# X-13-ARIMA-SEATS AS A TOOL SUPPORTING ENVIRONMENTAL MANAGEMENT PROCESS IN THE POWER PLANTS

## Włodarczyk A.\*

**Abstract:** A priority issue for Polish enterprises of the energy sector is limiting the emission not only of greenhouse gases but also industrial emissions that accompany energy production processes. Due to the fact that monitoring of industrial emissions is an important stage of the Environmental Management System, the decisions maker ought to be interested in access to new informatics technology enabling pollutant emissions forecasting. The usefulness of automatic procedure X-13-ARIMA-SEATS for forecasting monthly emission indexes of sulphur dioxide, nitrogen oxides, carbon oxide and dust for a certain power plant is verified in this paper. All generated forecasts are evaluated with the use of selected accuracy measures of *ex post* forecasts.

**Key words:** industrial emissions, energy production, X-13-ARIMA-SEATS, forecasting, environmental management

DOI: 10.17512/pjms.2017.16.1.24

Article history:

Received September 1, 2017; Revised September 23, 2017; Accepted October 10, 2017

#### Introduction

A priority issue for the energy sector is limiting the emission of not only carbon dioxide, but also industrial emissions which accompany heat and electricity production processes, especially emission of sulphur dioxide  $(SO_2)$ , nitrogen oxides (NO<sub>x</sub>), carbon monoxide (CO) or dust. The Directive of the European Parliament and Council 2010/75/UE of 24 November 2010 on industrial emissions (so called IED Directive), which had to be transposed by Member States by January 2013, introduced a series of vital changes to previous regulations concerning integrated environment protection, particularly in the scope of a serious tightening on industrial emission standards from the facilities of energy combustion and the use of derogating mechanisms (Directive, 2010). The efficiency of legal instruments of environmental management is frequently strengthened by implementing voluntary programmes for environment protection in the energy sector enterprises (Skowron-Grabowska and Kurp, 2014; Wong et al., 2017). These concern in particular implementing environmental and energy management systems which comply with international standards such as ISO 14001, ISO 50001 or EMAS. It is worth emphasizing that specific quantitative goals are not set for the majority of voluntary environmental programmes, which concern the results of

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actions taken in order to protect natural environment. Instead qualitative goals are defined or applying energy saving production technologies and environmentallyfriendly management practices are stressed. Energy enterprises have to only guarantee that their environmental management systems comply with valid regulations on environment protection and are obliged to constantly reduce emission of pollutants and incessantly undertake preventive actions in this scope (Androniceanu and Popescu, 2017). Numerous research has been conducted in order to evaluate the efficiency of voluntary certification programmes such as ISO 14001 in the scope of improvement in environmental actions effects in different countries (Potoski and Prakash, 2013; Ferrón-Vílchez, 2016; Androniceanu and Drăgulănescu, 2016; Prasad and Mishra, 2017). While evaluating the efficiency of the applied environmental management instruments one should take into consideration first of all forecasted volumes of reducing pollutant emission into the atmosphere, being the result of fossil fuels combustion (Liu et al., 2014). The importance of econometric analysis of air pollution in the development of ecological strategy at the regional level is often stressed by scientific (Zawada and Szajt, 2016; Włodarczyk and Mesjasz-Lech, 2016; Kasperowicz, 2015). It is worth emphasizing that the adoption of sustainable development strategies in companies in the region might protect them against changing conditions of the external environment (Romanowska, 2009; Malara and Kroik, 2012; Sedláková, 2016). Similar as the adjustment of information technologies to business strategies in the enterprises (Jelonek, 2016; Rajnoha and Lesnikova, 2016).

Taking above into consideration, the aim of this study is to evaluate the usefulness of automatic selection procedure of SARIMA(p,d,q)(P,D,Q)<sub>s</sub> models for forecasting monthly values of industrial emission indexes for the power plant located in Silesian Region. On the basis of historical emissions comprising the period from January 2010 until June 2016 the best prognostic models were selected with the use of X-13-ARIMA-SEATS algorithm, which were then used for out-of-sample forecasting of monthly SO<sub>2</sub>, NO<sub>x</sub>, CO and dust emissions per one unit of generated energy in the power plant for the period July 2016 – June 2017.

