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ARTIFICIAL INTELLIGENCE METHODS IN DIAGNOSTICS OF COAL-BIOMASS BLENDS CO-COMBUSTION IN PULVERISED COAL BURNERS

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МЕТОДИ ШТУЧНОГО ІНТЕЛЕКТУ У РОЗПІЗНАВАННІ ГОРІННЯ ВУГІЛЬНО-БІОМАСОВИХ СУМІШЕЙ У ПИЛОВУГІЛЬНИХ ПАЛЬНИКАХ

The paper presents technologies being developed in the Institute of Electronics and Information Technologies at Lublin University of Technology. They use optical sensors and artificial intelligence methods for process supervision and diagnostics. Research is aimed to develop a system allowing a parametric evaluation of the quality of pulverized coal burner operation. Due to the highly nonlinear nature of dependencies and lack of an analytical model, the artificial intelligence methods were used to estimate and classify the selected parameter, including a relatively new class of classification methods – artificial immunology algorithms. The article shows results for coal-shredded straw blends, yet the methodology may be applied for other types of blends.

Key words: biomass co-combustion, neuro-fuzzy modelling, artificial immune classification.

У роботі представлені технології, розроблені в Інституті електроніки та інформаційних технологій Люблінського технологічного університету. Вони використовують оптичні датчики та методи штучного інтелекту для контролю та діагностики процесу. Дослідження спрямовано на розробку системи, що дозволяє провести параметричну оцінку якості роботи пиловугільного пальника. Через високу нелінійну природу залежностей та відсутність аналітичної моделі для оцінки та класифікації обраного параметра були використані методи штучного інтелекту, включаючи відносно новий клас методів класифікації - алгоритми штучної імунології. У статті наведені результати для солом'яно-вугільних сумішей, але методологія може застосовуватися і для інших типів сумішей.

Ключові слова: спалювання біомаси, нейро-нечітке моделювання, штучна імунна класифікація.

Introduction

It seems that in spite of growing share of other types of energy sources, burning various types of fuels will remain the main source of energy throughout the next decades. Unfortunately, it will also remain the greatest source of atmospheric pollution. On 23rd January 2008, the European Commission put forward a far-reaching package of proposals where it commits itself to reduce its overall emissions to at least 20% below 1990 levels by 2020. It has also set the target of increasing the share of renewables in energy use to 20% by 2020. The latter commitment results in search of new technologies that partially or entirely make use of renewable energy sources. This is also a case of combustion technologies where alternative fuels obtained from renewable sources are used. In the case of pulverized coal burners, biomass co-combustion may be applied. The efficient and clean combustion of those fuels poses a number of technical challenges. In general, alternative fuels are characterised by low to very-low calorific values and by fluctuating properties (among different batches, or along the time in a continuous process). The variability of this type of fuels can bring the system to off-design operation and cause increased pollutant emissions, lower efficiency or flame stability problems. Therefore, permanent supervision and optimization becomes an issue that should be addressed in order to guarantee the reliability of a practical system.

The paper presents the technologies being developed in the Institute of Electronics and Information Technologies at Lublin University of Technology. They use optical sensors and artificial intelligence methods for process supervision and diagnostics. Research is aimed at developing a system allowing parametric evaluation of the quality of pulverized coal burner operation. The information about the status of the device is useful only when it has a form understandable to the operator or automatic control system and diagnostics. In the article, first we analyse the possibility to obtain quantitative information on the basis of optical signals originated by a flame, on the example of nitrogen oxides. Next we consider the diagnostic case when improper operation of the burner consists in too high or too low excess air coefficient, diagnostics will therefore be relied on to detect three states.

Due to the highly nonlinear nature of dependencies and lack of an analytical model, the artificial intelligence methods were used. Two examples will be shown, i.e. the fuzzy networks and artificial immunology algorithms.

Tests – methodology, facility and measurements

Combustion of pulverized coal was examined through optical methods, which were based on analysis of wide spectrum radiation emitted by the flame. The analysis also takes into account spatial features of such radiation source. Combustion of pulverized coal in the power burner takes place in a turbulent flow. In its each point, local fluctuations of both fuel and gaseous reagents concentrations, as well as temperature occur. It leads to permanent local changes in combustion process intensity, which result in continuous changes in flame luminosity that can be observed as flame flicker. As combustion process affects the turbulent movement of its products and reagents, it determines the way the flame flicker parameters such as e.g. mean luminosity and luminosity frequency spectrum. A number of combustion supervision and flame-fault protection systems use information contained within flame flicker. The multichannel fibre-optic flame monitoring system developed at Lublin University of Technology belongs to this class of solutions, but additionally it allows observation of selected areas of the flame [1,2].

