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A quality factor of co-firing pulverized coal and biomass

***Abstract**. This paper presents comparison image classification method of co-firing biomass and pulverized coal. Defined two class of combustion: stable and unstable for nine variants with different power value parameters and fixed amount biomass (20% straw). Compared the artificial neural networks, support vector machine, k nearest neighbor, linear and quadratic discriminant analysis methods. The sensitivity classification value was selected as a combustion process quality factor.*

Streszczenie.** W pracy przedstawiono porównanie wybranych metod klasyfikacji obrazów dla współspalania pyłu węglowego i biomasy. Zdefiniowano dwie klasy spalania: stabilne i niestabilne dla dziewięciu wariantów z różnymi parametrami mocy oraz stałą ilością biomasy (20% słomy). Porównano sztuczne sieci neuronowe, metodę wektorów nośnych, metodę k najbliższych sąsiadów, liniową i kwadratową analizę dyskryminacyjną. Wybrano wskaźnik jakości procesu spalania jako wartość parametru wrażliwość klasyfikacji. (**Wskaźnik jakości dla współspalania pyłu węglowego i biomasy).

Keywords: flame, combustion, image classification. quality factor.
Słowa kluczowe: płomień, spalanie, klasyfikacja obrazów, wskaźnik jakości.

Introduction

Fossil fuels constitute the primary energy source in the Polish power industry. According to forecasts, by 2030, they will continue to be in the major position of approx. 60% share in Poland and approx. 11% share in the EU. Constantly occurring problem of burning fossil fuels is the emission of noxious chemical compounds, mainly carbon dioxide, sulfur dioxide, nitrogen oxides and dust into the environment. The current policy of the European Union aims at the implementation of the climate and energy package. It is based on the reduction of greenhouse gas emissions and electricity consumption by 20% and increasing the share of energy production from renewable energy sources (RES) to 20%. The commitments made by Poland on renewable energy sources involve achieving a 15% share of renewable energy in total energy consumption in the country in 2020.

The quickest way to fulfill the EU requirements is the coal and biomass co-firing with the use of existing installations power plants. There are problems with the preparation of material for combustion, obtaining proper humidity and the required fineness of the raw material. Biomass has different physicochemical properties than coal; it is not a homogeneous mixture, with a different degree of granulation. For this reason, the share of biomass co-firing process stability deteriorates and reduces the capacity and efficiency of the boiler. Deterioration also occurs in the case of combustion stability, along with the percentage of biomass [1].

The use of the flame as a source of information about the process of combustion is one way to diagnose this process. By analyzing the flame image [2], one can obtain information about the process with virtually no delays. This is particularly important in the case of combustion of fuel characterized by high variability of the physicochemical properties. These include, among others, a mixture of biomass and coal, the combustion is the most common way to use the Polish renewable fuels.

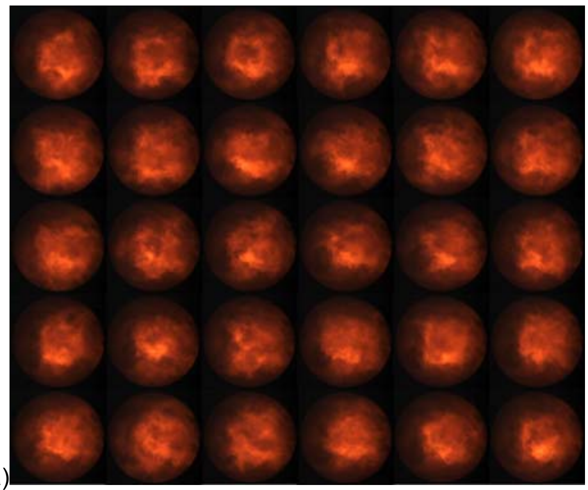
Flame is accompanied by an exothermic oxidation reactions. The presence of the flame is therefore associated with a place in the space where this type of reaction occurs. It is difficult in this case to indicate a line between the space in which combustion occurs because the reactant concentrations are not changed in step-wise manner. The main source of particulate radiation in the flame are heated to a high temperature solid particles (coal dust, soot, ash). Existing absorption and scattering of radiation introduce additional ambiguity in defining the border of the flame.

