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Review of Gasifier Control Methods

[1]***AMANKELDIN Shokan,** *Doctoral Student, amankeldin1992@gmail.com,*
[1]**KALININ Alexey,** *PhD, Head of Department, a.kalinin@kstu.kz,*
[1]*NPJSC «Abylkas Saginov Karaganda Technical University», Kazakhstan, Karaganda, N. Nazarbayev Avenue, 56,*
**corresponding author.*

Abstract. *Biomass, a sustainable energy source, offers fossil fuel-free potential. Researchers explore techniques like fuzzy control, PID control, and neural networks, often enhanced by AI and predictive modeling. These advances reshape optimization strategies in biomass gasificcation. Key areas include: Fuzzy Control: examining self-learning modules and fuzzy inference systems' adaptability, e.g., dual fluidized bed gasification. PI/PID Control: reviewing Proportional-Integral-Derivative control's role in gasifier temperature management, with DDE-PI tuning. Artificial Neural Networks (ANN): emphasizing ANN models for gas composition forecasts. Air Flow Control: optimizing power via neuro-fuzzy and PI control. This review underscores control's vital role in biomass gasification, offering insights into strategies and applications, advancing sustainable energy production and eco-friendly chemical synthesis.*

Keywords: *biomass, alternative source of energy, bioenergy, sustainable energy, biofuel, biomass gasification, control methods.*

Introduction

Biomass gasification represents a promising avenue for converting organic materials into valuable gases such as syngas, hydrogen, methane, and chemical feedstocks. However, harnessing its full potential necessitates precise control strategies and techniques to manage the intricate thermochemical reactions that occur during gasification. Researchers have diligently pursued a multitude of control methods, each with its unique advantages and applications, to steer biomass gasification systems toward higher efficiency, lower emissions, and improved product quality.

These control strategies encompass a wide spectrum of approaches, including fuzzy control, PID (Proportional-Integral-Derivative) control, neural networks, and more. Each technique offers distinct advantages and addresses specific challenges associated with biomass gasification. Furthermore, advancements in control technology have led to the integration of artificial intelligence and predictive modeling, enhancing our ability to optimize gasification processes.

In this comprehensive review, we delve into the various control strategies employed by researchers in the realm of biomass gasification. We explore the strengths and limitations of each approach, providing insights into their practical applications and effectiveness. By understanding the range of control methodologies available, we can appreciate the diversity of solutions that have been developed to unlock the potential of biomass gasification for sustainable energy production and environmentally friendly chemical synthesis.

Review of control methods

There are a variety of control strategies and techniques that have been employed by researchers to control biomass gasification.

Early works on gasifier control include fuzzy control, PI/PID control, H2/HN control, predictive control, PIP control and state-feedback control.

Fuzzy control:

Firstly, it was created a technique for building and updating the knowledge base of a fuzzy controller. Firstly, an expert system shell was used in parallel with structure identification to achieve self-generation of the rule base. A fuzzy self-learning predictive module was then implemented to maintain self-correction of the database. The outcomes showed that the technique might be suitable for a variety of processes. For example, modelling of operator skills for process control, or capable of acquiring a fuzzy model of a very complex process which cannot be efficiently controlled by human experts.

Then models of dual fluidized bed gasification were developed. Objectives were to show that the gasification temperature and fuel oxygen content have the main impact on a chemical's efficiency. The goal of the model was to tune the controller, and was based on using mathematical relationships for experimental data. It was found that the equilibrium model was accurate for thermodynamic considerations, and sensitivity analysis verified the objectives

Sagüés, García-Bacaicoa and Serrano [1] wanted to achieve good performance in biomass gasification, which was interdependent from the type of biomass and moisture that changes often. To achieve high efficiency from the conversion of biomass to produced gas, it was a vital part of the fuzzy system to select appropriately manipulated and processed variables. Therefore, the throat temperature (T) and the CO/CO2 ratio were selected as process variables, while humidity (Hp) and the elemental composition of the biomass (EC) were selected as disturbance (D).

