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# ASSESSMENT OF THE VARIABILITY OF ELECTRICITY DEMAND COVERAGE

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**Purpose:** A dynamic assessment of the risk associated with meeting electricity demand using photovoltaic and wind energy sources. The estimation aims to assess the demand for additional power capacity in the short term, i.e. one quarter-hour.
**Design/methodology/approach**: Application of the Value-at-Risk (VaR) metric to analyze dynamically changing parameters in the power system for estimating the risk of demand exceeding expected levels. The accuracy of the obtained estimates was verified using the Kupiec and Christoffersen exceedance tests.
**Findings:** Using VaR to assess electricity demand coverage by renewable energy sources (RES) enhances quantification of the probability that RES will fall short of meeting demand, accounting for their inherent variability. Such approach will support risk-aware planning performed by grid operators.
**Research limitations/implications**: For future outlook expanding the analysis beyond the investigated period will allow for capturing a wider range of market conditions, seasonal patterns, and demand fluctuations that significantly influence electricity prices. A longer dataset will improve the robustness and accuracy of forecasting models by reducing the risk of overfitting to short-term anomalies.
**Practical implications:** The use of VaR to assess electricity demand coverage by RES, i.e., photovoltaics and wind, supports grid operators to make data-based, risk-aware decisions to maintain system reliability and plan for contingencies.
**Social implications:** The assessment of the risk of variability in covering electricity demand should draw the attention of an average electricity user to the rational use of resources in accordance with recommendations of PSE (e.g., via the Energy Compass application).
**Originality/value:** Addressing the problem of risk estimation using econometric methods in commodity markets for dynamic variables measured at a fifteen-minute frequency.
**Keywords:** Value-at-Risk, ARIMA-GARCH models, Electric energy market, Power system balancing, Forecasting in power system.
**Category of the paper:** Research paper.

## 1. Introduction

The European energy market, as coordinated by the European Network of Transmission System Operators for Electricity (ENTSO-E)[1], continues to evolve rapidly in response to the energy transition and growing integration of RES. According to ENTSO-E (Summer Outlook, 2025), the European power system is expected to maintain overall adequacy, with no systemic risks identified across most of the continent. However, specific vulnerabilities remain in isolated or weakly interconnected, where planned generation outages and limited import capacities pose challenges. The report highlights a significant expansion of over 90 GW of solar PV capacity since the previous summer, contributing to periods of renewable overproduction. While battery storage capacity has doubled to 25 GW, ENTSO-E emphasizes the increasing importance of flexibility solutions to manage energy mix and ensure system stability (Summer Outlook, 2025).

In Poland, developments in the electricity sector are closely aligned with ENTSO-E's broader objectives, particularly in integrating renewable energy. According to ENTSO-E's analysis (Summer Outlook, 2025), Poland is expected to ensure system adequacy during the summer months, supported by increased PV capacity and growing interconnection capabilities. However, Polish grid continues to face challenges related to balancing renewables and securing flexibility, especially during peak demand or low generation periods. Poland is also actively participating in ENTSO-E's initiatives to modernize the European electricity market, including the Offshore Roadmap (Offshore Roadmap, 2025), which outlines regulatory and technical frameworks for integrating offshore wind and cross-border infrastructure. While Poland's offshore wind sector is still in early stages compared to countries like Germany or Denmark, the country is already working on future integration through grid upgrades and regulatory alignment. These efforts are crucial as Poland aims to reduce its reliance on coal and transition toward a more sustainable and interconnected energy system.

As of 2025, Poland's installed generation capacity stands at approximately 64 GW, with RES accounting for nearly 44% of it (PSE, 2024). Among renewables, wind power plays a significant role, with over 10 GW of installed capacity from onshore wind farms, primarily located in the northern and central regions of the country. To support the green transition goals, Poland is investing in its transmission infrastructure. The Transmission Grid Development Plan 2025-2034 (PSE, 2023) is aimed at integrating RES, including wind, and enhancing north-south energy flow through a new HVDC line, strengthening connection with the Baltic countries. These efforts are crucial for ensuring grid stability and meeting the country's decarbonization goals under the EU's "Fit for 55" package.

[1] https://www.entsoe.eu/

On top of RES increasing installed capacity Poland's nuclear power program is a key pillar of its long-term energy strategy. It is designed not only to diversify the energy mix but also to complement the growing share of RES. The first large-scale nuclear power plant is expected to begin operation in the late 2030s, with additional units planned to follow.

It is important to emphasize that the nuclear power plants in Poland are intended to operate in a flexible manner (Sawicki, Bury, 2025), adjusting their output to prevailing market conditions, including the real-time generation levels of RES within the power system. In the context of integrating nuclear power with RES, it is essential to accurately forecast the generation of PV and wind energy. These sources are inherently variable and dependent on weather conditions, which makes their output less predictable than conventional generation. Therefore, short-term and long-term forecasting models are crucial for ensuring grid stability and optimizing the operation of flexible power plants.

Moreover, it is essential to analyze the seasonality and variability of solar and wind generation. For example, solar output typically peaks in summer months, while wind generation may be higher in winter or during specific weather patterns. Understanding these patterns allows system operators to plan for adequate backup capacity, schedule maintenance, and make data-based decisions about energy storage and market participation.

To effectively integrate conventional generation such as, e.g., nuclear power plants with RES, it is necessary not only to forecast their generation but also to analyze the risks associated with their variability and seasonality. In this context, the Value-at-Risk (VaR) methodology, commonly used in financial risk management, can be adapted to assess the potential shortfalls or surpluses in RES generation over a given time horizon. The application of VaR metric in the power sector relies on the availability of relevant data provided by a Transmission System Operator (TSO).

Polish TSO, namely PSE, is required to publish data on the raporty.pse.pl platform to comply with both European Union regulations and national energy law, which mandate transparency in the electricity market. As the legal basis for this obligation, the following acts and regulations can be mentioned:

1. REMIT Regulation (EU No 1227/2011) – This regulation on wholesale energy market integrity and transparency obliges TSOs to publish information that may affect electricity prices, such as planned and unplanned outages, generation availability, and cross-border capacities. It results in stronger protection against market manipulations.
2. Transparency Regulation (EU No 543/2013) – This regulation requires TSOs to publish detailed operational data, including:
   - Load forecasts and actual load.
   - Generation forecasts and actual generation by type.
   - Transmission infrastructure availability.
   - Cross-border exchange capacities and flows.

3. Network Codes and Guidelines, such as e.g. the CACM Guideline (i.e., Capacity Allocation and Congestion Management), specify the types of data and their format to be published to ensure fair access to market-relevant information.

Based on the obligations established by the above mentioned documents, PSE publishes the following data on the raporty.pse.pl website:

– Real-time and historical data on electricity load and generation.
– Cross-border exchange capacities and actual flows.
– Planned and unplanned outages of transmission infrastructure.
– Market-related data, such as balancing and congestion management information.

The purpose of publishing such data is to ensure equal access to information for all market participants. Simultaneously, extensive data access enhances market transparency, and ultimately supports efficient and secure operation of the power system.

Due to the critical nature of the national power system managed and operated by each TSO, some operational data, such as power flows, are not publicly available, as they may be linked to sensitive internal wholesale market information or pose a threat to system security. Consequently, while TSOs are obligated to publish a wide range of operational and market data (e.g. via platforms like ENTSO-E Transparency Platform or national TSOs platforms), certain real-time data may be withheld for sensitivity and security reasons.

On the basis of system information about the Polish electricity market, papers have been published on demand forecasting over a longer time horizon (Raczkowski et al., 2022), studies on the long-term development of the country's electricity system (Pluta et al., 2023), energy price forecasting with a daily horizon (Pilot et al., 2024), among others.

The VaR methodology has frequently been applied in risk assessment within the electricity market, primarily to evaluate the risk associated with price fluctuations (Žiković et al., 2015; Halkos, Tsirivis, 2019; Westgaard et al., 2019; Bao et al., 2021). VaR forecasts based on models from the GARCH family have been employed to analyze daily price changes in energy commodities, as demonstrated by Laporta et al. (2018).