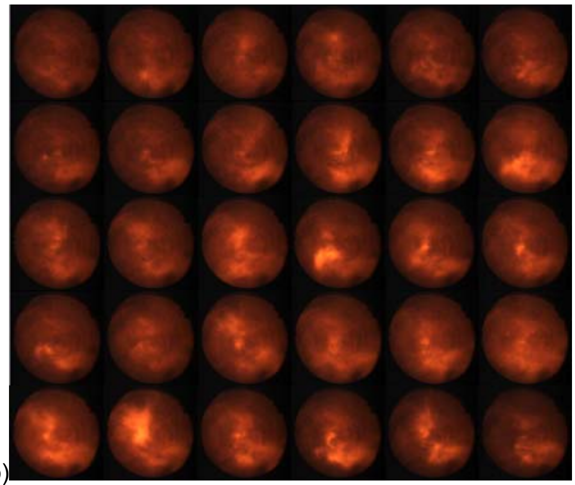
Combustion tests were carried out on the test bench at the Institute of Energy. Measurements were made at the position of the camera perpendicular to the axis of the flame for different variants of power. After the initial analysis of the images of the co-pulverized coal and biomass, the sequence of images of stable and unstable combustion was determined. Image classification method was used to determine the state of the process. The article compared five methods for image classification ANN, SVM, k-NN, LDA and QDA with 20% weight participation of biomass [3-9].

This study presents the possibility of using quality factor for the combustion process in the 20% weight fraction of biomass. The consequence of increasing the weight fraction of the biomass course, is the deterioration of the stability of the combustion process. However, from the point of view of the boiler operator, the most important parameter is the sensitivity of the classification, which directly determines the probability of detecting an unstable state.

Flame stability

Flame stability can be defined as a set of conditions for which the existence of the flame is still possible; their exceeding leads to its disappearance. The consequences of unstable combustion are economic, i.e. greater combustion loss, faster wear of the components of the burner and combustion chamber. The second is safety aspect, known as the ability to flame loss. The first 30 frames of stable and unstable combustion sequence are presented on figure 1.

a)




b)

Fig.1. The first 30 frames of combustion image sequences: a) stable combustion, b) unstable combustion

During the image sequences registration operator determined the images of stable and unstable combustion process. The distribution of stable and unstable combustion process is presented in table 1.

Table 1. Combustion process classes

Variant	Stable process		Unstable process	
	%*	Number of images	%*	Number of images
1	19	1710	81	7290
2	44	3960	56	5040
3	13	1170	87	7830
4	62	5580	38	3420
5	88	7920	12	1080
6	62	5580	38	3420
7	64	5760	36	3240
8	77	6930	23	2070
9	83	7470	17	1530

*) – the percentage of frame images for each process class.

Laboratory combustion facility

Combustion tests were done in a 0.5 MWth (megawatt of thermal) research facility, enabling scaled down (10:1) combustion conditions. The main part is a cylindrical combustion chamber of 0.7 m in diameter and 2.5 m long. A low-NOx swirl burner about 0.1 m in diameter is mounted horizontally at the front wall. The stand is equipped with all the necessary supply systems: primary and secondary air, coal, and oil. Pulverized coal for combustion is prepared in advance and dumped into the coal feeder bunker. Biomass in a form of straw is mixed with coal after passing through the combustion chamber has two lateral inspection openings on both sides, which enable image acquisition. A high-speed camera with CMOS area scan sensor was placed near burner's nozzle, as shown in Fig. 2.

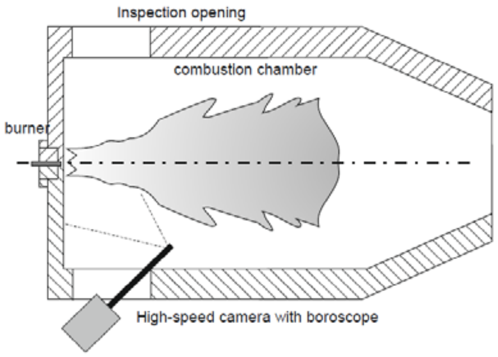


Fig.2. Combustion chamber with camera mounting

Flame images were transferred from the interior of the combustion chamber through a 0.7 m borescope. The camera was acquire 30 frames per second at its full resolution (1280x1024 pixels). The optical system was cooled with water jacket. Additionally, purging air was used to avoid dustiness of optical parts [10].

