STORAGE-BASED FREQUENCY CONTROL AND GRID-FREQUENCY DEVIATIONS FORECASTING

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Frequency containment reserves. Energy storage, Forecasting, Time series.

Summary

The Belgian frequency containment reserves market has recently been opened to assets with limited energy reservoirs. Such assets must implement an energy management strategy to deal with energy deviations. This paper is a contribution to the definition of such a strategy. A model for predicting grid-frequency deviations is built. Based on yearly series of grid-frequency measurements, seasonal trends in grid frequency are put in light. After having removed these trends, the remaining autocorrelation is explained through an ARMA-GARCH model. The overall model can be used to forecast average frequency deviations over 15-minute time steps, with any confidence interval. It is a tool to help dispatchers decide when to source energy on real-time energy markets.

Résumé

Le marché des réserves primaires a récemment été ouvert aux actifs ayant des réserves d'énergie limitées, lesquels doivent implémenter une stratégie de gestion de l'énergie. Cet article est une contribution a l'élaboration d'une telle stratégie. Un modèle est construit pour prédire les déviations de fréquence du réseau électrique. A partir de séries annuelles de mesure de la fréquence, la saisonnalité présente dans les données est mise en lumière et l'autocorrélation restante est expliquée par un modèle ARMA-GARCH. Le modèle complet peut être utilisé pour prédire les déviations moyennes de fréquence sur des pas de temps de 15 minutes, avec l'interval de confiance désiré. Il s'agit donc d'un outil pouvant aider le dispatcheur à décider quand sourcer l'énergie servant à la recharge du stockage.

Samenvatting

De Belgische markt voor frequency containment reserves is onlangs geopend voor activa met beperkte energiereservoirs. Deze activa moeten een energiebeheerstrategie implementeren. Dit paper is een bijdrage aan de definitie van een dergelijke strategie. Een model is gebouwd om frequentieafwijkingen van het net voor te spellen. Op basis van jaarlijkse reeks van het netfrequentie worden seizoensgebonden trends in licht gebracht. De resterende autocorrelatie wordt door een ARMA-GARCH model uitgelegd. Het algemene model kan worden gebruikt om gemiddelde frequentieafwijkingen te voorspellen over 15 minuten tijdstappen, met een betrouwbaarheidsinterval. Het is een hulpmiddel om dispatchers te helpen beslissen wanneer energie moet worden opgebouwd.

INTRODUCTION

The Belgian transmission system operator (TSO), Elia, has recently opened the frequency containment reserves (FCRs) market to "assets with limited energy reservoirs", which includes battery energy storage systems. Because of their limited energy reservoirs, these providers face the risk of being fully charged/discharged and thus unable to face their obligation of providing the service, especially in the case of sustained major system imbalances. Elia has therefore specified frequency-deviation situations from which an asset with limited energy reservoir is only required to be able to provide 100 % of the contracted FCR volume during a specified period of time. This is equivalent to requiring the asset to dispose of a fixed energy reserve at any time in normal grid-frequency situations. In other words, failure to provide FCRs is accepted given specified frequency deviation circumstances.

In normal grid-frequency situations, energy storages providing FCRs face deviations over time in their level of stored energy. These deviations are due to the storage's cycle efficiency, but also to frequency deviations. To remain able to provide the service in case of those normal grid-frequency situations, the storage operator is required to implement an energy management strategy. Energy can be sourced via e.g. the continuous intraday market (CIM), the imbalance market, or through another asset of the operator's portfolio. Reference [1] studies the provision of primary frequency control with a battery energy storage. The energy management strategy consists in a fixed charging power whenever the frequency lies in a dead band for which no primary frequency control is expected. Besides, resistors absorb power whenever the battery is fully charged and power has to be absorbed in the frame of the frequency control. This energy management strategy has the advantage to be simple and easily automated. However, as power is sourced on the imbalance market, it makes the storage exposed to high imbalance prices. Besides, it is not a "smart" strategy since charging is carried out automatically instead of when imbalance prices are low.

Whether energy deviations can be expected or not is a key point for optimizing the storage's operation. Indeed, if deviations can be predicted, a "smart" energy management strategy can be put in place in order to decrease the FCR provision cost. The goal of this paper is to better understand the grid frequency and the related energy deviations, to build a model to predict them and to put in light the underlying deterministic and stochastic natures of grid-frequency deviations.