The fuzzy inference system contained a rule-base, which had inference mechanism (IM) to make decisions, fuzzification interface to transform gasifier output to data for the IM and defuzzification interface to transform results of the IM to inputs for the gasifier. 'ErrorT' and 'ErrorCOCO2' were used to characterize the time variation of the errors T and CO/CO2. The airflow and grate were used to illustrate the time variation of air flow and grate frequency. In the first stage of the controller design, introducing just a few rules and few values of fuzzy variables is enough. More rules and values can be added after some succeeding stages. The fuzzy system helped to stabilize membership functions of the process variables. Overall, fuzzy control showed good control of biomass gasification, with the model attained by fitting equations to experimental data.

Wang, Yue and Wang [2] designed a predictive control based on the fuzzy controller. The main motivation for choosing this strategy is that fuzzy Gain-scheduled can solve the issues of constrained optimization, while the predictive control can propose systematic designs for multi-variable system. The gasifier was tested for the sinusoidal pressure disturbance and the frequency was 0.04 Hz. Thus, the sampling period shall be no more than 2.5 seconds. The system showed the ability to resolve multi-variable control problems and accurate prediction models. Simulations demonstrated good control effects, but the problem of reducing the calculating value of predictive control still needs to be addressed.

Zhou [3] used a fuzzy controller, optimized by a particle swarm optimization (PSO) algorithm, to control the gasifier temperature. The gasifier temperature has time-delay characteristics, which prevent continuous online measurement and control. A fuzzy controller was employed, but its operation was influenced by many elements. It included the selection of membership functions, fuzzification and defuzzification techniques, and obtaining fuzzy rules. The right choice of fuzzy rule contributes to success in designing a fuzzy controller. In the past, the rules were not always optimal, due to dependency from operator experience and expert knowledge. Therefore, a PSO algorithm was applied to achieve optimal control and solve difficulties within fuzzy control. Equivalent probability matrix was defined, and discrete variables were changed into continuous variables. The PSO algorithm was used to resolve the optimization problem because it has simple operation and fast convergence speed. The results showed the effectiveness of the PSO algorithm and achieved optimal control.

PI/PID control:

A type of PI controller based on desired dynamic equation (DDE) was implemented by Xue, Li and Liu [4]. The tuning method was used to check the viability of the gasifier temperature control. They concluded that the DDE-PI tuning has lower tuning efforts with scaling factor L and showed performance feasibility. Simulation showed that DDE-PI has reasonable performance with low tuning efforts. However, an efficient and straightforward DDE-PI controller needs to be developed.

Li, Xue, Wang and Sun [5] discovered DDE-PID tuning from a nonlinear controller with a relative degree of two has decent tracking performance and robustness through an extended state observer. The DDE-based PID controller in comparison to traditional PID controllers can be tuned separately. It was firstly used in the ALSTOM gasifier with the linear model and exceeded output limits only twice at 0% load. The controller has to work within outputs constraints under pressure disturbance, model error and load tests. The controlled inputs are inlet air flow rate, char extraction flow rate, and limestone flow rate. Syngas calorific value, syngas pressure and temperature are the system outputs. The limestone mass flow rate should be about 10% of the coal flow rate to catch the sulphur in the coal.

Linear model control simulation was completed at 0%, 50%, and 100% load. It was shown that the decentralized PI controller could reach the output restraints at 50% and 100% load for all disturbance tests. It was proven that DDE-based PI control has minimal violations, which show robustness of the system [5].

A created PI controller for linear gasifier model is applied to the nonlinear model without any changes. The simulation results met all the input and output restraints under given load conditions. Overall, the control system followed load changes immediately. It was the first control strategy, which can be enhanced from linear model to nonlinear gasifier model with decent performance and without any alteration [5].

It is known that control of coal gasifiers is strongly affected by the feed coal quality, as it worsens the performance of the control system. The calorific value and online measurement of the coal quality are usually provided to improve the results of coal quality variation. However, these methods are not suitable for ALSTOM gasifiers discussed in the paper, as there is no coal species data. In addition, accurate online measurement of the coal quality is quite problematic.

