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METHODOLOGY FOR ANALYSING THE RELATIONSHIPS BETWEEN PHYSICAL PARAMETERS AND PRICE VARIABLES IN REGIONAL DEMAND FOR WIND ELECTRICITY (AS APPLIED TO THE LATVIAN AGGREGATOR)

ABSTRACT: In this article, the methodology is proposed for the complex analysis of the correlation and regression dependencies of the relationship between the electricity price and the wind power generation in the electricity market in accordance with the National Energy and Climate Plan for 2021-2030 to increase the share of renewable energy sources (RES) in electricity generation. Both business models and technologies for regulating the supply and demand of electricity (EE) are changing significantly in the modern environment. The European Green Deal[1] has the main objective of becoming the world's first climate-neutral continent by 2050. The use of renewable energy significantly reduces the dependence on fossil fuels as a source of energy, helping to reduce greenhouse gas emissions. The growth of renewable energy sources can also help stabilize energy prices in the future, once they constitute a significant proportion of the electricity mix that powers businesses and households. Voluntary optimization of electricity consumption and energy-saving by the final consumer entails the economic impact carried out by the Demand Response (DR) mechanism. The adapted models help to understand this mechanism and establish the development of the Latvian regional aggregator, which, in turn, strengthens energy security in the European Union countries and improves energy sustainability and resilience.

KEYWORDS: natural and price indicators, electricity sector, correlation and regression models, sinusoidal dependence, Latvian regional aggregator

METODOLOGIA ANALIZY ZALEŻNOŚCI MIĘDZY PARAMETRAMI FIZYCZNYMI A ZMIENNYMI CEN REGIONALNEGO ZAPOTRZEBOWANIA NA ENERGIĘ WIATROWĄ (PRZYPADEK AGREGATORA ŁOTEWSKIEGO)

ABSTRAKT: W artykule zaproponowano metodologię kompleksowej analizy zależności korelacyjnych i regresyjnych relacji między ceną energii elektrycznej a produkcją energii wiatrowej na rynku energii elektrycznej, zgodnie z Krajowym Planem Energetyki i Klimatu na lata 2021-2030, w celu zwiększenia

[1] European Comisssion. European Green Deal, https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en (03.12.2022).

udziału odnawialnych źródeł energii (OZE) w wytwarzaniu energii elektrycznej. Zarówno modele biznesowe, jak i technologie regulacji podaży i popytu na energię elektryczną (EE) ulegają istotnym zmianom. Głównym celem Europejskiego Zielonego Ładu jest przekształcenie Europy do 2050 r. w pierwszy na świecie kontynent neutralny dla klimatu. Wykorzystanie energii odnawialnej znacznie zmniejsza zależność od paliw kopalnych jako źródła energii, pomagając ograniczyć emisje gazów cieplarnianych. Rozwój odnawialnych źródeł energii może również pomóc w ustabilizowaniu cen energii w przyszłości, gdy będzie ona stanowić znaczną część miksu energetycznego, który zasila przedsiębiorstwa i gospodarstwa domowe. Dobrowolna optymalizacja zużycia energii elektrycznej i oszczędność energii przez odbiorcę końcowego pociąga za sobą skutki gospodarcze realizowane przez mechanizm Demand Response (DR). Przedstawione adaptowane modele pomagają zrozumieć ten mechanizm i ustalić rozwój łotewskiego regionalnego agregatora, który z kolei wzmacnia bezpieczeństwo energetyczne w krajach Unii Europejskiej oraz poprawia zrównoważenie i odporność energetyczną.

SŁOWA KLUCZOWE: wskaźniki naturalne i cenowe, sektor energii elektrycznej, modele korelacji i regresji, zależność sinusoidalna, agregator łotewski

INTRODUCTION

Nowadays, in the energy industry, both business models and technologies for regulating the supply and demand of electricity (EE) are significantly changing, referring to the development of Demand Management (DM) mechanisms, in which consumers are transformed into active consumers, including those participating in demand changes for EE. Voluntary optimization of electricity consumption and energy-saving by the final consumer with a certain economic effect is carried out by the Demand Response (DR) mechanism. The main solution for the implementation of the DM and DR mechanisms is the creation of specialized organizations – demand management aggregators (DMA), whose commercial activity is to provide demand response services[2],[3]. Voluntary optimization of electricity consumption by the end user with a certain economic benefit is carried out by the Demand Response (DR) mechanism.

