGASMIX to analyse and optimise the gasification process for different combination of operating conditions. In his work, biomass type, equivalence ratios, temperature of gasification and gasification medium have been changed in order to analyse their influence on the process performance. The model uses iterative procedure for calculating an equilibrium composition of syngas at a specific temperature and pressure.

Castello [29] developed a detailed non-stoichiometric two-phase thermodynamic equilibrium model for the supercritical water biomass gasification process. His model is based on the Gibbs free energy minimisation approach (system has reached his equilibrium state) that is calculated using MATLAB's ® programming language with FMINCON routine. FMINCON uses the method of Lagrange multipliers, which enables to solve a minimisation

problem subject to constraints. Castello's model also enables the char and tar formation analysis.

Guo's [30] thermodynamic equilibrium model is based on the method of minimising Gibbs free energy in chemical equilibrium in the reactor and gas–liquid equilibrium of the high-pressure separator. Gas- liquid model uses universal functional activity coefficient model, Soave–Redlich–Kwong equation of state and modified Huron–Vidal second-order mixing rule. The model has been used for exergy and energy process analysis and to predict the product gas composition.

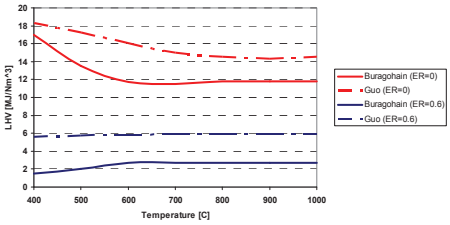

Figure 3. Comparison of simulation results of Buragohain's [19] and Guo's [30] modelling approach

Many authors in their research often analyse different kind of effects on gasification process so it is hard to correlate their simulation results. On Fig. 1 simulation results of two different modelling approaches have been shown. For analysis of syngas heating value in dependence of gasification temperature and equivalence ratio (ER), Buragohain [19] used a sawdust gasification process while Guo [30] used gasification process of biomass (5% of moisture) with steam under the pressure of 250 bar . Even these two processes are different by their nature, the simulation shows similar results. For low ER ratio, syngas heating value is high and have decreasing tendency till 800 °C. For high ER ratio, the syngas heating value is low with a slightly increasing tendency.

The thermodynamic equilibrium model developed by Khadse [31] takes four reactions as independent: oxidation; steam gasification; Bouduard reaction [32]; and the methanation reaction. The water gas shift reaction has been taken as subtraction of the steam gasification and the Bouduard reactions. For this kind of model, several assumptions have been made. Biomass is given in the general formula of CHxOy and the products of gasification are assumed be CO2, CO, H2, CH4, N2, H2O and un-burnt carbon. The reactions are adiabatic at thermodynamic equilibrium and the formation rate of the unburned carbon is considered.

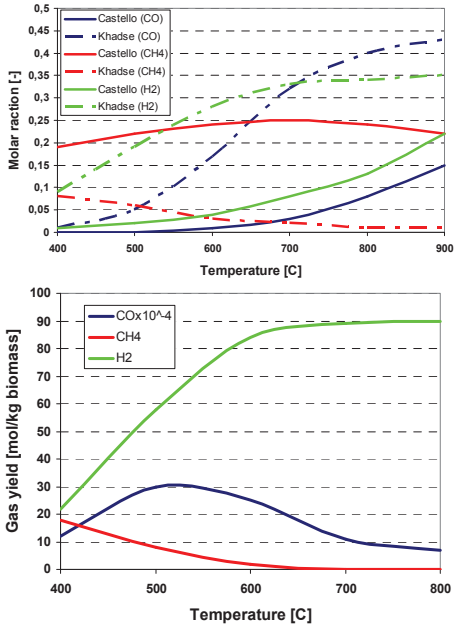

Figure 4. Comparison of simulation results of Castello's [29] and Khadse's [31] (uper) as well as Guo's [30] (lower) modelling approach

On Fig. 2 simulation results of different modelling approaches have been shown. For their analysis of molar fractions in the

sygas in dependence of gasification temperature, Castello [29] used gasification process of glycerol with steam under the pressure of 250 bar, Guo used gasification process of biomass (5% of moisture) with steam under pressure of 250 bar while Khadse used gasification process of sawdust with steam/air ratio of 1. Considering temperature interval 400-900 °C we can notice the difference in results of these 3 modelling approaches. In Khadse's results, line that represents mole fraction of H2 is intersecting with line that represents mole fraction of CO while in other results that is not the case. The amount of CO and CH4 in syngas in Guo's case is considerably lower than in Castello's and Khadse's cases.

Letellier [33] developed 2 equilibrium models for aqueous biomass gasification reactor and separator in supercritical water medium. The first model is based on chemical equilibrium and the second is based on chemical species conservation and on assumption of physical equilibrium between the liquid and the syngas. This model enables computation of solid, liquid and gas phases produced in gasification process. The composition is computed according to the derivation of balance equations on atoms and to the derivation of translational chemical equilibrium equations between species.

Pirc [34] used a system of linear equations that represents the mass and energy balances of the gasifier. This mathematical model is used to analyse influence of different biomass moisture on syngas composition and temperature, as well as system exergetic efficiency.

Ruggiero [35] presents a zero-dimensional equilibrium model for the biomass gasification process. In his model, the residence time of the species is supposed to be enough to complete reaction kinetics. A set of non-linear equations that describe the conservation of chemical species (C, O, H, N and S) and the additional equations for thermal equilibrium of the independed reactions have been solved by an iteration method. The model is used to predict gasification process output under given biomass composition and operating conditions.

Vaezi [36] developed a zero-dimensional model that uses thermo-chemical equilibrium approach to predict the performance of a biomass gasifier. He uses several assumptions in his modelling approach: the residence of the species is supposed to be enough to establish chemical equilibrium; the gasifier is considered to be adiabatic; the gases are presumed to be ideal; formation of char is neglected; ash in biomass is assumed to be inert; and tar is not considered in simulation.

Updraft fixed bed mathematical models for biomass gasification process control

Paes [37] reported a gasification model that can be used for online process control. First, he developed static gasification model in order to model static reaction equations and estimate all unknown values for his model. The model is one-dimensional and consists of number of horizontal segments in which species concentrations and gasification temperature is calculated in time. Segments are assumed to be perfectly mixed and all the elements behave identically. Integral conversion laws have been used for calculation of species concentration, mass flow and gasification temperatures. The static model is then shifted into a dynamic model by reduction of segment height due to solid material reactions. The static model has been modelled in Simulink.

Downdraft fixed bed mathematical models for biomass gasification process control

Many authors give special attention to downdraft fixed bed biomass gasifiers because these types of gasifier have proven their reliability in a lot of demonstration and test plants and are the most manufactured type of gasifiers in the EU, USA and Canada.

Babu [38] gives a thermodynamic equilibrium model to predict the effects of oxygen enrichment, preheating of air, steam to air ratio and reaction temperature on gasifier performance. The gasifier is divided into two major zones: pyrolysis and reduction zone. The residence of biomass particles in gasifier is considered to be long enough to allow pyrolysis products to burn and subsequently to achieve an equilibrium state in the reduction zone.

Barman [39] presents his equilibrium modelling approach to predict syngas composition and temperature. Heat balance equations have been used to predict syngas temperature. This study also considered possible deviations from equilibrium model in order to upgrade the model and to validate it. The correction factors have been implemented to the equilibrium model in order to make a better approximation of the gasification process in non-equilibrium conditions. Tar has been used as one of the input parameters for the model.

The equilibrium model developed by Koroneos [40] has been used to predict composition of syngas produced in a downdraft gasifier for cotton stalks biomass. The temperature of gasification was set to 800°C and the moisture content in cotton stalks has been varied from 0 to 30%. In chemical and thermodynamic equilibrium model developed by Melgar [41], equilibrium process equations have been used only for global process reactions to predict syngas composition and reaction temperature. The effects of main input variables such as biomass moisture and equivalence ratio on syngas heating LHV have been investigated. The model is easily implementable and can be used to predict final sygas composure and gasification process efficiency.

Sharma [42] uses an equilibrium model for downdraft gasifier in order to predict its steady state performance. Moving porous bed has been formulated as one-dimensional with finite control volumes. In these finite control volumes, conservation laws of mass, momentum and energy have been obtained for processes of heat transfer, drying, pyrolysis, oxidation and reduction. Equations for conservation laws have been solved in integral form using tri-diagonal matrix algorithm to analyse process reaction temperatures, pressure drops, heat exchange and product composition. Chemical equilibrium is used in oxidation zone while empirically predicted pyrolysis products (volatiles and char) and kinetic modelling approach for reduction zone enables model convergence. Predictions for the pressure drop and the power output (gasifier) are found to be very sensitive, while the gas composition or syngas LHV, the temperature profile and the gasification efficiency are less sensitive within the observed range of gas flow rate.

Zainal [43] developed an equilibrium model for a downdraft gasifier to predict the composition of sygas. The effect of different moisture contents of biomass on syngas quality and gasification temperature has been analysed. The predicted values have shown good correlation with the experimental data.

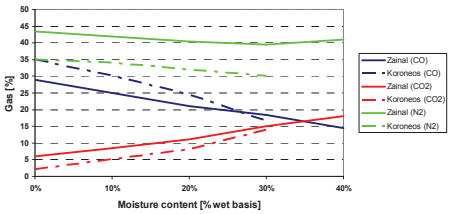

Figure 5. Comparison of simulation results of Koroneos [40] and Zainal [43] modelling approach

On Fig. 3 simulation results of analysis of syngas composition in dependence of biomass moisture content have been compared. Koroneos [40] used a cotton gasification process at 800 °C while Zainal [43] used gasification process of wood chips at same temperature. The results in both cases are similar. The lines that represent content of CO and CO2 intersect near point of 35% moisture in biomass and the species content in biomass are showing similar tendencies.

Fluidised bed mathematical models for biomass gasification process control

Guo's [28] research is based on development of neural network based prediction model for a fluidised bed gasifier. The model has been used to predict the gasification performance of a fluidised bed gasifier at atmospheric pressure with steam as gasification medium and for different types of biomass. Extensive measurements with different biomass types on bench scale facility have been done to utilise neural network model. The transient syngas production rate was not measured in this research. The results of model simulation showed good correlation with measured data.

Kaiser [44] used the Bettagli [45] approach for simulation of syngas composition after devolatilisation and static optimisation of a fluidised bed biomass gasification process. To calculate mass and energy balances and to estimate the gas composition, three linearly independent gasification reactions were considered. It has been assumed that the molar ratio of remaining char and CH4 is 3, CO2 is not formed and the molar ratio of H2O and CO is 1.

Loha [46] developed an equilibrium model for fluidised bed steam biomass gasifier. Modelling coefficients have been implemented to achieve good correlation with measured data. The model is used to predict performance of biomass gasifiers and to compare it with coal gasifiers. For this analysis, gasification temperature has been varied between 650 - 800 °C and steam to biomass ration between 0.75 - 2.00.

Schuster [47] describes thermodynamic a equilibrium steam gasification model for simulation of a decentralized combined heat and power station based on a dual fluidized bed steam gasifier. Effects of fuel composition, gasification temperature and amount of steam in gasification process on syngas composition and production rate have been analysed.

Entrained flow mathematical models for biomass gasification process control

Syed [48] uses a thermodynamic equilibrium approach to calculate the maximum gasification efficiency of four different feedstocks within the entrained flow gasifier with air as gasification agent. A gasification model is developed to calculate the seven different syngas species. The formation of syngas product species and char formation has been calculated using four elemental mass balance and three equilibrium constant relations.

Model	Advantages	Disadvantages
Comprehensive models for biomass gasification process control		
Burago-hain [19]	Analysis of different input process parameter effects on gasifier performance Detailed non-stoichometric model	Equilibrium model Without tar formation consideration Small number of output parameters
Castello [29]	22 different species are considered, including char and tar formation	Equilibrium non-stoichometric model Process temperature is not calculated
Guo [30]	Several different processes inside gasifier have been analysed and modelled	Equilibrium static model Process temperature is not calculated
Khadse [31]	4 independent gasification reactions analysis Char formation calculation	Simple thermodynamic equilibrium model Process temperature is not calculated
Letellier [33]	12 different species are considered, including char formation	Equilibrium static model Only for temperature > 700°C Process temperature is not calculated
Pirc [34]	Analysis of several input process parameter effects on gasifier performance	Simple model based on commercial solutions Model can operate only in 3 modes
Ruggiero [35]	Many different species are considered	Simple equilibrium model Simulation results differ from the experimental data
Vaezi [36]	Good correlation of simulation results with the experimental data	Simple equilibrium model Process temperature is not calculated
Updraft fixed bed mathematical models for biomass gasification process control		
Paes [37]	Static and simple dynamic model Applicable for on-line control	Problems with computational resources during simulation of dynamic model Many assumptions
Downdraft fixed bed mathematical models for biomass gasification process control		
Babu [38]	Process temperature calculation	Simple equilibrium model
Barman [39]	Tar formation calculation	Equilibrium model
Korone-os [40]	Simple to implement For preliminary analysis	Simple equilibrium model Simulation results differ from the experimental data
Melgar [41]	Sulphur oxides formation calculation Process temperature analysis	Equilibrium model
Sharma [42]	Many input and output parameters 4 different process analysis Detailed model	Equilibrium model
Zainal [43]	Analysis of different fuel types	Simple equilibrium model Small number of input and output process parameters
Fluidised bed mathematical models for biomass gasification process control		
Guo [28]	Neural network based model	No transient syngas production analysis Extensive measurements needed
Kaiser [44]	Power plant process optimisation	Simple model Many assumptions
Loha [46]	Analysis of different type of biomass and gasification medium on gasifier performance	Simple equilibrium model Implementation of site-dependent correction factors
Schuster [47]	Char formation calculation	Thermodynamic equilibrium model
Entrained flow mathematical models for biomass gasification process control		
Syed [48]	Char formation calculation Process temperature calculation	Equilibrium model

Table 5. Comparison of different modelling approaches for gasification process control

4. Conclusion

Biomass gasification faces issues relating syngas quality, process efficiency, emissions and environmental standards that are preventing the biomass gasification technology to become more economically viable. One of the approaches for the biomass gasification process improvement is the development of mathematical models that can be utilised for a more efficient process control. Kinetic models are useful in terms of delivered information regarding the process but due to their computational intensiveness they are impractical for online control. Black-box models are simpler in these terms and more applicable for online control but they often offer only a static process analysis without related information regarding processes inside the gasifier. Most of the literature is focused on the development of equilibrium models for downdraft fixed bed or fluidised bed gasifiers. Artificial neural network based models show potential in terms of fast process performance prediction but their potential for process control is yet to be considered.

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PAPER 2

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Artificial neural network modelling approach for a biomass gasification process in fixed bed gasifiers

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ABSTRACT

The number of the small and middle-scale biomass gasification combined heat and power plants as well as syngas production plants has been significantly increased in the last decade mostly due to extensive incentives. However, existing issues regarding syngas quality, process efficiency, emissions and environmental standards are preventing biomass gasification technology to become more economically viable. To encounter these issues, special attention is given to the development of mathematical models which can be used for a process analysis or plant control purposes. The presented paper analyses possibilities of neural networks to predict process parameters with high speed and accuracy. After a related literature review and measurement data analysis, different modelling approaches for the process parameter prediction that can be used for an on-line process control were developed and their performance were analysed. Neural network models showed good capability to predict biomass gasification process parameters with reasonable accuracy and speed. Measurement data for the model development, verification and performance analysis were derived from biomass gasification plant operated by Technical University Dresden.

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]. H_2 and CO contain only around 50% of the energy in the gas while the remained energy is contained in CH_4 and higher (aromatic) hydrocarbons [2]. Air, pure oxygen, steam, carbon dioxide, nitrogen or their mixtures could be used as gasifying agents. Products of the gasification are mostly used for separately or combined heat and power generation such as in dry-grind ethanol facilities [3] or in autothermal biomass gasification facilities with micro gas turbine or solid oxide fuel cells [4]. The products can also be used for hydrogen production using various processes [5] or various biomass stocks [6], as well as for liquid fuels, methanol and other chemical production [7].

The process of biomass gasification could be divided into three main stages: drying (100–200 °C), pyrolysis (200–500 °C) and gasification (500–1000 °C) [1,2]. The energy that is needed for the process is produced by partial combustion of the fuel, char and gases through various chemical reactions [8] with usage of different gasifying agents [9]. The performance of the 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 (which cannot be easily predicted) [10], geometrical configuration and the type of the gasifier [11], reaction/residence time, type of the gasifying agent, different size of biomass particles [1] derived from different feedstocks [12], gasification temperature [2,11] and pressure [11].

Gasifiers can be mainly classified as autothermal or allothermal gasifiers [13]. Autothermal and allothermal gasifiers could be further divided to: fluidised bed; fixed bed; and entrained flow gasifiers [14]. The downdraft gasifier is the most manufactured (75%) type of gasifier in Europe, the United States of America and Canada, while 20% of all produced gasifiers are fluidised bed gasifiers and the remaining 5% are updraft and other types of gasifiers [15]. Biomass gasification seems to have promising potential for

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Nomenclature

Main symbols

CH_xO_y	biomass composition, –
f	function
K_1	water gas shift reaction, –
K_2	methane reaction, –
K_3	methane reforming reaction, –
$LHV_{biomass}$	lower heating value of biomass, kJ/kg
LHV_{syngas}	lower heating value of syngas, kJ/m^3
M_b	biomass quantity, kg
M_{air}	air quantity, m^3
m	molar fraction of air, –
$Q_{reaction}$	energy for chemical reactions, kJ
Q_{in}	energy input, kJ
ΔT	temperature progression, °C/min
t	time, min
temp	temperature, °C
w	molar fraction of water/vapour/moisture, –
x_1	molar fraction of hydrogen, –
x_2	molar fraction of carbon monoxide, –
x_3	molar fraction of carbon dioxide, –
x_4	molar fraction of water/vapour, –
x_5	molar fraction of methane, –
x_6	molar fraction of tar, –

Abbreviations

ANFIS	adaptive network-based fuzzy inference system
ANN	artificial neural networks
C	carbon
$CH_{0.83}$	acenaphthene (tar)
C_2H_4	ethylene
CH_4	methane
CO	carbon monoxide
CO_2	carbon dioxide
EU	European Union
H_2	hydrogen
H_2O	water/vapour/moisture
NNM	neural network model
N_2	nitrogen
O_2	oxygen

electricity and heat cogeneration through conventional or fuel cells based technology. 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 [16] and especially in Germany [17], has been increased in the last few years [18] as shown in Table 1.

Mathematical models can be used to explain, predict or simulate the process behaviour and to analyse effects of different process variables on process performance. In order to improve efficiency and to optimise the process, a plant operation analysis in dependence of various operating conditions is needed. Large scale experiments for these purposes could often be expensive or problematic in terms of safety. Therefore, various mathematical models are utilized to predict the process performance in order to optimise the plant design or process operation in time consuming and financial acceptable way. Nowadays, special attention is given to the biomass gasification process modelling [19] which can contribute to more efficient plant design, emission reduction and syngas generation prediction or to support the development of suitable and efficient process control [20].

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 modelling such as in implementing complex mappings and system identification.

Table 1
The number of operational/planned/under construction biomass gasification facilities in Europe.

Country	Biomass gasification facilities in operation	Planned/under construction biomass gasification facilities
Germany	160 (>70 MW_{th} + 24 MW_{el})	150
Austria	6 (19 MW_{th} + 6 MW_{el})	2
Finland	3 (137 MW_{th} + 1.8 MW_{el})	2
Denmark	8 (12 MW_{th} + 1.4 MW_{el})	2
Other EU countries	31	15

2. Mathematical models for the biomass gasification process

Mathematical modelling is mostly based on the conservation laws of mass, energy and momentum. The complexity of models can range from complex three-dimensional models that take fluid dynamics and chemical reactions kinetics into consideration, to simpler models where the mass and energy balances are considered over the entire or a part of a gasifier to predict process parameters. The complexity of simpler models can also range from chemical reaction equilibrium based models that take only few important process reactions into consideration to more complex equilibrium or pseudo-equilibrium models where the tar formation is also considered. Due to need for intensive measurements, not many works on artificial intelligence system based biomass gasification models have been reported [1].

Kinetic mathematical models are used to describe kinetic mechanisms of the biomass gasification process. They take into consideration various chemical reactions and transfer phenomena among phases [1]. However, applicability of these models is limited due to several constraints. All possible reactions are not taken into account (almost all models assume pyrolysis and sub-stoichiometric combustion as instantaneous because these processes are much faster than the gasification process [21]) and the literature often offers different reaction coefficients, kinetics constants and model parameters that are related to the specific design of a gasifier [22]. However, kinetic models are very useful in detailed description of the biomass conversion during the gasification process [23], for the gasifier design and for process improvement purposes, but due to their computationally intensiveness and long computational time they are still impractical for online process control.

Models that do not solve particular processes and chemical reactions in the gasifier and instead consist of overall mass and heat balances for the entire gasifier are called equilibrium models. Equilibrium models are generally based on chemical reaction equilibrium and take into account the Gibbs free energy minimisation and the second law of thermodynamics for the entire gasification process [1]. These models are independent from the gasifier type, the gasifier design or the specific range of operating conditions but they describe only the stationary gasification process without a deep-in-analysis of processes inside the gasifier. In some cases

Table 2
Comparison of different modelling approaches.

