Forecasting of Frequency Containment Reserve Prices Using Econometric and Artificial Intelligence Approaches

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Abstract:

The forecasting of control reserve prices is essential in order to participate reasonably in the auctions. Having identified a lack of related literature, we therefore deploy approaches based on auto-regressive and exogenous factors originating from econometrics and artificial intelligence and set up a forecasting framework. We use SARIMA and SARIMAX models as well as neural networks and forecast based on a rolling one-step forecast with re-estimation of the models. It turns out, that the combination of auto-regressive and exogenous factors yields the best results compared to approaches solely considering auto-regressive or exogenous factors. Further, the artificial intelligence approach outperforms the econometric approach in terms of forecast quality, whereas for the further use of the generated models, the econometric approach has advantages in terms of interpretability.

Keywords: Control reserve power, balancing services, Frequency Containment Reserve, forecasting, SARIMA, SARIMAX, Artificial Neural Network, Artificial Intelligence.

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1 Introduction and Motivation

Since the EU Community Directive 96/92/EC electricity has become a freely tradable commodity on power markets. However, as storage opportunities for electricity are limited, ensuring that power feed-in and withdrawal in a synchronous grid are in balance is of great importance for the security of supply of electricity. Transmission system operators (TSOs) are responsible for a stable grid frequency within their designated control areas, which they achieve by continuously balancing power feed-in and withdrawal. To this end, TSOs procure positive and negative reserve capacities meeting different quality requirements through public tenders. The different quality requirements lead to market segments for primary (Frequency Containment Reserve, FCR), secondary (automatic Frequency Restoration Reserve, aFRR) and tertiary (manual Frequency Restoration Reserve, mFRR) control reserve power, in which FCR has with 30 seconds the shortest activation time. These coexist alongside derivate and spot markets, forming profit opportunities for generators meeting the respective requirements.

This paper focuses on forecasting the price level of the largest European FCR market, which consists of the market areas of Austria, Belgium, France, Germany, the Netherlands and Switzerland. Currently, the responsible TSOs of these countries jointly procure FCR capacities for an entire week with one week of lead time in a pay-as-bid tender. Providers of FCR get compensated for capacity reservation as activation is hardly predictable and the delivered balancing energy amount has an expected value of zero. Figure 1 provides an overview over the capacity provision by each of the countries jointly procuring FCR[2].

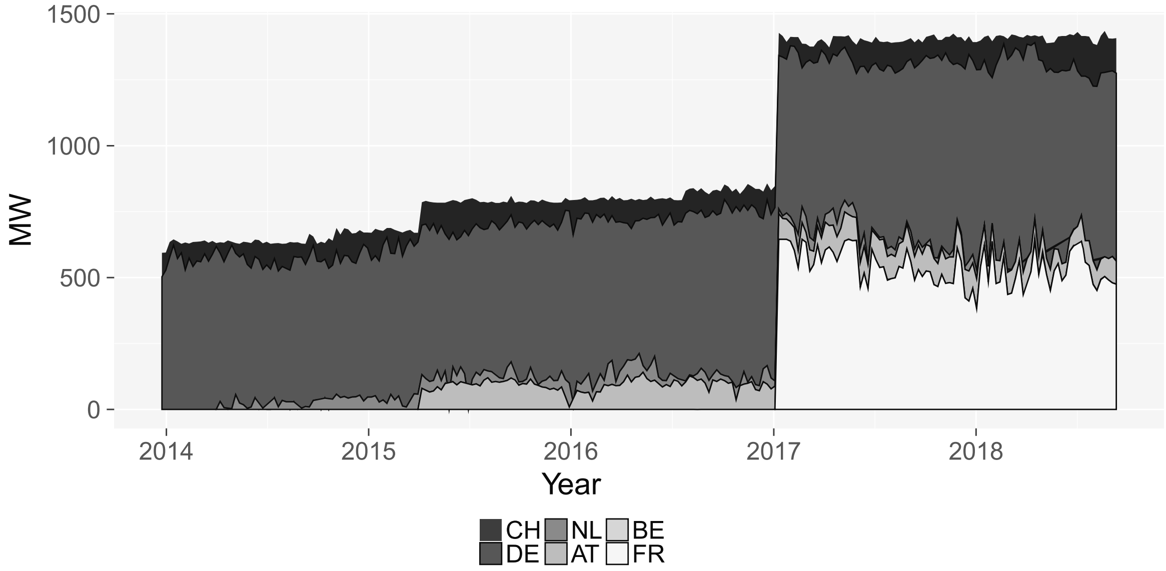

Figure 1: Provision of FCR capacity by country (own illustration based on data from [1])

