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Grażyna Trzpiot, Alicja Ganczarek

THE CLASSIFICATION OF RISK ON THE POLISH POWER EXCHANGE*

1. Introduction

The Polish Energy Exchange was established in July 2000. The Day Ahead Market (DAM) was the first market which was established on the Polish Energy Exchange. This market is a whole-day market, which consists of the twenty-four separate, independent markets where participants may freely buy and sell electricity. The advantage of the Exchange is that all participants of the market can buy and sell electric energy, irrespective of whether they are producers or receivers. This is a market of quicker changes in level of prices and demand. When we compare oil price fluctuations, ranging from 1% to 3%, and gas price fluctuations ranging for 2% to 4%, with electric energy price changes, which varies from 10% to 50%, we can see that both producers and receivers are forced to protect themselves against losses.

In this paper we adopted the downside risk measures such as Value-at-Risk (*VaR*) to describe the risk of change in the price on DAM. We use the Monte Carlo simulation to establish the level of *VaR*. When we want to choose an appropriate statistical method to estimate downside risk on the Polish electric energy market, we need to take the seasonal fluctuations into account. So we analyse several separate data sets, which are parallel from the summer period and from the winter period.

On the basis of existing energy price indexes, financial market indexes and energy price classification, we propose *new* group of indexes. We want to show that it is possible to manage more effectively the risk on the market. In order to reach this goal we use the classification of risk separately on each hour on Polish electric en-

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ergy market. Based on the daily logarithmic rates of return of another group of indexes we establish the *VaR*. The aim of this paper is to present applications of the results of classification in the management of risk on the Polish Power Exchange.

2. Value at risk

Financial decisions always include a number of risk such as: the changes of prices, the uncertainty of keeping the conditions of a contract, difficulties in closing a position on the financial market, the changes in law and the risk of strategy.

In order to estimate the future risk we can use: measures of volatility, measures of sensitivity or measures of downside risk. In this paper we present quantile downside risk measures such as Value-at-Risk (*VaR*). The downside risk measures are more effective than the measures of volatility to estimate risk on the electric energy market, because the biggest forward losses are more important than average forward losses for all the participants of the market [5].

The downside risk measure measures unwilling deviations from the expected rate of return. *VaR* is such a loss of value, which cannot exceed the given probability over a time period [4]:

$$P\left(X_{t+\Delta t} \le X_t - VaR\right) = \alpha, \tag{1}$$

where: $\alpha \in (0,1)$ is a given probability,

X_t is a present value of price,

$X_{t+\Delta t}$ is a random variable, which represent the future value of price at the end of the given investment period.

We can rewrite *VaR* also by formula:

$$VaR_\alpha = -Q_\alpha(z) X_t, \tag{2}$$

where $Q_\alpha(z)$ is α-quantile of the rate of return.

VaR is a number that represents an estimator of the value of how much we may lose due to market movements in a particular horizon and for a given confidence level. If we have fixed the horizon and the degree of confidence, we can measure risk [1]. There are three main methodologies to calculate *VaR*: variance-covariance, Monte Carlo simulation, historical simulation.

We use the Monte Carlo simulation to calculate *VaR*. In the Monte Carlo simulation $Q_\alpha(z)$ is α-quantile of the rate of return, which is calculated from the simulated distribution of the rate of return. In the simulation we use Generalized Error Distribution (GED) with a density function [3]:

$$f_G(x) = \frac{\lambda_G \cdot v_G}{2 \cdot \Gamma\left(\frac{1}{v_G}\right)} \exp\left\{-\lambda_G^{v_G} |x-\mu|^{v_G}\right\}, \tag{3}$$

where: $\Gamma(z) = \int_0^\infty e^{-t} t^{z-1} dt$ is Gamma Euler's function,

μ, λ_G, v_G are the parameters of this distribution.

We estimate the parameters by maximum likelihood method (ML) [3]:

$$\ln_G(\lambda_G, v_G) = T \ln(\lambda_G) + T \ln\left(\frac{v_G}{2 \cdot \Gamma\left(\frac{1}{v_G}\right)}\right) - \sum_{t=1}^{T} |\lambda_G z_t|^{v_G}, \tag{4}$$

where: T is a number of observations,

z_t is an empirical time series of rates of return.