1 GRID FREQUENCY

Each power system is characterized by a specific frequency, e.g. 50 Hz for the continental Europe (CE) grid and 60 Hz for grids of Northern America. The frequency can be considered uniform over a synchronous region. It is directly related to the rotational speed of synchronous generating machines[1] and varies with time according to mismatches between electricity generation and consumption. Frequency deviations can be modelled generalizing the swing equation to a whole synchronous power system:

$$J\frac{d\omega}{dt} = \frac{P_{mec} - P_{el}}{\omega}$$

with J [kg.m^2] the total moment of inertia, $\omega = 2\pi f$ [rad/s] the angular speed with f the grid-frequency and P_{mec} and P_{el} [W] respectively the mechanical and electrical powers. According to this relation, a decrease in the grid frequency happens when the mechanical power is lower than the electrical power. Inversely, an increasing frequency is linked to too much mechanical power compared to the electrical power. In practice, several mechanisms are put in place to constantly adjust P_{el} in order for the frequency to remain near its nominal value. These mechanisms are frequency containment reserves (FCRs), frequency restoration reserves (FRRs) and replacement reserves (RRs).

Several comments can be made on the grid-frequency distribution of Fig. 1. First, approximately 95 % of frequency realizations are included in the band [49.95, 50.05] Hz. Second, although the frequency distribution may look normally distributed, it actually does not pass the Anderson-Darling normality test as the associated p-value is less than 2.2e-16. Third, using the maximum-likelihood estimation (MLE), we observe that a student distribution, $t(50,0.0207,12)$, better fits the frequency data than a normal distribution, $N(50,0.0226)$. This comes from the fact that the grid frequency is characterized by a fat-tailed distribution, as can be emphasized by a quantile-quantile (Q-Q) plot. As shown on Fig. 1, frequency deviations of either less than one or more than two standard deviations have a greater probability of occurrence than predicted by the normal distribution. It is the opposite for frequency deviations from one to two standard deviations. The conclusions are also valid for the year 2013.

[1] Synchronous generation includes nuclear, gas, coal and biomass fired power plants, as well as former-generation hydraulic and wind turbines. Photovoltaic installations are always connected to the grid through power electronics converters and do not contribute to grid inertia. It is also the case, most of the time, for modern wind and hydropower. One should however emphasize that research is carried out on how renewable generation could support the grid frequency. The interested reader may look for “virtual inertia”.

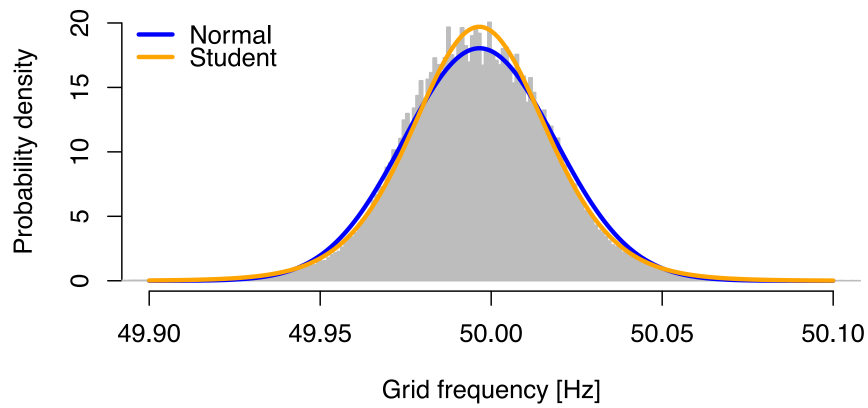


Fig. 1: Probability density of the grid frequency – 2012 Elia data at ten-second time steps.

While fat-tailness is a not well known characteristic of the grid frequency, it is a common topic in the financial industry [2,3], e.g. when dealing with asset returns, and it is a practical concern for the modeller. Building realistic time-series models requires to make a distributional hypothesis. In order to capture fat-tails, a popular choice in the financial industry is the student distribution. It includes the normal distribution as a special case when its shape parameter tends to infinity, and can therefore be seen as an extension of the classical Gaussian framework. In the following section, we come back to the fat-tail feature of the grid frequency when modelling energy deviations over 15-minute time steps.

