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Risk Management Innovations Through Neural Network Integration in Automated Boiler Combustion Systems

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ABSTRACT

In the early decades of the twenty-first century, the application of artificial intelligence has been expanding across all sectors of society, including industrial energy systems. This paper emphasizes the significance of integrating artificial neural networks into boilers with automatic firing, as part of a research project currently in its fifth year of experimental validation. The implementation of neural networks in such systems has demonstrated promising results in the domain of risk management, particularly through the prediction of system malfunctions and their proactive elimination via software interventions. The application of AI-based solutions in boiler control not only contributes to the reduction of environmental impact but also enhances operational safety by preventing accidents that may endanger human health and cause material losses.

1. Introduction

Risk management in industrial systems represents a fundamental component in ensuring operational safety, efficiency, and reliability. In the case of boilers with automatic firing—complex electromechanical energy systems—risk management becomes even more critical due to their inherent structural and functional specificities, as well as the potential hazards associated with their operation. Enhancing boiler performance through controlled operation contributes to energy conservation and a reduction in pollutant emissions. Furthermore, the implementation of scheduled maintenance can optimize system functionality and lower operational costs. However, recommended maintenance intervals can vary significantly across different boiler types. Consequently, there is a need for the implementation of an advanced early fault detection system, based on intelligent algorithms, to improve overall system efficiency, availability, and safety [1,2].

Boiler systems operate under high temperature and pressure conditions, which inherently increases the risk of serious incidents in the absence of adequate risk management strategies.

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Effective risk management enables the early identification of potential hazards, particularly those arising from overheating, which may be caused by equipment failures or anomalies in the fuel supply. The integration of artificial neural networks (ANNs) into the risk management framework of automatically fired boilers presents significant potential for improvement in several key areas.

Primarily, neural networks are capable of processing and analyzing large volumes of sensor-generated data in real time, enabling the prediction of system failures and facilitating timely intervention. Their application in combustion process optimization and temperature regulation contributes not only to reducing the likelihood of malfunction but also to improving operational efficiency. This, in turn, leads to lower energy consumption and a measurable reduction in environmental impact. The early detection of potential faults through intelligent systems supports prompt responses by both the control infrastructure and human operators, enhancing overall system resilience. Fault diagnosis, in particular, plays a critical role in energy conservation. Recent research emphasizes novel approaches to fault detection based on deep learning methodologies [3,4], aiming to reduce system downtime and associated maintenance costs. To this end, modern boiler manufacturers are increasingly adopting advanced fault detection and diagnosis (FDD) techniques, which can be broadly categorized into three groups: model-based methods [5,6], data-driven approaches [7], and statistical techniques [8,9]. While model-based methods are effective in addressing simple fault scenarios, their application to complex industrial processes is often limited due to high computational demands and cost. In contrast, data-driven and statistical methods have gained popularity for their adaptability and efficiency. These latter approaches employ machine learning algorithms [10], artificial neural networks [11], and multivariate statistical tools such as principal component analysis (PCA) [12], leveraging real-time data from monitoring systems to detect and diagnose faults. Boiler installations are commonly equipped with acoustic emission sensors [13,14] and various process monitoring instruments [15], which generate substantial datasets crucial for the accurate detection of anomalies and prevention of system failures.

2. Methodology: Application of Neural Networks in OZON 55 Type Boilers

Artificial neural networks (ANNs) have found extensive application across diverse domains, including advanced security systems, consumer technologies, and industrial automation [16]. Within industrial systems, and particularly in the control of combustion processes in automatically fired boilers, recurrent neural networks (RNNs) have proven to be particularly effective due to their capacity to process time-series and sequential data by retaining information from previous system states [17-22].

2.1. Neural Network Models for Combustion Control

For the control of combustion parameters in OZON 55 type boilers, the fundamental RNN architecture serves as the starting point. A basic RNN comprises recurrent nodes that receive both the current input and a feedback signal from the previous hidden state. This allows the model to capture temporal dependencies by sharing weights across time steps. However, standard RNNs encounter limitations in handling long-term dependencies, primarily due to the vanishing gradient problem during training. To address this issue, Long Short-Term Memory (LSTM) networks were employed. LSTM is a more advanced variant of RNN specifically designed to retain long-term dependencies through dedicated memory cells. Its architecture includes: Input gates, which regulate which new information is stored in the memory cell; Forget gates, which determine which parts of the stored information are discarded and Output gates, which control what portion of the memory is passed forward at each time step.

