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A looming revolution: Implications of self-generation for the risk exposure of retailers

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Abstract

Managing the risk associated with uncertain load has always been a challenge for retailers in electricity markets. Yet the load variability has been largely predictable in the past, especially when aggregating a large number of consumers. In contrast, the increasing penetration of unpredictable, small-scale electricity generation by consumers, i.e. self-generation, constitutes a new and yet greater volume risk. Using value-at-risk metrics and Monte Carlo simulations based on German historical loads and prices, the contribution of decentralized solar PV self-generation to retailers' load and revenue risks is assessed. This analysis has implications for the consumers' welfare and the overall efficiency of electricity markets.

Keywords: Electricity market, Solar photovoltaic, Self-generation, Retailers' risk, Monte Carlo CVaR

JEL classification: C10, C50, G10, Q42, Q48

1 Introduction

Unlike intermediaries in other commodity markets, retailers in competitive electricity markets are exposed to both volume and price risks (Weron, 2007; Boroumand and Zachmann, 2012;

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Boroumand et al., 2015). A crucial aspect for hedging these risks is the growing penetration of unpredictable, small-scale electricity generation from renewable energy sources (RES), such as wind and solar, in the residential sector, namely self-generation, and the consequent greater self-sufficiency of consumers. Self-sufficiency refers to the extent to which self-generation satisfies the electricity demand (Schreiber and Hochloff, 2013; Luthander et al., 2015). While they can be seen as energy conservation and have a considerably high economic value for energy systems, RES may critically affect the retailers' risks exposure. Especially, rooftop solar photovoltaic (PV) systems are characterized by a high correlation with weather conditions, high volatility over time and spatial distribution (Boroumand and Zachmann, 2012; Haas et al., 2013; Ruppert et al., 2016). By changing the standard withdrawal of electricity from the grid ascribed to the residential sector, self-generation can lead to a greater uncertainty in the retailers' load.

Whilst in wholesale markets load uncertainty is adjusted in the spot markets through spot prices, prices are generally fixed for a longer period in the retail markets (Boroumand et al., 2015). Therefore, the retailers are unable to transfer the spot price volatility to the final consumers. Furthermore, since electricity cannot be stored economically at scale yet (International Energy Agency, 2017), the retailers are required to balance their wholesale and retail portfolios on a real-time basis (Bunn, 2004; Boroumand et al., 2015; Di Cosmo and Malaguzzi Valeri, 2018). This real-time dimension can be further exacerbated in the presence of a high penetration of decentralized solar PV systems.

The aim of this study is to assess the extent to which an increasing self-generation, as driven by rooftop solar PV systems, can affect the exposure of electricity retailers to load and price risks. The German market is considered since it is at the forefront of solar PV installation: In 2016, Germany accounted for 14% (41 GWp) of the cumulative PV capacity installed worldwide (292 GWp), corresponding to 1.6 million PV systems (International Renewable Energy Agency, 2017b). Rooftop installations, i.e. usually systems with a capacity up to 12 kWp (International Renewable Energy Agency, 2017a), represented about 42% of the 2016 German total solar PV installed capacity, corresponding to 17 GWp (Fraunhofer Institute for Solar Energy Systems ISE, 2017). In all, in 2016 solar PV generation represented 10% of households' electricity demand in Germany, corresponding to 14.5 TWh (BMJV, 2017). Hence, Germany can be regarded as a representative model when considering the development of solar PV systems in other European countries and worldwide (Ketterer, 2014; Gersema and Wozabal, 2017).

The Conditional Value-at-Risk (CVaR) and Monte Carlo simulations based on day-ahead prices and loads over the period January 2015 - December 2016 are used to evaluate the retailers' risk exposure. Drawing from the literature on quantitative models for electricity prices and loads, traditional finance approaches are adopted, which allow for seasonal variations, jumps and stochasticity in the hourly electricity price and load time series, and for the association between load and prices (Coulon et al., 2013; Weron, 2014). In all, this analysis is relevant when considering the impact of the retailers' hedging costs on the consumers' welfare, and the implications of a high penetration of intermittent self-generation for electricity markets efficiency.

The remainder of this paper is organized as follows. In Section 2, the literature is reviewed. Section 3 focuses on the data and the methodological framework. Results of the retailers' risk assessment are reported in Section 4 and discussed in Section 5. Finally, Section 6 concludes the paper.

2 Literature Review

The specific characteristics of the electricity demand, namely mean-reversion, seasonality, high short-term variability, inelasticity, lead to a strong volatility of the electricity spot prices (e.g. Lucia and Schwartz, 2002; Stoft, 2002; Huisman and Mahieu, 2003; Bunn, 2004; Escribano et al., 2011). In a competitive electricity market, retailers buy electricity in the wholesale market from the generators, through futures and forward contracts, or on the spot market (day-ahead and intraday markets), and sell electricity to the consumers in the retail market at generally fixed prices, i.e. tariffs (Boroumand and Zachmann, 2012; Batlle, 2013). Since electricity is not economically storable yet, any load imbalances between wholesale and retail market are adjusted on the spot market at unpredictable prices, and the retailers are unable to transfer this unpredictability to the consumers. By sourcing electricity for resale to final consumers, retailers are therefore exposed to the volume risk, namely load risk, mostly over short-term horizons, i.e. from a few days or hours to real-time (Boroumand and Zachmann, 2012).

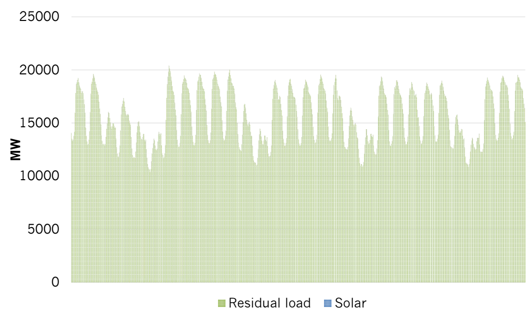
The inability to perfectly transfer risks across market players highlights the incompleteness of the electricity markets (Bessembinder and Lemmon, 2002; Willems and Morbee, 2010). Given the observed positive correlation between price and load in wholesale electricity markets (e.g. Deng and Oren, 2006; Weron, 2007; Gelabert et al., 2011), depending on the load variability and the difference between spot and retail prices, large losses can emerge in the short-term for the retailers who are not effectively hedged against a multiplicative risk of load and price (Willems and Morbee, 2010; Aïd et al., 2011; Dagoumas et al., 2017).

In the past, load variability was highly predictable by aggregating a large number of consumers, since aggregation reduces the inherent load variability and results in smooth load shapes (e.g. Räsänen et al., 2010; Chicco, 2012; Rhodes et al., 2014). Therefore, notwithstanding the market incompleteness argument, static hedging strategies were adopted against the multiplicative load-price risk faced by the retailers. These strategies were based on forward, futures and options contracts that were not re-balanced until the maturity of the shortest-term contracts (Carr and Wu, 2002), and were argued to offer an optimal risk management (Oum and Oren, 2010; Willems and Morbee, 2010; Coulon et al., 2013).