Process modelling approach		Advantages	Disadvantages
Kinetic models		More realistic process description	All possible process reactions are not considered
		Extensive information regarding process operation	Different model reaction coefficients and kinetics constants
		Good for gasifier design and improvement purposes	Dependable on the gasifier design
			Impractical for online process control
Equilibrium models		Independent from gasifier type and design or specific range of operating conditions	Describe only stationary gasification process
		Useful in prediction of gasifier performance under various different operational parameters	Do not offer insight in gasification process
		Easy to implement	
		Fast convergence	
	Stoichiometric models	Applicable for describing complex reactions in general	Only some reactions are taken into consideration
			Reaction mechanisms must be clearly defined
			Equilibrium constants are highly dependable on specific range of process parameters
	Non-stoichio-metric models	Simplicity of input data	Describe gasification process only in general
		Used to predict the syngas composition	Lack of detailed process information
	Pseudo-equilibrium models	More realistic equilibrium models	Estimation of methane, carbon and tar in outlet steam is necessity
			Model is dependable on site specific measurements and type of the gasifier
Artificial neural networks models		Do not need extensive knowledge regarding process	Depends on large quantity of experimental data
			Many idealised assumptions
	Hybrid neural network model		Knowledge regarding process is needed

the gasifier is divided into black-box regions where specific processes are assumed to be dominant and different models, based on equilibrium or kinetics, are applied [19]. They are useful in prediction of the gasifier performance under various different stationary operating conditions and therefore are often used for preliminary design and optimisation purposes. According to [1], due to lack of extensive measurements, many equilibrium models have been verified just on several particular operating points or with data derived from the literature.

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 [24]. ANN models have proven their potential in prediction of process parameters in energy related processes such as in biodiesel production process [25], coal combustion process [26,27], Stirling engines [28] and for syngas composition and yield estimation [29] from different biomass feedstocks [30] in fluidised bed biomass gasifiers but their potential to predict parameters of a biomass gasification process

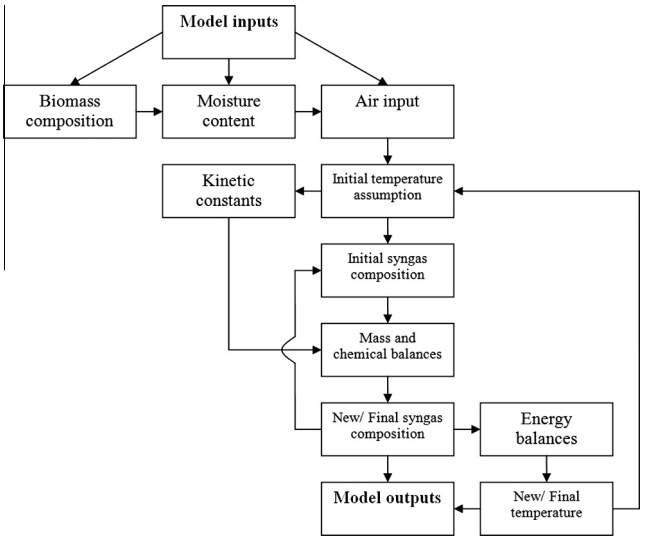

Fig. 1. Modelling scheme – equilibrium model.

Table 3
Summary of two different equilibrium modelling approaches.

	Equilibrium model without tar calculations	Equilibrium model with tar calculations
Mass balance	$CH_xO_y + wH_2O + mO_2 + m \cdot 3.76N_2 = x_1H_2 + x_2CO + x_3CO_2 + x_4H_2O + x_5CH_4 + 3.76N_2$ (1)	$CH_xO_y + wH_2O + mO_2 + m \cdot 3.76N_2 = x_1H_2 + x_2CO + x_3CO_2 + x_4H_2O + x_5CH_4 + 3.76N_2 + x_6CH_{0.83}$ (2)
Chemical balance	$K_1 = f(\text{temp}) = \frac{H_2 \cdot CO_2}{CO \cdot H_2O}$ $K_2 = f(\text{temp}) = \frac{CH_4}{(H_2)^2}$ (3), (4)	$K_1 = f(\text{temp}) = \frac{H_2 \cdot CO_2}{CO \cdot H_2O}, K_2 = f(\text{temp}) = \frac{CH_4}{(H_2)^2}, K_3 = f(\text{temp}) = \frac{CO \cdot (H_2)^3}{CH_4 \cdot H_2O}$ (3), (4), (5)
Energy balance	$Q_{in} + LHV_{biomass} = LHV_{syngas} + Q_{reactions}$ (6)	$Q_{in} + LHV_{biomass} = LHV_{syngas} + Q_{reactions}$ (6)

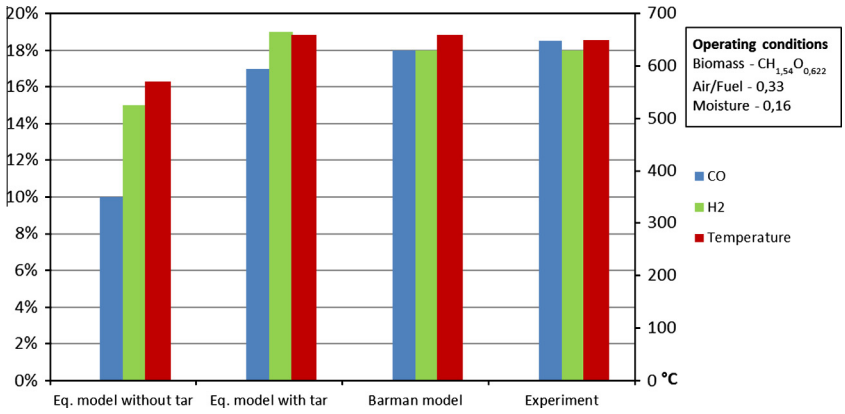

Fig. 2. Comparison of results derived from different models.

in a downdraft-fixed bed gasifier for different operating points that occur during the plant operation is yet to be analysed.

The literature [20,29,31–53] offers several comprehensive gasification models that could be used for biomass gasification process parameter prediction, control and optimisation. Devised models are mostly equilibrium based models and offer only static process analysis and optimisation. Often, for the development of this kind of models, several assumptions have to be made. Many authors analyse different kind of effects on gasification process in their research so it is hard to correlate results derived from their research. Most of the literature is focused on the development of equilibrium models for downdraft fixed bed or fluidised bed gasifiers because these types of gasifier have proven their reliability in a lot of demonstration and test plants and are the most manufactured type of gasifiers in the EU, USA and Canada. A comparison of different modelling approaches is described in Table 2 [31].

3. Equilibrium models analysis

One of modelling approaches that can be used for on-line process control is equilibrium modelling approach. However, poten-

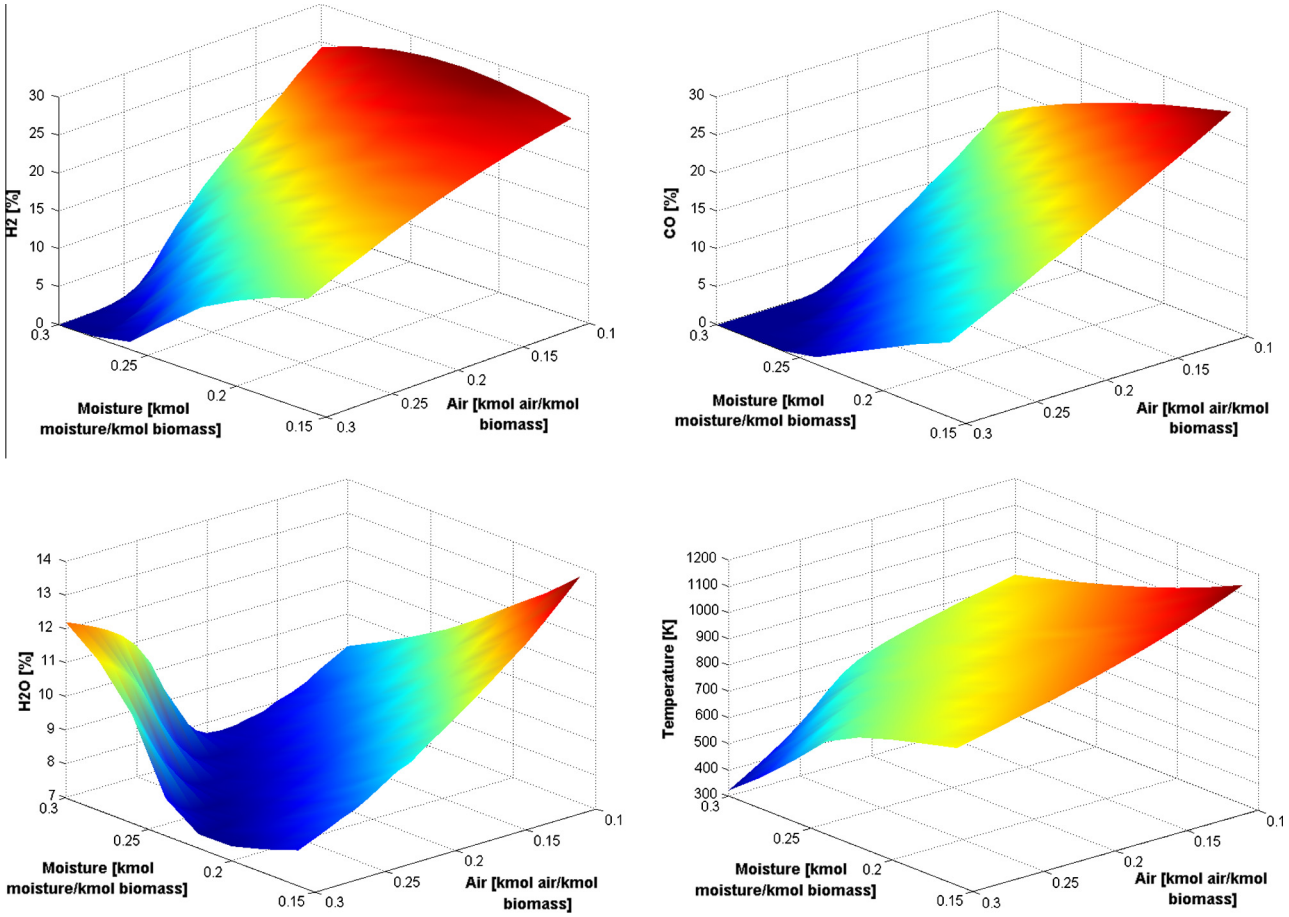

Fig. 3. Results of the equilibrium model without tar calculations.

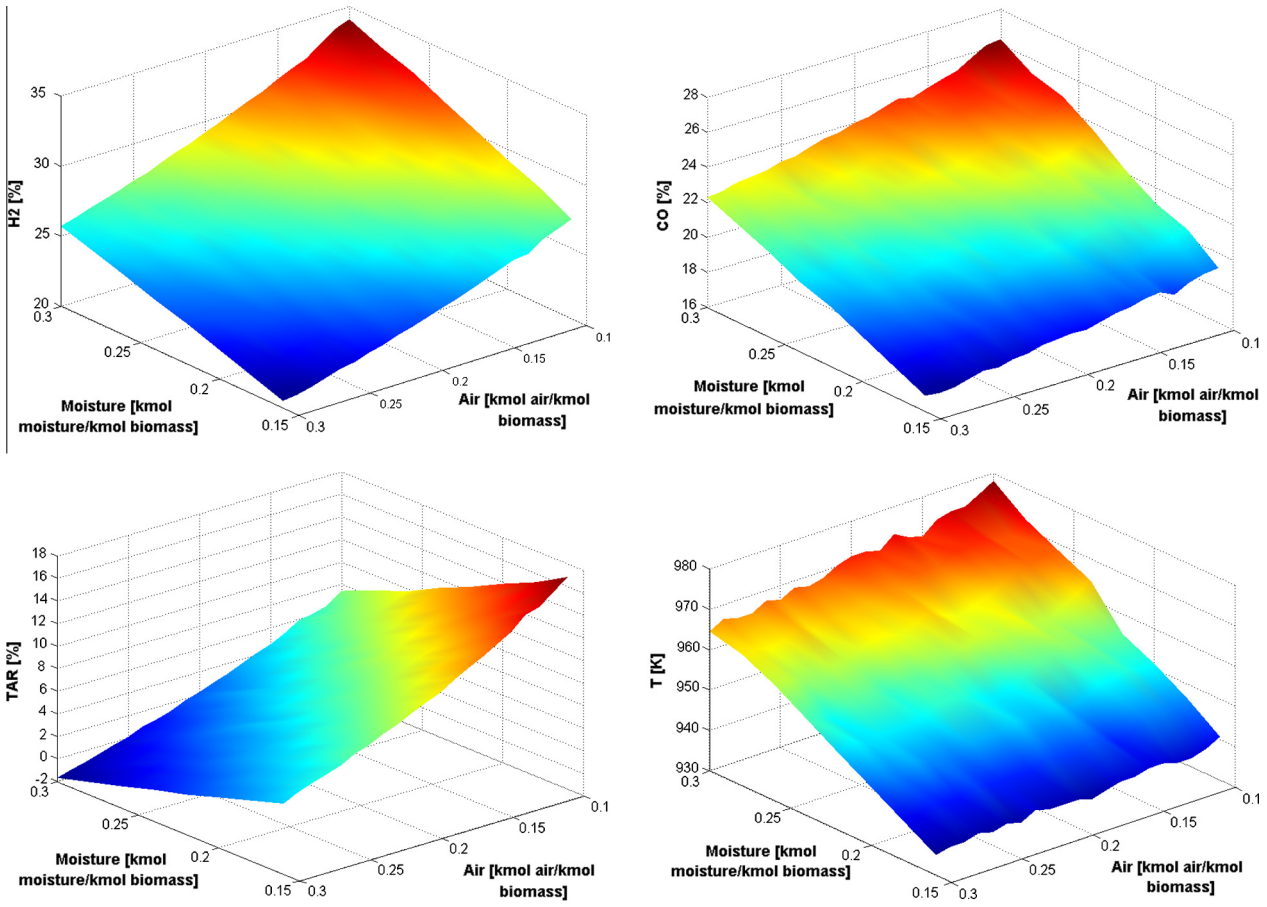

Fig. 4. Results of the equilibrium model with tar calculations.

tial of these kinds of models to predict process performance for various operating conditions that could occur during the gasifier operation has not been analysed in details. Therefore, for the biomass gasification process and equilibrium models performance analysis, two different equilibrium modelling approaches have been devised. The equilibrium model without tar calculations is based on methodology presented in [40] while the equilibrium model with tar calculations is based on the methodology presented in [41]. Both models are based on energy and mass conservation laws as well as equilibrium chemical balances calculations. Equilibrium chemical balances of the water gas shift reaction (K_1), methane reaction (K_2) and methane reforming reaction (K_3) have been taken into consideration. Input parameters of both models are biomass composition, biomass moisture content and air input. Output model parameters are syngas composition and process temperature. The syngas is assumed to consist of H_2, CO, CO_2, H_2O (vapour), CH_4, N_2 gases and tar. In the equilibrium model with tar calculation, the chemical compound "Acenaphthene" ($CH_{0.83}$) has been used to represent tar in model calculations. The energy that is released or consumed during process reactions is taken from [8]. The summary of both modelling approaches is presented in Table 3. The models with and without tar calculations are based on an iterative approach for the process parameter calculation. The modelling scheme is presented in Fig. 1.

The results derived from the equilibrium model with tar calculations for specific operating conditions described in [41] show good correlation with the simulation results and experiments described in [54] while equilibrium model without tar calculation shows a great difference between simulated and experimental results for the same operating conditions (Fig. 2).

Fig. 3 represents results derived from the equilibrium model without tar calculations. The results show that with an increase of the moisture content in the biomass together with an increase of the air flow, the process temperature decreases. Due to the temperature dependence of different chemical reactions, similar tendency can be seen for the H_2, CO and H_2O syngas composition values. With the moisture and air flow increase H_2 and CO values decrease. The water/steam values firstly decrease with the air flow and moisture content increase but after some point they start to increase. Temperature values below 0 °C that occur on high air flow and moisture contents are not physically explainable and they are result of model calculations.

The results from equilibrium model with tar calculations (Fig. 4) show that the temperature increases with the moisture content while with different air flows it remains relative constant. CO values follow the tendency of temperature changes due to strong dependence of the chemical reactions with process temperature. These results differ from the results derived from model without tar calculations due to additional temperature dependable correlation (methane reforming reaction) that has been introduced in the model. The tar calculations show that the tar is increased with moisture content in biomass and with air flow decrease. Negative tar values are not physically explainable. They are result of modelling approach (equations that define the equilibrium gasification model).

The results derived from different equilibrium modelling approaches (for various operating conditions) cannot be compared or explained in some cases. Results from devised equilibrium models are comparable with results derived from literature only for specific operating points.

In order to predict process parameters for various operating conditions with high speed and accuracy a more comprehensive

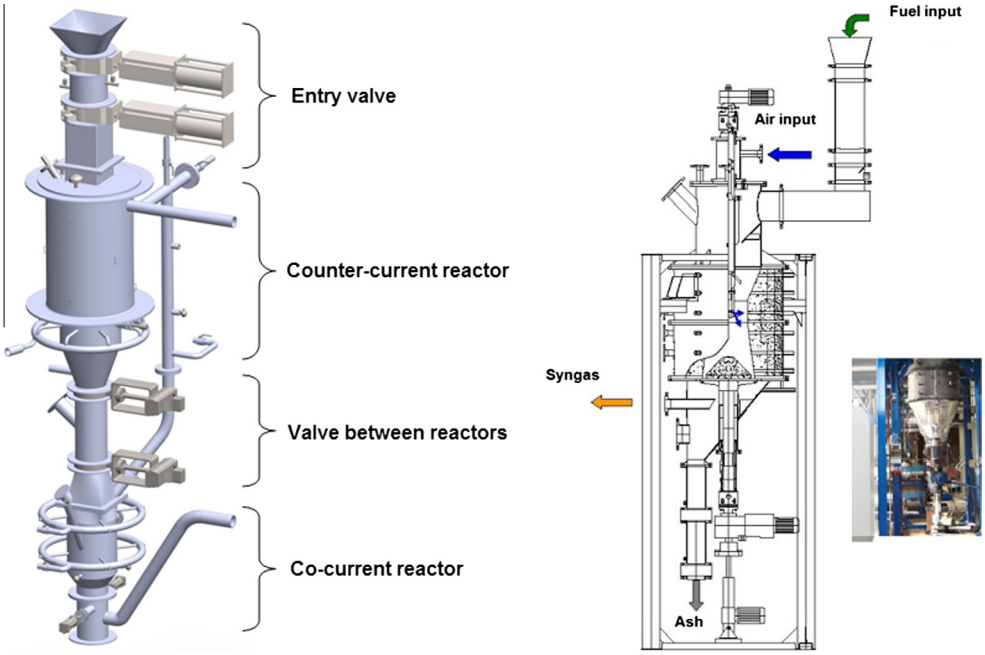

Fig. 5. Experimental biomass Combi-gasifier (100 kW_{th}) located in Schwarze Pumpe (left) and Co-current, fixed bed gasifier (75 kW_{th}) located in Pirna (right), Germany.

Table 4
Measurement methodology and equipment.

Process parameter	Measurement methodology and equipment
Biomass mass flow	Manual weight measurement
Air volume flow	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 – Nondispersive infrared absorption methodology H_2 – Thermal conductivity methodology O_2 – Electrochemical process (Emerson – MLT 2 multi-component gas analyzer)
Pressure in the reactor	Wheatstone bridge circuit based measurement methodology (piezoresistive strain gauge)
Temperature of inlet air	Measurement based on platinum resistance effect (Pt 100)

Table 5
Comparative analysis of different neural network modelling approaches.

	Case 1	Case 2	Case 3	Case 4
Model inputs				
Fuel flow	Total fuel supplied (from beginning) (kg)	Fuel supplied in the last 10 min (kg)	Fuel supplied in the last 10 min (kg)	Fuel supplied in the last 10 min (kg)
Air flow	Current air flow (m^3/h)	Current air flow (m^3/h)	Air injected in the last 10 min (m^3)	Air injected in the last 10 min (m^3)
Related time	Time passed from the last fuel supply (min)	Time passed from the last fuel supply (min)	Time passed from the last fuel supply (min)	Time passed from the last fuel supply (min)
Temperature	Current temperature (°C)	Current temperature (°C)	Current temperature (°C)	Current temperature (°C)
Other	–	–	Gaussian curve built-in membership function between neural network nodes/layers	Gaussian combination membership function between neural network nodes/layers
Model outputs				
Model output	Temperature progression (°C/min)	Temperature progression (°C/min)	Temperature progression (°C/min)	Temperature progression (°C/min)
Average error	10.60%	52.83%	14.35%	7.77%

neural network model has been developed. The general modelling methodology comprises of data acquisition (measurements), measured data analysis, neural network training, model prediction performance analysis, neural network model changes and model verification.

4. Neural network model

For utilizing a neural network model (NNM), the prediction model has to learn/to be trained from observed/measured data. Neural network models require a large number of measurements

Table 6
Analysis of influence of time periods for fuel and air quantities calculation on model prediction error for the gasifier in Schwarze Pumpe.