LSTM networks are especially valuable in combustion systems, where it is crucial to retain and use information from earlier time steps—for example, variations in fuel quality, pressure, or air mixture properties [21,22]. The parameter prediction model built on RNN or LSTM architectures was tasked with forecasting key combustion parameters—such as temperature, pressure, air, and fuel flow—based on historical sequences of sensor data. In the real-time adjustment phase, the network dynamically updates predictions in response to new sensor inputs, thereby maintaining efficient combustion under varying operating conditions.

2.2. Experimental Data Collection

To address control challenges identified in one of the OZON 55 type boilers, a decision was made to conduct experimental data acquisition. For this purpose, an Arduino Uno microcontroller was employed, interfaced with various sensors: Type K thermocouples were installed at critical measurement points—within the firebox, in the smoke channel one meter above the flue gas exit, and for both external and internal air temperature monitoring; Humidity sensors were used to monitor the relative humidity of both ambient air and pellet fuel; Gas sensors, placed in the chimney, measured the composition and concentration of combustion gases.

By May 2022, the data acquisition system had undergone several hardware and software upgrades to improve accuracy and measurement fidelity. Experimental measurements for the research commenced in October 2022 [23].

2.3 Mathematical Modeling

Simultaneously with the development of the measurement system, efforts were initiated to define an appropriate mathematical model. The analysis revealed that the boiler system exhibits non-linear and multivariate behavior. Moreover, due to the nature of the collected time-series data, a discrete-time dynamic model was adopted as the most suitable framework for describing and analyzing the system's behavior. For this reason, the required model is of the following form $\mathrm{y(x)} = \mathrm{f\big(Y\big(t, D_y\big), X_1(t, D_1), X_2(t, D_2) \dots\big)}$ (1)

where $\mathrm{f}: \mathbb{R}^{D_y + D_{x_1} + D_{x_2} + \cdots} \to \mathbb{R}$ is a continuous non-linear map representing the required model. The problem solved initially is the determination of the dimensions of vectors $\mathrm{Y, X_1, X_2, \dots}$ $\mathrm{i.e.}\, \mathrm{D_Y, D_1, D_2, \dots}$which are the orders of the models autoregressive and transregressive dependencies of the system. The method used for this has been described in Djukic work [24]. The essence of this method consists in computation of probability that the collected data are produced by a system whose model is a linear map.

The synaptic and the activation coefficients of the neural network, represented by matrices, have been optimised using the method of back-propagation of the error gradient.

The entire system is conceived as a recurrent neural network that determines one sequence element at a time. We introduce a set of measured values to the input and after that we start the calculation. The next mesh is added only after the calculation for the previous mesh has already been performed. A recurrent network maintains a so-called hidden state and has the current hidden state at each step. For a given input, given that input and the current hidden state, it computes a new hidden state as a linear combination of the matrices with the vectors of the current hidden state and the current input. An activation function is applied to the obtained result and thus a new hidden state is obtained. An activation function is applied to the obtained result and thus a new hidden state is obtained. After that comes a new set of measurements, based on the current state and representation of the set, with the help of the same matrices, linear transformations are performed,

activation functions are applied and a new state is obtained, and so on for all sets of measurements. At each step, some output can be generated from the hidden state.

3. Analysis of the obtained values

The discussion of the results cannot begin before we point out that The neural network training phase incorporates several internal processes and elements, which ensure proper handling and parametrization of the training phase.

1.Number of epochs – Each epoch represents passing the entire dataset forward and backward through the neural network once. Number of epochs is set to 100 for the purposes of the training outlines by this approach.

2.Batch Size – Number of instances processed together before the update of neural network's parameters [18]. Batch size is set to 256, due to the large number of network flow instances.

3.Callback for Learning Rate Reduction – Learning rate influences the size of adjustments made to the model weights based on the calculated gradients. This callback ensures dynamic reduction of learning rate, enhancing and speeding up model's convergence.

4.Callback for Early Stopping – Callback which prevents unnecessary computations and therefore overfitting. After 7 unsuccessful epochs, training phase is terminated and weights from the model's best performing epoch are selected and restored as they encapsulate model's optimal state achieved in the training phase, for further model's performance evaluation.

The carefully designed methodology integrates multiple components to ensure correct and effective neural network's training and evaluation in case of network intrusion detection. The strategic combination of parameters such as the number of epochs, batch size and callbacks ensure both effective and performance-oriented training phase.

By using this model, and after comparing the results, deviations between the computationally obtained hidden states and the actual measured values were seen. By increasing the number of measurement points, the error decreased.

