Desalination and Water Treatment
www.deswater.com
doi: 10.1080/19443994.2015.1017319

57 (2016) 993–1011
January

Modelling of air micropollutant's fluctuations on the background of the primary air pollutants emission as a tool supporting environmental management in thermal power plant

Aneta Włodarczyk*, Agata Mesjasz-Lech

Management Faculty, Częstochowa University of Technology, Armii Krajowej 19b, 42-200 Częstochowa, Poland, Tel. +48 34 3250 384; emails: aneta.w@interia.pl (A. Włodarczyk), agata.mesjasz@poczta.fm (A. Mesjasz-Lech)

Received 14 July 2014; Accepted 29 December 2014

ABSTRACT

Power industry belongs to those branches of the industry in Poland whose impact on the environment is extremely negative, especially due to the emission of different types of pollutants into atmosphere. Therefore, appropriate prevention or dealing with the threats to the natural environment is a key issue of the environmental management system in each thermal power plant. That involves planning, designing and implementation of such activities that may prevent or reduce air pollution emissions to the safe level. These activities should be directed not only on the primary air pollutants (CO_2, CO, SO_2, NO_x and dust), but also micropollutants (Cl_2, Cu, Cr, Pb and F), which pose a serious threat to the natural environment, as well as peoples' health and life. In order to plan appropriate ventures aimed at reducing the micropollutants emissions, it is imperative to conduct the analysis of the micropollutants emissions size changeability in time. Seasonal patterns for micropollutants emissions in the thermal power plant, situated in the Silesian Region in Poland, is identified by using two of the seasonal adjustment time series methods (X-12-ARIMA and seasonal dummies model). Next, Markov switching models were estimated on the basis of monthly data from January 2006 to June 2012 (78 months) in order to detect switches in volatility regimes of micropollutants emissions.

Keywords: Environmental management; Micropollutants emissions; Thermal power plant; Seasonal adjustment time series methods; Markov-switching models

1. Introduction

The main goals of national energy policy and strategic directions of State's operations in this area have been included in the Polish Energy Policy until 2030. Apart from energy security, an increase in energy effectiveness, a greater use of renewable energy sources and development of competitive fuel and energy markets, the energy sector has been set new tasks connected with environment protection, in particular limiting the negative impact of power industry on environment [1]. However, the implementation of

*Corresponding author.

Presented at the 12th Scientific Conference on Microcontaminants in Human Environment 25–27 September 2014, Czestochowa, Poland

the objectives of environmental policy is associated with incurring high capital expenditures. The Operational Program Infrastructure and Environment was one of the EU programmes, planned for 2007–2013 for supporting environmental activities in Poland [2].

Environment protection is mentioned as one of the energy problems in the global social perspective [3]. Ecological actions are mainly aimed at elimination of solutions which are harmful to the environment and increased energy economy effectiveness. Moreover, the research has shown that it is possible to reconcile the environmental protection and the financial success in the case of businesses. It has been proved that environmental measures and activities such as environmental impact assessment, design for environment, pollution prevention and cleaner production, or environmental management systems are related to gaining competitive advantages and higher financial performance [4].

In the case of thermal power plants, mainly products of fuel burning have an impact on the environment, so do the ones that come from the fuel circle including:

(1) exhaust gases containing—uncaptured by dust collectors—fly ash,
(2) sulphur dioxide,
(3) nitric oxides, carbon monoxide and carbon dioxide, fly ash captured by dust collectors,
(4) slag,
(5) copper, chromium, lead, benzo(a)pyrene, chlorine, fluorine and
(6) waste and sewage from the exhaust gases desulfurization.

Unfortunately, hard coal and lignite coal have been comprising the basic energy source in the process of production of both thermal energy and electricity in Poland [5]. Thermal power stations should then aim at changing the energy sources from conventional ones into renewable ones due to more and more restrictive law regulations in the scope of air protection. In Poland limits of pollutants on the level of national emission is defined by the decree of the Ministry of Environment of the 3rd of March 2008 regarding the acceptable level of some substances in the air (Journal of Laws 2008 nr 47 pos. 281). These limits reflect the commitments included in the directive of the European Parliament and Council 2001/81/WE of 23rd October 2001 on national emission levels of some air pollutants. The regulations of the abovementioned directive transfers on Polish ground the Law on Environment Protection (Journal of Laws nr 25 pos. 150 with future amendments). Apart from the mentioned acts, there are numerous other law regulations applicable concerning immission and emission of air pollutants, which will not be discussed in the paper since they do not refer to the main subject matter.

Due to economic effectiveness one should try to achieve such a level of particular pollutants, including micropollutants, which could ensure that the costs of their reduction are possibly the lowest and they do not exceed external costs. It may be helpful here to apply technologies which reduce pollution and introduce new clean production systems. Moreover, each economic subject producing pollutants, in this power plants, is obliged to comply with the rules of environment protection policy, the aim of which is also to prevent negative effects of enterprise activity.

Although the amount of emission of such pollutants as: copper, chromium, lead, benzo(a)pyrene, chlorine and fluorine is relatively small, they pose a serious threat to health and people's lives as well as the natural environment. Therefore, it is important to take into consideration pro-environment activities aimed at this group of pollutants in environmental managing of the thermal power plant and applying pro-environmental assumptions and standards.

To authors' knowledge, there are, statistically, an insufficient number of studies examining the micropollutants emission process focused on decomposition of the quantity of emission into both deterministic and stochastic components. Most of this type of statistical research has been devoted to carbon dioxide emission [6,7]. Additionally, this paper differs from the existing literature because the authors have implemented Markov-switching models for detecting switches between the low and high volatility regimes of air pollutants emissions and energy production in the thermal power plant. Such information may be useful in the decision-making process about the size of energy production from non-renewable sources in the thermal power plant simultaneously with the maintaining of the control over the issues of the micropollutants emissions into the atmosphere.

Micropollutants, being a negative side effect of fuel burning process, should be thoroughly analysed. A partial solution to the problem may be the application of renewable energy sources. Renewable energy is becoming a key pillar of a new energy paradigm due to the role it plays in increasing energy security and decarbonisation of global economy [8].

2. Environmental management system in the thermal power plant

All applied in power plants methods which prevent or minimize the negative impact on the natural environment should bring not only ecological effects but also the economic ones. This is in line with the basic assumption of the ecological policy that involves pro-ecological activities contributed to environment protection through limiting negative effects for particular elements of the environment, caused by production, distribution and consumption processes, preserving at the same time quantity and economic standards. Economic effects are mostly connected with limiting the costs due to applied technologies and designing material flow models in closed cycles. Ecological effects are reflected primarily in decreased pollution emission and waste generation. Environment protection processes in thermal power plants should be integrated with the general management system. This is possible through the implementation of environmental management concept in the power plant operations. Integrated systems of pollutants flow and information associated with them are created within this concept in order to produce and transform physical goods optimally. One of the goals of environmental management is to perceive and comply the processes realized in power plants with required standards of environment protection preserving at the same time desired standards of quality and economy.

Environmental management systems involve ecological aspects of the functioning of an enterprise [9]. More and more frequently the attention is paid to green energy created in the process which does not pose a threat to the natural environment [10]. Implementation of environmental management is indispensable in order to decrease a negative impact of thermal energy on natural environment. Power stations constitute an exceptional danger to the ecosystem mainly because of the type of fuel used in the energy production and the technological process itself. The basic energy source in the examined power station is coal. Energetic coal is characterized by:

(1) calorific value, i.e. combustion heat and fuel value,
(2) moisture,
(3) combustible elements content,
(4) ash content,
(5) sulphur and trace elements content and
(6) susceptibility of pulping.

For the sake of environment protection: the calorific value, the ash and sulphur content, the trace and radioactive elements content are important. The calorific value determines the amount of coal which should be burned in the electric and heat energy production. The ash content determines the ash dirty fumes, the ash fall on the ground, the amount of dust in atmospheric air and the amount of removed slag. The sulphur content tells about the extent of sulphur air pollution, the trace and radioactive elements content about the additional harmfulness of ash fall and dust that is in the air. Trace elements, after the coal has been burnt, become the constituents of fly ash and slag. Coal parameters influence exploitation of thermal power station and therefore indirectly have an influence on natural environment. Considering the fact that there is no direct dependence between coal parameters and pollutants emission and low coal parameters volatility of the examined power station in the assumed period of research, the author decided not to determine cause–result dependencies of these variables and concentrated on time series analysis.