2 Modelling frequency deviations over 15-minute time steps

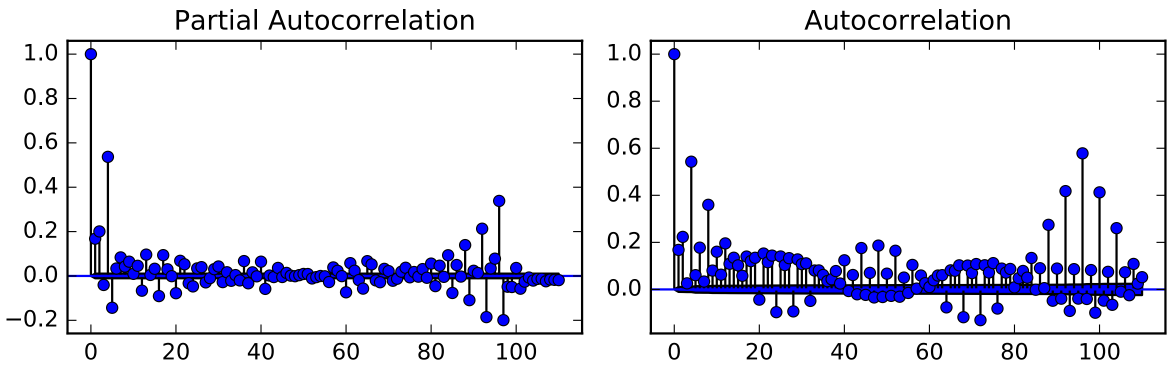
We are looking at time steps of around 15 minutes. Over such time steps, the mean of frequency deviations is generally different from zero, which makes FCR providers as storages face energy deviations, i.e. changes in their level of stored energy. According to the 2013 frequency measurements, there is a 9 % probability for one-hour-averaged frequency deviations to induce more than 0.1 hour of energy deviation for each megawatt of contracted FCR. We want to model such frequency deviations in order to take them into account in the operation of the storage, i.e. the objective is to build a model for generating credible 15-minute time-step series of frequency deviations. First, we average over 15-minute time-steps the frequency measurements given as series of 10-second time-step frequency deviations. Then, the next thing to do before fitting a model to this new 15-minute time-step series is to remove its seasonal components.

2.1 Seasonality removal

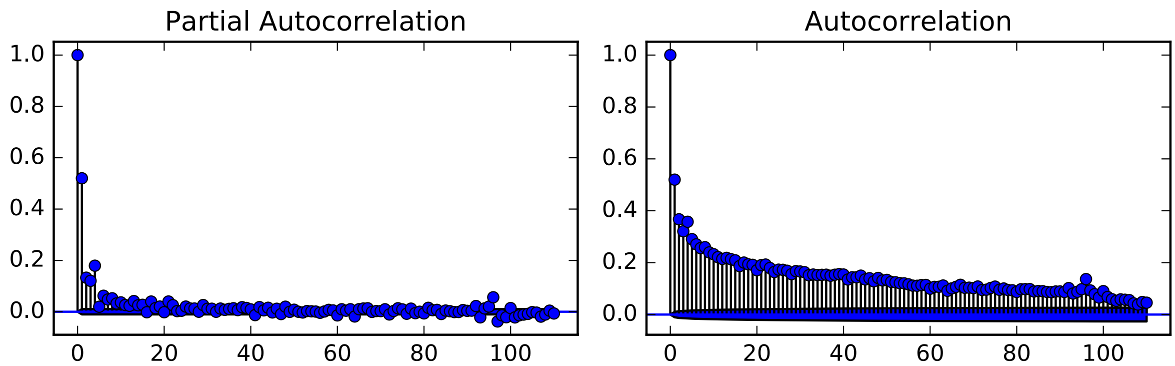
As emphasized on Fig. 2a, the partial autocorrelation function (PACF) of the 15-minute time-step series has a high value at lag 4. A fast Fourier transform (FFT) of this series, not displayed here, shows a component of 1-hour period, which indicates an hourly pattern in frequency deviations. This result is consistent since power is traded on DAMs at constant power for time steps of one hour, while the load is constantly varying, increasing in the morning and decreasing in the evening. We also observe high values of the PACF around lag 96, i.e. around a 24-hour lag, while the FFT exhibits high values around a frequency of 0.01 Hz, corresponding to signals of 24-hour period. As emphasized by the ACF, PACF and FFT, our series contains at least hourly and daily trends. The first step before fitting a model is to remove them.

We consider a 24x4 matrix, 24 hours x 4 quarters, in which will be stored the mean of 15-minute frequency deviations over one year, differentiating by quarter of the day. We see that when the first column of the matrix is positive, the last one is generally negative and vice versa. In other words, positive frequency deviations at the beginning of an hour are generally followed by negative deviations at the end of the hour, and vice versa. Subtracting those means from the 15-minute-averaged time series decreases the lag-4 coefficient of approximately 0.2 compared to its initial value. More broadly, the shape of the partial autocorrelation function improves and the 0.25 Hz component of the FFT also gets reduced. Now if we repeat the process but with a 12x24x4 matrix, i.e. differentiating by month and quarter of the day, we are able to reduce the lag-4 coefficient to 0.2 and even a bit less than 0.2 adding another differentiation between week and week-ends. Lag-1 coefficient increases, lag-2 coefficient decreases while lag-3 coefficient increases. The other coefficients move toward zero including around lag 96.