This article proposes a methodology for the complex analysis of correlation and regression dependencies of the relationship between electricity price and wind power generation on the electricity market[4], as according to the "National Energy and Climate Plan for 2021-2030" Latvia plans to increase the share of renewable energy sources (RES) in electricity generation[5].

The developed methodology is based on the adaptation of correlation and regression classical models' analysis in relation to the analysis of industry statistical indicators of electricity production and imports in the period 2014-2019, the average hourly electricity consumption and the price of one MWh of wind power in 2019, and similar indicators for hours of peak consumption from 8:00 to 12:00. Because the electricity price is determined by demand and

[2] Latvijas Republikas Saeima, Electricity Market Law, Riga 2005, https://likumi.lv/ta/en/en/id/108834 (20.11.2022).

[3] J Stede, *The role of aggregators in facilitating industrial demand response: Evidence from Germany*, "Energy Policy" 2020, Vol. 147, 111893, https://doi.org/10.1016/j.enpol.2020.111893.

[4] S. Uğur, S. Ramazan, *Routledge Handbook of Energy Economics. Energy Modelling*, London 2021, pp. 230-257.

[5] Cabinet of Ministers Republic of Latvia. Rīkojums Nr. 46 "Par Latvijas Nacionālo enerģētikas un klimata plānu 2021.–2030. gadam". Riga 2020, https://likumi.lv/ta/id/312423 (24.11.2022).

supply[6] and, therefore, endogenously specified within the market, hourly expected wind generation have been used as a variable to proxy electricity prices. The statistical indicators are supplemented with details of electricity consumption and wind power generation unit price on average per day and at peak hours (from 8:00 to 12:00) monthly in 2019. There regression dependencies of monthly wind power data were established. The calculated data on the validation of the obtained models were also presented. Calculations were made using the algorithmic language *MATHCAD*.

The proposed adapted models can be used to understand the peculiarities of the DR mechanism and the development process of the Latvian regional aggregator. This will help boost energy security in the European Union's countries and improve energy sustainability and resilience[7].

Energy regulation is complex and broad. In 2021, the European Commission proposed strengthening the EU Energy Efficiency Directive with the aim of meeting the 2030 climate target and reducing net greenhouse gas emissions by at least 55% compared to 1990. All 27 EU Member States vigorously supported European Green Deal initiative and transformational change to transform the European Union into the first climate neutral continent by 2050. The energy policy strategies of the European Union must advance in energy efficiency, especially renewable energy, to ensure compliance with the European Green Deal goals. Russia's invasion of Ukraine exposed vulnerability in the European energy system and accelerated the need to increase its resilience and independence from Russian fossil fuels.

THE UNDERLYING REGRESSION MODEL – CLASSICAL ANALITICAL MODEL

In general, regression allows for approximating a mathematical relationship between two or more variables if their values are known in a number of points. For analysis purposes, the processed statistical data is usually presented in general by indicators *V1* and *V2* are interrelated indicators related to the same object of research and calculated in increasing time intervals (*i*). For the electricity sector *V1* means physical indicators expressed in MWh and *V2* are price indicators in EUR/ MWh.

In the following formulas, the available statistical data are presented in the form of the corresponding matrices *Tj*. The average value, dispersion, and standard deviation for the data represented by the vector *V* (*V* takes the value *V1* or *V2*) of matrix *Tj* are calculated using the usual equations[8]:

$$E(V) = \frac{1}{n}\sum_{i=1}^{n} V_i, \tag{1}$$

[6] A. Cretì, F. Fontini, *Economics of Electricity. Markets, Competition and Rules*, Cambridge 2019, pp.237-244.
[7] B. Cointe, A. Nadaï, *Feed-in Tariffs in the European Unions. Renewable energy policy, the internal electricity market and economic expertise*, Cham 2018, pp. 87-110.
[8] A.A. Afifi, S.P. Azen, *Statistical Analysis. A Computer Oriented Approach*, New York – San Francisco – London 2015.