A technological process of power plant consists of following cycles: fuel, steam, water and electric [11,12]. In fuel cycle the production fuel (coal) is supplied. Due to the fact that mainly the quality of coal has an impact on environment, the following processes have to take place in the fuel cycle: removing and clearing of boiler fumes, removing of fly ash retained in pollutant reduction systems, removing of slag from under the boilers. A steam cycle is a self-contained system, filled up with additional water and consists of: a boiler, steam pipelines, turbine with steam condenser, condensation pumps, condensation pipelines, water supply pumps, regeneration heater, gas reduction installations and water supply pipelines. A water cycle is connected with a steam cycle. It includes a water cooling system (self-contained-cooling tower, open-natural water reservoirs), additional water installation, a steam cycle supply water system and a self-contained system of cooling water. In the electric cycle, electric and heat energy production takes place. The cycle consists of: a generator, a transformer raised voltage, power brought lines, a transformer fallen voltage and own power plants equipment (e.g. distributors, cables and electric motors).

Implementing some pro-environmental activities in thermal power plants aim at minimizing micropollutants emission, which poses some threats to both the environment and people, should be the consequence not only of the legal and administrative obligations and prohibitions in this respect, but a display of ecological awareness of the managerial staff. Ecological awareness influences the value system and contributes to pro-ecological attitudes [13,14]. Electro energy is one of the most important sub-systems of the state's energy infrastructure [15]. Therefore, thermal power plants should consequently implement pro-ecological activities in order to increase their competitiveness and satisfy the ecological demands of more and more aware clients.

3. Micropollutants emission data description

The problem of micropollutants emitted by thermal power plants is not discussed in the literature of the subject. This is connected with a low level of such emission generated by these economic subjects and its high volatility. Empirical goal of this article is to analyse the quantity and costs of the micropollutants emission into the atmosphere, which were produced by the thermal power plant, situated in the Silesian Region in Poland. This subject seems to be very important in the context of the environmental management issue, the statutory limitations of emissions of greenhouse gases resulting from the ratification of the Kyoto Protocol and the history of the region, whose economy was based on coal mining. The statistical–econometric analysis was conducted on the bases of the following time series of micropollutants emission: chlorine ($Cl_{emission}$), fluorine ($F_{emission}$), some heavy metals (lead ($Pb_{emission}$), copper ($Cu_{emission}$), chromium ($Cr_{emission}$)). Monthly frequency data-set covered the period from January 2006 to June 2012 (Fig. 1). Values of particular pollutants emission used in the research come from the database of the examined power station. Data concerning pollutants emission are mainly gathered for the need of statistical and government reports, which the power station is obliged to prepare. The goal of measuring the level of pollutants emission guarantees therefore high accuracy and quality of the data-set concerning it.

Analysing Fig. 1, the authors noticed a similar dynamism of the amount of heavy metals generated when coal is burned in the process of energy production ($Pb_{emission}$, $Cr_{emission}$ and $Cu_{emission}$) and emitted dust and fluorine ($F_{emission}$), while each of these time series was characterized by a decreasing tendency in the analysed period. In order to find out the regularity in shaping air pollutants emission into the atmosphere descriptive statistics were determined and tests (a stationarity test (ADF, PP), a serial correlation test (B–P) and a heteroscedastisity test (ARCH)) verifying the dynamic structure of time series were conducted (Tables 1 and 2) [16,17].

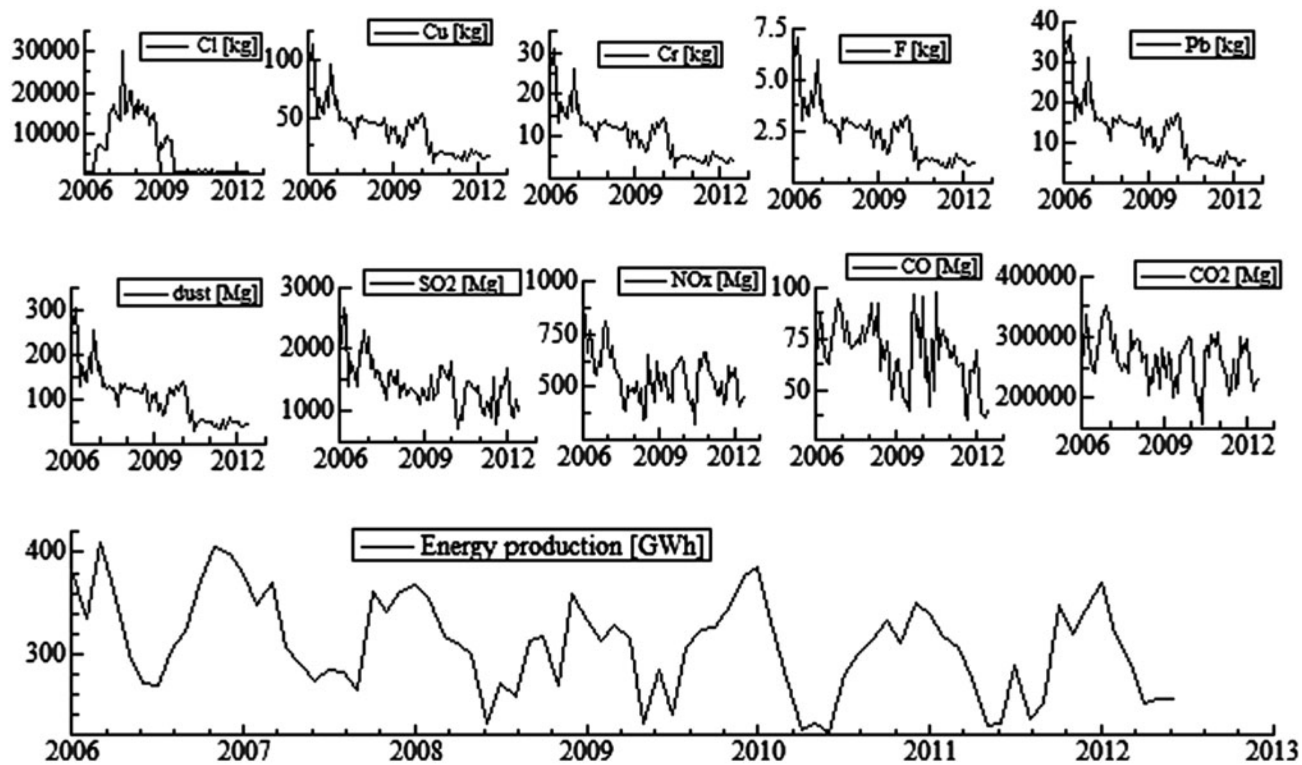

Fig. 1. Micropollutants (upper panel) and primary air pollutants (middle panel) emissions into the atmosphere, energy production (lower panel) in thermal power plant, January 2006–June 2012.

Table 1
Descriptive statistics of monthly air pollutants emissions by thermal power plant

Statistics	Minimum	Mean	Maximum	Standard deviation	Variation coefficient [%]	Skewness	Excess Kurtosis	Jarque–Bera
$Cl_{emission}$ [kg]	162.4	6,263.68	30,039.4	7,061.85	112.74	0.958 [0.000]	−0.023 [0.965]	11.935 [0.003]
$Cu_{emission}$ [kg]	10.47	39.18	113.58	22.21	56.69	1.152 [0.000]	1.567 [0.004]	25.243 [0.000]
$Cr_{emission}$ [kg]	2.83	10.59	30.70	6.00	56.66	1.152 [0.000]	1.567 [0.004]	25.243 [0.000]
$Pb_{emission}$ [kg]	3.40	12.71	36.84	7.20	56.65	1.152 [0.000]	1.567 [0.004]	25.243 [0.000]
$F_{emission}$ [kg]	0.65	2.44	7.06	1.38	56.56	1.152 [0.000]	1.567 [0.004]	25.243 [0.000]
$Energy_{production}$ [GWh]	222.26	310.20	409.88	47.32	15.25	−0.003 [0.991]	−0.765 [0.155]	1.901 [0.387]
$Dust_{emission}$ [Mg]	28.30	105.89	306.96	60.02	56.68	1.152 [0.000]	1.567 [0.004]	25.243 [0.000]
$SO_{2emission}$ [Mg]	704.75	1,441.60	2,653.67	381.90	26.49	0.798 [0.003]	0.899 [0.945]	10.920 [0.004]
$NO_{xemission}$ [Mg]	327.48	551.50	887.45	112.34	20.37	0.558 [0.040]	0.240 [0.656]	4.238 [0.120]
$CO_{2emission}$ [Mg]	156,428.2	262,365.9	351,761.1	37,218.90	14.19	−0.167 [0.539]	−0.060 [0.911]	0.375 [0.829]
$CO_{emission}$ [Mg]	34.77	67.70	97.25	15.48	22.87	−0.288 [0.289]	−0.474 [0.379]	1.811 [0.404]

Source: Own calculation in PcGive 14—an econometric software, *p*-value in brackets.