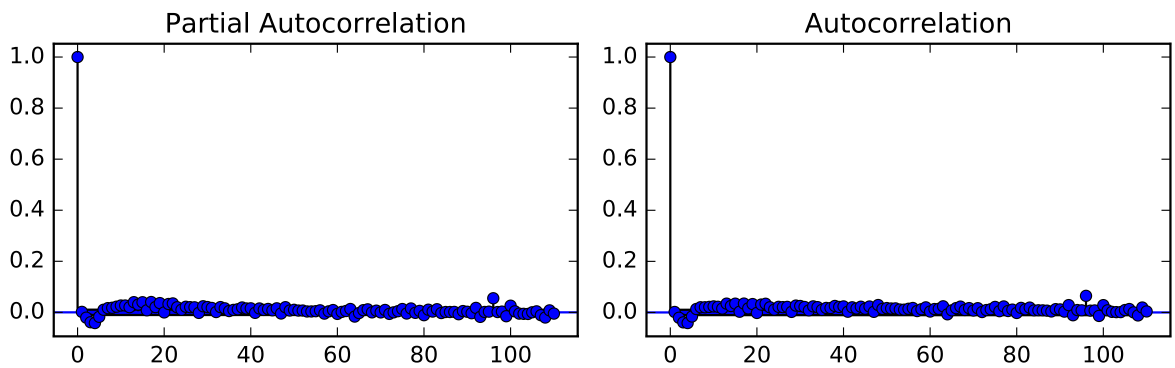
To sum up, it is found that the autocorrelation in our original time series is mainly affected by monthly and hourly seasonality. Instead of fitting an arbitrary function to remove seasonality, e.g. a cosine, we have computed it as means, differentiating by month, by weekday/end, by hour and by quarter. Those means, which can be stored in a 12x2x24x4 matrix, are then removed from the original 15-minute time-step series. As indicated on Fig. 2, the results are PACF and ACF exhibiting less autocorrelation for the series with seasonality removed compared to the original 15-minute time-step series. It should be noted that removing the computed 2012 seasonality from the 2013, 2014 and 2015 data does also significantly improve the PACF and ACF, as indicated on Fig. 3, 4 and 5, although not as well as for the 2012 data. This check, which is important to do, shows that (i) the seasonality observed in 2012 generalizes well to the 2013 data and (ii) the proposed methodology to derive seasonality does not lead to significant overfitting. The importance of seasonality in the data can be better appreciated noting that the computed means in the 12x2x24x4 matrix range from zero up to 0.049 Hz, while the standard deviations associated to each mean remain roughly around 0.01 Hz.



(a) PACF and ACF of the original 2012 15-minute time-step series, before seasonality removal.

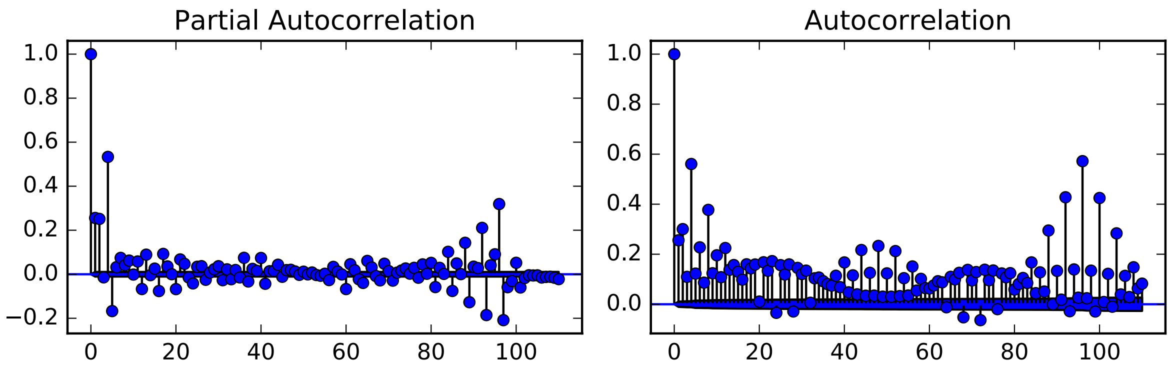


(b) PACF and ACF of the 2012 15-minute time-step series after seasonality removal.