### X-13-ARIMA-SEATS Procedures for Selecting a Forecasting Model

Decomposition of monthly time series of industrial emissions indexes is a vital issue from the point of view of the decision maker at the power station, who monitor the plant's impact on the environment. Occurrence of strong seasonal fluctuations in the time series representing energy production volume and the level of industrial emissions into the atmosphere hinder comparison and interpretation of monthly changes of emission indexes determined for the power plant. The most popular comprehensive procedure of seasonal time series adjustment by means of ARIMA model-based signal extraction techniques is X-13-ARIMA-SEATS. X-13-ARIMA-SEATS is the Census Bureau's latest program in the X-11 line of seasonal adjustment of time series that has access to the SEATS algorithm (*X-13-ARIMA*-

SEATS Reference..., 2017).<sup>†</sup>This algorithm uses the seasonal ARIMA (SARIMA(p,d,q)(P,D,Q)<sub>s</sub>) models in the form (Błażejowski, 2009):  $\phi(L)\Phi(L^{s})(1-L)^{d}(1-L^{s})^{D}y_{t} = \theta(L)\Theta(L^{s})\varepsilon_{t}$  (1)

where: y<sub>t</sub> –original or transformed time series of industrial emission indexes,

L – lag operator (Ly<sub>t</sub> = y<sub>t-1</sub>), L<sup>s</sup> – seasonal lag operator of period s (L<sup>s</sup>y<sub>t</sub> = y<sub>t-s</sub>),  $\phi(L)$  and  $\Phi(L^s)$  – lag polynomials for respectively non-seasonal and seasonal autoregressive part,  $\theta(L)$  and  $\Theta(L^s)$  – lag polynomials for respectively nonseasonal and seasonal moving average part,  $\varepsilon_t$  – white noise process, *d* – integration level of y<sub>t</sub> series, *D* – seasonal integration level of y<sub>t</sub> series, *p* and *P* –order of respectively non-seasonal and seasonal autoregressive process, *q* and *Q* –order of respectively non-seasonal and seasonal moving average process.

SARIMA class models make it possible to eliminate non-seasonal and seasonal unit roots through d-time determination of first differences of the variable  $((1-L)^d y_t = \Delta^d y_t)$  and D-time calculation of seasonal differences of the variable  $((1-L)^d y_t = \Delta^d y_t)$  in order to obtain a station provide seasonal differences of the variable  $((1-L)^d y_t = \Delta^d y_t)$  is order to obtain a station provide seasonal differences of the variable  $((1-L)^d y_t = \Delta^d y_t)$  is order to obtain a station provide seasonal differences of the variable  $((1-L)^d y_t = \Delta^d y_t)$  is order to obtain a station of seasonal differences of the variable  $((1-L)^d y_t = \Delta^d y_t)$  is order to obtain a station of seasonal differences of the variable  $((1-L)^d y_t = \Delta^d y_t)$  is order to obtain a station of seasonal differences of the variable  $((1-L)^d y_t = \Delta^d y_t)$  is order to obtain a station of seasonal differences of the variable  $((1-L)^d y_t = \Delta^d y_t)$  is order to obtain a station of seasonal differences of the variable  $((1-L)^d y_t = \Delta^d y_t)$  is order to obtain a station of seasonal differences of the variable  $((1-L)^d y_t = \Delta^d y_t)$  and  $((1-L)^d y_t = \Delta^d y_t)$  is order to obtain a station of seasonal differences of the variable  $((1-L)^d y_t = \Delta^d y_t)$  and  $((1-L)^d y_t = \Delta^d y_t)$  of  $((1-L)^d y_t = \Delta^d y_t)$  and  $((1-L)^d y_t = \Delta^d y_t)$  and

 $((1-L^s)^D y_t = \Delta^D y_t)$ , in order to obtain a stationary series as a final result.

It is worth stressing that subsequent specifications of the SARIMA(p,d,q)(P,D,Q)<sub>s</sub> model are checked in the X-13-ARIMA-SEATS, starting from the simplest one (characterized by the most economical parametrisation) and finishing with the specification for which residuals possess white noise properties. The decision-maker is not obliged to perform an initial identification of the six model parameters (1), as selection of all options and parameters estimation by means of maximum likelihood method are carried out automatically. One of the main enhancements in the X-13-ARIMA-SEATS program involves the incorporation of SEATS method into the X-12-ARIMA seasonal adjustment program. X-13-ARIMA-SEATS improves the set of diagnostic tests used in the automatic selection procedure of regression model with ARIMA errors (regARIMA) that is fitted to the original time series(*X-13-ARIMA-SEATS Reference...*, 2017).