Table 2
Dynamic specification tests of time series of monthly air pollutants emissions

Statistics	Box–Pierce(1)	Box–Pierce(5)	Box–Pierce(12)	ARCH 1–1	ARCH 1–5	ADF (intercept and trend)	P–P (intercept and trend)
$Cl_{emission}$ [kg]	61.10 [0.000]	266.32 [0.000]	439.59 [0.000]	53.426 [0.000]	19.621 [0.000]	−3.087	−2.660 [0.256]
$Cu_{emission}$, $Cr_{emission}$, $Pb_{emission}$, $F_{emission}$ [kg], $Dust_{emission}$ [Mg]	54.63 [0.000]	170.24 [0.000]	280.27 [0.000]	150.56 [0.000]	28.00 [0.000]	−3.419	−4.812 [0.001]
$Energy_{production}$ [GWh]	32.39 [0.000]	69.60 [0.000]	166.40 [0.000]	55.61 [0.000]	18.87 [0.000]	−6.518*	−4.596 [0.000]
$SO_{2emission}$ [Mg]	35.83 [0.000]	83.58 [0.000]	139.77 [0.000]	69.48 [0.000]	13.55 [0.000]	−4.984*	−5.267 [0.000]
$NO_{xemission}$ [Mg]	35.67 [0.000]	67.57 [0.000]	85.68 [0.000]	90.21 [0.000]	13.38 [0.000]	−3.890	−4.414 [0.004]
$CO_{2emission}$ [Mg]	26.34 [0.000]	48.79 [0.000]	101.50 [0.000]	40.99 [0.000]	11.56 [0.000]	−5.778*	−4.973 [0.001]
$CO_{emission}$ [Mg]	22.75 [0.000]	51.98 [0.000]	61.83 [0.000]	23.37 [0.000]	7.77 [0.000]	−3.944	−5.612 [0.000]

Source: Own calculation in PcGive 14—an econometric software, *p*-value in brackets.
*indicates the significance of the result at the 0.01 level.

Analysing the results from Table 1, the authors notice that in the category of micropollutants, the thermal power plant, on average, emitted the largest amount of chlorine (6263.68 kg, which constitutes 98.974% of the emission level of all other micropollutants), then copper (39.18 kg—0.62% emission of all micropollutants), lead (12.71 kg—0.2%), chromium (10.59 kg—0.17%) and fluorine (2.44 kg—0.04%) monthly into the atmosphere. It should be also stressed that chlorine emission was characterized by the highest volatility in the monthly scale (112.74%). Generally, monthly volatility of an emission scale of other micropollutants was relatively high (about 56.7%) in comparison with carbon dioxide emission volatility which amounted to 14.19% or sulphur dioxide (26.49%). Due to such high fluctuations of the rate of micropollutants into the atmosphere by thermal power plants the issue of modelling their emission volatility, undertaken by the authors, seems to be important and justified, particularly in the context of their harmfulness to the whole ecosystem. Presented in Table 1 results of Jarque–Bera test indicate a normal distribution of energy production quantity and CO_2, CO and NO_x emission rate. Moreover, the authors noticed that skewness coefficients, kurtosis characteristic of distribution of the micro-pollutant emission into the atmosphere took the same value for all micropollutants and dusts emission. Similar regularities can be observed while analysing autocorrelation tests statistics (orders 1, 5 and 12), ARCH effect (orders 1, 5) and unit roots occurrence for time series of micropollutants and dusts emission, which indicates a similarity in a dynamic development of these phenomena.

In the case of all analysed time series the authors have confirmed the effect of autocorrelation dependencies occurrence from the 1st order to the 12th inclusively (Box–Pierce statistics in Table 2), which may indicate the occurrence of seasonal effects connected with some different energy production structures in particular months of the year. The importance of the statistics in the ARCH effect test for each order of pollutants indicates the occurrence of the variance grouping effect (Table 2) and justifies heteroskedastic specification of Markov-switching model used in the next stage of research.

Additionally, using the EViews 8 econometric software package the Phillips–Perron test (PP) was conducted for investigating the stationarity of the micropollutants emissions level, primary pollutants emissions and energy production. The PP test is more powerful than the ADF test and the PP test does not require any assumptions about the type of serial correlation or heteroscedasticity in the error disturbances [6]. The results of the PP test indicate non-stationarity of only one time series, namely, chlorine emission into the atmosphere.

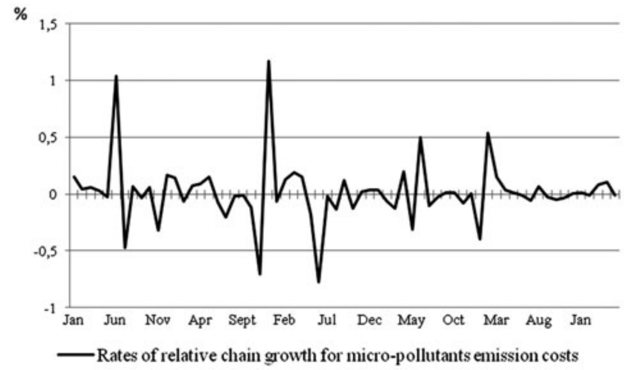

Fig. 2. Monthly changes for the micropollutants emission cost in Silesian thermal power plant, January 2006–June 2012.

The next type of data taken into consideration in the analysis refers to micropollutants emission costs into the atmosphere (Fig. 2).

In order to evaluate the dynamics of air pollutants emission cost in the thermal power plant from January 2006 to June 2012 the monthly relative changes for these variables were computed (Fig. 2). Both changes in the micropollutants emission level and costs of this emission are high and irregular. The biggest changes for the distinguished variables were observed in July 2006, December 2007, January and July of the third analysed year, July 2009, February and March of the fifth analysed year. Particularly in the case of chlorine and lead emission costs, the year 2006 was characterized by very high emission costs relative to ones observed in subsequent years, which can be explained by the lack of required emission decisions resulting in an increase in charges.[1] In other words, the authors observed periods during which the pollutants emission cost process were generated by various regimes to which part of variable values is attributed.

This observation can be confirmed while comparing the values of determined variation coefficients for the emission costs, which for chromium emission reached the value of 164% and for lead 135% (Table 3). A very high cost variation was also observed in the case of chlorine emission (110.2%). In the half of analysed months the total micropollutants emission cost

[1]The authors treated this situation as unusually but likely to be repeated in the future, because of the fact that fluctuations of the pollutant emission costs may be caused among others by improper forecasting values of emission quantities and future legal changes concerning the issues of the impact of energy production on the environment.

Table 3
Descriptive statistics of monthly micropollutants emissions costs by thermal power plant

Statistics	Minimum	Mean	Maximum	Median	Standard deviation	Variation coefficient [%]
Cl_{cost} [€]	36.43	1,206.32	5,591.11	201.60	1,329.33	110.20
Cu_{cost} [€]	2.25	7.25	21.68	5.70	4.10	56.63
Cr_{cost} [€]	25.85	222.18	1,538.19	92.81	364.80	164.19
Pb_{cost} [€]	24.82	156.27	922.91	89.10	210.60	134.77
F_{cost} [€]	0.14	0.48	1.35	0.50	0.25	52.22

Source: Own calculation in PcGive 14—an econometric software.

into the atmosphere did not exceed 398.71 €, while the highest cost was connected with chlorine (201.60 €), chromium (92.81 €) and lead (89.20 €). Insignificant costs accompanied the emission of copper and fluorine into the atmosphere.

Thus, it is difficult to notice any regularities regarding both rise and falls of emission level and costs. Because of this the analysis of the amount of emitted pollutants and the costs connected with it is difficult and needed the use of more advanced statistical methods. This situation justified the use of Markov-switching models in order to describe dynamics of processes that are subject to discrete (either rapid or gradual) changes with time, for example, such as the ones observed in 2006. Therefore, the irregular behaviour of pollutants emission amount and cost time series, indicative of the occurrence of different volatility regimes, may be characterized by the use of Markov-switching models, in which the change of parameters occurs together with the regime change.

4. Research methodology

In the first step of analysis the authors investigated the seasonal patterns for micropollutants emissions and compared them to the seasonal patterns for both the primary air pollutants emissions (carbon dioxide ($CO_{2emission}$), dust, carbon monoxide ($CO_{emission}$), nitrogen oxides ($NO_{xemission}$), sulphur dioxide ($SO_{2emission}$)) and energy production observed in the thermal power plant. In the second part of the empirical research the time-varying volatility process over different volatility regimes for monthly quantity and the cost of micropollutants emissions were examined. Finally, a degree of similarity between the occurrence of periods of high volatility of primary air pollutants emissions, energy production and periods of high volatility of micropollutants emissions was determined. The concept of a research study is presented in Fig. 3.