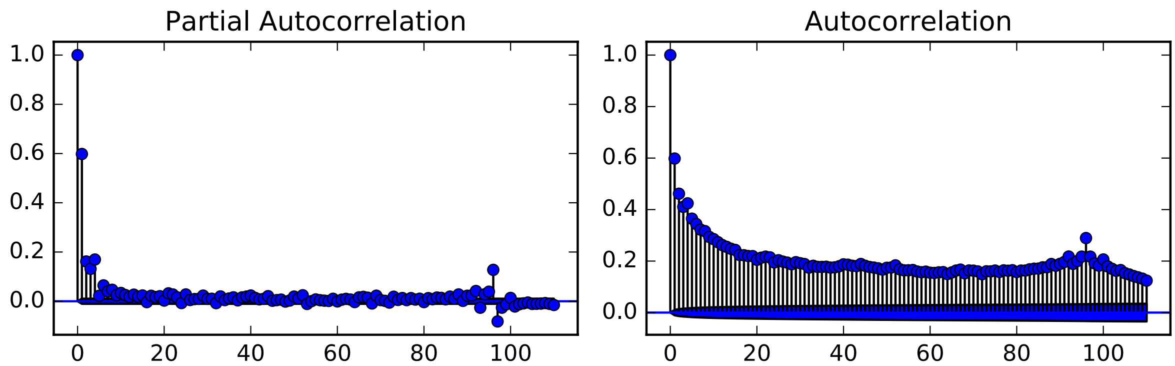


(c) PACF and ACF of the 2012 15-minute time-step series after seasonality removal and ARMA-GARCH fit.

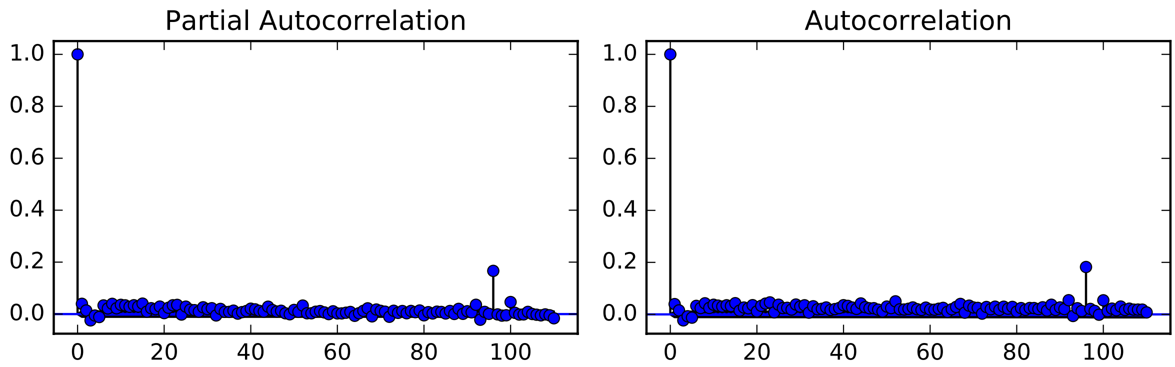
Fig. 2: Autocorrelation in the 2012 15-minute time-step series is explained by seasonality trends and an ARMA-GARCH model.



(a) PACF and ACF of the original 2013 15-minute time-step series, before seasonality removal.

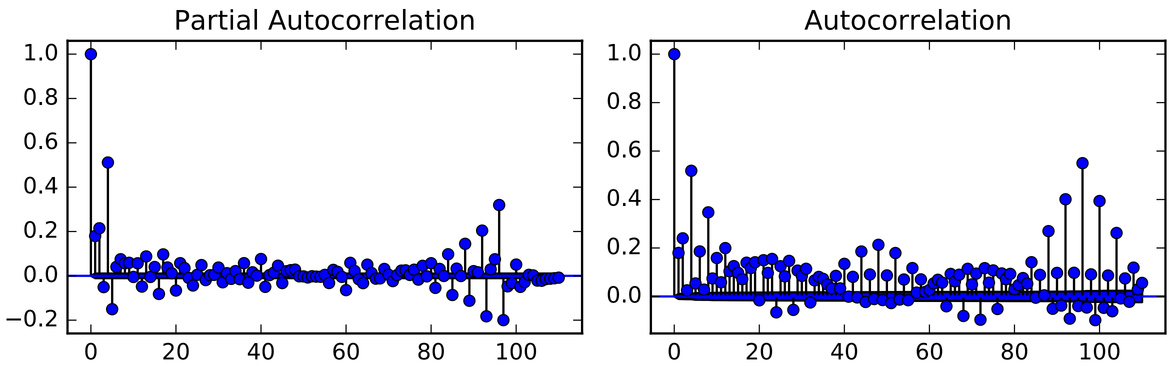


(b) PACF and ACF of the 2013 15-minute time-step series after 2012 seasonality removal.