The decentralized PI controller is improved in two stages: optimization and selection. Disturbance rejection is the key task in the first stage. Non-dominated resolutions are achieved by multi-objective algorithm NSGA-II. All the output and input restraints can be met under numerous load conditions and disturbances. The second stage considers the coal quality variation. Selection process upon non-dominated resolutions produces results with the best coal quality flexibility. The selection and optimization process improve the PI operation with greater dynamic responses and simultaneous coal quality flexibility.

The results showed stable control performance under different pressure disturbances and load conditions. Overall, PI controller achieved excellent dynamic responses [5].

Sun, et.al. [6] introduced PID/PI controllers for a multivariable coupled Shell gasifier based on the probability theory. The main advantage is that it can overcome the restrictions of the optimization technique established on the nominal circumstances, and that global robustness cannot be guaranteed without consideration of parameter uncertainties. In comparison to the other design techniques, it can produce broad consideration for various particular demands from industry. The results showed large potential and wide applicable prospects of the technique established on probabilistic robustness.

Zhang and Wei [7] proposed a controller that combines a PID and a model reference adaptive control (MRAC). The results in MATLAB showed the desired results of good convergence speed and performance. The convergence performance of the combined controller is better than the MRAC control.

A Multi-Objective Particle Swarm Optimization (MOPSO) algorithm was used for PI controller optimization by Kotteeswaran and Sivakumar They assessed the performance of the gasifier under 0%, 50% and 100% operating points, using a load change test and pressure disturbance test. It was concluded that the PI-controller fully and adequately meets all restraints at any load conditions [8].

Load change, coal variation, and pressure disturbance tests were carried out to analyze the robustness of the created PI controller. The condition for the response was to meet the restraints at all working points. Response of the controller should be faster than the process, therefore the selected sampling time was 1s [8].

At 100% operation point, maintaining the alteration in quality of coal at 0%, V = 0.2 bar and f = 0.04 Hz, a sinusoidal change was employed at 30s and the response showed 5 minutes. Maximum Absolute Error and Integral of Absolute Error were determined. This method was duplicated for 0% and 50% operating points [8].

As defined, the most complicated task is to satisfy the operation requirement at 0% load for sinusoidal change in pressure disturbance, the authors were motivated to check the performance of controller with MOPSO algorithm. The stability of the gasifier with PI controller is confirmed across the working range of the plant. The response time showed 600s during a ramp change from 50% to 100% load. Coal flow and char flow reached the steady state immediately, while Bedmass needs more time to achieve a steady state. The same kind of response is attained for ramp change in load between 0% to 50% working point. The operation of the designed PI controller during ramp load variation guarantees the stable performance of the system [8].

Seepersad, Ghouse and Adams [9] implemented a multi-loop PI control, where disturbance scenarios and a set point change were examined. The control of the counter-current achieved a better settling time than the co-current system, it rejected a severe disturbance of 50% decline in gasifier flow rate. The control of the co-current was slower because of the significant distance from the measurement location to the disturbance source.

The temperature of exit gas was regulated by changing tube flow rate, while CH_4 slip was regulated by changing the steam-to-carbon ratio. Heat duty for the gasifier was a disturbance. A chain of set point alteration and disturbance scenarios were examined with internal model control tuned regulating criteria applied as an initial guess, followed with optimized tunings acquired by decreasing the integral absolute error. Regarding the decreasing integral average error and settling time, the regulation of co-current system was inferior to counter-current and could dismiss a detrimental disturbance of a 50% decline in gasifier flow rate. Co-current regulation was subsequently slower because of the enlarged interval from the measurement location to the source of disturbance. Nevertheless, performance of the regulation after tuning was still suitable to reject moderate disturbances and set point alterations.