The first stage of the analysis is connected with the seasonal adjustment of time series of air pollutants generated in the thermal power plant and the series of

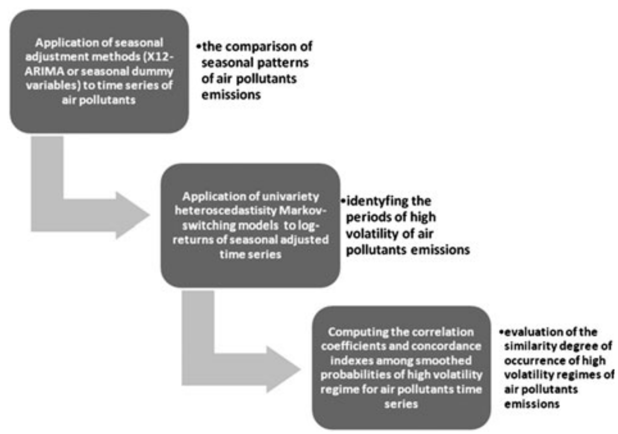

Fig. 3. The concept of studying the similarity among micropollutants emissions, primary air pollutants and energy production in Silesian thermal power plant.

produced energy. Two approaches have been used in the article to data seasonal adjustment: the first one is connected with the application of seasonal dummies [6,18], and the second one uses the procedure X-12-ARIMA, developed by Census Bureau in US [7,19,20]. At the beginning the conditional mean equation was specified on the basis of properties of analysed time series (seasonal patterns and strong serial correlation). Eq. (1) includes seasonal dummies, whose task is to describe a monthly seasonality in the shaping of energy production and air pollutants emissions[2]:

$$\ln y_t = \alpha_0 + \alpha_1 t + \sum_{i=2}^{12} \beta_i D_{it} + \varphi_1 \ln y_{t-1} + \xi_t \quad (1)$$

where D_{it}—dummy variable which equals 1 in month "i" and 0 otherwise ($i = 2, 3, \ldots 12$), t—time variable, y_t—time series of pollutants or energy production, α_i , β_i , φ_1—model parameters, ξ_t—residuals.

[2]The logarithmic transformation of time series brings two advantages: variance stabilization and multiplicative character of seasonal deviations.

This model for each analysed time series of air pollutants and energy production was estimated with the OLS method. Seasonal fluctuations amplitudes for the model specification (1) which can be determined in accordance with the relations (2) [18]:

$$\beta_1^* = -\frac{1}{12}\sum_{i=2}^{12}\beta_i, \quad \beta_i^* = \beta_i + \beta_1^*, \quad i = 2, 3, \ldots, 12 \tag{2}$$

The next stage of the analysis is connected with studying monthly volatility of micropollutants emission (in quantitative and cost grasp) and comparing it with the emission of main pollutants generated in the process of coal burning in the thermal power plant and volatility of energy production. To achieve this goal Markov-switching ARMA(p,q) models, proposed by Hamilton [21], were considered according to the specification (3) (MS-ARMA(N,p,q,Switch)[3] [22]:

$$y_t = \mu_{s_t} + \sum_{i=1}^{p}\varphi_{i,s_t}(y_{t-i} - \mu_{s_{t-i}}) + \varepsilon_t - \sum_{j=1}^{q}\theta_{j,s_t}\varepsilon_{t-j}, \quad \varepsilon_t \sim N(0, \sigma^2_{s_t}) \tag{3}$$

where y—endogenous variable, s_t—non-observable variable modelled as homogenous Markov chain of N states and the matrix of transition probabilities $P = \lfloor p_{ij} \rfloor_{i,j \in \{0,1,2,\ldots,N-1\}}$, determining the regime in which the variable y_t is at the t-moment, φ_{i,s_t}, θ_{j,s_t}—regime-dependent model parameters, μ_{s_t}—conditional mean of the process, which is dependent on the regime variable s_t,$\sigma^2_{s_t}$—conditional variance of the process, which is dependent on the regime variable s_t, ε_t—residuals.

[3]Indicator *Switch* in the specification of Markov-switching ARMA model means: 0—regime-independent ARMA coefficients and only intercept switches between volatility regimes, 1—switching ARMA coefficients.

Therefore, it is possible to determine in the following way the transition probabilities matrix P (4) [23]:

$$\mathrm{P} = (p_{i|j}) = \left(\begin{array}{c|cccc} & s_t = 0 & s_t = 1 & \ldots & s_t = N-1 \\ \hline s_{t+1} = 0 & p_{0|0} & p_{0|1} & \cdots & p_{0|N-1} \\ s_{t+1} = 1 & p_{1|0} & p_{1|1} & \cdots & p_{1|N-1} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ s_{t+1} = N-1 & p_{N-1|0} & p_{N-1|1} & \cdots & p_{N-1|N-1} \\ \hline \sum & 1 & 1 & \ldots & 1 \end{array}\right) \tag{4}$$

under the two conditions (5) which guarantee the stochastic structure of this matrix:

$$\sum_{i=0}^{N-1} p_{i|j} = 1, \quad p_{i|j} \geq 0 \quad \text{for } i, j = 0, 1, \ldots, N-1 \tag{5}$$

The P matrix elements, defining the transition probabilities of the process from the j state at the moment t to the state i at the moment $t+1$, fulfil the Markov property (6):

$$P(s_{t+1} = i \mid s_t = j, s_{t-1} = k, \ldots, y_t, y_{t-1}, \ldots, y_0) = P(s_{t+1} = i \mid s_t = j) = p_{i|j} \tag{6}$$

According to the Markov property the transition probabilities depend exclusively on the state in which the observable economic process was at the previous moment, and not dependent on the whole history of this process.

The most frequently used method of the parameter estimation in Markov-switching model is the maximum likelihood method [21–24]. Doornik and Hendry in order to estimate parameters of the Markov-switching model recommended that the feasible sequential quadratic programming (FSQP) algorithm developed by Lawrence and Tits should be used [24,25].

A by-product of the Markov-switching model parameter estimation are regime smoothed probabilities series making it possible for the authors to assign each observation to particular volatility regimes. Moreover, on the basis of estimated transition probabilities (elements of the stochastic matrix P) one can determine expected further duration of the system in i–nth regime (7) [26]:

$$d_i = \frac{1}{1 - p_{i|i}} \quad (i = 0, 1, \ldots, N - 1) \tag{7}$$

where d_i—average time of economic variable's duration in i–nth regime.

In order to determine the number of regimes in Markov-switching models one may use regime classification measure (RCM) (8), which was proposed by Ang and Bekaert [27]:

$$\mathrm{RCM}(N) = 100 \cdot N^2 \cdot \frac{1}{T} \sum_{t=1}^{T} \left(\prod_{i=0}^{N-1} P(s_t = i \mid \Phi_{t-1}) \right) \tag{8}$$

where $P(s_t = i \mid \Phi_{t-1})$—regime smoothed probabilities series ($i = 0, 1, \ldots, N-1$ and $t = 1, 2, \ldots, T$), Φ_{t-1}—information set available up to time $t-1$.

For the two-state model the RCM statistics ranges from 0 to 100 and smaller value of this measure means better regime classification. Low RCM value may indicate that the model cannot successfully distinguish between regimes from the behaviour of the data.

The next step of the analysis is connected with evaluating the similarity level of switch occurrences between the regimes of high and low volatility for time series of micropollutants, primary air pollutants and energy production. This evaluation will be conducted on the basis of Pearson linear correlation coefficients determined for probabilities corresponding to high volatility regime probabilities. Moreover, according to Harding and Pagan [28] the concordance index (CI) was computed by using the formula (9) [28]:

$$\mathrm{CI}_{ij} = \frac{1}{T} \left[\sum_{t=1}^{T} S_{it} S_{jt} + \sum_{t=1}^{T} (1 - S_{it})(1 - S_{jt}) \right] \tag{9}$$

where S_{it} and S_{jt} denote binary variables that take the value unity in case of high volatility regime and zero—in case of low volatility regime at time t, for variables i and j, respectively.

The CI ranges from 0 to 1 and the higher the value of this index, the more volatility regime periods (identified separately for two variables on the basis of Markov-switching model) coincide over time. In other words, high values of CI mean that there is a high