$$D(V) = \frac{1}{n-1}\sum_{i=1}^{n}\left(V_i - E(V)\right)^2, \quad (2)$$

$$\sigma(V) = \sqrt{D(V)}. \quad (3)$$

The covariance of two variables, presented in the Table 1, is calculated by the equation[9]:

$$cov(V1, V2) = \frac{1}{n}\sum_{i=1}^{n} V1_i V2_i - E(V1)E(V2). \quad (4)$$

The correlation coefficient is defined as follows:

$$corr(V1, V2) = \frac{cov(V1,V2)}{\sigma(V1)\sigma(V2)}. \quad (5)$$

The general polynomial regression model[10] assumes the dependence of the random variable *Yi* from the values of the factors (related variables, regressors) $x_{i,1}, x_{i,2}, \ldots, x_{i,k}$ in the *i*-th observation:

$$,Y_i = \beta_0 + \beta_1 x_{i,1} + \cdots + \beta_k x_{i,k} + Z_i, i = 1, \ldots, n, \quad (6)$$

where $\beta_0, \beta_1, \ldots, \beta_k$ – regression coefficients, Z_i – random component with a zero average value and final standard deviation, *n* –number of observations.

The regression task is to estimate the coefficients $\beta_0, \beta_1, \ldots, \beta_k$ based on *n* observations. In the *i*-th observation, the values of the related variables $x_{i,1}, x_{i,2}, \ldots, x_{i,k}$ and the value of the random variable Y_i are fixed. The estimate of the regression coefficients $\beta_0, \beta_1, \ldots, \beta_k$ is presented in vector-matrix form. In regard to this, the following vectors and matrices are considered:

$Y = (Y_1, \ldots, Y_n)^T$ – a column vector of dependent variables (*T* means matrix transposition);

$X = (x_{i,j})$ – matrix of related variables of size $n\times(k+1)$, whose lines correspond to the observations, but columns to the regression coefficient;

$\beta = (\beta_0, \ldots, \beta_k)^T$ – column vector.

The classical estimate of the regression coefficients is calculated by the equation[11]:

$$\hat{\beta} = (X^T X)^{-1} X^T Y, \quad (7)$$

where $(X^T X)^{-1}$ means the matrix inverse to $X^T X$.

In this case, the estimate of the random variable Y_i is:

$$\hat{Y}_i = \ddot{\beta}_0 + \widehat{\beta_1} x_{i,1} + \cdots + \hat{\beta}_k x_{i,k}, i = 1, \ldots, n. \quad (8)$$

[9] G.A.F.Seber, A.J. Lee, *Linear regression analysis*, New Jersey 2003, pp.139-184.
[10] Ibidem.
[11] A.A. Afifi, S.P. Azen Stanley, op. cit.

ADAPTATION OF CLASSICAL MATHEMATICAL MODELS FOR THE ANALYSIS OF CORRELATION AND REGRESSION DEPENDENCIES OF NATURAL AND PRICE INDICATORS OF THE ELECTRICITY SECTOR

To start with, mathematical models for the analysis of the electricity sector natural and price indicators have been developed in relation to the processing of statistical data presented by tables with specific natural and price indicators of:

- electricity production and imports in the time period 2014-2019 (Table 1);
- average hourly electricity consumption and the price of one MWh of wind power in 2019 (Table 2);
- similar indicators (Table 2) for hours of peak consumption from 8:00 to 12:00 CET/GTM+2 (Table 3).

The motivation to choose the variables for Table 2 and table 3 is as follows. Implementation of DR programs can result in shift peak demand, enhance system reliability, can reduce transmission bottleneck and highly priced energy bills by shifting or re-adjusting consumption patterns[12],[13]. It can also reduce the effects of intermittent RE generation since the capacity of introduced RE sources will be optimally minimal, and the consumer can also be encouraged to embark on self RE generation and sell self-produced excess energy to the grid. The calculation of trends of indicators, approximating formulas dependencies and the coefficients of determination for the relevant diagrams and charts are based on big data collected from the Latvian transmission system operator, Central Statistical Bureau of Latvia[14] and the Nord Pool[15], power exchange. All the calculations in this and subsequent sections were carried out using the *Mathcad* programming language.

Table 1. Latvian electricity sector net electricity production and import, MWh, 2014-2019

Indicator, MWh	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Net electricity production	4857	5384	6228	4401	6500	6108
Import	5338	5247	4827	4074	5172	4612

Source: created by the authors based on statistical data[16].

Table 2 contains calculations of average indicators (1-3), dispersion and standard deviations, according to the data in Table 1.

