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The Use of Weather Variables in the Modeling of Demand for Electricity in One of the Regions in the Southern Poland

A b s t r a c t. The main objective of the paper is the verification of usefulness of the ARFIMA-FIGARCH class models in the description of tendencies in the energy consumption in a selected region of the southern Poland taking into consideration weather variables.

K e y w o r d s: weather variables, the ARFIMA-FIGARCH class model, weather risks.

1. Introduction

The companies specializing in the production or distribution of power are particularly exposed to the weather risk, understood as the possibility of change in the financial result of a company caused by the variability of daily weather conditions: air temperature, rainfall and snowfall, sun light exposure, wind speed and humidity. Furthermore, the inability to store the power leads to the necessity of a precise measurement of the future demand for electricity by the companies specialising in its sale. Therefore the search for statistical and econometrical tools enabling the modeling and forecasting of the demand for power in varying weather conditions has become such an important research problem.

2. Review of Research in the Scope of the Impact of the Climatic Factors on the Electrical Energy Consumption

Identification and measurement of the weather risk are connected with the necessity to isolate from the observable electrical energy consumption a part which is sensitive to the effects of climatic factors. While analyzing historical time series relating to the demand for electrical energy, containing daily, weekly or monthly data from a dozen years, one may notice a strong long-term tendency, whose occurrence has been affected by social, demographic and economic factors. In order to isolate the demand for electrical energy which is sensitive to weather factors, various ways of data filtration can be used. In empirical research on modeling the above relation the following methods are used:

1. the method of the decomposition of time series into the trend component, the calendar component, the periodic component and the irregular component (Moral-Carcedo, Vicéns – Otero, 2005; Bessec, Fouquau, 2008):

$$E_t = \alpha_0 + \sum_{j=1}^{m} \alpha_j t^j + \delta I_{aug,t} + \kappa WD_t + FE_t, \tag{1}$$

or

$$E_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \alpha_3 t^3 + \delta Y_t + FE_t, \tag{2}$$

where E_t is the demand for electricity, $I_{aug,t}$ is a dummy variable taking the value 1 if the observation of the demand corresponds to the month of August, WD_t is the variable describing working day effect, Y_t is the seasonal unadjusted production in total manufacturing at time t, FE_t is the electricity demand with the deterministic component filtered out.

2. the index-related equalization of the long term tendencies which do not result from weather conditions in terms of the demand for electrical energy (Sailor, Muñoz, 1997; Valor, Meneu, Caselllles, 2001):

$$MSVI_{ij} = \frac{E_{ij}}{\overline{E}_j}, \tag{3}$$

$$DSVI_{ijk} = \frac{E_{ijk}}{\overline{E}_{jk}}, \tag{4}$$

where $MSVI_{ij}$ is the index value for month i in year j, E_{ij} is the monthly electricity consumption for month i in year j, $\overline{E}_j$ is the monthly average electricity load for year j, $DSVI_{ijk}$ is the index value for day i of week j of year k, E_{ijk} is the electricity consumption for this same day, $\overline{E}_{jk}$ is the daily average electricity load for week j in year k.

After the estimation of the demand for electrical energy which is sensitive to climatic factors, the strength and nature of the relations between the weather variables and the electrical energy consumption should be assessed. Different types of models were used in the previous research:

1. Pardo, Meneu, Valor (2002) estimated the following model:

$$LE_t = \alpha_0 + \alpha_1 t + \beta(L)HDD_t + \gamma(L)CDD_t + \sum_{i=1}^{6} \delta_i D_{it} + \sum_{k=1}^{11} \varphi_k M_{kt} + \varpi \cdot H_t + \varepsilon_t, \tag{5}$$

$$(1-\phi_1 L-\phi_2 L^2-\ldots-\phi_9 L^9)\varepsilon_{3t}=\xi_{3t}, \tag{6}$$

where D_{it} is dummy variable for daily data (D_{1t} = 1 for Monday, D_{1t} = 0 for other days of the week), M_{it} is dummy variable for monthly data (M_{1t} = 1 for January, M_{1t} = 0 for other months of the year), H_t is dummy variable for holidays (H_t = 1 for holidays, H_t = 0 for other days of the year).

