http://doi.org/10.35784/iapgos.1835

# RESEARCH ON THE COMBUSTION PROCESS USING TIME SERIES

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***Abstract.*** *In the combustion process, one of the most important tasks is related to maintaining its stability. Numerous methods of monitoring, diagnostics, and analysis of the measurement data are used for this purpose. The information recorded in the combustion chamber constitute one-dimensional time series. In the case of non-stationary time series, which can be transformed into the stationary form, the autoregressive integrated moving average process can be employed. The paper presented the issue of forecasting the changes in flame luminosity. The investigations discussed in the work were carried out with the ARIMA model (p,d,q). The presented forecasts of changes in flame luminosity reflect the actual processes, which enables to employ them in diagnostics and control of the combustion process.*

**Keywords**: time series, ARIMA model, flame luminosity

## BADANIA PROCESU SPALANIA Z WYKORZYSTANIEM SZEREGÓW CZASOWYCH

***Streszczenie.*** *W procesie spalania jednym z najważniejszych zadań jest zachowanie jego stabilności. Do tego celu wykorzystywanych jest wiele metod z zakresu monitorowania, diagnostyki i analizy danych pomiarowych. Zarejestrowane w komorze spalania informacje są jednowymiarowymi szeregami czasowymi. W przypadku niestacjonarnych szeregów czasowych, które można przekształcić do formy stacjonarnej, znalazły zastosowanie scałkowane procesy autoregresji i średniej ruchomej. W artykule przedstawiono problematykę prognozowania zmian intensywności świecenia płomienia. Badania zaprezentowane w pracy zostały przeprowadzone z wykorzystaniem modelu ARIMA(p,d,q). Przedstawione prognozy zmian intensywność świecenia płomienia odwzorowują rzeczywiste przebiegi, co pozwala wykorzystać je w diagnostyce i sterowaniu procesem spalania.*

**Słowa kluczowe**: szereg czasowy, model ARIMA, jasność świecenia płomienia

## Introduction

Coal constitutes the main source of energy used in the energy economy. The need to protect the natural environment against its exploitation and increasing pollution necessitates implementation of Renewable Energy Sources in the energy sector [6, 8, 16, 19]. The application of biomass in the combustion process technologies contributes, i.a., to a reduction in the generation of sulphur and nitrogen oxides. The co-combustion of coal and biomass is usually realized through a direct co-combustion, involving simultaneous burning of the mixture in a combustion chamber [7, 15, 20, 25].

Combustion is a complex process. Its diagnostic is aimed at ensuring the stability of the process. The monitoring of the combustion process is implemented using optoelectronic systems, which enable acquiring measurement data from the flame in a non-invasive way [5, 9, 17, 18]. Since the obtained signal contains numerous variables characterizing the combustion process, it can be analyses using different methods [10, 21–24].

The measurement data recorded using a fiber optic probe are available in discrete, equal time steps – 1000 samples per second. They form a time series which reflects the changes occurring in flame during the combustion process. Identifying the transition from the stable to the unstable state, which may occur due to the changes in the process parameters or disturbances, is essential in the diagnostics of the combustion process. Conducting the forecast of changes in flame luminosity enables to detect such state.

The forecasting of future time series values can be carried out with the ARIMA model. In the autoregressive integrated moving average process, it is possible to employ non-stationary time series, which can be transformed into the stationary form. The selection of model parameters can be performed using the dependences of the autocorrelation function. The analysis of the selected model can be considered using Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC), mean square error, as well as the significance criterion of model parameters [1, 3, 14].

The paper discusses one-dimensional time series of changes in flame luminosity for the selected cases of the combustion process: the first variant concerned 100% pulverized coal, whereas the second – a mixture of 80% coal and 20% biomass. The measurements were performed for different flame zones. The data from the first zone, which contained the most information, were presented. For the discussed cases, such parameters as the number of collected samples or measurement time were identical. The analysis of data was performed in time domain using autoregressive integrated moving average process. Using the ARIMA model, the time series for the flame luminosity data were presented and single-step, multi-step as well as interval forecasts were subsequently conducted on their basis. In the case of the interval forecasts, they were determined with 95% probability. This means that the forecast value of one-dimensional time series belongs to the confidence interval [18]. Due to the high correlation between the measurements and one-step forecasts, these models can be employed for the diagnostics as well as control of the combustion process. The application and forecasting using the ARIMA model was presented in literature [2, 4, 11–13].