The main objective of this study is to estimate the risk associated with fluctuations in the coverage of electricity demand by RES over a very short time horizon of 15 minutes. To assess this risk, VaR was calculated using autoregressive ARIMA-GARCH models, which account for the daily cycle of variability. On the basis of diagnostic tests, the effectiveness of the approach used was assessed.

The study was based on system data provided by PSE, published in reports on the operation of the National Power System, covering the period from June 14 to August 31, 2024 (79 days, 7,584 15-minute intervals). The following variables were used in the analysis:

- GREEN [MW] – the amount of electricity generated in a given quarter from photovoltaic and wind source.
- DEMAND [MW] – electricity demand in a given quarter.
- GREEN/DEMAND [%] – the percentage of demand covered by the overall production from photovoltaic and wind sources.

In the following analysis, the term "Demand" refers to the amount of electrical power consumed at a specific time, based on real-time or historical measurements. In reports published by TSOs, this quantity is often referred to as "load." In practice, the terms are frequently used interchangeably, especially in operational contexts. However, since "demand" also encompasses the required or forecasted power needed for planning purposes, this term is used throughout the analysis.

The paper is organized into four sections. The second section discusses the methodological approach used in the study, based on a review of the relevant literature. In the third section the research results are presented. The fourth section summarizes the key findings, provides recommendations, and outlines directions for future research.

## 2. Methodology

In this paper, the quantile measure of Value at Risk (VaR) was used to estimate risk. VaR is defined as such loss of value, that is not exceeded with the given probability $\gamma$ at the given time period h, and it is expressed by the following formula (Jajuga, 2008; Ganczarek-Gamrot et al., 2021).

$$P(Y_{t+h} \le Y_t - \mathrm{VaR}) = \gamma \tag{1}$$

where:
$Y_t$ – a present value,
$Y_{t+h}$ – a random variable.

The variable $Y_t$ (GREEN/DEMAND [%]) analyzed in this study represents the coverage of electricity demand by photovoltaic and wind generation in each 15-minute interval *t*.

$$Y_t = \frac{\mathrm{GREEN_t}}{\mathrm{DEMAND_t}} \tag{2}$$

where:
$\mathrm{GREEN}_t$ – the electricity production [MW] from photovoltaic and wind sources per quarter-hour *t*,
$\mathrm{DEMAND}_t$ – the electricity demand [MW] per quarter-hour *t*.

Absolute increments measured in percentage points [p.p] were used to assess absolute difference in $\Delta Y_t$ demand coverage:

$$\Delta Y_t = Y_t - Y_{t-1} \tag{3}$$

and relative increments measured as relative difference in percentage [%]:

$$R_t = \frac{\Delta Y_t}{Y_{t-1}} \tag{4}$$

In financial literature, the VaR measure is typically evaluated over a single-period time horizon ($h = 1$) and is defined as the γ-quantile of the conditional distribution of returns (Doman, Doman, 2009):

$$P(Z_{t+1} \leq -\mathrm{VaR}_{t+1}(\gamma)|\Omega_t) = \gamma \tag{5}$$

where:

$\Omega_t$ – the set of information available at time *t*,

$Z_t$ – the changes of considered value at time *t*.

In this study, the risk of changes in demand coverage was estimated over a 15-minute horizon. Both absolute (3) and relative (4) increments were used to characterize coverage variability.

For dynamically varying time series values $\mathrm{VaR}_{t+1}(\gamma)|\Omega_t$ can be estimated using the stochastic ARIMA-GARCH model (McNeil and Frey, 2000):

$$Z_t = \mu_t + \varepsilon_t\sqrt{\sigma_t^2} \tag{6}$$

where:

$\mu_t$ – the expected value of a process is described by ARIMA (Auto-Regressive Integrated Moving Average) model,

$\sigma_t^2$ – the variance of a process is described by GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model,

$\varepsilon_t$ – white noise $E(\varepsilon_t) = 0;\ D^2(\varepsilon_t) = 1$.

In electricity markets, where variables often exhibit seasonal patterns, the classical ARIMA model is typically extended to its seasonal form (SARIMA) to better capture this behavior. Seasonal ARIMA (*p*,*d*,*q*) (*P*,*D*,*Q*) (Box et al., 2008; Brockwell, Davis, 2016, p. 177) (SARIMA) models were used to describe the $\mu_t$ process:

$$\Delta_s^d Z_s = (1-B)^d(1-B^s)^D Z_t \tag{7}$$

where:

$Z_t$ – the value of the series at time *t*,

*B* – the backshift operator,

*d* – the order of integration of the model,

*D* – the order of seasonal integration of the model,

*s* – the seasonal lag.

The series $\Delta_s^d Z_{st}$ represents the values of $Z_t$ after eliminating seasonality and a trend, and it is an ARMA process defined as follows:

$$\phi(B)\Phi(B^s)\Delta_s^d Z_{st} = \theta(B)\Theta(B^s)e_t \tag{8}$$

where:

$\phi(B) = 1 - \sum_{i=1}^{p} \phi_i B^i$;

$\Phi(B) = 1 - \sum_{i=1}^{P} \phi_i B^i$;

$\theta(B) = 1 - \sum_{i=1}^{q} \theta_i B^i$;

$\Theta(B) = 1 - \sum_{i=1}^{Q} \phi_i B^i$;

$\phi_i$ – parameter of the autoregressive part,

$\Phi_i$ – parameter of the seasonal autoregressive part,

$\theta_i$ – parameter of the moving average part,

$\Theta_i$ – parameter of the seasonal moving average part,

$p$ – order of the autoregressive part of the model,

$P$ – order of the seasonal autoregressive part of the model,

$q$ – order of the moving average part of the model,

$Q$ – order of the seasonal moving average part of the model,

$e_t$ – residuals $\mathrm{E}(e_t)$, $D^2(e_t) = \sigma_t^2$.

The $\mathrm{GARCH}(p_\sigma, q_\sigma)$ model (Bollerslev (1986)) may be written as:

$$\sigma_t^2 = \varpi + \sum_{i=1}^{q_\sigma} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p_\sigma} \beta_i \sigma_{t-i}^2. \tag{9}$$

where:

$p_\sigma, q_\sigma -$ orders of the model,

$\varpi -$ unconditional part of variance.

The choice of rows $p, q, p_\sigma, q_\sigma$ of model (6) was based on minimising the value of the loss function (Schwarz, 1978) according to the BIC (Bayesian Information Criterion) criterion:

$$\mathrm{BIC} = \frac{-2LL}{T} + \frac{mln(T)}{T} \tag{10}$$

where:

$T$ – length of time series,

$m$ – number of model parameters,

$LL$ – the logarithm of the maximum likelihood function used to estimate the model parameters.

Estimation and quality assessment of the estimated models, was carried out using methods implemented in the R package rugarch (Ghalanos, 2025). The choice of the model was dictated by minimising the value of the BIC criterion and the positive results of the diagnostic tests. The significance of the parameters of model (6) was tested using a robust estimation procedure (White, 1982). The Adjusted Pearson Goodness-of-Fit Test (for various histograms intervals: 20, 30, 40, 50) was used to assess the consistency of the distribution of residuals with the distribution determined in the estimation process (Palm, 1996). Under the Ljung-Box Test (lag=1), autocorrelations of residuals and squares of residuals were assessed (Fisher, Gallagher, 2012). Based on the Sign Bias Test, the consistency of the prediction of the direction of change was checked (Lundbergh, Teräsvirta, 2002).

Among the conditional variation models the following were compared: GARCH (Engleand, Bollerslev, 1986), EGARCH (Nelson, 1991), TGARCH (Zakoian, 1994), ALLGARCH (Hentschel, 1995). The best results were obtained for the classical form of GARCH with Skew-Student distribution (sstd) (Hansen, 1994) and The Generalized Hyperbolic Distribution (ghyp) (Barndorff-Nielsen, 1978, Jiang et al., 2024) of residuals.