Experiments were conducted on test rig located in the Institute of Power Engineering in Warsaw. It is a combustion chamber with a single pulverized coal swirl burner made in 1:10 scale in relation to a low-emission industrial burner. This object was chosen because of its ability to perform experiments with a single burner, and its good instrumentation. All measured quantities are visualized and recorded by the data acquisition system. Sampling period is 1s. The combustion chamber is equipped with the above-mentioned optical fibre probe which allows observation of five different areas of the flame.

The experiment begins with bringing the chamber to the proper temperature. When the temperature stabilizes, series of measurements are performed with changing air and fuel flows. During an individual measurement the amounts of fuel and air are kept constant. A single measurement lasts approximately 300 seconds. Such measurement method is used in order to eliminate the impact of the transport delay of gas analysers. It is assumed that during the measurement the conditions are fixed and the emission values stabilized. The tests were conducted at three different thermal loads, for pure pulverised coal and 10% blend with biomass (shredded straw). The amount of secondary air was being changed in order to achieve the air excess corresponding to normal operation, too high and too low conditions. Voltage signals corresponding to the instantaneous brightness of the flame of the areas observed by individual optical fibres were sampled at the rate of 8KS/s and saved by a dedicated system. Figure 1 shows example measurements corresponding to normal, too low and too high air excess ratio.

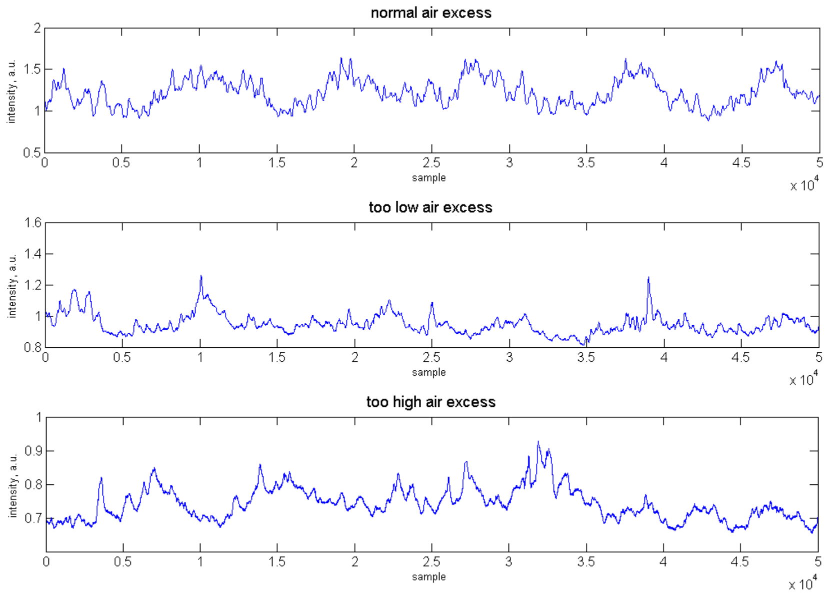

Fig.1. Example measurements corresponding to normal, too low and too high air excess ratio

Neuro-fuzzy algorithms

As first, the diagnostic capability of the combustion process is shown on the example of fuzzy neural network. The combination of neural networks with fuzzy logic has many benefits, especially where traditional methods and solutions do not give good results or to use them for specific tasks would be too time-consuming or costly. This method usually yields better results than SVM and classical neural networks [3]; besides, by removing the last layer of the network fuzzy, information can be obtained and used for warning when symptoms of malfunction (or failure) appear.

Neuro-fuzzy is one of the concepts of artificial intelligence that refers to combinations of artificial neural networks and fuzzy logic, proposed by J. S. R. Jang [4]. Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the connectionist structure of neural networks and the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main advantage of neuro-fuzzy systems is that they are universal approximators with the ability to solicit interpretable IF-THEN rules, yet it involves two contradictory requirements in fuzzy modeling: interpretability versus accuracy. The approach presented in the article focuses on the latter one, implementing the Takagi-Sugeno-Kang (TSK) model. The structure of the model is determined before training and does not change. Training takes the form of adjusting the fuzzy membership functions parameters, in order to minimise the model error.

The Matlab fuzzy logic toolbox and its ANFIS (adaptive neuro-fuzzy inference system) tool were used to design neuro-fuzzy models. The tool allows the construction and training of the Sugeno models using the methods typical for neural networks, e.g. error backpropagation. For this purpose the fuzzy model is converted into an equivalent neural network with the structure of a multilayer perceptron. Due to the strategy of measurements the data were grouped in distinct centres so the fuzzy model structure was generated by subtractive clustering.

