Vol. 32, No. 4 (2022) | DOI: 10.37190/ord220405

OPEN ACCESS

Operations Research and Decisions

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OPERATIONS RESEARCH AND DECISIONS QUARTERLY

Portfolio management of a small RES utility with a structural vector autoregressive model of electricity markets in Germany

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Abstract

Electricity producers and traders are exposed to various risks, among which price and volume risk play very important roles. This research considers portfolio-building strategies that enable the proportion of electricity traded in different electricity markets (day-ahead and intraday) to be chosen dynamically. Two types of approaches are considered: a simple strategy, which assumes that these proportions are fixed, and a data-driven strategy, in which the ratios fluctuate. To explore the market information, a structural vector autoregressive model is applied, which allows one to estimate the relationship between the variables of interest and simulate their future distribution. The approach is evaluated using data from the electricity market in Germany. The outcomes indicate that data-driven strategies increase revenue and reduce trading risk. These financial gains may encourage energy traders to apply advanced statistical methods in their portfolio-building process.

Keywords: *intraday electricity market, day-ahead electricity market, structural vector autoregressive model, probabilistic forecasting, trading strategy*

1. Introduction

In recent decades, thanks to the development of short-term electricity markets, new trade opportunities have opened for generation utilities and demand units. Their operation is no longer optimized centrally and power plant managers act in the market to maximize utility profits. Market participants can now choose, whether to trade via organized power exchanges such as Nord Pool or EEX in Europe and PJM in the USA, broker platform or to sign over-the-counter (OTC) contracts. Although trade in power exchanges is voluntary, market parties are encouraged to self-balance their positions. This means that no electricity should be left intentionally for the trade on the balancing market [16, 23]. Self-balancing is particularly valid for RES utilities, which generation is based on intermittent energy sources, such as wind and solar [6, 14, 15].

Received 4 July 2022, accepted 14 December 2022, published online 8 February 2023
ISSN 2391-6060 (Online)/

The costs of publishing this issue have been cofinansed by the program *Development of Academic Journals* of the Polish Ministry of Education and Science under agreement No. RCN/SP/0241/2021/1

Table 1. Structure of electricity generation in Germany [%]

Source	Year	
	2015	2020
Fossil	51.36	37.30
Nuclear	0.70	12.53
RES	32.94	50.17
wind	14.32	26.66
solar	6.31	9.99
biomass	7.64	8.79
hydro	3.72	3.48
waste	0.83	0.95

The changes in electricity markets have been motivated and accompanied by dynamic development of generation from renewable energy sources (RES), among which wind, solar and hydro play the most important role. In the year 2020 in Germany, RES accounts for 50.17% of electricity production and has increased by 17.23 percentage points since 2015. Table 1 reveals some more details about the recent changes in the German generation structure. It can be observed that in the years 2015–2022 RES successfully replaced fossil fuels in electricity production. Moreover, when different sources of RES are analyzed, it is clear that the wind experienced the fastest growth, from 14.32% in 2015 to 26.66% in 2020, and has the largest input to the generation mix among RES sources. It is followed by solar and biomass, which shares reached in 2020, 9.99% and 8.79%, respectively.

The increase of RES penetration would not be possible without a variety of support schemes introduced by European countries. First, RES generation is granted priority during the dispatch, ensuring that all green electricity is efficiently traded. Second, different financial incentives, starting with feed-in-tariffs (FIT) have been proposed to increase the profitability of RES investments. In FIT, RES generators are paid a fixed price at a guaranteed level (irrespective of the wholesale price) for the electricity produced and fed into the grid. In Germany, *the 2000 Renewable Energy Act* guaranteed FIT for wind and solar generation for 20 years. For many installations, this two-decade guarantee is going to expire soon. As the result, RES producers will need to sell their generation at market prices either via the power exchange or bilateral contracts. At the same time, one could observe a general change in the approach toward support schemes and the shift from FIT to the feed-in-premium (FIP) mechanism. In the case of FIP, producers receive a premium price, which is a payment (€/MWh) in addition to the wholesale price. This premium can be either fixed (Denmark, Lithuania) or floating (Germany, Greece and the Netherlands among others). It should be noticed that the ongoing changes lead to a closer relationship between the revenues of RES generators and wholesale electricity prices. They encourage financially sustainable investments, which respond to market incentives.

As the result, RES producers become more exposed to various market risks. The major ones are price and volume risks [28]. The price risk reflects the fact that electricity prices are stochastic and depend on the unknown future levels of demand and generation structure [9, 29, 30]. Additionally, electricity producers face now a cascade of trade opportunities, which includes different markets (bilateral, day-ahead, intraday) and contract types. From the perspective of RES utility, the volume risk can be analysed at two levels: state-wise and individual. The uncertainty about the (individual) utility production stems from intermittent weather conditions, which change continuously up to the delivery time. At the same time, the aggregated generation and consumption volumes are affected by a wider range of factors, which include weather conditions, social events, trading strategies and conventional power plant outages. These two types of risks, price and volume, are closely connected with each other. In particular, the aggregated volume risk impacts the variability of electricity prices. This property has recently attracted attention and has been discussed in the literature (see, i.e., [13, 19, 25]). The research indicates that wind and solar forecast errors impact both the variance and the whole distribution of electricity prices and are one of the major factors influencing the spread between the day-ahead and intraday prices [14, 28].

The exposure to price and volume risks leads to a rise in income uncertainty and hence increases the need for appropriate risk management. The reduction of the revenue risk can be obtained in various ways. Kath et al. [11] show that generators can sign a contract with a trading company, which will allow them to sell all the produced electricity at, for example, day-ahead price and therefore limit its trade risk. On the other hand, Maciejowska et al. [20] as well as Janczura and Wójcik [10] suggest that generators can reduce their price uncertainty by an active trade on two markets: day-ahead and intraday market. The results indicate that model-based choice of the market, which offers a higher price, can increase the revenues of the utility and reduce its risk. Similarly, Kath and Ziel [12] show that the choice between different types of contracts in an intraday market (continuous vs. auctions) can be profitable and lead to considerable financial gains.