To assess the validity of the estimated VaR values, Kupiec's proportion of failures test (Kupiec, 1995) and Christoffersen's independence of failures test (Christofersen, 1998) were used. The number of the excesses of $\mathrm{Va}R(\gamma)$ has binomial distribution with a given size of the sample $T$. The test statistic is:

$$\boldsymbol{LR_{uc}} = -2\ln[\gamma^{T-K}(1-\gamma)^{K}] + 2\ln\left\{\left[1-\left(\frac{K}{T}\right)^{T-K}\right]\left(\frac{K}{T}\right)^{N}\right\} \quad (11)$$

where:

$K$ – is the number of the crossing of $\mathrm{VaR}(\gamma)$,

$T$ – is the length of a time series,

$1-\gamma$– is a given probability with which $\mathrm{VaR}(\gamma)$, cannot exceed the loss of value.

For the hit function:

$$I_t(\gamma) = \begin{cases} 1, r_t < \mathrm{VaR}(\gamma) \\ 0, \text{otherwise} \end{cases} \quad (12)$$

test statistic for the independence of exceedances is given by formula:

$$LR_{cc} = -2\ln\left\{\frac{(1-\bar{w})^{K_{00}+K_{10}}\bar{w}^{K_{01}+K_{11}}}{(1-w_{01})^{K_{00}}w_{01}^{K_{01}}(1-w_{11})^{K_{10}}w_{11}^{K_{11}}}\right\} \quad (13)$$

where:

$K_{ij}$ – the number of observations for which $I_t(\gamma) = j$ provided $I_{t-1}(\gamma) = i$, $w_{ij} = \frac{K_{ij}}{K_{i0}+K_{i1}}$, $\bar{w} = \frac{K_{01}+K_{11}}{T} = \frac{K}{T}$.

The statistics $LR_{uc}$ and $LR_{cc}$ have $\chi^2$ asymptotic distribution with one degree of freedom.

## 3. Empirical results

This section is divided into three subsections. The first presents the time series under analysis. The second subsection contains the results of the volatility model estimations. The final subsection provides the estimated risk measures along with their corresponding diagnostic tests.

### 3.1. Data visualization

The study was conducted based on system data available on the PSE platform during the summer of 2024, covering the period from July 14 to August 31 (79 days, 7584 quarters).

Box plot visualizations (Figure 1) present the distributions of the total amount of electricity generated from photovoltaic and wind sources (denoted as GREEN [MW]) across individual quarters of the day. The highest daily production from these sources of renewable energy occurs between sunrise and sunset. Extreme values are associated with unusually high wind generation during nighttime and elevated photovoltaic output during the day, which are atypical for the analyzed period.

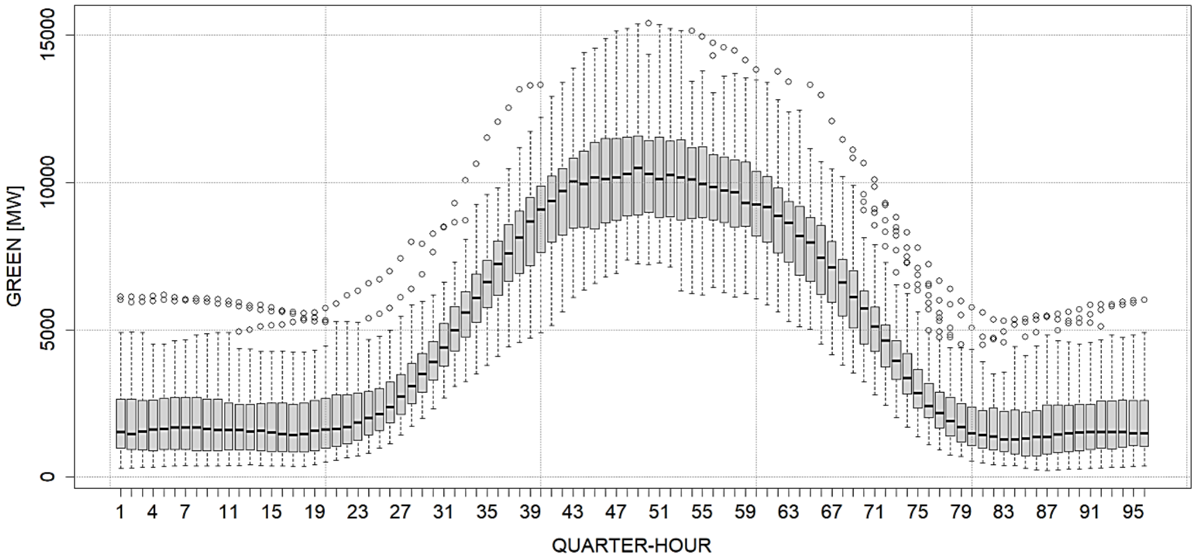


**Figure 1.** Box plots presenting the distribution of electricity generated from photovoltaic and wind sources in each quarter-hour of the day during the analyzed period.

Source: Own calculation.

Box plot visualizations (Figure 2) present the distribution of electricity demand (i.e. DEMAND [MW]) for each quarter-hour of the day during the analyzed period. Demand remained stable throughout the period, with only one outlier observed. The highest daily demand occurred between the 36th and 84th quarters (9:00 AM to 9:00 PM).

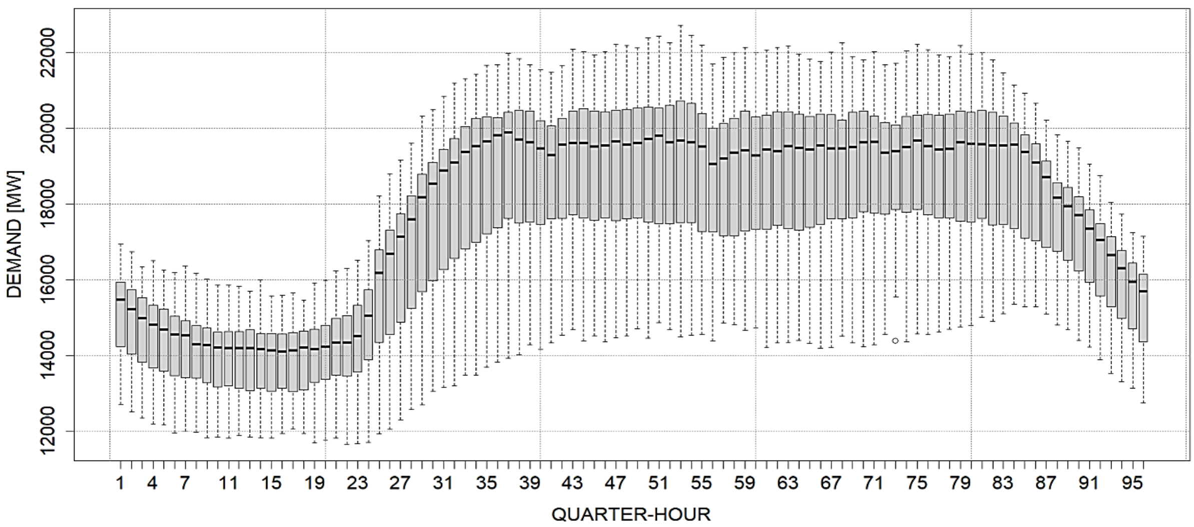


**Figure 2.** Box plots presenting the distribution of electricity demand in each quarter-hour of the day during the analyzed period.

Source: Own calculation.

Box plot visualizations (Figure 3) illustrate the distribution of the share of electricity generated from RES in each quarter-hour of the day relative to the electricity demand for that quarter (denoted as *Y*□, GREEN/DEMAND [%]). During peak sunlight hours, the median share of RES generation reaches up to 50% of the electricity demand. Under favorable conditions, demand coverage could reach as high as 80%. At night, when demand is lower, the median coverage from RES drops to around 10%. In the early hours of the day, when demand is limited, the upper range of variability reaches nearly 40% coverage. During evening hours, when demand is elevated, this range is significantly narrower. Higher evening coverage is associated with atypical periods of increased RES generation.