3. Empirical analysis

Daily, weekly and yearly seasonal peaks and lows characterize the electric energy volumes and prices. We divided the data set of price of electric energy noted at each hour in period from 30.03.03 to 26.10.05 on DAM into four periods parallel with the change from the summer time to the winter time:

1) the time series in summer: from 30.03.03 to 25.10.03,
2) the time series in winter: from 26.10.03 to 27.03.04,
3) the time series in summer: from 28.03.04 to 30.10.04,
4) the time series in winter: from 31.10.04 to 26.03.05.

We describe every period by 24 time series of prices of electricity. Next, based on our earlier research [6], we separate the data set into four groups of prices according to two principal components. In table 1 we present the results of the

Table 1. Yearly seasonal in classification prices of electric energy on DAM

Date	K_1	K_2	K_3	K_4	$\sum_{i=1}^{2} w_i$	T
30.03.03–25.10.03	X_7, ..., X_{19}	X_{20}, X_{21}	X_6, X_{22}, ..., X_{24}	X_1, ..., X_5	0,65	210
26.10.03–27.03.04	X_{17}, ..., X_{21}	X_9, ..., X_{16}	X_7, X_8, X_{22}, ..., X_{24}	X_1, ..., X_6	0,72	154
28.03.04–30.10.04	X_7, ..., X_{18}, X_{22}	X_{19}, X_{20}, X_{21}	X_6, X_{23}, X_{24}	X_1, ..., X_5	0.66	217
31.10.04–26.03.05	X_{17}, ..., X_{21}	X_9, ..., X_{16}	X_7, X_8, X_{22}, ..., X_{24}	X_1, ..., X_6	0.72	147

Source: own calculations.

classifications. The principles components describe variance of 24 prices in 65% (or 66%) in summer and in 72% in winter.

3.1. Energy price indexes

The prices on financial markets are usually correlated. We can describe the common changes in levels of prices by indexes. On the Polish energy market there are two electric energy indexes:

IRDN – day ahead market index of prices during a day:

$$IRDN = \frac{\sum_{i=1}^{n} P_i W_i}{\sum_{i=1}^{n} W_i}, \tag{5}$$

SRDN – day ahead market index of prices of peak hours from 19 to 21:

$$SRDN = \frac{\sum_{i=1}^{3} P_i W_i}{\sum_{i=1}^{3} W_i}, \tag{6}$$

where: n – number of hours during a day (23 or 24 or 25),
P_i – price of i^{th} hour during a day,
W_i – electricity volume of i^{th} hour during a day.

Value of *IRDN*, it is average price of electric energy during a day. Value of *SRDN*, it is average price of electric energy noted in hour from 19 to 21. So value of *SRDN* characterizes higher average and higher volatility than value of *IRDN*. When we look at the time series of this two indexes, we can see weekly and yearly seasonal peak and low. But we should remember, that excessively aggregation is not good in risk analysis, because in this process we lose a real big volatility of electric energy prices during a day and daily seasonal of prices. So based on the existing energy price indexes (5-6) and energy price classification (table 1) the *new* group of indexes is proposed. The groups of hours in every index corresponding to obtained groups of classification (table 1). So we propose sixteen indexes, that means four indexes in every period. For example, in the period from 30.03.03 to 25.10.03 we propose and notice four indexes:

$IRDN_{1\text{-}5}$ – the weighted average price in the group of hours {1-5}:

$$IRDN_{1\text{-}5} = \frac{\sum_{i=1}^{5} P_i W_i}{\sum_{i=1}^{5} W_i}, \tag{7}$$

$IRDN_{7\text{-}19}$ the weighted average price in the group of hours {7-19}:

$$IRDN_{7\text{-}19} = \frac{\sum_{i=1}^{13} P_i W_i}{\sum_{i=1}^{13} W_i}, \tag{8}$$