[2] Note that France joined the procurement union in 2017 and subsequently provides more than a third of the required FCR. However, the market entry of France is considered in the model building, as the structural change may have introduced correlations and dynamics, which data from before 2017 do not contain.

A potential supplier faces the trade-off between the profit from selling FCR and the opportunity costs of the alternative use of the flexible capacity. In order to prepare an adequate offer for the FCR tender and the other market segments, high-quality price forecasts are inevitable.

In this context, in Chapter 2 we review different approaches to forecast short-term electricity market prices. In a second step, in Chapter 3 we deploy econometric approaches considering auto-regressive processes and exogenous drivers, precisely a linear regression, a seasonal auto-regressive integrated moving average (SARIMA) and a seasonal auto-regressive integrated moving average approach with exogenous factors (SARIMAX). In Chapter 4, we then build a neural network model, which also considers auto-regression and exogenous variables. Finally, in Chapter 5 we apply the approaches to the stated forecasting problem and compare the performances.

2 Related Literature

Among the first looking into the issue of reserve pricing and costs from a market perspective were Kirsch and Singh [2]. They provide an overview over the cost components of reserve power: opportunity costs of foregone sales, costs of uneconomic operation, potential start-up/shut-down costs, costs resulting from frequent load changes and costs caused by efficiency losses.

Weron [3] finds that the actual modeling and forecasting of prices from balancing and ancillary services markets has been comparatively rare in the literature. Exceptions include Olsson and Söder [4] who model real-time balancing power market prices in the Nordic balancing market by using combined SARIMA and discrete Markov process models. They conclude that the developed model combination is suitable to use for generation of real-time balancing power price scenarios. Klæboe et al. [5] benchmark time series based forecasting models and Dimoulkas et al. [6] apply a Hidden Markov Model to forecast balancing market prices for the Nordic balancing market. They conclude that activation of the control reserve occurs randomly and an activation-based price is therefore hardly predictable. Unfortunately, unlike the tenders considered in the present paper, the considered market design is based on payments for reserve activation and not for the reservation of reserve power.

Just and Weber [7] consider an equilibrium model with two alternative competitive markets, a secondary reserve power and an hourly electricity spot market. However, they do not apply the equilibrium model to forecast prices and do not include primary reserve power in their investigations.

Finally, Wang et al. [8] investigate the application of established stochastic approaches for modeling the behavior of operating reserve and regulation prices in the North American electricity markets. However, the investigated models are descriptive and not designed for generating short-term forecasts. They point out that reserve and regulation prices are characterised by higher volatility, lower mean, more frequent price spikes and a more skewed distribution compared to electric energy prices. Thus, modelling their reserve power prices is potentially more challenging.

However, unfortunately commercial forecast providers do not publish their methodologies in detail. In the next chapter, we will therefore follow Weron [3] who suggests classifying short-term price forecasting models into time series analysis approaches and artificial intelligence (AI) or machine learning approaches. We will thus set up and deploy forecasting models for the FCR price based on both time series analysis (SARIMA and SARIMAX) and AI (artificial neural network, ANN).

3 Methodology

The literature review in the previous section displayed a lack of scientific publications in the field of FCR price forecasting and suggested the application of, on the one hand, approaches coming from time-series analysis, and on the other hand, approaches coming from AI. To obtain a benchmark that is neither time-series-based nor AI-based, a simple linear regression model is set up. In the following sections, first the dependent variable is defined and its time series is analysed briefly. In Section 3.2, the exogenous variables required for the forecasting approaches are introduced and their preprocessing is explained. Sections 3.3 finally presents the set up and training of the linear regression, the SARIMA, the SARIMAX and the ANN model.