## 1. Diagnostic system and data acquisition

The measurements of flame luminosity were conducted using fiber optic measurement probe which constitutes an element of the diagnostic system. This device was placed in the combustion chamber, where it acquired the data on the combustion process from the flame. The measurements were performed for four different flame zones (see Fig. 1).

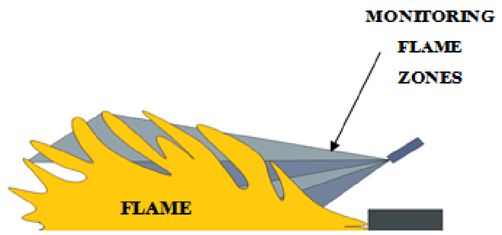


*Fig. 1. Flame zones*

The measurement data recorded by the flame monitoring system present the changes in flame luminosity in the form of a one-dimensional time series. The investigations were performed for two variants – pure coal and a mixture of 80% coal and 20% biomass, at constant parameters, constant thermal power of 400 kW and excess air coefficient $\lambda$=0.85. In both cases, the recorded data are characterized with identical measurement time and number of collected samples, i.e. over two millions for each configuration.

The figure below presents the time series of changes in flame luminosity for 100% pulverized coal (Fig. 2a) and mixture with biomass (Fig. 2b) recorded in the same flame zone.

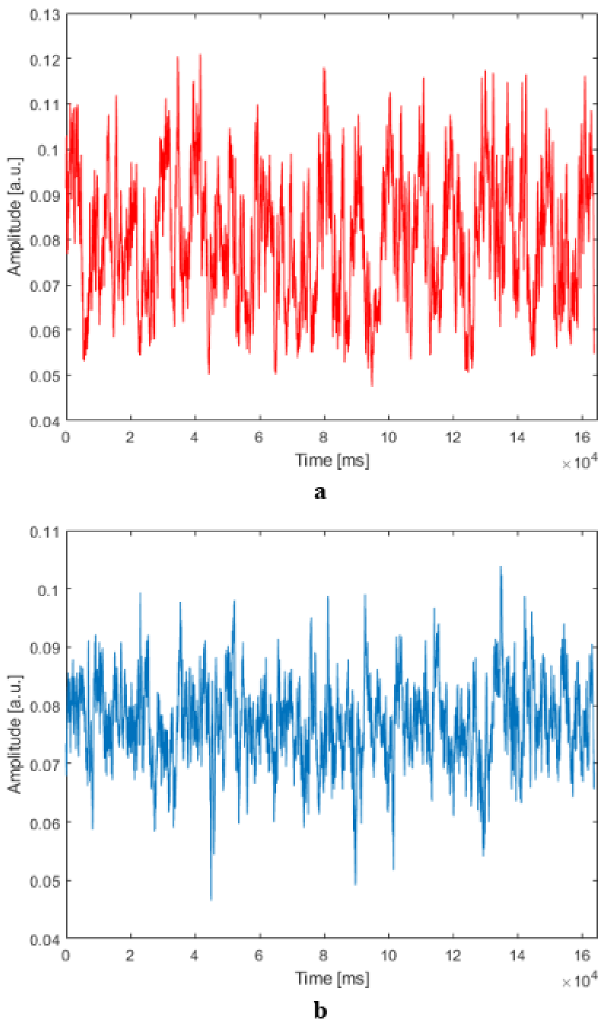


*Fig. 2. Time series of changes in flame luminosity of a) coal, b) mixture of coal and biomass*

## 2. Model ARIMA

ARIMA (Autoregressive Integrated Moving Average) models are frequently employed in the time series forecasting processes [18–22]. The basis for the model includes the autoregressive (AR) and moving average (MA) processes. This model finds application in the case of non-stationary time series, which may be transformed into stationary ones using, e.g. logarithmic transformations or differencing. The ARIMA model (p,d,q) is described by the components determining [18]:

- p – number of autoregressive parameters,
- d – order of differencing,
- q – number of parameters in the moving average.