Although portfolio management seems to be of great importance for practitioners, it has not been studied much in the electricity market literature. Most of the articles address only one source of risk, price or volume. An exception is a paper by Faria and Fleten [4], who propose a model of bidding strategy for a hydro-power plant, which takes into account the stochastic nature of both market prices and generation. Therefore, the main goal of this research is to fill the existing literature gap. In this paper, the structural vector autoregressive (SVAR) model is proposed, which allows one to analyse jointly different types of risk and hence considers the input uncertainty [5]. Four sources of uncertainty are considered: weather conditions, demand shocks and unpredictable behaviour of market participants in day-ahead and intraday markets (called speculative shocks). It is shown that the SVAR model can be used for forecasting and simulating the next-day revenue distribution. The outcomes are finally employed for the selection of the optimal portfolio weights. Similarly to Maciejowska et al. [20], the resulting trade strategies are evaluated with two types of financial measures: average revenue and associated value at risk (VaR).

Vector autoregressive (VAR) models, although widely used in time series analysis, have not been explored much in modelling electricity markets. Silva et al. [27] apply structural VAR (SVAR) to analyze the relationship between economic growth and electricity prices. Bernstein and Madlener [2] used yearly data to build a vector error correction model (VECM) to asses the price elasticity of electricity. In both articles, the macroeconomic approach is adopted and low-frequency data are analyzed. The higher frequency information with the hourly or daily resolution has also been explored [18, 24, 28]. Spodniak et al. [28] use VAR models to assess the relevance of different short-term markets, such as day-ahead, intraday and balancing market. They show that due to an increase in the wind power share in the generation mix, the markets closer to the delivery are becoming more important. The impact of different market shocks on day-ahead electricity prices is described with the SVAR model in [18, 24]. Paschen [24] uses the estimates of the SVAR model to obtain impulse response functions and to analyse dynamic interrelations between spot prices and RES power. Finally, Maciejowska [18] shows that speculative shocks, defined as the unpredictable behaviour of electricity traders, have the largest share in the electricity price variance. Up to the author's knowledge, data on exploring the potential usage of the SVAR model in the decision process of an electricity generator has not been published so far.

In the article, Section 2 describes briefly the data used in the analysis. In Section 3, an SVAR model of the electricity market is presented, which is next applied to predict a revenue distribution and to support the decision process of a RES utility (Section 4). Section 5 presents the results of the experiment and a statistical comparison of the performance of proposed trading strategies. Finally, Section 6 concludes.

2. Data

In this research, the electricity market in Germany is considered. The analysis is based on data published by TSOs and EPEX exchange and covers the period from 01-Oct-2015 to 31-Sep-2019. Since Austria separated itself from the German bidding zone, only the data on the generation level and structure in Germany is used. The data sets consist of day-ahead (DAth) and intraday (IDth) prices, with the latter being described by an $ID3$ index (volume-weighted prices from the last 3 hours of trade). The electricity prices are complemented by information on actual levels and system forecasts of fundamental variables: the total load (Lth) and RES (RESth) generation. In the remaining part of the paper, the index h stands for an hour and t for a day.