3.1 Definition of dependent variable, analysis of time series

As FCR tenders are pay-as-bid auctions, there is no uniform settlement price but each market participant receives its price bid as remuneration. Prior to setting up a highly sophisticated forecasting model, it is therefore necessary to invest thoughts into the definition of a suitable dependent variable. We therefore conduct an analysis of the FCR market results from 2014 to Q3 2018. Figure 2 shows the range of accepted bids as well the capacity-weighted average price in each auction. From the relatively low gap between the average price and the respective marginal price (except for single spikes), we conclude that the capacity-weighted average is a suitable dependent variable for the forecast.

The time series contains seasonality, mainly induced by a strong increase over the Christmas holidays and a moderate price increase in early summer of each year, and seems to have a general tendency to decrease. To check the time series for stationarity, it was

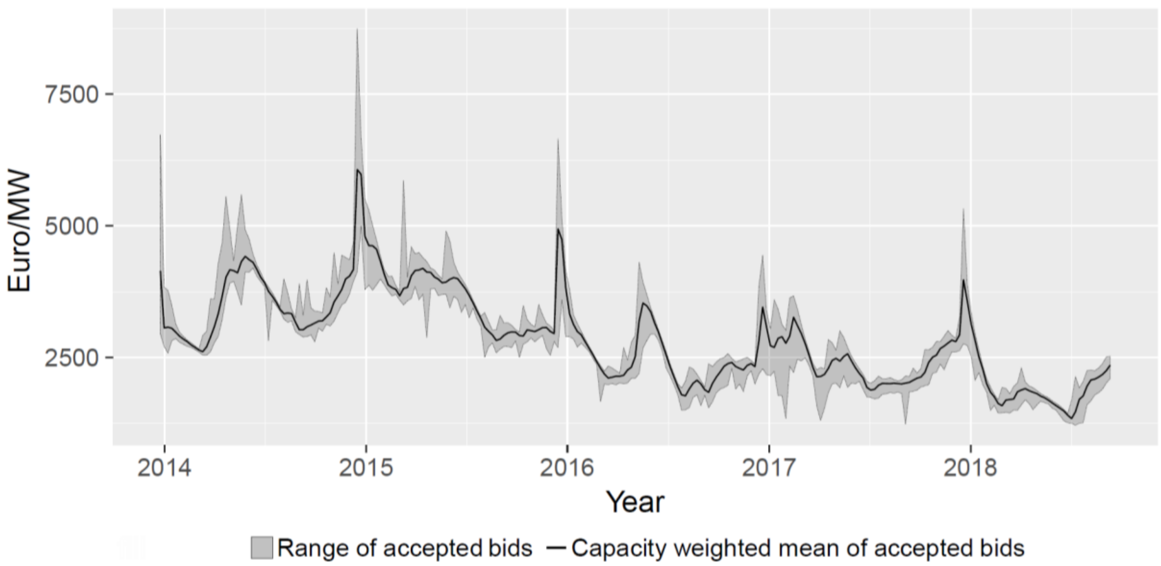

Figure 2: FCR price development 2014 to Q3/2018 (own illustration based on data from [1]).