2. Moral-Carcedo, Vicéns – Otero (2005) have constructed the following models in order to describe the non-linear relation between the energy consumption and air temperature:

   a) switch regression model

$$FE_t=\mu_{St}+TMP_t\beta_{St}+\varepsilon_t, \tag{7}$$

   b) threshold regression model

$$\Pr(S_t=i|\psi_t)=\frac{f\left[DF_t|S_t=i\right]\Pr\left[S_t=i\right]}{\sum_{St=1}^{2}f\left(DF_t|S_t\right)\Pr(S_t)}, \tag{8}$$

$$DF_t=\begin{cases}\mu_1+\beta TMP_t+\varepsilon_t & TMP_t<Th1,\\ \mu_2+\gamma TMP_t+\varepsilon_t & Th2>TMP_t>=Th1,\\ \mu_3+\eta TMP_t+\varepsilon_t & TMP_t>Th2.\end{cases} \tag{9}$$

In a warmer climate the relation between air temperature and energy consumption has a non-linear character with the form resembling letter U (Valor, Meneu, Casellles, 2001; Sailor and Muñoz, 1997); i.e. the maximum demand for energy is observed at the low and high temperatures. The introduction of the HDD and CDD indices, which separate the winter and summer seasons, enables better quantification of the analysed relation. Furthermore, the research by other authors (Bessec and Fouquau, 2008; among others) proves that in the climate zone, which includes Poland, the effect of a bigger demand for energy in the summer season connected with the use of air conditioning equipment is not significant.

3. Statistical Analysis of Characteristics of Analysed Time Series

For the purposes of this paper the authors used information concerning: power consumption (in kWh), air temperature (in ^{o}C) and wind speed (in m/s) in one of the regions in the southern Poland in the period from September 1, 2005 to June 30, 2008. In the analysis and further calculations daily data was used in the following way:

– the HDD index (*heating degree days)* was calculated on the basis of the relation: HDD = max (0,18^{0}C – T_i),where T_i – average daily air temperature on day number *i*;

– the CDD index (*cooling degree days)* was calculated on the basis of the relation: CDD = max ($0, T_i$ - 18^0C).

The figure 1 presents the daily power consumption and values of particular weather variables indicating the existence of similar time structure (for time cycles of varying length) in the average of analysed processes and the effect of grouping of variances.

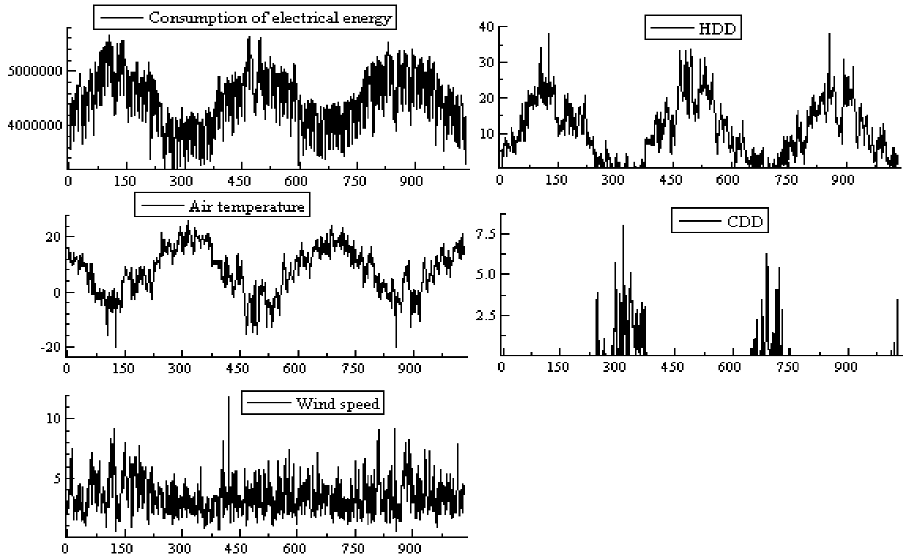

Figure 1. Changes in the daily power consumption, the HDD index (upper panel), the CDD index, air temperature (middle panel) and wind speed (lower panel) in a region in the southern Poland from September 1, 2005 till June 30, 2008