Moreover, the following set of *ex post* forecast error measures has been calculated in order to assess accuracy of in-sample forecasts of industrial emissions indexes (Swanson et al., 2011; Chauvet and Potter, 2013):

- root mean squared error (RMSE)

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n-k} \sum_{t=k+1}^{n} (y_t - y_t^p)^2}$$
(2)

- mean absolute percentage error (MAPE)

$$MAPE = \frac{1}{n-k} \sum_{t=k+1}^{n} \left| \frac{y_t - y_t^{\,p}}{y_t^{\,p}} \right| \cdot 100 \tag{3}$$

- Theil inequality coefficient (I)

<sup>&</sup>lt;sup>†</sup> This program is a modification of the previous X-12-ARIMA version of automatic seasonal time series adjustment procedure.



$$I^{2} = \frac{\sum_{t=k+1}^{n} (y_{t} - y_{t}^{p})^{2}}{\sum_{t=k+1}^{n} y_{t}^{2}} = \frac{MSE}{\frac{1}{n-k} \sum_{t=k+1}^{n} y_{t}^{2}}$$
(4)

- the prediction bias proportion coefficient  $(I_1^2)$ 

$$I_{1}^{2} = \frac{(\bar{y}_{t} - \bar{y}_{t}^{p})^{2}}{\frac{1}{n-k}\sum_{t=k+1}^{n} y_{t}^{2}} \div I^{2} = \frac{(\bar{y}_{t} - \bar{y}_{t}^{p})^{2}}{MSE}$$
(5)

- the variance proportion coefficient  $(I_2^2)$ 

$$I_2^2 = \frac{(s_Y - s_{Y^p})^2}{\frac{1}{n - k} \sum_{t=k+1}^n y_t^2} \div I^2 = \frac{(s_Y - s_{Y^p})^2}{MSE}$$
(6)

- the covariance proportion coefficient  $(I_3^2)$ 

$$I_{3}^{2} = \frac{2 \cdot s_{Y} \cdot s_{Y^{p}} \cdot (1 - r_{Y,Y^{p}})}{\frac{1}{n - k} \sum_{t=k+1}^{n} y_{t}^{2}} \div I^{2} = \frac{2 \cdot s_{Y} \cdot s_{Y^{p}} \cdot (1 - r_{Y,Y^{p}})}{MSE}$$
(7)

where:  $y_t$  – real industrial emission index in a t month,  $y_t^p$  – in-sample forecast of industrial emission index for the t month, n-k –number of in-sample forecasts,

MSE - mean squared error,  $s_{Y}$  and  $s_{Yp}$  - standard deviations respectively of real and forecasted industrial emission indexes,  $r_{Y,Yp}$  – Pearson correlation coefficient between real and forecasted pollutant emission indexes.

The presented above *ex post* forecasts errors allow to systemize the decisionmaker's knowledge in the scope of errors committed in the forecast process of industrial emission indexes for the power plant, taking into consideration such aspects of in-sample forecasts errors as accuracy or bias.

### Accuracy Evaluation of Industrial Emission Indexes Forecasts at the Power Plant Obtained from X-13-ARIMA-SEATS

On the basis of data on monthly electricity production volume [MWh] and heat production [GJ] at the power plant located in the Silesian Region, and also accompanying these processes emission of sulphur dioxide  $(SO_2, [Mg])$ , nitrogen oxides (SO<sub>x</sub>, [Mg]), carbon monoxide (CO, [Mg]) and dust (dust, [Mg]), indexes of industrial emission have been determined for the period January 2010 – June 2016 (Figure 1).

In order to recognize the properties of analysed time series, descriptive statistics have been calculated on the basis of industrial emission indexes (Table 1).

It can be observed that the highest volatility characterized the series of dust emission (48.157%) and carbon monoxide emission (19.506%). Considering the results of the Jarque-Bera test one can notice that majority of the variables has a normal distribution at the significance level of 0.05.