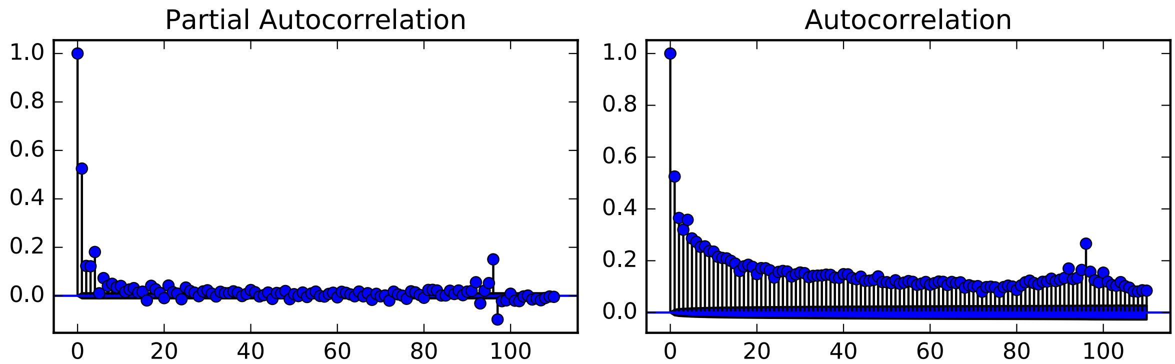


(c) PACF and ACF of the 2013 15-minute time-step series after 2012 seasonality removal and ARMA-GARCH fit.

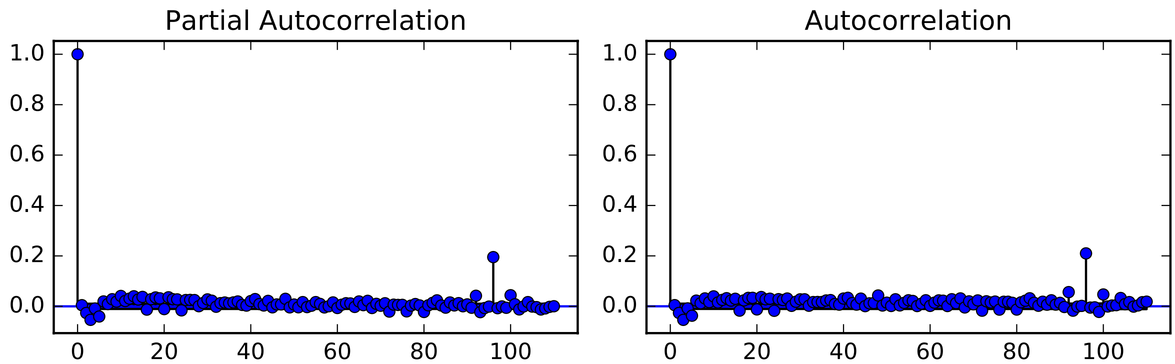
Fig. 3: Autocorrelation in the 2013 15-minute time-step series is explained by 2012 seasonality trends and ARMA-GARCH fit.



(a) PACF and ACF of the original 2014 15-minute time-step series, before seasonality removal.

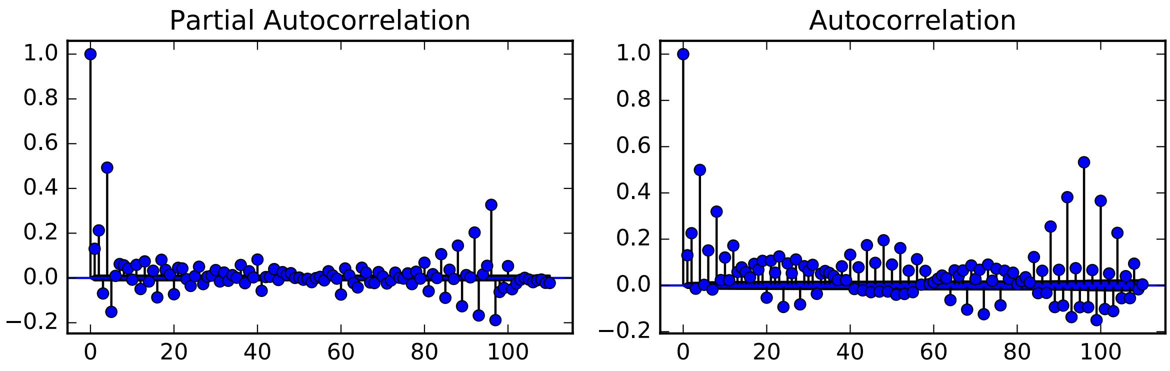


(b) PACF and ACF of the 2014 15-minute time-step series after 2012 seasonality removal.