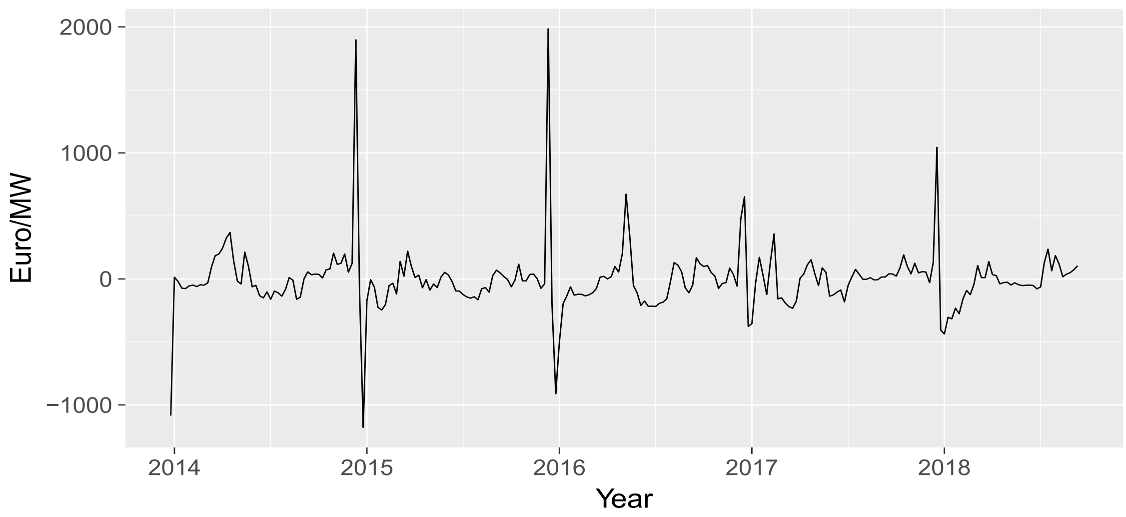

Figure 3: First differences of capacity-weighted average of accepted FCR bids from 2014 to Q3/2018 (own illustration based on data from [1]).

tested with Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests [9]. The non-differenced time series rejects the stationarity null hypothesis at 1% significance, the series of first differences (shown in Figure 3) does not reject the stationarity null hypothesis. The time series models will therefore be estimated based on the first differences time series, which leads to the SARIMA and the SARIMAX approach.

3.2 Identification and preprocessing of exogenous variables

Several variables were considered as exogenous predictors in the study. Representing opportunity costs for reserve provision and a scarcity in the market, following possible predictors were selected:

- Price range and skewness of FCR bids in previous auction [1],
- Average price of week-ahead future German-Austrian (DE-AT)[3] and French (FR) market area [10],
- Average day-ahead price in DE-AT and FR [10],
- Average load forecast and realised load for DE-AT and FR [11],
- Number of German public holidays in a week [11],
- Planned unavailable capacity in DE-AT and FR [11].

Note that exogenous factors like wind and photovoltaic power feed-in were not considered as the auction takes place one week ahead and they are hardly predictable in these time scales. However, the future price with the spot market price and the load forecast with the realised load of a single market area show very high correlations. It is therefore inevitable to consider multicollinearity in the predictor selection.

[3] As the DE-AT future product was split up into DE and AT future products, the volume-weighted average of DE-AT and DE futures is taken for 2018.

For predictor selection, the corrected Akaike Information Criterion (AICc) [12] of the linear regression model for the 2017 data was used. Over all predictor combinations, the set of exogenous predictors containing the *FCR price range*, the *future price DE-AT*, the *future price FR*, the *load in DE-AT*, the *load in FR* and the *planned unavailable capacity in DE* achieved the lowest AICc, corresponding to the best fit of a linear regression on the 2017 data amongst all predictor sets. Although this predictor set may not be the best for all model classes, in the following all forecasting approaches are deployed with the selected set for reasons of consistency and comparability.

3.3 Set up and training of SARIMA, SARIMAX and ANN models

To generate the forecasts, a time series cross-validation approach called rolling one-step forecast with model re-estimation is applied for each of the models (see e.g. [13]). Hereby, for each forecast step, the models are estimated based on the training data set, which initially consists of the 2017 data[4] and is extended by the data that are available at the prior time step. As can be seen in Figure 4, the training data set for week one of 2018 consists of all 2017 data, the training data set for week two of 2018 consists of the 2017 data plus week one of 2018, and so on. Like that, the best information available at the forecasting time is used in the forecast.

A parameter grid search is performed to fit the optimal model of the respective type (SARIMA, SARIMAX, ANN) to the training data. For the SARIMA and SARIMAX type models this is done with the help of a variation of the Hyndman-Khandakar algorithm [14], which combines unit root tests, minimization of the AICc and maximum-likelihood estimation to obtain the model order. For further details, see [14].