Combustion tests

Combustion testes were done for different variants (combinations) of the combustion facility, where thermal power (P_{th}) and excess air coefficient (λ) were set independently for known biomass content (20%), where λ is defined as quotient the mass of air to combust 1kg of fuel to mass of stoichiometric air. The exact values of thermal power and excess air coefficient are collected in Table 2.

Table 2. Combustion process variants

Variant	$P_{th,}$ kW	λ	Fuel, kg/h	Secondary air, nm^3/h
1	250	0.75	36.0	73.2
2	250	0.65	39.4	62.9
3	250	0.85	35.2	103.6
4	300	0.75	43.5	96.4
5	300	0.65	42.6	67.4
6	300	0.85	44.2	132.5
7	400	0.75	59.7	181.3
8	400	0.65	56.8	152.8
9	400	0.85	59.4	205.1

By drawing, a division was made into sets: training, validation and test, each of them counted the three thousand cases. Data sets were divided in equal proportions to excessive number of training set had no effect on reducing the number of sets of observations used to assess the accuracy of classifiers. In each of these three sets retained the same ratio between the number of cases the state of the process: stable and unstable, which full data set. As a result, each variant composed of different amounts of instances of the class stable and unstable. In order to classify the status of the process it is necessary to identify the characteristics that are distinguishing features between the images of the groups. Descriptors should be defined as numerical values describing the image in a quantitative way. The descriptors are: the shape of the object, the length of the contour, the surface area of the flame, coordinates of the center of heaviness (X,Y), circularity, central moments, content, convexity, squareness. The main goal of the tests are detected when co-firing is stable or unstable using appropriates methods.

Classification parameters

In order to assess the classification quality is necessary to apply appropriate measures. In the present paper were used the most popular measure of the classification task (accuracy, specificity and sensitivity). The first parameter, sensitivity (*TPR*), is defined by the formula:

$$TPR = \frac{TP}{TP + FN}, \quad (1)$$

where *TP* is the number of unstable combustion images classified to the class of unstable combustion (true-positive classification) and *FN* is the number of unstable combustion images classified to the class of stable combustion (false-negative classification). It gives the estimation of the probability of correct classification of the case as unstable, provided that it belongs to the class of unstable combustion. The second parameter, specificity (*TNR*), is defined by the formula:

$$TNR = \frac{TN}{TN + FP}, \quad (2)$$

where *TN* is the number of stable combustion images classified to the class of stable combustion (true-negative classification) and *FP* is the number of stable combustion images classified to the class of stable combustion (false-positive classification). It gives the estimation of the probability of correct classification for the case as stable, provided that it belongs to the class of stable combustion. The last parameter is classification error. Error is the probability of incorrect classification belonging to both class, calculated using the formula:

$$ERR = \frac{FP + FN}{TP + TN + FP + FN} . \tag{3}$$

In the remaining part of this paper, the results of the study are presented. Three parameters have been used to assess the quality, namely sensitivity (1), specificity (2), and error (3) classification. However, from the point of view of the boiler operator, the most important parameter is the sensitivity of the classification, which directly determines the probability of detecting an unstable state.

Classification using artificial neural networks (ANN)

Artificial neural networks are a concept of data processing based on the operation of neuronal organisms.

For the construction of classifiers based on artificial neural networks (ANN) used the simplest MLP network with one hidden layer. After performing a series of tests as the best, selected model is ANN. This model is characterized by the following parameters: function activation softmax, five neurons in the hidden layer. It adopted as possibility direct connection to the input layer to the output and the maximum number of iterations equal to a thousand. Determined the specificity, sensitivity, and the accuracy of classification model ANN-5.