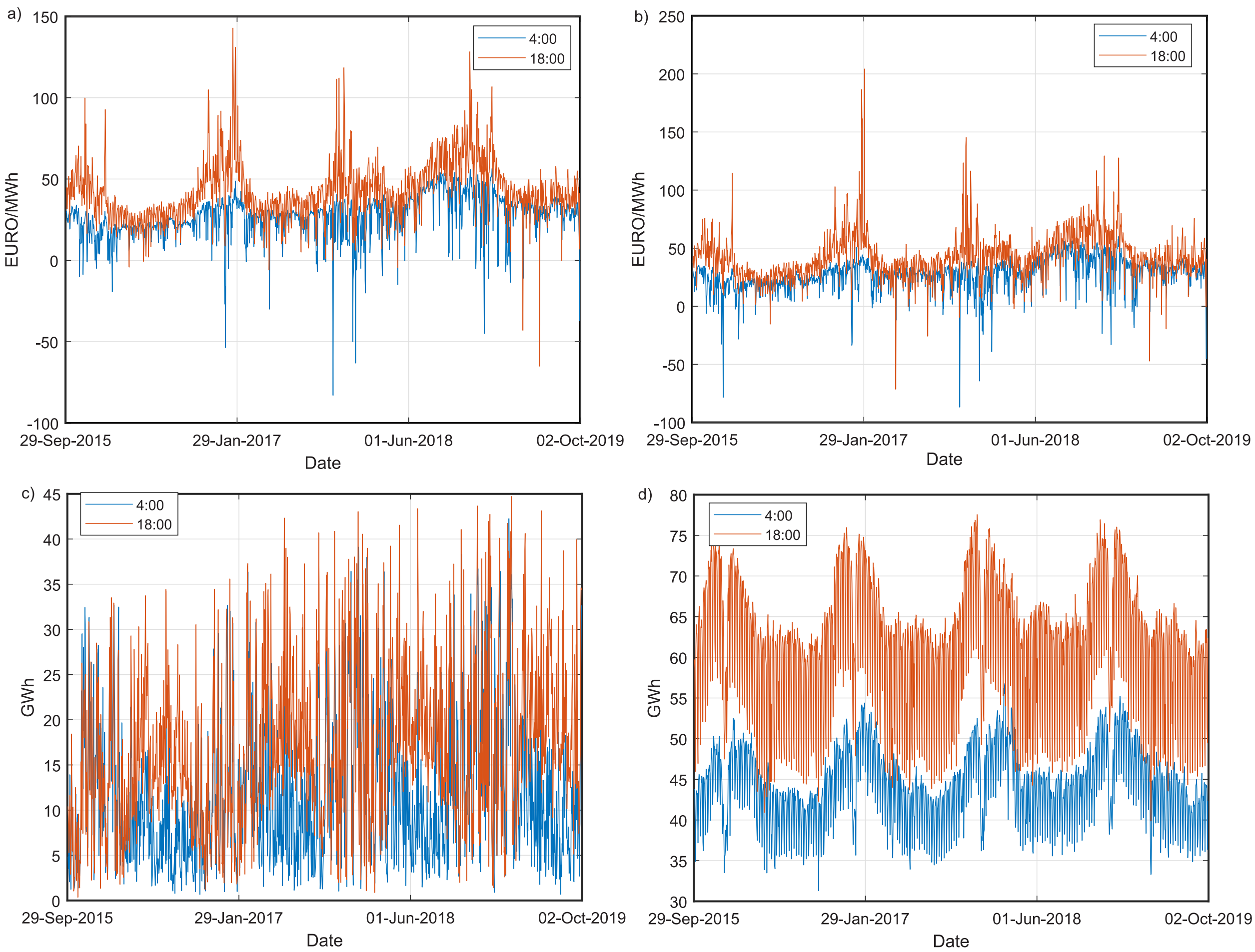

Figure 1. Day-ahead (a) and intraday (b) electricity prices, RES generation (c) and load for hours 4:00 and 18:00 (d)

The properties of times series describing the electricity market in Germany have been extensively studied in the literature. It is well documented that both total load and electricity prices have a strong seasonal pattern. They are on average the highest on working days, during peak hours. The exemplary time plots of day-ahead and intraday prices together with total load and RES generation are presented in Fig 1. Two hours are shown, $h = 4, 18$, which represent the peak and the off-peak periods of a day. They confirm the weekly and yearly seasonal behaviour of electricity generation. Additionally, it can be observed that day-ahead and intraday prices co-move together, with the intraday prices being more volatile. Finally, RES generation reveals different fluctuation patterns, with only minor differences between night and day hours and high variability.

Table 2. Statistical properties of the data

	RES	Load	DA	ID
Mean	16.40	61.97	36.11	36.24
St. dev	8.82	8.18	15.61	17.06
ADF	24	18	24	24

The statistical properties of the data are presented in Table 2. ADF indicates the number of hours for which the test rejects the null of a unit root. First, the mean and the standard deviation of the variables of interest are computed separately for each hour. The table shows their average values across the day. The DA prices are on average slightly lower than ID prices, but also less volatile. Finally, the results of the augmented Dicky–Fuller (ADF) test for the presence of unit roots are presented. The majority of analyzed data are stationary. This could be due to the relatively short period of time – four years – used for analysis. The result is important for the modelling approach presented below, as it supports the usage of a VAR model for the data in levels.

3. SVAR model of electricity market

In this research, the VAR model is used to describe the joint behaviour of electricity prices and generation, which in turn impact the revenue of a small RES utility. The literature (see [30] for a review) indicates that the electricity market has a strong daily seasonality, which impacts not only the level of prices and generation but also its dynamics. Therefore each hour is typically modelled separately (see [32] for discussion). Here, this implies that the VAR model is built and estimated independently for each hour, h.

In order to capture the major stochastic shocks influencing the variables of interest, a four dimension model is applied:

$$Y_{t,h} = A_{0,h}X_{t,h} + \sum_{p=1}^{7} A_{p,h}Y_{t-p,h} + \varepsilon_{t,h} \tag{1}$$

where $Y_{t,h} = (RES_{t,h}, L_{t,h}, DA_{t,h}, ID_{t,h})'$ is a vector of endogenous variables. Notice that the vector $Y_{t,h}$ could be extended to include a generation of a particular RES utility, $G_{t,h}$ if such information is accessible. Then, $Y_{t,h} = (G_{t,h}, RES_{t,h}, L_{t,h}, DA_{t,h}, ID_{t,h})'$. Since in this research no such data are available, it is assumed that an exemplary RES producer owns a few wind and solar farms, which are spread across Germany. For simplicity, it is assumed that $G_{t,h}$ is proportional to the aggregated level of

RES generation, with $G_{t,h} = \rho RES_{t,h}$. As the result, $RES_{t,h}$, represents in the model both, the total and the individual generation of RES.

The vector $X_{t,h}$ consists of dummy variables indicating weekdays, TSO forecasts of RES generation and the total load. Additionally, some nonlinear transformation of lagged prices (similar to [22, 29, 32]) are used: $DA_{min,t-1}$ (a minimum price from the last day), $DA_{max,t-1}$ (a maximum price from the last day) and $DA_{t-1,24}$ (the last known price). The parameters $A_{0,h}$ and $A_{p,h}$ are matrices of dimensions (4×12) and (4×4), respectively. They are estimated separately for each hour, h. The residuals, $\varepsilon_{t,h}$, are (4×1) random vectors with zero mean and a variance-covariance matrix Σ_h. Since (1) is a reduced form of the VAR model, then the residuals are allowed to be cross-correlated and hence the Σ_h is not diagonal.