Time period (min)	Average error (%)
1	36.64
5	17.29
10	7.77
15	7.85
20	10.02

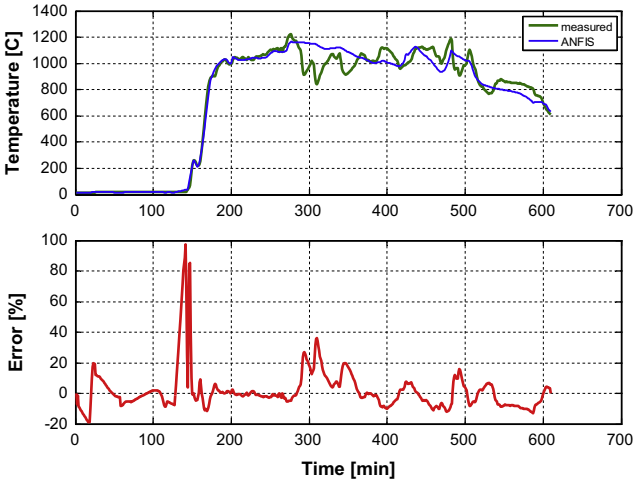

Fig. 6. Results of the neural network model for syngas temperature prediction – Schwarze Pumpe gasifier.

Table 7
Analysis of influence of time periods for fuel and air quantities calculation on model prediction error for the gasifier in Pirna.

Time period (min)	Average error (%)
10	14.46
15	9.40
20	6.74
25	6.48
30	7.42
35	7.91
40	7.37

to form input and output data sets for neural network training. With various sets of input and output data as well as different training procedures, results from NNM will differ. NNM are often dependable on site specific measurements. Data for neural network training were extracted from a database attached to 2 biomass gasification facility operated by the TU Dresden, Germany. One of the biomass gasifiers, the combined counter- and Co-current gasifier (Combi-gasifier) has thermal input of 100 kW_{th} and it is located in Schwarze Pumpe, Germany. The second biomass gasifier is Co-current fixed bed gasifier with thermal input of 75 kW_{th} and it is located in Pirna, Germany. The facility scheme of the gasifier located in Pirna, Germany is presented in Fig. 5. Data was collected in several measuring campaigns comprising following measurements/analyses: biomass mass flow; air volume flow; syngas temperature at the exit of the gasifier; syngas composition; pressure in the reactor; temperature of inlet air. All data were recorded on a 30 s base in a correspondence with relevant international standards for this type of measurements. The uncertainty of an overall test results is dependent upon the collective influence of the uncertainties of the measurement equipment that has been used (Table 4).

In order to devise NNM with acceptable average model prediction error (set by a model user), the comparative analysis of different neural network modelling approaches (different input and output sets and training procedures) has to be performed. The example of the comparative analysis of temperature prediction modelling approach (Cases 1–4) for the biomass gasification facility located in Schwarze Pumpe is shown in Table 5. For different cases, the process temperature is considered to be influenced by (to be function of) different process parameters. These parameters (together with the desired output) are introduced into neural network training process as input variables. Due to lack of extensive gas composition measurements on the gasifier in Schwarze Pumpe, only a temperature prediction model has been devised and a neural network modelling methodology for this kind of gasifier has been described.

The time interval for calculations of injected fuel and air quantities has been varied (5–60 min) in order to find the case with minimum prediction error. The lowest average prediction error of NNM for the gasifier in Schwarze Pumpe is in case when the time period is set to be 10 min. The analysis of influence of time periods for calculations of injected fuel and air quantities on model prediction performance for Case 4 has been shown in Table 6.

The comparative analysis shows that a minimum average model prediction error can be found in the case where the process temperature progression (desired output data in neural network training procedure) is function (Eq. (7)) of fuel and air injected in the last 10 min together with the time passed from the last fuel supply and current outgoing syngas temperature (input data).

$$\Delta T = f(M_{b10\ \mathrm{min}}, M_{air10\ \mathrm{min}}, t_{M_b}, \mathrm{temp}) \quad (7)$$

Temperature model prediction performance for the gasifier in Schwarze Pumpe (Case 4) can be seen on Fig 6. The prediction error

Table 8
The summary of temperature and composition prediction neural network models for gasifier located in Pirna.

	Syngas temperature (gasifier exit)	Syngas composition (CO, CO_2, CH_4, H_2 and O_2 values)				
Model inputs						
Fuel flow	Fuel supplied in the last 25 min (kg)	Fuel supplied in the last 60 min (kg)				
Air flow	Air injected in the last 25 min (m^3)	Air injected in the last 60 min (m^3)				
Related time	Time passed from the last fuel supply (min)	Time passed from the last fuel supply (min)				
Temperature	Current syngas temperature	Syngas temperature				
Number of daily experiments used for NNM training	4	4				
Neural network training method	Gaussian curve membership function	Gaussian curve membership function				
Model boundaries	Modelled syngas temperature: 20–450 °C	For syngas temperature (gasifier exit): 250–430 °C				
Model outputs						
Model output	Temperature progression (°C/min)	Gas content (%)				
Average error/syngas component prediction error (daily basis)	6.48%	CO	CO_2	CH_4	H_2	O_2
		0.01%	0.05%	0.12%	0.45%	0.97%

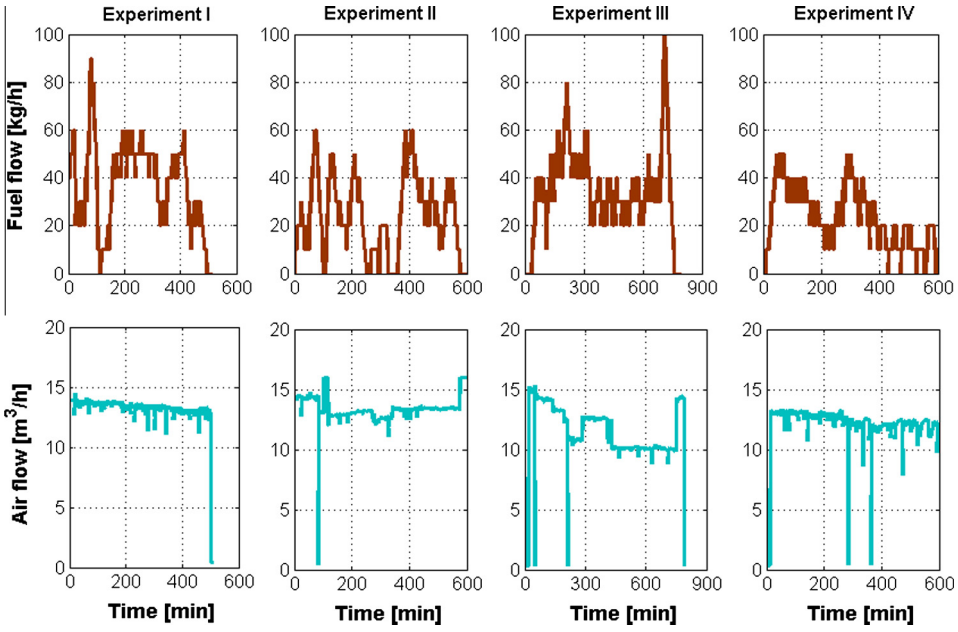

Fig. 7. Fuel and air flow during the experiments – Pirna gasifier.

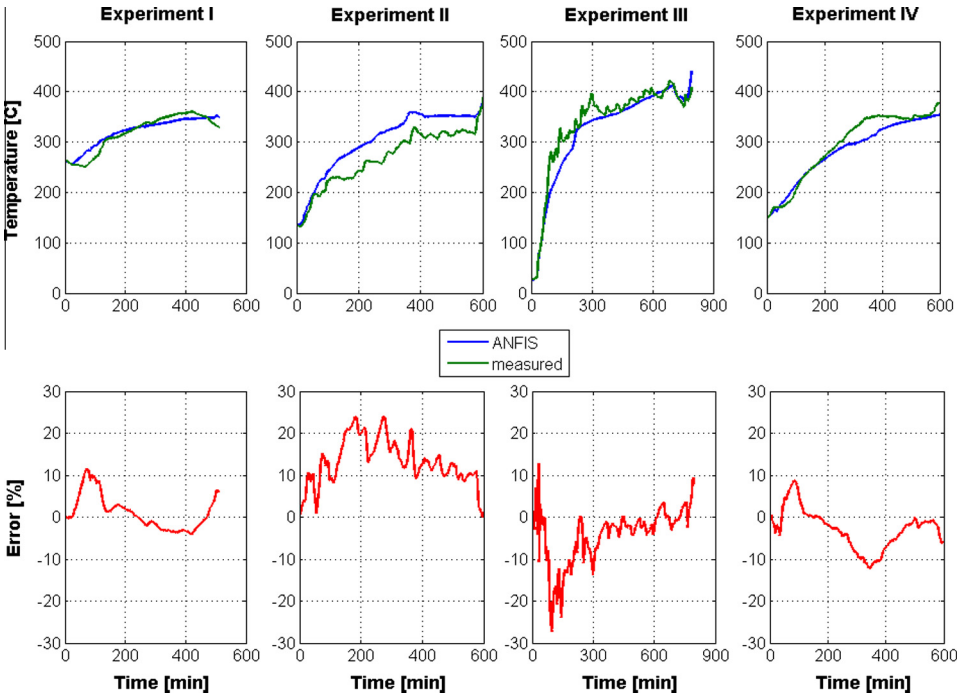

Fig. 8. Results of the neural network model for syngas temperature prediction – Pirna gasifier.

percentage has been calculated by division of prediction error (the difference between simulated and measured values) with measured values. The prediction error is mostly between ±20% but in some cases can reach up to 100% in some cases (due to division of relative small temperature prediction error with small temperature values in the denominator). Neural network prediction model for the gasifier in Schwarze Pumpe has shown good correlation with the measured data for different operating points during the gasifier operation (from start-up till stationary operation). At the start-up of the process, the NNM can predict process temperature with relative high precision due to specific operating conditions and procedures (relative constant biomass composition and specific fuel and air flows that are used in the start-up procedure). During the stationary operation of the gasifier due to small variations in operating conditions (such as biomass quality) the process temperature is changed. The NNM is developed to predict the average temperature for the specific operating conditions (fuel and air flow) and therefore during the operation with the biomass of lower quality (from those that is considered in NNM training), the predicted temperature could be higher than measured and during the operation with the biomass of higher quality the predicted temperature could be lower than measured.

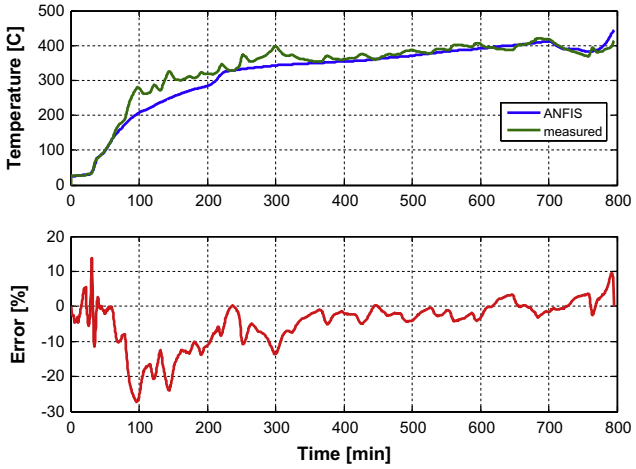

Fig. 9. Neural network model verification test for syngas temperature prediction – Pirna gasifier.

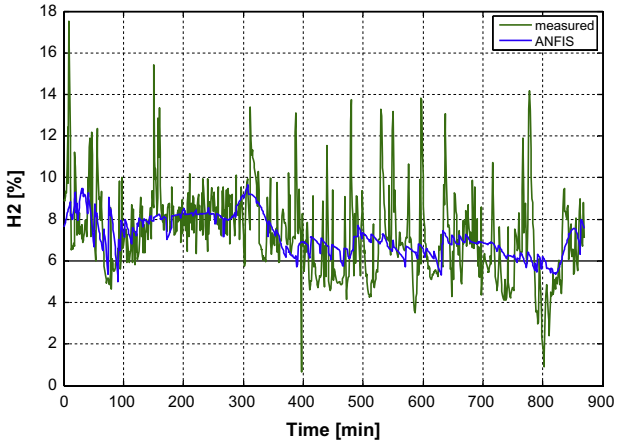

Fig. 11. Neural network model verification test for syngas composition prediction (H_2) – Pirna gasifier.

Similar modelling procedure has been conducted for Co-current – fixed bed gasifier located in Pirna, Germany. This gasifier has different operation and design characteristics than the gasifier in Schwarze Pumpe. Nevertheless, similar modelling approach, which has been used for the temperature prediction for the gasifier located in Schwarze Pumpe, has shown good prediction capabilities (in terms of average prediction error).

Different time periods for calculations of injected fuel and air quantities into the gasifier have been used in order to find prediction model with the lowest prediction error. The analysis of influence of time periods for calculations of injected fuel and air quantities on model prediction performance has been shown in Table 7. The lowest average prediction error of NNM for the Pirna gasifier is in case when the time period is set to be 25 min.

The similar type of input data sets (described in temperature prediction model) has been used in order to devise neural network prediction model for the syngas composition. Neural network models are very sensitive in terms of air/fuel ratio variations on model prediction of temperature, CO and H_2 values and less sensitive to CO_2 and CH_4 values prediction [29]. Due to measurement characteristics, the syngas composition prediction model has been devised for the outgoing syngas temperature between 250 and 430 °C. The summary of both models can be found in Table 8.

The biomass composition and the heating value are calculated regarding specifications given by the laboratory. Biomass lower heating value has been taken as constant (based on laboratory analysis of biomass composition). The lower heat capacity value of the fuel is 17.473 MJ/kg, the carbon content is 47.40%, the hydrogen content is 5.63%, the moisture content is 7.87%, the ash content is 0.55% and the content of chlor is 0.01%. In modelling approaches that utilise neural networks, the biomass composition has a strong influence on syngas composition and some smaller influence on syngas production [29].

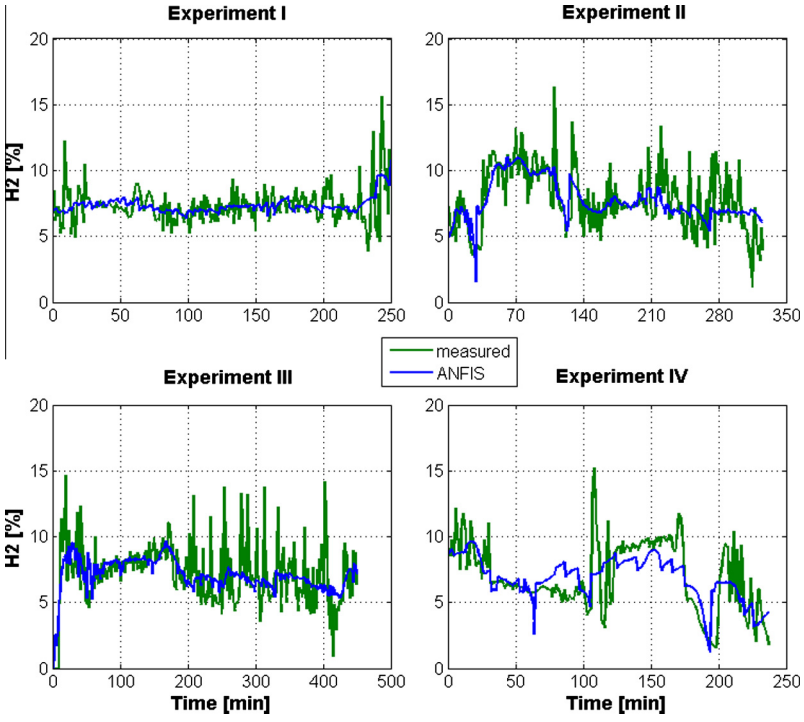

Fig. 10. Results of the neural network model for syngas composition prediction (H_2) – Pirna gasifier.

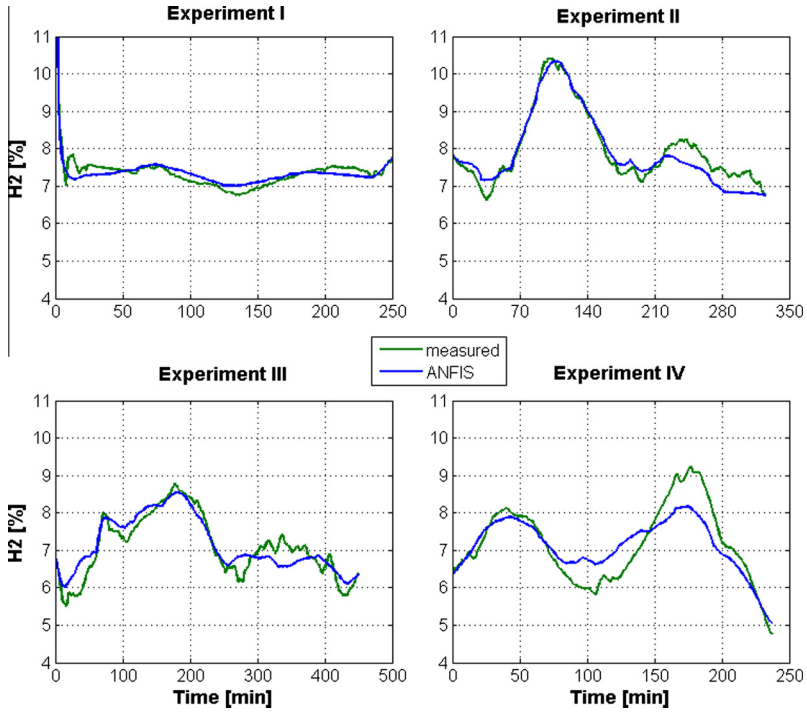

Fig. 12. Results of the neural network model for hourly averaged syngas composition prediction (H_2) – Pirna gasifier.

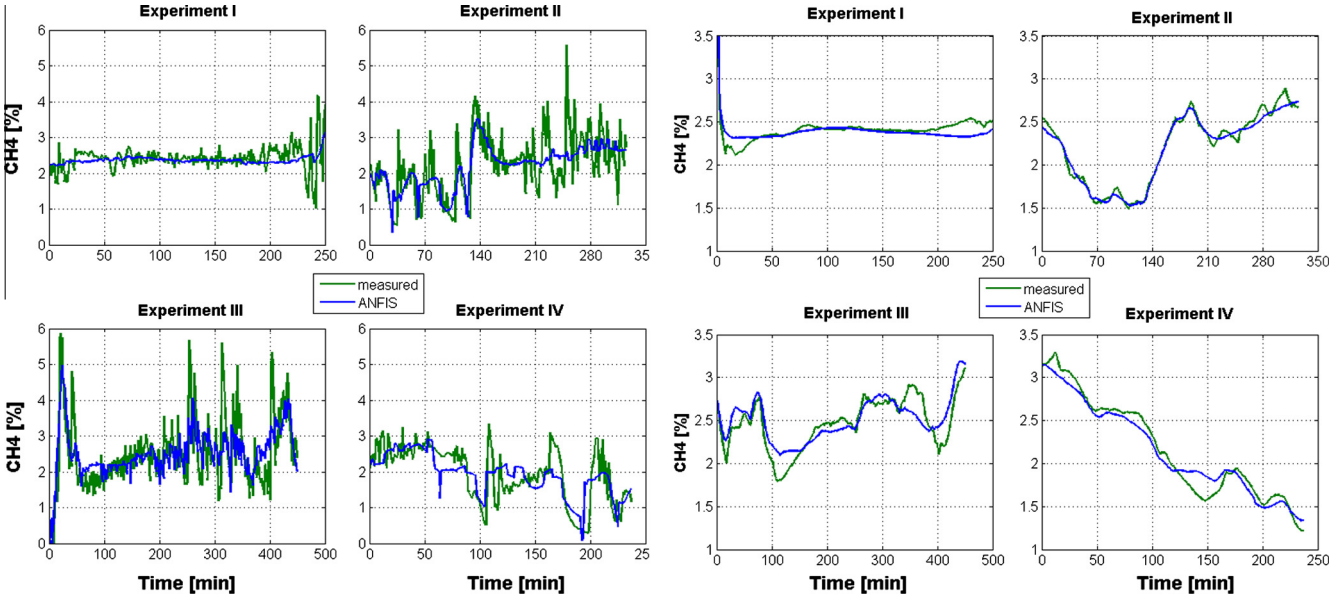

Fig. 13. Results of the neural network model for current (left) and hourly averaged (right) syngas composition prediction (CH_4) – Pirna gasifier.

5. Results

Performance of NNM prediction potential has been analysed on 5 different experiments (4 experiments for NNM training and 1 experiment for model verification). Experimental conditions differ from experiment to experiment. In Experiment III and the verification experiment the gasifier operation starts from non-preheated conditions (cold start). The operation in Experiments II and IV starts from preheated conditions while in Experiment I the gasifier operation starts from highly-preheated condition (hot-start). The biomass composition is considered as constant because the biomass from the same delivery has been used. The environment temperature has been considered as constant. The fuel and the air flows have been varied during the experiments and their values are showed in Fig. 7.

The neural network prediction model (ANFIS) shows good results for the syngas temperature prediction (see Fig. 8). The error between measured and calculated values is mostly between ±10% which represents a good prediction of the syngas temperature during the plant operation. In some marginal cases the error can reach up to ±25%. The neural network prediction model shows good prediction possibilities in terms of the syngas temperature progression prediction during the plant operation with different operating starting points (“cold” start and “warm/preheated” start). Devised model is suitable for syngas temperature prediction between 20 °C and 450 °C.