In order to analyse the characteristics of the distributions of the electricity consumption and particular weather variables, the basic descriptive statistics were determined (cf. Table 1).

One of the phenomena characteristic for the power market is periodicity (with various lengths of the cycles: daily, weekly, annual) in the demand for power. Meteorological data have a similar characteristic (cf. Benth and Benth, 2009). While focusing on the demand for power and the variables presented in this paper the authors analysed the significance of autocorrelation to the fiftieth (5, 10, 20, 30, 40, 50) order with the use of the Ljung-Box test[1]. All the obtained test statistics were significant at the 0.001 significance level. The results of the McLeod and Li test are, in turn, the basis for the conclusion that there is a

[1] Table 1 presents the results of the Ljung-Box test only for the order 30. A detailed description of the tests used in the paper, whose results are shown in Table 1 was presented by the authors (Włodarczyk, Zawada, 2006, p. 313-321).

strong correlation of squares of given series, which is characterised by the ARCH effect.

Table 1. Descriptive statistics for the analysed variables

Statistic	Consumption	Temperature	Wind	HDD
Mean	4532400.0000	7.5579	3.4495	10.6700
Standard deviation	504420.0000	8.4172	1.5052	8.0799
Minimum	3204400.0000	-20.2080	0.4583	0.0000
Maximum	5657800.0000	26.0420	11.9170	38.2080
Skewness	-0.2376	-0.3741	0.9086	0.5307
Kurtosis	-0.4689	-0.3992	1.3241	-0.3965
L-B(30)	10188.3000**	19372.2000**	539.6100**	19103.6000**
L-B^2(30)	10402.1000**	16759.9000**	498.9290**	12120.5000**
KPSS	1.1764**	1.0654**	0.8796**	1.0585**

Note: Symbol ** indicated the significance of the result at the 0.01 level. Calculations made in G@RCH™.

Air temperature and the HDD index have the biggest impact on the power consumption, whereas the influence of wind force and of the CDD index is significantly lower (Figure 2).

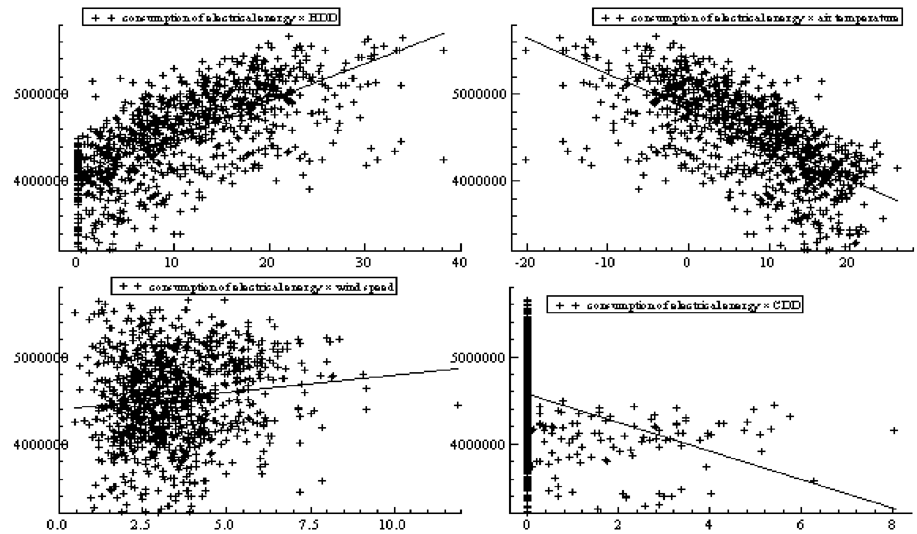

Figure 2. Correlative graphs presenting the dispersion of points for the energy consumption, the HDD index and air temperature (upper panel), energy consumption, wind speed and the CDD index (lower panel)

