Application of convolutional networks to detect the operating phases of energy systems using a biomass boiler as an example

Szymon Podlasek[1*], Piotr Książek[1]
AGH University of Krakow, Poland[1]
podlasek@agh.edu.pl

Abstract: *The development of neural algorithms opens new perspectives for the analysis of technological processes. Particularly relevant are strongly nonlinear and complex objects, such as power plants. One of the modern solutions enabling data analysis are convolutional neural networks (CNNs). The research presents the application of CNNs to monitor and optimize combustion processes in biomass boilers. The fuel analyzed was gray straw, which is difficult to control due to the nature of combustion. The proposed technique is based on the processing of temporal data, which represent different stages of the combustion process. The work examined the effectiveness of the model in identifying key operating parameters and detecting the stages of firing from ignition initialization to nominal operation. Analysis of images of parameter curves from the time waveforms makes it possible to capture repeatable relationships that enable faster response to future changes in the conditions of the combustion process. Determining the phase of the process, based on data and trends of selected parameters, allows the control system to react faster, without operator intervention. As a result of the study, the efficiency of process stage change detection by the convolutional network, expressed by means of an error matrix, through the F1-score parameter (harmonic mean between precision and sensitivity) was achieved at a level close to 96%. The proposed solution can be effectively applied to a number of technological processes including those that are part of Industry 4.0 effectively influencing technological transformation..*
Keywords*: RES, COMPUTER MODELING, CONVOLUTIONAL NEURAL NETWORKS, OPTIMIZATION ALGORITHMS, PREDICTION*

1. Introduction

Modern biomass boilers play a crucial role in renewable energy production, forming an essential part of strategies to reduce greenhouse gas emissions (Fig.1). Biomass, as an energy source, is characterized by low costs and wide availability, making it an attractive alternative to fossil fuels. However, the biomass combustion process is complex and requires precise management of various variables, such as fuel moisture content, chemical composition, and boiler operating conditions.

One of the main challenges in biomass combustion is ensuring an efficient and stable combustion process that minimizes the emission of pollutants, such as nitrogen oxides (NO_x) and carbon monoxide (CO) [1-3]. Traditional methods of controlling the combustion process are often not flexible enough to respond to dynamic changes in combustion conditions. Effective management of this process requires advanced technologies capable of processing large amounts of data and adjusting operational parameters in real-time.

Fig. 1 *Tested object - biomass boiler fueled by gray straw..*

Convolutional Neural Networks (CNNs) are one such technology that is finding increasing application in the energy industry [4]. This method is increasingly used in Renewable Energy Sources (RES) to both forecast and support the operation of solar and wind installations [5, 6]. Also, research has been undertaken on the use of neural networks to reduce emissions from boilers by predicting components of the combustion process [7, 8]. CNNs, a type of deep neural network, are particularly effective in analyzing spatial data structures, such as images [9-11], making them ideal for analyzing operational data from biomass boilers or prediction of the occurrence of an event such as air pollution [12].

This article presents the application of CNNs for analyzing and predicting combustion processes in biomass boilers. Operational data from actual boilers and numerical simulations were used to train and test the CNN model. The objective of the study was to optimize the combustion process and reduce pollutant emissions. The results show that the application of CNNs can significantly improve combustion efficiency and reduce the negative environmental impact. The approach presented can serve as a basis for future research on the application of advanced machine learning technologies in optimizing industrial processes. Additionally, this solution aligns with Industry 4.0 standards through advanced analysis of measurement data.

2. Prerequisites and means for solving the problem

The work analyzed the possibility of using neural networks to detect the combustion stage. The turbulent nature of straw combustion requires a rapid response to a change in a parameter, which calls for the study of new algorithms for controlling these processes. In the study, it was decided to analyze the time courses of boiler parameters using CNNs.

Convolutional Neural Networks are a special class of deep neural networks particularly effective in processing grid-like data structures, such as images. Convolutional networks can also be used to analyze and interpret time series data, where the dependent variable, such as the intensity of electrical energy flow, is recorded at regular intervals. Such data can be treated analogously to images, where the time axis corresponds to the width of the image, and the variable values represent pixel intensities. By training on historical or simulated data, a CNN can learn to recognize recurring patterns in variable profiles and predict planned changes or anomalies.