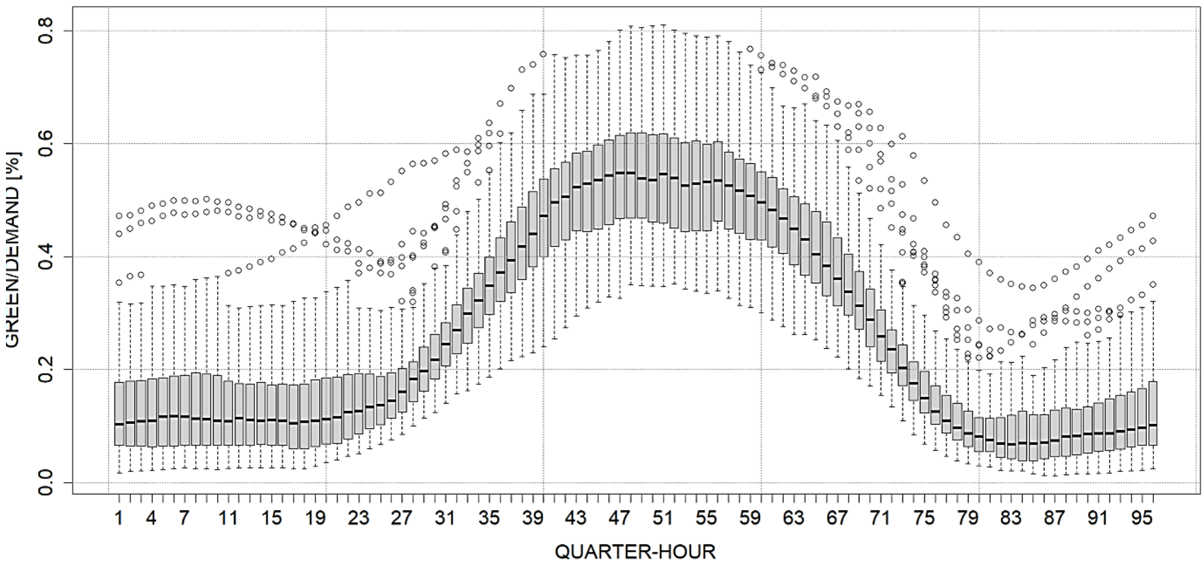


**Figure 3**. Box plots presenting the distribution of electricity demand coverage by power generated from solar and wind sources in each quarter-hour of the day during the analyzed period.

Source: Own calculation.

Figure 4 presents the time series of electricity demand coverage ($Y$□, GREEN/DEMAND [%]) by power generated from photovoltaic and wind sources, along with the ACF(96) and PACF(96) functions. No trend is observed during the analyzed period. In addition to autocorrelation and the daily cycle (PACF, lag = 96), a stronger autocorrelation is also noticeable for the five subsequent quarter-hours (PACF, lag = 5).

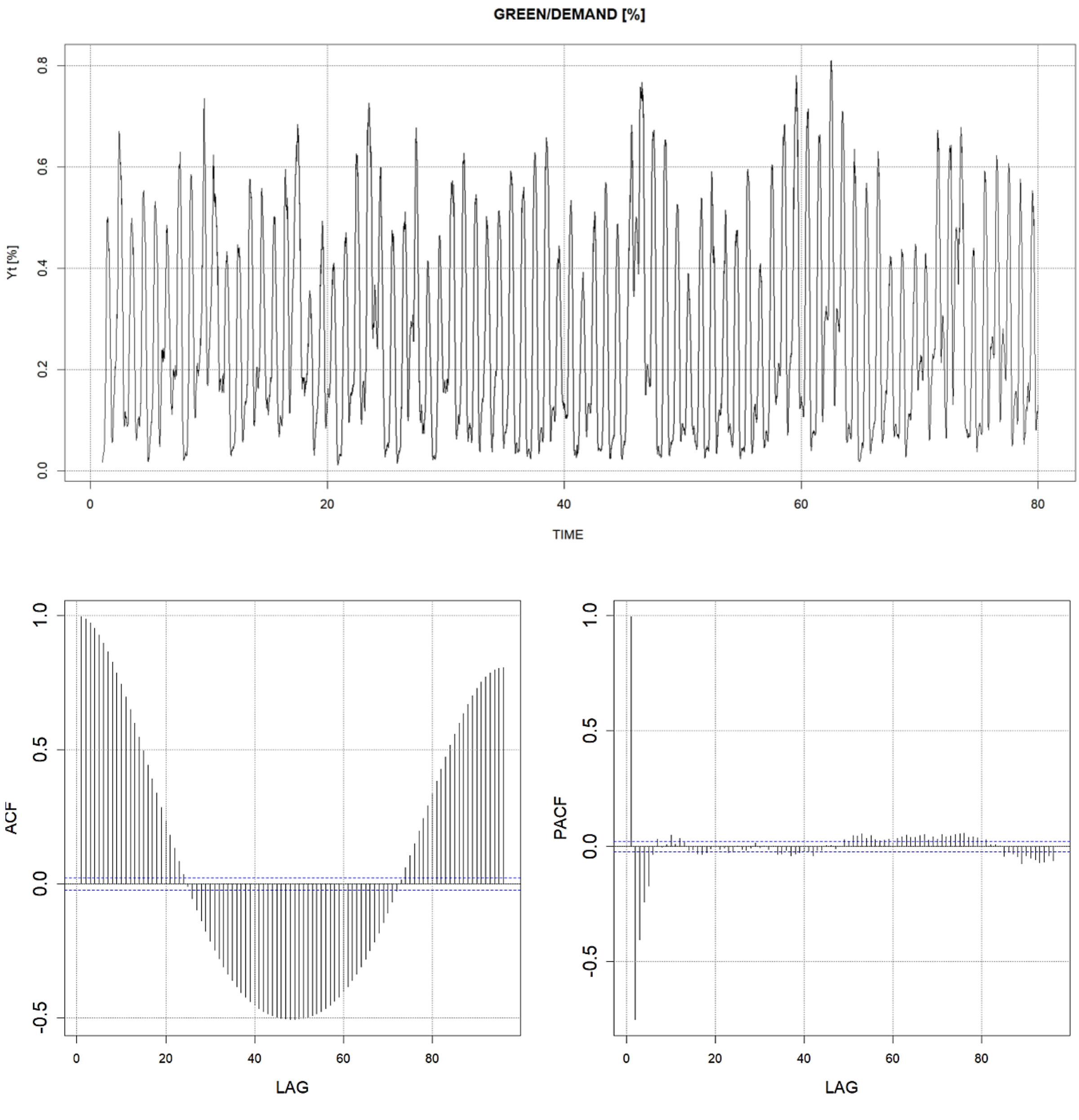


**Figure 4.** Time series of electricity demand coverage by generation from photovoltaic and wind sources, along with the ACF(96) and PACF(96) functions.

Source: Own calculation.

To assess the risk of changes in the degree of demand coverage by RES, time series of absolute increments $\Delta Y_t$ (3) and relative increments $R_t$ (4) were considered, illustrating the change in demand coverage by RES from one 15-minute interval to the next. Figure 5 presents the distributions of changes for each quarter-hour of the analyzed period. The largest absolute changes are observed during periods of full sunlight (top chart). The greatest relative changes (bottom chart) occur at sunrise (18th interval) and sunset (85th interval), resulting in an increase in energy production from one interval to the next by 60% or a decrease by 50%, respectively.