For the ANN model, feed-forward neural networks are fitted with lagged values of the dependent variable and the external predictors as inputs and a single layer of hidden neurons. The number of lags is chosen by the optimal number of lags of the respective

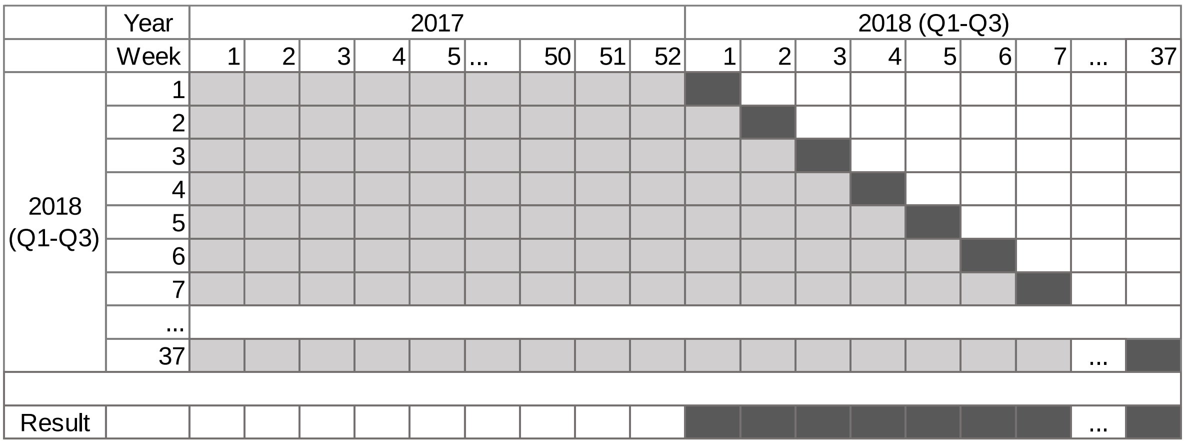

Figure 4: Visualisation of rolling one-step forecast model re-estimation (own illustration).

[4] As France joined the joint auction with the start of 2017, data from before may not include all interdependencies and lead to a wrong model fitting.

SARIMA model. The number of neurons in the hidden layer is set to half of the number of input nodes. For each training data set, 50 networks are estimated with different random starting weights and a logistic activation function. These 50 network models are then averaged to obtain the forecast.

The re-estimation and the number of models complicate a fundamental model interpretation, as model lags, parameters and coefficients vary between the models. However, the focus in this paper is to make the forecast as accurate as possible and re-estimation increases the adaptiveness of the forecast.

4 Results

The goal of this paper is to investigate approaches and configure a suitable model framework to forecast FCR prices. Therefore, in the results section we focus on the comparison of the different approaches and on their performance in forecasting rather than on the detailed discussion of single models and their coefficients' interpretation. However, to gain more insights regarding the interdependencies and predictive power of the single exogenous variables, a detailed investigation of exemplary models from the considered approaches would be easily possible in the present model framework but is not conducted due to conciseness.

Figure 5 shows the time series of the rolling one-step point forecasts for each of the proposed model types. In addition, the rolling forecasts from re-estimated linear regressions (LR) of the dependent variable on the external predictors are shown as a non-auto-regressive benchmark model. The Root Mean Squared Errors (RMSE) comply with the model fit, whereat a RMSE of zero would mean the model matches the realisations perfectly. It can be seen that all proposed models perform reasonably well.