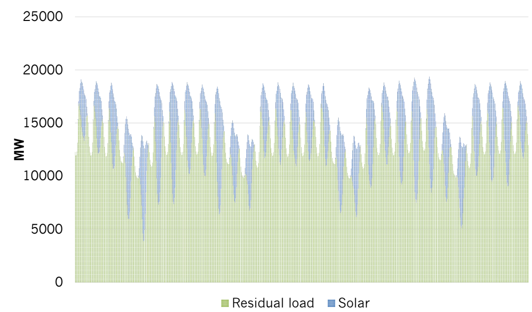
While investigating the hedging problem faced by the electricity retailers, Boroumand and Zachmann (2012) assumed that the load risk *de facto* translates into a price risk, since prices reflect discrepancies between the retailers' buying and selling portfolios, and are positively correlated with the demand. Therefore, the retailers minimize the load and price risks by hedging a ceratin amount of their aggregated load requirements based on a standard load profile. The authors adopted value-at-risk metrics and numerical simulations based on the observed hourly price-load pairs to assess the retailers' exposure to the multiplicative risk of load and price in the French market. In a similar vein, Boroumand et al. (2015) and Boroumand and Goutte (2017) investigated the retailers' risk exposure in the French and German-Austrian markets, respectively, and highlighted the need for intra-day hedging strategies, fitting the characteristics of the electricity demand. Nonetheless, whilst the standard load profile can be used to represent the shape of the electricity demand of the residential sector, it is based on historical data and does not capture the ongoing transformation of the electricity sector and, in particular, the technological trends in distributed electricity systems (Hayn et al., 2014; McLoughlin et al., 2015; Sevlian and Rajagopal, 2018). Kettunen et al. (2010) focused on the price and load correlation to address the risk management problem faced by the electricity retailers'. They argued that this correlation directly affects the hedging strategy efficiency, thus implying that retailers' risk exposure is time-varying and subject to the joint movements of price and load.

Managing the risk associated with a variable load in the wholesale markets through derivatives contracts has always been a challenge. These contracts, in particular futures and forward contracts, are daily contracts and available are different maturities: up to a few days ahead (e.g 7 in the German market, 5 in the UK); weekly contracts (up to 4 weeks ahead in most of the European countries); monthly contracts (up to 6 months ahead); quarterly and annual contracts (ranging from 6 quarters to 3 years ahead). Yet these contracts are settled against base (24 h, weekdays and weekends), peak (8 am to 8 pm, weekdays), and off-peak (8 pm to 8 am of the next day, weekdays) loads, while the contracted price and volumes remain constant through the delivery period. In the short-term, only day-ahead contracts allow for the risk management of the load variability on an hourly basis, thus permitting the adjustment of base, peak and off-peak contracts into hourly physical commitment (Kettunen et al., 2010). Yet the increasing penetration of self-generation requires a finer adjustment to balance the differentials between forecasted and actual loads.

Whilst intraday markets allow for a finer adjustment of the day-ahead positions up to 15-minute resolution, the electricity generated by RES has to be traded day-ahead to be adjusted intra-daily (Kiesel and Paraschiv, 2017). Furthermore, significant differences can emerge between day-ahead and intraday prices depending upon substitution effects between thermal and RES generation (i.e. merit order effect), with intraday prices decreasing relatively to the day-ahead prices for increasing levels of RES generation (Karanfil and Li, 2017; Kiesel and Paraschiv, 2017). The electricity de-



(a) June 2010



(b) June 2016

Figure 1: **German hourly load of the residential sector (Source: Based on data from the Open Power System Data Platform)**

mand by households is an obligation placed on the retailers at pre-specified tariffs and for a named amount of their sales (Newbery et al., 2018). Nonetheless, with increasing self-generation, their actual supply becomes highly dependent upon the level of self-sufficiency, resulting in a greater load and price risk exposure of the retailers on the day-ahead markets.

Self-generation does not have to be traded via the wholesale market (Ackermann et al., 2001) and results in a number of potential benefits for the energy system, among which there is the reduced peak generation requirement (see Luthander et al., 2015, for a survey). Nonetheless, self-generation from rooftop solar PV systems increases the load dependence on weather, seasons, and time of the day (Ruppert et al., 2016), thus resulting in less smooth and spikier grid load shapes, which can make the existing standard load profiles inappropriate. This inappropriateness is highlighted in Fig.1, which shows the German hourly load (in MW) of the residential sector in June 2010 and 2016 (chart (a) and chart (b), respectively), and the contribution of rooftop solar PV self-generation in satisfying the electricity demand of the residential sector (blue area in the charts) in the period[1].

The high load unpredictability led by the increasing PV self-generation in the residential sector represents a new and yet greater challenge for the retailers in electricity markets. This unpre-

[1]Based on data from the Open Power System Data Platform. `https://data.open-power-system-data.org/time_series/`

dictability implies greater hedging pressure for retailers increasingly exposed to real-time changing loads, and can translate in a high risk premium in the electricity price paid by the consumers (Newbery et al., 2018). Yet research focusing on risk assessments with increasing RES penetration mainly relies on the portfolio optimization theory (Markowitz, 1952) to address the risks faced by electricity generators (Bhattacharya and Kojima, 2012; Sadorsky, 2012; Janghorbani et al., 2014; Bhattacharya et al., 2016) and investment decisions of the optimum energy mix (Delarue et al., 2011; Sunderkötter and Weber, 2012; Lynch et al., 2013; Gatzert and Kosub, 2016). The extent to which self-generation can affect the electricity retailers' risk exposure is a research question that, to the best of our knowledge, is still under-researched in literature.

3 Data and Methodological Framework

3.1 Data Description

The German electricity market has been subject to a high RES penetration, in particular rooftop solar PV systems in the residential sector, making this market a suitable case study to investigate retailers' risk exposure to the increasing self-generation. The period under investigation runs from January 2015 to December 2016.

Data on the household solar PV installed capacity (in kWp) and generation (in GWh) are collected, as published on a monthly basis by the national regulator (Bundesnetzagentur) in accordance with the German Renewable Energy Sources Act (EEG) 2014 (BMWI, 2014) and the Core Energy Market Data Register Ordinance, MaStRV (BMJV, 2017)[2]. Following Ruppert et al. (2016), residential installations with a maximum capacity of 12 kWp are considered, since this capacity corresponds to rooftop PV systems for areas up to 80 m^2 and with an average size of 6.5 kWp, which is in line with the data reported by International Renewable Energy Agency (2017a) in the period 2010-16. Therefore, in the remainder of this study, we refer to rooftop PV systems with

[2] https://www.bundesnetzagentur.de/EN/Areas/Energy/Companies/DataCollection_Monitoring/CoreEnergyMarketDataRegister/CoreDataReg_node.html

a maximum capacity of 12 kWp when considering self-generation from solar PV systems in the residential sector. The households' standard load profile (in kWh) is used to fit the electricity demand of the residential sector. This profile is based on hourly historical data available from the German Association of Energy and Water Industries (BDEW) (Schieferdecker et al., 1999; Hayn et al., 2014). Therefore, 24 profiles are obtained, which describe the hourly residential electricity demand over the period.

Data on the German import/export exchanges, total load, run-off-river hydro load and biomass load are collected from the ENTSO-E Transparency Platform on a quarter-hour frequency (in MW)[3]. Data on wind and solar system loads are obtained from the four German TSOs websites, namely 50Hertz, Amprion, Tennet, TransnetBW on a quarter-hourly basis. Hence, the residual load is computed by subtracting from the total load the import/export flows, wind and solar loads, the run-off-river and biomass loads, and a must-run requirement of thermal generation, which is assumed to be 20 GW (Schill, 2014). The residual load is aggregated on an hourly basis by using the average in the period and organized in 24 time series of daily observations, such that each series contains 731 hourly observations.

The German/Austria hourly day-ahead auction prices (DE/AT Phelix, Euro/MWh) are obtained from EPEX-Spot[4]. The price time series is thus re-arranged in 24 daily series of hourly observations, in line with the residual load series.