The confusion matrix, also known as an error matrix or confusion table, is a tool used in machine learning, such as CNNs, to evaluate the quality of classification. It is a table that allows for the visualization of the performance of a classification algorithm. The confusion matrix shows the numbers of true positive, false positive, true negative, and false negative results (Fig. 2).

These four terms are key to calculating classifier performance metrics, such as Precision, Recall, Specificity, Accuracy, and F1-Score. The formulas for these indicators are presented in equations (r1) to (r5).

$$\boldsymbol{Precision} = \frac{TP}{TP + FP}$$
(r1)

Precision measures what percentage of positive predictions is actually positive.

$$Recall = \frac{TP}{TP + FN} \quad \text{(r2)}$$

Recall measures what percentage of actual positive cases was correctly identified.

$$Specificity = \frac{TN}{TN + FP} \quad \text{(r3)}$$

Specificity measures what percentage of actual negative cases was correctly identified.

$$Accuracy = \frac{TN + TP}{TN + TP + FP + FN} \quad \text{(r4)}$$

Accuracy measures what percentage of all classifications (positive and negative) is correct.

$$F1 - Score = \frac{Precision \ \cdot Recall}{Precision \ + Recall} = \frac{\frac{TP}{TP+FP} \cdot \frac{TP}{TP+FN}}{\frac{TP}{TP+FP} + \frac{TP}{TP+FN}} \quad \text{(r5)}$$

F1-Score is the harmonic mean of precision and recall, providing a single measure of classifier accuracy.

In the context of change detection, CNNs can be used to analyze data from sensors or time records, identifying patterns that are unusual or indicate potential problems. The confusion matrix in this context would serve to evaluate the effectiveness of models in detecting and correctly classifying these changes.

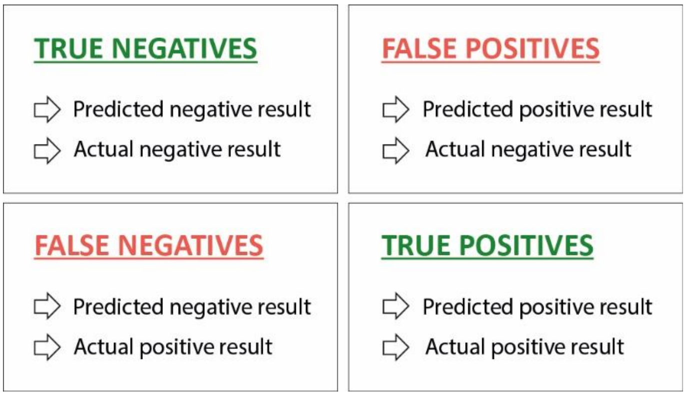

Fig. 2. Example representation of a confusion matrix for a case with two possible states and the assessment of their proper detection based on actual and predicted values [13].

3. Solution of the examined problem

As part of the work, experimental data from straw combustion were used as input data for analyzing combustion runs. The process was carried out under the same conditions, the only difference was the air feeding point to introduce some variability in the data. In addition, modeling and simulation work was carried out to increase the amount of information for the neural network. A full analysis of the impact of location on the process is available in article [14].

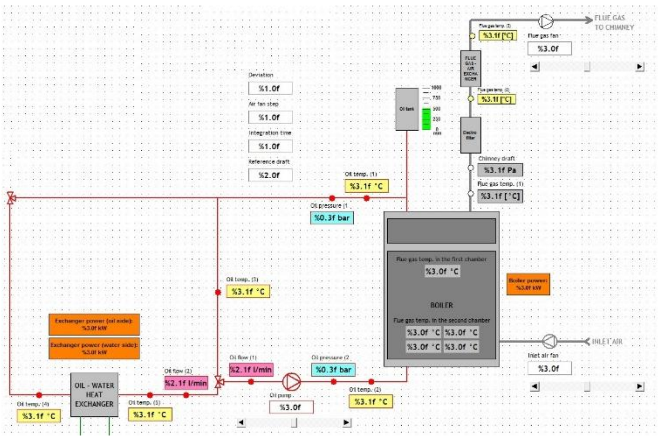

Fig. 3. Visualization of the experimental stand with measurement points [15].