[12] J. Rawlings, S. Pantula, D. Dickey, *Applied Regression Analysis*, New York 2006, pp. 235-262.
[13] A. Adams, D. Bloomfield, P. Booth, P. England, *Investment Mathematic and Statistics*, London 1993.
[14] Central Statistical Bureau of Latvia, Electricity Production, Imports, Exports and Consumption, Riga 2021, https: //stat.gov.lv/en/statistics-themes/business-sectors (25.05.2022).
[15] Nord Pool. Merchant Electricity Prices. Historical market data, http://nordpoolspot.com/historical-market-data (20.03.2022); Nord Pool. Merchant Electricity Prices. Market Data, https://www.nordpoolgroup.com (20.03.2022); Nord Pool. Maximum Net Transfer Capacities (NTC), https://www.nordpoolspot.com/globalassets/download-center/tso/max-ntc.pdf (20.03.2022).
[16] Central Statistical Bureau of Latvia, Electricity Production, Imports, Exports and Consumption, Riga 2021, https: //stat.gov.lv/en/statistics-themes/business-sectors (25.05.2022).

Table 2. The calculated values of the indicators (1 – 3) according to Table 2

	Net electricity production	**Import**
Average, *E*	5413×10^3	4.878×10^3
Dispersion, *D*	4.978×10^5	2.308×10^5
Standard deviation, σ	705.541	480.41

Source: created by the author.

The covariance calculated by formulas (4) for net electricity production and import is 5.772×10^4, and the correlation coefficient calculated by formulas (5) is 0.17. It could be easily seen that these indicators "Net electricity production" and "Import of electricity" are positively correlated, but the degree of correlation is low.

Furthermore, the wind energy indicators in Latvia for 2019 could be considered (Table 3 and 4).

Table 3. Average hourly calculated natural and price indicators of wind energy in Latvia, 2019

Indicator	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Average hourly wind power generation (MWh)	171	219	222	141	135	89	122	58	161	159	183	224
Average wind power price (EUR/MWh)	56	47	40	44	44	45	49	39	49	47	45	39

Source: created by the authors based on statistical data[17].

Table 4. Average hourly calculated natural and price indicators of wind energy during peak hours (from 8:00 to 12:00 CET/GTM+2) in Latvia, 2019

Indicator	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Average hourly peak wind power generation (MWh)	174	211	230	118	123	76	96	47	149	153	181	213
Average peak wind power price (EUR/MWh)	64	50	43	52	57	66	61	60	67	56	48	42

Source: created by the authors based on statistical data[18].

The calculated average per diem and peak hours indicators of wind energy are equal to 157 and 147.6 MWh, 45.3 and 55.5 EUR/ MWh accordingly Tables 3 and 4. Indicators differ insignificantly in volume (6%) and significantly, in price (18%); moreover, during peak hours, the average consumption of wind power is less, but the average hourly price is higher. As the next step, author developed a regression model that describes the dependence of the indicators in Table 3 and 4 from month number *i*. The number of observations is the number of months, i.e. $n = 12$.

[17] Central Statistical Bureau of Latvia. Electricity Production, Imports, Exports and Consumption. Riga 2021. https: //stat.gov.lv/en/statistics-themes/business-sectors (25.05.2022).
[18] Ibidem.

The related variables should be chosen so that the smoothing of the presented data is acceptable. The smoothing criterion is the sum of the squares of the deviations:

$$R = \sum_{i=1}^{12}\left(Y_i - \hat{Y}_i\right)^2. \quad (9)$$

Initially, it was supposed to use a general polynomial regression model (8):

$$,Y_i = \beta_0 + \beta_1 i^2 + \beta_1 i + \cdots + \beta_k i^k + Z_i, i = 1, \ldots, 12.$$

However, the results were completely unsatisfactory. This is explained by various researchers offering advanced mathematical and statistical application for analysis[19]. Based on the assumptions that the matrix $X^T X$ is quite poorly conditioned, they mention that one of the ways to reduce the influence of bad conditionality of the matrix $X^T X$ is to use Chebyshev polynomial. This possibility was tested, but the result was again unsatisfactory. The authors adopted for further research the sinusoidal dependence of the indicator on the month number:

$$Y_i = \beta_0 + \beta_1 \sin\left(\frac{i-c}{6}\pi\right) + Z_i, i = 1, \ldots, 12, \quad (10)$$

where c – known integer with possible values from 0 to 11.