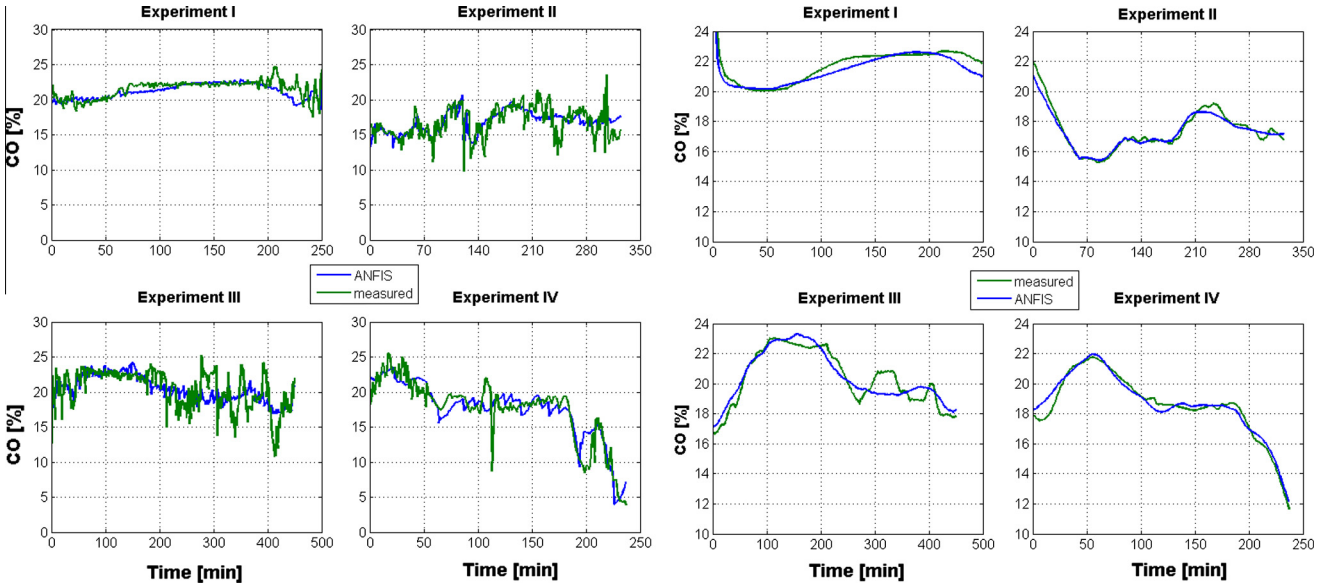

Fig. 14. Results of the neural network model for current (left) and hourly averaged (right) syngas composition prediction (CO) – Pirna gasifier.

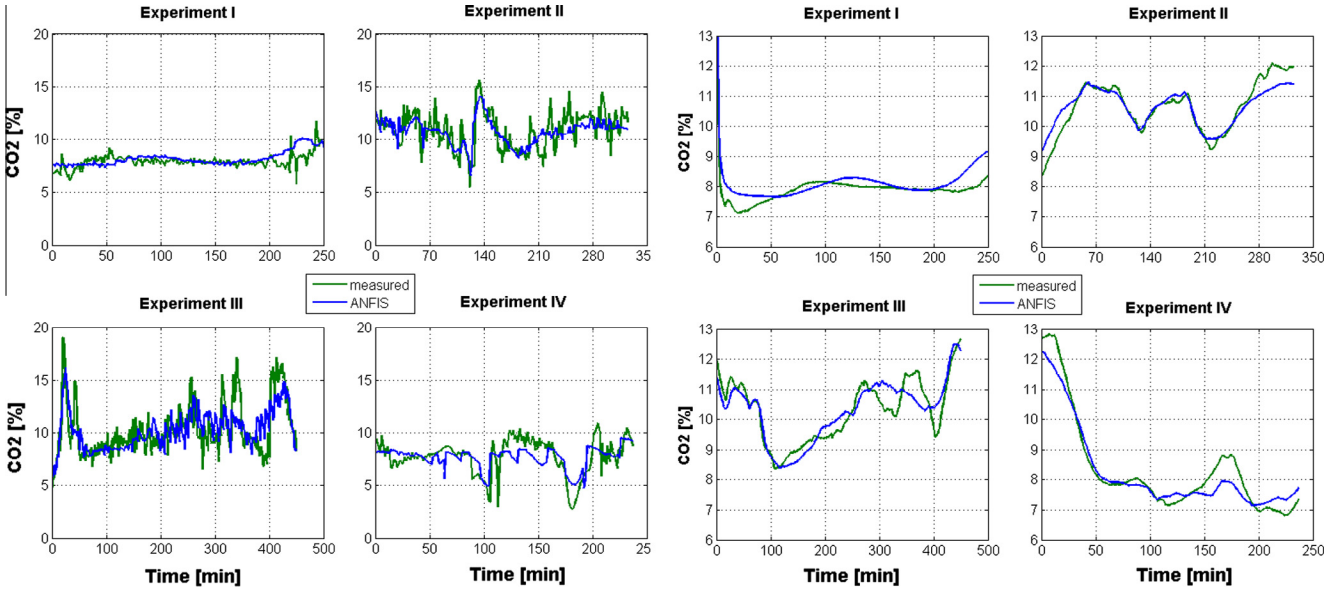

Fig. 15. Results of the neural network model for current (left) and hourly averaged (right) syngas composition prediction (CO_2) – Pirna gasifier.

In order to verify the neural network syngas prediction model devised for the Pirna gasifier, additional model prediction test has been performed on the new set of measured data. Model prediction has showed good correlation with the new input data. The prediction error is mostly between ±10% and in some marginally cases it reaches −25%. The model verification test has been performed for the syngas temperature range between 25 °C and 425 °C. The results from NNM verification test are presented in Fig. 9.

Similar to the syngas temperature prediction model, the syngas composition prediction model has also been analysed. The H_2 neural network prediction model for 4 different experimental sets/measurement campaigns is presented in Fig. 10. The predicted H_2 values and progression of these values during the plant operation is in good correlation with the measured data. During the plant operation, H_2 values are mostly between 5% and 10% of total volume gas composition, with maximum value of 11%.

The syngas composition prediction model has been verified on the new set of measured data (Fig. 11). Although measured H_2 values range significant from minute to minute, neural network model predicts average H_2 values and their progression tendency with reasonable accuracy.

Due to significant differences between minute based measurements of syngas components, prediction model potential to predict averaged syngas composition values has been analysed. The prediction of hourly averaged H_2 values from the gasification process is presented in Fig. 12. Neural network prediction model enables good approximation of hourly averaged H_2 values as well as time progression of these values during the gasifier operation. Averaged H_2 values are ranging mostly between 6% and 10%.

The results of neural network prediction models for other syngas components are presented on Figs. 13 (CH_4), 14 (CO), 15 (CO_2) and 16 (O_2). On the left side of the figures are current syngas

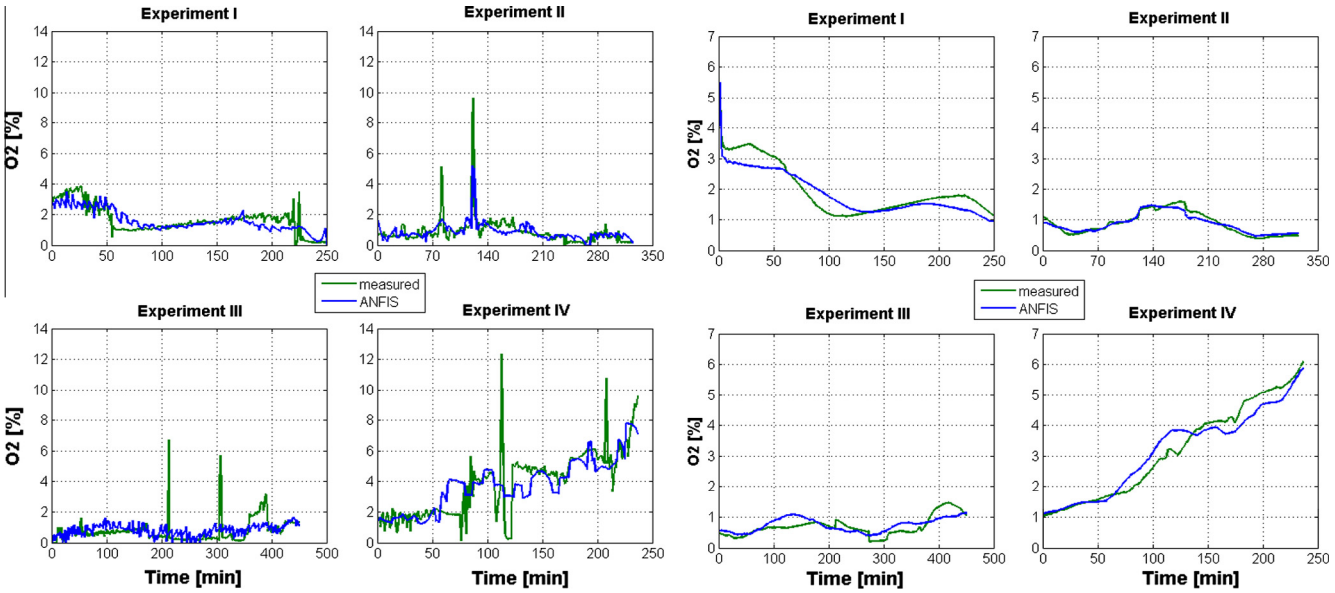

Fig. 16. Results of the neural network model for current (left) and hourly averaged (right) syngas composition prediction (O_2) – Pirna gasifier.

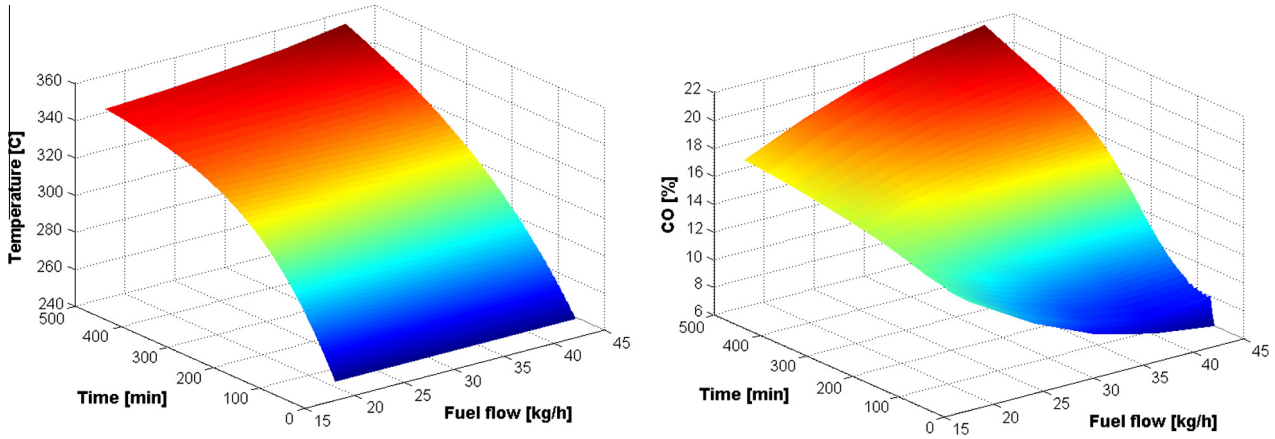

Fig. 17. Process analysis with the fuel flow changes.

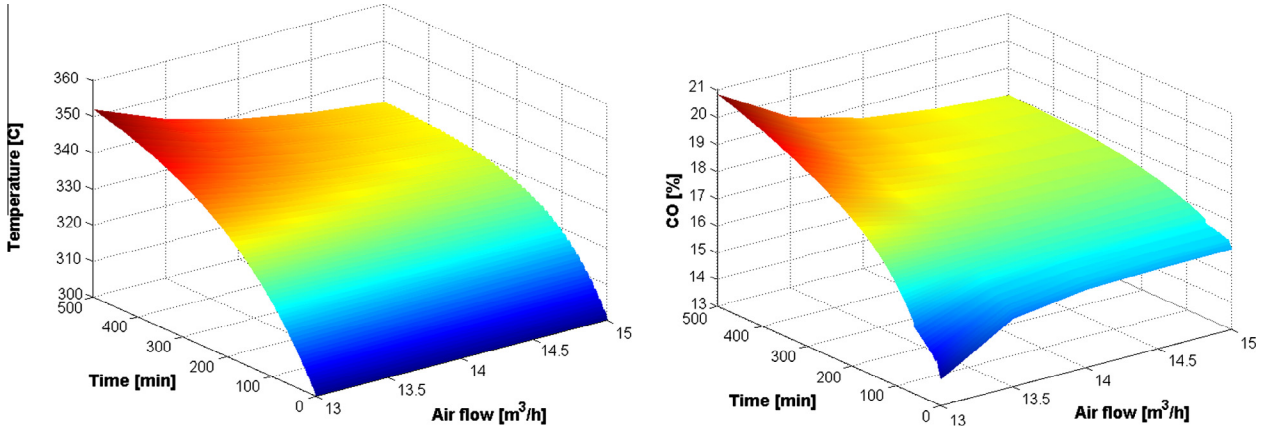

Fig. 18. Process analysis with the air flow changes.

composition values and on the right side of the figures are hourly averaged values. In all 4 cases, the developed NNM shows a good syngas composition prediction potential. During the gasifier operation CH_4 values are ranging between 1.5% and 3.5%, CO values between 15% and 25%, CO_2 values between 7% and 13% and O_2 values between 0.5% and 6%. The rest of the syngas composition is composed mostly of nitrogen oxides and higher hydrocarbons (in much smaller amount).

For the purpose of process analysis, simulation results from neural network models have been used. The fuel and air flow has been varied and their influence on the process temperature and syngas composition (based on simulation results) has been analysed. The process temperature rises with the gasifier operation for both analyses (where the fuel flow and air flow influence on the process have been analysed). On higher fuel flow rates (with the same air flow) the temperature progression is faster and process reaches higher stationary temperature due to higher energy input through the fuel flow (Fig. 17). Carbon monoxide (CO) values are dependable on process temperature and on fuel to air flow ratio. With the higher fuel flow (air flow is constant), CO values rise due to higher carbon input. With the higher process temperature, CO values rise due to higher carbon conversion rate. Faster increase of CO during the operation can be obtained on higher fuel flow rates. With the higher air flow rate (and the constant fuel flow), the process temperature progression is slower and the temperature reaches lower stationary values. The higher air flow enables better formation of CO_2 which results in lower CO formation rate (Fig. 18). Generally, with higher air flow rates, CO values are smaller. Faster increase of temperature and CO during the operation can be obtained on lower air flow rates.

6. Conclusion

In this paper the possibilities of different modelling approaches that can be used for an on-line process control to predict biomass gasification process parameters with high speed and accuracy have been analysed and the results have been presented. Models from the literature often differ in terms of delivered process information and they are often lacking extensive experimental data for verification purposes. After related literature review and measurement data analysis, two different modelling approaches for the process parameter prediction have been developed. Two similar modelling approaches have been used to develop equilibrium biomass gasification models. Results derived from these models differ in terms of calculated parameter values. These kinds of models are suitable for process prediction at specific operation points. In order to describe the process and to predict process parameter values for various operating points, neural network model has been developed. The particular modelling methodology that has been used in this paper to develop the neural network prediction model is applicable for different kinds of gasifier designs. The temperature and syngas composition neural network prediction model has been verified on the new set of experimental data and model outputs have been analysed. Neural network models show good correlation with measured data and good capability to predict biomass gasification process parameters with reasonable accuracy and speed.

Acknowledgements

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PAPER 3

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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.

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 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

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Nomenclature

Main symbols

$mair$	air flow rate, m^3/h
$mair_{av}$	average air flow rate, m^3/h
mb	biomass flow rate, kg/h
mb_{av}	average biomass flow rate, kg/h
mb_{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

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 generalisation 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 75 kW_{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.

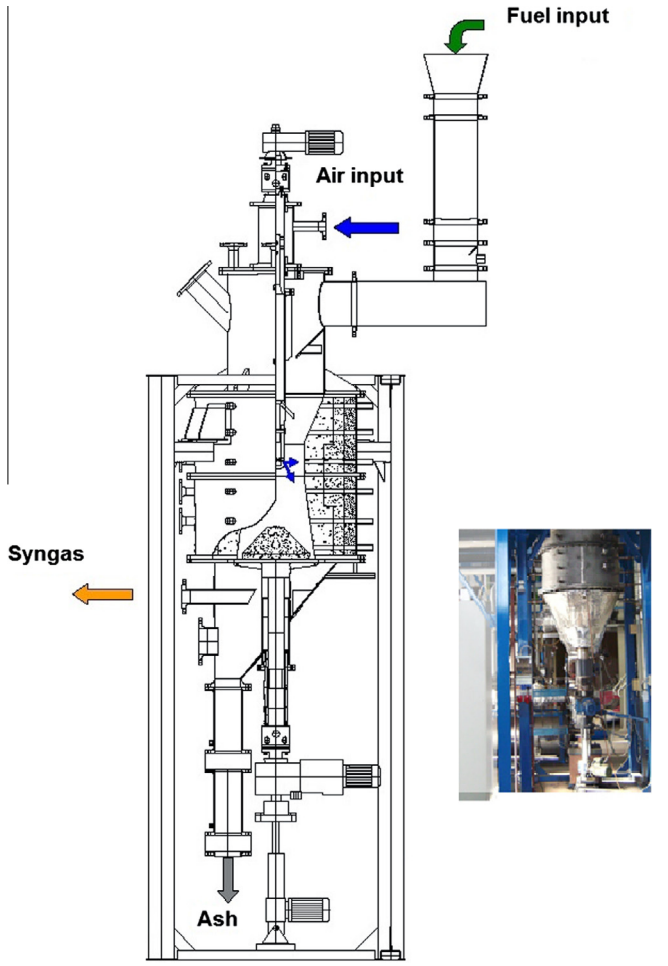

Fig. 1. Scheme of co-current fixed bed biomass gasification facility operated by TU Dresden.

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 h of operation. The second set of 5 experiments (Experiments 5–9) were performed in 2013 and resulted in more than 35 h 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 s 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 min basis, together with the air flow rate (Eqs. (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 Figs. 2–4.

$$mb_{av} = \int_{t=i-25}^{t=i} mb\,dt \tag{1}$$

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)

$$mair_{av} = \int_{t=i-25}^{t=i} mair\,dt \tag{2}$$

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 min without fuel injection (while in Experiments 1–4 the time without fuel injection is generally less than 7 min). 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 m^3/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 Suggeno 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 Fig. 5 has been used.

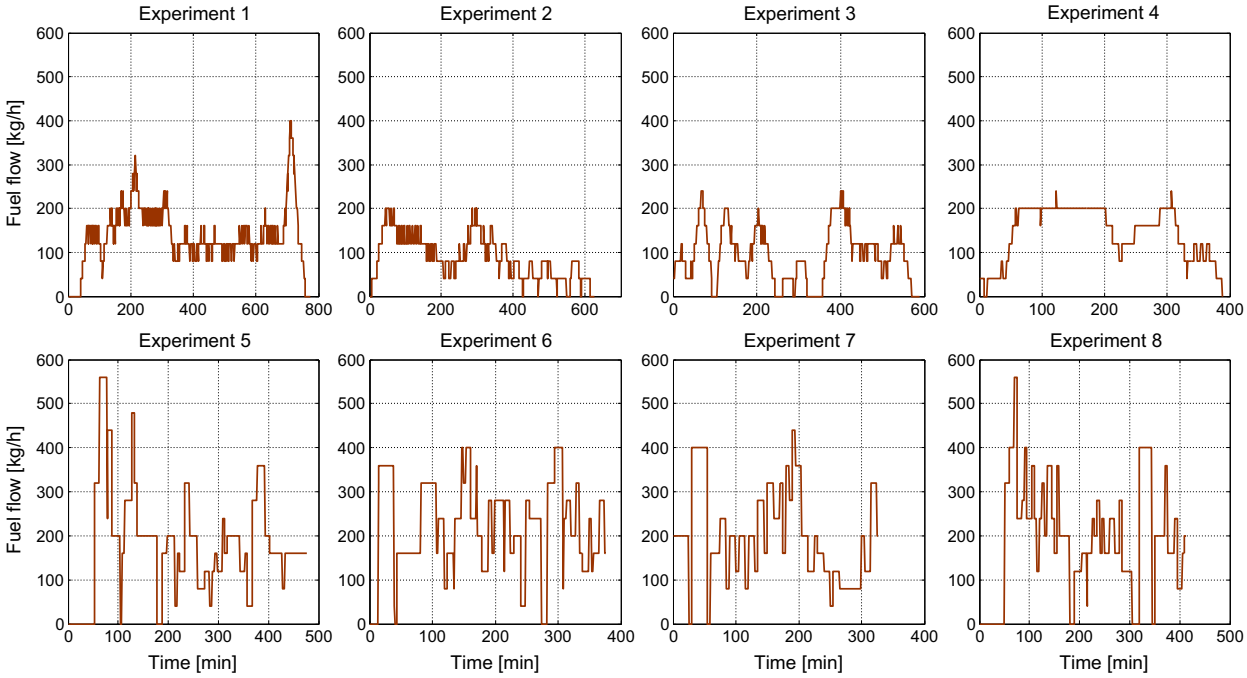

Fig. 2. Average fuel flow rate for Experiments 1–8.