Table 2. Parameters of distribution of logarithmic rates of return of electric energy prices indexes on DAM

Date	*T*	Indexes	Average	Standard deviation	Skew ness	Kurtosis
30.03.03– –25.10.03	209	*IRDN*	0,0005	0,0470	0,6044	1,7837
		SRDN	0,0008	0,0472	0,2613	3,5599
		$IRDN_{7\text{-}19}$	0,0006	0,0688	0,5276	2,1416
		$IRDN_{20\text{-}21}$	0,0005	0,0509	0,3742	4,7457
		$IRDN_{6,\,22\text{-}24}$	0,0002	0,0273	0,1483	1,0592
		$IRDN_{1\text{-}5}$	0,0002	0,0554	0,6803	16,5697
26.10.03– –27.03.04	153	*IRDN*	0,0002	0,0858	0,3466	1,6178
		SRDN	0,0003	0,1162	–0,5813	4,9805
		$IRDN_{17\text{-}21}$	0,0002	0,1050	0,0855	2,1659
		$IRDN_{9\text{-}16}$	0,0003	0,1232	0,3196	1,2942
		$IRDN_{7,\,8,\,22\text{-}24}$	0,0000	0,0750	–0,0975	1,7106
		$IRDN_{1\text{-}6}$	0,0001	0,0872	0,2328	1,9672
28.03.04– –30.10.04	216	*IRDN*	0,0002	0,0578	0,3717	1,1366
		SRDN	0,0008	0,0721	0,2212	1,8582
		$IRDN_{7\text{-}18,\,22}$	0,0001	0,0744	0,2827	2,0684
		$IRDN_{19\text{-}21}$	0,0008	0,0721	0,2212	1,8582
		$IRDN_{6,\,23,\,24}$	–0,0001	0,0457	0,1484	1,7472
		$IRDN_{1\text{-}5}$	0,0001	0,0733	–0,2232	5,6704
31.10.04– –26.03.05	143	*IRDN*	0,0018	0,0662	0,0181	2,4072
		SRDN	0,0003	0,0642	–0,4817	3,4436
		$IRDN_{17\text{-}21}$	0,0005	0,0635	0,0736	1,3969
		$IRDN_{9\text{-}16}$	0,0029	0,0926	0,2203	4,4415
		$IRDN_{7,\,8,\,22\text{-}24}$	0,0017	0,0723	0,4769	3,3811
		$IRDN_{1\text{-}6}$	0,0019	0,0993	–0,0962	2,0039

Source: own calculations.

Table 3. Parameters of GED of the electric energy price indexes fluctuations on DAM

Date	T	Indexes	$\ln_G \delta \beta_G, v_G \gamma$	v_G	λ_G	K	AD
30.03.03––25.10.03	209	*IRDN*	–280,26	0,9209	1,6107	0,0751	0,1503
		SRDN	–269,76	0,8022	2,1641	0,0269	0,1483
		$IRDN_{7\text{-}19}$	–268,27	0,6778	3,1655	0,0378	0,1514
		$IRDN_{20\text{-}21}$	–260,07	0,7420	2,6644	0,0711	0,3066
		$IRDN_{6,\,22\text{-}24}$	–290,51	1,2283	1,0515	0,0267	0,0893
		$IRDN_{1\text{-}5}$	–237,24	0,7167	3,2131	0,0109	0,0959
26.10.03––27.03.04	153	*IRDN*	–207,92	0,9932	1,4106	0,0338	0,1263
		SRDN	–182,4	0,5909	5,0625	0,0526	0,2040
		$IRDN_{17\text{-}21}$	–195,59	0,7111	2,8353	0,0689	0,2621
		$IRDN_{9\text{-}16}$	–207,84	0,9406	1,5309	0,0225	0,2142
		$IRDN_{7,\,8,\,22\text{-}24}$	–199,61	0,7401	2,5228	0,0291	0,1342
		$IRDN_{1\text{-}6}$	–190,32	0,5314	6,8071	0,0477	0,2858
28.03.04––30.10.04	216	*IRDN*	–295,88	1,0375	1,3130	0,0422	0,1260
		SRDN	–291,35	0,9953	1,4205	0,0461	0,1454
		$IRDN_{7\text{-}18,\,22}$	–286,68	0,8523	1,8625	0,0533	0,1650
		$IRDN_{19\text{-}21}$	–291,35	0,9953	1,4205	0,0461	0,1454
		$IRDN_{6,\,23,\,24}$	–292,71	1,0386	1,3305	0,0357	0,1661
		$IRDN_{1\text{-}5}$	–236,88	0,5299	7,9686	0,0198	0,0844
31.10.04––26.03.05	143	*IRDN*	–190,12	0,7876	2,2188	0,0333	0,1280
		SRDN	–187,07	0,7955	2,2207	0,0188	0,2322
		$IRDN_{17\text{-}21}$	–197,68	0,9618	1,4861	0,0500	0,1396
		$IRDN_{9\text{-}16}$	–180,46	0,6802	3,2907	0,0868	0,1736
		$IRDN_{7,\,8,\,22\text{-}24}$	–182,6	0,7459	2,6171	0,0801	0,1603
		$IRDN_{1\text{-}6}$	–170,3	0,4692	11,8932	0,0292	0,0969