In this case, there is a single related variable $x_{i,1} = \sin\left(\frac{i-c}{6}\pi\right)$. Statistics are given by the vector $Y = (Y_1, Y_2, \ldots, Y_{12})$ and the smoothing criterion is written as:

$$R = \sum_{i=1}^{12}\left(Y_i - \hat{Y}_i\right)^2 = \sum_{j=1}^{12}\left(\hat{\beta}_0 + \widehat{\beta_1}\sin\left(\frac{j-c}{6}\pi\right) - Y_i\right)^2. \quad (11)$$

It allows you to get simple estimation equations:

$$\beta_0 = \frac{1}{12}\sum_{i=1}^{12} Y_j, \quad (12)$$

$$\beta_1 = \left(\sum_{i=1}^{12}\sin\left(\frac{i-c}{6}\pi\right)(Y_i - \beta_0)\right) * \frac{1}{\sum_{i=1}^{12}\left(\sin\left(\frac{i-c}{6}\pi\right)\right)^2}.$$

The latter formula follows from the fact that the derivative to $\beta_1$from R gives the following relation:

$$\beta_0 \sum_{i=1}^{12}\sin\left(\frac{i-c}{6}\pi\right) + \beta_1 \sum_{i=1}^{12}\left(\sin\left(\frac{i-c}{6}\pi\right)\right)^2 - \sum_{i=1}^{12} Y_i \sin\left(\frac{i-c}{6}\pi\right) = 0.$$

Constant c is chosen so that the criterion R is minimal. Application of the obtained estimates shows that individual outliers violate smoothing. The estimates can be improved by introducing an additional related variable of (+1) for the cases with the highest values and (-1) for the cases with the lowest values [11]. According to Tables 3 and 4 the highest values of average hourly wind power generation and average hourly peak wind power generation are in February, March and December, but the lowest values are in June and August. If using Boolean variables

[19] A. Adams, P. Booth, D. Bowie, D. Freeth, *Investment Mathematics*, New Jersey 2003, pp. 149-155; A. Adams, D. Bloomfield, P. Booth, P. England, *Investment Mathematic and Statistics*, London 1993; J. Rawlings, S. Pantula, D. Dickey, *Applied Regression Analysis*, New York 2006, pp. 235-262.

$$x_{i,2} = \begin{cases} -1, \text{if } i = 6 \text{ or } 8, \\ 1, \text{if } i = 2, 3 \text{ or } 12, \\ 0, \text{otherwise}, \end{cases} \quad (13)$$

where i – number of months, then the modified regression model can be written as follows:

$$Y_i = \beta_0 + \beta_1 \sin\left(\frac{i-c}{6}\pi\right) + \beta_2 x_{i,2} + Z_i, i = 1, \dots, 12, \quad (14)$$

Model (14) assumes that the maximum and minimum outliers have the same average deviations from the total average. If this is not the case, then additional related variables should be introduced to identify the maximum and minimum outliers:

$$x_{i,2} = \begin{cases} -1, \text{if } i = 6 \text{ or } 8, \\ 0, \text{otherwise}, \end{cases} \quad (15)$$

$$x_{i,3} = \begin{cases} 1, \text{if } i = 2, 3 \text{ or } 12, \\ 0, \text{otherwise}. \end{cases} \quad (16)$$

The regression model will now look as follows:

$$Y_i = \beta_0 + \beta_1 \sin\left(\frac{i-c}{6}\pi\right) + \beta_2 x_{i,2} + \beta_3 x_{i,3} + Z_i, i = 1, \dots, 12. \quad (17)$$

Next, a regression model that approximates Table 3 and Table 4 at once, is considered. To perform it, we will introduce an additional related variable identifying the table under consideration, and the estimation will be carried out on all data from both Tables 3 and 4. Let us illustrate this using the example of the last model (17). A related variable $x_{i,4}$ will be added here:

$$x_{i,4} = \begin{cases} 1, \text{if the observation refers to table 1}, \\ 0, \text{otherwise}. \end{cases} \quad (18)$$

As a result, we get the model:

$$Y_i = \beta_0 + \beta_1 \sin\left(\frac{i-c}{6}\pi\right) + \beta_2 x_{i,2} + \beta_3 x_{i,3} + \beta_4 x_{i,4} + Z_i, i = 1, \dots, 12. \quad (19)$$

THE RESULTS OF PROCESSING MONTHLY FLUCTUATIONS OF THE INDICATORS IN TABLES 3 AND 4

The calculated indicators of natural and price statistics – average hourly wind power and average hourly price from Tables 3, and average hourly peak wind power and average hourly peak prices from Table 4 are given in Table 5. The covariance for the two presented indicators is 5.25 for Table 3 and -308 for Table 4. The corresponding correlation coefficients are 0.021 and -0.626. It can be stated that the statistical characteristics of these two tables are substantially different.