Its generalized form is expressed with the dependence [18]:

$$\varphi^*(B)z_t = \varphi(B)\nabla^d z_t = \theta_0 + \theta(B)a_t, \tag{1}$$

where,

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p, \tag{2}$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q, \tag{3}$$

$$\varphi^*(B) = \nabla^d \varphi(B) \tag{4}$$

The variables represent [18]:

- $\varphi(B)$ – autoregressive operator
- $\varphi^*(B)$ – non-stationary autoregressive operator,
- $\theta(B)$ – moving average operator,
- $\nabla$ – differencing operator.

On the basis of the methodology presented by Box&Jankins, the time series identification model involves: identification, estimation of parameters, and model verification.

## 3. Research results

For the analysis of time series and forecasting, 16384 ($2^{14}$) observations of changes in flame luminosity were conducted for the pulverized coal and the mixture of coal and biomass. The assessment of series shape for both configurations was performed and logarithmized in order to stabilize the series. The selection of ARIMA model parameters (p,d,q) was based on the analysis of autocorrelation plots. For the considered time series, the Autocorrelation function (ACF) and Partial Autocorrelation Function (PACF) plots were drawn (Fig. 4).

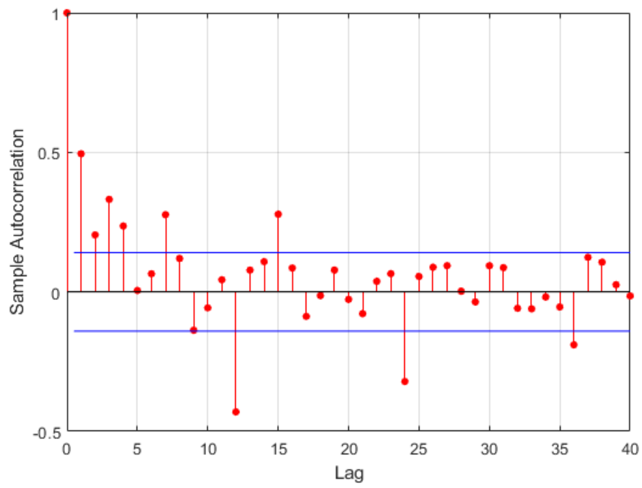


*Fig. 3. Autocorrelation function of changes in flame luminosity for the mixture of pulverized coal and biomass*

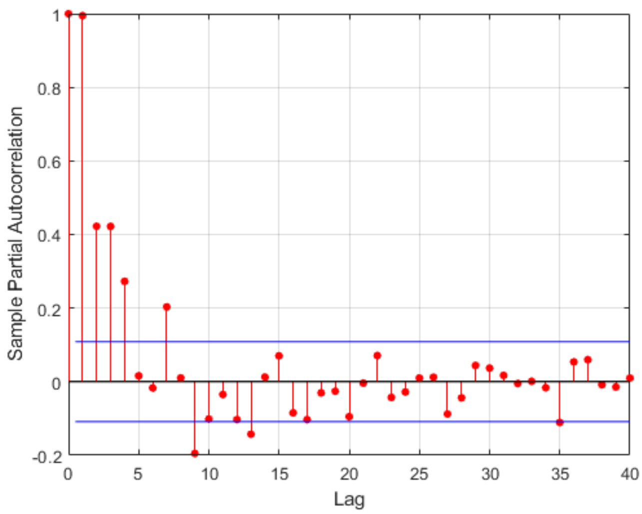


*Fig. 4. Partial autocorrelation function of changes in flame luminosity for the mixture of pulverized coal and biomass*

Then, the Box&Jankins methodology was employed to determine the p, d, and q parameters of the ARIMA model. When analyzing the number of statistically significant ACF parameters, the number of lags in the autoregressive model was determined, which amounted to p = 4 for the first series configuration and p = 7 for the mixture of coal and biomass. Using the same approach, the number of lags in the moving average was determined on the basis of the PACF parameters, amounting to q = 4 (pulverized coal) and q = 4 (mixture of coal and biomass). The differencing degree was set at d = 1 for both considered variants. Simultaneously, this means that in order to transform the time series into the stationary form, another differencing operation has to be performed.