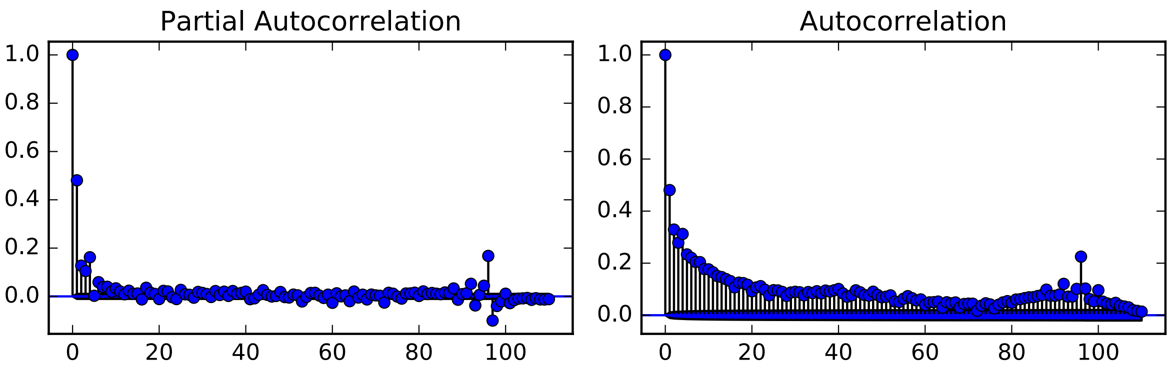


(c) PACF and ACF of the 2014 15-minute time-step series after 2012 seasonality removal and ARMA-GARCH fit.

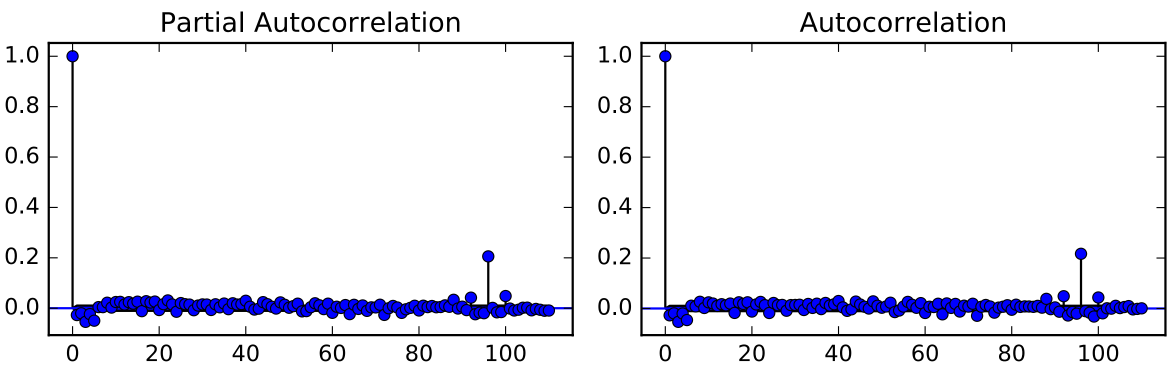
Fig. 4: Autocorrelation in the 2014 15-minute time-step series is explained by 2012 seasonality trends and ARMA-GARCH fit.



(a) PACF and ACF of the original 2015 15-minute time-step series, before seasonality removal.



(b) PACF and ACF of the 2015 15-minute time-step series after 2012 seasonality removal.



(c) PACF and ACF of the 2014 15-minute time-step series after 2012 seasonality removal and ARMA-GARCH fit.

Fig. 5: Autocorrelation in the 2015 15-minute time-step series is explained by 2012 seasonality trends and ARMA-GARCH fit.

2.2 ARMA(4,0)-GARCH(1,1) model

In the previous subsection we have seen that removing seasonality reduces the autocorrelation in the data. Some unexplained autocorrelation is however remaining, in particular from lag-1 to lag-4, as indicated in red on the PACF of Fig. 2b. This autocorrelation can be taken into account by considering in our model an autoregressive moving average process ARMA(p,q). The shapes observed on the PACF and ACF of Fig. 2b can be identified as characteristic of an ARMA(4,0) process. After fitting an ARMA(4,0) model, we notice two things. First the residuals still exhibit a fat-tail feature, i.e. they are not normally distributed, which is a problem as most tools for fitting ARMA models use MLE with the hypothesis of normally distributed residuals. Second, the ACF and PACF of the squared residuals show that residuals are characterized by a variable volatility, also referred to as volatility clustering. Although this effect seems of low magnitude, volatility clustering explains part of the fat-tail feature of the residuals and it is therefore decided to take it into account using a generalized autoregressive conditional heteroskedastic (GARCH) model. As it is usually done in finance [4,5], a GARCH(1,1) process is fitted and a student distribution is specified for the residuals. The ARMA-GARCH model is thus given by the following relations:

$$X_t = \mu + \sum_{i=1}^{4} \varphi_i \, X_{t-i} + \sigma_t \epsilon_t \qquad with \qquad \epsilon_t \sim t_\nu$$

$$\sigma_t^2 = \sigma + \beta \sigma_{t-1}^2 + \alpha \epsilon_{t-1}^2$$

with the fitted parameters are given in Table I. All those parameters are significantly different from zero, at the 1 % level, as emphasized by the p-value and significance columns. It should be noted that the shape parameter is related to the student distribution fitted to the standardized residuals, i.e. $t(0{,}1{,}7.86)$. Considering non-standardized residuals, the student distribution becomes $t(0{,}0.0099{,}6.54)$. The Q-Q plot of Fig. 6 shows that the residuals actually follow this distribution. The values obtained on the PACF and ACF of the residuals are close to zero, as indicated on Fig. 2c, showing that nearly no autocorrelation is remaining in the residuals. As indicated on Fig. 3, 4 and 5, the ARMA-GARCH model fits rather well the 2013, 2014 and 2015 data once the 2012 seasonality has been removed. However, we observe in the residuals a remaining daily correlation, through lag 96. This remaining correlation means that unexpected frequency deviations happening at a particular moment tend to reproduce on the following days. An idea to improve our model would be to fit seasonality based on several years, instead of only one, and then fit an ARMA-GARCH model taking into account lag 96. This point is left to future investigations.

Table I: Fitted parameters of the ARMA(4,0)-GARCH(1,1) model with residuals following a student distribution.

	Estimate	Std. Error	t value	p value	Significance
φ_1	4.171e-01	5.562e-03	74.99	<2e-16	***
φ_2	7.127e-02	5.870e-03	12.14	<2e-16	***
φ_3	7.274e-02	5.809e-03	12.52	<2e-16	***
φ_4	1.461e-01	5.314e-03	27.49	<2e-16	***
σ	1.482e-05	1.272e-06	11.65	<2e-16	***
α	9.943e-02	6.076e-03	16.37	<2e-16	***
β	7.451e-01	1.743e-02	42.74	<2e-16	***
shape	7.860e+00	3.016e-01	26.06	<2e-16	***

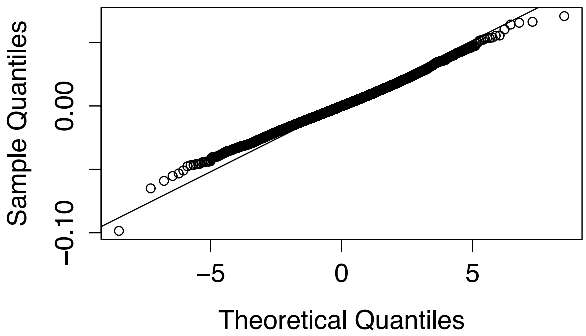


Fig. 6: Q-Q plot of the residuals against a Student $t(0,0.0099,6.54)$ distribution.

To sum up, we have developed a model for 15-minute averages of frequency deviations over one year. This model is composed of seasonality terms, the deterministic part of the model, plus an ARMA(4,0)-GARCH(1,1) model which is the stochastic part. Although the model has been fitted based on 2012 data, it performs well when applied to the 2013, 2014 and 2015 data, which validates the modelling approach. The model has been the object of an IEEE conference paper [6] as well as a Python package which can be installed using pip. The code is open source and freely available on GitHub[2].

[2] https://github.com/thmercier/grid_toolkit

CONCLUSIONS

Elia has recently opened the Belgian FCRs market to assets with limited energy reservoirs, which typically includes energy storages. Nevertheless, providing FCRs with such assets is still a technical challenge since it makes them face unexpected energy deviations, which have to be compensated for in real time, e.g. on the imbalance market. In this frame, Elia requires the asset operator to implement an energy management strategy. The objective is to continuously be able to provide FCRs in situations of "normal" frequency deviations. A common energy management strategy is to arbitrarily, and ex-ante, define periods during which the storage is charged. This strategy has the advantage to be clear and easy to implement but exposes the storage to an imbalance price risk.

This paper shows that energy deviations can be predicted. Based on frequency measurements, an ARMA-GARCH model is built in order to forecast average 15-minute time-step frequency deviations. The model accounts for important grid-frequency features, seasonality, autocorrelation, stochasticity and fat-tailness, and generalizes well to other data sets. It is implemented in a freely available Python package, enabling the quick generation of scenarios. Given a storage providing FCRs, the model can be used to predict future energy levels with the desired confidence interval. For the dispatcher, such a tool would enable to manage storages' energy level at the lowest cost, taking advantage of favorable imbalance prices while mitigating the risk of being fully charged/discharged.

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