Table 5. The calculated values of the indicators (1 –3) according to the Tables 3 and 4

	Average hourly wind power production (MWh)		Average price (EUR)	
	Table 3	Table 4	Table 3	Table 4
Average, *E*	157	147.583	45.583	55.5
Dispersion, *D*	2.713×10^3	3.302×10^3	23.5154	73.182
Standard deviation, σ	52.084	57.462	4.849	8.555

Source: created by the author.

Now it is pertinent to present the results of the analysis of monthly fluctuations in the statistical data of Tables 3 and 4, where the regression coefficients β_0 and β_1 are estimated for different values of the constant *c*, and the criterion smoothing (11) is calculated to "remove noise" from a data set, allowing important patterns to stand out. Tables 6 and 7 show the obtained results. It should be highlighted that the best results are in that case, when the value of the constant *c* is equal to 4. This value will be used in the next calculations.

Table 6. The values of criterion (11) at different *c* for the indicators of Table 3

C	0	1	2	3	4	5	6	7	8	9	10	11
R_1	155	173	157.37	118.23	90.88	115.44	155.29	172.72	157.37	118.23	90.88	115.14
R_2	16	16	15.869	15.868	15.967	16.067	16.069	15.97	15.869	15.868	15.967	16.067

Source: created by the author.

Table 7. The values of criterion (11) at different *c* for the indicators of Table 4

c	0	1	2	3	4	5	6	7	8	9	10	11
R_1	171.67	190.58	171.13	124.11	92.48	124.85	171.64	190.58	171.13	124.11	92.48	124.85
R_2	25.57	28.08	27.89	25.14	22.31	22.55	25.57	28.08	27.89	25.14	22.31	22.55

Source: created by the author.

For the model (10) with $c = 4$, the coefficients calculated by formulas (11) and (.12) were as follows – Table 3: for the first indicator $\beta_0 = 157$ and $\beta_1 = -59.974$; for the second indicator $\beta_0 = 45.333$ and $\beta_1 = -0.789$. Table.4: for the first indicator $\beta_0 = 147.583$ and $\beta_1 = -68.029$; for the second indicator $\beta_0 = 55.5$ and $\beta_1 =7.157$. Comparison of actual and smoothed data is given in Tables 8 and 9.

Table 8. Actual and smoothed monthly data for the indicators of Table 3

I	1	2	3	4	5	6	7	8	9	10	11	12
Y_1	171	219	222	141	135	89	122	58	161	159	183	224
$\hat{Y}_i$	216.9	208.9	187.0	157.0	127.0	105.1	97.0	105.1	127.0	177.0	187.0	209.0
Y_2	56	47	40	44	44	45	49	39	49	47	45	39
$\hat{Y}_2$	46.12	46.02	45.73	45.33	44.94	44.65	44.55	44.65	44.94	45.33	45.73	46.02

Source: created by the author.

Table 9. Actual and smoothed monthly data for the indicators of Table 4

I	1	2	3	4	5	6	7	8	9	10	11	12
Y_1	174	211	230	118	123	76	96	47	149	153	181	213
$\hat{Y}_i$	215.6	206.5	181.6	147.6	113.6	88.7	79.6	88.7	113.6	147.6	181.6	206.5
Y_2	64	50	43	52	57	66	61	60	67	56	48	42
$\hat{Y}_2$	48.3	49.3	51.9	55.5	59.1	61.7	62.7	61.7	59.1	55.5	51.9	49.3

Source: created by the author.

The next step is to repeat the calculations for the case of introducing an additional related variable (13). (See model (14)). The data presented in Tables 10 and 11 indicate that the best values of the constant c are: $c = 2$ for the first indicator in Table 3 and $c = 3$ in other cases.