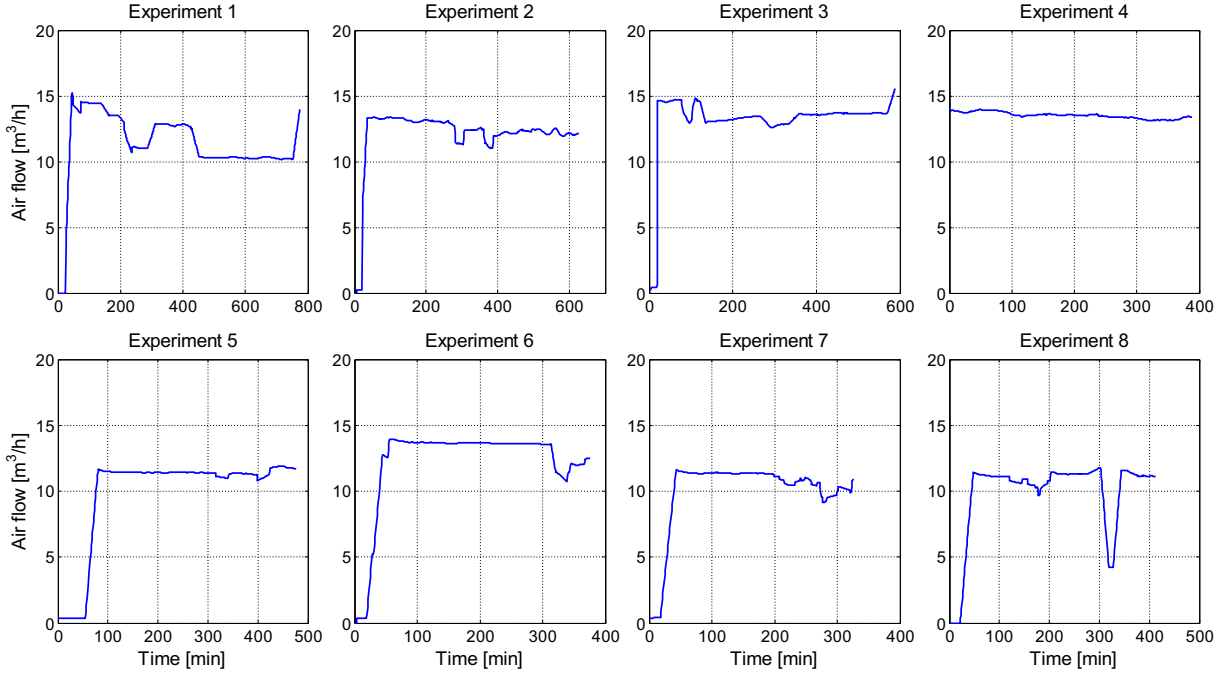

Fig. 3. Average air flow rate for Experiments 1–8.

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.

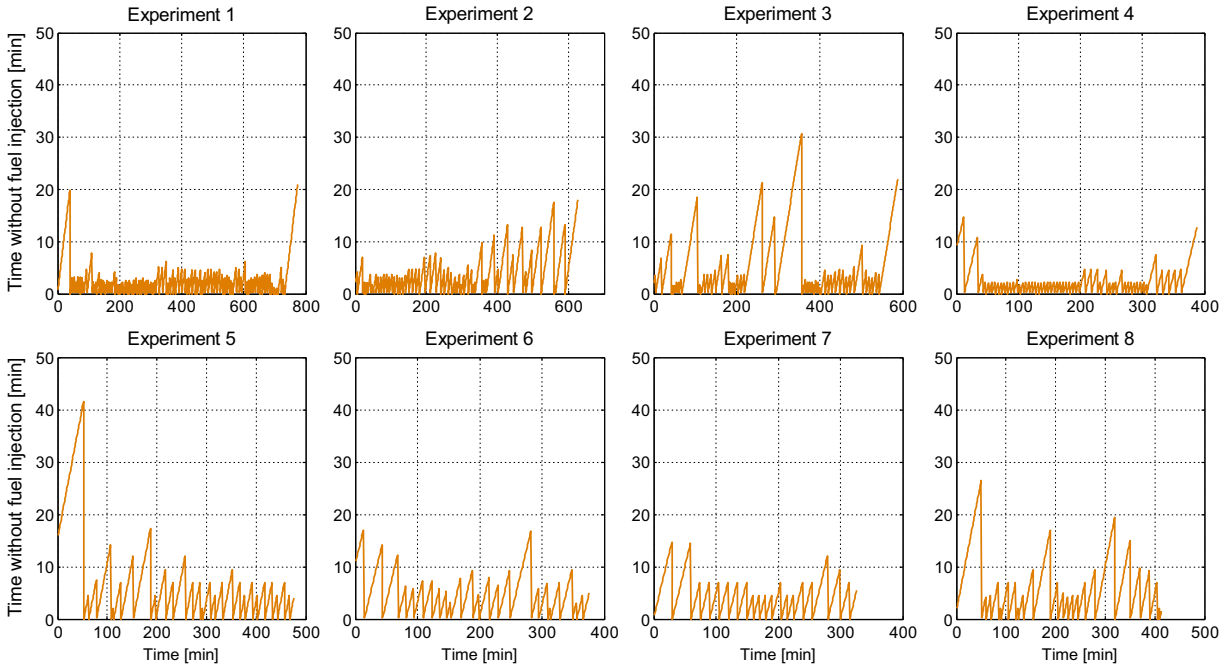

Fig. 4. Time without fuel injection for Experiments 1–8.

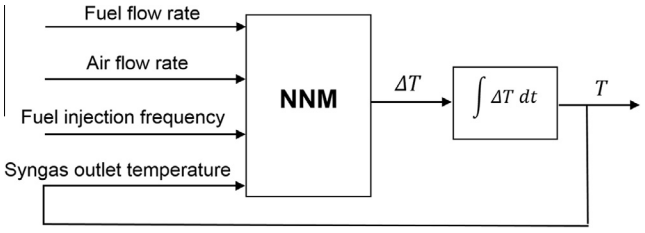

Fig. 5. General scheme of artificial network based temperature prediction model.

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 +∞) 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 min 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 ±100% for the next 3 min 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 Fig. 6.

$$error = \frac{T_{predicted} - T_{measured}}{T_{measured}} \tag{3}$$

$$error_{av} = \frac{\int_{t=i-50}^{t=i} |error| dt}{50} \tag{4}$$

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].

$$\Delta T = \beta_0 + \beta_1 \cdot mb_{av} + \beta_2 \cdot mair_{av} + \beta_3 \cdot mb_{freq} + \beta_4 \cdot T \tag{5}$$

$$\begin{aligned}\Delta T = {} & \beta_0 + \beta_1 \cdot mb_{av}^2 + \beta_2 \cdot mair_{av}^2 + \beta_3 \cdot mb_{freq}^2 + \beta_4 \cdot T^2 + \beta_5 \\ & \cdot mb_{av} \cdot mair_{av} + \beta_6 \cdot mb_{av} \cdot mb_{freq} + \beta_7 \cdot mb_{av} \cdot T + \beta_8 \\ & \cdot mair_{av} \cdot mb_{freq} + \beta_9 \cdot mair_{av} \cdot T + \beta_{10} \cdot mb_{freq} \cdot T\end{aligned} \tag{6}$$

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 (Eqs. (7)–(11)) for statistical analysis of temperature prediction model are following:

$$R^2 = 1 - \frac{\sum_{t=0}^{t=i} (T_{measured} - T_{predicted})^2}{\sum_{t=0}^{t=i} (T_{measured} - T_{mean})^2} \tag{7}$$

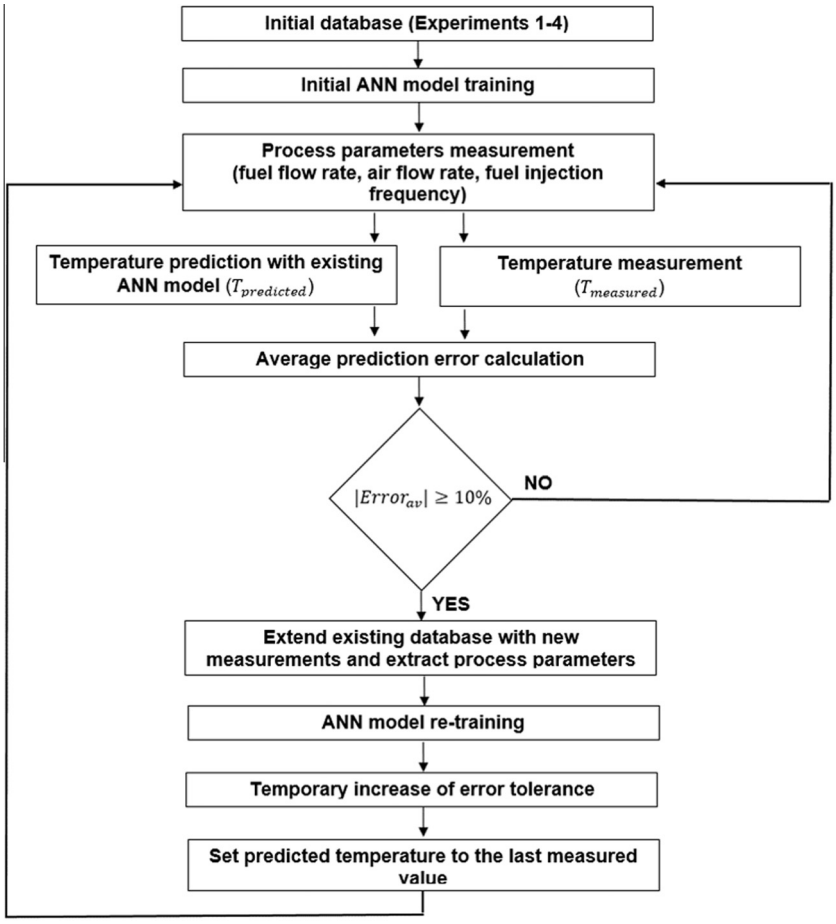

Fig. 6. NNM modelling scheme with 10% of error tolerance threshold.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=0}^{t=i}(T_{measured} - T_{predicted})^2}{N}} \tag{8}$$

$$\mathrm{APE} = \frac{\sum_{t=0}^{t=i}\left|\frac{T_{predicted} - T_{measured}}{T_{measured}}\right|}{N} \tag{9}$$

$$\mathrm{MFB} = \frac{1}{N}\sum_{t=0}^{t=i}\frac{T_{predicted} - T_{measured}}{\frac{T_{predicted}+T_{measured}}{2}} \tag{10}$$

$$\mathrm{NMFB} = \frac{\sum_{t=0}^{t=i}T_{predicted} - \sum_{t=0}^{t=i}T_{measured}}{\left|\sum_{t=0}^{t=i}T_{predicted} - \sum_{t=0}^{t=i}T_{measured}\right|}\left[exp\left(\left|ln\frac{\sum_{t=0}^{t=i}T_{predicted}}{\sum_{t=0}^{t=i}T_{measured}}\right|\right) - 1\right] \tag{11}$$

4. 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 Fig. 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

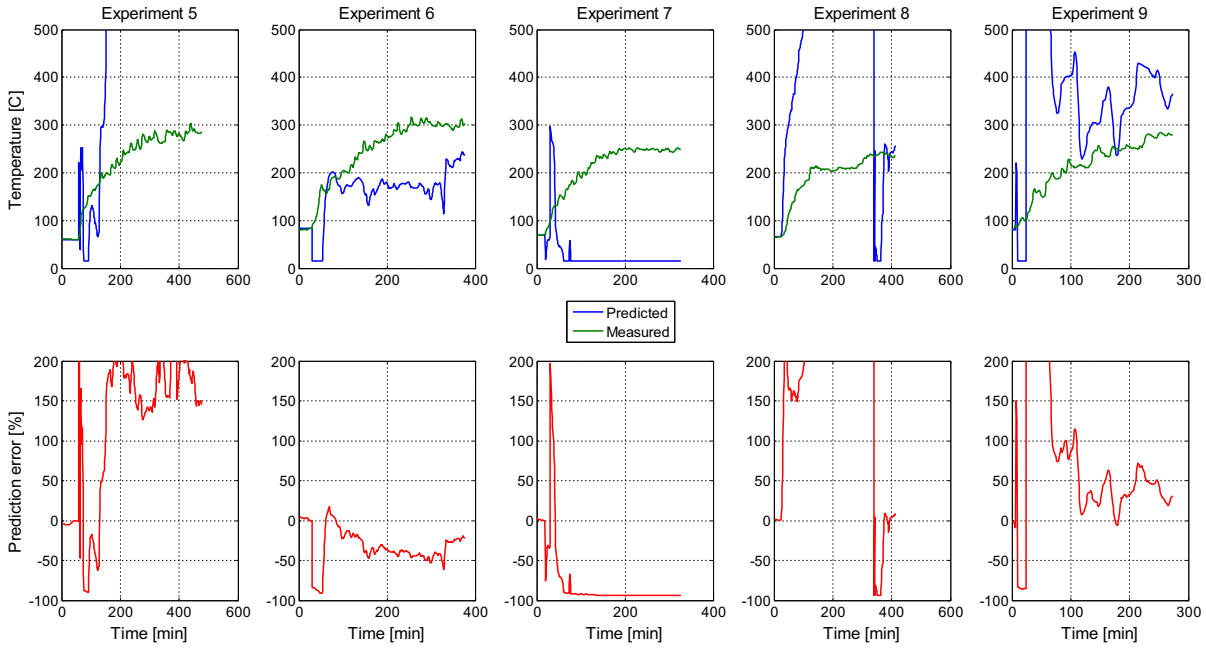

Fig. 7. NNM prediction result with initial database from Experiments 1–4.

would be unpractical for on-line process analysis. Approach that has been proposed in Section 3 (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 Fig. 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 ±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 min 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 Fig. 9. With the proposed dynamic modelling approach the prediction error has been reduced significantly. The prediction error is mostly within ±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

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

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 min of plant operation. This is due to large prediction errors that occur in the first 200 min 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 200 min (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.

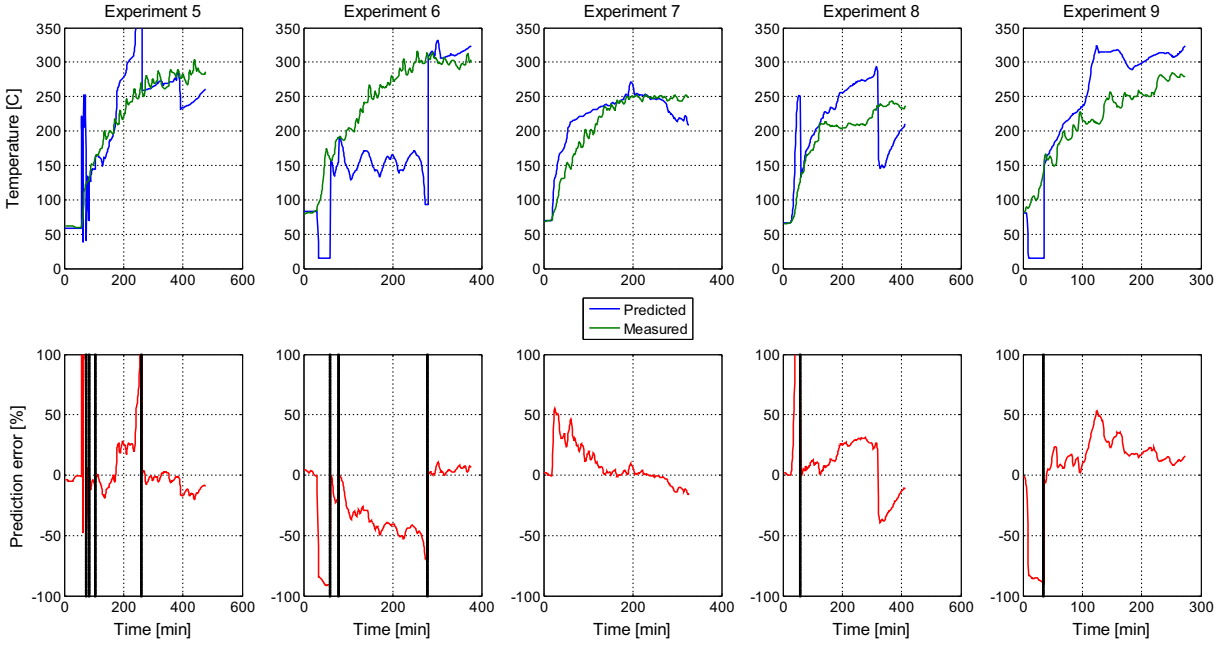

Fig. 8. Dynamic NNM prediction result with 50% of error tolerance threshold.

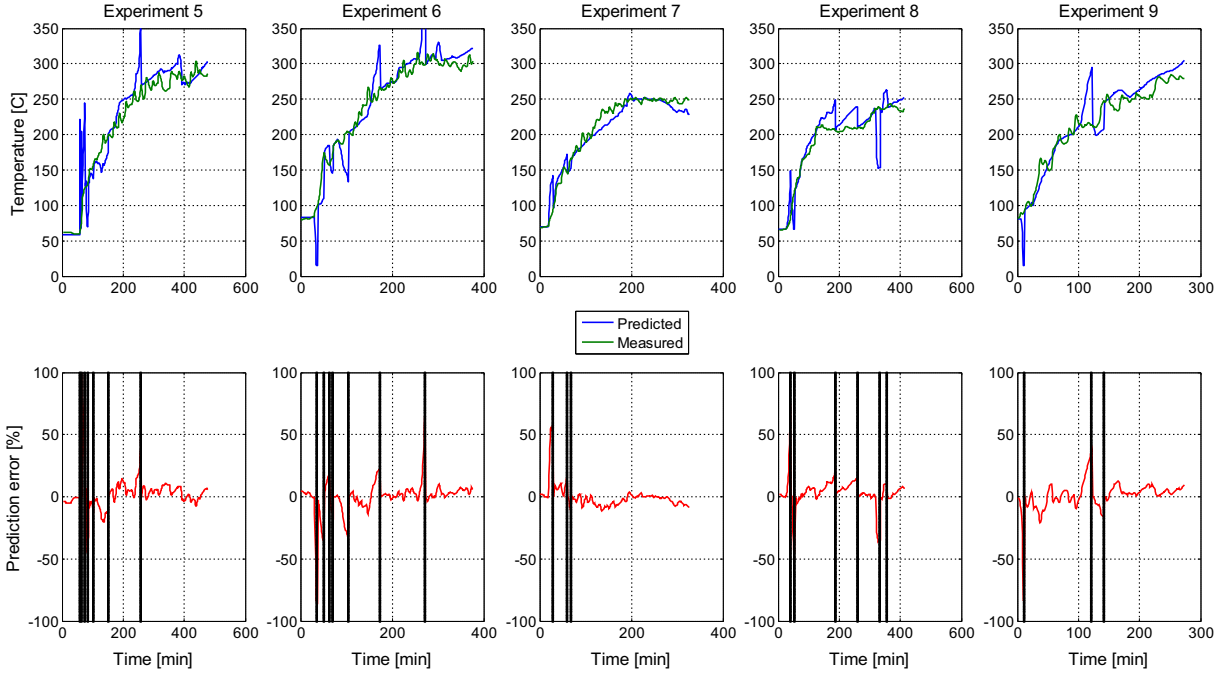

Fig. 9. Dynamic NNM prediction results with 10% of error tolerance threshold.

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 min has been used for model re-training. In the other cases the data from the last 1500, 2000 and 2350 min 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

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

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 min 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 s are necessary for one re-training session. That enables re-training between 2 measurements (measurement sampling

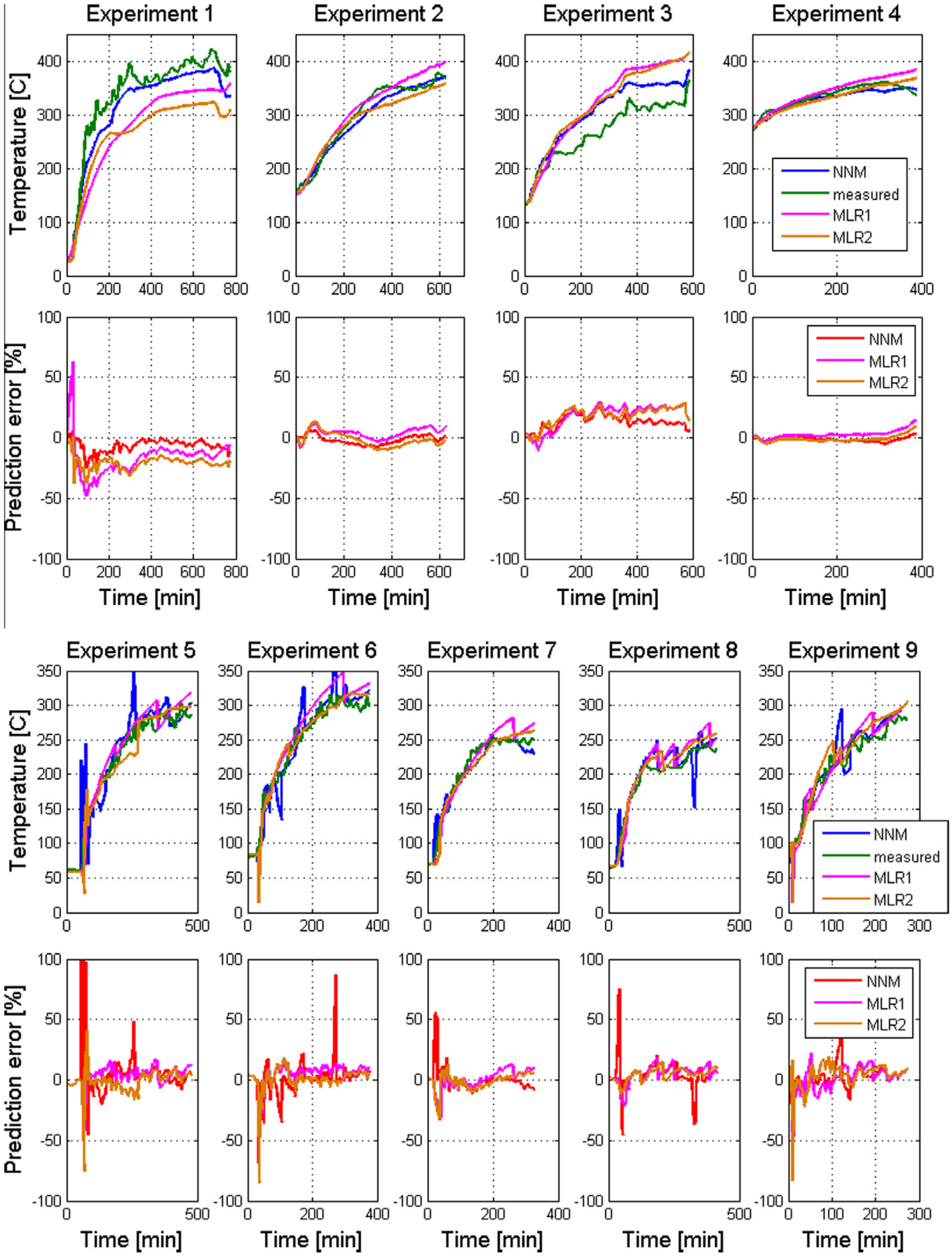

Fig. 10. Detailed performance analysis of different dynamic modelling approaches.