Source: own calculations.

$IRDN_{20\text{-}21}$ the weighted average price in the group of hours {20-21}:

$$IRDN_{20\text{-}21} = \frac{\sum_{i=1}^{2} P_i W_i}{\sum_{i=1}^{2} W_i}, \tag{9}$$

$IRDN_{6,\,22\text{-}24}$ the weighted average price in the group of hours {6, 22-24}:

$$IRDN_{6,\,22\text{-}24} = \frac{\sum_{i=1}^{4} P_i W_i}{\sum_{i=1}^{4} W_i}. \tag{10}$$

Next we apply the *new* indexes to describe prices fluctuation. So we calculate the *new* indexes and next we look for distribution of variable of level *new* indexes. In table 2 we present the parameters the logarithmic rates of return of indexes distribution.

Based on the results of the analysis (table 2) we can say that the rates of return of the indexes have the leptokurtic distribution. We tested the hypothesis that the time series have the GED, because these theoretical distributions are as leptokurtic as the empirical distributions of the indexes. In table 3 we present the results of GED estimations, Kolmogorow's (K) and Anderson-Darling's (AD) statistics. The values of nonparametric statistics are very small (at median K, and in the tails of distribution AD), and in every case we do not reject the null hypothesis.

3.2. Classification of risk

Based on the results of the estimations (table 3) we simulate the distribution for all indexes. We make $T \times 1000$ simulations in every period:

1) 30.03.03–25.10.03, $T = 209$;
2) 26.10.03–27.03.04, $T = 153$;
3) 28.03.04–30.10.04, $T = 216$;
4) 31.10.04–26.03.05, $T = 143$.

At the end, we estimated the downside risk measure (VaR) based on the new theoretical distribution. For the short position – $VaR_{0,01}$ and $VaR_{0,05}$, and for the long position – $VaR_{0,95}$ and $VaR_{0,99}$. In this paper, in place of calculated numbers, we present the result of the classification [2] of risk during a day on DAM (figure 1 – – figure 4).

Taking into consideration quantile downside risk measures for market participants and the classification of risk, we can say that: VaR estimated for different hours in summer periods, belongs to the same clusters as VaR estimated in another summer. At the opposite, VaR estimated for different hours in winter periods, belongs to the same clusters as VaR estimated in another winter (on figures 1 – 4 we use such a description as: VaR of indexes estimated in summer has number 1 or 3 on the beginning of his name, VaR of indexes estimated in winter has number 2 or 4 on the beginning of his name). In many cases VaR estimated for parallel groups of hours in different periods of a year belongs to the same clusters. There is a smaller number of clusters for the lower probability of incurring losses than for the higher one. Additionally, we obtain a smaller number of clusters for risk for the short position than for the long position on the market – the participants of the market, who would like to buy electric energy, are subject to more different sources of risk, than the participants, who want to sell it at the same time.