On the basis of the determined parameters, several ARIMA model configurations were devised: (1,1,1); (4,1,4); (4,1,5) for 100% pulverized coal and (4,1,1); (3,1,4); (7,1,4) for the mixture.

*Table 1. Values of information criteria for particular ARIMA models*

| | Akaike's Information Criterion (AIC) | Bayesian Information Criterion (BIC) |
|---|---|---|
| ARIMA model for 100% pulverized coal | | |
| p = 1,d = 1,q = 1 | -1,9041e+06 | -1,9040e+06 |
| p = 4,d = 1,q = 4 | -1,9911e+06 | -1,9910e+06 |
| p = 4,d = 1,q = 5 | -1,9679e+06 | -1,9679e+06 |
| ARIMA model for mixture of 80% coal and 20% biomass | | |
| p = 1,d = 1,q = 1 | -1,8464e+06 | -1,8464e+06 |
| p = 3,d = 1,q = 4 | -1,9118e+06 | -1,9117e+06 |
| p = 7,d = 1,q = 4 | -2,0054e+06 | -2,0053e+06 |

In order to select the best ARIMA model parameters, the Akaike's Information and Bayesian Information criteria were employed. Table 1 presents the results of analysis for particular models.

While comparing the results presented in table 1, it was checked for which of the presented variants the value of information criterions was the lowest. As a result, the ARIMA model (4,1,4) was selected for the pure coal time series and ARIMA (7,1,4) was picked for the mixture of coal and biomass.

The next step involved conducting forecasts for the assumed model. Figures 5 and 6 present the one-step and multi-step forecasts and interval forecast for 95% probability of the analyzed time series of changes in flame luminosity for pulverized coal and the mixture of coal and biomass.

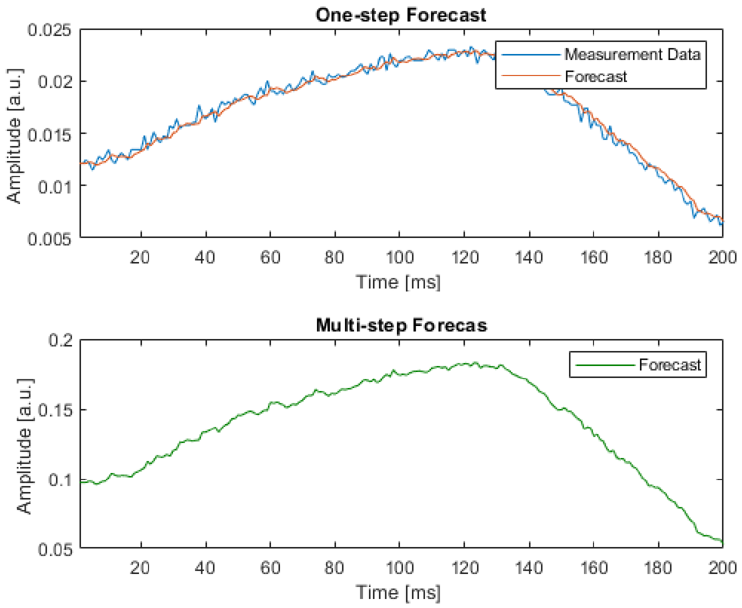


*Fig. 5. Selected measurement data and one-step and multi-step forecasts of changes in flame luminosity for pulverized coal using the ARIMA model (4,1,4)*