Table 4
Model performance analysis for different dynamic model types.

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

frequency is 30 s). 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 4. 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

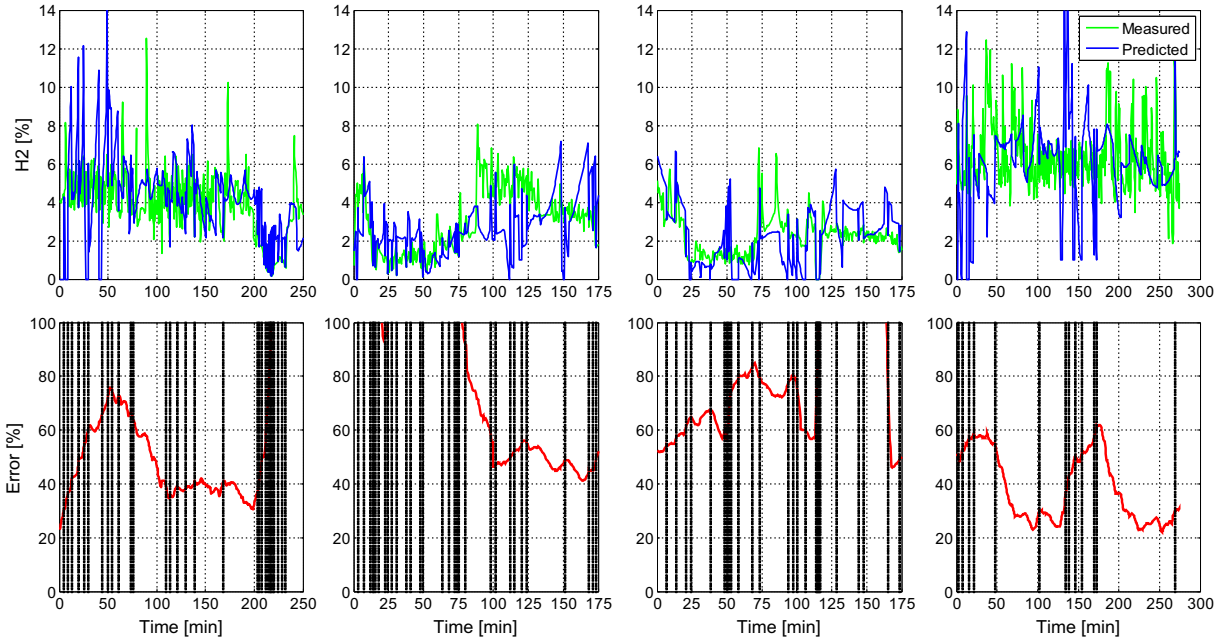

Fig. 11. Dynamic NNM performance for H_2 predictions (Experiments 5–8).

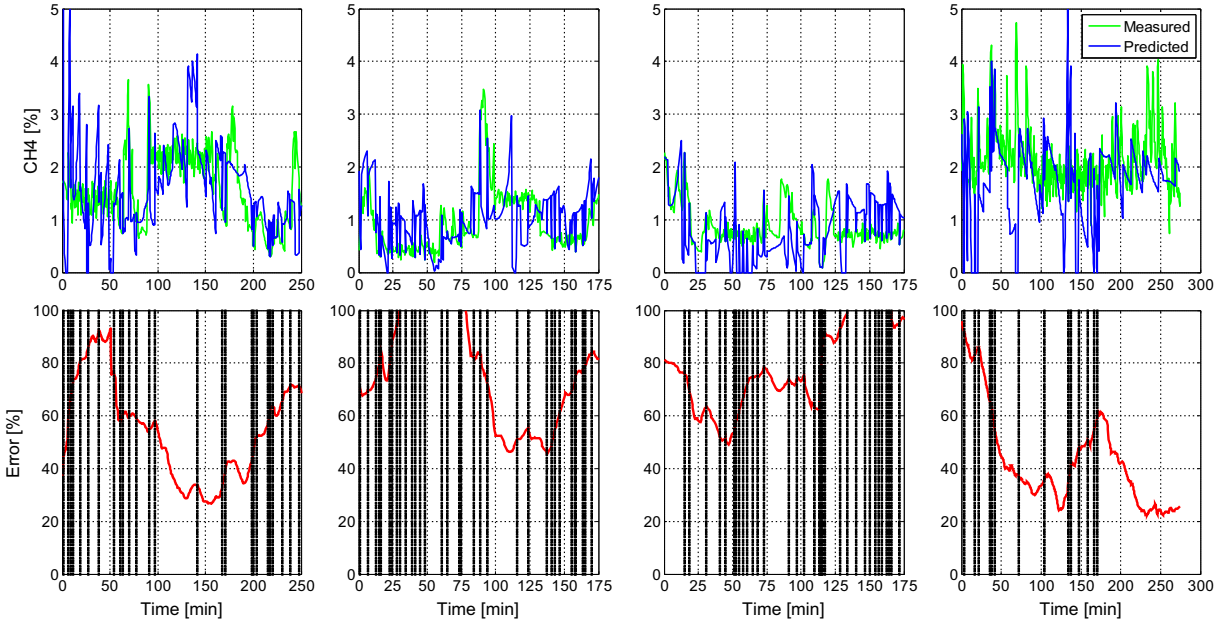

Fig. 12. Dynamic NNM performance for CH_4 predictions (Experiments 5–8).

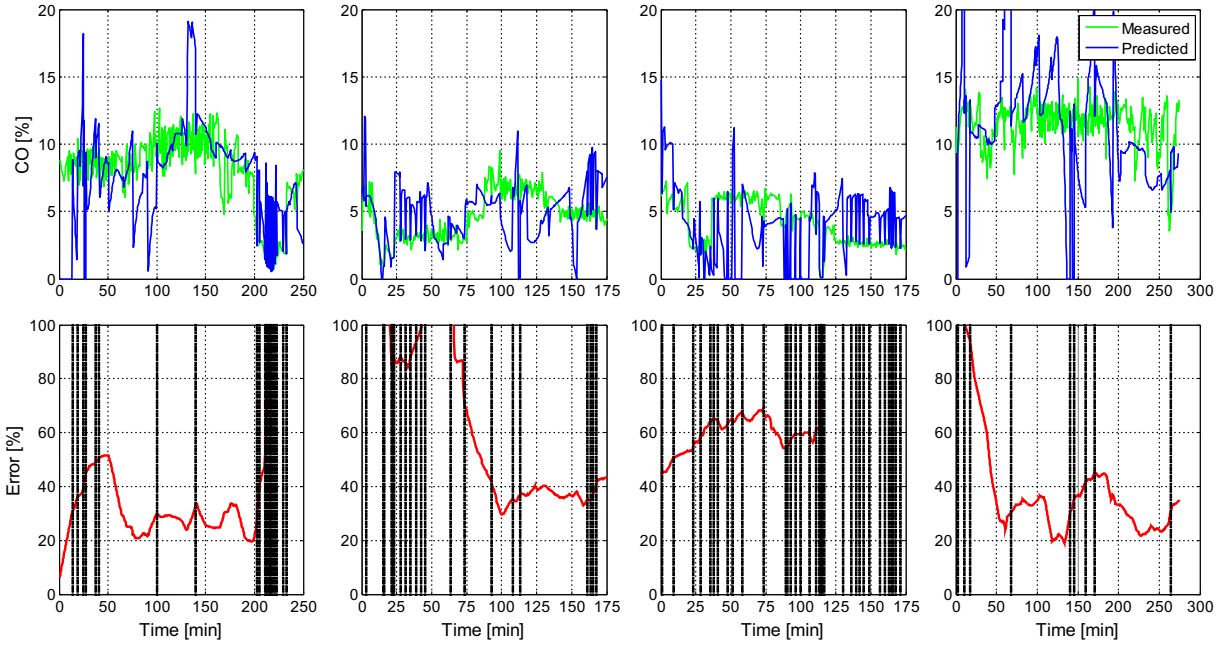

Fig. 13. Dynamic NNM performance for CO predictions (Experiments 5–8).

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 Fig. 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 Fig. 11 (H_2), Fig. 12 (CH_4) and Fig. 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 min of available data) than in the case for temperature prediction model (2300 min 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 min of operation) the total re-training time lasts less than 15 min in total. One re-training session takes around 7.5 s 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.

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

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 s. 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

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

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.

5. Conclusion

For the purpose of temperature and syngas composition prediction in a 75 kW_{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 h of plant operation while the syngas composition prediction error is around 30%. The associated neural network retraining time of 10 s 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.

Acknowledgements

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PAPER 4

Temperature prediction in a fixed bed biomass gasifier using NARX modelling

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ABSTRACT

Biomass gasification is a promising technology for efficient, clean and diverse utilisation of biomass and biomass residues through production of syngas. It is a complex thermo-chemical process where specific mass and energy accumulation plays an important role in overall process performance. To improve process efficiency through process control and to tackle existing technical issues related to the process a lot of attention has been given to development of models that can predict process parameters in real time and changing operating conditions. Therefore, biomass gasification models for process improvement and control should be able to describe such a complex and site dependent system while keeping high prediction speed and accuracy. The paper analyses the potential of a nonlinear autoregressive exogenous (NARX) model to predict syngas temperature during plant operation with variable operating conditions. The model has been designed and trained based on measurement data from 100kW_{th} fixed bed gasification plant operated by Technical University Dresden. Developed model is able to predict syngas temperature under changeable operating conditions with coefficient of determination (R^2) of 0.98.

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 'raw syngas', using gasifying agents [1]. Although, gasification is a relatively well known technology, the share of gasification in overall energy demand is small due to current barriers concerning biomass pre-treatment, gas cleaning, process efficiency and syngas quality issues [2]. Overview of process utilisation potential and process advantages and disadvantages can be found in a review paper written by Sikarwar et al [3].

Biomass gasification is a complex thermochemical process which performance is influenced by a large number of operational parameters. One of the most important ones are biomass quality, fuel and air flow rate, particle reaction/residence time and type of a gasifying agent [4]. 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 [5].

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 the process behaviour and to analyse effects of different process variables on process performance. Most of the available models for biomass gasification simulation are based on equilibrium models for Gibbs free energy minimisation [6], computational fluid dynamics (CFD) analysis [7], kinetic reactions modelling [8] or artificial neural network [9] based models. Detailed review of available models for biomass gasification process can be found in the research done by Baruah and Baruah [10]. Most of presented models are used to describe process equilibrium while taking into consideration well defined (or assumed) operating conditions. However, they are not suitable to describe the process when operation parameters like biomass quality or level of bed sintering are changing and/or when they are not well defined. Furthermore, reactor dependable process mass and energy accumulation impose need for a model that will take a large number of process thermo-chemical interactions into account together with mass and energy accumulation while preserving high prediction speed.

*corresponding author

To describe process of biomass gasification in changing operating conditions Mikulandric et al. [11] used a dynamic artificial neural network which had to be retrained continuously to provide good prediction quality. In order to define such a model and to define level of mass and energy accumulation they took into account a prior knowledge regarding the process where important model input parameters were already defined. Therefore, to implement such a model into existing control system some engineering experience regarding particular process behaviour is needed.

Dynamic type of neural networks like nonlinear autoregressive network with exogenous inputs (NARX) can be useful tool to describe process dynamics of nonlinear chaotic systems [12]. 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 that way mass and energy accumulation could be described. In comparison with static (feedforward) networks (like standard artificial neural networks) dynamic neural networks (like NARX) have feedback elements and contain parameter delays. With static networks the output is calculated directly from the input through feedforward connections. One of major drawbacks of dynamic neural networks (including NARX models) is that 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.

In the recent research done by Asgari et al. [13] 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). Maximal 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 200kWth sorption enhanced reforming steam gasification plant [14]. NARX models seems to be a promising technology 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 in a 75kW_{th} fixed bed gasifier, operated by TU Dresden. The model should be able to predict syngas temperature based on raw measured data 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.

2. 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 open loop NARX model training a feedforward multilayer neural network is trained using backpropagation algorithms to define main structure of neural network. Afterwards, in closed loop NARX model training model outputs are estimated on current and previous inputs together with previously estimated outputs (making a closed loop) [14]. A detailed explanation of NARX structure can be found in [15]. 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 (resulted from mass and energy accumulation) without any prior knowledge about the process only raw measurement data will be used.

Gasification plant and operating conditions

The object of modelling is a co-current fixed bed gasifier with thermal input of 75 kWth , 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. Details regarding plant design and operation can be found in [11].

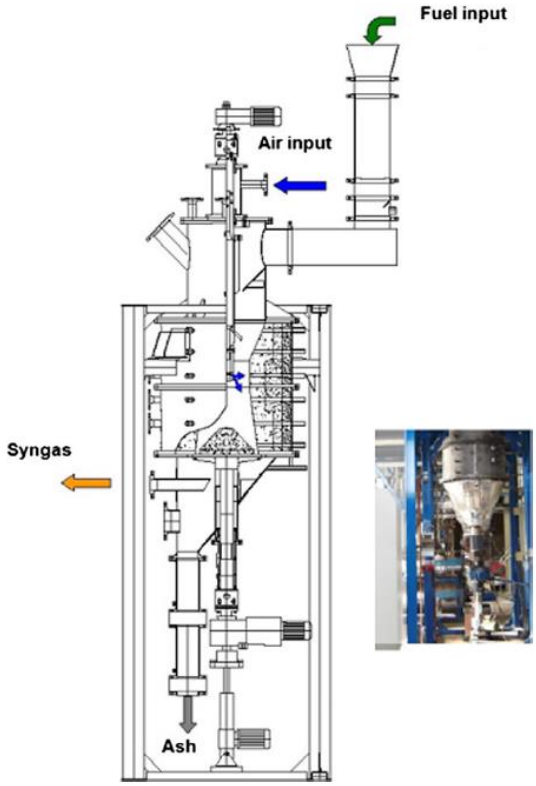

Fig 1. Scheme of co-current fixed bed biomass gasification facility operated by TU Dresden

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 5-8) 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.

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 1: Measurement methodology and equipment

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. that there is an obvious difference between Experiments 1-4 (conducted in 2006) and experiments 5-8. In Experiments 1-4 fuel flow rate is relative constant and ranges between 50 and 100 kg/h while in Experiments 5-8 fuel flow rate is generally higher and usually ranges between 50 and 200 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 has not been changed (the system is described in [11]) 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.

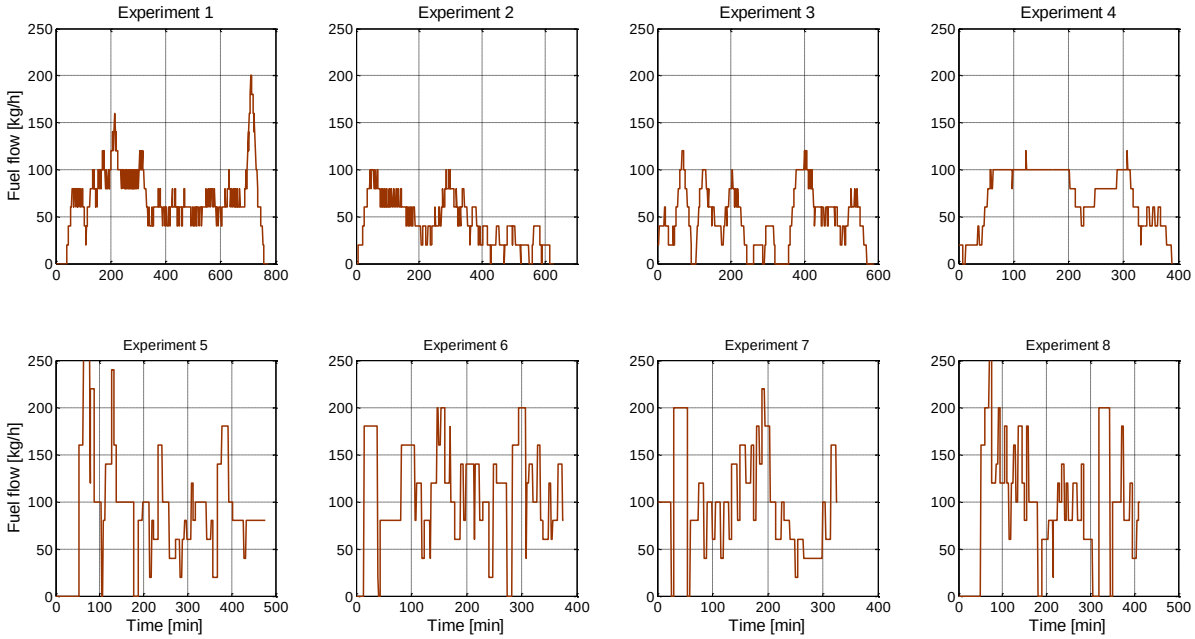

Figure 2. Fuel flow rate for experiments 1-8

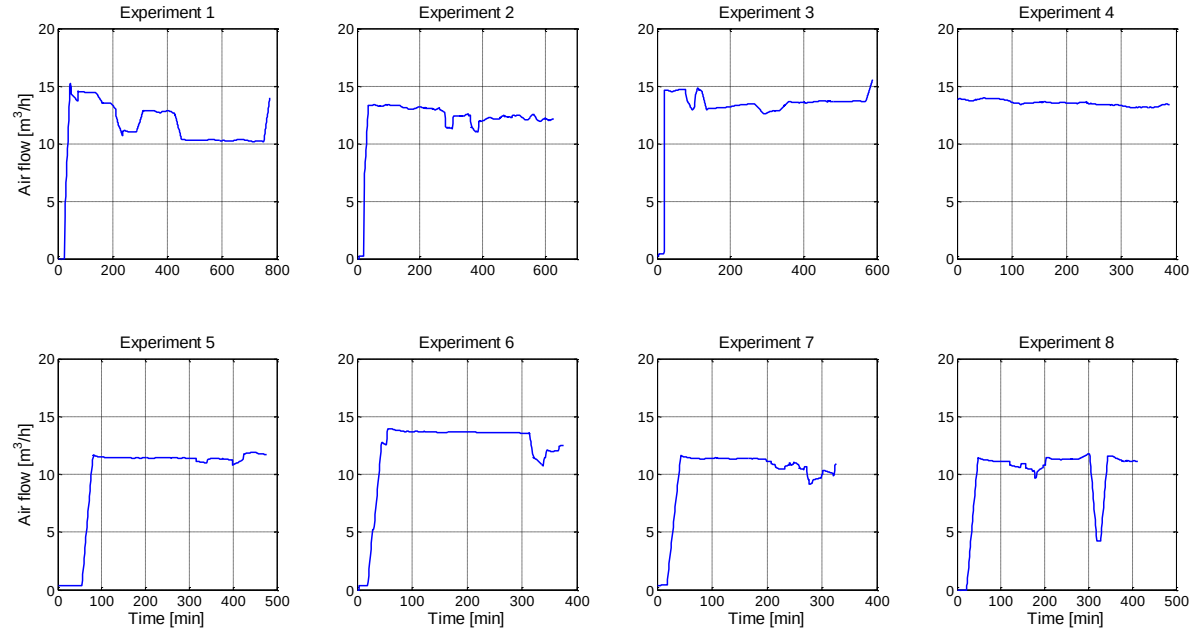

Figure 3. Air flow rate for experiments 1-8

NARX model

Syngas temperature 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) itself. Each sub-model can be represented as a nonlinear time series with following equation (Eq.1):

$$y(t) = f\left(y(t-1), \dots, y(t-d_y), u(t-1), \dots, u(t-d_u)\right) + e(t) \quad \text{(Eq.1.)}$$

Where $y(t)/y_m(t)$ represents model output for time t, $u(t)/u_m(t)$ model input for time t, $d_y, d_u/n_u$ corresponding number of lags (delays) for input and output and $e(t)$ error or noise for time t. Simplified structure of the NARX model is presented in Figure 4.

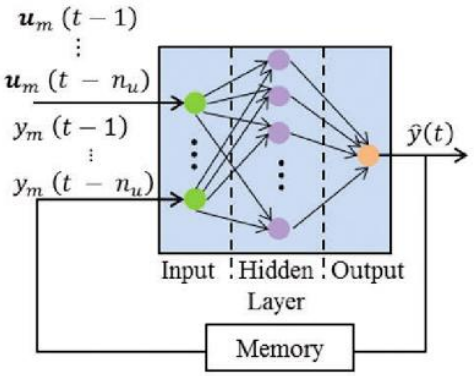

Figure 4. Simplified structure of NARX model [14]

For prediction of syngas temperature 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 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. Fuel and air flow rates have been chosen as model inputs while syngas temperature is chosen as model output (Figure 5).