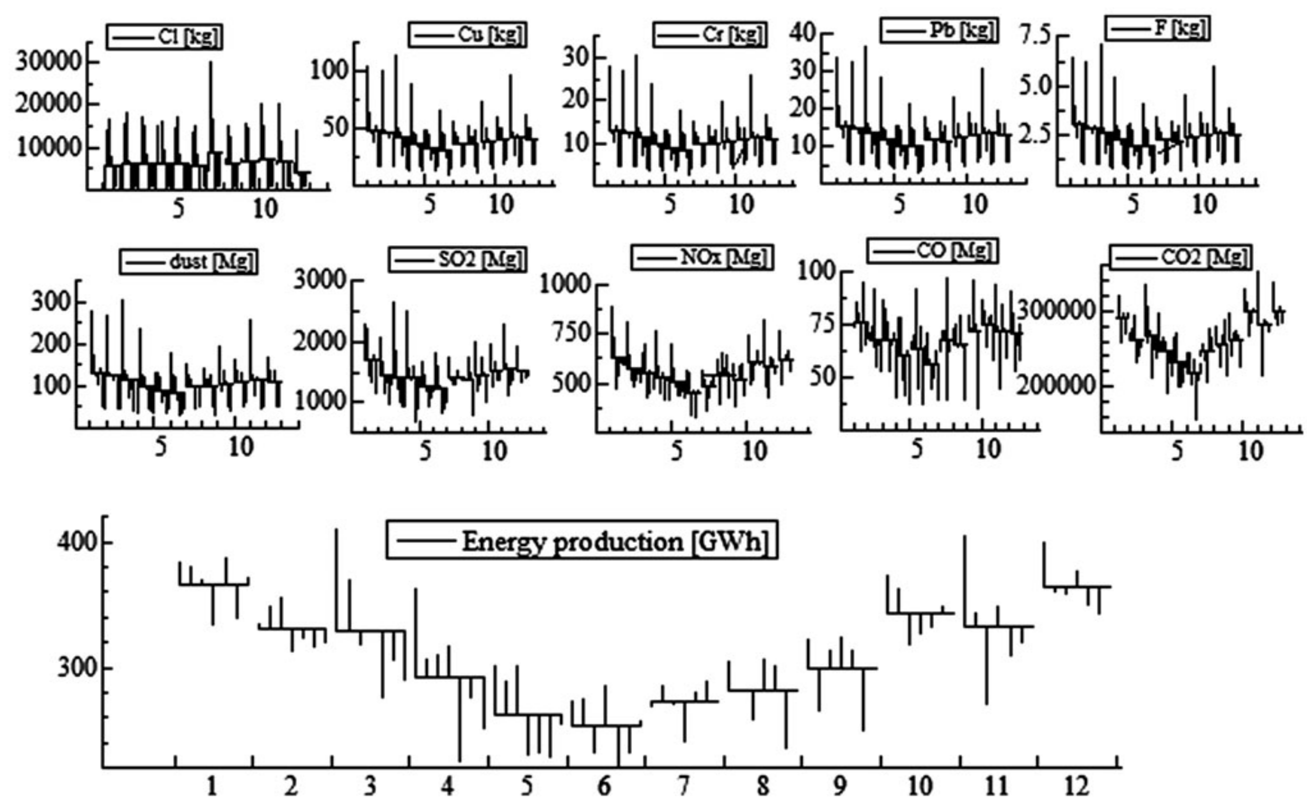

Fig. 4. Seasonal subplot for micropollutants (upper panel) and primary air pollutants (middle panel) emissions time series, energy production time series (lower panel).

degree of similarity between the occurrences of high volatility regimes for two variables.

5. Seasonal pattern and volatility regimes modelling for micropollutants emissions

In order to evaluate preliminarily the seasonal cycle pattern the authors created seasonal sub-plots (Fig. 4), on which one can observe a characteristic for Polish climate increase in demand for energy, and therefore an increase in emission of main pollutants which are created in the process of coal burning ($CO_{2emission}$, $SO_{2emission}$ and $NO_{xemission}$), during the winter period (December, January and February), early spring (March) and late autumn (October and November).

The model with deterministic seasonality and trend (1) for each analysed time series of air pollutants and energy production was estimated with the OLS method (Table 4). Additionally, in order to verify the predictive ability of an estimated model the data-set was divided into a training sample: January 2006—December 2011 used to estimate model parameters and a testing sample: January 2012—June 2012 used to prepare in-sample forecasts.

On the basis of the model (1) the authors can verify the seasonal fluctuations model provided that at least one parameter at the seasonal dummies is statistically significant. What follows, for the time series of the following micropollutants emission rate: Cu, Cr, Pb and F as well as for SO_2 emission on the relevance level 0.05 the authors cannot conclude seasonal fluctuations occurrence. Determining the seasonal fluctuations amplitude for January (2) the authors can observe that energy production in all summer months (from April to September) is lower than the one observed in January. It is connected with the impact of seasonal factors such as air temperature, length of the day and the level of sun light exposure on the demand for energy. A similar seasonal pattern can be observed in the case of carbon dioxide emission into the atmosphere.

Verification of forecasting abilities of the model (1) through evaluation of ex-post forecasts errors (RMSE, MAE and MAPE) confirms that seasonal fluctuations are an important component of the time series model of energy production as well as the series of carbon dioxide, nitric oxide and sulphur dioxide emission into the atmosphere (Table 5) [18].

In the second part of the analysis for the seasonally adjusted monthly series of logarithmic returns of micropollutants emission the authors estimated Markov-switching models in a heteroskedastic version (3)–(6), and the results for chosen series are presented in Table 6. Occurrence of two regimes was assumed in the process of model parameters estimation: the low volatility regime (regime 0) and the high volatility regime (regime 1).

On the basis of smoothed probabilities assigned to each monthly quantity of pollutants emission into the atmosphere the authors can also assess the moment of process switching among particular volatility regimes. In the case of Cu_{cost}, Cr_{cost} and Pb_{cost} common periods characterized by increased volatility of micropollutants emission costs into the atmosphere were: autumn of 2006 and winter of 2006/2007, the second quarter of 2010, the third quarter of 2011. Possibly, the reason for this volatility is the volatility of coal use and its parameters, in particular the content of sulphur, ash and calorific value.

On the basis of the results included in Table 7 one can conclude that the volatility ratio (σ_1/σ_0) reflecting changeability of micropollutants emission quantities and the costs of the thermal power plant are the highest for chlorine (9.93 and 10.88) and copper (4.92 and 5.57). Moreover, time series of micropollutants created in the process of coal burning in thermal power plants in the Silesian Region are characterized by a larger leap in the volatility level at moving to regime 1 than time series of other pollutants or energy production (the lowest volatility coefficient corresponds to the emission of NO_x (1.77) and SO_2 (2.04)). Analysing average times of process duration in the high volatility regime (7) one can observe that they were the longest in the case of $CO_{emission}$ (17 months), $NO_{x\ emission}$ (10 months), $CO_{2emission}$ (9.3 months) and Cu_{cost} (7 months), and shortest for the series of $Cr_{emission}$, $Pb_{emission}$, $dust_{emission}$ and $SO_{2emission}$ (1.1 months). It is also worth emphasizing that for time series of $Cu_{emission\ and\ Cucost}$ a switch to the high volatility regime occurred relatively often, which is confirmed by the number of observations assigned to this regime: 44.59 and 55.26%. To compare the periods of increased volatility of energy production level lasted on average 1.8 of month and only 18.67% of the observations were assigned to this regime. The most typical regime for the majority of micropollutants (apart from Cu) was the low volatility regime, considering the percentage of observations assigned to it and the average duration of this volatility regime.

It is worth noticing that the time series of $Cr_{emission}$, $Pb_{emission}$ and $dust_{emission}$ Markov-switching models show identical dynamism of analysed processes in low and high volatility regimes. This regularity has already been observed.

On the basis of relatively low values of the RCM measures (8) (Table 7) one can draw a conclusion that each estimated model is able to distinguish which regimes occur at each point in time [29].

Table 4
Estimates of the parameters of the model with deterministic seasonality and trend for thermal power plant, January 2006–December 2011

Parameter	$Cl_{emission}$	$Cu_{emission}$	$Cr_{emission}$	$Pb_{emission}$	$F_{emission}$	$Energy_{production}$	$SO_{2emission}$	$NO_{xemission}$	$CO_{2emission}$	$CO_{emission}$
Const	0.824*	2.479*	1.767*	1.866*	0.102	5.981*	4.846*	2.166*	9.485*	2.831*
February	−0.614*	−0.041	−0.041	−0.041	−0.039	−0.092*	−0.120	−0.005	−0.097*	−0.141
March	−0.122	−0.129	−0.129	−0.129	−0.111	−0.089*	−0.115	−0.006	−0.035	−0.065
April	−0.302	−0.175	−0.175	−0.175	−0.114	−0.200*	−0.086	0.006	−0.122*	−0.224*
May	−0.353	−0.210	−0.210	−0.210	−0.112	−0.321*	−0.168	−0.034	−0.179*	−0.096
June	−0.347	−0.278	−0.278	−0.278	−0.149	−0.357*	−0.162	−0.140	−0.232*	−0.260*
July	−0.101	−0.021	−0.021	−0.021	0.150	−0.276*	−0.004	0.031	−0.071	−0.080
August	−0.405	−0.149	−0.149	−0.149	−0.070	−0.245*	−0.112	0.101	−0.073	−0.136
September	−0.273	−0.044	−0.044	−0.044	0.046	−0.185*	−0.031	−0.028	−0.044	−0.069
October	−0.199	0.034	0.034	0.034	0.082	−0.037	0.030	0.154*	0.079*	−0.009
November	−0.393*	−0.054	−0.054	−0.054	−0.059	−0.073*	0.001	0.020	−0.016	−0.100
December	−0.548	0.020	0.020	0.020	0.026	0.029	0.016	0.108*	0.072*	−0.077
Time	–	−0.013*	−0.013*	−0.013*	–	−0.003*	−0.005*	–	−0.002*	−0.003*
Phi1	0.934*	0.455*	0.455*	0.455*	0.880*	–	0.366*	0.652*	0.251	0.380*
Adjusted R^2	0.859	0.805	0.805	0.805	0.753	0.680	0.4887	0.484	0.518	0.246
AIC	141.66	12.54	12.54	12.54	28.54	−132.76	−27.99	−63.3	−106.79	−16.049
Serial correlation in residuals	0.493 [0.909]	1.128 [0.362]	1.128 [0.362]	1.128 [0.362]	1.941 [0.054]	1.157 [0.341]	0.504 [0.901]	1.285 [0.259]	1.367 [0.217]	1.184 [0.323]
Heteroscedasticity in residuals	21.865 [0.057]	11.70 [0.701]	11.70 [0.701]	11.70 [0.701]	10.99 [0.611]	11.57 [0.563]	14.45 [0.491]	31.22 [0.003]	25.31 [0.046]	25.75 [0.046]

Source: Own calculation in Gretl—an econometric software, *p*-value in brackets.
*indicates the significance of the result at the 0.05 level.