The test stand was equipped with automatic data acquisition from temperature probes and an industrial exhaust gas analyzer (fig. 3). For a detailed analysis of combustion processes in batch boilers, four key operational parameters were identified as the basis for validating the simulation model. The focus was on examining the dynamics of changes in carbon monoxide (CO) and carbon dioxide (CO2) concentrations, as well as oxygen (O2) in the flue gases, and monitoring the temperature in the secondary combustion chamber. For components with a high response time (such as an air damper), tripping the system before the information about the need for a shortage is essential to respond in time.

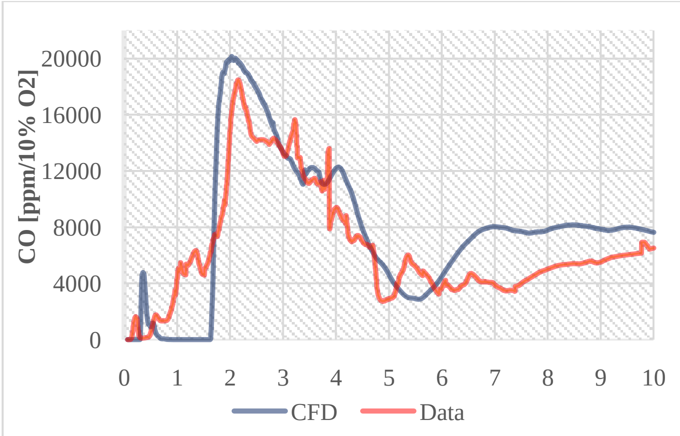

Fig. 4. Comparison of experimental data and CFD simulations, dynamics of concentration changes for selected CO parameter. In red the average measurement, in blue the CFD results.

The entire startup period of the installation – igniting the boiler – lasting 10 minutes can be represented in the form of intermediate states, where the detection of their start and end can serve as a faster signal than direct parameter measurement. The decision scheme for such an algorithm may look as follows:

Initialization: Preliminary Heating: The algorithm starts from an initial state, preparing the system for ignition by monitoring initial parameters such as temperature and chemical composition in the combustion chamber.

- Stage 1: Ignition (up to 60 seconds)

Ignition Detection: The algorithm detects an increase in CO emissions and other chemical products, as well as a temperature rise, indicating local ignition.

Parameter Adjustment: In response to detected ignition, the algorithm adjusts the fan and damper settings to ensure an optimal amount of air for the combustion process.

- Stage 2: Flame Spread (60 – 240 seconds)

Monitoring and Adaptation: During the intensive flame spread phase, the algorithm monitors and analyzes changes in emissions and temperature. It adjusts the fan and damper settings to avoid a rich mixture or suboptimal chemical reaction conditions.

- Stage 3: Stabilization (240 – 360 seconds)

Process Stabilization: When the algorithm detects a decrease in flame spread dynamics, it transitions to maintaining optimal parameters for balanced combustion – i.e., nominal operation.

- Stage 4: Nominal Combustion (360 – 600 seconds)

Maintaining Nominal Combustion: The algorithm maintains stabilized system parameters while being ready to detect and respond to potential anomalies resulting from fuel load fluctuations.

Intervention - Anomaly Response**:** In the event of anomaly detection, the algorithm immediately responds by adjusting the system parameters to prevent inefficient combustion or potential hazards.

Process Conclusion - Combustion Finalization: After completing the nominal combustion process, the algorithm switches to a monitoring state, checking whether the residual fuel smoldering process is proceeding correctly.

Continuous Learning: Data Analysis and Optimization: At each stage, the collected data is analyzed, and the algorithm learns and optimizes its actions for the future, increasing efficiency and reducing emissions.

It is also essential to observe that for such complex processes, there is partial overlap of stages, illustrating the process's complexity and the need to provide multiple runs based on models and experimental work to train the state transition detection algorithm.

Analysis of the results of the experimental work makes it possible to observe certain relationships that can serve as flags for subsequent stages of combustion. It is possible to identify common trends and characteristic points that can be used to optimize a control algorithm with a predictive component (Fig. 4). Data from the initial phase of combustion is crucial for quick and efficient process startup. Subsequent phases of combustion require the algorithm to adjust and maintain optimal conditions for full and even combustion. As in the case above, it is possible to analyze a whole range of data and their time courses, such as circulating medium temperature, losses or boiler efficiency. Comprehensive data analysis indicates the need for a flexible algorithm that adapts to changing conditions in real time and predicts next steps to respond more quickly to changing demands, such as air.

