Combustion anomalies detection for a thermal furnace based on Recurrent Neural Networks

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Abstract. This paper describes the application of Recurrent Neural Networks (RNN) for effectively detecting anomalies in time series data obtained from experimental study of the combustion and gasification of mechanically activated coal fuel in a thermal furnace. We train Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM) units to learn the normal time series patterns and predict anomaly values. The resulting prediction errors between real and expected values are analyzed to give anomaly scores. To investigate the most suitable configuration of RNN and evaluate the effectiveness of the anomaly detection model, we used three datasets of real-world data that contain several types of anomalies. The developed RNN algorithm detected 9 out of the 9 collective anomalies in the hold-out sample with one false positive anomaly event.

1. Introduction

Russia is the largest coal country, one third of the world's resources is concentrated in its interior. At the same time, the quality of coal supplied to the power plants is constantly deteriorating. At that, burning of low-grade coals at the boiler plants is associated with considerable difficulties, when igniting a coal flame, stabilizing its combustion, fuel burn-out with simultaneous reduction of ecological parameters of power plants [1,2].

The use of coal in power engineering meets various difficulties, leaving immense potential for improving and optimizing the efficiency of combustion technologies. To improve the ignition and stabilization of combustion of the pulverized coal flame, the methods of increasing the grinding fineness, high heating of the air mixture and secondary air, using dust of high concentration, and joint use of fuel oil and coal are usually used. However, these methods have some disadvantages and only partially solve the above-mentioned problems.

The fact of an increase in the chemical activity of coals at their grinding in highly stressed disintegrator mills have been established at the Institute of Thermophysics of the SB RAS. A number of investigation results on the processes of ignition and combustion of mechanically activated fine coal of different stages of metamorphism have been published [3,4]. Based on data obtained, a new technology is proposed to replace high-reaction gases and fuel oil by fine coal at the power plants.

The development of modern machine learning algorithms has provided researchers and engineers with new effective tools for data mining of large complex multivariate databases and generalizing contained valuable information by building mathematical model of process. The application of such intellectual data driven approaches is relevant for improving the performance of technical devices,
preventing failures and unplanned stops, because trouble-free operation of complex technical systems is one of the priorities of any production process [5]. Anomaly detection includes a large arsenal of machine learning methods that allows to solve the above mentioned technical problems. Anomaly detection refers to search for unexpected values (patterns) in sequence of measurements. Anomaly (error, outlier, novelty) is the deviation of system behavior from the standard (normal or expected). Recently, Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM) units have proven themselves in solving a wide range of problems in anomaly detection, because they have the advantage of considering the multivariate measurement sequences (instead of individual observations, as in most approaches) [6,7,8].

The purposes of this work were: 1) An experimental study of the combustion and gasification of mechanically activated coal fuel in a thermal furnace; 2) An approbation of approach and development of machine learning model based of Recurrent Neural Networks capable to detect collective anomalies in multidimensional time series obtained from experimental measurements of pulverized coal combustion regimes in a thermal furnace.

2. Experimental setup
To study the gasification process, 1 MW thermal furnace with tangential scroll supply of coal-air suspension and cylindrical reaction chamber was used. Brown coal (one of the main coal deposits of Siberia) was used in experiments. The technical composition of coal is as follows (mass %, dry): moisture Wrl – 30.8, ash Ar - 11.1, volatile content - 49.1, sulfur Sdl - 0.29, high heat value Qdaf - 6900 kcal/kg. Coal was fed to the high-energy mills and then was directed by an ejector with transport air to the scroll burner.

Pulverized coal was ignited by a gas igniting device with the power of 50 kW. Coal consumption (30 kg/h) was controlled by voltage sensors of the feeders on the basis of preliminary calibration. Gas composition along the reaction chamber was measured by the optical-absorption gas analyzer at three points; temperature is measured in the same cross-sections of the chamber by the platinum-platinum-rhodium thermocouples. The flow rate of supplied air was obtained by the metering orifices and rotameters. The coefficient of air excess in the reaction chamber was 0.5. During experimental study ignition and gasification on coals of various grinding were investigated.

The thermal setup of 1-MW power for coal combustion and gasification is depicted in figure 1. Coal, ground in the standard boiler mill, was supplied by the feeder to the disintegrator (D) or vibrocentrifugal mill (VCM) and then was fed with transport air to the scroll inlet of the reactor-burner.