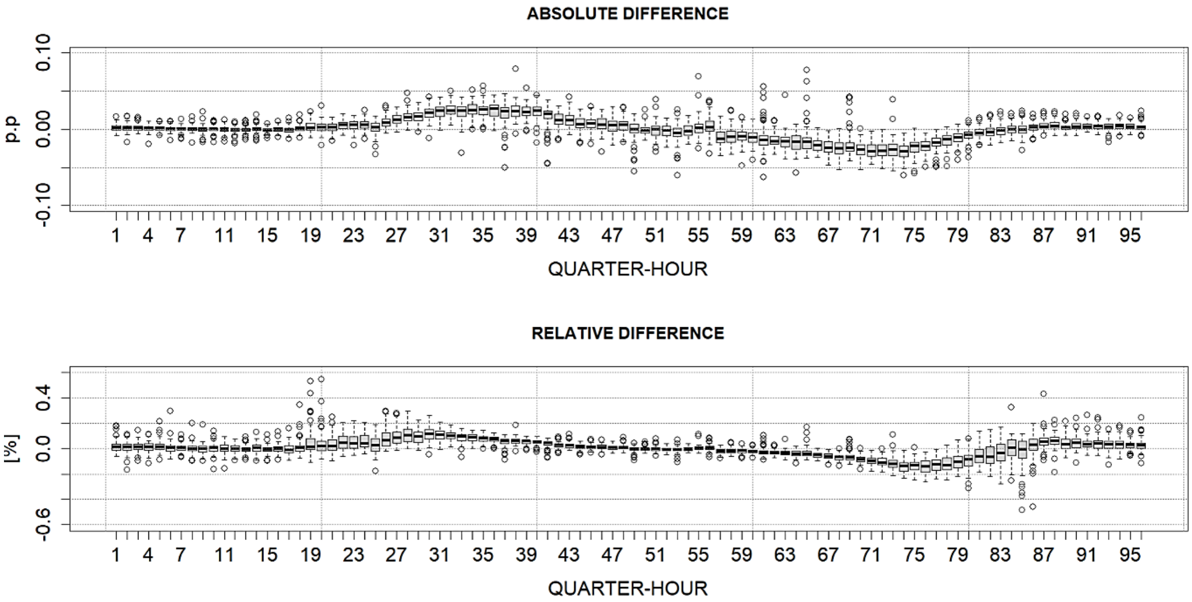


**Figure 5.** Changes of the energy produced from photovoltaic and wind sources in comparison to the previous quarter-hour.

Source: Own calculation.

Figure 6 presents a time series of absolute changes in demand coverage within each quarter-hour. The largest decreases fluctuate around 6 percentage points, while increases do not exceed 8 percentage points. Greater variability can be observed in July (the first month of the study). A significant increase in demand coverage in August is associated with the public holiday on August 15, 2024 (Thursday). The values of the ACF function confirm the daily cyclicality of coverage. Based on the PACF function values, stronger correlations can be observed within the previous four quarter-hours (i.e., a full hour).

Figure 7 presents a time series of relative changes in demand coverage within each quarter-hour. Here, the range of variability spans from a 50% decrease to a 60% increase compared to the previous quarter-hour. Greater fluctuations can be observed in July than in the following month. Analyzing the ACF function values, one can again notice daily repetition, as well as a clearly stronger correlation with the values from the previous quarter-hour (PACF).

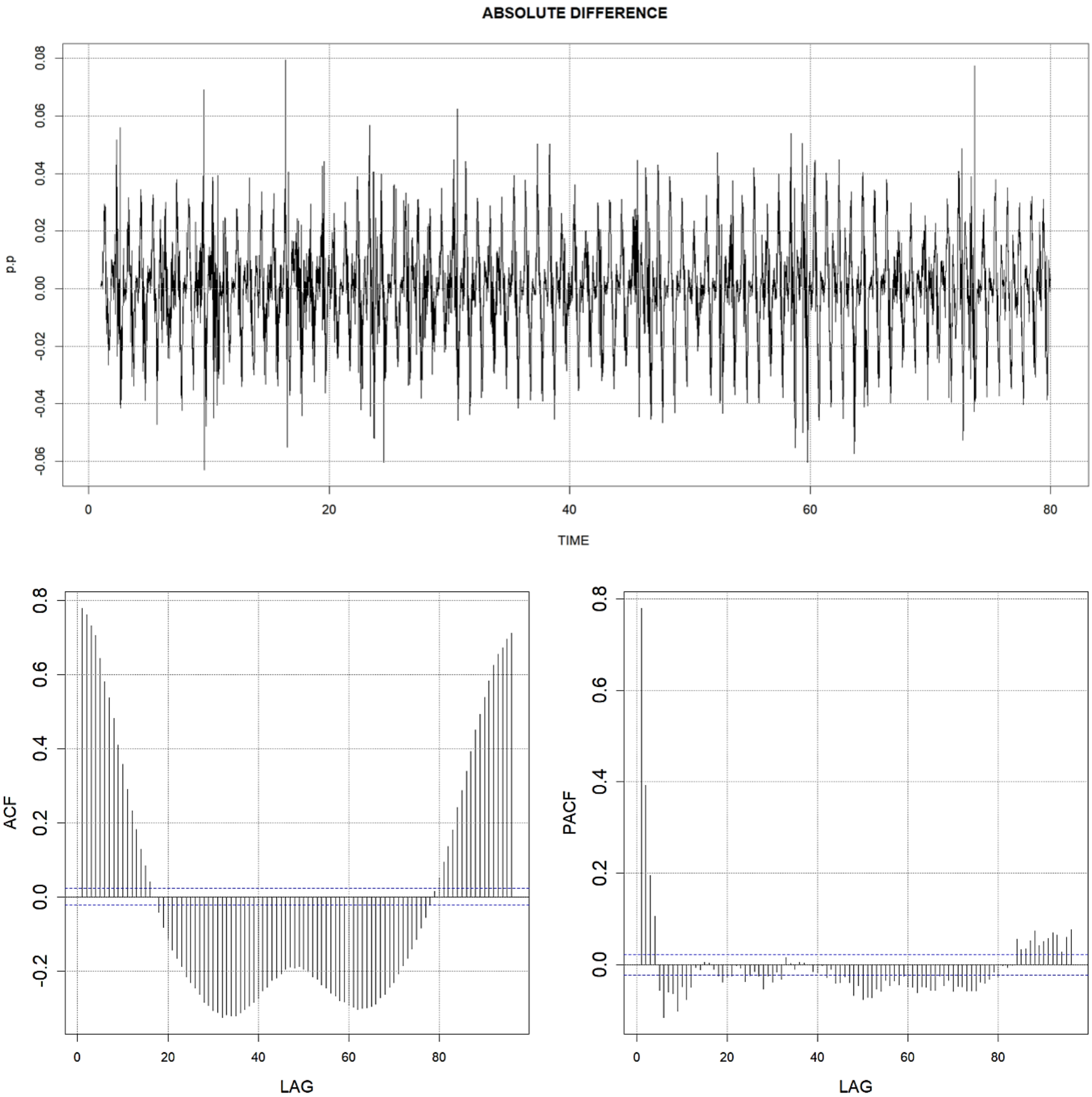


**Figure 6.** Time series of absolute changes in demand coverage by photovoltaic and wind production, along with the ACF(96) and PACF(96) functions.

Source: Own calculation.