4. Results and discussion

The model was trained using a dataset consisting of experimental results and numerical simulations of boiler ignition. Each measurement was labeled by an experienced user and constituted the training dataset. Supervised learning was utilized for training, with cross-entropy as the loss function and the Adam optimization algorithm used to update the network weights based on the calculated loss. To prevent overfitting, cross-validation was employed, where the data was divided into training and validation sets. After each iteration, the model's performance was assessed on the validation set, and the best model was saved and tested on a separate test set. A classic split was applied, with 80% of the input data used for training, 10% for validation, and 10% for the test set.

After the initial training, hyperparameter optimization was conducted, including the number of layers, the size of convolutional filters, and the number of neurons in fully connected layers, to achieve the best possible performance. The model was validated using a previously unseen dataset to evaluate its ability to generalize to new data.

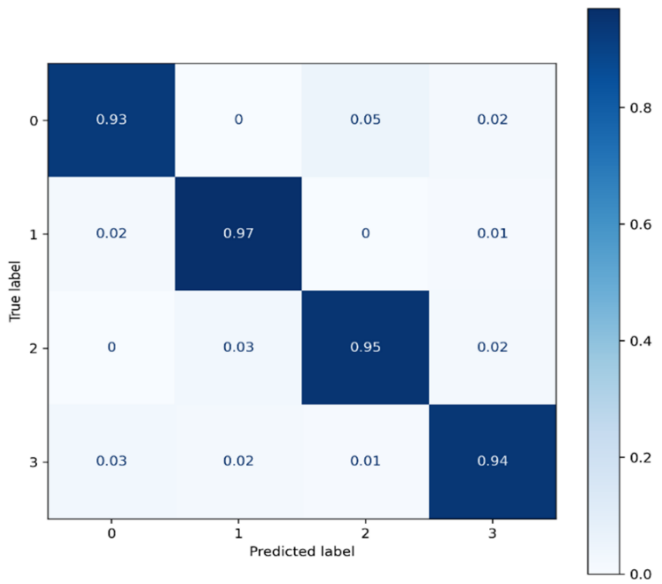

Fig. 5. *Confusion matrix for convolution network for classification of combustion stages.*

Based on the obtained confusion matrix (Fig. 5) and according to the formulas (r1) to (r5) presented in section 4.3, the following coefficients for the entire system were calculated: Recall: 95.8%, Accuracy: 95.8%, F1-Score: 95.79%, Precision: 95.80%. Additionally, the F1-Score for individual combustion stages was calculated as follows:

- Stage 0 (Ignition): 0.93
- Stage 1 (Flame Spread): 0.97
- Stage 2 (Process Stabilization): 0.95
- Stage 3 (Nominal Combustion): 0.94

Based on the confusion matrix (Fig. 5), it can be concluded that the neural network performs well in classifying the combustion stages. For each combustion stage, the majority of the network's predictions match the actual labels, indicating a high ability to recognize the characteristic features of each stage. For stages "0" and "3", small FP values are observed, where the network incorrectly classified the stage as "3" or "0". Similarly, for stage "2", a small number of FN values were obtained, where the network failed to recognize stage "2" and incorrectly classified it as "1". These low values indicate good specificity and sensitivity of the model.

5. Conclusion

The high F1-Score values for each stage (close to 1) indicate a good balance between precision and recall, meaning that the model performs well in identifying positive cases while avoiding false positives. The high values along the diagonal of the matrix indicate that the network has a high capability for correctly classifying each combustion stage. Based on the conducted training, it can be concluded that the model is capable of predicting the ignition stages based on measurement data, which allows for the automation of the monitoring process and potentially the optimization of the entire process. The designed algorithm can be implemented in a biomass boiler controller, enabling automatic regulation of the combustion process based on continuous analysis of measurement data and identification of combustion stages.

The research confirmed the significant utility of numerical models and their simulation results, which serve as the basis for analyzing the combustion process using neural networks. The application of convolutional neural networks allowed for the determination of combustion phases, even in such a complex process as straw ignition. Identifying the phase of the process based on data and trends of selected parameters enables faster responses in the installation without operator intervention. As a result of the research, the effectiveness of detecting process stage changes by the convolutional network was achieved, expressed using the confusion matrix through the F1-score (the harmonic mean between precision and recall) at a level close to 96%.

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