Table 5
In-sample forecasts of logarithmic of micropollutants and primary air pollutants emissions, January 2012–June 2012

Parameter	$Cl_{emission}$	$Cu_{emission}$	$Cr_{emission}$	$Pb_{emission}$	$F_{emission}$	$Energy_{production}$	$SO_{2emission}$	$NO_{xemission}$	$CO_{2emission}$	$CO_{emission}$
January	7.158	2.904	1.596	1.778	0.251	5.787	7.137	6.296	12.476	4.155
February	6.899	2.831	1.522	1.705	0.284	5.692	6.959	6.269	12.357	4.046
March	7.202	2.696	1.388	1.570	0.239	5.693	6.894	6.250	12.387	4.077
April	7.285	2.577	1.268	1.451	0.199	5.580	6.892	6.250	12.305	3.927
May	7.274	2.474	1.166	1.348	0.165	5.455	6.807	6.211	12.226	3.996
June	7.282	2. 347	1.038	1.221	0.098	5.417	6.775	6.078	12.151	3.855
RMSE	0.589	0.233	0.233	0.233	0.243	0.092	0.196	0.120	0.116	0.269
MAE	0.557	0.161	0.161	0.161	0.215	0.082	0.173	0.101	0.098	0.235
MAPE	8.432	5.786	10.911	9.712	162.6	1.453	2.431	1.654	0.791	6.358

Source: Own calculation in Gretl—an econometric software, *p*-value in brackets.

Table 6
Estimates of Markov-switching parameters for thermal power plant

	$Cl_{emission}$		Cl_{costs}		$Pb_{emission}$		Pb_{cost}	
Parameter	Parameter estimates	p-value/ standard error	Parameter estimates	p-value/ standard error	Parameter estimates	p-value/ standard error	Parameter estimates	p-value/ standard error
Const (0)	0.016	[0.631]	0.025	[0.193]	0.006	[0.692]	0.009	[0.503]
Const (1)	−0.608	[0.052]	0.595	[0.393]	−0.103	[0.005]	−0.107	[0.200]
AR-1(0)/AR-1(1)	0.315	[0.048]	−0.131	[0.003]	−0.278/−1.128	[0.000]/[0.000]	−0.406	[0.000]
AR-2	–	–	–	–	–	–	−0.142	[0.049]
MA-1	−0.422	[0.004]	–	–	–	–	–	–
Sigma (0)	0.154	0.019	0.164	0.015	0.105	0.014	0.123	0.019
Sigma (1)	1.526	0.405	1.786	0.341	0.350	0.082	0.471	0.093
P matrix	R (0, t)	R (1, t)	R (0, t)	R (1, t)	R (0, t)	R (1, t)	R (0, t)	R (1, t)
R (0, t + 1)	0.9164	0.6818	0.9325	0.6320	0.8118	0.7835	0.8644	0.3837
R (1, t + 1)	0.0836	0.3182	0.0675	0.3680	0.1882	0.2165	0.1356	0.6163
AIC	0.2996		0.3084		−0.4739		−0.0369	
B–P (40)	36.838	[0.430]	31.858	[0.666]	46.752	[0.108]	41.008	[0.260]
ARCH(2)	1.117	[0.334]	1.464	[0.239]	0.003	[0.997]	0.120	[0.948]
J–B	0.560	[0.756]	0.140	[0.932]	3.517	[0.172]	0.823	[0.663]

Source: Own calculation in PcGive 14—an econometric software, p-value in brackets, standard error of estimated parameter value without brackets.

Table 7
The average duration of the air pollutants emission volatility regimes

Pollutant	MS-ARMA (N,p,q,switch)	The average duration of the low volatility regime (in months)	Number of observations assigned to low volatility regime	The average duration of the high volatility regime (in months)	Number of observations assigned to high volatility regime	Sigma (1)/ sigma (0)	RCM
$Cl_{emission}$	MS-ARMA(2,1,1,0)	11.5	69 (90.79%)	1.4	7 (9.21%)	9.93	9.01
$Cu_{emission}$	MS-ARMA(2,3,0,0)	6.8	41 (55.41%)	4.7	33 (44.59%)	4.92	34.6
$Cr_{emission}$	MS-ARMA(2,1,0,1)	7.3	66 (86.84%)	1.1	10 (13.16%)	3.33	28.5
$Pb_{emission}$	MS-ARMA(2,1,0,1)	7.3	66 (86.84%)	1.1	10 (13.16%)	3.33	28.5
CL_{cost}	MS-ARMA(2,1,0,0)	14	70 (92.11%)	1.5	6 (7.89%)	10.88	6.86
Cu_{cost}	MS-ARMA(2,1,0,1)	6.8	34 (44.74%)	7	42 (55.26%)	5.57	32.75
Cr_{cost}	MS-ARMA(2,2,0,0)	16.8	67 (89.33%)	2.7	8 (10.67%)	3.80	15.43
Pb_{cost}	MS-ARMA(2,2,0,0)	8.7	61 (81.33%)	2.3	14 (18.67%)	3.84	34.15
$Energy_{production}$	MS-ARMA(2,2,1,1)	6.8	61 (81.33%)	1.8	14 (18.67%)	2.31	32.17
$Dust_{emission}$	MS-ARMA(2,1,0,1)	7.3	66 (86.84%)	1.1	10 (13.16%)	3.33	28.5
$SO_{2emission}$	MS-ARMA(2,1,1,1)	4.4	62 (81.58%)	1.1	14 (18.42%)	2.04	21.3
$NO_{xemission}$	MS-ARMA(2,1,1,1)	11.5	46 (60.53%)	10	30 (39.47%)	1.77	18.34
$CO_{2emission}$	MS-ARMA(2,1,1,0)	9.8	39 (51.32%)	9.3	37 (48.68%)	2.92	35.01
$CO_{emission}$	MS-ARMA(2,2,2,0)	20.5	41 (54.67%)	17	34 (45.33%)	2.61	23.26

Source: Own calculation in PcGive 14—an econometric software.