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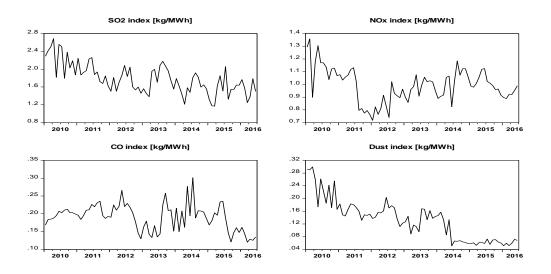


Figure 1. Industrial emission indexes in the period January 2010 – June 2016 for the Silesian power plant

| Table 1. Descriptive statistics for industrial emission indexes determined for the |
|--|
| Silesian power plant   |

| Statistics               | $SO_2$         | NOx             | CO             | Dust            |
|--------------------------|----------------|-----------------|----------------|-----------------|
| Mean                     | 1.7893         | 0.9918          | 0.1902         | 0.1329          |
| Median                   | 1.7757         | 0.9934          | 0.1949         | 0.1375          |
| Maximum                  | 2.6862         | 1.3581          | 0.3014         | 0.2996          |
| Minimum                  | 1.1695         | 0.7177          | 0.1201         | 0.0509          |
| Standard deviation       | 0.3354         | 0.1321          | 0.0371         | 0.0640          |
| Variability coefficient  | 18.745%        | 13.319%         | 19.506%        | 48.157%         |
| Skewness                 | 0.5248         | 0.2031          | 0.1724         | 0.6262          |
| Kurtosis                 | 2.9264         | 3.0207          | 3.1211         | 2.9399          |
| Jarque-Bera statistics   | 3.5981         | 0.5379          | 0.4342         | 5.1095*         |
| Jarque-Dera statistics   | [0.1655]       | [0.7642]        | [0.8048]       | [0.0777]        |
| Zivot-Andrews statistics | -7.5109*** (0) | -6.1787**** (0) | -6.0599*** (0) | -6.3731**** (0) |
| Break date               | 2013 M03       | 2012 M07        | 2014 M07       | 2011 M03        |
|                          |                |                 |                |                 |

Note: (\*\*\*),(\*\*),(\*) point at the rejection of the null hypothesis in Jarque-Bera and Zivot-Andrews tests at 1%, 5% and 10% levels of significance, respectively. The numbers inside the parentheses are the optimum lag lengths determined using Schwarz information criterion. p-value in brackets

In turn, the results of Zivot-Andrews test indicate that the structural breaks are detected for all-time series describing air pollutant emissions relative to energy production in the power plant. Due to this fact an important stage of the decomposing procedure of monthly pollutant emission is adjusting proper smoothing filters for the analysed series, which will recognise the type of outliers occurring in the series.

The analysed period has been divided into the training sample (January 2010 -June 2015) and the testing one (July 2015 – June 2016). In the training sample parameters of the SARIMA model (1) have been identified and estimated, the trend-cycle component, irregular component and seasonal component have been distinguished and with the use of diagnostic tests the smoothing level of particular time series components has been evaluated. Forecasts of monthly indexes of industrial emissions have been generated in the testing sample and then *ex post* forecasts error measures (2)-(7) have been calculated in order to assess their accuracy. Table 2 presents the final specification of the forecasting model for each industrial emission index, which was automatically selected by the X-13-ARIMA-SEATS and X-12-ARIMA procedures.<sup>‡</sup>

| mucaes m u                | ie perioù iroin sanuar y 2010 to   | June 2015                          |
|---------------------------|------------------------------------|------------------------------------|
| Industrial emission index | X-13-ARIMA-SEATS algorithm         | X-12-ARIMA algorithm               |
| SO <sub>2</sub>           | SARIMA(1.0.1)(0.1.1) <sub>12</sub> | SARIMA(0.1.1)(0.1.1) <sub>12</sub> |
| NO <sub>x</sub>           | SARIMA(1.0.1)(1.0.1) <sub>12</sub> | SARIMA(1.0.1)(0.1.1) <sub>12</sub> |
| СО                        | SARIMA(1.1.1)(1.0.1) <sub>12</sub> | SARIMA(1.1.1)(0.0.1) <sub>12</sub> |
| Dust                      | SARIMA(1.1.0)(0.1.1) <sub>12</sub> | SARIMA(0.1.1)(0.1.1) <sub>12</sub> |

Table 2. Identification of the SARIMA(p,d,q)(P,D,Q)<sub>s</sub> model for industrial emission indexes in the period from January 2010 to June 2015

Note: All industrial emission indicators data were automatically transformed into logarithmic value by either X-13-ARIMA-SEATS or X-12-ARIMA procedure.