Neuro-fuzzy modelling

After completing the measurements the stored time series from each fibre was filtered in order to obtain the same time basis as for process parameters (1 sample per second) and to obtain the following parameters calculated over a period of 1 second: the average intensity value, intensity variance, number of mean value crossings and number of zero crossings (changes of sign) of the signal derivative. Such a choice of parameters was made on the basis of previous studies [5]. Figure 2 shows example waveforms of the signal average intensity and the number of zero crossings of a signal derivative during two subsequent tests for pure coal and secondary swirler angle of 50°. The amount of secondary air was higher for samples 1 to 300 than for samples 300 to 600). The other two aforementioned parameters are omitted so as not to obscure the drawing. The dependence of these parameters on the conditions of combustion of pulverized coal is evident, but this information is not very useful from the viewpoint of managing the process of combustion. Then the next step is such processing of these parameters as to give information about the important parameters of the combustion process The NOx emission was selected for further analysis using neuro-fuzzy modelling.

The goal was to obtain models which error does not exceed 10%. As the simple RMS error value can be misguiding when solitary overshots appear we put an additional criterion that for not more than 5% of samples the error exceeds 10%. The number of 5% was also used for the test data selection i.e. every 20th sample was chosen as a testing one. The best possible set of data to model NOx emissions resulted to be the intensity and the number of zeros of the derivative from fibres 3, 4 and 5.

Next the generalization ability of the method was tested. The first test consisted in reducing the size of the training set in favour of the testing set. Figure 3 shows the results for the scenario when half of the samples were used for training and the other half for testing. Even such a high reduction of the training set did not significantly increase the testing error. The second test was made to check if the model trained for pure coal is able to correctly predict NOx the values for 10% biomass mix. Unfortunately, the test failed basically due to the fact that some input values are outside of the specified input range.

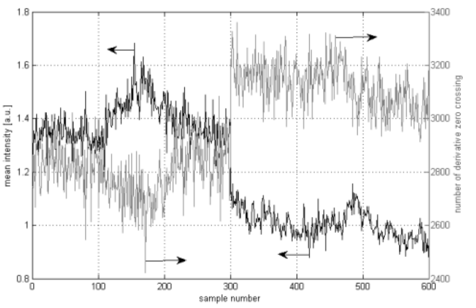

Fig. 2. Plot of example time series parameters for two secondary air flowrates

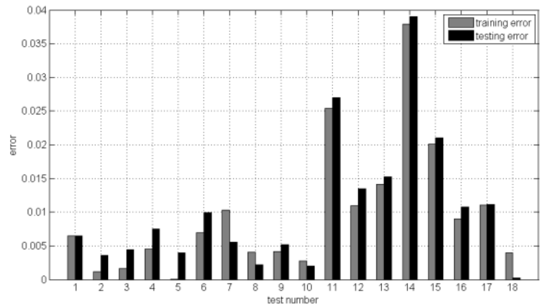

Fig. 3. Training error (gray) and testing error (black). First 9 tests were made using pure coal next 9 tests 10% mix with biomass

Neuro-fuzzy classification

After completing the measurements, the stored time series from each fibre was filtered in order to obtain the same time basis as for process parameters (1 sample per second) and to obtain the following parameters calculated over a period of 1 second: the average intensity value, intensity variance, number of mean value crossings and number of zero crossings (changes of sign) of the signal derivative. Such a choice of parameters was made on the basis of previous studies [5].

As an example, results for a mixture consisting in 90% of the pulverized coal and 10% biomass (shredded straw) are shown. The mixture was prepared prior to the combustion test.

Because both the PCA analysis and orthogonality analysis did not demonstrate the possibility to omit any of the features, all 30 were used. Due to the methodology of research in which the series of tests were made during which constant conditions were kept, measurements were clearly grouped. Therefore, subtractive clustering method was used to determine the number of membership functions. The set of features of a total of 2700 measurements has been divided into a learning part and testing part, 80% and 20% respectively. Using 31 membership functions a classification error of 0.21% for the training set and 1.85% for the test set was obtained. The network was also trained using measurements of both the pure pulverized coal, as well as mixtures with the biomass. A total of 18 variants of burner operation were included with 3 power levels, 3 excess air levels, and 2 types of fuel. The resulting classifier was more versatile. For 80% to 20% learning/testing set division the classification error was 0.8% and 1.3%, respectively. For 60% to 40% division, the error has risen to 1.7% and 5.8%, respectively. This is partly due to the fact that some input was out of training range – neural networks do not have the ability to extrapolate. Leaving the fuzzy outputs Fig.2 enables to notice a rising uncertainty in the low-power rich-biomass region.