The reduced form model, although useful for point forecasting of endogenous variables, is not suited for risk analysis – for example impulse responses or simulations. Therefore, a structural extension of the model (1) is used. The SVAR model could take various forms (see [17]). Here, the B-model is adopted, which focuses on residuals of the model (1). The SVAR model assumes that the within-sample errors, $\varepsilon_{t,h}$, are a linear transformation of structural shocks, $u_{t,h}$, which are uncorrelated and have a diagonal variance-covariance matrix, Λ_h. The relationship between reduced form and structural shocks is described by the following equation

$$\varepsilon_{t,h} = B_h u_{t,h} \tag{2}$$

The matrix B_h is called an instantaneous effect matrix, because it describes how structural shocks affect endogenous variables in the current time period, t. For example, $B_{23,h}$ describes the impact of the third structural shock, $u_{3,th}$ on the second element of $Y_{t,h}$, which is the total load. Notice that equation (2) implies that $\Sigma_h = B_h \Lambda_h B_h'$, so there is a direct relationship between B_h and the variance of errors $\varepsilon_{t,h}$. It is typically assumed that either structural shocks have an identity variance-covariance matrix, $\Lambda_h = I$, or the diagonal elements of B_h are equal to one. Here, the first approach is adopted. Since the structural shocks are assumed to be uncorrelated, which in the Gaussian framework implies independence, their behaviour is much easier to model and predict. They could be also simulated separately. Unfortunately, the SVAR model cannot be directly estimated due to a lack of identification. As discussed in the literature (see [17] for a comprehensive discussion on VAR models), the structural model requires the estimation of K^2 elements of the B matrix, where K is the number of endogenous variables. In the current study, $K = 4$, hence the structure is defined by 16 parameters. At the same time, the variance-covariance matrix Σ of the reduced form, due to its symmetry, consists of only $K(K+1)/2 = 10$ parameters. This implies that there is not enough information to identify the structural parameters. So additional $K(K-1)/2$ assumptions need to be imposed, which will restrict the parameter space. In the presented model, six identification restrictions are needed to ensure model identifiability.

In this research, four structural shocks are considered: weather shock $u_{1,th}$, demand shock $u_{2,th}$, day-ahead speculative shock $u_{3,th}$ and intraday speculative shock $u_{4,th}$. The energy market has its particular features, which help to recover the structure of the SVAR model. First, due to the dispatch priority and support schemes, RES generation depends neither on demand nor on price shocks. Second, the literature indicates the limited price elasticity of demand, because market participants require time to adjust their production to the market situation. In particular, the demand response to the unpredicted price innovations is assumed to be insignificant. Finally, the spot prices are set day ahead, before the intraday trade rises and hence it could be assumed that they do not depend on the intraday speculative shocks. As the result, the instantaneous effect matrix becomes a lower triangular

$$B_h = \begin{bmatrix} * & 0 & 0 & 0 \\ * & * & 0 & 0 \\ * & * & * & 0 \\ * & * & * & * \end{bmatrix} \tag{3}$$

The zeros in the above matrix correspond to the "no impact" restrictions. Notice that in the presented solution, the ordering of endogenous variables and structural shocks play an important role. The model implies, for example, that the shock $u_{1,\,th}$ – which is the weather shock – influences all variables, whereas $u_{4,th}$ – which is the intraday speculative shock – impacts only intraday prices.

4. Decision problem of a RES utility

In this article, the SVAR model presented in Section 3 is used for designing trading strategies of a RES utility. Additionally, it is assumed that the generator participates in the day-ahead and the intraday market and is small enough not to impact directly the market prices. It does not receive FIT and hence its revenue is related to wholesale prices. The utility needs to place an order in the day-head market at noon of the day before the delivery. Due to the stochastic nature of RES, the offered generation differs from the actual product and therefore it needs to trade the difference between the scheduled and the final generation in the intraday market. The power plant self-balances its position and therefore no trade is left for the balancing market.

For illustrative purposes, it is assumed that $G_{t,\,h} = \rho\,\mathrm{RES}_{t,\,h}$. In order to ensure that the RES producer has a minor influence on market prices, the ρ is set to equal 0.5%. This implies that in the year 2018, it generated around 85 MWh per hour and accounted for 0.2% of the total electricity production in Germany.

The utility needs to choose on the day $t-1$, which part, g, of the expected generation, $\hat{G}_{t,\,h}$ is offered in the day-ahead market. The remaining part of the production, $G_{t,\,h} - g\hat{G}_{t,\,h}$, is sold in the intraday market. Notice that in general, the variable g may change across days and hours. Since the utility focuses on the real trade, it is assumed that it does not speculate and hence $g \in [0, 1]$. As the result, the revenue from the trade becomes

$$\pi_{t,\,h}(g) = g\hat{G}_{t,\,h}DA_{t,\,h} + (G_{t,\,h} - g\hat{G}_{t,\,h})ID_{t,\,h} \tag{4}$$

It should be mentioned here that the values of prices and generation are not known at the moment of taking the decision. They depend on stochastic factors, which change throughout the day, such as the weather condition and human behaviour. As the result, the actual level of revenue, $\pi_{t,\,h}(g)$ becomes random. It is expected that its distribution is non-normal, as it includes both the level and the product of a few random variables. Moreover, since the generation and electricity price forecast errors are allowed to be correlated, the expected level of revenue will generally be different than $E(\pi_{t,\,h}(g)) \neq g\hat{G}_{t,\,h}E(DA_{t,\,h}) + (E(G_{t,\,h}) - g\hat{G}_{t,\,h})E(ID_{t,\,h})$.

4.1. Trading strategies

The utility places its order in the DA market on the day preceding the delivery and this transaction cannot be changed, as the new information on weather conditions and prices arrive. Therefore, its revenue depends directly on the amount of electricity sold there, $g\hat{G}_{t,h}$. As mentioned before, g does not have to be constant and may adjust to the market situation. Therefore in the remaining part of the paper, it will be indexed with a day (t) and an hour (h): $g_{t,h}$.

4.1.1. Simple DA and ID strategies

First, two simple approaches are considered: day ahead strategy, which assumes that $g_{t,h} = 1$ and intraday strategy, for which $g_{t,h} = 0$. They are two boundary approaches, which assume a fixed value of the share $g_{t,h}$ that does not depend on market conditions. In the first case, all the predicted production is sold on DA, whereas in the second case the utility decides to wait with the trade till the next day and leave all the generation for the intraday market.