The analysis of characteristics of time series made in this part constitutes a significant stage of econometric modelling, as the identification of regularities in the shape of analysed variables brings effects in the form of the relevant specification of equations of conditional mean and the conditional variance of the process of demand for power. In other words, it enables the construction of the congruent econometric model according to the concept of Z. Zieliński (Zieliński, 1984).

4. Estimation and Verification of Models of the Demand for Electricity

At the first stage of the research the authors identified a deterministic trend connected with the impact of demographic, economic and social factors on the demand for power in a region in the southern Poland. From the estimated various models of trend for the daily power consumption the author selected a third degree polynomial trend, taking into account the value of determination coefficient and the significance of the estimates of structural parameters of the models. Due to the object of the research, which was the description of the relation between the impact of weather factors on the energy consumption, in the equation of demand for power the author included also the analysed weather variables- giving them a dynamic structure. Additionally the equation includes also dummies, whose task is to describe a weekly periodocity, annual seasonality and holiday effect in the shaping of demand for energy. Finally the authors proposed the following specification of the model of energy consumption, expressed in logarithms:

$$\ln E_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \alpha_3 t^3 + \sum_{k=0}^{5} \lambda_{k+1} temp_{t-k} + \sum_{k=0}^{5} \beta_{k+1} wind_{t-k} + \\ + \sum_{i=1}^{6} \delta_i D_{it} + \sum_{j=1}^{11} \varphi_j M_{jt} + \kappa_1 S_t + \kappa_2 S_{t-1} + \kappa_3 S_{t+1} + u_t, \qquad (10)$$

where:

D_{it} – dummy variable equals one for the day i, and zero otherwise,

M_{jt} – dummy variable equals one for the month j , and zero otherwise,

S_t – dummy variable is equal to one for the holiday, and zero otherwise,

S_{t-1} – dummy variable equals one for the day preceding the holiday, and zero otherwise,

S_{t+1} – dummy variable is equal to one for the day following the holiday, and zero otherwise.

The models of power consumption without weather variables, including the impact of air temperature, wind, as well as the HDD index were estimated with the OLS method. On the basis of information criteria, tests for model residuals and the parameter significance test the authors selected the following models with the weather variables (Table 2).

The results of parameter estimation of the model (10) indicate that the current and one period lagged air temperature as well as one day lagged wind force have the significant impact on the power consumption in a given day. Moreover, estimates of parameters which stand by dummy variables and model periodicity in the weekly cycle on demand on energy indicate that on Mondays, Saturdays and Sundays energy consumption is lower than the average level and higher in the other days of the week. In the case of dummy variables associated with monthly seasonal effects all estimates of parameters are significant and negative for summer months (May, June, July, August, and September). It is connected with the impact of seasonal factors, such as, air temperature, length of the day, level of sun light exposure on the demand for energy. All parameters standing by dummy variables associated with holidays and neighbouring days are statistically significant and negative which indicates that the energy consumption on holidays and neighbouring days is significantly lower in comparison with regular working days (as indicated by results of the Wald test for equality of parameters).