The collected data are used to assess the retailers' risk exposure to increasing self-sufficiency in the residential sector, as driven by the decentralized solar PV generation, through a three-step procedure. This procedure is described below.

3.2 Methodology

First, the German hourly households' standard load profile and the solar system load are used to compute increasing degrees of self-sufficiency and the corresponding levels of decentralized PV generation on an hourly basis. Therefore, the data on the German monthly household solar PV

[3] https://transparency.entsoe.eu/

[4] http://www.epexspot.com/en/market-data/dayaheadauction

installed capacity and generation are used to compute the solar PV capacity factor and estimate the additional amount of PV capacity required to satisfy the increasing degrees of self-sufficiency. Second, the relationship between hourly residual load and day-ahead prices in the German market is modelled, and the effect of the decentralized PV generation on the residual load and, in turn, on the prices (i.e. merit order effect) is accounted for. Third, Monte Carlo simulations are used to evaluate the sensitivity of residual load and day-ahead prices to increasing levels of decentralized solar PV generation and assess the retailers' load and revenue risk exposure. Parameters and notation are introduced below.

3.2.1 Self-sufficiency and self-generation from rooftop solar PV

Following Schreiber and Hochloff (2013) and Luthander et al. (2015), the annually balanced self-sufficiency is defined as the amount of annual electricity demand of the residential sector SLP that is satisfied through self-generation from rooftop solar PV systems PVG, i.e.:

$$Annually\ Balanced\ Self - Sufficiency = \frac{PVG}{SLP}, \tag{1}$$

where SLP is the cumulative value of the hourly households' standard load profile $SLP_{h,t}$ over a one-year period, i.e. $SLP = \sum_{h=0}^{23} \sum_{t=1}^{365} SLP_{h,t}$. While assuming different degrees of self-sufficiency, two aspects of the electricity demand in the residential sector are considered. The first aspect concerns the dynamics of electricity demand, which change depending on the season and the hour of the day, as highlighted by the time-varying households' standard load profile $SLP_{h,t}$ (e.g. Hayn et al., 2014). The second aspect refers to the solar generation, which relies on the solar irradiation and is thus weather-dependent (e.g. Ruppert et al., 2016). Consequently, the self-generation PVG in Eq.1 is allowed to change across the year and tally with the solar system load in the sample period as follows:

$$PVG_{h,t} = PVG \times \frac{Solar\ Load_{h,t}}{\sum_{h=0}^{23} \sum_{t=1}^{365} Solar\ Load_{h,t}}, \tag{2}$$

where $Solar\ Load_{h,t}$ is the solar system load at the hour h of the day t and $\sum_{h=0}^{23}\sum_{h,t=1}^{365} Solar\ Load_{h,t}$ represents the annual solar system load. Based on the annually balanced self-sufficiency in Eq.1 and the self-generation PVG (Eq.2), the self-sufficiency is defined as:

$$Self - Sufficiency_{h,t} = \frac{PVG_{h,t}}{SLP_{h,t}}. \tag{3}$$

Consequently, while on an annual basis the self-sufficiency is positive (Eq.1), on an hourly and daily basis its values are allowed to be zero, depending on the weather conditions, solar irradiation and hour of the day (Eq.3). The household solar PV capacity factor is defined in Eq.4 and can be regarded as a measure of the average PV generation delivered over a one-year period and is computed as the ratio of the actual PV generation to the maximum PV generation from the installed PV capacity, i.e.:

$$Solar\ PV\ capacity\ factor = \frac{PVG}{(PVC_0 + 0.5 * \Delta PVC) * 8760}, \tag{4}$$

where PVC_0 is the installed solar PV capacity at the start of the year; ΔPVC represents the (average) new installed PV capacity over the year; $8760 = 365\ days \times 24\ hours/day$ is the maximum available operational time in one-year period assuming the continuous operation of the installed capacity at its full nameplate capacity.

On average, a solar PV capacity factor of 10% was observed in Germany during the period 2015-16, as recovered from the historical data. By assuming that this capacity factor remains constant, the additional amount of PV capacity ΔPVC required to satisfy a given degree of self-sufficiency, as defined in Eq.1, is computed as:

$$\Delta PVC = 2 * \left(\frac{PVG}{Solar\ PV\ capacity\ factor * 8760} - PVC_0 \right). \tag{5}$$

Annually balanced self-sufficiency degrees of 10%, 20% and 30% are assumed in Eq.1, which resemble three different cases by (Ruppert et al., 2016), with increasing installation rates of rooftop solar PV systems [5]. The 10% degree represents a reference scenario, which accounts for the status of the German market in 2016 (BMJV, 2017) and with no additional rooftop PV capacity in the residential sector; 20% represents a moderate scenario, corresponding to 13 GWp of additional rooftop solar PV capacity (ΔPVC in Eq.5) with respect to the installed capacity at the end of 2016 (17 GWp). Finally, the 30% scenario implies 28 GWp of new installed rooftop solar PV capacity and is broadly in line with the PRIMES reference scenario for 2030 (European Commission, 2016). The three self-sufficiency scenarios, and the corresponding additional and total installed PV capacity in the residential sector are summarized in Table 1.

Table 1: **Self-sufficiency scenarios for the residential sector**

Scenario	Annually balanced self-sufficiency (%)	Additional PV capacity residential sector (GWp)	Total installed PV capacity residential sector (GWp)
1	10	0	17
2	20	13	30
3	30	28	58

In order to account for the time- and weather-dependencies of the decentralized solar PV generation and annually balanced self-sufficiency (Eq.2 and Eq.3, respectively), the analysis in this study is performed on a hourly basis and focuses on the hours: 5:00, 8:00, 11:00, 14:00, 17:00, as described below.

3.2.2 Modeling the residual load and day-ahead prices

The methodology used in this study follows the strand of the literature adopting finance-inspired reduced-form models. These models capture the main properties and dynamics of the electricity markets (e.g. Deng, 2000; Lucia and Schwartz, 2002; Weron, 2007; Escribano et al., 2011) and have been found to be suitable for the risk assessment in power markets (Benth and Koekebakker, 2008; Coulon et al., 2013; Weron, 2014; Mayer et al., 2015). Building on these reduced-form models,

[5] In Ruppert et al. (2016), the installation rate is defined as the percentage of households with a PV system installed.

some ideas from the structural fundamental models (see Carmona and Coulon, 2014, for a survey) are embodied to reflect the relationship between load and prices, and the impact of increasing renewable generation. Inspired by Coulon et al. (2013), in this study the residual load is first investigated. Therefore, its link with the day-ahead prices is modelled based on the historical data of the German market.

Residual load

The residual load $L_{h,t}$ is defined in an additive way as:

$$L_{h,t} = T^L_{h,t} + s^L_{h,t} + X_{h,t}, \tag{6}$$

where $T^L_{h,t}$ is the long-term seasonal component (LTSC); $s^L_{h,t}$ is the short-term seasonal component (STSC); and $X_{h,t}$ is the deseasonalized and stochastic component of the residual load factor. As in Coulon et al. (2013), sine-cosine trigonometric functions are used to fit the LTSC. The root mean square error (RMSE) between the actual data and the fitted LTSC is used to identify the optimal sine-cosine function. The STSC, which represents the weekly periodicity, is removed by using a 7-day moving-average filter (e.g. Nowotarski and Weron, 2013).