A feedforward control system should be employed in case of detrimental gasifier upsets, because feedback control between coal-derived syngas flow and steam methane reformer is insufficient for the co-current system. If the emphasis is on electricity generation, set point of the steam methane reformer exit gas temperature can be reduced to 100 K from the nominal set point to decrease steam methane reformer throughout. If the emphasis is on maximum liquid fuel production, the set point of exit gas temperature can be decreased to 125 K from the nominal set point.

Anitha, Sivakumar and Jayakumar [10] developed a multivariable PID controller based on a Genetic Algorithm. The new GA optimized the robustness and performance of the system. The controller met all design objectives under three operating loads (no-load, 50% and 100% load). Simulation results showed the excellence of proposed method.

Striugas, et.al., [11] implemented a PID control system for feedstock feeding, char discharge, and air supply. The frequency of the air blower is adjusted by the output signal. Due to the maximum permitted temperature in the reactor, the limit of the tertiary air flow is fixed automatically. The maximum process temperature is one of the correction factors of the tertiary air flow control. If the temperature achieves a set point, the supplementary air supply to the reactor is disabled. Therefore, the amount of air flowing and the yield of created producer gas are the key parameters affecting process automation. Optimized pressure value controls the residual discharge and fuel feed, while tertiary air adjustments control air flow supply.

Work by Wang, et.al., [12] showed typical test results of BG. A programmable logic controller (PLC) was implemented to monitor gasification facilities.

The PLC system had an alarm, motor frequency regulators, buttons, and gas flow rate controlled by PID. Several tests of the PLC system showed a marked effect of the oxygen level in the syngas composition and slightly on the H2/CO ratio.

If the pyrolyser temperature rises above 350°C, the gasification temperature rises to around 800°C after the warm-up period. The flow rates of oxygen and air are fixed to certain desired values relating to the various oxygen concentrations. The biomass feed rate and the flow rate of air adjust the gasification temperature. Experiments were done at gasification temperatures from 900°C to 1250°C. The temperature of the pyrolyser was regulated at 350°C-450°C. Various oxygen concentrations were applied to investigate the impact of oxygen concentration on the gasifier operation. The syngas was examined after the temperature in the pyrolyser and gasifier became reasonably stable. CO, H_2, CO_2 and CH_4 in the syngas are measured by Agilent 3000 Micro GC gas chromatograph. Equivalence ratio and Gas yield were defined to evaluate the process technology. A liquid level meter is fixed at the top of the movable tank and attached to a pressure transmitter. It can record the pressure alterations that indicate the height of the movable tank at the time of the gas charging.

The temperature distribution has a significant impact on the creation of the gasification products. It is an essential aspect to assess the operation of the gasifier. The gasification temperature is largely prevailed by the feed rate of biomass and the amount of oxygen supplied into the gasifier temperature. The temperature and flow rate of the hot flue gas controls the pyrolysis temperature. Pressure transmitters and thermocouples are placed at different points for continuous monitoring the pressures and temperatures.

Artificial Neural Networks (ANN):

ANN is a common modelling tool comprising a multilayer perceptron (MLP) paradigm. MLP has an output-layer, a hidden-layer, and an input-layer of neurones. The input-layer neurones send signals to the hidden neurones. ANN is usually considered as a non-analytical and non-equilibrium model, it produces numerical results to forecast the composition of produced gas from the gasifier. Nevertheless, the ANN simulation of downdraft gasifier needs an extensive amount of BG data, and has many restrictions in dynamic modelling.

ANN can catch the latent characteristics of the experimental data, such as nonlinearities. For biomass gasification modelling, the multilayer perceptron neuron networks were employed. Operating conditions of the gasifier and biomass data were correlated by ANN models. It was proven that the model shows excellent performance with parsimonious units, when it was designed for a specific gasifier. Predictive and observed data achieved high correlation rates. The developed ANN model requires little computational time, which makes it very appealing in the process optimization and real-time control. ANN is simply calibrated and, at any time, new data can be added to the database. Consequently, the ANN can be retrained to improve predictive capability.