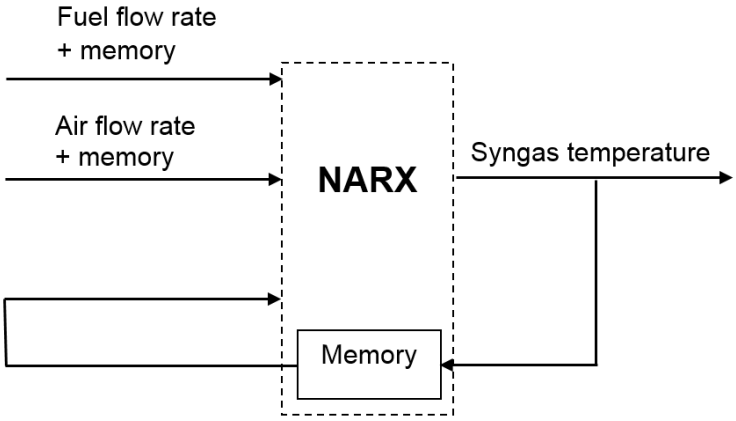

Figure 5. General scheme of NARX temperature prediction model (for model training)

To analyse the effect of training data quantity on prediction performance 8 different cases with different training data quantity have been defined. 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 predicted based on developed model and measured model inputs. In CASE 3 data from first experiment has been used for NARX training. Experiments 2-9 were used for model validation and prediction potential analysis. 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. Each simulation delay represents an actual time delay of 30 seconds. Therefore, time delays for model inputs will range from 30s to 10 minutes.

Continuous model prediction error will be analysed using Equation 2. while overall model prediction performance will be defined by using coefficient of determination (R^2).

$$error = \frac{T_{predicted} - T_{measured}}{T_{measured}} \qquad \text{(Eq. 2)}$$

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. Model prediction performance and model validations 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 6.) first 60 minutes of Experiment 1 have been used as training data set for NARX model. The rest of the process (second part of Experiment 1 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 process has been described with very low prediction error that ranges between ±10%. This is understandable because this data set was training data set for model development. However, the rest of the process has not been described properly and the prediction error is very high which suggests that used training data size is generally not sufficient for modelling purpose. Prediction error can go over 100% due to nature of equation that has been used (Equation 2) to continuously monitor progression of prediction error. Resulting coefficient of determination (R^2) has been defined at the end of performed simulation.

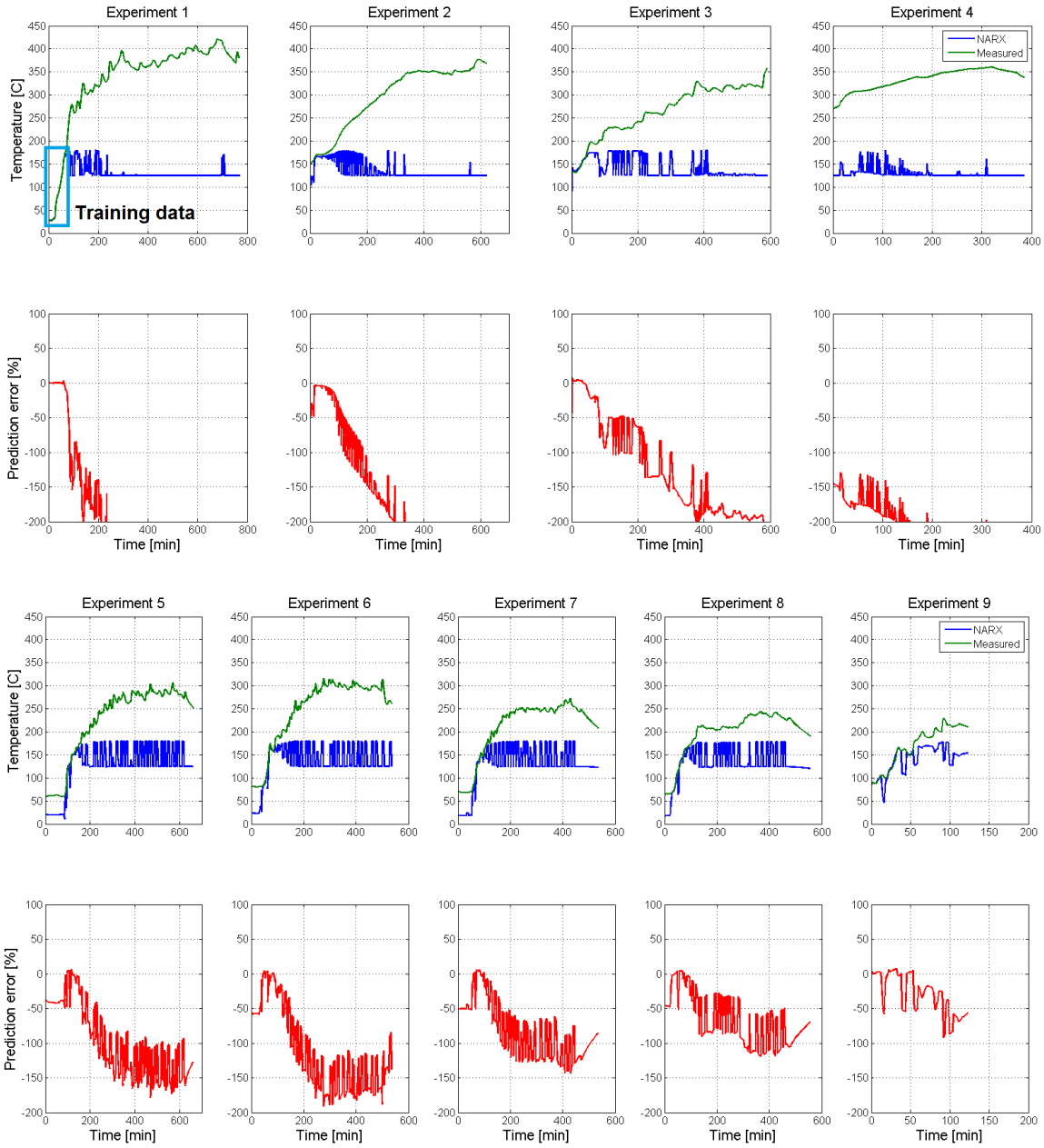

Figure 6. Model performance with 60 minutes of training data set (CASE 1)

Due to a high prediction error from the first simulation case the training data set has been increased. In CASE 3 data from the first experiment (whole) has been used as training data set and syngas temperature from Experiments 2-9 was predicted based on developed model and model inputs. Simulation results show that for training data set (Experiment 1) model prediction error is usually below ±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 ±8%. After changes in operating conditions (Experiment 5-9) the prediction error generally rises but remains under ±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. However, a prediction error under ±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 7.

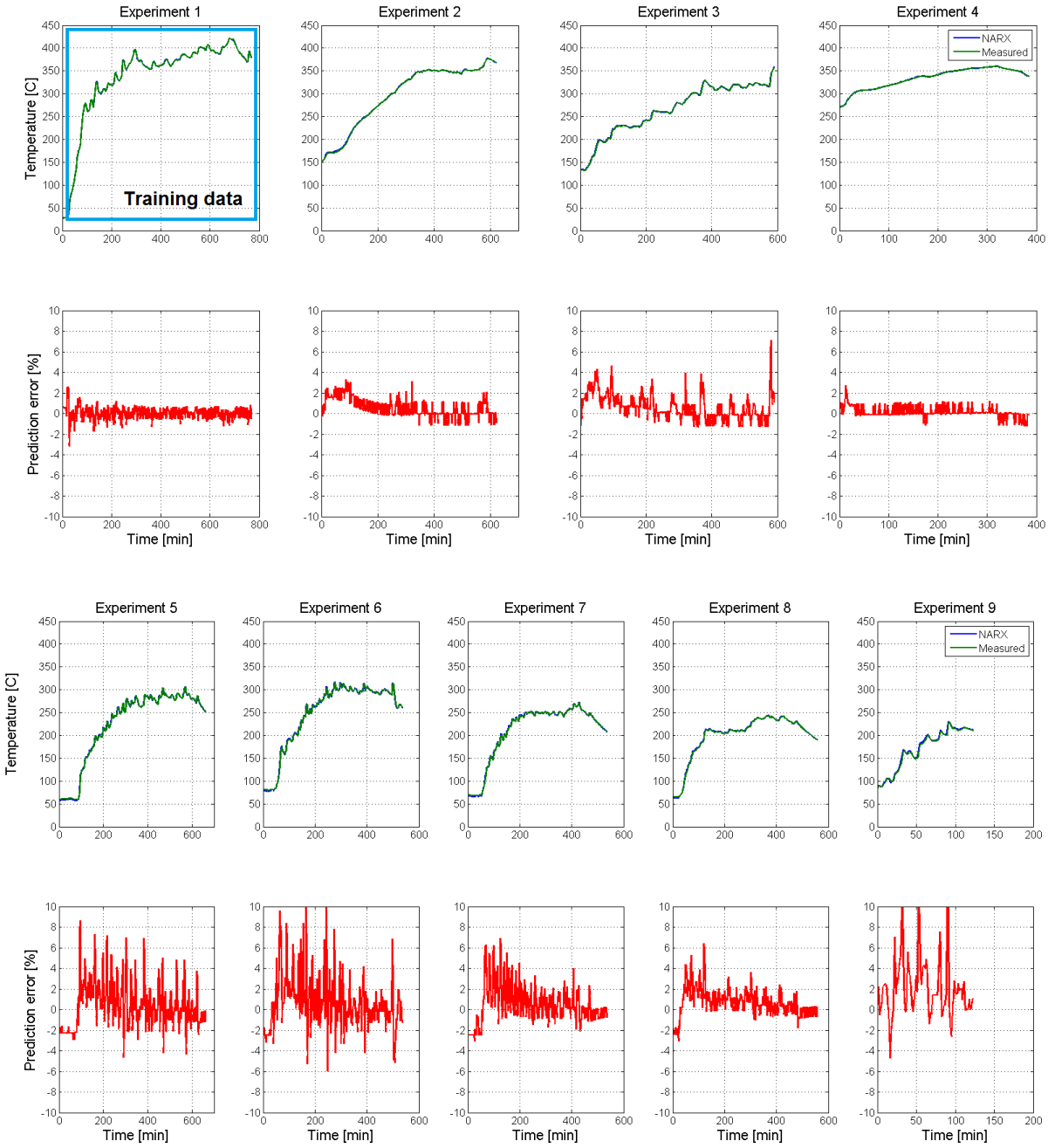

Figure 7. Model performance with Experiment 1 as training data set (CASE 3)

Different training data sizes have been used to analyse model prediction performance. Summary of the analysis is presented in Table 2. First 60 minutes as a data set for model training is not sufficient to develop a NARX model with reasonable prediction accuracy. 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

set size of measurements from Experiment 1 the model prediction performance does not increase significantly and it some cases it even declines. This leads to conclusion that increasing data size (after including data from Experiment 1) leads to over-fitting and does not contribute to increase of model prediction accuracy.

CASE	Training experiments	Validation experiments	Prediction error for training data set [%]	Prediction R^2 [-]	Average prediction error [%]
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

Table 2.: Model performance analysis for different training data sets

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 minute) 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. The summary of model prediction performance for different number of time delays is presented in Table 3.

Number of delays	R^2 [-] Temperature prediction model
1	0.96
2	0.98
3	0.92
4	0.95
5	0.97
10	0.95
20	0.90

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

The overall training and prediction time of developed NARX model for Experiments 1-9 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.

4. CONCLUSION

In order to predict syngas temperature in a $75kW_{th}$ biomass gasification plant a nonlinear autoregressive exogenous (NARX) model has been developed. Such models take current and past values of model inputs and output into consideration to model specific system time delays caused by accumulation of mass and energy. Therefore it was important to define the right size of model data history for model training and development. Furthermore, the quality of the prediction 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. 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 prediction error of developed NARX model is below 1% with R^2 of 0.98. It requires a relative small amount of data for training and can predict syngas temperatures in changing operating conditions. Due to fast prediction speed such models are applicable for on-line process analysis of fixed bed biomass gasification systems.

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PAPER 5

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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 h 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.

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 Ref. [5]. Hydrogen production potential from oil palm shells through gasification has been analysed in Ref. [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 Ref. [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 Ref. [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 N m^{-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

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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/kg K)
c_{pgases}	specific heat capacity of flue gases (kJ/kg K)
$c_{psyngas}$	specific heat capacity of syngas (kJ/kg K)
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 (–)

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 MW_{th} + 24 MW_{el})	150
Austria	6 (19 MW_{th} + 6 MW_{el})	2
Finland	3 (137 MW_{th} + 1.8 MW_{el})	2
Denmark	8 (12 MW_{th} + 1.4 MW_{el})	2
Other EU countries	31	15

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 al. [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]. Furthermore, this kind of approach has been implemented for syngas yield control purposes [37], model based performance analysis in fluidised bed steam biomass gasifiers [38] or model based simulation tool for economic analysis of biomass facility scaling [39]. 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]. Seyab and Cao [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 kWth, 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 chloro 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 Ref. [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 Suggeno 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 Ref. [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

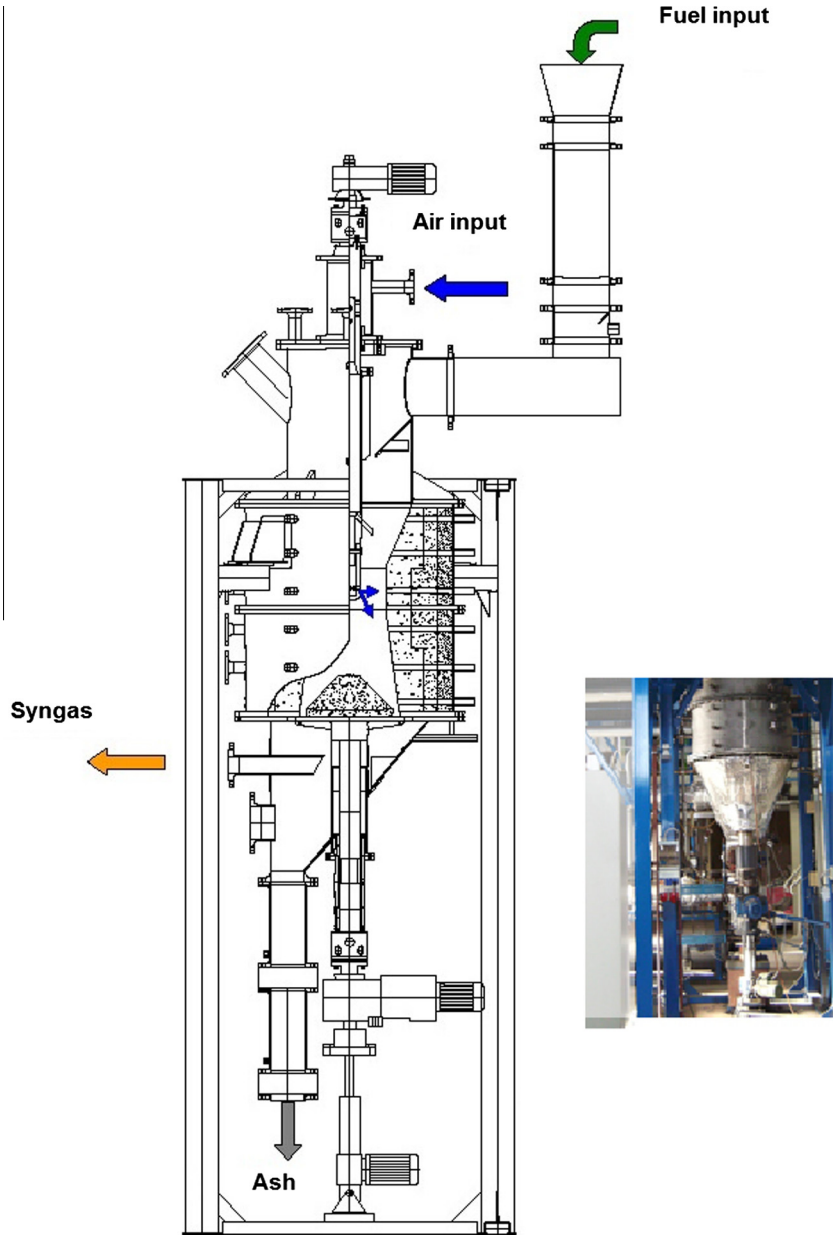

Fig. 1. Scheme of biomass gasification facility operated by TU Dresden.

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.

$$\eta_{\text{process}} = \frac{m_{\text{syngas}} \cdot [Hd_{\text{syngas}} + Cp_{\text{syngas}} \cdot (T - T_{\text{env}})] + m_{\text{gases}} \cdot Cp_{\text{gases}} \cdot (T - T_{\text{env}})}{m_{\text{biom}} \cdot Hd_{\text{biom}}} \quad (1)$$

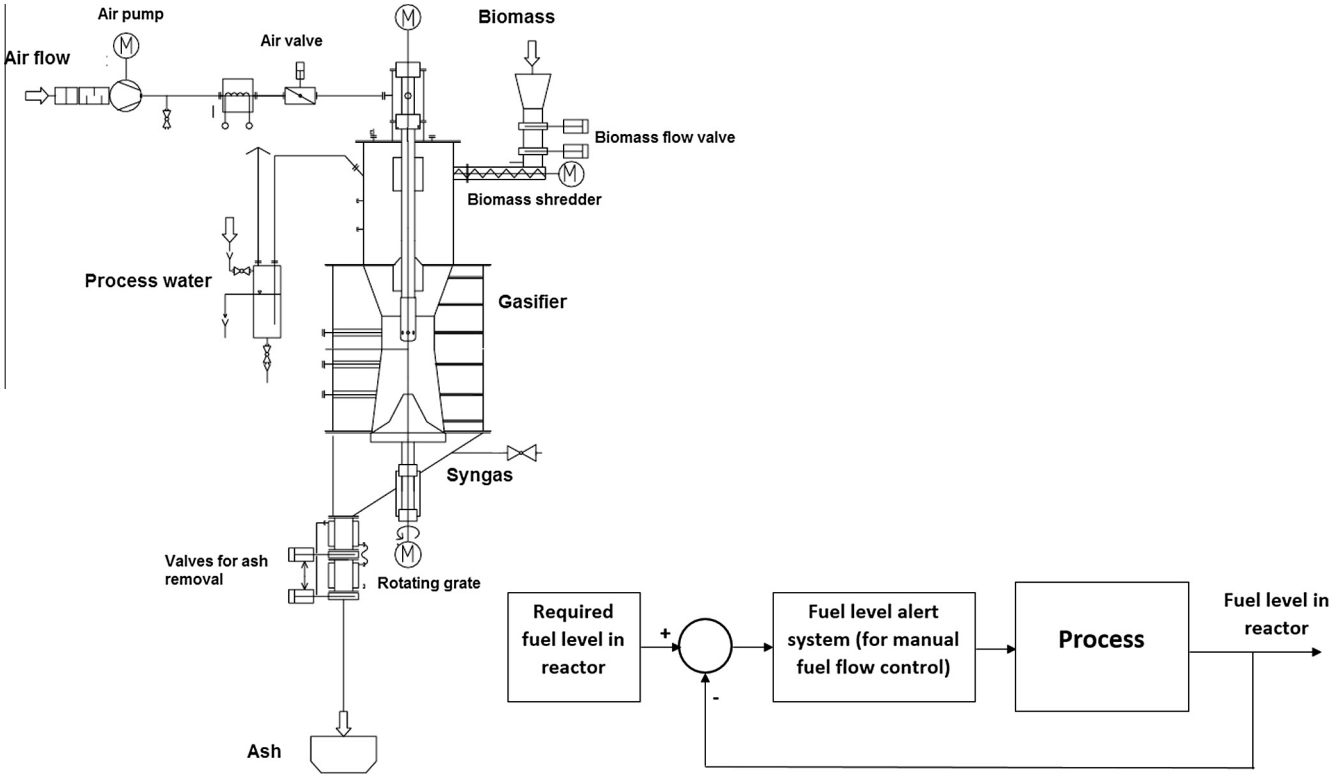

Fig. 2. Process diagram of biomass gasification facility with existing control block diagram for fuel flow control.

$$m_{\text{syngas}} + m_{\text{gases}} \approx m_{\text{biom}} + m_{\text{air}} \tag{2}$$

$$P_{\text{th}} = \frac{m_{\text{syngas}} \cdot [Hd_{\text{syngas}} + Cp_{\text{syngas}} \cdot (T - T_{\text{env}})] + m_{\text{gases}} \cdot Cp_{\text{gases}} \cdot (T - T_{\text{env}})}{75} \tag{3}$$

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 constrains is listed in Table 2. Goals for process performance improvement were set to maximise process performance score derived from equations that are presented in Eqs. (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)

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	$m_{\text{biom}} \geqslant 0$ $m_{\text{air}} \geqslant 0$ $m_{\text{biom-freq}} \geqslant 0$
Inequality constrains for semi-controllable variables	$\eta_{process} \geqslant 0$ $T \geqslant 0$ $Hd \geqslant 0$

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.

$$P_{\text{SCORE}} = c_{\text{eff}} \cdot \frac{\eta_{\text{process}}}{\eta_{\text{process max}}} + c_T \cdot \frac{T}{T_{\text{max}}} + c_{Hd} \cdot \frac{Hd}{Hd_{\text{max}}} \tag{4}$$

$$c_{\text{eff}} + c_T + c_{Hd} = 1 \tag{5}$$

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.