Based on k-average methods we divide VaR into 6 and 4 groups (table 4 – table 5). The results of hierarchical classifications and k-average methods are similar.

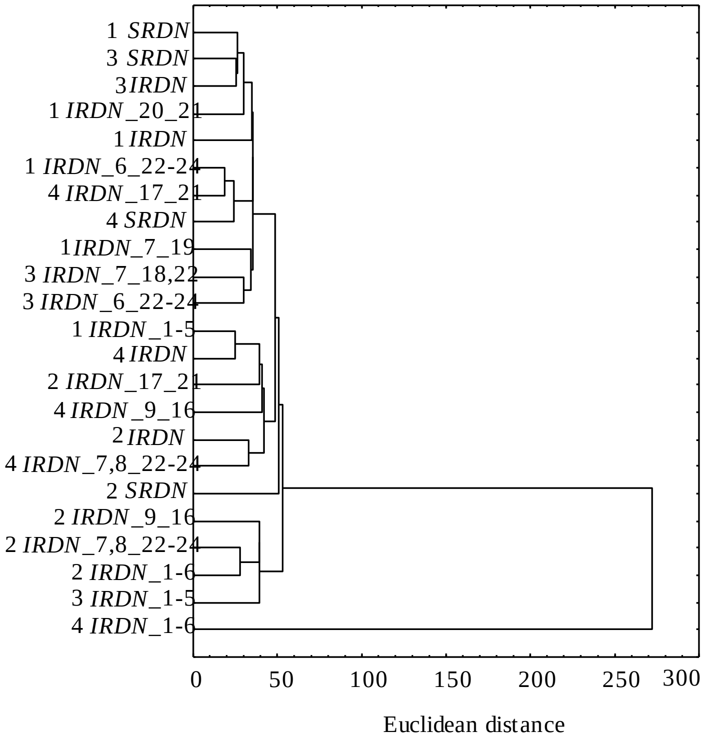

Fig. 1. Classification of $VaR_{0,01}$ of electric energy on DAM 30.03.03–26.03.05

Source: own calculations.

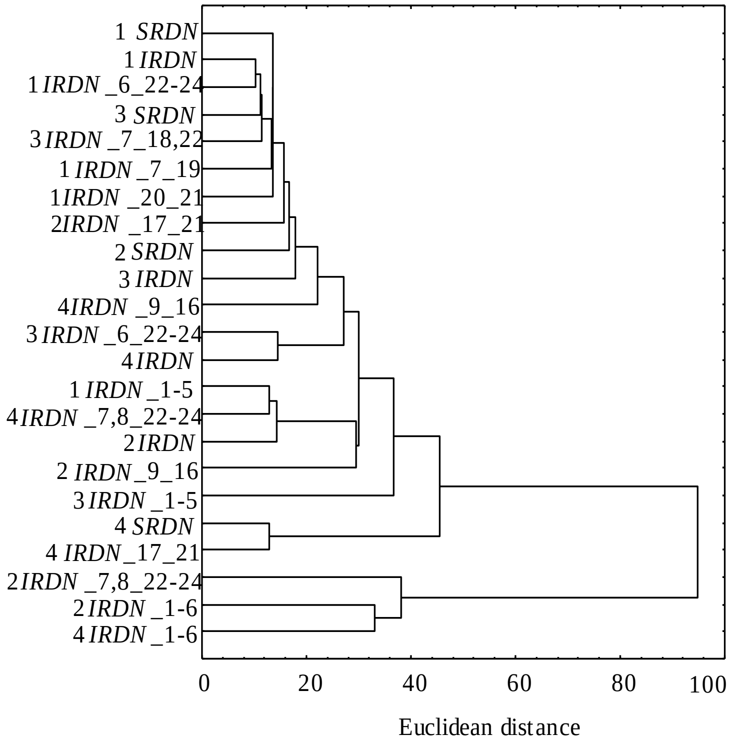

Fig. 2. Classification of $VaR_{0,05}$ of electric energy on DAM 30.03.03–26.03.05

Source: own calculations.