The system outputs processed temperature and syngas composition, while the inputs handled fuel and air flow prediction of syngas composition and temperature. The proposed ANN confirmed its potential to forecast BG process parameters on various loads with feasible accuracy. It was used as a simulation tool to examine the impacts of process variables (such as air and fuel flow), with fuel injection frequency. Simulations showed that the process improves the efficiency and syngas quality by 25%. However, the controller needs to be tested in real time gasifier operation [13].

Air flow control:

It reduced fan power consumption by averting the temperature violation from the desired heat. The neuro-fuzzy fan speed control evaluates the required speed, which keeps the temperature close to the anticipated temperature and helps to decrease power consumption to 30%. According to air flow and load results, PI control is faster but has greater overshoot, while PI-fuzzy control is much slower and smoother.

Nae [14] presented PI control within a supersonic blowdown wind tunnel, as it was important to control air flow to keep the imposed experimental conditions. A developed control model was analyzed using PI control. The control strategy was validated using experimental data collected from real tests. The results showed that the PI control has greater overshooting than the imposed by 10%, and its acceleration time is too great. Therefore, fuzzy-PI control was implemented, where rise time is close to ideal (1.5 seconds), and overshooting is kept below the imposed.

The proper setting of exact values of air flow speed (<0.06 m·s-1) or pressure drop (<50 Pa) allowed the reproducibility of the tests. The Arduino has confirmed to be an efficient and cost-effective system for the proposed control method. This technique decreased the settling time per set point by 77.6%. Pressure drop and airflow speed set points can be assigned with heterogeneous or homogeneous distribution.

The operation of the fuzzy control, PID control, and the fuzzy PID control was examined. Compared to PID control, the fuzzy PID control showed smaller overshoot, faster response, and higher precision. Compared to fuzzy control, the fuzzy PID control eliminated the steady-state control. Regarding fan power consumption, the fuzzy PID control is economical and energy efficient.

Membrane hydration dynamics model, anode and cathode mass flow transients were developed in Matlab. An FFPID controller can adapt PID parameters to adjust air flow using a fuzzy logic optimization loop. Thus, preventing oxygen starvation. The simulation showed the effectiveness of the developed FFPID in controlling the oxygen excess ratio and in decreasing power loss.

Baroud, et.al. [15], proposed a fuzzy-PID control for air supply on PEMFC systems. The aim is to regulate the oxygen excess ratio at a given set point, preventing oxygen starvation. The control system has a fuzzy logic control, a fuzzy-based self-tuned PID and a fuzzy selector. The fuzzy selector chooses the control method based on the value of the error between the set point and current value of oxygen excess ratio. Simulations for different load variations demonstrated that fuzzy-PID control operates considerably better than the classical PID control regarding overshoot, settling, and acceleration time.

The nominal feedback control (NFC) was compared with MRAC in the air management system, under steady state, and transient responses. MRAC was fast to return the air mass flow rate to normal conditions during the surge in the system. This showed that the MRAC demonstrated a better operation than the NFC concerning surge recovery and the transient behaviours of an automotive FCS.

Conclusion

In the realm of biomass gasification, an array of sophisticated control strategies and techniques has emerged, each contributing to the advancement of this promising technology. These control methods, which range from fuzzy logic and PID control to neural networks and predictive modeling, serve as critical tools for optimizing gasification processes, increasing efficiency, and ensuring product quality.

Furthermore, the integration of artificial intelligence, machine learning, and advanced modeling has opened new frontiers in the control of biomass gasification. These technologies offer the potential for real-time optimization, adaptive control, and the ability to respond to varying feedstock compositions and operating conditions, making gasification systems more robust and versatile.

However, the journey towards harnessing the full potential of biomass gasification is far from over. Researchers and engineers continue to explore innovative control strategies and adapt existing ones to meet the challenges posed by different feedstocks, moisture levels, and gasifier configurations. Additionally, the scale-up of gasification processes for commercial use demands even greater control precision and efficiency.

As sustainability and renewable energy sources become increasingly vital, biomass gasification stands as a promising technology for converting organic materials into valuable resources. The control strategies discussed here play a pivotal role in realizing this potential, ensuring that biomass gasification remains a viable and sustainable path toward a greener future. Further research, development, and collaboration will be key in unlocking the full benefits of this transformative technology.