Table 10. Values of criterion (11) for model (14) at different c for indicators of Table 3

c	0	1	2	3	4	5	6	7	8	9	10	11
R_1	52.65	45.75	38.30	40.58	54.88	57.29	52.65	45.75	38.30	40.58	54.88	57.29
R_2	15.92	15.72	15.47	15.39	15.81	16.01	15.92	15.72	15.47	15.39	15.81	16.01

Source: created by the author.

Table 11. Values of criterion (11) for model (14) at different c for indicators of Table 4

c	0	1	2	3	4	5	6	7	8	9	10	11
R_1	74.86	65.72	54.30	54.06	74.40	79.98	74.86	65.72	54.30	54.06	74.40	79.98
R_2	19.10	19.10	19.02	18.83	18.83	19.00	19.10	19.10	19.02	18.83	18.83	19.00

Source: created by the author.

For model (14) with the chosen values c the coefficients calculated by formula (7) are as follows – Table 3: for the first indicator β_0 = 151.2, β_1 = -14.77 and β_2 = 69.72, for the second indicator β_0 = 45.49, β_1 = -2.03 and β_2 = -1.92. Table 4: for the first indicator β_0 = 142.55, β_1 = -28.86 and β_2 = 60.37, for the second indicator β_0 = 56.24, β_1 = 0.92 and β_2 = -8.90. Comparison of actual and smoothed data is given in Tables 12 and 13.

Table 12. Actual and smoothed monthly data for model (14) and indicators of Table 3

I	1	2	3	4	5	6	7	8	9	10	11	12
Y_1	171	219	222	141	135	89	122	58	161	159	183	224
$\hat{Y}_i$	158.57	220.91	213.53	138.40	136.42	68.68	143.81	81.47	158.57	163.98	165.96	233.7
Y_2	56	47	40	44	44	45	49	39	49	47	45	39
$\hat{Y}_2$	47.25	44.59	43.58	44.48	43.74	45.38	43.74	46.39	45.93	46.51	47.25	45.61

Source: created by the author.

Table 13. Actual and smoothed monthly data for model (14) and indicators of Table 4

I	1	2	3	4	5	6	7	8	9	10	11	12
Y_1	174	211	230	118	123	76	96	47	149	153	181	213
$\hat{Y}_i$	167.55	217.36	202.93	128.22	117.56	53.32	117.56	67.75	142.55	156.98	167.55	231.79
Y_2	64	50	43	52	57	66	61	60	67	56	48	42
$\hat{Y}_2$	55.45	46.88	47.34	56.70	57.04	66.06	57.04	65.60	56.24	55.78	55.45	46.23

Source: created by the author.

The next step is a repeat of the calculations for the case of introducing two additional related variables (15) and (16), identifying the maximum and minimum outliers. (See model (17)) As in the previous case, the data presented in Tables 14 and 15 indicate that the best values of the constant c are: $c = 2$ for the first indicator of Table 3 and $c = 3$ – in other cases.

Table 14. Values of criterion (11) for model (16) at different c for indicators of Table 3.

C	0	1	2	3	4	5	6	7	8	9	10	11
R_1	52.41	45.59	38.00	39.37	53.54	56.70	52.41	45.59	38.00	39.37	53.54	56.70
R_2	12.78	12.69	12.39	11.95	12.16	12.63	12.78	12.69	12.39	11.95	12.16	12.63

Source: created by the author.

Table 15. Values of criterion (3.11) for model (3.17) at different c for indicators of Table 4

C	0	1	2	3	4	5	6	7	8	9	10	11
R_1	74.84	65.62	54.25	53.88	73.76	79.93	74.84	65.62	54.25	53.88	73.76	79.93
R_2	17.96	17.90	17.78	17.68	17.81	17.95	17.96	17.90	17.78	17.68	17.81	17.95

Source: created by the author.

For model (17) with the chosen values c the coefficients calculated by formula (7) are as follows - Table 3: for the first indicator $\beta_0 = 152.1$, $\beta_1 = -14.51$, $\beta_2 = -72.32$ and $\beta_3 = 67.92$, for the second indicator $\beta_0 = 57.86$, $\beta_1 = 1.26$, $\beta_2 = 4.20$ and $\beta_3 = -12.23$. Table 4: for the first indicator $\beta_0 = 142.0$, $\beta_1 = -28.98$, $\beta_2 = -58.77$ and $\beta_3 = 61.51$, for the second indicator $\beta_0 = 47.71$, $\beta_1 = -1.56$, $\beta_2 = -4.55$ and $\beta_3 = -6.49$. Comparison of actual and smoothed data is given in Tables 16 and 17.