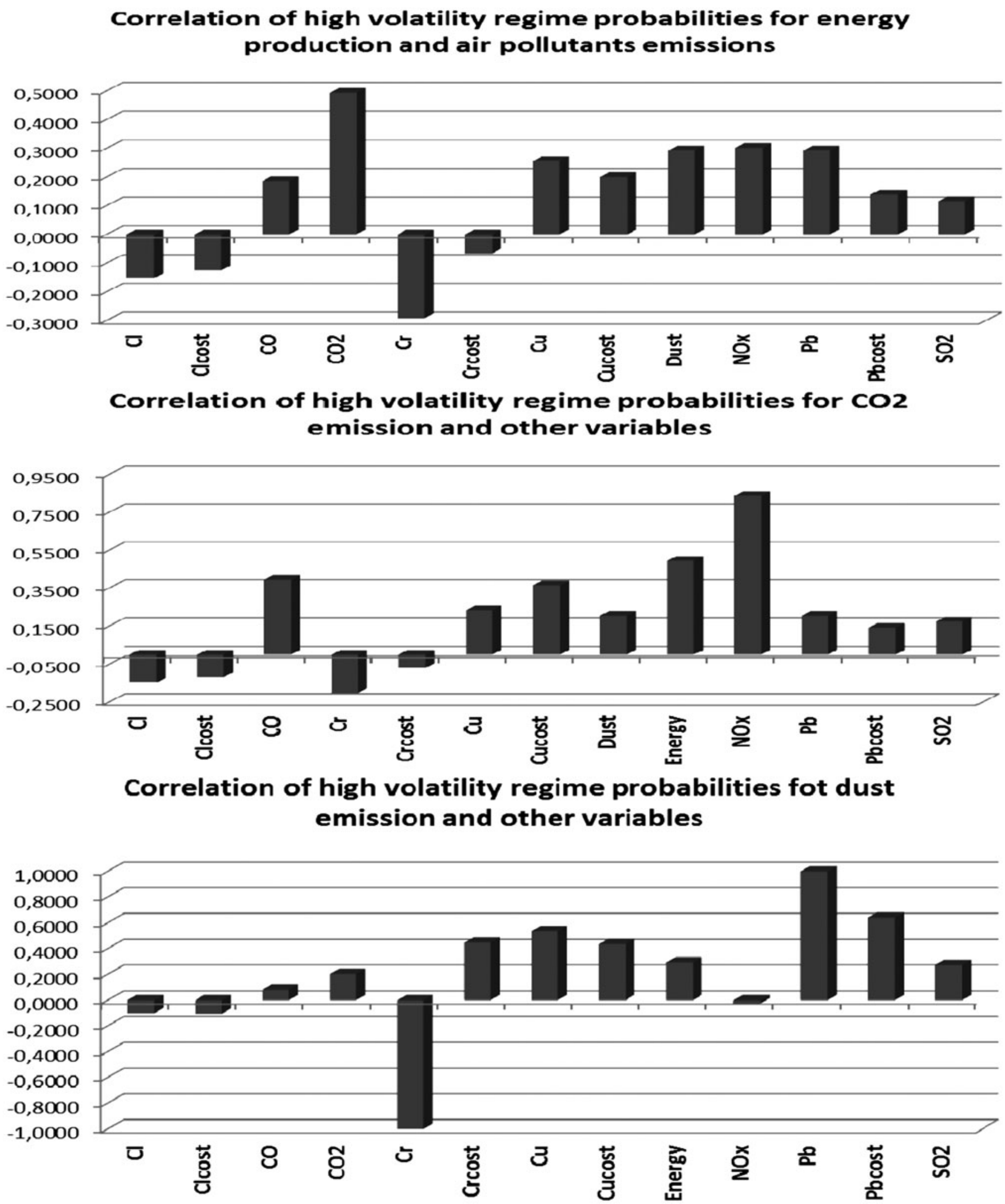

Fig. 5. Correlation of high volatility regime probabilities between energy production and air pollutants emissions in thermal power plant, January 2006–June 2012.

Table 8
CIs for air pollutants and energy production

Pollutants	Concordance index	Pollutants	Concordance index
$Cl_{emission}$–$Energy_{production}$	0.716	$Cl_{emission}$–$CO_{2emission}$	0.473
$Cu_{emission}$–$Energy_{production}$	0.635	$Cu_{emission}$–$CO_{2emission}$	0.608
$Cr_{emission}$–$Energy_{production}$	0.203	$Cr_{emission}$–$CO_{2emission}$	0.419
$Pb_{emission}$–$Energy_{production}$	0.797	$Pb_{emission}$–$CO_{2emission}$	0.581
Cl_{cost}–$Energy_{production}$	0.730	Cl_{cost}–$CO_{2emission}$	0.486
Cu_{cost}–$Energy_{production}$	0.514	Cu_{cost}–$CO_{2emission}$	0.676
Cr_{cost}–$Energy_{production}$	0.730	Cr_{cost}–$CO_{2emission}$	0.486
Pb_{cost}–$Energ_{production}y$	0.757	Pb_{cost}–$CO_{2emission}$	0.568
$Dust_{emission}$–$Energy_{production}$	0.797	$Dust_{emission}$–$CO_{2emission}$	0.581
$SO_{2emission}$–$Energy_{production}$	0.757	Cl_{cost}–$Dust_{emission}$	0.797
$NO_{xemission}$–$Energy_{production}$	0.676	Cu_{cost}–$Dust_{emission}$	0.581
$CO_{2emission}$–$Energy_{production}$	0.676	Cr_{cost}–$Dust_{emission}$	0.878
$CO_{emission}$–$Energy_{production}$	0.568	Pb_{cost}–$Dust_{emission}$	0.878

Source: Own calculation.

Subsequently, the values of Pearson's linear correlation coefficients determined for three groups of variables: (1) carbon dioxide emission and emission of other pollutants generated in the thermal power plant, (2) dust emission and other variables, (3) energy production and pollution emission were presented in Fig. 5. Such an approach is aimed at identifying a factor whose volatility over time is most similar to volatility of micropollutants emission into the atmosphere. Information of this kind could be vital taking into account monitoring emitted pollutants and controlling the costs connected with their emission in the future. Pollutants emission costs constitute an important criterion of evaluating pro-environmental activities effectiveness in the thermal power plant, as they constitute a basic economic category determining the entire activeness. Influencing the micropollutants emission costs through activities directed at variables associated with them can lead to a multifaceted impact of decisions made within environmental management.

Statistical significant (0.05 significance level) and positive linear correlation has been observed between probabilities corresponding to the high volatility regime:

(1) for CO_2 emission and emission of NO_x, CO, Cu, as well as emission of carbon dioxide and Cu emission costs;
(2) for dust emission and emission costs for Cu, Cr, Pb, for dust emission and emission of Cu, Pb, SO_2;
(3) for energy production and emission of CO_2, dust, NO_x, Cu, Pb.

Thus, for example, periods of high volatility of energy production are often periods of higher volatility of Cu and Pb micropollutants emission.

Presented in Table 8 CIs (9) indicate that high synchronization of periods of high volatility occurrence may be observed for the energy production series and series of Cl_2, Pb, dust and SO_2 emission and also the series of energy production and series of Cl_2, Cr and Pb emission costs. Moreover, one can observe a high similarity of periods of high volatility of emission costs occurrence for such micropollutants as: Cl_2, Cr and Pb as well as dusts emission in the thermal power plant. Thus, monitoring and forecasting the rate of dusts emission enables the authors to foresee periods characterized by higher volatility of micropollutants emission costs. Micropollutants together with dusts constitute constant air pollutions. Due to the magnitude scale and taking into account the costs, the analysis of dust emission level and its volatility is conducted more frequently than the analysis of micropollutants. Showing the above-mentioned relationships will allow the authors to verify on the basis of one analysis that supports their standpoint regarding both dusts and micropollutants.

6. Summary

Carbon dioxide is the basic pollutant in the energy industry [30,31]. This fact should not be a surprise in the era of climate change mitigation. In the subject literature one can find a statement that an attempt to achieve energy efficiency practically means a decrease in CO_2 emission [32]. Comparing micropollutants emission with the emission of two primary air pollutants characteristic of thermal power plants the authors concluded on the basis of the conducted research that the monthly volatility of the micropollutants emission rate was relatively high in comparison with the volatility of carbon dioxide emission amounting to 14.19%, or sulphur dioxide. Moreover, the results of conducted tests and basic statistical characteristics indicate the similarities in regularity of distribution of energy production scale and CO_2, CO and NO_x emission rate, in skewness coefficients levels, kurtosis characteristic of the distribution of micropollutants emission and dusts emission, in the autocorrelation order, ARCH effect and unit roots occurrence for the time series of micropollutants and dusts emission. Thus, the development dynamism of the studied phenomena is similar.

Also emission costs are characterized by high volatility, particularly in the case of chromium and lead. This results from the principles of emission costs charging. In the studied power plant a substantial increase in the unit emission cost of chromium and lead occurred in 2006, which was caused by lack of required permissions for these pollutants emission in this period.

A vital role in the environmental policy of enterprises should play economic instruments, as it is by means of them that the impact on decisions made by these economic subjects takes place. Economic instruments make it possible to provide the subjects with information on the desired state taking into account the ecological policy. Basic economic instruments in environment protection are:

(1) takes and charges,
(2) subsidies and
(3) right to emit pollutants.

In the case of thermal power plants the most frequently used economic instrument is the trade of CO_2 emissions. Carbon dioxide is regarded as a primary greenhouse gas, and therefore, as the most harmful pollutant causing most damages to the climate. In the case of micropollutants emitted by thermal power plants, presently used economic instruments constitute:

(1) charges for polluting various environment components,
(2) ecological taxes imposed on emission of environmentally harmful substances and
(3) fines for exceeding the scope of legally allowed level of widely understood emissive activity, exceeding acceptable concentration of environment pollutants.

However, these instruments are perceived as the ones which extort compliance with standards, obligations, prohibitions and other forms of direct regulation. It is difficult to notice in the operation of thermal power plants conscious and voluntary actions aimed at greening their functioning, also with reference to micropollutants emission. Still, the problem of micropollutants in thermal power plants is being marginalized, mainly due to their small amounts in relation to other pollutants. For this reason thermal power plants sometimes neglect the requirement to possess emissive permissions for micropollutants, which results in growth of emission costs and efficiency loss of applied pro-environmental solutions which aim at reducing the negative impact of electricity and heat production process on natural environment. Therefore, within the environmental management the authors should strive to supervise all responsibilities connected with the costs of environment protection, and proposed by the authors' methods of analysis undoubtedly allowing for control in this scope.