Classification using k Nearest Neighbor

k-nearest neighbor is a method for classifying objects using training examples in the feature space. From all machine learning algorithms k-nearest neighbor is the simplest. Training process for this algorithm only consists of storing feature vectors and labels of the training images. In the classification process, the unlabeled query point is simply assigned to the label of its k nearest neighbors. Typically the object is classified based on the labels of its k nearest neighbors by majority vote. If k=1, the object is simply classified as the class of the object nearest to it. When there are only two classes, k must be a odd integer. However, there can still be ties when k is an odd integer when performing multiclass classification. After we convert each image to a vector of fixed-length with real numbers, we used the most common distance function for KNN which is Euclidean distance:

$$d(x,y) = \|x - y\| = \sqrt{(x-y)(x-y)} = \sqrt{\sum_{i=1}^{m}(x_i - y_i)^2} , \tag{4}$$

In the k-NN classifier learning process, tested the full data set for all combustion variants with different k parameter value (range 1-10). The lowest values of classification errors obtained for the parameter K = 7 (model 7-NN).

Classification using Support Vector Machine (SVM)

SVM is generalized lineral (non-linear with RBF kernel) classifier and its characterized as classifier that can minimize the error. The main conception of SVM learning system is a separate hyperplane by two parallel hyperplane. A vector is mapped to the interval to establish a hyper-plane of the largest higher-dimensional space. The optical plane *H* is found by maximizing the margin value $2/||w||$. Hyperplanes H_1 and H_2 are the planes on the border of each class and also parallel to the optical hyperplane *H*. The data located on H_1 and H_2 are called support vectors This method can be effective, real-time to determine the brightness of the flame and to analyze the combustion state. There are several kernels that can be used in support vector machines models. These include linear, polynomial, radial basis function (RBF) and sigmoid function.

After performing a series of tests as the best, selected model SVM-1. This model is characterized by the following values: parameter γ = 2, polynomial kernel function, the degree of the polynomial D = 1, the free value δ = 10. They determined the sensitivity, specificity, and accuracy of the classification model SVM

Classification using k Nearest Neighbor

Linear discriminant analysis and quadratic discriminant Analysis, are also popular classification techniques, using space division features. In the case of, linear and quadratic discriminant analysis, there is no typical validation stage classifier arising from the specifics of these methods. For the linear separability criterion classes can be regarded an expression:

$$F = \mathbf{S}_b / \mathbf{S}_w , \tag{5}$$

where: S_b -beetwen class scatter, S_w - with class scatter. The higher the value of F, the greater the probability linear separation classes. The best results obtained for LDA and QDA models.

Results

Combustion process classification state is based on artificial neural networks, support vector machine, k-nearest neighbor, linear and quadratic discriminant analysis.

Table 3 presents all models classification error for 20% of the weight of biomass compared to variants.

Table 3. Various classifying error model

Variant	ANN-5	SVM-1	7-NN	LDA	QDA
1	0.2119	0.2176	0.2237	0.2435	0.2494
2	0.2074	0.2056	0.2013	0.2297	0.2466
3	0.2188	0.2018	0.2185	0.2192	0.2297
4	0.2023	0.2098	0.1974	0.2335	0.2544
5	0.2021	0.1978	0.1926	0.2409	0.2449
6	0.2032	0.1998	0.1954	0.2344	0.2295
7	0.2006	0.2016	0.1976	0.2295	0.2367
8	0.2064	0.1986	0.1906	0.2273	0.2247
9	0.2023	0.1931	0.1854	0.2491	0.2585