Table 2. Estimates of the parameters of the model (10)

Parameter	Coefficient	p-value	Parameter	Coefficient	p-value
α_0	15.3739	0.0000***	φ_1	0.0579	0.0000***
α_1	-0.0002	0.0000***	φ_2	0.0261	0.0000***
α_2	4.336e-07	0.0000***	φ_3	0.0262	0.0000***
α_3	-1.729e-010	0.0089***	φ_4	0.0073	0.0667**
λ_1	-0.0009	0.0358**	φ_5	-0.0568	0.0000***
λ_2	-0.0036	0.0000***	φ_6	-0.0830	0.0000***
β_2	0.0024	0.0040***	φ_7	-0.0491	0.0000***
δ_1	-0.0067	0.0235**	φ_8	-0.0478	0.0000***
δ_2	0.0293	0.0000***	φ_9	-0.0185	0.0000***
δ_3	0.0392	0.0000***	φ_{10}	0.0199	0.0000***
δ_4	0.0408	0.0000***	φ_{11}	0.0500	0.0000***
δ_5	0.0404	0.0000***	κ_1	-0.1845	0.0000***
δ_6	-0.0059	0.0442*	κ_2	-0.0369	0.0000***
Adjusted R^2	0.88326		κ_3	-0.0859	0.0000***
AIC	-3785.4470		-	-	-
BIC	-3652.0610		-	-	-
Hannan-Quinn	-3734.8310		-	-	-

Note: The symbol *** indicates the significance of the result at the 0.001 level. Calculations made in Gretl.

In order to identify the autocorrelation effect, Box-Pierce test (the lag level: 5, 10, 20, 50) has been used for residuals of model (10) – all test statistics indicate for the significant autocorrelation in residuals. To verified the ARCH effect, two different test have been used: Engle test (for 1, 2, 5, 10, and 20 lags) for residuals and Box-Pierce test for squared residuals (level of lag: 5, 10, 20, 50). Similarly, in this case all test statistics indicate for the significant autocorrelation in squared residuals. Using the Geweke-Porter-Hudak test, the long memory effect in residuals and squared residuals of the electricity demand model has been captured[2]. With regard to the verification of residuals properties, the model of ARFIMA (*P*, *D*, *Q*)-FIGARCH (*p*, *d*, *q*) class can be used for description of correlation between weather variables and energy consumption[3]:

$$\phi(B)\Delta^D(u_t-\mu_t)=\theta(B)\varepsilon_t, \tag{11}$$

$$\varepsilon_t = z_t\cdot\sqrt{h_t}, \qquad z_t \sim IID(0,1), \tag{12}$$

$$\varphi(B)\Delta^d\varepsilon_t^2=\omega+\sum_{k=1}^{r}\omega_k x_{k,t}+[1-\beta(B)](\varepsilon_t^2-h_t), \tag{13}$$

where: $\Delta^D=(1-B)^D=\sum_{j=0}^{\infty}\binom{D}{j}(-1)^j B^j$ - filter difference of order *D,*

$\Delta^d=(1-B)^d=\sum_{s=0}^{\infty}\binom{d}{s}(-1)^s B^s$ - filter difference of order *d*,

$-1< D<0{,}5,\ 0<d<1,\ \omega+\sum_{k=1}^{r}\omega_k x_{k,t}>0$,

$\phi(B)=1-\phi_1 B-\ldots-\phi_P B^P,\ \theta(B)=1+\theta_1 B+\ldots+\theta_Q B^Q$,

$\varphi(B)=1-\varphi_1 B-\ldots-\varphi_q B^q,\ \beta(B)=\beta_1 B+\ldots+\beta_p B^p$.

Introduction to the equation of conditional variance of regressor, which is a variability of weather factors or dummy variables which model periodicity of variance enables to connect dynamics of variability of energy consumption with variability of weather conditions of different structure of energy consumers in working days and holidays. In the current framework the following descriptive variables have been introduced to the equation of conditional variance of the process:[4] dummy variables which model the effect of week day, dummy variables which model the month effect in the year, dummy variables which model holidays, square of increment of daily average temperature in subsequent days, square of increment of wind power in subsequent days.

Orders of models ARFIMA(*P*,*D*,*Q*)-FIGARCH(*p*,*d*,*q*) were chosen on the basis of information criteria and significance of the model parameters. The best models in this class are presented in Table 3.

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[2] Because of limited size of this framework, results of conducted tests for model residuals have not been presented.

