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Development of a vision-based soft sensor for estimating equivalence ratio and major species concentration in entrained flow biomass gasification reactors

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HIGHLIGHTS

- A vision-based soft sensor was developed for monitoring biomass gasification.
- Vision-based monitoring was evaluated on a pilot-scale gasifier.
- Different data processing methods were compared.
- Results show that vision-based monitoring is applicable in biomass gasification.
- The soft sensor predicted equivalence ratio and gas composition with good accuracy.

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ABSTRACT

A combination of image processing techniques and regression models was evaluated for predicting equivalence ratio and major species concentration (H_2, CO, CO_2 and CH_4) based on real-time image data from the luminous reaction zone in conditions and reactors relevant to biomass gasification. Two simple image pre-processing routines were tested: reduction to statistical moments and pixel binning (subsampling). Image features obtained by using these two pre-processing methods were then used as inputs for two regression algorithms: Gaussian Process Regression and Artificial Neural Networks. The methods were evaluated by using a laboratory-scale flat-flame burner and a pilot-scale entrained flow biomass gasifier. For the flat-flame burner, the root mean square error (RMSE) were on the order of the uncertainty of the experimental measurements. For the gasifier, the RMSE was approximately three times higher than the experimental uncertainty – however, the main source of the error was the quantization of the training dataset. The accuracy of the predictions was found to be sufficient for process monitoring purposes. As a feature extraction step, reduction to statistical moments proved to be superior compared to pixel binning.

1. Introduction

The production of carbon–neutral motor fuels from entrained flow gasification (EFG) of biomass has shown techno-economical potential [1]. In the EFG technique, the fuel is fed as a powder or droplets into the – preferably pressurized – reactor that is operated by using pure oxygen as oxidizer. This technology results in a relatively hot reactor (with temperatures in excess of 1000 °C) compared to other gasification technologies; therefore, only a low amount of tar is formed and a clean synthesis gas (syngas), ideal for upgrading to motor fuels [2], is produced. The high process temperature melts the ash which therefore can be extracted continuously at the bottom of the gasifier thus enabling prolonged, continuous operation. The possibility to continuously remove the ash allows ash-rich fuels such as black liquor [3] or coal [4] to be used. The EFG technique has also shown good scalability [5] compared to other gasification techniques.

The EFG process generates significant quantities of soot [6] that reduces the final extent of the fuel-syngas conversion – and consequently the overall efficiency – of the process. Another issue with the EFG of biomass powder is fluctuations and interruptions in the fuel

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feeding that are inevitable due to the properties of the granular fuel [7]. High-frequency fluctuations can have magnitudes up to 20% of the nominal value [8], altering the temperature and gas composition and also affecting the efficiency of the gasifier; therefore, it is essential to detect and minimize these fluctuations if maximum efficiency is desired. Other factors, such as the moisture content, size distribution and compression of the fuel powder and the characteristics of the feeding system itself affect the expected fuel feeding and process efficiency. Since interruptions and variation in the fuel feeding can extinguish the flame and potentially contribute to slagging problems, the process requires tenacious monitoring.

It has been shown in numerous works that monitoring cameras can be installed in a gas-flushed probe for visualization and monitoring of the high temperature and pressurized gasification process. The process visualization can help the operator successfully detect the most obvious process failures such as ash depositions [9] or plugging of the slag tapping hole [10] together with process information such as the powder ignition [11] and the flame appearance with respect to burner settings [12]. Additionally, the camera-based monitoring provides high-frequency data compared to those of conventional, probe-based instruments, the vision-based monitoring can therefore potentially resolve the problematic fast fluctuations by observing their effect on the appearance of the flame. Several past studies demonstrated that parameters relevant to combustion can be extracted from simple digital images.

The use of vision-based systems directly monitoring the reaction zone in conjunction with on-line image processing has been demonstrated in several applications. For example, Chen et al. showed that excess air can be estimated based on real-time image data [13] and Nan et al. showed that the NO_x emissions during the combustion of biomass can be monitored using image processing via artificial neural networks (ANN) in the deep learning ansatz [14]. Lu, Yan & Colechin showed that the furnace load can be correlated to processed image data [15] and Zhou et al. demonstrated that images of the flame can be used for online identification of coal type fired in a full-scale boiler [16]. One of the most important parameters during combustion is the burner settings. Allen et al. demonstrated an ANN-based monitoring system for the recognition of burner parameters in systems firing liquid fuels [17], and Lu, Yan & Huang reported on a similar system for gaseous fuels [18]. González-Cencerrado et al. studied the possibility of using processed image data for regressing excess air in swirling pulverized coal combustion [19].