Figure 1. Experimental setup of up to 1 MW.
3. Recurrent Neural Network

Figure 2 depicts the structure of RNN (top) and single LSTM cell (bottom), which is a complex four-layer neural network. The key component of LSTM is the cell state - a horizontal line that locates along the center of the circuit. LSTM can delete information from the cell state. This process is regulated by structures called filters (input, output and forget gates). Filters allow you to skip information based on certain conditions. They consist of a layer of a sigmoidal neural network and a pointwise multiplication operation (marked as “x”). The sigmoidal layer (marked as “S”) returns numbers from zero to one, which indicates which fraction of each block of information should be passed further along the network. Zero in this case means "do not miss anything", unit - "skip all" [9]. We modified the structure of the Recurrent Neural Network by adding fully-connected layers to LSTM layers.

4. Results

A certain obstacle in the development of effective statistical anomaly detectors is the possibility of false positives: notifications of nonexistent deviations. If the anomaly detector has too many false positives, the user will turn off notifications or mark them as «spam», or simply ignore them, and such a detector is clearly not very effective. The approach that we applied in this work can reduce the number of false positives and detect only the most significant collective (joint) anomalies, when several process parameters (time series) immediately exceed the permissible threshold values.

The anomalies that arose in the experimental setup were associated with supply failure of coal fuel, excess air and a low degree of mixing. In our experimental datasets we observed 9 pronounced anomaly events. We focused on collective (joint) anomalies, where a set of measurements of different parameters is anomalous with respect to the entire dataset, even when a particular measurement at a given time can be within the limits of normal behavior. All the time series with evident anomalies were placed into hold-out sample, on which the neural network was not trained. The precision and recall of the anomaly detector algorithm was calculated by using the hold-out sample.
In the first step, we trained LSTM Recurrent Neural Network to reproduce and predict each time series of sensors for 5 ms. The Recurrent Neural Network consists of a LSTM layer of 64 units (neurons) and two fully connected layers of 32 and 8 neurons and an output with a linear activation function. To prevent overfitting, dropout procedure and L2-regularization for fully-connected layers were used [10]. We also experimented with the addition of several LSTM layers. As the optimizer, Adam was chosen. Neural network trained no more than 10 epochs. As predictors for training the neural network, we used time series of 8 physical parameters on temperature and gas components, collected during the experiment, as well as their shifts and derivatives and other statistical window functions. The dataset included many metering runs for different types of coals and milling degrees. Time series sampling was 1 ms.

In the second step for each time series, we calculated the squared deviation between the last and expected values. The essence of our anomaly detector is the following: at each moment of data acquisition we assume that there will be a large value of the squared deviation for a set of measurements of the physical process parameters. If a high number of events with a large error value is detected, an anomaly notification will be received. In a considerable number of cases, anomalies can be detected before the physical parameters of the process have changed dramatically to affect the operation of the furnace.

Figure 3 shows three process parameters: temperature (left part of the picture) and concentrations of oxygen and carbon dioxide (right part) during combustion of coal fuel. We chose a measurement when an anomaly was present in the time series data to demonstrate the operation of the algorithm. The blue curves show the real values of the physical parameter, and the red curves correspond to expected value of the parameter, predicted by the Recurrent Neural Network for 5 ms. The black curves show the normalized square of the deviation of the two curves. On all three curves, the moment of the beginning and the end of the anomaly can be clearly detected by a sharp increase in the error deviation (anomaly score). It can be noted that, on the temperature curve, a sharp drop in temperature, associated with coal supply failure & poor mixing, predicts the occurrence of anomalous deviations for CO$_2$ and O$_2$ measurements.
5. Conclusions
The article is devoted to experimental research of burning and gasification of coal fuel in a 1 MW thermal furnace. A comparative analysis for coals pulverized at high-pressure mills (in a disintegrator and vibrating centrifugal mill) is carried out.

We have proposed a model for collective anomaly detection in time series based on Long Short-Term Memory Recurrent Neural Network. We demonstrated that LSTM networks may be a viable technique to model normal time series behaviour, which can then be used to detect anomalies. The resulting prediction errors between real and expected values are analyzed to give anomaly scores. The developed RNN algorithm detected 9 out the 9 collective anomalies in the hold-out sample with one false positive anomaly event.

Acknowledgements
The work was financially supported by the Russian Ministry of Education and Science, according to Subsidiary Agreement No. 14.604.21.0162.

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