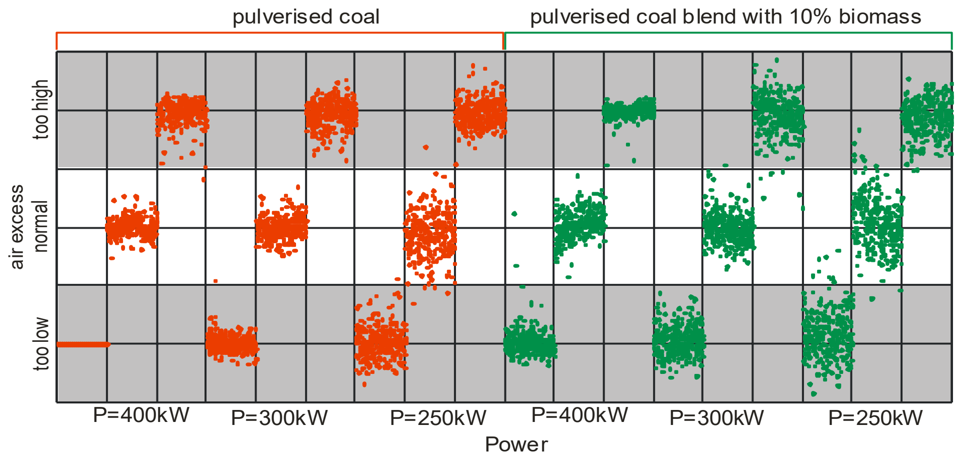

Fig. 4. Fuzzy classification of the excess air ratio for different burner output and two types of fuel

On the basis of the analysis it can be concluded that method presented above is suitable for detecting deviation of the excess air ratio λ of ± 0.1 from the correct value. In the case of coal and biomass co-firing increase in sensitivity may be difficult, especially at a low load of the burner. Method performance is also confirmed by the test in which type of fuel (coal or blend) is being recognised on the basis of optical signals with the accuracy of 99%.

Artificial immune algorithms

In the 1990s, Artificial Immune System (AIS) emerged as a new computational research filed inspired by the simulation of biological behaviour of Natural Immune System (NIS). The NIS is a very complex biological network with rapid and effective mechanisms for defending the body against a specific foreign body material or pathogenic material called antigen.

The Artificial Immune Systems, as defined by de Castro and Timmis [6] are: "Adaptive systems inspired by theoretical immunology and observed immune functions, principles and models, which are applied to problem solving". However, AIS are one of many types of algorithms inspired by biological systems, such as neural networks, evolutionary algorithms and swarm intelligence. There are many different types of algorithms within AIS and the research to date has focused primarily on the theories of immune networks, clonal selection and negative selection. These theories have been abstracted into various algorithms and applied to a wide variety of application areas, such as anomaly detection, pattern recognition, learning and robotics [7,8,9].

Artificial immune classification

In this particular case, the selected coefficients of discrete wavelet transform (DWT) within the local signal intensity of the flame radiation were chosen as the features of the flame. The negative clonal selection was used as classification algorithm. There are three classes to be recognised; hence, the classifier contained three subsets of detectors. The measurement data was processed with DWT (Daubechies 6) in the windows of length of 16,384 samples. Subsequently, the statistical parameters (maximum value, minimum and average and standard deviation) of the most significant transform coefficients – D1, D2, D3, D4 and A1 – were calculated to give the vector of 20 features for each class. A set of features was randomly divided into learning and testing subsets by 30% / 70% and 70% / 30% out of 2400 data points.

In order to avoid the bias associated with the random sampling of the training data, the k-fold cross-validation was also performed. In k-fold cross-validation, the data is partitioned into k subsets of approximately equal size. Training and testing the algorithm is performed *k* times. Each time, one of the *k* subsets is used as the test set and the other *k*–1 subset are put together to form a training set. Thus, *k* different test results exist for the algorithm. However, these *k* results are used to estimate performance measures for the classification system.