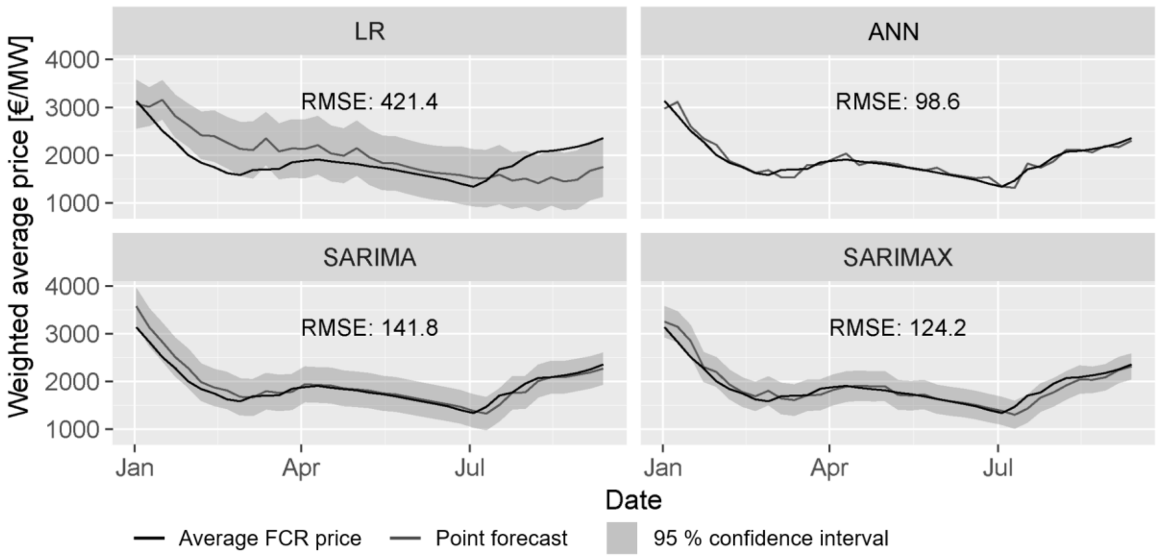

Figure 5: FCR price forecasts[5] in test period Q1-Q3 2018 (own illustration, validation data from [1]).

[5] Confidence intervals are on a 95% level for the econometric approaches. A similar robustness measure for the ANN approach may consist of having 200 networks instead of 50 and to exclude the