The Image processing can either include extracting pre-defined parameters from the images [18] or the raw pixel intensity values can be used directly without pre-processing [20]. The extracted features can be geometrical such as flame length and width or radiometric such as maximum, mean and standard deviation of image pixel intensities and flicker frequency [21]. After pre-processing, the image data can be related to process parameters relevant to the combustion or gasification technology. Artificial Neural Networks [22] and Gaussian Process Regression (GPR) [23] are two examples of machine learning methods that have been shown to be successful as regression techniques in combustion and energy applications [24]. Parameters with a directly interpretable physical meaning, such as temperature [25] and flow rates [26] can also be used as inputs for the regression algorithms. The use of real-time process data in conjunction with ANN has been demonstrated for real-time and future estimations of NO_x emissions during coal combustion [27] and demolition wood combustion [28]. The capability of the method for providing forecasts suggest that a time delay within the data can be handled by the regression technique.

The method of combining process data with image data has also recently been demonstrated and used for prediction of the thermal output from a grate-fired biomass boiler [29]. The concept of applying these machine learning algorithms is to take the actual physics of the monitored facility into account without having to analytically derive the underlying relationship between the physics and image features. This concept implies that the developed data-driven regression models are limited to operating ranges defined by major parameters such as the characteristics of the facility and the fuel type with which the model was trained.

The equivalence ratio can be estimated in a responsive and non-intrusive way in fuel rich environments through the measurement of the ratio of chemiluminescence signals [30]. However, chemiluminescence measurements applied to the diagnostics of gasifiers would require a strategy to distinguish the chemiluminescence signal from the wide-band emission originating from walls, soot and ash. Furthermore, in a real-scale industrial setting, the usage of expensive and sensitive equipment required for chemiluminescence imaging (e.g., intensified CCD cameras) is impractical.

Other measurement techniques, such as on-line gas analysis using gas chromatography (GC) together with trace-gas analysis can be used for calculating the equivalence ratio from the mass balance; this works well if fuel conversion is near-complete. In gasification, the mass balance is difficult to close due to the generally unknown amount of intermediate reaction products. Another drawback to consider when applying GC measurement is its time delay: due to gas sampling, condensation, cooling, dilution, analysis, etc., the response time of GC-based process monitoring is on the order of minutes. Here, with respect to sampling rate, optical methods such as tunable diode laser absorption spectroscopy (TDLAS) or camera-based monitoring is capable of near-instantaneous measurements of major species. More specifically, the response time of the described instrument is on the order of the reciprocal of the frame rate; i.e., 20 ms for regular video cameras. The response time of a control system based on the proposed method is of course a function of many factors, most of which are process-specific.

The objective of this work is to investigate the capabilities and potential of vision-based monitoring to estimate the equivalence ratio and concentration of major gas species in EFG. Two regression methods, GPR and ANN were evaluated, along with two image pre-processing methods for data reduction, data representation through statistical moments and pixel binning. As per the authors knowledge, these techniques have not been demonstrated on gasifier reactors yet.

The developed monitoring system was first evaluated on fuel-rich, premixed C_2H_4–O_2–N_2 flames stabilized on a McKenna (flat-flame) burner. The simplicity of this setup allowed for the accurate calculation of the equivalence ratio from the input mass flow rates directly. After validating the proposed technique by using the McKenna setup, the monitoring system was further tested in operation on a pilot-scale EFG reactor, using wood powder as fuel.

2. Materials and methods

2.1. Flat-flame burner and gasifier setup

The premixed C_2H_4-O_2-N_2 flames studied in this work were stabilized on a McKenna burner with a central jet opening. The diameter of the burner was 60 mm and the outer diameter of the central jet was 9.5 mm. For the premixed flames, a $O_2/(O_2+N_2)$ molar ratio of 35% was used. Oxygen enrichment was used to increase the burning velocity of the flames and consequently extend the range of equivalence ratios that can be stabilized on the burner without blow-out. A total flow of 10 L/min of the premixed gas was used together with 15 L/min of N_2 supplied in a shroud stream in order to protect the flame from ambient air intrusion. The flow rates of the gases to the burner were measured by using calibrated mass flow controllers (Bronkhorst EL-flow) from which the equivalence ratio was calculated with an uncertainty of ±0.031, based on the uncertainty of the flow controllers. The equivalence ratio of the flames was varied between 1.9–3.2 in increments of 0.05 by adjusting the flow rates. The arrangement of the burner and the camera systems can be seen in Fig. 1a. The pilot-scale gasifier used in the experiments was cylindrical with a height of 4 m and was covered by a steel shell. The gasifier had a 0.2 m thick ceramic lining and an