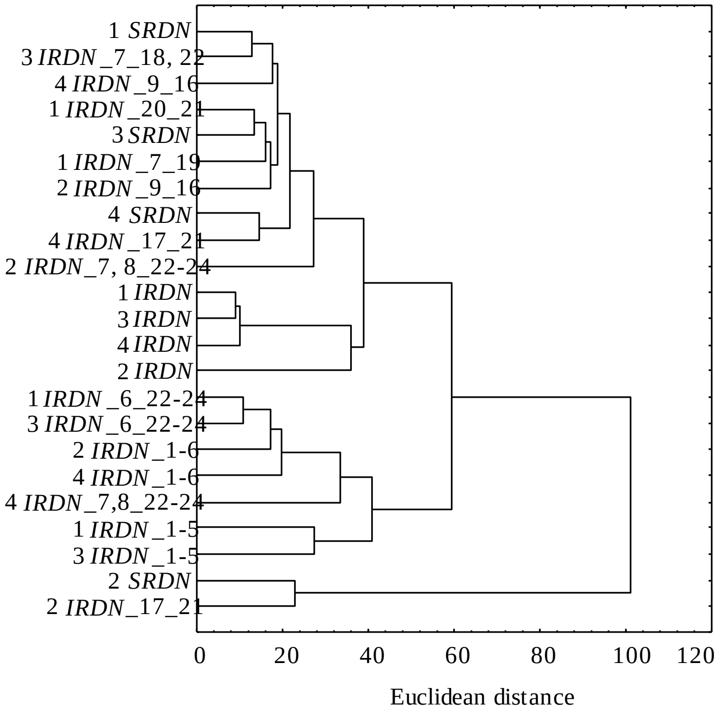

Fig. 3. Classification of $VaR_{0,95}$ of electric energy on DAM 30.03.03–26.03.05

Source: own calculations.

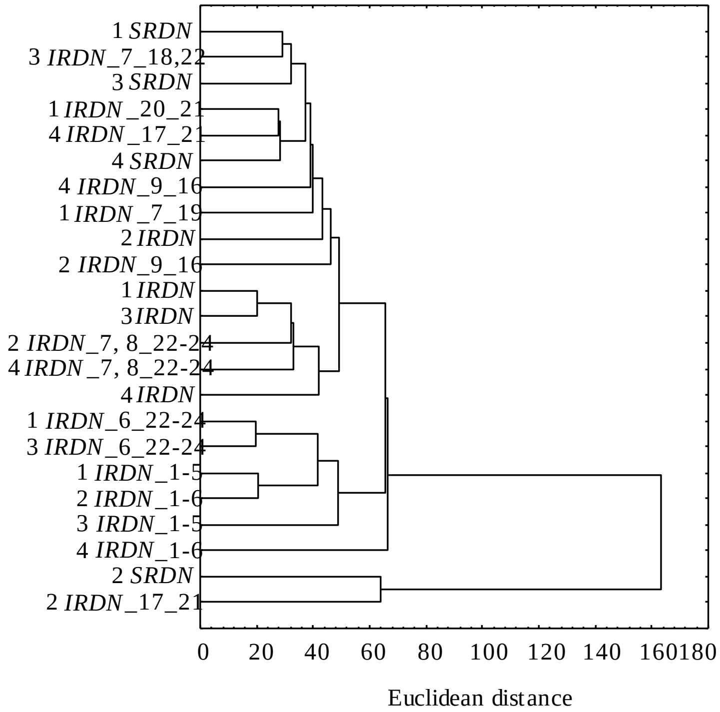

Fig. 4. Classification of $VaR_{0,99}$ of electric energy on DAM 30.03.03–26.03.05

Source: own calculations.