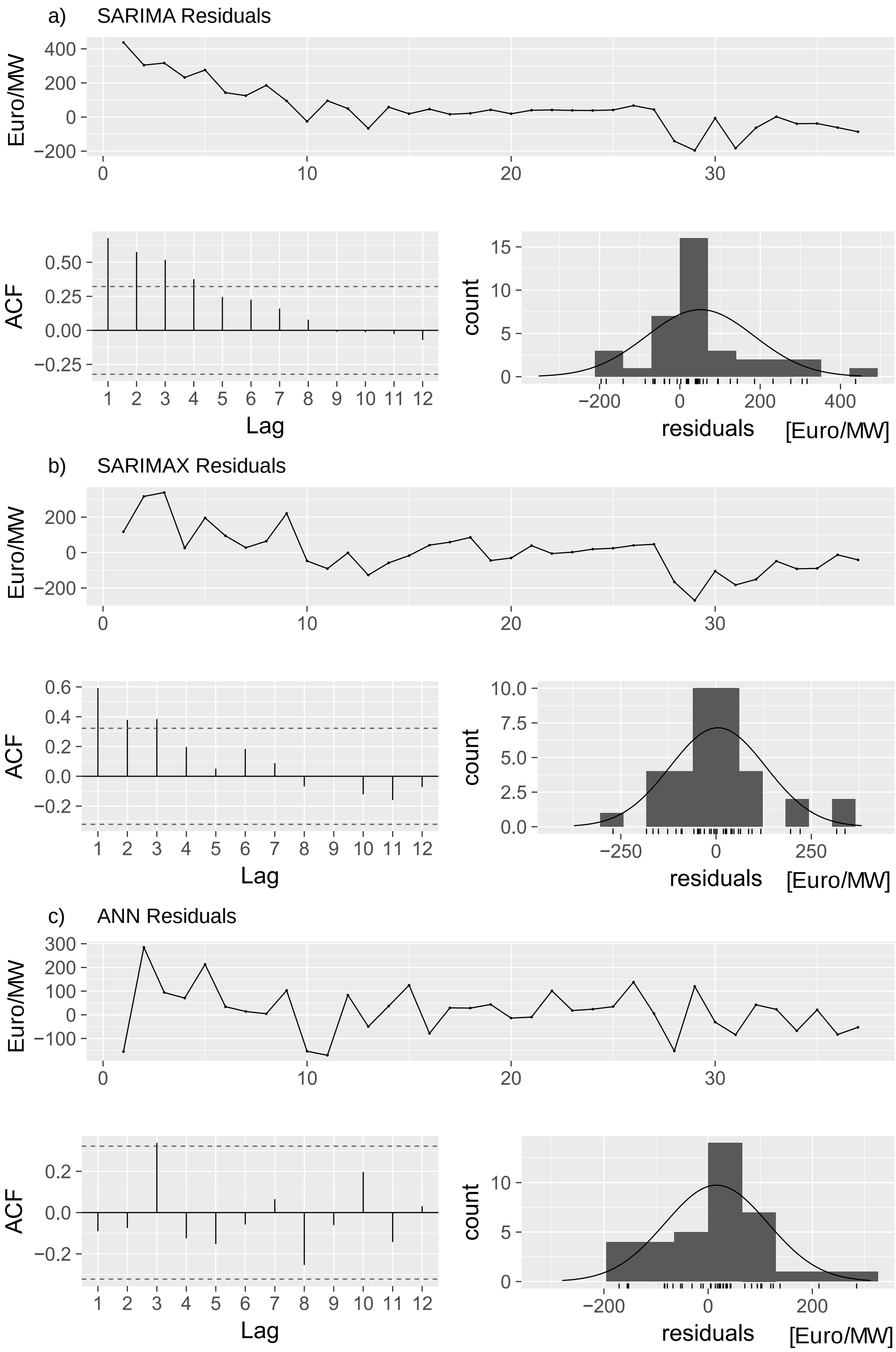

Figure 6: Time series of residuals, the autocorrelation function (ACF) and the density distribution of residuals for a) SARIMA, b) SARIMAX and c) ANN forecasts.

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ten extreme point forecasts (e.g. five highest and five lowest values). However, this methodology is hardly comparable to the confidence intervals of econometric models and was thus excluded to avoid confusion.

A naïve method of always taking the FCR price of the previous week as a forecast, a so-called persistence forecast, yields an RMSE of 144.4, which is slightly worse than the SARIMA forecast. The SARIMAX and ANN forecasts, which combine auto-regressive and external predictors, have a significantly higher forecast quality than the purely auto-regressive SARIMA model and the forecast purely based on exogenous predictors. Actually, with a RSME of 421.4 the forecast quality of the benchmark linear regression is unsatisfactory. The ANN forecasts are on average noticeably closer to the true values than the SARIMAX forecasts. The analysis of the forecast errors emphasises this suggestion. A good forecasting method will yield test residuals which are ideally uncorrelated and unbiased (i.e., have an expected value of zero).

Figure 6 shows the time series of residuals, the autocorrelation function and the density distribution of residuals for the SARIMA; SARIMAX and ANN forecasts. It can be observed that the SARIMA models suffer from a high dependence on previous observations as there is significant auto-correlation in the forecast residuals. Between January and March 2018 the FCR price decreased strongly, so a forecast which relies exclusively on previous observations is more prone to produce large errors which can also be seen in the forecast residual time series. A similar effect can be detected in the SARIMAX residuals. The forecast residuals from the ANN approach in turn display no auto-correlation and appear to be stationary with zero mean.

5 Conclusion and Outlook

In this paper, we investigated approaches to forecast the price of FCR, the fastest control reserve that is jointly procured in weekly tenders by TSOs in Austria, Belgium, France, Germany, the Netherlands and Switzerland. As this research scope was not formerly discussed in literature, several approaches were deployed, considering auto-regressive and exogenous variables. Such a model framework has to our knowledge not been formerly set up or discussed in literature.

The exogenous factors with most explanation power were identified as the price range of the previous tender, the future prices of the German-Austrian and the French market area, the load in the German-Austrian and the French market area and the planned unavailable capacity in Germany. The models based on auto-regressive and exogenous factors are suitable to forecast prices, whereas models solely based on exogenous factors or solely based on auto-regression perform worse. Within the models considering both, the ANN outperformed the SARIMAX.

In the ongoing research, the models will be used as a basis for an agent-based simulation model of the control reserve market. In this context, different instances and configurations of the forecast approaches can generate different price expectations of agents. Combined with the definition of bidding strategies and the diversification of risk affinity, agents participating in the control reserve market can be modelled. In this context, the application of SARIMAX models has the advantage that the models are open to an interpretation of the estimated coefficients, whereas the ANN approach is more of a Black Box approach that yields the best results but lacks in interpretability.

In addition, the market design for FCR is in an ongoing process of change. On the one hand, the involved TSOs aspire to change the product duration from one week to one day by 2019 [15]. This makes the consideration of forecast-based exogenous factors like wind and solar generation necessary in price formation and therefore needs to be included in future studies of FCR prices. On the other hand, a change from pay-as-bid towards uniform pricing is planned [15]. This change introduces a new dependent variable, as there is only the uniform price. However, the approaches deployed in this study are well suited to cope with these changes and to produce reliable forecasts of FCR prices in a modified market design.

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