After removing long- and short-term seasonal components, the remaining stochastic component of the residual load is calibrated based on a mean-reverting jump diffusion model for its increments, as defined below:

$$dX_{h,t} = -\beta^L X_{h,t}dt + \sigma^L X^{\gamma^L}_{h,t} dB^L_{h,t} + J dq^L_h, \tag{7}$$

where $-\beta^L X_{h,t}$ is the drift term forcing the process to mean-revert. The mean-reverting process is assumed to be zero-mean, since the mean level is incorporated in the LTSC $T^L_{h,t}$. $\sigma^L X^{\gamma^L}_{h,t}$ is the volatility term that, as in Janczura and Weron (2010), aims to account for any general heteroscedasticity of the process. This volatility is dependent on the current residual load level. For positive values of the coefficient γ^L, the higher the absolute value of the residual load, the larger are the residual load changes. $Vice\ versa$, for negative values of γ^L, the lower the absolute level of the residual load, the larger are its changes. Consequently, this specification suits the high variability induced by the intermittent renewable generation in the residual load factor very well. $dB^L_{h,t}$ are increments of a standard Brownian motion; J is the normally distributed jump size with mean μ^{JL} and standard deviation σ^{JL} while dq^L_h represents the increments of a homogeneous Poisson process independent of $dB^L_{h,t}$ and with constant intensity λ^L. When approximating the likelihood function, the process is discretized by assuming $dt \to 1$, i.e. 1 day. Therefore, the Poisson process is given by the binary probabilities of a jump (λ^L) and no-jumps ($1 - \lambda^L$).

Day-ahead prices

Inspired by Burger et al. (2004) and Schermeyer et al. (2018), the day-ahead prices $P_{h,t}$ are modelled as a function of the residual load factor as follows:

$$P_{h,t} = f(L_{h,t}) + \bar{P}_{h,t}, \tag{8}$$

where $f(L_{h,t})$ is a deterministic function of the residual load $L_{h,t}$, which captures the power-plant dispatch and merit-order effect on prices, that is the impact of high RES penetration on prices; $\bar{P}_{h,t}$ is the residual process of the prices, which thus appears to be uncorrelated with the residual load process. Consequently, in line with Burger et al. (2004), $f(L_{h,t})$ and $\bar{P}_{h,t}$ are assumed to be stochastically independent. This assumption is supported by the cross-correlation analysis in Appendix A.1.

In the literature, the relationship between prices and load has been observed to be concave (e.g. Pirrong and Jermakyan, 2008; Carmona et al., 2013; Coulon et al., 2013) or concave-convex (Burger et al., 2004; He et al., 2013; Wozabal et al., 2016) and has therefore been modelled through exponential functions or polynomial functions, respectively. The relationship between day-ahead prices and residual load in the German market during the period January 2015-December 2016 and at hours 5:00, 8:00, 11:00, 14:00, 17:00 is illustrated in Fig.2 via scatter plots. This relationship appears to be concave-convex, mainly at 11:00, 14:00 and 17:00, despite some outliers, in particular in the lower tail. Similar to Burger et al. (2004) and Schermeyer et al. (2018), polynomial

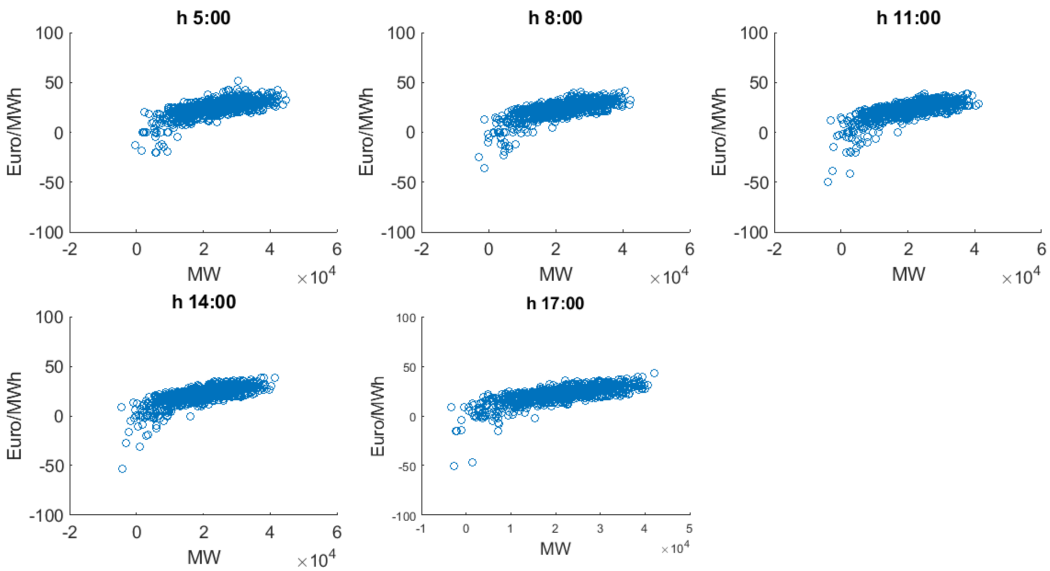


Figure 2: **Relationship between day-ahead price (Euro/MWh) and residual load (MW)**

functions are used to approximate the deterministic function of the residual load $f(L_{h,t})$ in Eq.8, after removing the outliers, i.e. observations above and below the upper and lower 2.5% percentiles of the empirical distributions, and replacing them with the corresponding percentile (e.g. Janczura et al., 2013).

The residual component of the price series $\bar{P}_{h,t}$ in Eq.8 is depicted in Fig.3 and exhibits long- and short-term seasonal behaviors, which are assumed to be uncorrelated with the residual load. Given the observations above, the residual component of the price $\bar{P}_{h,t}$ is defined in an additive way as:

$$\bar{P}_{h,t} = T^P_{h,t} + s^P_{h,t} + Y_{h,t}, \tag{9}$$

where $T^P_{h,t}$ and $s^P_{h,t}$ are the LTSC and STSC of the price process, respectively, and $Y_{h,t}$ represents the stochastic component of the price series. In line with the residual load in Eq.6 and following Escribano et al. (2011) and Coulon et al. (2013) sine-cosine trigonometric functions and a 7-day moving average process are used to fit the LTSC and STSC, respectively. As in previous research (i.e. Weron, 2014), the stochastic component of the price series $Y_{h,t}$ is assumed to follow a mean-

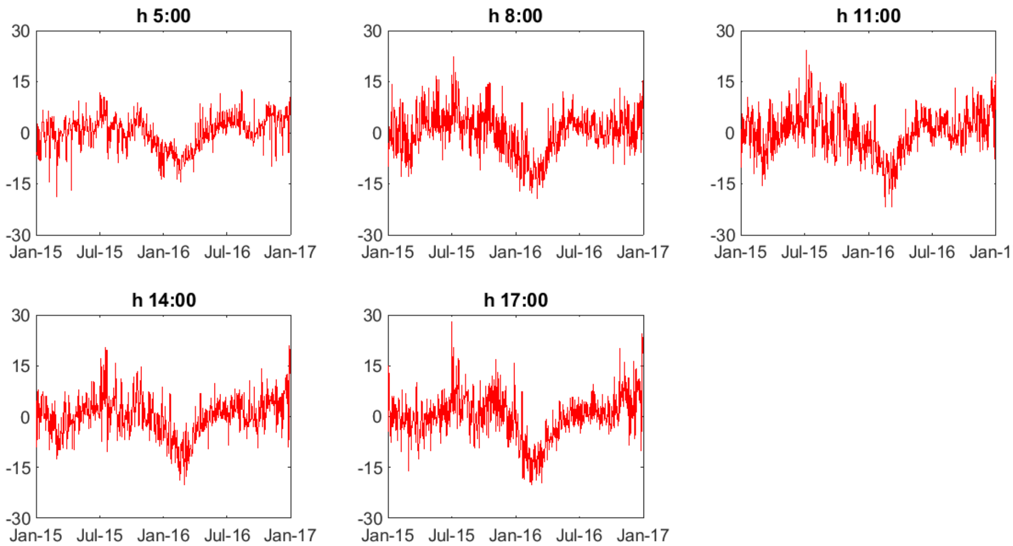


Figure 3: **Residual component day-ahead prices (Euro/MWh)**

reverting jump diffusions process with stochastic volatility, i.e.:

$$dY_{h,t} = -\beta^{\bar{P}} Y_{h,t} dt + \sigma^{\bar{P}} Y_{h,t}^{\gamma^{\bar{P}}} dB_{h,t}^{\bar{P}} + J dq^{\bar{P}}. \tag{10}$$