[3] In order to guarantee stationarity of analysed models of time series, it is assumed that roots of polynomial $\phi(B)=0$, $\varphi(\mathrm{B})=0$ lie outside the unit circle (Preś, 2007, p. 206; Laurent, 2007, p. 55–74).

[4] Because of large number of model parameters and problems associated with estimation, proposed variables were separately attached to the equation of conditional variance.

Table 3. Parameter estimates of ARFIMA(1,1)-GARCH(1,1) models

Parameter	ARMA(1,1)-GARCH(1,1)+R	ARFIMA(1,1)-GARCH(1,1)+R	ARFIMA(1,1)-GARCH(1,1)
Cst(M)	0.001950 [0.4575]	0.0020 [0.5154]	0.0023 [0.4644]
D-ARFIMA	-	0.0426 [0.6560]	0.04460 [0.6341]
AR(1)	0.7198 [0.0000]	0.6904 [0.0000]	0.6774 [0.0000]
MA(1)	-0.0929 [0.0925]	-0.1104 [0.0694]	-0.0983 [0.1168]
Cst(V)	0.0004 [0.0000]	0.0003 [0.0000]	0.0003 [0.0032]
Dif(temp)	0.87e-5 [0.0000]	0.55e-5 [0.0000]	-
ARCH1	0.2611 [0.0000]	0.2091 [0.0000]	0.2314 [0.0049]
GARCH1	0.2709 [0.0032]	0.4439 [0.0000]	0.3931 [0.0299]
Skewness	-0.1157 [0.0173]	-0.1217 [0.0130]	-0.1202 [0.0165]
Df-Student	5.2049 [0.0000]	5.0735 [0.0000]	5.1046 [0.0000]
AIC	-4.3980	-4.3939	-4.3926
SC	-4.3549	-4.3460	-4.3494
H-Q	-4.3816	-4.3757	-4.3762
Shibata	-4.3981	-4.3941	-4.3927

Note: p-values have been presented in the brackets. Calculations made in G@RCH™.

Table 4. Summary statistics for model residuals of models ARFIMA-GARCH

Statistic	ARMA(1,1)-GARCH(1,1)+R	ARFIMA(1,1)-GARCH(1,1)+R	ARFIMA(1,1)-GARCH(1,1)
Q (Box-Pierce) Statistics on Standardized Residuals			
Q(5)	4.76412 [0.1899]	4.9544 [0.1752]	4.7439 [0.1915]
Q(10)	15.8704 [0.0443]	15.9747 [0.0427]	15.5973 [0.0485]
Q(20)	29.4930 [0.0427]	30.0496 [0.0370]	30.0668 [0.0368]
Q(50)	57.5181 [0.1633]	57.7321 [0.1586]	58.5882 [0.1407]
Q (Box-Pierce) Statistics on Squared Standardized Residuals			
Q(5)	0.9382 [0.8162]	1.4152 [0.7020]	1.4080 [0.7037]
Q(10)	3.9715 [0.8597]	4.8275 [0.7758]	5.0532 [0.7519]
Q(20)	6.1725 [0.9954]	7.2110 [0.9882]	7.2413 [0.9879]
Q(50)	27.6562 [0.9919]	27.9235 [0.9909]	27.3902 [0.9927]
Engle's LM ARCH Test			
ARCH(1-2)	0.2695 [0.7638]	0.4347 [0.6476]	0.4418 [0.6430]
ARCH(1-5)	0.1866 [0.9677]	0.2834 [0.9224]	0.2819 [0.9231]
ARCH(1-10)	0.3822 [0.9547]	0.4635 [0.9137]	0.4853 [0.9003]
Nyblom Stability Test			
Nyblom Statistic for parameter vector	1.4860 stability	1.6558 stability	1.2591 stability
Nonstability parameter by Nyblom test	Nonstability parameter MA(1)	Nonstability parameter : D-ARFIMA, AR(1), MA(1)	Nonstability parameters : D-ARFIMA, MA(1)
Sign Bias Test			
SB	1.6800 [0.0930]	1.7303 [0.0836]	1.7104 [0.0872]
NSB	1.2895 [0.1972]	1.0867 [0.2772]	1.1378 [0.2552]
The Joint Test	4.3732 [0.2239]	5.3313 [0.1491]	5.1391 [0.1619]
Adjusted Pearson Goodness-of-fit Test	Empirical distribution is congruent with theoretical distribution	Empirical distribution is congruent with theoretical distribution	Empirical distribution is congruent with theoretical distribution

Note: p-values have been presented in the brackets. Calculations made in G@RCH™.