As far as adjusting economic instruments with respect to pollutants emission, including micropollutants to the needs of the economy is concerned, the analysis should be conducted on the level of a region or even the whole state. The tools used in the article due to their universality allow one to use them in an analysis taking into account global data. Unfortunately, acquisition of such a data-set is not easy because it is not commonly accessible. The goal of the authors then is to extend the analyses in the future to the micropollutants level generated by the industrial sector in the whole territory of Poland. The authors are convinced that the results of global analyses will contribute to developing effective instruments of preventing micropollutants emission.

Symbols

$Cl_{emission}$	—	chlorine emissions time series [kg]
$Cu_{emission}$	—	copper emissions time series [kg]
$Cr_{emission}$	—	chromium emissions time series [kg]
$Pb_{emission}$	—	lead emissions time series [kg]
$F_{emission}$	—	fluorine emissions time series [kg]
$Energy_{production}$	—	total energy production time series [GWh]
$Dust_{emission}$	—	dust emissions time series [Mg]
$SO_{2emission}$	—	sulphur dioxide emissions time series [Mg]
$NO_{xemission}$	—	nitrogen oxides emissions time series [Mg]
$CO_{2emission}$	—	carbon dioxide emissions time series [Mg]

$CO_{emission}$	—	carbon monoxide emissions time series [Mg]
Cl_{cost}	—	chlorine emissions costs time series [€]
Cu_{cost}	—	copper emissions costs time series [€]
Cr_{cost}	—	chromium emissions costs time series [€]
Pb_{cost}	—	lead emissions costs time series [€]
F_{cost}	—	fluorine emissions costs time series [€]
B–P(p)	—	Box–Pierce autocorrelation test; p is the order of autocorrelation
ARCH 1−q	—	Engle's ARCH test (Lagrange multiplier test); q is the number of lags
ADF	—	Augmented Dickey–Fuller unit root tests
P–P	—	Phillips–Perron unit root test
J–B	—	Jarque–Bera normality test
RMSE	—	root mean squared error
MAE	—	mean absolute error
MAPE	—	mean absolute percentage error
OLS	—	ordinary least squares method
FSQP	—	feasible sequential quadratic programming algorithm
ARMA(p,q)	—	autoregressive–moving-average models; p is the order of the autoregressive part and q is the order of the moving average part
MS-ARMA(p,q)	—	Markov-switching ARMA(p,q)
AIC	—	Akaike information criterion
Adjusted R^2	—	adjusted coefficient of determination
Const (0)	—	intercept in low volatility regime
Const (1)	—	intercept in high volatility regime
AR-1 (0)	—	coefficient of first order autoregressive part in low volatility regime
AR-1 (1)	—	coefficient of first order autoregressive part in high volatility regime
AR-2	—	regime-independent coefficient of second order autoregressive part
MA-1	—	regime-independent coefficient of first order moving-average part
Sigma (0)	—	time series variance in low volatility regime
Sigma (1)	—	time series variance in high volatility regime
R (0, t)	—	low volatility regime at time t
R (0, t + 1)	—	low volatility regime at time t + 1
R (1, t)	—	high volatility regime at time t
R (1, t + 1)	—	high volatility regime at time t + 1
RCM	—	regime classification measure
CI	—	concordance index

References

[1] Polish Energy Policy until 2030, Ministry of Economy, Warsaw, 10 November 2009, pp. 7–8, 21–24. Available from: <http://www.mg.gov.pl/files/upload/8134/Polityka%20energetyczna%20ost.pdf> (in Polish).

[2] E. Bień, A. Wójcik-Mazur, The effective use of EU funds for environmental activities in the Operational Program Infrastructure and Environment (OP I&E), Desalin. Water Treat. 52 (2014) 3871–3878.

[3] C.H. Antunes, Energy efficiency for a more sustainable world, Energy Policy 67 (2014) 1–3.

[4] F. Figge, T. Hahn, Is green and profitable sustainable? Assessing the trade-off between economic and environmental aspects, Int. J. Prod. Econ. 140 (2012) 92–102.

[5] J. Lewandowski, Cutting emissions in the energy sector: A technological and regulatory perspective, Yearbook Antitrust Regul. Stud. 4 (2011) 84–85 (in Polish).

[6] F. Chan, M. McAleer, Analysing trends and volatility in atmospheric carbon dioxide concentration levels, in: C. Pahl-Wostl, S. Schmidt, A.E. Rizzoli, A.J. Jakeman (Eds.), Complexity and Integrated Resources Management Transactions of the 2nd Biennial Meeting of the International Environmental Modelling and Software Society, University of Osnabrück, Germany, 2004, pp. 1455–1461.

[7] J.H. Park, T.H. Hong, Analysis of South Korea's economic growth, carbon dioxide emission, and energy consumption using the Markov switching model, Renewable Sustainable Energy Rev. 18 (2013) 543–551.

[8] H.A. Simsek, N. Simsek, Recent incentives for renewable energy in Turkey, Energy Policy 63 (2013) 521–530.

[9] T. Nitkiewicz, Ecological evaluation of product life cycle in decision-making processes in manufacturing companies, Publishing House of Czestochowa University of Technology, Czestochowa, 2013 (in Polish).

[10] D. Maftei, A new approach for energy security—The efficient management of funds for investment in infrastructure for green energy, Pol. J. Manage. Stud. 5 (2012) 253–260.

[11] J. Kucowski, D. Laudyn, M. Przekwas, Power engineering and the environment, Scientific-Technical Publishers WNT, Warsaw, 1997 (in Polish).

[12] D. Laudyn, M. Pawlik, F. Strzelczyk, Power Stations, Scientific-Technical Publishers WNT, Warsaw, 2000 (in Polish).

[13] O. Seroka-Stolka, Ecological awareness level of businessmen as an element of balanced development—Comparative analysis, J. Ecol. Health 15 (2011) 159–165.

[14] O. Seroka-Stolka, Ecological awareness and attitudes of managers, J. Ecol. Health 15 (2011) 71–76 (in Polish).

[15] M. Zawada, Dynamic econometric models in modelling and forecasting the demand for electricity, in: M. Zawada (Ed.), The Use of Quantitative Methods in the Economic-Social Studies, Publishing House of Czestochowa University of Technology, Czestochowa, 2007, pp. 202–221 (in Polish).

[16] R.S. Tsay, Analysis of Financial Time Series. Financial Econometrics, Wiley, New York, NY, 2002.

[17] P.H. Franses, D. van Dijk, Non-linear Time Series Models in Empirical Finance, Cambridge University Press, Cambridge, 2004.
[18] T. Kufel, Econometrics. Solving problems with using the GRETL Package, Scientific Publishers PWN, Warsaw, 2011 (in Polish).
[19] D.F. Findley, B.C. Monsell, W.R. Bell, W.R. Otto, B.C. Chen, New capabilities and methods of the X-12-ARIMA seasonal-adjustment program, J. Bus. Econ. Stat. 16 (1998) 127–177.
[20] J.A. Doornik, D.F. Henndry, Econometric Modelling, PcGiveTM14, vol. III, Timberlake Consultants Ltd., London, 2013.
[21] J.D. Hamilton, A new approach to the economic analysis of nonstationary time series and the business cycle, Econometrica 57 (1989) 357–384.
[22] C.-J. Kim, J. Kim, Bayesian inference in regime-switching ARMA models with absorbing states: The dynamics of the ex-ante real interest rate under structural breaks, August 2013. Available from: <http://mpra.ub.uni-muenchen.de/51117/1/MPRA_paper_51117.pdf>.
[23] J.A. Doornik, D.F. Henndry, Econometric Modelling, PcGiveTM14, vol. IV, Timberlake Consultants Ltd., London, 2013.
[24] Z. Psaradakis, M. Sola, Finite-sample properties of the maximum likelihood estimator in autoregressive models with Markov switching, J. Econometrics 86 (1998) 369–386.
[25] C.T. Lawrence, A.L. Tits, A computationally efficient feasible sequential quadratic programming algorithm, SIAM J. Optim. 11 (2001) 1092–1118.
[26] J.D. Hamilton, Time Series Analysis, Princeton University Press, Princeton, NJ, 1994.
[27] A. Ang, G. Bekaert, Regime switches in interest rates, J. Bus. Econ. Stat. 20 (2002) 163–182.
[28] D. Harding, A.R. Pagan, Dissecting the cycle: A methodological investigation, J. Monetary Econ. 49 (2002) 365–381.
[29] K. Choi, S. Hammoudeh, Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment, Energy Policy 38 (2010) 4388–4399.
[30] W.M. Budzianowski, Negative carbon intensity of renewable energy technologies involving biomass or carbon dioxide as inputs, Renewable Sustainable Energy Rev. 16 (2012) 6507–6521.
[31] N.Y. Mansouri, R.J. Crookes, T. Korakianitis, A projection of energy consumption and carbon dioxide emissions in the electricity sector for Saudi Arabia: The case for carbon capture and storage and solar photovoltaics, Energy Policy 63 (2013) 681–695.
[32] K.-H. Chai, C. Yeo, Overcoming energy efficiency barriers through systems approach—A conceptual framework, Energy Policy 46 (2012) 460–472.