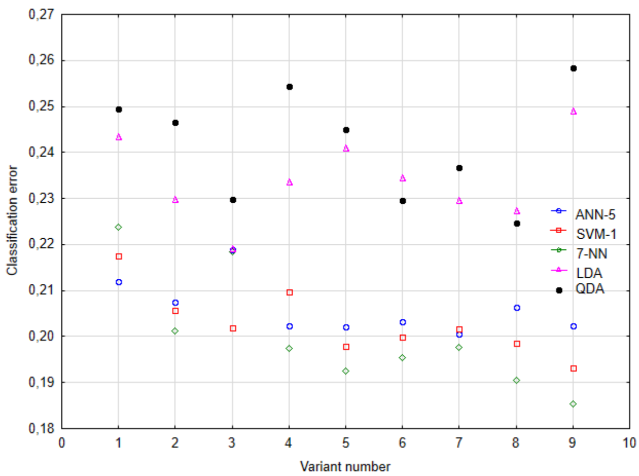


Fig.3. Classification error for the various models

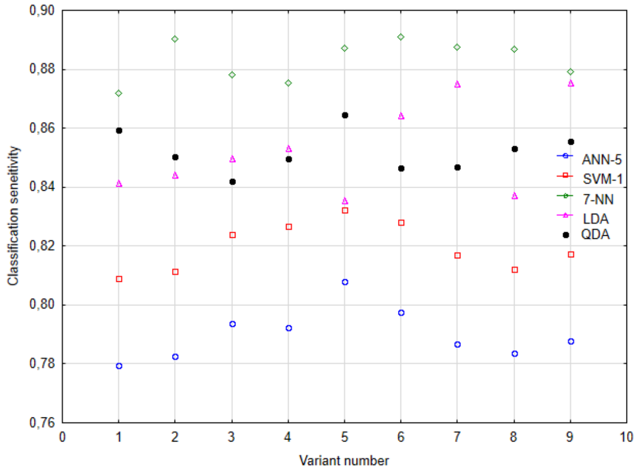


Fig.4. Classification sensitivity for the various models

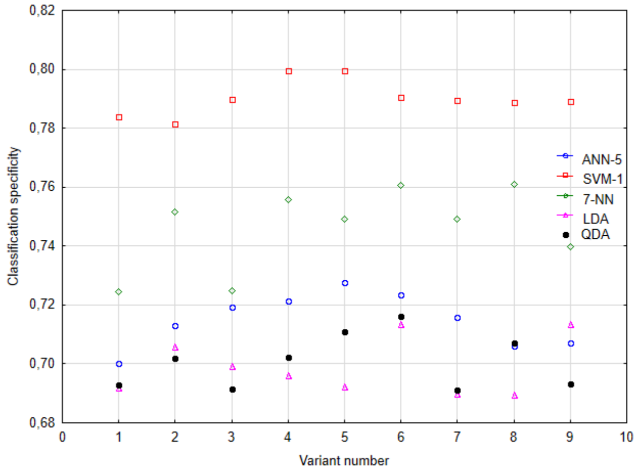


Fig.5. Classification specificity for the various models

In contrast, figures 3-5 shows the classification error, sensitivity and specificity for different models and different combustion variants. Based on the above results, it is found that the lower classification error obtained model 7-NN for all combustion variants expect 1 and 3. 7-NN classification model also obtained best results for the sensitivity parameter which is more important for classification quality. k-NN classifier handle worse in the first and third variant of combustion process, which is more than 80% of unstable combustion cases. For the specificity parameter, SVM classifying model gives better outcome for all combustion variants than other models.

Table 4 presents sensitivity, specificity and error average value for five classifying models.

Table 4. Sensitivity, specificity and error for classifier models

Model	Sensitivity	Specificity	Error
ANN-5	0.7902	0.7149	0.2061
SVM-1	0.8198	**0.7931**	0.2029
7-NN	**0.8830**	0.7463	**0.2003**
LDA	0.8528	0.6990	0.2419
QDA	0.8520	0.7008	0.2579

The highest sensitivity achieved 7-NN classifier of 0.8830 and relatively good specificity of 0.7463. Other models reached lower values of sensitivity appropriately SVM-1 7.7% and ANN-5 10.5%. It was found that 7-NN classifier model with classification error of 0.2003, provides the highest sensitivity. In operator point of view, the most important quality factor is sensitivity. It gives the estimation of the probability of correct classification of the case as unstable, provided that it belongs to the class of unstable combustion. Based on sensitivity value 7-NN model was considered to be the best.

Conclusions

Continuous attempts to increase the reliability of the power boilers and increasing restrictions on their work in the economic and ecological context require the use the latest available methods of diagnosis and assessment the combustion process. In this paper we propose a quality factor for combustion process state which is sensitivity. 7-NN classifying model obtained the best value of this parameter of 0.883. From the boiler operator point of view the methods and factors are adequate to correctly assess the state of the process.

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