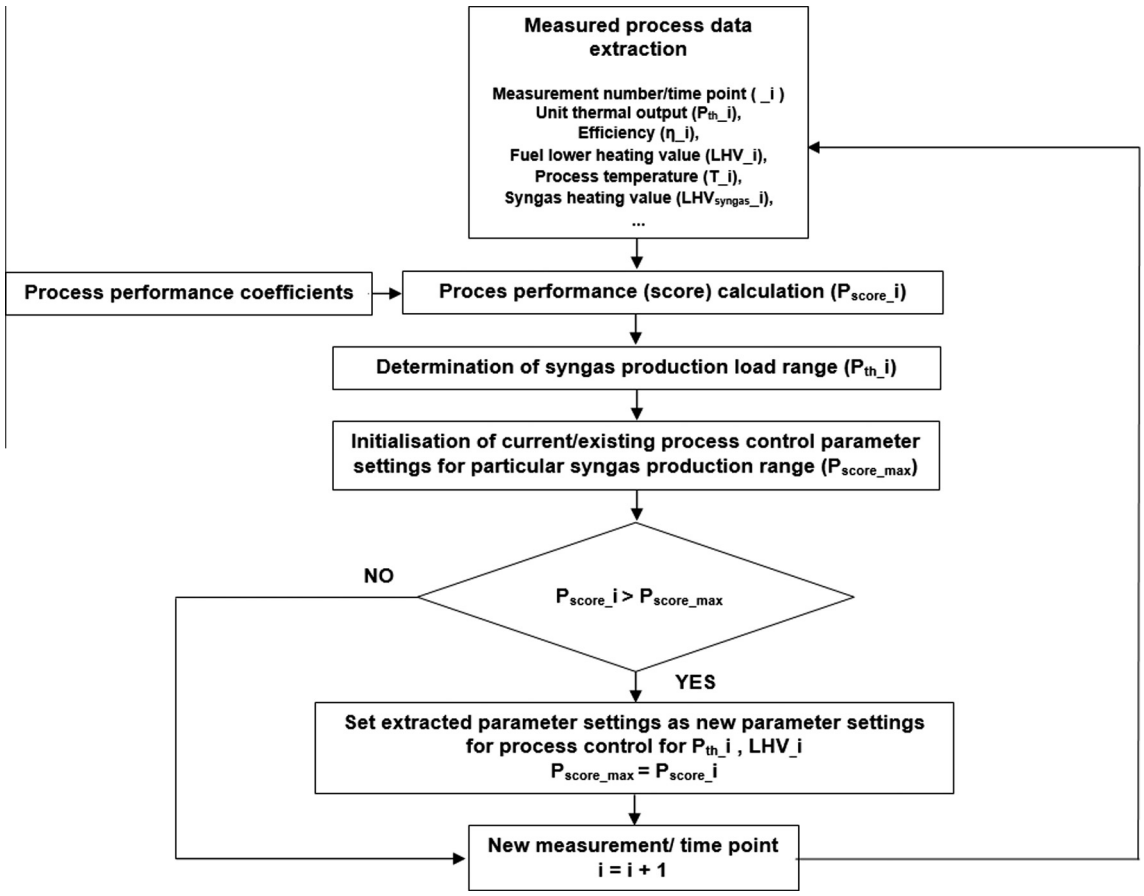

Fig. 3. Flow chart of algorithms for adaptive control map development.

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 Eqs. (2) and (3). Process performance for is calculated based on Eqs. (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 ±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 h of gasifier operation have been collected to develop described control system. Operating regimes with the highest calculated process performance values (red[1] squares) related to facility load (blue squares) are presented in 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

[1] For interpretation of color in Figs. 4 and 7, the reader is referred to the web version of this article.

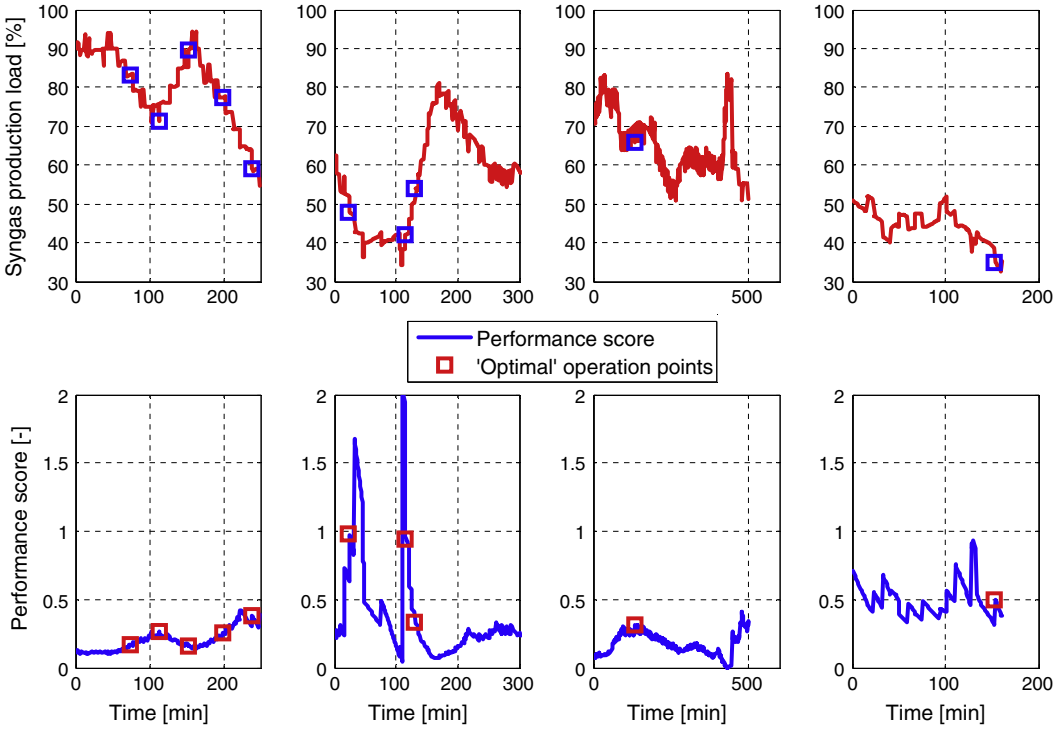

Fig. 4. Analysis of operating points for the best available process performance.

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 in 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 in 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

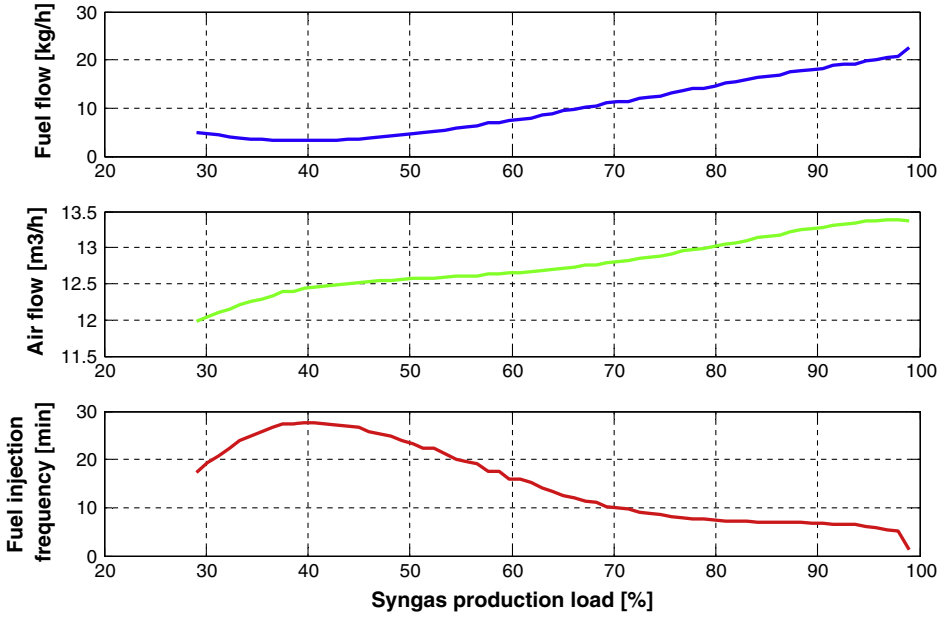

Fig. 5. Process parameters for different syngas production loads derived from developed algorithms for process performance improvement.

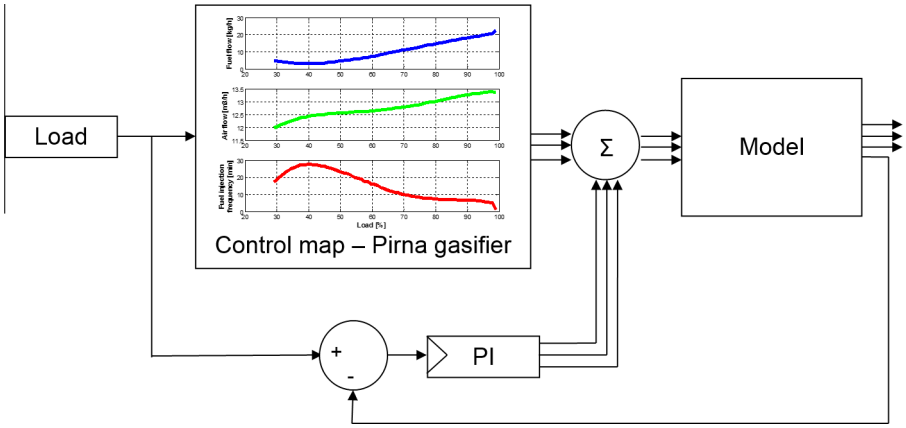

Fig. 6. Advanced control scheme for biomass gasification process.

Pirna has been conducted in MATLAB/Simulink® simulation tool. Simulation results from 4 different experiments that resulted in more than 20 h of gasifier operation are presented in 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 h 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 ±10%.

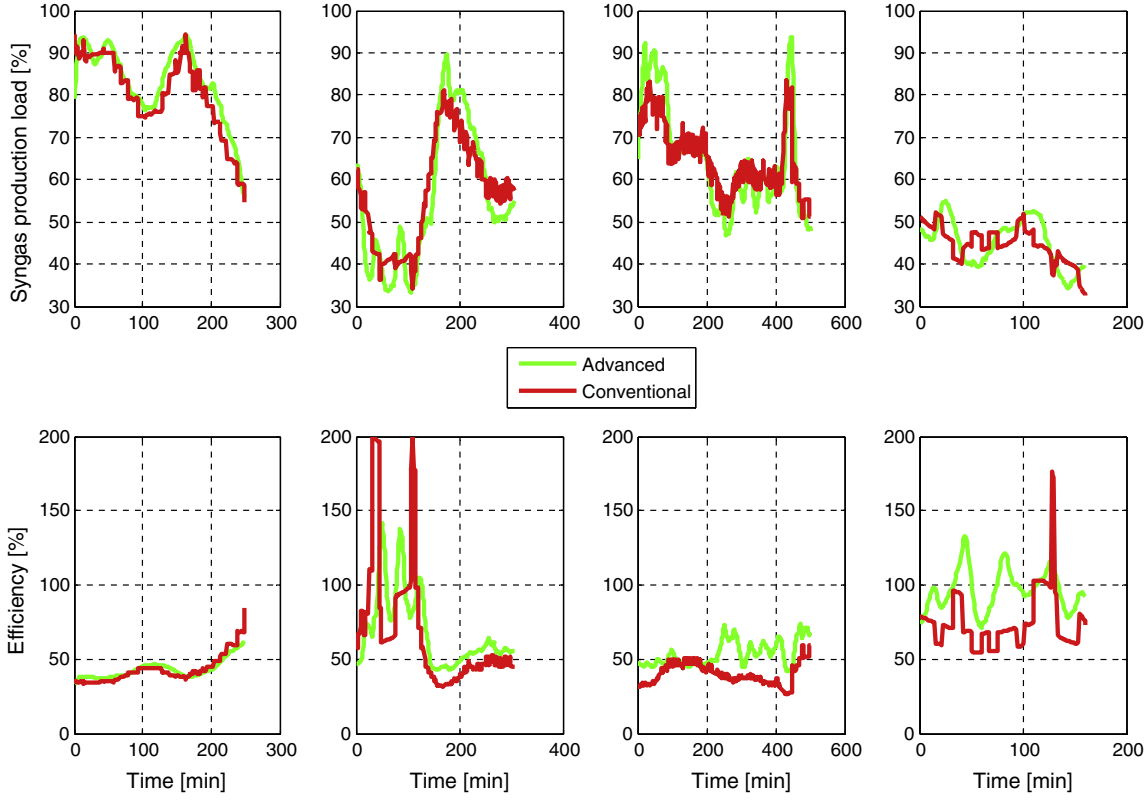

Fig. 7. Effects of process control modifications on gasification process.

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 ±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, CH_4 and H_2 formation rate which results in higher syngas heating value. Syngas heating value with advanced control system is ranging between 3 and 5 MJ/m^3 while with conventional control system it is ranging between 2.8 and 4.5 MJ/m^3. 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 in Fig. 10. H_2 values are ranging between 4 and 14 vol.% while CO values are ranging between 8 and 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

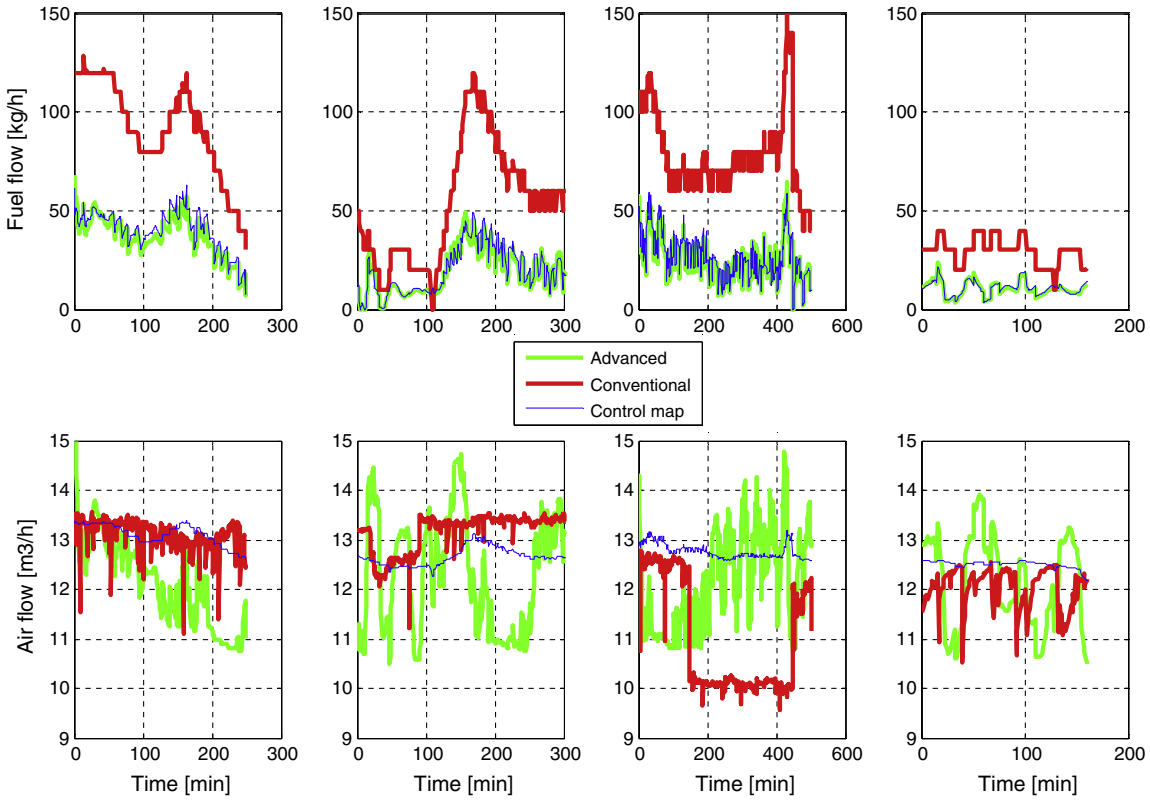

Fig. 8. Simulation results of fuel and air flows with and without advanced control system.

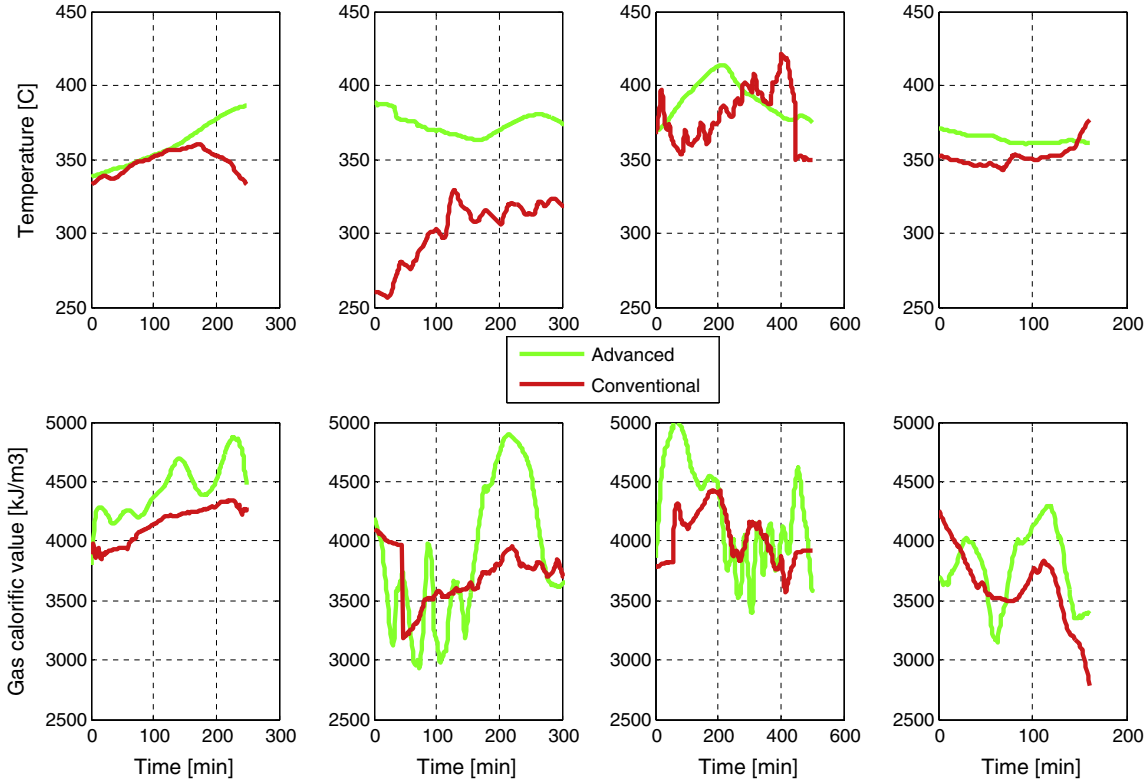

Fig. 9. Simulation results of temperature and syngas heating values with and without advanced control system.

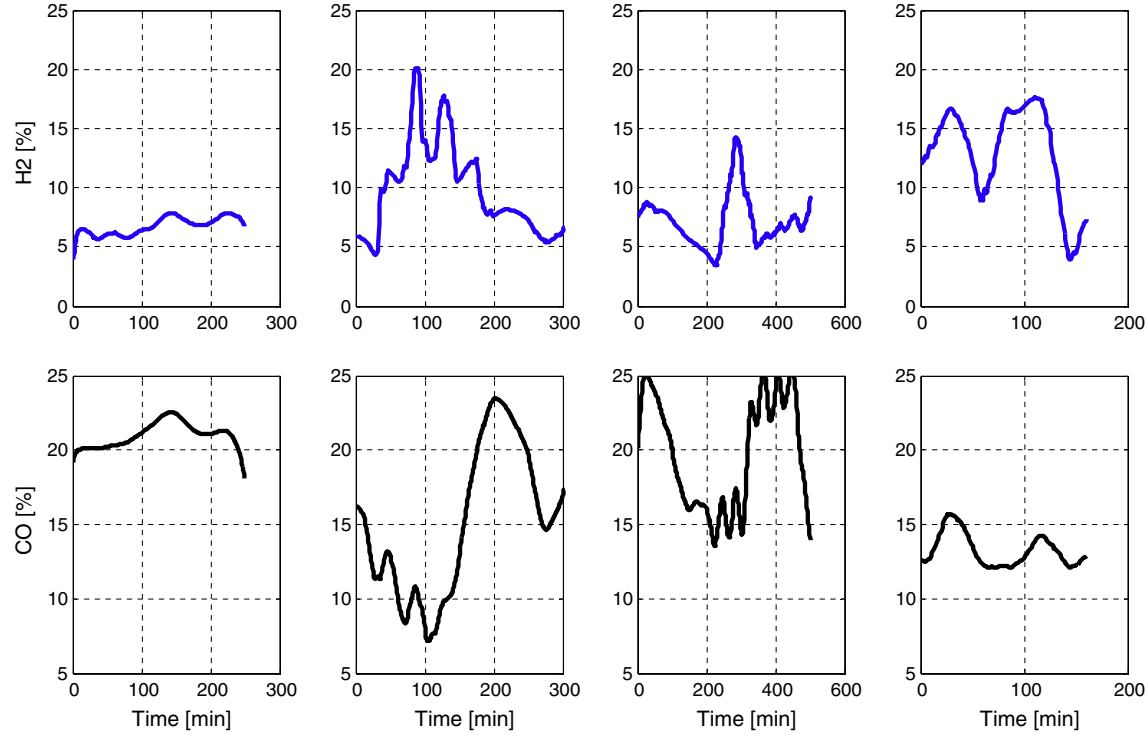

Fig. 10. Simulation results of syngas composition with advanced control system.

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.

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. 11. Process performance quality analysis.

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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