Table 16. Actual and smoothed monthly data for model (17) and indicators of Table 3

I	1	2	3	4	5	6	7	8	9	10	11	12
Y_1	171	219	222	141	135	89	122	58	161	159	183	224
$\hat{Y}_i$	159.36	219.90	212.64	139.54	137.60	67.22	144.85	79.78	159.36	164.67	166.62	232.46
Y_2	56	47	40	44	44	45	49	39	49	47	45	39
$\hat{Y}_2$	49.01	42.00	41.22	46.94	46.36	41.61	46.36	42.39	47.71	48.49	49.06	42.78

Source: created by the author.

Table 17. Actual and smoothed monthly data for model (17) and indicators of Table 4

I	1	2	3	4	5	6	7	8	9	10	11	12
Y_1	174	211	230	118	123	76	96	47	149	153	181	213
$\hat{Y}_i$	167.10	218.00	203.51	127.51	116.91	54.26	116.90	68.74	142.00	156.49	167.10	232.45
Y_2	64	50	43	52	57	66	61	60	67	56	48	42
$\hat{Y}_2$	56.77	45.00	45.63	58.49	58.95	63.31	58.95	62.68	57.86	57.23	56.77	44.37

Source: created by the author.

As the tables show, the developed model of the regression quite precisely describes our data. R-square is much closer to the unit that means that the model is qualitative. In addition, the lack of residual autocorrelation indicates the quality of the forecast.

Comparison of the two models (14) and (17) for the purpose of their practical use leads to the following recommendations. If we proceed from the formal criterion, the sum of squares of deviations (9), then the preference should be given to the model (17). However, expert analysis shows that the results provided by the model (14) are more logically justified. In this regard, model (14) is recommended for practical use.

CONCLUSIONS

In May 2022 a Special meeting of the European Council has been held where the Conclusions on Ukraine, food security, security and defence, and energy were adopted[20]. The key to rapidly reducing the European Union's dependence on Russian fossil fuels is the acceleration of the energy transition. Improving energy efficiency, deploying renewables and enhancing the interconnection of European gas and electricity networks are crucial to achieve a more resilient energy system. The European Council called for work on the optimisation of the functioning of the European electricity market. Analyzing the effectiveness and efficiency of the electricity market and statistics authors believe there is a significant potential to increase the share of renewable energy sources in electricity generation.

The authors substantiated the use of the sinusoidal dependence of wind energy indicators on the month of the year, as a basic model, for the correlation study. It is shown that if the maximum and minimum outliers of the studied data do not have the same average deviations from the general average level, then it is necessary to introduce additional accompanying variables that identify these outliers, which leads to the corresponding modified model. The regression dependence of monthly wind power data is established and the correctness of the obtained models is supported by the corresponding calculations.

The main conclusions are as follows:

[20] European Council. Conclusions on Ukraine, food security, security and defence and energy. Brussels 2022, https://www.consilium.europa.eu/en/press/press-releases/2022/05/31/european-council-conclusions-30-31-may-2022 (24.11.2022).

1. The use of a sinusoidal dependence as a basic mathematical model is justified for regression and correlation analysis of monthly statistical data on wind power and its price. It has been shown that polynomial regression is an ineffective tool for the corresponding study.
2. The model has been modified with additional accompanying variables for cases where the maximum and minimum outliers of the studied data do not have the same average deviations from the total average.
3. The developed models are recommended to be used as analytical tools for the electricity aggregator development in Latvia.
4. Such results can be a valuable input for analysis on the necessity for compensation between aggregators and balance responsible parties or basis for further analysis for policy makers when considering the necessity for state support to accelerate the introduction of the service.

The European Green Deal[21] has the main objective of becoming the world's first climate-neutral continent by 2050. The use of renewable energy significantly reduces the dependence on fossil fuel as a source of energy, helping to cut the greenhouse gas emissions. The growth of renewable energy sources can also help stabilize energy prices in the future once it makes up a significant proportion of the electricity mix that powers businesses and households.

Implementation of the results of the study will help improve the efficiency of the functionality of the regional energy regulator and, consequently, strengthen the national energy security and independence in line with the European Union resolution to strengthen security, stability and prosperity in Europe.

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