Parameters of chosen SARIMA models have been estimated by means of the maximum likelihood method and residuals series have been positively verified against the occurrence of Gaussian white noise properties. It is also worth mentioning that the identified by the X-13-ARIMA-SEATS and X-12-ARIMA procedures outliers for the series of  $NO_x$ , CO and dust emission correspond with the observations for which an occurrence of a structural change was assigned in the Zivot-Andrews test. The X-13-ARIMA-SEATS procedure has indicated the occurrence of additional outliers for the majority of the pollutant emission indexes. In particular, the outlier in the nitrogen oxides emission index series has been identified as the one causing a permanent change of the level of  $NO_x$  emission at the power plant (August 2011). The distinguished date can be associated with the decommissioning of the old energy block and the implementation of new technology of hard coal combustion in the energy production process.

Then, forecasting properties of selected SARIMA models have been verified through calculating in-sample forecasts for industrial emission indexes for subsequent months from July 2015 to June 2016. Ex post forecast errors (2) - (7) have been determined in order to select a better automatic forecasting model selection procedure on this basis (Table 3).

<sup>&</sup>lt;sup>‡</sup> In order to evaluate the improvement in the forecasting performance of the X-13-ARIMA-SEATS algorithm, the results obtained from this procedure have been compared with the forecasts generated from the older X-12-ARIMA procedure.

| Industrial        | X     | X-13-ARIMA-SEATS algorithm |       |                                      |             |                                      |       | X-12-ARIMA algorithm |       |                          |                          |                                      |  |
|-------------------|-------|----------------------------|-------|--------------------------------------|-------------|--------------------------------------|-------|----------------------|-------|--------------------------|--------------------------|--------------------------------------|--|
| emission<br>index | RMSE  | MAPE                       | Ι     | I <sub>1</sub> <sup>2</sup> /<br>MSE | $I_2^2/MSE$ | I <sub>3</sub> <sup>2</sup> /<br>MSE | RMSE  | MAPE                 | Ι     | I1 <sup>2</sup> /<br>MSE | I2 <sup>2</sup> /<br>MSE | I <sub>3</sub> <sup>2</sup> /<br>MSE |  |
| SO <sub>2</sub>   | 0.146 | 13.506                     | 0.685 | 0.006                                | 0.270       | 0.724                                | 0.154 | 14.628               | 0.689 | 0.105                    | 0.248                    | 0.647                                |  |
| NO <sub>x</sub>   | 0.100 | 77.709                     | 3.206 | 0.791                                | 0.089       | 0.120                                | 0.101 | 82.680               | 3.310 | 0.891                    | 0.016                    | 0.093                                |  |
| CO                | 0.515 | 24.694                     | 3.587 | 0.898                                | 0.041       | 0.061                                | 0.523 | 25.769               | 3.635 | 0.943                    | 0.002                    | 0.055                                |  |
| Dust              | 0.224 | 6.861                      | 1.564 | 0.433                                | 0.197       | 0.370                                | 0.247 | 7.632                | 1.723 | 0.644                    | 0.138                    | 0.218                                |  |

Table 3. Ex post forecasting errors for emission indexes in the period from July 2015to June 2016

Note: The Theil inequality coefficient was rescaled into percentage value. Bold values point at the lower forecast errors

While evaluating the quality of forecasting models only on the basis of the RMSE<sup>§</sup> criterion, which is sensitive to the scale of values taken by the forecasted variable, one can notice that in each case errors of in-sample forecasts generated with the use of the X-13-ARIMA-SEATS algorithm have been smaller. Similar results have been obtained for two next criteria of in-sample forecast accuracy evaluation, which use in the comparison process MAPE and Theil coefficient.<sup>\*\*</sup> Relatively low values of both forecast measures for the in-sample forecasts generated with the use of the X-13-ARIMA-SEATS algorithm for the emission indexes of SO<sub>2</sub> and dust confirm good forecasting properties of the constructed SARIMA models. For the series depicting NO<sub>x</sub> and CO emissions with the reference to energy production volume it has not been possible to generate accurate forecasts for the period from July 2015 to June 2016, considering the MAPE value. In order to check to source of forecast errors the measures obtained as a result of the Theil coefficient decomposition have been analysed (5)-(7). According to Pindyck and Rubinfeld (1998), accurate forecasting method is characterized by the relatively small values of the bias proportion and variance proportion. Taking into consideration that the bias, variance and covariance proportions sum up to one, it is expected the highest values of the covariance proportion, which measures the remaining unsystematic forecasting errors. The above condition is fulfilled for two forecasting models: SARIMA(1.0.1)(0.1.1)<sub>12</sub> and SARIMA(0.1.1)(0.1.1)<sub>12</sub> adjusted to sulphur dioxide emission indexes series. In these cases forecast errors resulted mainly from a low correlation of forecasts and empirical values of the emission indexes, which confirm a limited ability of forecasting turning points for the  $SO_2$  emission series on the basis of chosen SARIMA models. Optimum SARIMA models selected by the automatic procedure X-12-ARIMA, have been characterized by a very high share of errors caused by forecast bias in the mean square error: 89-percent share for  $NO_x$  emission index, 94-percent share for CO emission index or 64-percent