4.1.2. Data driven strategies

Next, data-driven strategies of choosing the level of $g_{t,h}$ are proposed, which utilize the estimated structure of the forecast errors. Using a bootstrap simulation, the optimal proportion of generation offered in the DA market is selected to either maximize the expected revenue ($E\pi(g_{t,h})$) or to minimize the risk. Here, the risk is evaluated with two measures: the Sharpe ratio ($SR(g_{t,h})$) and value-at-risk ($VaR(g_{t,h})$), which have been shown relevant and useful by the financial literature [1, 7, 8, 10, 26].

In this research, a bootstrap procedure is proposed to generate the distribution of $Y_{t,h}$. This allows us to approximate the distribution of the revenue for different levels of g and to optimize its value. The algorithm consists of the following steps

1. For a selected hour h and the calibration window $\{t_0, t_0 + 1, \ldots, t-1\}$ estimate the parameters of SVAR model: $\hat{A}_{p,h}$ for $p = 0, 1, \ldots, 7$ and the instantaneous effect matrix $\hat{B}_h$.
2. Calculate the point forecasts of $\hat{Y}_{t,h}$ according to (1) as
$$\hat{Y}_{t,h} = \hat{A}_{0,h} X_{t,h} + \sum_{p=1}^{7} \hat{A}_{p,h} Y_{t-p,h} \tag{5}$$
and $\hat{G}_{t,h}$ as $\hat{G}_{t,h} = \rho \hat{RES} = \rho \hat{Y}_{1,t,h}$.
3. Compute residuals $\hat{\varepsilon}$ of a reduced model (1) and corresponding structural shocks $\hat{u} = \hat{B}_h^{-1}\hat{\varepsilon}$.
4. Approximate the distribution of the next day $Y_{t,h}$ and profits $\pi_{t,h}(g)$ using a bootstrap sampling of structural shocks. For each iteration $b = 1, \ldots, B$
   - Pick independently a realization of each shock and obtain a (4×1) vector $\tilde{u}^{(b)}$.
   - Transform structural shocks into forecast errors: $\tilde{\varepsilon}^{(b)} = \hat{B}_h \tilde{u}^{(b)}$.
   - Calculate $\tilde{Y}_{t,h}^{(b)} = \hat{Y}_{t,h} + \tilde{\varepsilon}^{(b)}$, where $\tilde{Y}_{t,h}^{(b)} = (\tilde{RES}_{t,h}^{(b)}, \tilde{L}_{t,h}^{(b)}, \tilde{DA}_{t,h}^{(b)}, \tilde{ID}_{t,h}^{(b)})'$, and $\tilde{G}_{t,h}^{(b)} = \rho \tilde{RES}_{t,h}^{(b)}$.
   - For the chosen level of g compute the corresponding profit $\tilde{\pi}_{t,h}^{(b)}(g)$ according to (4).

5. Estimate the expected value and the variance of incomes, $E\pi_{t,h}(g)$ and $\sigma^2_{t,h}(g)$ as the mean and the mean squared deviation of $\tilde{\pi}^{(b)}_{t,h}(g)$ across b. Using this information, compute the Sharpe ratio as $SR_{t,h}(g) = E\pi_{t,h}(g)/\sigma_{t,h}(g)$ and approximate $VaR^{\tau}_{t,h}(p)$ by a τ quantile of $\tilde{\pi}^{(b)}_{t,h}(g)$.

The selection of the level of $g_{t,h}$ depends on the optimal condition considered. The first approach picks $g^*_{t,h}$, which maximizes the expected revenue $E\pi_{t,h}(g)$. This method, although profitable, may result in an increase in the transaction risk. Therefore, alternative trading strategies are also examined, which aim at minimizing the risk by choosing $g^*_{t,h} = argmax_g SR_{t,h}(g)$ or $g^*_{t,h} = argmax_g VaR^{\tau}_{t,h}(g)$. The brief description of the approaches together with their notation is presented in Table 3.

Table 3. Trading strategies

Name	Description	Optimality criteria	g
S_{DA}	sell the expected generation on DA market	–	1
S_{ID}	sell all the generation on intraday market	–	0
$S_{E\pi}$	maximise expected profit	$\max E\pi(g)$	$g^*_{t,h}$
S_{SR}	maximise Sharpe ratio	$\max SR(g)$	$g^*_{t,h}$
S_{VaR}	maximise the value of risk for the 5% quantile	$\max VaR_{0.05}(g)$	$g^*_{t,h}$

4.2. Evaluation of trading strategies

The trading strategies presented above can be compared according to various dimensions. Here, three features are used to evaluate their performance: the level of revenue, its predictability and variability.

4.2.1. The level of income

In this article, the average hourly revenue is used to analyze the performance of the presented approaches. It is computed as follows:

$$\bar{\pi} = \frac{1}{T_{\text{eval}} \times 24} \sum_{t,h} \pi_{t,h}(g_{t,h}) \tag{6}$$

where T_{eval} is the number of days used for evaluation. In order to verify, if a chosen strategy, i, yields a higher average income than the strategy j, a new variable is defined

$$d_{t,h} = \pi_{t,h}(g^{(i)}_{t,h}) - \pi_{t,h}(g^{(j)}_{t,h})$$

if both strategies are characterized by the same expected value then $Ed_{t,h} = 0$. Hence, the natural hypothesis in this setup are $H_0 : Ed_{t,h} = 0$ and $H_1 : Ed_{t,h} > 0$. Under the null, both strategies provide the same average revenue, whereas under the alternative, the strategy i is more profitable than j. In order to verify the hypothesis, a Diebold–Mariano [3] type testing procedure is applied to the mean daily level of $d_{t,h}$: $d_t = \frac{1}{24}\sum_{h=1}^{24} d_{t,h}$. The variable d_t can be viewed as a counterpart of the loss differential, e.g., a difference of squared forecast errors. The statistic takes the form

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi \hat{f}_d(0)}{T_{\text{eval}}}}} \tag{7}$$

where $\bar{d}$ is the average value of d_t and $\hat{f}_d(0)$ is an estimator of spectral density of d_t at frequency 0. As $2\pi\hat{f}_d(0)/T_{\text{eval}}$ is an estimator of the variance of $\bar{d}$, DM converges asymptotically to a standard normal distribution, $N(0, 1)$.

