Modeling a boiler unit in the automation systems of transport infrastructure

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Abstract. The goal is to develop a model that takes into account the dynamics of the operation of the combustion device of the boiler unit. The article discusses the application of the technique of D.Zh. Box and G. Jenkins to identify the steam production process. A boiler unit used in transport infrastructure automation systems was chosen as the object of research. The boiler unit is a dynamic stochastic object with uncontrollable disturbing influences. Using statistical methods, a mathematical model has been obtained that can be used to predict and regulate the operating modes of the boiler unit.

1. Introduction

It is hard to imagine today's life without equipment that uses the energy and properties of water vapor. This includes various types of boiler units, turbine generators, etc. A boiler unit as a control object is widely used in almost all spheres of life: agriculture, light and food industries, and the chemical industry. It is also worth noting the widespread use of boiler units in transport infrastructure systems for heating railway stations, heating fuel, etc.

The efficient operation of the boiler unit is impossible without the organization of a high-quality regulation process at each of its stages, which starts from water treatment, water supply to the boiler drum and ends with ensuring the correct operation of the combustion chamber. To provide a given combustion process, it is necessary to constantly supply a certain amount of fuel and the corresponding amount of secondary air to the furnace. This function is performed by the fuel-air regulator, which maintains the specified ratio between the amount of fuel and air throughout the entire range of fuel delivery. The amount of supplied fuel varies depending on the steam load of the boiler unit. However, this regulator has its drawbacks, since it does not take into account the quality indicators of the fuel: composition, temperature, humidity, etc.

An alternative to this regulator is a regulator that takes into account the oxygen content in the flue gases, keeping it within the specified limits (usually 1-1.5%). The oxygen content in the flue gases is a qualitative indicator indicating the optimal ratio of fuel and air supplied to the furnace.

2. Identification

This article deals with the development of a dynamic stochastic model that takes into account the relationship between the secondary air flow rate and the oxygen content in the exhaust gases. The following technological parameters were selected as the studied data:
Secondary air pressure, \( X \)
- oxygen content in flue gases, \( Y \).

To obtain data, the method of passive experiment was used. The data were obtained by observing the normal course of the steam generation process on a steam boiler of the BKZ-420-140 brand.

The volume of data for the study is 1800 measurements with a sampling rate of 10 seconds.

Since the measured values of these parameters are in different ranges (percentage of oxygen in flue gases and secondary air pressure in kPa), for further analysis it is necessary to bring these time series to a single form. To do this, we will perform the alignment procedure for each row.

As an example, Figure 1 shows the time series: secondary air pressure and oxygen content in exhaust gases in a standardized form [1].

![Graph of selected variables (rows)](image)

Figure 1. The graph of the investigated time series

In the course of studying the time series for stationarity, it turned out that these time series are non-stationary. Since the method of Box and Jenkins can be used only for stationary series, it is necessary to bring the studied series to a stationary form by taking successive differences. In this regard, for the above time series, difference time series were obtained using the operator for taking differences:

\[
x_t = \Delta^d X_t; \quad y_t = \Delta^d Y_t \quad \text{with} \quad d > 0,
\]

where \( d \) is the order of the difference; \( x_t, y_t \) - normalized values of time series:

\[
x_t = (X_t - \overline{X_t}) / \sigma_x, \quad y_t = (Y_t - \overline{Y_t}) / \sigma_y,
\]

in which

\( \overline{X_t}, \overline{Y_t} \) – mean values of the series, \( \sigma_x, \sigma_y \) – standard deviation.

Bringing the series to a stationary form in the future will make it possible to use the method of cross correlation functions to determine in the structure of the model those lag times for which the coupling coefficients between the secondary air pressure and the oxygen content in the exhaust gases are most significant [2].

As an example, Figure 2 shows a graph of the cross-correlation function \( R_{xy} (k) \) between the observed series, obtained as a result of processing statistical material.
A visual analysis of this graph does not allow making an unambiguous conclusion about those time intervals at which the secondary air pressure on the left side significantly affects the oxygen content in the flue gases on the left, since the mechanism of interaction is veiled by the correlation of the values of the input series, but it helps to determine the significance of the coefficients of cross-correlation [3].

Further, in accordance with the methodology, we will carry out a preliminary identification of the studied time series to establish the correspondence of the selected class of the model with the available experimental data. The main criterion for identification is the behavior of the autocorrelation and partial autocorrelation functions.