<sup>&</sup>lt;sup>\*\*</sup> The Theil inequality coefficient and the Mean Absolute Percentage Error are scale invariant.



<sup>&</sup>lt;sup>§</sup> RMSE depends on the scale of the dependent variable, so it should be used only to compare forecasts for the same variable derived from different forecasting models. The lower RMSE value, the better forecasting model.

share for dust emission index. Similar results have been obtained for the X-13-ARIMA-SEATS procedure in case of CO and  $NO_x$  series. These are distinct signals indicating that the average value of generated forecasts to a small extent imitates the average empirical value of industrial emission indexes in the testing period, and thus, the decision maker should change the forecasting model.

The last part of the analysis concerns generating the monthly out-of-sample forecasts of industrial emission indexes at the power plant for the period from July 2016 to June 2017. Due to the fact that in most cases the X-13-ARIMA-SEATS algorithm generated better forecasts than the X-12-ARIMA procedure, the combined forecasts for the SO<sub>2</sub>, NO<sub>x</sub>, CO and dust emission indexes will be constructed with the use of subjectively proposed weights: 0.7 and 0.3 (Table 4). It should be remembered to treat some of the presented in Table 4 forecasts for the NO<sub>x</sub> and CO emission indexes very carefully due to weak forecasting properties of SARIMA models, which were used to calculate them (Table 3).

Table 4. Forecasts of pollutant emission indexes for the Silesian power plant for the<br/>period from July 2016 to June 2017

| period if onit July 2010 to Jule 2017 |                                 |                 |       |       |                           |                 |       |       |                    |                 |       |       |
|---------------------------------------|---------------------------------|-----------------|-------|-------|---------------------------|-----------------|-------|-------|--------------------|-----------------|-------|-------|
| Forecast<br>horizon                   | Forecasts -<br>X-13-ARIMA-SEATS |                 |       |       | Forecasts -<br>X-12-ARIMA |                 |       |       | Combined Forecasts |                 |       |       |
| 10112011                              | SO <sub>2</sub>                 | NO <sub>x</sub> | CO    | Dust  | $SO_2$                    | NO <sub>x</sub> | CO    | Dust  | $SO_2$             | NO <sub>x</sub> | CO    | Dust  |
| 2016-7                                | 1.625                           | 0.962           | 0.127 | 0.074 | 1.604                     | 0.939           | 0.111 | 0.071 | 1.619              | 0.955           | 0.122 | 0.073 |
| 2016-8                                | 1.571                           | 0.968           | 0.129 | 0.069 | 1.591                     | 1.033           | 0.108 | 0.065 | 1.577              | 0.988           | 0.123 | 0.068 |
| 2016-9                                | 1.608                           | 0.961           | 0.123 | 0.070 | 1.580                     | 0.929           | 0.098 | 0.066 | 1.600              | 0.951           | 0.116 | 0.068 |
| 2016-10                               | 1.525                           | 0.966           | 0.128 | 0.067 | 1.534                     | 0.936           | 0.106 | 0.062 | 1.528              | 0.957           | 0.122 | 0.065 |
| 2016-11                               | 1.583                           | 0.970           | 0.126 | 0.065 | 1.559                     | 0.940           | 0.113 | 0.061 | 1.576              | 0.961           | 0.122 | 0.064 |
| 2016-12                               | 1.501                           | 0.961           | 0.127 | 0.061 | 1.492                     | 0.909           | 0.108 | 0.057 | 1.498              | 0.945           | 0.121 | 0.060 |
| 2017-1                                | 1.531                           | 0.949           | 0.127 | 0.060 | 1.512                     | 0.878           | 0.118 | 0.056 | 1.525              | 0.927           | 0.125 | 0.059 |
| 2017-2                                | 1.429                           | 0.957           | 0.125 | 0.062 | 1.413                     | 0.893           | 0.107 | 0.059 | 1.424              | 0.938           | 0.119 | 0.061 |
| 2017-3                                | 1.354                           | 0.949           | 0.121 | 0.055 | 1.421                     | 0.861           | 0.100 | 0.052 | 1.374              | 0.923           | 0.115 | 0.054 |
| 2017-4                                | 1.429                           | 0.960           | 0.124 | 0.056 | 1.420                     | 0.935           | 0.102 | 0.052 | 1.426              | 0.952           | 0.117 | 0.055 |
| 2017-5                                | 1.489                           | 0.973           | 0.121 | 0.058 | 1.476                     | 1.002           | 0.102 | 0.055 | 1.485              | 0.982           | 0.115 | 0.057 |
| 2017-6                                | 1.475                           | 0.946           | 0.122 | 0.054 | 1.469                     | 0.925           | 0.103 | 0.051 | 1.473              | 0.939           | 0.116 | 0.053 |