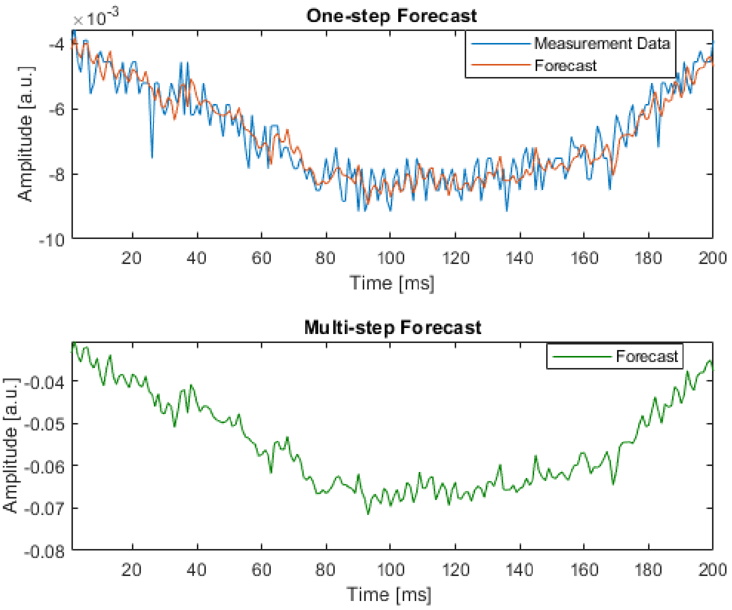


*Fig. 6. Selected measurement data and one-step and multi-step forecasts of changes in flame luminosity for the mixture of 80% coal and 20% biomass using the ARIMA model (7,1,4)*

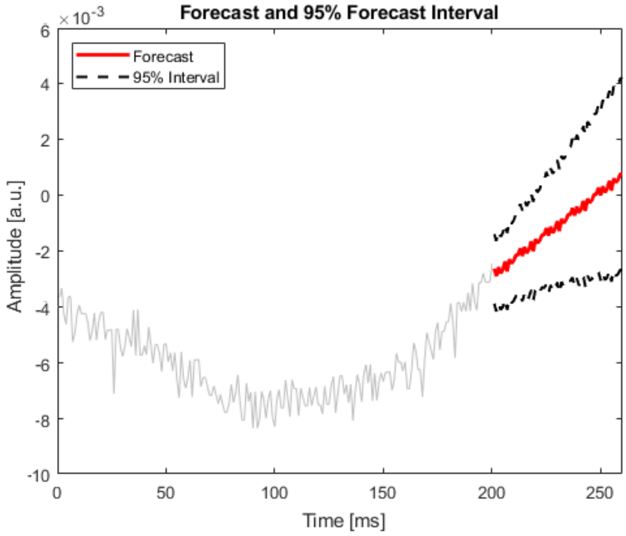


*Fig. 7. Selected measurement data and interval forecast of changes in flame luminosity for mixture of 80% coal and 20% biomass using the ARIMA model (7,1,4)*

The time series for 200 observations were plotted in order to present the forecast results in detail. The multi-step forecasts presented above were prepared for $l = 2$ offsets. When comparing forecasting charts, it should be noted that the multi-step forecast is far away from the measured data. The interval forecasts shown on plots present the interval to which the time series value corresponds with 95% probability. While comparing the shape of measurement data characteristics with a one-step forecast, a high correlation can be seen. The ARIMA model can be successfully used for diagnosing and controlling the combustion process. One-step forecasts, owing to their accuracy, are best suited for the analysis of changes occurring in flames during the combustion process.

## 4. Conclusions

The analysis of changes occurring in the flame during the combustion of pulverized coal or co-combustion of its mixtures, can be performed using numerous methods. The acquisition of data from the flame requires the application of specialist diagnostic systems, such as fiber optic measurement probe. These devices are resistant to high temperatures or possible dusting. The acquisition of measurement data using measurement systems enables recording large amounts of information on the changes occurring in flame. In the monitoring system, the data acquisition process is performed in the following steps: obtaining the data from the flame in the optical form, passing the data to the optoelectronic block, and transforming the information into the electronic form. Afterwards, the measurement data are subjected to further processing and analyses.

The measurement data were presented in the form of time series in two variants: I – pulverized coal and II – mixture of coal and biomass.

The paper presented the process of forecasting the changes in flame luminosity using the ARIMA model. Verification of the selected models using the quantitative criterion indicated that the forecasts should be performed using the ARIMA model (4,1,4) in the first variant and model p = 7, d = 2, q = 4 for the second variant. One-step and multi-step forecasts for $l = 2$ offsets and interval forecasts with 95% probability were prepared for the analyzed time series. The conducted one-step forecasts of changes in flame luminosity indicate high correlation with the real data. Forecasting can be successfully employed for the diagnostics of the combustion process, both for the time series of pure coal and its mixture with biomass.

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*otrzymano/received: 08.05.2020* *przyjęto do druku/accepted: 26.06.2020*