Let us construct for the investigated time series models of autoregressive and moving average (ARSS) [4]:

$$\alpha_t = x_t - \sum_{i=1}^{p} \Phi_i x_{t-i} + \sum_{j=1}^{q} \Theta_j \alpha_{t-j};$$

$$\beta_t = y_t - \sum_{i=1}^{p} \Phi_i y_{t-i} + \sum_{j=1}^{q} \Theta_j \beta_{t-j};$$

where $\alpha_t, \beta_t$ – aligned series, respectively, for input and output difference series; $\Phi_i$ – parameter values for auto regression model; $\Theta_j$ – parameter values for the moving average model; $p$ – autoregressive model order; $q$ – order of the moving average model.

The time series of the secondary air flow rate is described by the ARIMS autoregressive model $\langle 210 \rangle p = 2; q = 0$. The time series of the oxygen content in the exhaust gases is described by the model $\langle 110 \rangle p = 1; q = 0$.

Next, for the obtained time series, we construct a cross-correlation function (Figure 3).
To obtain estimates of $p$, $q$, $\Phi I$, a nonlinear least squares algorithm was applied [5].

3. Estimation

Dynamic stochastic models of the influence of secondary air on the left side on the oxygen content in the exhaust gases were obtained using the Box-Jenkins method in the class of models $y_t = \delta \cdot 1(B) \omega(B) xt-b + nt$, where $B$ – operator of shift back one step, $b$ - delay parameter [6]:

$$
\delta(B) = 1 - \delta_1 B - \delta_2 B^2 - \ldots - \delta_r B^r;
$$

$$
\omega(B) = \omega_0 - \omega_1 B - \omega_2 B^2 - \ldots - \omega_s B^s.
$$

The developed dynamic stochastic models are presented below.

Dependence of the oxygen content in the exhaust gases on the secondary air flow rate:

$$
(1 - 0.307 B - 0.049 B^2) \Delta O_2_{left}(t) = -0.035 \Delta f(t-34) + 0.05 \Delta f(t-39) - 0.047 \Delta f(t-55) - 0.044 \Delta f(t-56) - 0.031 \Delta f(t-64) + 0.05 \Delta f(t-239) + 0.043 \Delta f(t-254) - 0.049 \Delta f(t-364) - 0.048 \Delta f(t-371) + n_t
$$

where $\Delta$ are the first differences, and the values under the coefficients are their standard errors.

4. Diagnostic check

The obtained models are analysed for the adequacy of the real process of influence of the secondary air flow rate on the oxygen content in the exhaust gases in the furnace. The analysis is performed using a diagnostic check [7]. This check consists of two stages. Initially, the coefficient $\chi^2$ is calculated - statistics for the values of the autocorrelation function of residual errors $r_{ua}(k)$ as $Q = (N-s-b-r); \sum_{k=1}^K r_{ua}(k)$. Here $N$ is the number of observations, $k$ is the maximum delay of autocorrelations and cross-correlations, $S$ is the number of “right-handed” parameters of the dynamic stochastic model, $r$ is the number of “left-handed” parameters. Then $\chi^2$ statistics are calculated using the cross correlation functions $r_{aa}(k)$ between the equalized input series $t$ and a series of residual errors, and now $H = (N-s-b-r) \sum_{k=1}^K r(k)$.
In the first case, \( Q \) is compared with \( \chi^2 \) – distribution with \( K-p-q \) degrees of freedom, and in the second - \( H \) is compared with \( \chi^2 \) – distribution with \( K-r-S \) degrees of freedom [10]. The calculated value of \( H \) should not exceed the tabular value for the investigated number of degrees of freedom with a significance factor of 0.05.

As the results of the diagnostic check in table 1 show the values of the coefficients \( \chi^2 \) – statistics on the autocorrelation function.

**Table 1.** Coefficient values \( \chi^2 \) statistics.

| Input             | output | Number of degrees of freedom | \( H \) | Number of degrees of freedom | \( Q \) |
|-------------------|--------|-----------------------------|--------|-----------------------------|--------|
| air pressure      | \( \text{O}^2 \) | 30                          | 38.45  | 30                          | 43.8   |

Diagnostic testing for autocorrelation and cross-correlation functions using the values of \( \chi^2 \) statistics does not give grounds for doubting the adequacy of the model [11,12].

5. Conclusion
As a result of the research carried out, a model has been obtained that makes it possible to evaluate the effect of the secondary air flow rate on the oxygen content in the exhaust gases.

The model can be used to predict and control the boiler units used in the transport infrastructure automation system.

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