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Газификаторлармен басқару әдістеріне шолу

*[1]*АМАНКЕЛДІ Шоқан Аманкелдіұлы,* *докторант, amankeldin1992@gmail.com,*
[1]КАЛИНИН Алексей Анатольевич, *PhD, кафедра меңгерушісі, a.kalinin@kstu.kz,*
[1]«Әбілқас Сағынов атындағы Қарағанды техникалық университеті» КеАҚ, Қазақстан, Қарағанды,
Н. Назарбаев даңғылы, 56,

**автор-корреспондент.*

Аңдатпа. *Биомасса тұрақты энергия көзі ретінде қазбалы шикізатты пайдалануды қажет етпейді. Зерттеушілер анық емес басқару, PID басқару және нейрондық желілер сияқты әдістерді қарастырады, және олар көбінесе жасанды интеллектпен және болжамды модельдеумен толықтырылады. Бұл биомассаны газдандыру саласындағы оңтайландыру стратегияларын өзгертеді. Негізгі қамтылатын бағыттар: анық емес басқару: өздігінен үйренетін модульдерді және анық емес қорытынды жүйелерінің бейімделгіштігін тексеру, мысалы, қос сұйық қабат газдандыру. PI/PID бақылау: пропорционалды-интегралдық-туынды бақылаудың DDE-PI баптауымен газификатордың температурасын басқарудағы рөлін қарастыру. Жасанды нейрондық желілер (ANN): газ құрамын болжау үшін ANN үлгілеріне ерекше мән беру. Ауа ағынын басқару: нейро-анық емес және PI басқару арқылы қуатты оңтайландыру. Бұл шолу басқару жолдарының биомассаны газдандырудағы маңызды рөлін атап көрсетеді, стратегиялар мен қолдану тәсілдері туралы түсінік береді, тұрақты энергия өндіруге және экологиялық таза химиялық синтезді жүзеге асыруды көмектеседі.*

Кілт сөздер: *биомасса, баламалы энергия көзі, биоэнергетика, тұрақты энергетика, биоотын, биомассаны газдандыру, басқару әдістері.*

Обзор методов управления газификатором

*[1]*АМАНКЕЛЬДИН Шокан Аманкельдыулы,* *докторант, amankeldin1992@gmail.com,*
[1]КАЛИНИН Алексей Анатольевич, *PhD, зав. кафедрой, a.kalinin@kstu.kz,*
[1]НАО «Карагандинский технический университет имени Абылкаса Сагинова», Казахстан, Караганда,
пр. Н. Назарбаева, 56,

**автор-корреспондент.*

Аннотация. *Биомасса, являясь устойчивым источником энергии, обладает потенциалом, не требующим использования ископаемого сырья. Ученые исследуют такие методы, как нечеткое управление, ПИД-регулирование и нейронные сети, часто дополняемые искусственным интеллектом и прогностическим моделированием. Это меняет оптимизационные стратегии в области газификации биомассы. Ключевые области включают: Нечеткое управление: изучение самообучающихся модулей и адаптивности систем нечетких выводов, например, при газификации в двойном псевдоожиженном слое. ПИ/ПИД-регулирование: рассмотрение роли пропорционально-интегрально-деривативного управления в регулировании температуры в газификаторе, с настройкой DDE-PI. Искусственные нейронные сети (ИНС): особое внимание уделяется моделям ANN для прогнозирования состава газа. Управление воздушным потоком: оптимизация мощности с помощью нейро-нечеткого и ПИ-регулирования. Данный обзор подчеркивает важную роль управления в процессе газификации биомассы, дает представление о стратегиях и способах применения, способствующих устойчивому производству энергии и осуществлению экологически чистого химического синтеза.*

Ключевые слова: *биомасса, альтернативный источник энергии, биоэнергетика, устойчивая энергетика, биотопливо, газификация биомассы, методы контроля.*

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