The load-price pairs in Eq.6 -Eq.9 are estimated using the seemingly unrelated regressions (SUR) method, thus accounting for possible cross-sectional correlations between the hours (Huisman et al., 2007). For increasing degrees of self-sufficiency in Eq.1, the amount of self-generation through rooftop PV PVG in Eq.2 represents the main source of load uncertainty faced by the retailer, which therefore represents his/her load risk. $Ceteris\ paribus$, higher self-generation implies lower residual load (Eq.6), which in turn affects the day-ahead prices (Eq.8).

The impact of different degrees of self-sufficiency on the residual load is measured as follows:

$$L_{h,t}^{i} = L_{h,t} - PVG_{h,t}^{i}, \tag{11}$$

where i=1,2,3 indicates the three self-sufficiency scenarios in Tab.1, $PVG_{h,t}^{i}$ is the self-generation in Eq2, and $L_{h,t}^{i}$ in the recomputed residual load at each scenario. Therefore, the analysis is conducted by only varying the level of self-generation from rooftop PV and maintaining unchanged the other components of the residual load. The new day-ahead price series $P^i_{h,t}$ is therefore modelled as a function of the recomputed residual load $L^i_{h,t}$ as follows:

$$P^i_{h,t} = f(L^i_{h,t}) + \bar{P}_{h,t}, \tag{12}$$

where $f(L^i_{h,t})$ represents the deterministic function of the residual load under the scenario i. The residual component $\bar{P}_{h,t}$ is assumed to be constant across scenarios since, as mentioned above, it is uncorrelated with the residual load.

For each scenario i in Tab.1, N simulated series of the recomputed residual load in Eq.11 are obtained through a Monte Carlo experiment, along with the corresponding self-generation $PVG^i_{h,t}$ and new price series $P^i_{h,t}$ (Eq.12). An assessment of the retailers' risk exposure is thus performed, as described below.

3.2.3 Risk assessment through Monte Carlo simulations

For each scenario i, the parameters of the discretized stochastic models in Eq.7 and Eq.10 $\hat{\beta}, \hat{\sigma}, \hat{\gamma}, \hat{\mu}^J, \hat{\sigma}^J, \hat{\lambda}$ (L and $\bar{P}$ are suppressed to ease notation) are calibrated on the historical time series, after removing the deterministic components, and are used in the Monte Carlo experiment to simulate the stochastic components of the residual load and day-ahead prices, according to the actual real-world probabilities. Hence, the final simulated residual load and price series are obtained by adding to the simulated stochastic components the fitted long- and short-term seasonal components (Eq.6 and Eq.9, respectively) and, in the case of the price series, the third-degree polynomial of the simulated residual load under each scenario (Eq.8).

The simulations are conducted with N=5,000 trials and over a 2-year period, after assuming for each trial a burn-in period of 10% of the daily series, that is 73 observations. The resulting self-generation-price pairs ($PVG^i_{h,t}, P^i_{h,t}$) are used to assess the retailers' exposure to the load risk, and to the multiplicative risk of load and price, i.e. revenue risk, for different degrees of self-sufficiency.

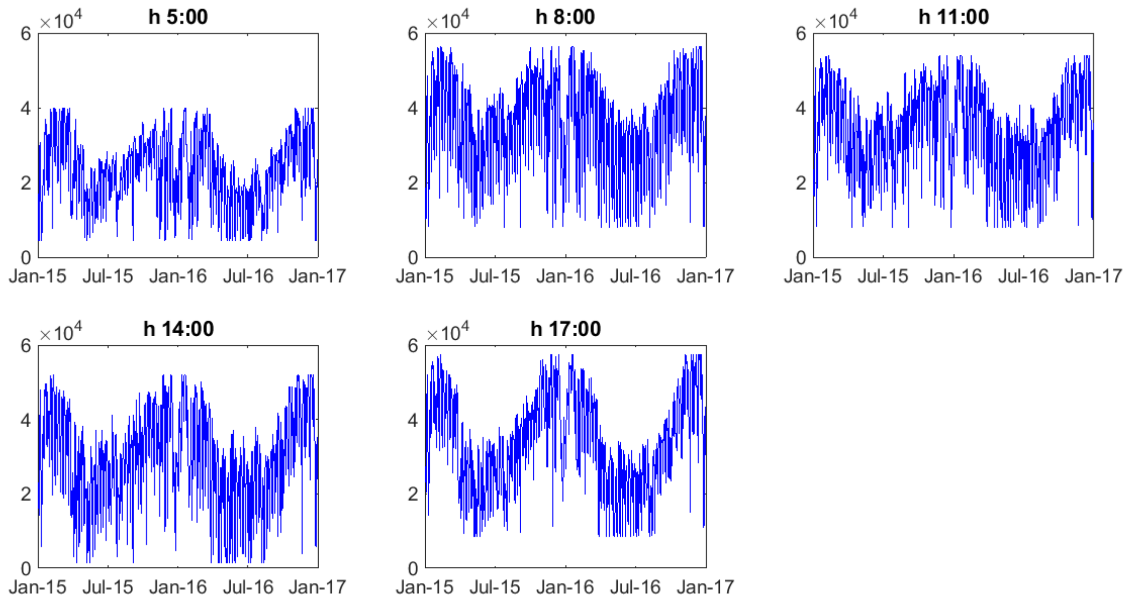
The conditional value-at-risk metric CVaR(α) is used to assess these risks, and represents the conditional expectation of the portfolio losses beyond the VaR(α) (e.g. Alexander, 2008). This risk metric accounts for possible heavy tails in the loss distributions and thus has been argued to be more reliable for risk assessment compared to the VaR metric (e.g. Rockafellar and Uryasev, 2000). The CVaR metrics of the load and revenue are obtained from the simulated distributions of the self-generation and day-ahead prices, which satisfies a pre-specified degree of self-sufficiency. A level of confidence α=99% is assumed and the risk metric is computed on an hourly and daily basis, so to preserve the seasonal and periodic dynamics of the residual load and price time series, thus providing an overview of the retailers' risk exposure according to these dynamics.