The common performance measures used in diagnostics are accuracy, sensitivity and specificity. Accuracy expresses the ability of the classifier to produce accurate diagnosis. The ability of the model to identify the occurrence of a target class accurately is determined by sensitivity. Specificity is determined by the ability of the algorithm to separate the target class. The accuracy can be expressed as:

$$Accuracy(Z) = \frac{\sum_{i=1}^{|z|} Assess(z_i)}{|Z|}, \quad Assess(z) = \begin{cases} 1, & if\ calssify(z) = z.c \\ 0, & \text{otherwise} \end{cases}$$

where: *z* denotes the patterns in testing set to be classified, *z.c* is the class of pattern *z*, *classify*(*z*) returns the classification of *z* by classification algorithm. For sensitivity and specificity analysis, the following equations can be used:

$$Sensitivity = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \quad Specificity = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}$$

where: TP, TN, FP and FN denote respectively true positive, true negative, false positive and false negative classification.

Classification tests using negative clonal selection algorithm were made according to the algorithm described in [10]. Table 1 contains the results of performance analysis. Average accuracy was about 98.99%. Classification accuracy obtained using fuzzy networks (TSK) was about 96.4%. Normalised execution time of both algorithms was similar.

Table 1. Performance measures for negative clonal selection algorithm

learning set/testing set distribution	accuracy	sensitivity	specificity
40/60	98.95	99.25	99.10
60/40	99.18	99.20	99.45
80/20 5-fold cross-validation	98.85	98.75	99.25
mean	98.99	99.07	99.27

Conclusions and remarks

Optical signal can be used for diagnostics of an individual burner. The optical signal is the fastest and provides a selective way of getting information about the quality of combustion. Its interpretation, however, poses many difficulties.

The studies, described in the article, confirm that in order to obtain the information about correct range of a pulverized coal burner air excess ratio, the estimate calculated on the basis of immediate optical signals can be used instead of the delayed signals from the gas analyzers. The use of neuro-fuzzy models allows to obtain diagnostic signals of satisfactory accuracy and time, which allows application in control systems. The method has the disadvantage of neural network techniques. Although it has sufficient accuracy within the trained input space, it is unable to extrapolate, leading to erroneous results in the case of combustion conditions in which the inputs to the network are out of boundaries that were previously trained.

The modified negative selection procedure that uses optimization, as well as the artificial immune network for optimization parameters detectors was developed. A distinctive feature of this procedure is a modification of the learning process, through which the adaptive selection of settings, as well as the number and location of detectors is implemented.

Experimental studies have shown high efficiency of the proposed procedure, which is evident in its stability through adaptive value of cross-reactive threshold; optimality due to the adaptive immune network configuration size, i.e. the number of required detectors; accuracy by reducing the number and size of the created “cavities”.

Classification accuracy of the negative clonal selection algorithm was better than the one of fuzzy (TSK) algorithm when applied to the problem of detection of anomalies in air excess ratio using optical system. Considering similar computational complexity of the above-mentioned algorithms, the advantage of the former one is clear. The negative clonal selection algorithm can then be used for diagnostics of correct co-firing of pulverised coal blends with biomass in individual PC burner.

Acknowledgements

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РЕЗЮМЕ

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Методи штучного інтелекту у розпізнаванні горіння вугільно-біомасових сумішей у пиловугільних пальниках

У роботі представлені технології, розроблені в Інституті електроніки та інформаційних технологій Люблінського технологічного університету. Вони використовують оптичні датчики та методи штучного інтелекту для контролю та діагностики процесу спалювання палива. Дослідження спрямоване на розробку системи, що дозволяє провести параметричну оцінку якості роботи пічного палива. Через високу нелінійну природу залежностей та відсутність аналітичної моделі використовувались методи штучного інтелекту. У роботі показано два приклади - нечіткі мережі та алгоритми штучної імунології. Дослідження, описані в статті, підтверджують, що для отримання інформації про правильний діапазон надлишкового співвідношення повітря для пиловугільного пальника можна використати оцінку, яка розраховується на основі безпосередніх оптичних сигналів, замість сигналів з газових аналізаторів, що надходять із запізненням. Використання нейро-нечітких моделей дозволяє отримати діагностичні сигнали задовільної точності та часу для застосовування в системах управління. Розроблена модифікована процедура негативного відбору, яка використовує оптимізацію, а також штучну імунну мережу для детекторів параметрів оптимізації. Відмінною рисою цієї процедури є модифікація навчальної процедури, за допомогою якої реалізується адаптивний вибір параметрів, а також кількість та місце детекторів. Експериментальні дослідження показали високу ефективність запропонованої процедури. Точність класифікації за алгоритмом негативного клонування була кращою за один із наведених нечітких алгоритмів при застосуванні до проблеми виявлення аномалій в надлишку повітря використовуючи оптичну систему. Даний алгоритм може бути використаний для діагностики правильного спільного зпалювання вугільних сумішей з біомасою в окремих пиловугільних пальниках.

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