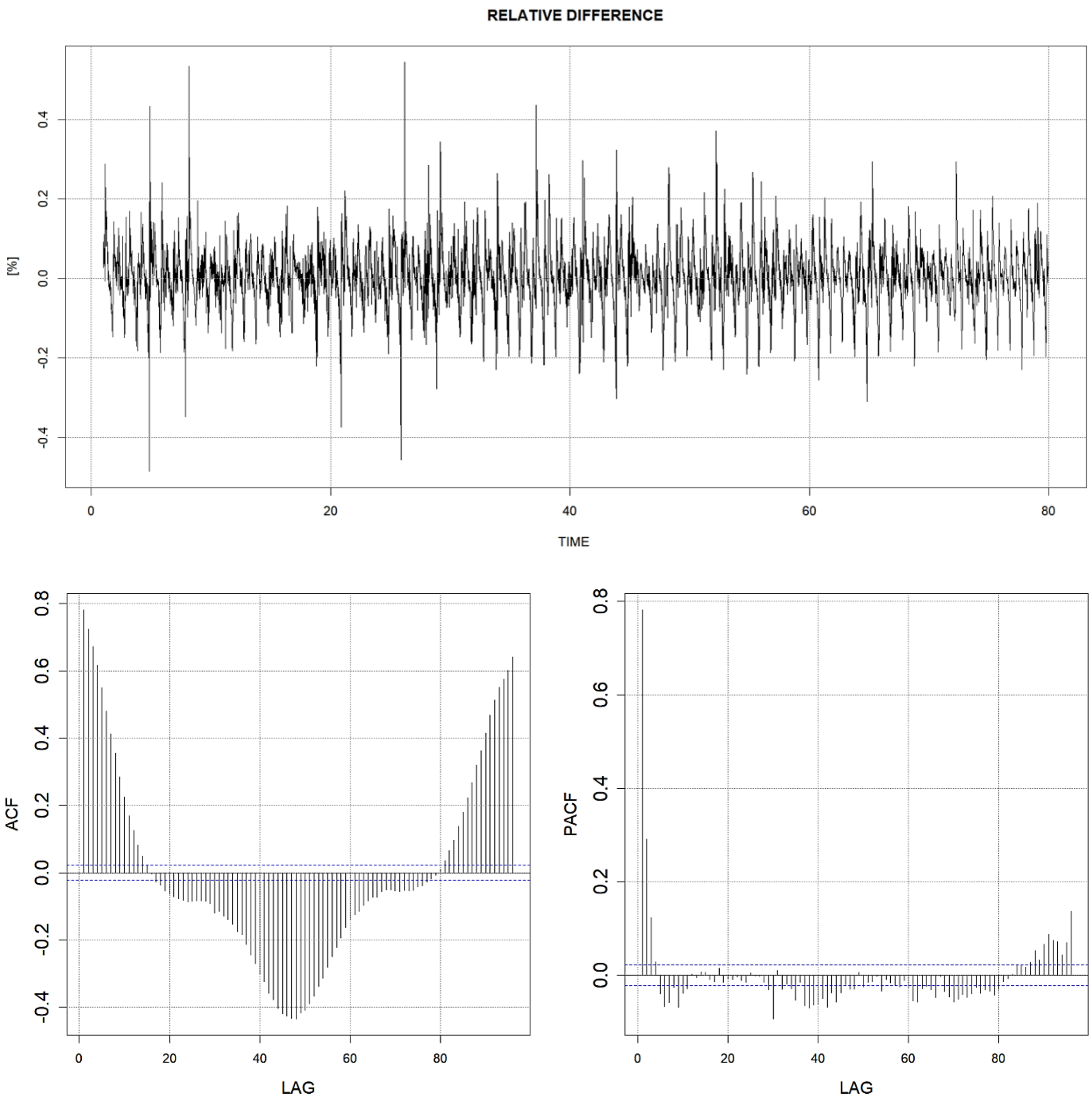


**Figure 7.** Time series of relative changes in demand coverage by photovoltaic and wind production, along with the ACF(96) and PACF(96) functions.

Source: Own calculation.

### 3.2. Volatility models

Table 1 presents the BIC values for selected model orders (6) and the $p$-values of the applied diagnostic tests. Models were considered separately for absolute increments $\Delta Y_t$ (3) and relative changes $R_t$ (4). Additionally, for both types of time series, models were fitted with and without accounting for daily seasonality. For both absolute and relative series, the optimal models in terms of fit to empirical data were identical in their general form. Models incorporating daily seasonality ($s$ = 96) required the inclusion of the previous four quarter-hours to describe the expected value. Models without daily differencing achieved the best results with lags of up to three quarter-hours. Models that did not account for daily seasonality performed worse in diagnostic tests (p-values highlighted in red).

**Table 1.**
*Basic indicators for assessing models ARIMA-GARCH*

| DIFF | Model | BIC | p-value | | | |
|---|---|---|---|---|---|---|
| | | | Ljung-Box Test on (Lag = 1) | | Sign Bias Test | Adjusted Pearson Goodness-of-Fit Test (for 20, 30, 40, 50 histograms intervals) |
| | | | Residuals | Squared Residuals | | |
| ABSOLUTE (3) | sARIMA(4,0,0)(0,1,0)[96] - GARCH(1,1) | -6.6568 | 0.2250 | 0.2601 | 0.2601 | 20 0.4318<br>30 0.2446<br>40 0.8110<br>50 0.7611 |
| | ARIMA(3,0,0) - GARCH(1,1) | -7.0691 | 0.0032 | 0.5469 | 0.5907 | 20 0.0322<br>30 0.0172<br>40 0.0045<br>50 0.1232 |
| RELATIVE (4) | sARIMA(4,0,0)(0,1,0)[96] - GARCH(1,1) | -3.4091 | 0.0713 | 0.2677 | 0.4124 | 20 0.5641<br>30 0.4321<br>40 0.3413<br>50 0.2761 |
| | ARIMA(3,0,0) - GARCH(1,1) | -3.8606 | 0.7636 | 0.8066 | 0.0444 | 20 0.0278<br>30 0.0335<br>40 0.2023<br>50 0.1349 |

Source: Own calculation.

The residuals of the obtained models follow the skewed Student's t-distribution (sstd), except for the ARIMA(3,0,0) – GARCH(1,1) model for relative increments, for which a better fit was achieved using the Generalized Hyperbolic Distribution (ghyp).

Table 2 presents the assessment of model parameters from Table 1. Most parameter estimates are statistically significant, with exceptions marked in lighter font in Table 2. Both seasonal and non-seasonal models, applied to absolute and relative quarter-hourly changes in demand coverage, yield similar estimates for identical lags. In models integrated at order 96, significant parameters correspond to lags up to four quarter-hours (i.e. one hour). Non-seasonally differenced models show significance for the last three quarter-hours. Variance models consistently include only the previous quarter-hour. Models based on absolute increments fall into the IGARCH class, which lacks a defined variance but remains stationary. Residuals are right-skewed.

**Table 2.**
*Parameter estimates of models for changes in electricity demand coverage by RES*

| Part of model (6) | Parametrs | ABSOLUTE DIFFERENCE | | RELATIVE DIFFERENCE | |
|---|---|---|---|---|---|
| | | sARIMA(4,0,0)(0,1,0)[96] GARCH(1,1) sstd | ARIMA (3,0,0) GARCH(1,1) sstd | sARIMA(4,0,0)(0,1,0)[96] GARCH(1,1) sstd | ARIMA (3,0,0) GARCH(1,1) ghyp |
| $\mu_t$ | $\phi_1$ | 0.2452 | 0.5203 | 0.2943 | 0.5212 |
| | $\phi_2$ | 0.2153 | 0.2877 | 0.2133 | 0.2796 |
| | $\phi_3$ | 0.1362 | 0.1044 | 0.1127 | 0.1169 |
| | $\phi_4$ | 0.1006 | $x$[2] | 0.0771 | $x$ |
| $\sigma_t^2$ | $\varpi$ | <0.0001 | 0.1044 | 0.0002 | 0.0002 |
| | $\alpha$ | 0.2382 | 0.2557 | 0.2640 | 0.3263 |
| | $\beta$ | 0.7608 | 0.7433 | 0.7162 | 0.6356 |
| $\varepsilon_t$ | skew | 0.9980 | 0.9255 | 1.0252 | 0.8913 |
| | shape | 5.1166 | 5.7378 | 4.6403 | 0.2500 |
| | gh_lambda | $x$ | $x$ | $x$ | -2.3768 |

Source: Own calculation.