4.2.2. Risk

The risk associated with a strategy is evaluated according to two features: the possibility to predict accurately the next day's revenue and the variability of the income. In order to assess the revenue forecast quality, we use the outcomes of an SVAR model. The revenue predictions are calculated as the average of $\tilde{\pi}^{(b)}(g)$ across bootstrap iterations:

$$\hat{\pi}_{t,h} = \frac{1}{B}\sum_{b=1}^{B}\tilde{\pi}^{(b)}_{t,h}(g_{t,h}) \tag{8}$$

First, it is checked, how much the predicted revenue differs from its actual values, $\pi_{t,h}(g_{t,h})$. In this research, similarly to other EFP papers, the forecast quality is evaluated with root mean squared error ($RMSE$) and mean absolute error *(MAE)*

$$RMSE = \sqrt{\frac{1}{24T_{\text{eval}}}\sum_{t,h}(\pi_{t,h} - \hat{\pi}_{t,h})^2} \tag{9}$$

$$MAE = \frac{1}{24T_{\text{eval}}}\sum_{t,h}|\pi_{t,h} - \hat{\pi}_{t,h}| \tag{10}$$

In order to statistically verify if forecasts stemming from two different strategies, i nad j, are equally accurate, the DM test is applied to the following loss differentials:

$$d_t = \frac{1}{24}\sum_{h=1}^{24}(u^2_{t,h}(i) - u^2_{t,h}(j))$$

for $RMSE$ and

$$d_t = \frac{1}{24}\sum_{h=1}^{24}|u_{t,h}(i) - u_{t,h}(j)|$$

for MAE measure.

The $u_{t,h}(i)$ and $u_{t,h}(j)$ are forecast errors of analyzed strategies: $u_{t,h}(i) = \pi_{t,h}(g^{(i)}_{t,h}) - \hat{\pi}_{t,h}(g^{(i)}_{t,h})$ and $u_{t,h}(j) = \pi_{t,h}(g^{(j)}_{t,h}) - \hat{\pi}_{t,h}(g^{(j)}_{t,h})$. The test statistics have a form analogous to (7).

Finally, the risk associated with the variability of income is measured by the VaR of revenues for a given hour. In order to aggregate the results, the average VaR is used to compare the outcomes of different strategies.

5. Results

5.1. Experiment design

In order to assess different trading strategies, a forecasting experiment is run, in which a moving window methodology is applied. In the experiment, the calibration window includes 731 observations and the results are assessed with the last two years from 01-Oct-2017 to 31-Sep-2019 (T_{eval}=730 observations). Moreover, in order to bring the experiment as close as possible to the empirical problem, different information sets are used for hours before and after the time of taking the decision. In this work it is assumed that the generator places an order on the DA market at 12:00. Therefore, when performing predictions it knows the actual generation and intraday prices only for hours from midnight till 10:00. For the remaining hours, the actual values ($L_{t-1,h}$, $RES_{t-1,h}$) are not known and are replaced by their TSO predicted levels (see [21] for more details). In the case of $ID_{t-1,h}$, which is also unavailable, it is assumed that it has no impact on endogenous variable and hence the last column of $A_{1,h}$ matrix is set to equal zero. Finally, following the energy forecasting literature [22, 29, 31], three lags are selected in the VAR model: $p = 1, 2, 7$.

5.2. Comparison of trading strategies

Let us first look at the aggregated results for each trading strategy. The outcomes are reported in Table 4, in which the second column presents the average hourly revenue, $\bar{\pi}$. The remaining three columns focus on the risk that is measured by $RMSE$ and MAE of revenue forecasts and $VaR_{1\%}$ and $VaR_{5\%}$ of income. It should be noticed that the benchmark results of S_{DA} strategy are expressed in nominal values. The remaining outcomes are presented relative to the benchmark, as the percentage difference ($\%\Delta$). Hence for all the strategies, apart from S_{DA}, values lower than zero indicate that the given strategy reduces the indices and larger than zero prove the opposite.

Table 4. The average hourly revenue and risk measures

Strategy	$\bar{\pi}$	$RMSE$	MAE	$VaR_{1\%}$	$VaR_{5\%}$
S_{DA}	3215.6	1196.0	635.5	–1803.1	758.7
			$\%\Delta$		
S_{ID}	1.20	8.95	7.46	–39.96	–1.04
$S_{\text{E}\pi}$	1.84	–3.24	0.66	–4.13	7.07
S_{SR}	1.28	–8.00	–6.67	19.51	10.29
S_{VaR}	0.91	–6.50	–6.29	–4.44	6.09

The analysis of simple strategies, which assume a constant level of $g_{t,h}$, confirms that the transactions made in the ID market are slightly more profitable than in the DA market. However, the rise of the average revenue in S_{ID} is achieved at the cost of higher risk. The revenue forecasts suffer from the loss of accuracy (RMSE increases by 9% and MAE by 7.5% as compared to S_{DA}). Moreover, the income itself is substantially more volatile – the $VaR_{1\%}$ drops by almost then 40%.

At the same time, the data-driven approaches provide results characterized by a higher income and lower risk than the benchmark. As expected, the $S_{\text{E}\pi}$ strategy allows one to earn the largest revenue among all the strategies. It reduces RMSE but its impact on risk is mixed: it lowers $VaR_{1\%}$ and increases $VaR_{5\%}$. The S_{VaR} strategy, which aims at maximizing the $VaR_{5\%}$ of revenue, leads to a rise of income by less than 1%, which is the weakest result among the data-driven approaches. It provides more accurate predictions than the simple DA strategy and reduces RMSE and MAE by more than 6%. Similar to the $S_{\mathrm{E}\pi}$ case, its impact on risk is ambiguous.