Table 4. Results of k-average ($k = 6$) method in classification of *VaR* of electric energy on DAM 30.03.03–26.03.05

$VaR_{0,01}$	$VaR_{0,05}$	$VaR_{0,95}$	$VaR_{0,99}$
1 *IRDN*_1-5 2 *IRDN*_17_21 4 *IRDN* 4 *IRDN*_9_16	3 *IRDN*_6_22-24 4 *IRDN* 4 *IRDN*_9_16	2 *IRDN* 1 *IRDN* 3 *IRDN* 4 *IRDN*	1 *IRDN* 2 *IRDN*_7, 8_22-24 3 *IRDN* 4 *IRDN* 4 *IRDN*_7, 8_22-24
2 *IRDN*_9_16 2 *IRDN*_7, 8_22-24 2 *IRDN*_1-6 3 *IRDN*_1-5	1 *IRDN*_1-5 2 *IRDN* 4 *IRDN*_7, 8_22-24	1 *SRDN* 1 *IRDN*_20_21 2 *IRDN*_7, 8_22-24 3 *SRDN* 3 *IRDN*_7_18, 22 4 *IRDN*_9_16	1 *SRDN* 2 *IRDN* 3 *SRDN* 3 *IRDN*_7_18, 22
1 *SRDN* 1 *IRDN*_20_21 1 *IRDN*_7_19 3 *SRDN* 3 *IRDN* 3 *IRDN*_7_18, 22 3 *IRDN*_6_22-24	2 *IRDN*_9_16 3 *IRDN*_1-5 1 *SRDN* 1 *IRDN* 1 *IRDN*_20_21 1 *IRDN*_7_19 1 *IRDN*_6_22-24 2 *SRDN* 2 *IRDN*_17_21 3 *SRDN* 3 *IRDN* 3 *IRDN*_7_18, 22	1 *IRDN*_7_19 2 *IRDN*_9_16 4 *SRDN* 4 *IRDN*_17_21	4 *IRDN*_1-6
2 *SRDN* 2 *IRDN* 4 *IRDN*_7, 8_22-24	2 *IRDN*_7, 8_22-24 2 *IRDN*_1-6 4 *IRDN*_1-6	2 *SRDN* 2 *IRDN*_17_21	1 *IRDN*_20_21 1 *IRDN*_7_19 2 *IRDN*_9_16 4 *SRDN* 4 *IRDN*_17_21 4 *IRDN*_9_16
1 *IRDN* 1 *IRDN*_6_22-24 4 *SRDN* 4 *IRDN*_17_21	4 *SRDN* 4 *IRDN*_17_21	1 *IRDN*_6_22-24 1 *IRDN*_1-5 2 *IRDN*_1-6 3 *IRDN*_6_22-24 3 *IRDN*_1-5 4 *IRDN*_7, 8_22-24 4 *IRDN*_1-6	1 *IRDN*_6_22-24 1 *IRDN*_1-5 2 *IRDN*_1-6 3 *IRDN*_6_22-24 3 *IRDN*_1-5
4 *IRDN*_1-6			2 *SRDN* 2 *IRDN*_17_21

Source: own calculations.

Finally, we conclude that the classification of risk during a day in compared four periods proves, that proposed index definitions may be used to construct the futures contracts for the electric energy market. To estimate the future risk of these contracts measures of downside risk such as Value-at-Risk may be used. However, one should remember about assumptions and disadvantages of VaR. VaR is not a coherent risk measure. In particular it is not convex and monotonic. It should not be estimated as a sum of contract components. When the futures contract is constructed, it should first be verified if its underlying model distribution holds. New VaR for this contract should then be estimated.

Table 5. Results of k-average ($k=4$) method in classification of VaR of electric energy on DAM 30.03.03–26.03.05