### 3.3. Risk measure

Based on time series models of changes in demand coverage by RES, both absolute $(\Delta Y)_t$ and relative $(\mathrm{R}_t)$, we estimated the risk of deviations in coverage in the following quarter-hours (5) from the expected values. Figure 8 presents one-step-ahead VaR forecasts, calculated with the use of the estimated models at a fixed probability level of $\gamma = 0.01$. The red part of the plot marks the 1% VaR for the largest drops in coverage, while the green line indicates the 1% VaR for the largest increases. Notably, seasonal autoregressive models using a rolling daily window adapt well to observed daily and weekly cycles (left panel). For these models, extreme changes are clearly separated from the rest. In contrast, models without daily cyclicality (right panel) also appear to capture daily and weekly patterns, but their VaR estimates span over nearly the entire range of observed changes, making the identification of extremes less distinct.

[2] $x$ in Table 2 – variable not included in the model for the given parameter.

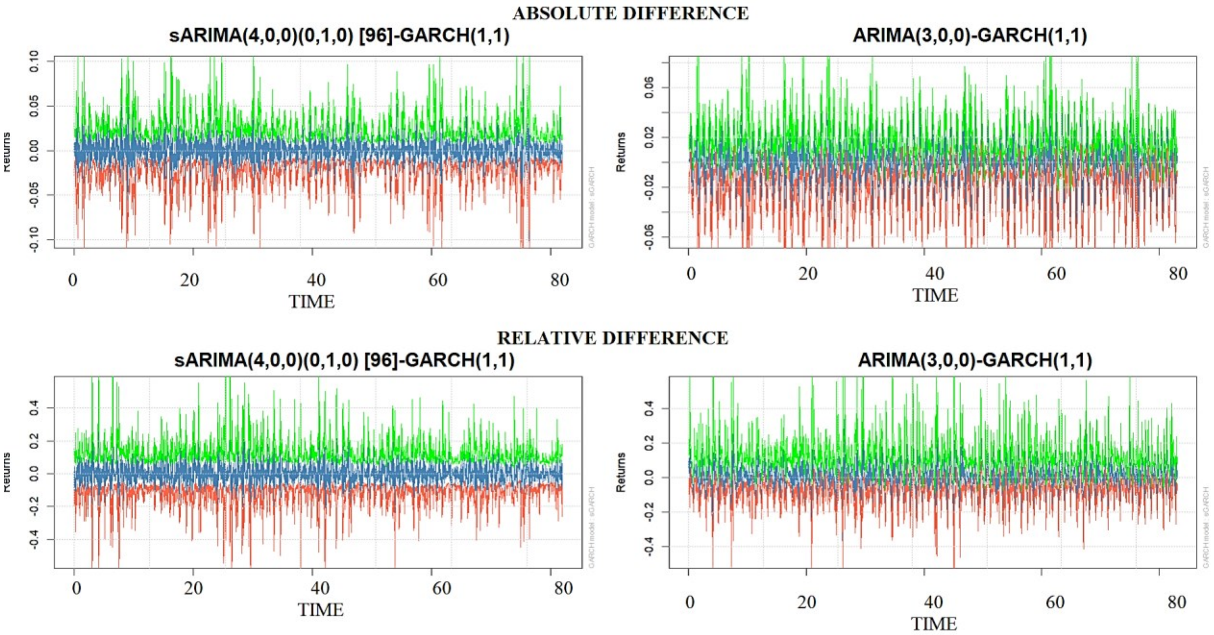


**Figure 8.** VaR(0.01) estimated by ARIMA-GARCH.

Source: Own calculation.

Table 3 presents VaR forecast statistics for decreases in demand coverage at $\gamma = 0.01$ and 0.05, and for increases at $\gamma = 0.99$ and 0.95, estimated independently using each of the four considered models.

**Table 3.**
*Statistics of selected distributions of VaR(γ) forecasts for the next quarter*

| STATISTICS \ MODEL | | ABSOLUTE DIFFERENCE | | | | RELATIVE DIFFERENCE | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | sARIMA(4,0,0)(0,1,0) [96] GARCH(1,1) sstd | | ARIMA(3,0,0) GARCH(1,1) sstd | | sARIMA(4,0,0)(0,1,0) [96] GARCH(1,1) sstd | | ARIMA(3,0,0) GARCH(1,1) ghyp | |
| SHORTFALLS | **γ** | **0.01** | **0.05** | **0.01** | **0.05** | **0.01** | **0.05** | **0.01** | **0.05** |
| | Min. | -0.1691 | -0.1090 | -0.1795 | -0.1175 | -0.7751 | -0.5384 | -0.6930 | -0.5322 |
| | 1stQu. | -0.0326 | -0.0201 | -0.0336 | -0.0227 | -0.1511 | -0.0943 | -0.1219 | -0.0870 |
| | Median | -0.0214 | -0.0127 | -0.0151 | -0.0084 | -0.1086 | -0.0636 | -0.0751 | -0.0462 |
| | Mean | -0.0258 | -0.0155 | -0.0217 | -0.0131 | -0.1284 | -0.0775 | -0.0884 | -0.0563 |
| | 3sdQu. | -0.0146 | -0.0080 | -0.0080 | -0.0032 | -0.0848 | -0.0466 | -0.0451 | -0.0184 |
| | Max. | -0.0044 | 0.0020 | 0.0193 | 0.0260 | -0.0143 | 0.0174 | 0.0996 | 0.1438 |
| SURPLUSES | **γ** | **0.99** | **0.95** | **0.99** | **0.95** | **0.99** | **0.95** | **0.99** | **0.95** |
| | Min. | 0.0017 | -0.0053 | -0.0248 | -0.0301 | 0.0183 | -0.0320 | -0.0849 | -0.1415 |
| | 1stQu. | 0.0152 | 0.0086 | 0.0093 | 0.0044 | 0.0880 | 0.0473 | 0.0722 | 0.0285 |
| | Median | 0.0220 | 0.0132 | 0.0164 | 0.0100 | 0.1132 | 0.0650 | 0.1110 | 0.0609 |
| | Mean | 0.0259 | 0.0156 | 0.0197 | 0.0123 | 0.1334 | 0.0787 | 0.1300 | 0.0708 |
| | 3sdQu. | 0.0323 | 0.0199 | 0.0284 | 0.0199 | 0.1584 | 0.0968 | 0.1680 | 0.1082 |
| | Max. | 0.1972 | 0.1267 | 0.1638 | 0.1199 | 0.8046 | 0.5929 | 1.0385 | 0.7155 |

Source: Own calculation.

Interpreting the maximum loss based on absolute increments estimated at $\gamma = 0.01$, one can say that with 0.99 probability, demand coverage will not decrease by more than 16.91 percentage points (17.95 for the non-cyclical model) in the next quarter-hour. This threshold may be exceeded with a probability of 0.01. During the study period, the median for this probability reached 2.58 percentage points (2.17 for the non-cyclical model), meaning that in

50% of the analyzed quarter-hours, the forecasted coverage is not expected to drop by more than 2.58 (2.17 for the non-seasonal model) percentage points with 0.99 confidence.

For losses estimated based on relative increments at $\gamma$ = 0.01, one can say that with 0.99 probability, demand coverage will not decrease by more than 77.51% (69.30% for the non-cyclical model) in the next quarter-hour.

Analyzing the estimated VaR values based on cyclical and non-cyclical models, it can be observed (with few exceptions) that models accounting for the daily cycle indicate greater shortfalls in demand coverage.

Positive maximum values of the VaR distributions for $\gamma$ = 0.01 (0.05) indicate that, with a probability of 0.99 (0.95), an increase in the share of electricity demand covered by RES production was forecasted for the following 15-minute interval.

Interpreting the maximum increase in the share of electricity demand covered by RES production, it can be stated that, with a probability of 0.99, the coverage will not increase by more than 19.72 percentage points (16.38 percentage points for the non-cyclical model) in the next 15-minute interval. This level of increase may be exceeded with a probability of 0.01. In the case of surpluses estimated based on relative increments for $\gamma$ = 0.99, it can be concluded that, with a probability of 0.99, the coverage of demand will not increase by more than 80.46% (103.85% for the non-cyclical model) in the subsequent 15-minute period.