Finally, the strategy based on the Sharpe Ratio provides the most promising results. It allows one to increase the revenue and at the same time reduces the risk measure by both RMSE and VaR. The decrease in uncertainty is substantial, as it reduces RMSE and MAE by 8% and 6.7%, respectively. Moreover, it increases 1% and 5% VaR by 19.5% and 10.3%.

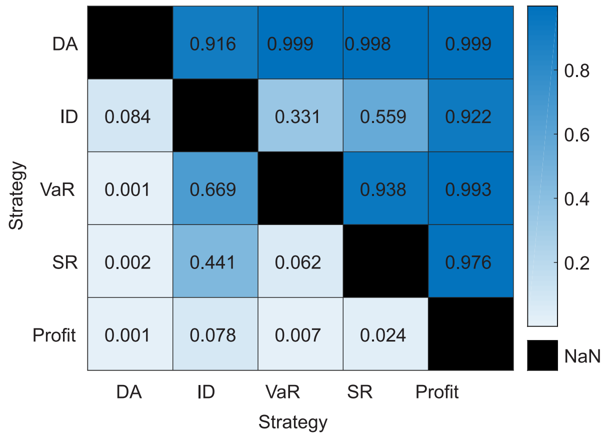

Figure 2. Results of equal profitability test: p-values

Figure 2 presents the asymptotic p-values of test statistics used to compare the profitability and Figure 3 depicts a comparison of RMSE (left panel) and MAE (right panel) forecast accuracy measures. It should be recalled that if the p-value of $DM_{i,j}$ statistic is smaller than 10%, then it implies that the strategy i provides a higher revenue or more accurate predictions than the strategy j. The results confirm previous outcomes that all strategies provide higher income than the benchmark, S_{DA}. Moreover, $S_{\mathrm{E}\pi}$ (denoted on plots as Profit), brings the largest revenue among the presented approaches. When the RMSE and MAE of forecast errors are considered, the outcomes show that S_{DA} allows one to predict the next day's revenue more accurately than S_{ID}, which is the worst strategy according to this measure. Finally, the data-driven methods aiming at minimizing the risk lead to a significant reduction of both forecast accuracy measures.

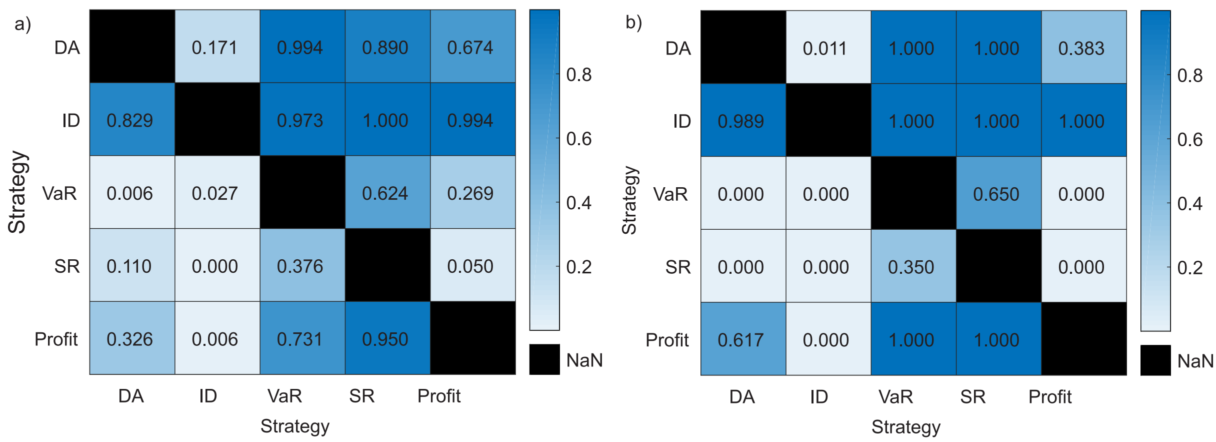

Figure 3. Results of equal forecast accuracy test for the loss functions: a) RMSE, b) MAE: p-values

To sum up, the aggregate results indicate that using a bootstrap method based on the SVAR model for forecasting generation and constructing trading strategies could bring additional profit and at the same time reduce the risk. Hence, it is preferable from the perspective of a small RES utility. Among the presented approaches, S_{SR} is the most attractive one. It does not only increase substantially VaR but brings on average 41.16 € more revenue per hour than the benchmark, which is equivalent to an increase of profit within two years by 721 117.59€.

5.3. Distribution of predicted generation g

Let us now look more into the details of the presented outcomes. First, the data-driven approaches allow one to choose a proportion of predicted generation, which is offered in the DA market. Table 5 shows the average level of optimal $g_{t,h}$ for different strategies ($\bar{g}$) together with the proportion of its values in three groups: $g = 0$, $0 < g < 1$ and $g = 1$. All the quantities are expressed in % points.

Table 5. The averaged proportion of generation offered on DA market [% points]

Strategy	$\bar{g}$	$g = 0$	$0 < g < 1$	$g = 1$
S_{DA}	100.0	0.000	0.000	100.0
S_{ID}	0.000	100.0	0.000	0.000
$S_{E\pi}$	49.05	50.95	0.000	49.05
S_{SR}	51.36	12.47	84.46	3.08
S_{VaR}	52.72	9.68	85.84	4.48

It is clear that simple strategies provide two boundary outcomes with $\bar{g} = 1$ or $\bar{g} = 0$. This is due to the fact that for these two approaches all the predicted generation is offered either in the DA or ID market. The more complex results are observed for the data-driven strategies, for which the average level of g oscillates around 50%. First, it can be noticed that in the case of $S_{E\pi}$ strategy $g_{t,h}$ takes only the extreme values: 0 or 1. It selects the ID market at 50.95%, which confirms the previous findings that indicate the larger profitability of this market.