$VaR_{0,01}$	$VaR_{0,05}$	$VaR_{0,95}$	$VaR_{0,99}$
1 *IRDN*_1-5 2 *SRDN* 2 *IRDN* 2 *IRDN*_17_21 2 *IRDN*_9_16 2 *IRDN*_7, 8_22-24 2 *IRDN*_1-6 3 *IRDN*_1-5 4 *IRDN* 4 *IRDN*_9_16 4 *IRDN*_7, 8_22-24	2 *IRDN*_7, 8_22-24 2 *IRDN*_1-6 4 *IRDN*_1-6	1 *IRDN* 2 *IRDN* 3 *IRDN* 4 *IRDN*	1 *IRDN*_6_22-24 1 *IRDN*_1-5 2 *IRDN*_1-6 3 *IRDN*_6_22-24 3 *IRDN*_1-5
1 *SRDN* 1 *IRDN*_20_21 1 *IRDN*_7_19 3 *SRDN* 3 *IRDN* 3 *IRDN*_7_18, 22 3 *IRDN*_6_22-24	1 *IRDN*_1-5 2 *IRDN* 2 *IRDN*_9_16 3 *IRDN*_6_22-24 3 *IRDN*_1-5 4 *IRDN* 4 *IRDN*_7, 8_22-24	1 *SRDN* 1 *IRDN*_20_21 1 *IRDN*_7_19 2 *IRDN*_9_16 2 *IRDN*_7, 8_22-24 3 *SRDN* 3 *IRDN*_7_18, 22 4 *SRDN* 4 *IRDN*_17_21 4 *IRDN*_9_16	1 *IRDN* 2 *IRDN*_7, 8_22-24 3 *IRDN* 4 *IRDN* 4 *IRDN*_7, 8_22-24
1 *IRDN* 1 *IRDN*_6_22-24 4 *SRDN* 4 *IRDN*_17_21	1 *SRDN* 1 *IRDN* 1 *IRDN*_20_21 1 *IRDN*_7_19 1 *IRDN*_6_22-24 2 *SRDN* 2 *IRDN*_17_21 3 *SRDN* 3 *IRDN* 3 *IRDN*_7_18, 22 4 *IRDN*_9_16	2 *SRDN* 2 *IRDN*_17_21	1 *SRDN* 1 *IRDN*_20_21 1 *IRDN*_7_19 2 *IRDN* 2 *IRDN*_9_16 3 *SRDN* 3 *IRDN*_7_18, 22 4 *SRDN* 4 *IRDN*_17_21 4 *IRDN*_9_16 4 *IRDN*_1-6
4 *IRDN*_1-6	4 *SRDN* 4 *IRDN*_17_21	1 *IRDN*_6_22-24 1 *IRDN*_1-5 2 *IRDN*_1-6 3 *IRDN*_6_22-24 3 *IRDN*_1-5 4 *IRDN*_7, 8_22-24 4 *IRDN*_1-6	2 *SRDN* 2 *IRDN*_17_21

Source: own calculations.

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KLASYFIKACJA RYZYKA NA POLSKIEJ GIEŁDZIE ENERGII ELEKTRYCZNEJ

Streszczenie

Bazując na funkcjonujących indeksach cen energii elektrycznej, indeksach finansowych oraz wynikach klasyfikacji cen energii elektrycznej, w pracy zaproponowano nową grupę indeksów cen energii elektrycznej. Propozycje nowych indeksów wykorzystano do oceny ryzyka zmiany ceny na Rynku Dnia Następnego Towarowej Giełdy Energii SA. Ryzyko wyrażono za pomocą miar zagrożenia szeregów czasowych logarytmicznych stóp zwrotu zaproponowanych indeksów.

Głównym celem pracy jest klasyfikacja ryzyka na polskiej giełdzie energii elektrycznej w ciągu dnia. Do klasyfikacji wykorzystano: metodę głównych składowych, metodę *k*-średnich oraz metodę hierarchiczną. Ze względu na sezonowość energii elektrycznej klasyfikację ryzyka w okresie od marca 2003 r. do marca 2005 r. przeprowadzono niezależnie w czterech okresach badawczych, odpowiadających zmianie czasu z letniego na zimowy i z zimowego na letni. Porównując wyniki klasyfikacji indeksów, oceniono ich przydatność w zarządzaniu ryzykiem na polskiej giełdzie energii elektrycznej w ciągu dnia.

Grażyna Trzpiot – dr hab., prof. AE, kierownik Zakładu Demografii i Statystyki Ekonomicznej w Katedrze Statystyki Akademii Ekonomicznej w Katowicach.

Alicja Ganczarek – dr, adiunkt w Katedrze Statystyki Akademii Ekonomicznej w Katowicach.