3.3 Preliminary Data Analysis

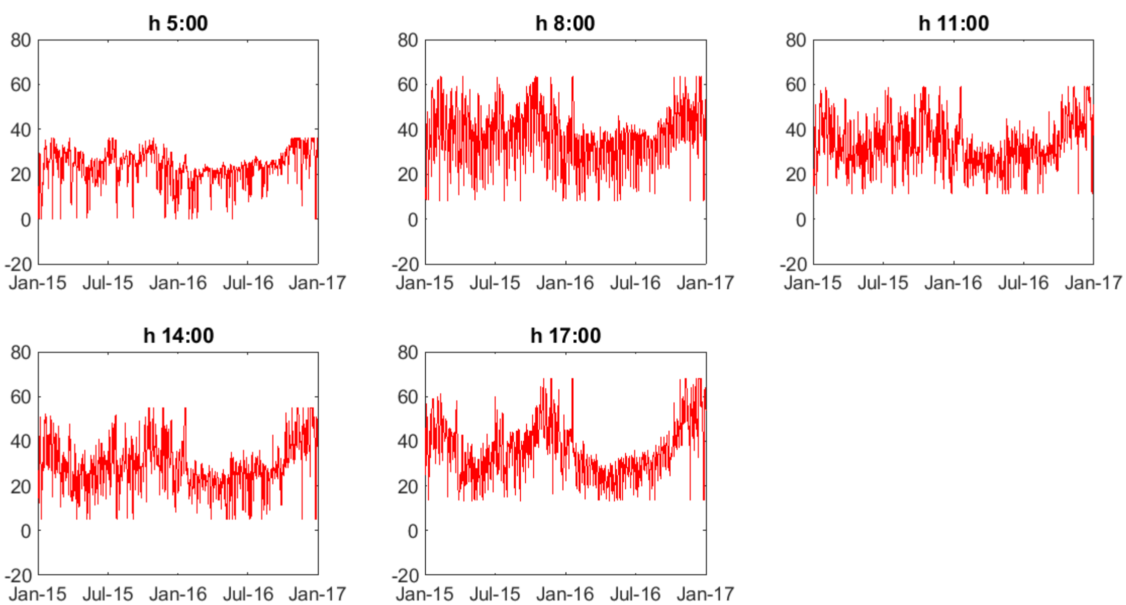
The daily time series of the hourly residual load and day-ahead prices are depicted in chart (a) and (b) of Fig.4, respectively. Different levels and variabilities of the load can be observed across the hours, which are mainly evident at 8:00 and 14:00 and reflected in more volatile price series. Prices can be observed to be lower during the summer, when the residual load is reduced.

The descriptive statistics of the residual load factor and day-ahead price time series in Fig.4 are presented in Tab.2 and Tab.3, respectively. The first four moments of the distributions (i.e. mean, standard deviation, skewness and kurtosis) are reported in the columns two to five. Median, first and third quartile are shown in columns six to eight. Column nine and ten give the Jarque-Bera statistics for the null hypothesis of a normal distribution at the 5% level of significance, and the corresponding *p-value*. The last column of the tables shows the number of observations, N.

The mean and standard deviation statistics indicate higher and more volatile residual load and day-ahead prices at 8:00, thus supporting the empirical evidence in Fig.4. Overall, the skewness and kurtosis statistics imply a departure from the assumption of a normally distributed residual load and day-ahead price time series, as also highlighted by the Jarque-Bera statistics. Finally, while the distribution of the residual load appears to be negatively skewed, and this is consistent across hours, the distribution of the price series shows a change in its skewness across hours, which becomes positive at 11:00, 14:00 and 17:00. Hence, an extremely negative residual load is more likely to occur across the day, and the probability of observing an extremely high or low price changes during the day. This evidence has implications for the retailer risk assessment when considering increasing self-generation and self-sufficiency in the residential sector.



(a) **Residual load (in MW)**



(b) **Day-ahead prices (in Euro/MWh)**

Figure 4: **Residual load and day-ahead prices**

Table 2: **Descriptive statistics of the residual load**

Hour	Mean	SD	Skew	Kurt	Median	P_{25}	P_{75}	Jarque-Bera	Prob	N
5:00	23251	9263	-0.172	2.284	23760	16919	30147	19.240	0.001	731
8:00	36353	12820	-0.478	2.434	37774	28179	46527	37.567	0.001	731
11:00	34070	11807	-0.328	2.390	34743	25987	43080	24.410	0.001	731
14:00	29726	13050	-0.297	2.365	30290	21233	39479	23.013	0.001	731
17:00	33928	12925	-0.054	2.218	33509	25013	44532	18.991	0.001	731

Table 3: **Descriptive statistics of the day-ahead prices**

Hour	Mean	SD	Skew	Kurt	Median	P_{25}	P_{75}	Jarque-Bera	Prob	N
5:00	23.230	7.705	-0.902	4.103	24.070	19.808	28.280	136.27	0.001	731
8:00	36.936	12.729	-0.176	2.756	37.300	29.708	45.440	5.60	0.057	731
11:00	33.049	11.124	0.325	2.727	31.930	25.360	39.948	15.17	0.003	731
14:00	28.777	11.197	0.275	2.963	27.710	22.560	34.938	9.28	0.014	731
17:00	35.911	12.671	0.495	2.920	34.150	27.035	44.018	30.04	0.001	731

By affecting the households' withdrawal of electricity from the grid, self-generation has a direct impact on the merit-order and the electricity dispatch and distribution, thus affecting the residual load and day-ahead prices. Furthermore, giving different levels and variability of the households' and solar load profiles during the day and throughout the year, this impact can be expected to be time-varying. Therefore, a time-varying exposure of retailers' to load and revenue risks can be also expected. The results of the retailers' risk assessment are presented in the following section.

4 Results

4.1 Decentralized Solar PV Generation and Self-Sufficiency in the Residential Sector

Fig.5 shows the self-generation through rooftop PV $PVG^i_{h,t}$ in Eq.2 at 10%, 20% and 30% degree of the annually balanced self-sufficiency in Eq.1 (green, red and blue lines, respectively). Greater self-generation is observed at 11:00 and 14:00, and during the summer, when solar load is expected to be higher. The self-sufficiency in Eq.3 is shown in Fig.6. Assuming an annually balanced degree of 10% of the electricity demand of the residential sector, the self-sufficiency reaches 50% at 11:00, 14:00, 17:00, due to the low household' electricity demand and the high solar load. Yet, when considering a degree of 30%, the self-sufficiency peaks to 200%, i.e. households export electricity to the grid during these peaks. Therefore, the evidence in Fig.5-6 supports a time-varying assessment of the retailers' exposure to the load and revenue risks, as led by increasing self-generation through PV systems and self-sufficiency in the residential sector.

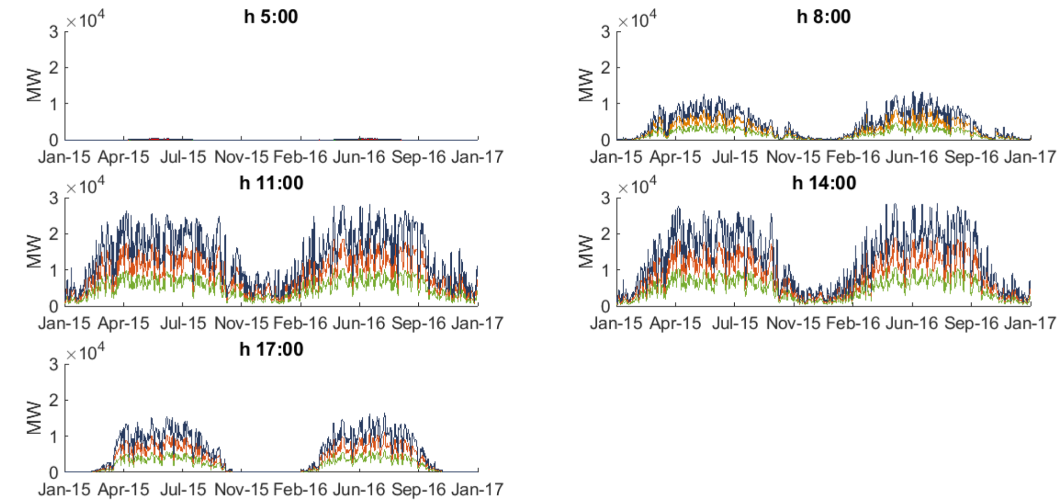


Figure 5: **Self-generation at 10% (green), 20% (red) and 30% (blue) degree of self-sufficiency (in MW)**