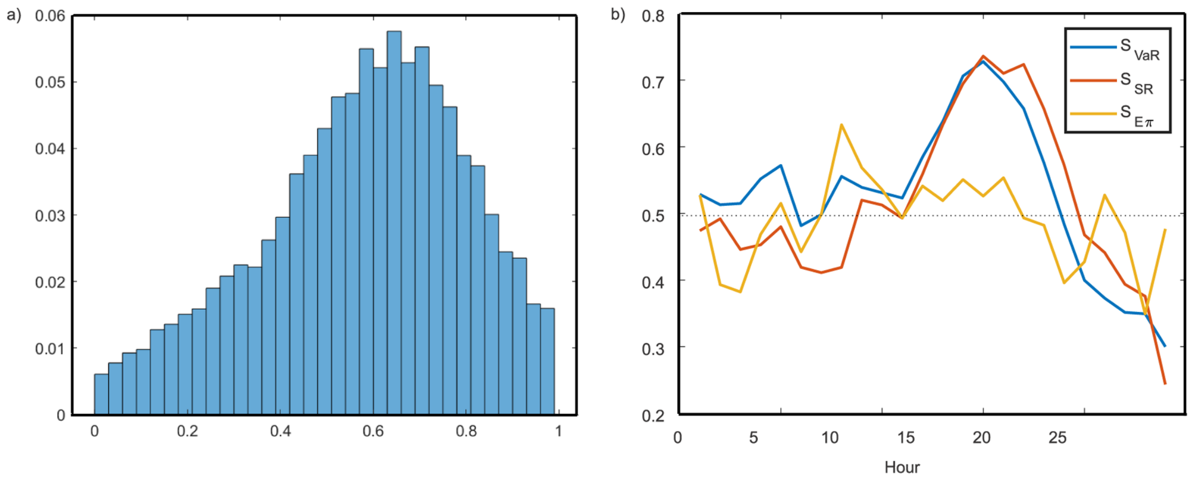

Figure 4. Distribution of a share of predicted generation offered on a DA market, $g_{t,h}$
a) frequencies of g values such that $0 < g_{t,h} < 1$ for a S_{SR} strategy,
b) average value of $g_{t,h}$ across hours

When the strategies aiming at minimizing the risk, S_{SR} and S_{VaR}, are considered, it can be observed that the algorithm selects $g_{t,h} = 0$ and $g_{t,h} = 1$ in around 11% and 4% cases, respectively. Hence, for around 85% of hours, the proportion of generation soled in the DA market falls into the interval $(0, 1)$. The distribution of $0 < g_{t,h} < 1$ for S_{SR} is depicted in the left panel of Figure 4. The plot shows that in the majority of cases, $g_{t,h}$ takes the value between 0.5 and 0.8. Moreover, its distribution is skewed to the right indicating that the DA market is more attractive than the ID one.

The average levels of $g_{t,h}$ across 24 hours are presented in the right panel of Figure 4. The riskiest, $S_{E\pi}$ strategy is characterized by lower values of g and hence tends to sell a larger share of the generation in the ID market than S_{VaR} and S_{SR}. When these two are considered, it can be observed that the highest average value of g is obtained for hours 15–17, when on average more than 70% of predicted generation is offered in the DA market. On the contrary, during the evening hours, from 19–24, these strategies suggest selling the majority of the production in the ID market. For night and early morning hours, the results are mixed, as the average value of g is close to 50%.

6. Conclusions

The changes in the electricity markets expose RES generators to various risks, among which price and volume risk play a vital role. RES generators, which revenue depends on the market prices and the offered quantity, can now actively build a portfolio from different types of contracts. In this research, it is assumed that it trades produced electricity either in the day-ahead or intraday market. It can be noticed that due to intermittent generation and stochastic electricity prices, the entrepreneur acts under strong uncertainty.

In this research, it is assumed that the trading portfolio constructed by the utility depends on two major factors: the predicted level of production and the chosen share of generation, $g_{t,h}$, offered in the DA market. Since the utility does not speculate, it is assumed that $g_{t,h}$ belongs to an interval $(0, 1)$. As a result, two types of trading strategies are considered: simple strategies – which assume a fixed value of $g_{t,h}$ – and data-driven strategies. In the latter one, the SVAR model is used to predict the future level of generation and to select an optimal level of $g_{t,h}$ in order to either maximize the revenue or minimize the transaction risk.

The performance of the presented trading strategies is next compared using the data from the electricity market in Germany. The results of the research indicate that the transactions in the ID market are on average more profitable than in the DA market. They are however burden with a significantly larger risk. Second, the data-driven strategies provide revenues larger than the benchmark, S_{DA}, strategy and at the same time allow one to reduce risk measured by the predictability (RMSE, MAE) of a next-day revenue and its variability (VaR). Among the proposed approaches, the strategy maximizing the Sharpe Ratio is the most promising one, as it provides the most robust outcomes.

Finally, the selected shares of predicted generation offered in the DA market, $g_{t,h}$, are analyzed. The results show that the strategy aiming at maximizing the profit chooses only the two boundary values of $g_{t,h}$ and hence offers all the forecasted production in either the DA or ID market. On the contrary, approaches minimizing the risk, are more prone to build portfolios from both markets at the same time.

This research provides a promising approach for constructing the trading portfolio of a small RES producer. This comprehensive method allows one to explore information on different aspects of the market: the structure of generation and electricity prices. The results indicate that using such a diversified information set can lead to a significant increase in profits and a reduction of transaction risk. Finally, the proposed approach can be further extended to allow for other types of contracts or trading strategies.

Acknowledgement

This work was partially supported through SONATA grant no. 2016/21/D/HS4/00515.

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