For the specified exceedance probabilities of potential shortfalls or surpluses in RES generation over the given time horizon, both absolute and relative increments were considered. During the analyzed period, the risk associated with potential surpluses was found to be greater than that of shortfalls.

Tables 4 and 5 present the results of diagnostic tests for VaR estimates, calculated using a rolling daily window (96 quarters of an hour), always forecasting the next 15-minute interval. The accuracy of the VaR estimation was independently verified for July and August, based on both absolute and relative changes.

Based on the backtesting results, one can conclude that the VaR values measured in percentage points (Table 4), estimated using models both with and without consideration of the daily cycle, were accurately calculated. These estimates can be reliably used to forecast changes of demand covered by RES production in the next 15-minute interval, for both potential shortfalls and surpluses.

**Tabela 4**

*Results of consistency and independence tests of VaR(γ) exceedances for the change in demand coverage by PV and wind production [absolute changes]*

| Model | Period | Backtesting | γ | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | **0.05** | **0.025** | **0.01** | **0.95** | **0.975** | **0.99** |
| sARIMA(4,0,0)(0, 1,0) [96] GARCH(1,1) sstd | JULY | Actual % exceed | 0.051 | 0.027 | 0.009 | 0.051 | 0.024 | 0.011 |
| | | LR.uc p-value: | 0.833 | 0.514 | 0.627 | 0.896 | 0.801 | 0.450 |
| | | LR.cc p-value: | 0.687 | 0.502 | 0.483 | 0.912 | 0.965 | 0.497 |
| | AUGUST | Actual % exceed | 0.045 | 0.024 | 0.009 | 0.055 | 0.028 | 0.0097 |
| | | LR.uc p-value: | 0.207 | 0.779 | 0.745 | 0.237 | 0.378 | 0.89 |
| | | LR.cc p-value: | 0.064 | 0.791 | 0.727 | 0.387 | 0.604 | 0.744 |
| ARIMA(3,0,0) GARCH(1,1) sstd | JULY | Actual % exceed | 0.046 | 0.022 | 0.009 | 0,058 | 0,034 | 0,013 |
| | | LR.uc p-value: | 0.347 | 0.235 | 0.627 | 0.042 | 0.002 | 0.153 |
| | | LR.cc p-value: | 0.607 | 0.448 | 0.483 | 0.006 | 0.002 | 0.216 |
| | AUGUST | Actual % exceed | 0,049 | 0,027 | 0,11 | 0,0498 | 0,0247 | 0,0101 |
| | | LR.uc p-value: | 0.964 | 0.478 | 0.682 | 0.964 | 0.929 | 0.958 |
| | | LR.cc p-value: | 0.138 | 0.493 | 0.642 | 0.478 | 0.739 | 0.728 |

Source: Own calculation.

Moreover, based on the backtesting results $\gamma$ (Table 5), the VaR estimates derived from models that do not account for the daily cycle should be rejected for August 2024. The diagnostic tests for the remaining estimates indicate no justification for rejecting the approach in assessing the risk of extreme changes in electricity demand covered by RES production.

**Tabela 5.**

*Results of consistency and independence tests of VaR(γ) exceedances for the change in demand coverage by PV and wind production [relative changes]*

| Model | Period | Backtesting | γ | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | **0.05** | **0.025** | **0.01** | **0.95** | **0.975** | **0.99** |
| sARIMA(4,0,0)(0, 1,0)[96] GARCH(1,1) sstd | JULY | Actual % exceed | 0.051 | 0.027 | 0.011 | 0.0502 | 0.027 | 0.011 |
| | | LR.uc p-value: | 0.833 | 0.445 | 0.682 | 0.961 | 0.514 | 0.682 |
| | | LR.cc p-value: | 0.885 | 0.443 | 0.145 | 0.767 | 0.46 | 0.636 |
| | AUGUST | Actual % exceed | 0.043 | 0.021 | 0.007 | 0.045 | 0.021 | 0.007 |
| | | LR.uc p-value: | 0.074 | 0.135 | 0.056 | 0.207 | 0.105 | 0.134 |
| | | LR.cc p-value: | 0.118 | 0.315 | 0.141 | 0.328 | 0.262 | 0.277 |
| ARIMA(3,0,0) GARCH(1,1) ghyp | JULY | Actual % exceed | 0.049 | 0.023 | 0.0104 | 0,0480 | 0,0240 | 0,0098 |
| | | LR.uc p-value: | 0.974 | 0.55 | 0.815 | 0.658 | 0.63 | 0.903 |
| | | LR.cc p-value: | 0.763 | 0.819 | 0.636 | 0.147 | 0.878 | 0.731 |
| | AUGUST | Actual % exceed | 0.042 | 0.02 | 0.008 | 0,0360 | 0,0190 | 0,0080 |
| | | LR.uc p-value: | **0.03** | 0.077 | 0.285 | **<0,001** | **0.017** | 0.38 |
| | | LR.cc p-value: | **<0.001** | 0.059 | 0.459 | **0.001** | **0.04** | 0.545 |

Source: Own calculation.

## 4. Conclusion and future outlook

This study presents a dynamic risk estimation framework for short-term electricity demand coverage by photovoltaic and wind sources, using ARIMA-GARCH models and the VaR metric. The methodology is applied to high-frequency data from the Polish TSO, PSE, for the summer of 2024, with model accuracy validated through Kupiec and Christoffersen exceedance tests. The results provide actionable insights for short-term system balancing and contribute to the limited body of literature on high-frequency risk modeling in energy markets.

Based on the results obtained for the analyzed period, it can be concluded that the coverage of electricity demand by photovoltaic and wind energy production follows an autoregressive process, characterized by pronounced volatility clustering, cyclicality, and a right-skewed heavy-tailed error distribution. Among the considered models of this class, the best results were achieved using the ARIMA(4,0,0)(0,1,0)[96]-GARCH(1,1) model with a right-skewed Student's t-distribution. This further emphasizes the strong relation between demand coverage on an hourly basis (4 quarters) and the importance of daily cyclicality in demand modeling (96 quarters). The obtained VaR forecasts based on this model can be used to estimate the risk of changes (decrease/increase) in demand coverage by RES generation. The results were compared with estimates obtained from models that do not account for daily cyclicality. During the period of increased volatility (i.e. July), both approaches performed comparably well. In the stable period (i.e. August), the model that did not account for cyclicality tended to overestimate VaR for both decreases and increases in coverage.

In the course of discussion of increased integration of RES in Europe and specifically in Poland, it is important to emphasize that accurate forecasting of PV and wind generation remains essential for balancing the grid and optimizing the operation of flexible assets. Applying the VaR approach enables quantification of the potential discrepancy between renewable generation and electricity demand at a given confidence level, allowing system operators to anticipate and prepare for extreme imbalances in supply.

Future research should consider incorporating multi-year datasets to enable the analysis of not only intraday patterns but also annual seasonality. While weekly cyclicality plays a significant role in modeling of electricity demand, it appears to be negligible in the context of RES generation.

So far in our analysis we have used publicly available data published by PSE on raporty.pse.pl website. For further research we intend to utilize other sources of high-resolution, standardized, information on electricity generation and consumption, which is essential for improving the accuracy and robustness of our modeling approaches. That is why it is important to emphasize that the production launch of a new data repository was scheduled for 1st of July 2025. This repository is referred to as CSIRE (from Polish abbreviation meaning Central Energy Market Information System) and PSE has been designated as the Energy Market

Information Operator (Polish abbreviation OIRE, used below) in Poland, according to The Act of 20 May 2021 amending the Energy Law.

The central data hub operated by PSE, i.e. CSIRE, is designed to centralize and automate market processes. The system will serve as a single point of access for stakeholders such as DSOs, suppliers, and consumers. The overarching goal of CSIRE is to improve transparency and enhance consumer awareness and involvement through access to real-time and historical energy data. From a research perspective, CSIRE will serve as a data hub, providing scientists with access to energy market data for advanced analytics, modeling, and developing forecasting tools to support the achievement of energy transition targets.

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