When model estimates are assessed with regard to its quality the following results of tests conducted on its standardized residuals should be analysed: verification of uncorrelated standardized residuals (Box-Pierce test), lack of ARCH effect (Box-Pierce test for squared residuals and Engle's test), testing parameters stability in the model (Nyblom test), lack of diversity of influence made by negative and positive innovations on the level of variability (SB test), lack of diversity of influence made by large and small negative (positive) innovations on the variability (NSB test), fit of a distribution of empirical standardized residuals with assumed distribution (Pearson's chi-square goodness-of-fit test).[5]

Each time, the introduction of GARCH structure with conditional skewed distribution of t-Student has been made, the result was that the effect of grouping variances, which was present in residuals of ARFIMA model has been eliminated. In the case of different estimated models of ARFIMA-FIGARCH class the estimate of fractional integration parameter *d* in conditional variance equation was statistically insignificant. Even when dummy variables which model the effect of week day, month, and holidays in the equation of conditional variance of the process were considered, the characteristics of the model were not improved significantly. Next, the authors introduce the variability of the weather factors as the regressor to the conditional variance equation of the electricity demand. The result is that the autocorelation effect, which is found in standardized residuals of ARFIMA-GARCH model, has been decreased or eliminated.

5. Summary

Demonopolization in energy industry in Poland has forced companies from energy industry to work out and implement internal procedures of risk management, because the risk is present in energy trade. Companies from this industry more and more often use weather derivatives to hedge against effects of weather risk, because this activity allows to make financial results independent of changing weather conditions.

Analysis of influence of particular weather factors on energy consumption conducted by the Authors concerned only a particular region of southern Poland. Unfortunately, Polish conditions does not allow straight-forward access to these type of data because of the high cost of data purchase, whereas in many countries, databases concerning weather variables are available for free on web pages of meteorological stations of national entities which collect this type of data.

Introduction to the equation of conditional variance of the regressor, which is a variability of average daily temperature increase in the coming days (Dif(temp)) enables to connect the dynamics of volatility of energy consump-

[5] All above-mentioned methods have been described in the econometric literature (Doman, Doman, 2004, p. 295–308; Laurent, 2007, p. 41–46).

tion with the volatility of weather conditions. Moreover, the assessment of the ARFIMA-GARCH models on the basis of the residuals of model (10) made it possible to assess the conditional volatility of the process of demand for electrical energy. With the use of conditional volatility one can measure the volatility of the demand for electrical energy, i.e. the risk related to unpredictable change in the energy consumption under the influence of e.g. changing weather conditions. While extending analysis of the impact of weather factors on the functioning of the power energy industry branch company, one should apply the Value at Risk methodology to measure the weather risk. Such approach will make companies dealing with the energy production and sales aware of the potential losses they may suffer as a result of unexpected change of weather factors.

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Zastosowaniem zmiennych pogodowych w modelowaniu zapotrzebowania na energię elektryczną w jednym z regionów Polski południowej

Z a r y s t r e ś c i. Głównym celem opracowania jest zweryfikowanie przydatności modeli klasy ARFIMA-FIGARCH do opisu kształtowania się zużycia energii elektrycznej w wybranym regionie południowej Polski z uwzględnieniem zmiennych pogodowych.

S ł o w a k l u c z o w e: zmienne pogodowe, model ARFIMA-FIGARCH, ryzyko pogodowe.