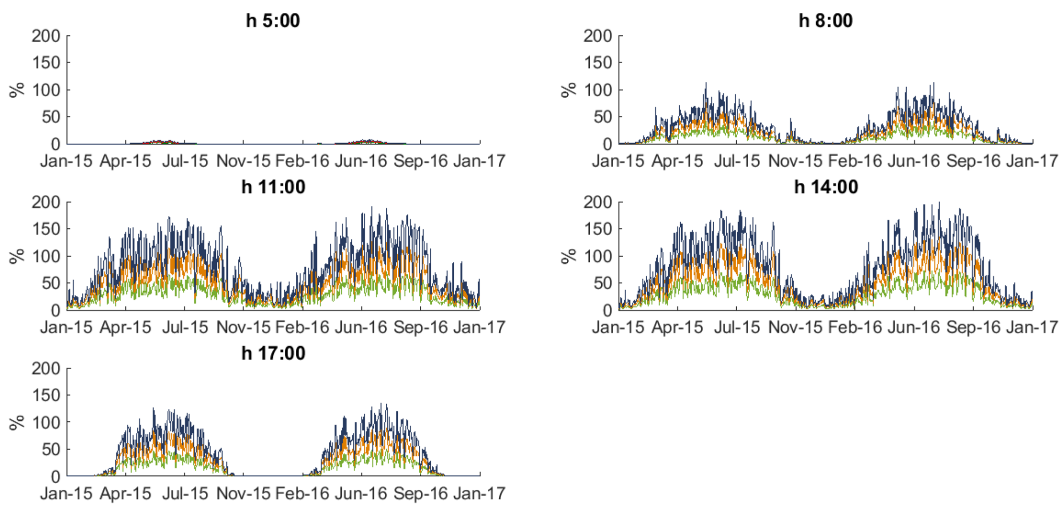


Figure 6: **Self-sufficiency at 10% (green), 20% (red) and 30% (blue) degree**

4.2 Parameter Estimation and Calibration of the Residual Load and Day-Ahead Prices

The estimated day-ahead price polynomial functions of the residual load (Eq.8), and the fitted seasonal components of the residual load and price time series (Eq.6 and Eq.9) are reported in Appendix A.2. After removing the determinist components, the stochastic component of the residual load and day-ahead prices ($X_{h,t}$ and $Y_{h,t}$ in Eq.7 and Eq.10, respectively) are calibrated on the German historical data. The calibrated parameters are presented in Tab.4 and Tab.5. Overall, the mean-reverting coefficients β are positive and imply similar reverting speed on a daily time-scale across hours. Higher volatility is observed at 8:00, 11:00 and 17:00 in both the components (σ^L, $\sigma^{\bar{P}}$, and σ^{JL}, $\sigma^{J\bar{P}}$). The parameters λ^L and $\lambda^{\bar{P}}$ imply higher probability of jumps at 5:00, reasonably due to the higher impact of wind generation on the residual load and day-ahead prices in the offpeak hours (Nicolosi, 2010). Finally, the coefficients γ^L and $\gamma^{\bar{P}}$ are positive, thus suggesting that the higher the absolute value of the residual load and prices, the greater is their volatility. These parameters and the fitted deterministic and seasonal components (Appendix A.2) are used in the Monte Carlo experiment to simulate the residual load and day-ahead prices under different degrees of the annually balanced self-sufficiency in Eq.1.

Table 4: **Calibrated parameters stochastic component residual load**

Hour	β^L	σ^L	μ^{JL}	σ^{JL}	λ^L	γ^L
5:00	0.3821	0.0070	0.0010	0.0142	0.1873	0.1038
8:00	0.4156	0.0089	0.0020	0.0297	0.0644	0.1168
11:00	0.4645	0.0094	0.0011	0.0215	0.0630	0.0970
14:00	0.4443	0.0069	0.0000	0.0128	0.0562	0.0395
17:00	0.3893	0.0076	0.0000	0.0156	0.0644	0.0872

The simulated hourly residual load and day-ahead price duration curves at 30% degree of self-sufficiency are depicted in Fig.7 (the duration curves at 10% and 20% degree of self-sufficiency are presented in Appendix A.3). These curves indicate the daily variability of the hourly residual load and price series, and are obtained by sorting the observations simulated at each Monte Carlo trial in a descending order according to the actual series. The actual (black dot) and simulated

Table 5: **Calibrated parameters stochastic component day-ahead prices**

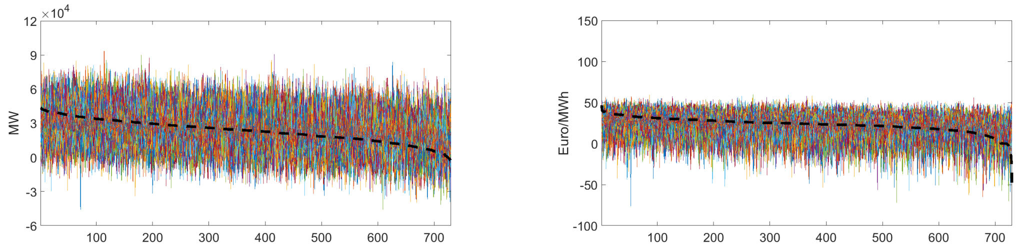
Hour	β^P	σ^P	μ^{JP}	σ^{JP}	λ^P	γ^P
5:00	0.6149	0.0045	0.0000	0.0093	0.1468	0.0911
8:00	0.7075	0.0093	0.0040	0.0165	0.0589	0.1286
11:00	0.6326	0.0072	0.0011	0.0147	0.0493	0.0815
14:00	0.6689	0.0071	0.0037	0.0128	0.0438	0.0980
17:00	0.7312	0.0071	0.0030	0.0138	0.0507	0.0888

residual load duration curves are depicted on the left side of the figure; the duration curves of the corresponding price series are shown on the right.

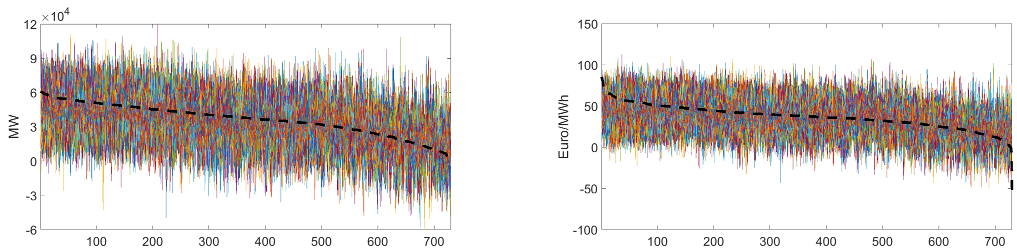
Greater variability can be observed at 14:00 and 17:00 (Fig.7, charts (d)-(e)) in both the residual load and price curves, that is when higher are the self-generation and self-sufficiency (Fig.5-6). Yet, when compared to the duration curves as 10% degree of self-sufficiency (Fig.15 in Appendix A.3), a merit order effect is noticeable, such that lower residual load and day-ahead prices are observed for increasing level of self-generation and self-sufficiency from rooftop solar PV systems. This effect is mostly evident at 8:00 (charts (b)), i.e. when the switch from the off-peak to the peak time-window occurs. In contrast, a negligible effect is found in the duration curve at 5:00 (charts (a)). Furthermore, the duration curves at 30% degree of self-sufficiency suggest greater volatility and more frequent negative peaks of the day-ahead prices for decreasing levels of the residual load, mainly at 14:00. A performance evaluation of the Monte Carlo simulations is summarized in Appendix A.4. The simulated residual and price series are thus used to compute the CVaR metrics. These metrics are presented below.