Also average out-of-sample forecasts values of pollutant emission indexes for the period from July 2016 to December 2016 have been compared with the recorded industrial emissions level calculated per unit of produced energy at the Silesian power plant. It can be noticed that out-of-sample forecasts of sulphur dioxide emissions obtained with the use of each forecasting method were overestimated, while the forecasts of nitrogen oxides emissions were underestimated. Closest to the real measures have been forecasts of dust obtained with the use of the combined method and forecasts of nitrogen oxides generated from the algorithm X-13-ARIMA-SEATS.

|                | I.              | n the power plant |               |            |
|----------------|-----------------|-------------------|---------------|------------|
| Industrial     | Mean Forecast - | Mean Forecast -   | Mean Combined | Real value |
| emission index | X-13-ARIMA      | X-12-ARIMA        | Forecast      | [kg/MWh]   |
| $SO_2$         | 1.569           | 1.560             | 1.566         | 1.502      |
| NOx            | 0.965           | 0.948             | 0.960         | 0.969      |
| Dust           | 0.068           | 0.064             | 0.067         | 0.066      |

| Table 5. Summary of average monthly forecasts with real pollutant emission indexes |
|--|
| for the power plant  |

### Conclusion

This paper presents the evaluation of the usefulness of the X-13-ARIMA-SEATS algorithm in the scope of an automatic selection of the SARIMA(p.d.q)(P.D.Q)<sub>s</sub> forecasting model. The main advantage of the X-13-ARIMA-SEATS algorithm is the possibility of making comparison between the seasonal adjustment results derived from the SEATS procedure and the X-11 procedure by means of the same set of diagnostic tests. This feature ought to help in the selection of the accurate forecasting model. Such type of the analysis was unavailable in the older version of this algorithm; therefore the usefulness and the limitations of the automatic modeling and forecasting procedures of the TRAMO/SEATS and the X-12-ARIMA were the subject of many research studies (McDonald-Johnson et al., 2007; Błażejowski, 2009). McDonald-Johnson et al. (2007) found that the diagnostic tests conducted for the X-12-ARIMA models were at least as good as those obtained for the TRAMO models. In turn, Błażejowski (2009) showed that the accuracy of predictions of monthly unemployment rate in Poland's voivodships was significantly better in the case of the X-12-ARIMA models than the TRAMO/SEATS models.

In this paper, the forecasting properties of the X-13-ARIMA-SEATS models were verified on the basis of *ex post* forecasts errors of industrial emission indexes for the power plant. The obtained results allow to notice that the X-13-ARIMA-SEATS algorithm generated better in-sample forecasts for the industry emission indexes than its older version. Creation of combined forecasts has also been proposed, which combine results generated by both automatic algorithms. The issue which needs to be solved is weight selection in the construction process of combined forecasts. While evaluating the accuracy of out-of-sample forecasts, one can also notice an advantage of the X-13-ARIMA-SEATS method and the combined one over the X-12-ARIMA. Therefore, the industrial emission forecasts derived from the X-13-ARIMA-SEATS algorithm may be used in the environmental management process in the power plant.