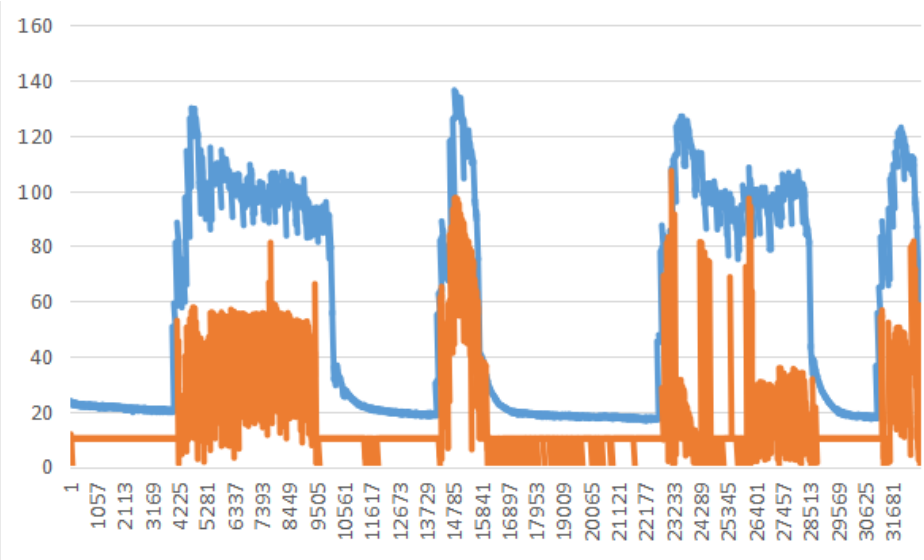

Fig. 1. Comparison of measured values and values obtained by calculation

The Figure 1 shows the relationship between measured valuesand values obtained by calculation, it can be seen that the calculated value generally follows the measured value, but there is an error.

In this research, the neural network obtained an approximate value to the measured value. The error decreased with the number of measurements. And in some cases, the neural network of this type gave results that are not in agreement with the measured results.

A big problem in the development of this model is the short period of operation of the boiler, which is contributed by uneven weather conditions. We see the need to develop a model that, in addition to the parameters necessary for fire maintenance and pellet quality monitoring, will also include parameters related to the climatic conditions of the microregion where the measurements are made.

At this point, we must mention that the introduction of these systems requires costs and hardware modifications of conventional boilers. First, it is necessary to prepare a study of the profitability of the system implementation. Specifically for boilers of the OZON class, which vary in power, ranging from 25 kW to 75 kW, the system itself is profitable to install, since the investments are of the order of magnitude of the annual energy savings. Namely, OZON boilers have a microcontroller in them that can support the aforementioned additions and modifications. Namely, OZON boilers have a microcontroller in them that can support the aforementioned additions and modifications. In addition, they have a set of sensors that satisfy the measurements of the temperature of the exhaust air and the exhaust smoke. Therefore, it is only necessary to place one humidity and temperature sensor inside the pellet tank, for example. DHT 11 and particle sensor PM 2.5. The modification itself does not require large financial investments for hardware modifications. After that we have the new software loading.

4. Conclusions

In the context of escalating environmental pollution and the growing market presence of automatically fired boilers, it is imperative to prioritize fuel efficiency in their operation. Improving the degree of fuel utilization not only reduces the emission of harmful gases into the atmosphere but also minimizes the consumption of biomass or fossil fuels, thereby contributing to environmental protection and enhancing the quality of life [25]. The integration of intelligent systems based on neural network models offers a promising pathway for advancing risk management through predictive diagnostics, fault prevention, and operational optimization. However, challenges such as limited access to real-time information and personnel shortages can hinder the prompt identification and resolution of system malfunctions, resulting in extended downtime and economic losses [26]. The development and implementation of neural network-based models for the optimization of control parameters in automatically fired boilers can yield measurable benefits, including significant reductions in fuel consumption and improved combustion efficiency. Predictive modeling of key variables—such as combustion chamber temperature, pellet calorific value, and oxygen concentration in the air-fuel mixture—can enhance overall system performance, improve thermal comfort, and contribute to environmental sustainability [27-30].

These insights lead to the conclusion that the application of neural networks in boiler management systems significantly reduces various categories of risk, while simultaneously advancing energy efficiency and ecological responsibility.

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Conflicts of Interest

The authors declare no conflicts of interest.

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