The Environmental Management System is an important pillar of the Integrated Enterprise Management System, which is dedicated to control and reduce the negative impact of the coal-fired power generation processes on the environment. A comparison of the SO<sub>2</sub>, NO<sub>x</sub> and dust emission forecasts, that are generated by the X-13- ARIMA-SEATS algorithm, to the permitted emission levels described in the Integrated Permit, enables to evaluate the compliance of the power plant

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operations with the applicable law. These forecasts may also be compared to the industrial emission indices for electricity produced in the combustion plants in Poland, calculated by the National Centre for Emissions Management (KOBiZE). The forecasts of SO<sub>2</sub>, NO<sub>x</sub>, CO and dust emission indices for the Silesian power plant do not significantly exceed the industrial emission indices calculated by KOBIZE, which amount respectively: 1.539, 0.968, 0.238 and 0.063 kg/MWh. Moreover, the forecasted emissions of  $SO_2$ ,  $NO_x$  and dust are respectively about 33.12, 47.03 and 15.48% of the current emission limits in the analyzed power plant. In case, when the forecasts of  $SO_2$ ,  $NO_x$  and dust emissions indicate the high use of the allocated limits, it is necessary to take measures leading to the proecological modernization of the power plant involving new protective devices such as: electrostatic precipitators, desulphurization or denitrogenation installations of gas flue. The importance of analyses of this kind should be stressed due to the obligation imposed on the EU member states and large combustion sources located within the territory of these countries to prepare a periodical balance and forecasts of SO<sub>2</sub>, NO<sub>X</sub>, CO, PM<sub>10</sub>, PM<sub>2.5</sub> emission (Directive (EU) 2016/2284 of the European Parliament...). Moreover, the decision-maker who possesses the knowledge in the expected level of pollutant emission that accompanies the processes of electricity and heat production can monitor in a more aware way the process of environmental management and evaluate future influence of energy production processes on the environment. In particular through the comparison of SO<sub>2</sub>, NO<sub>x</sub>, CO and dust emission indexes forecasts to the valid emission standards in the country and the whole European Union, the decision-maker can plan future investments connected with low-emission modernization of the power plant. Włodarczyk and Mesjasz-Lech (2016) also stressed the importance of air pollutants emissions modelling in the planning, designing and implementation of such activities in the power plant that may reduce air pollution emissions to the safe level. They used the econometric model with deterministic seasonality and trend for the forecasting of monthly micropollutants emissions and energy production in the power plant. Additionally, these authors estimated the Markov-switching models in order to detect switches in volatility regimes of micropollutants emissions. Above described approach requires the decision-maker to possess both specialist knowledge in the scope of econometric modelling and advanced econometric software. The X-13-ARIMA-SEATS automatic procedure of model selection and forecasting is free of such restrictions; therefore this algorithm is becoming increasingly popular among practitioners.

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### X-13-ARIMA-SEATS JAKO NARZĘDZIE WSPOMAGAJĄCE PROCES ZARZĄDZANIA ŚRODOWISKOWEGO W ELEKTROWNI

**Streszczenie:** Priorytetową kwestią dla polskich przedsiębiorstw z sektora energetycznego jest ograniczenie emisji nie tylko dwutlenku węgla, ale również emisji przemysłowych towarzyszących procesom wytwarzania energii. Ze względu na fakt, że monitorowanie emisji przemysłowych jest ważnym etapem Systemu Zarządzania Środowiskowego, decydent powinien być zainteresowany dostępem do nowych technologii informatycznych umożliwiających prognozowanie emisji zanieczyszczeń. W związku z tym w pracy zweryfikowano przydatność automatycznej procedury X-13-ARIMA-SEATS w procesie prognozowania miesięcznych wskaźników emisji dwutlenku siarki, tlenków azotu, tlenku węgla i pyłu dla pewnej elektrowni. Wszystkie wygenerowane prognozy zostały ocenione za pomocą wybranych miar trafności prognoz *ex post*.

**Słowa kluczowe:** emisje przemysłowe, produkcja energii, X-13-ARIMA-SEATS, prognozowanie, zarządzanie środowiskowe

### X-13-ARIMA-SEATS作为工具支持电厂的环境管理过程

**摘要:**波兰能源部门的一个优先问题是限制温室气体的排放,而不仅限于伴随能源生 产过程的工业排放。由于监测工业排放是环境管理体系的重要阶段,决策者应该有兴 趣获得新的信息技术,从而实现污染物排放预测。验证了自动程序X-13-ARIMA SEATS预测某电厂二氧化硫,氮氧化物,碳氧化物和粉尘月排放指标的有效性。 所有生成的预测都使用选定的事后预测准确度量度进行评估。 关键词:工业排放,能源生产,X-13-ARIMA-SEATS,预测,环境管理