4.3 Assessing the Retailers' Risk Exposure

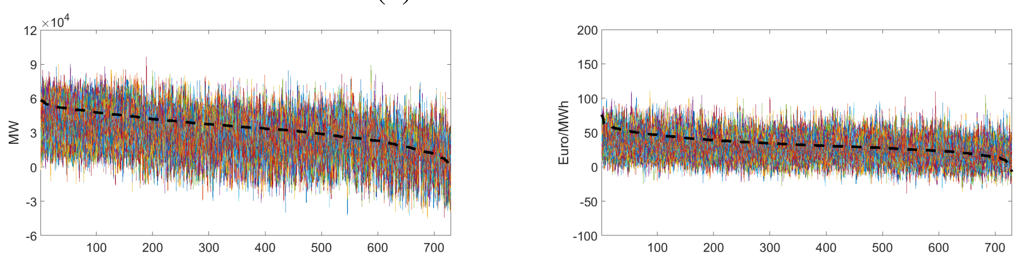
The CVaR(99%) load and revenue risk metrics at different degrees of self-sufficiency and decentralized solar PV generation are reported in Fig.8-Fig.10. The metrics have been computed on a daily and monthly basis by using the mean values in the period, so as to provide an assessment of the retailers' risk exposure while accounting for the seasonality and periodicity of the electricity demand in the residential sector. The left column of the figures show the load CVaR(99%) and



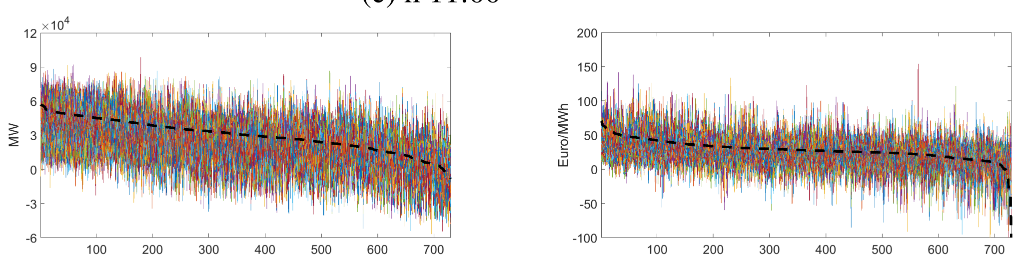
(a) h 5:00



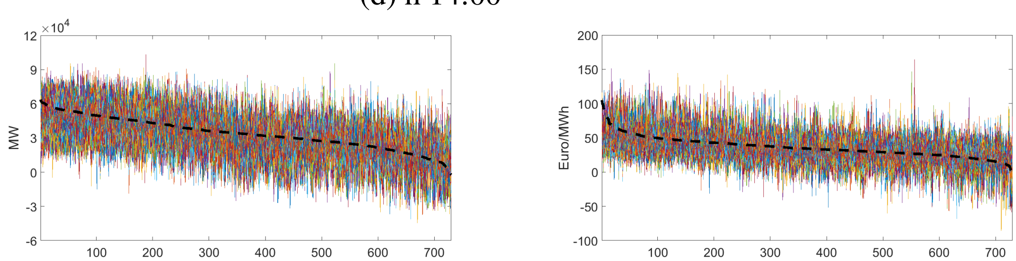
(b) h 8:00



(c) h 11:00



(d) h 14:00



(e) h 17:00

Figure 7: **Actual (black dot) vs simulated residual load (left) and day-ahead price (right) duration curves: 30% self-sufficiency**

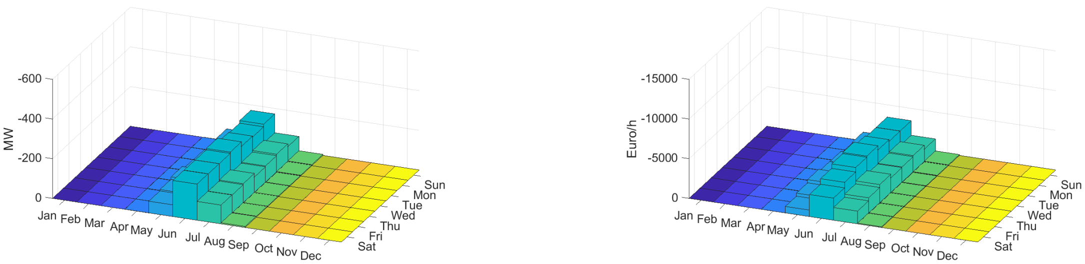
unveils the retailers' average expected hourly load losses (in MW) for different degrees of self-sufficiency in Fig.6. On the right column, the corresponding revenue CVaR(99%) is shown, which is the average expected hourly revenue losses (in Euro/h) the retailers can face due to an increasing self-generation from rooftop solar PV systems and self-sufficiency penetration in the residential sector. Therefore, whilst the load CVaR(99%) assesses the German retailers' load risk ascribed to an increasing reduction of the households' electricity withdrawal from the grid, the revenue CVaR(99%) assesses the German retailers' monetary risk associated with this load risk.

On average, the expected load risk is observed to be greater at 11:00 and 14:00 (charts (c)-(d) of Fig.8-Fig.10, respectively) and during the period April-September, thus tallying with the dynamics of the self-sufficiency in Fig.6. Nonetheless, whilst the expected load risk appears to be more homogeneously distributed across the week, the expected revenue risk is observed to be higher on weekdays, mostly from Tuesdays to Thursdays. Finally, non-linear behaviors can also be observed between expected load and revenue risk, such that, on average, the expected load risk appears to grow more than the revenue risk at increasing degrees of self-sufficiency.

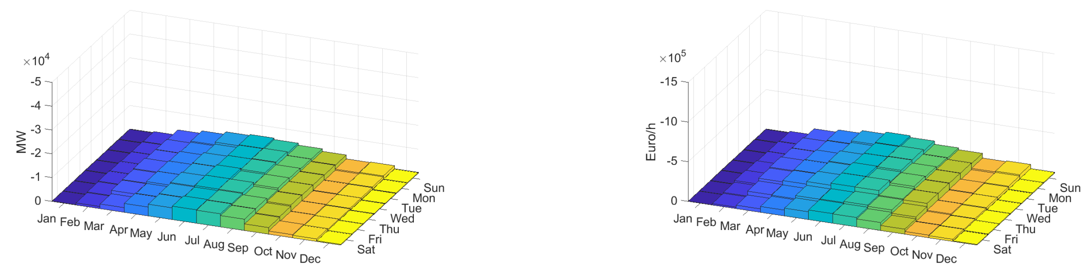
Overall, the results suggest an increasing exposure of the electricity retailers' to the load and revenue risks when considering the impact of a growing self-generation through rooftop solar PV systems in the residential sector. Moreover, they imply differences in the distribution of these risks across the week and throughout the week, which have implications when considering different risk mitigation options for the retailers, as discussed in the next section.

5 Discussion

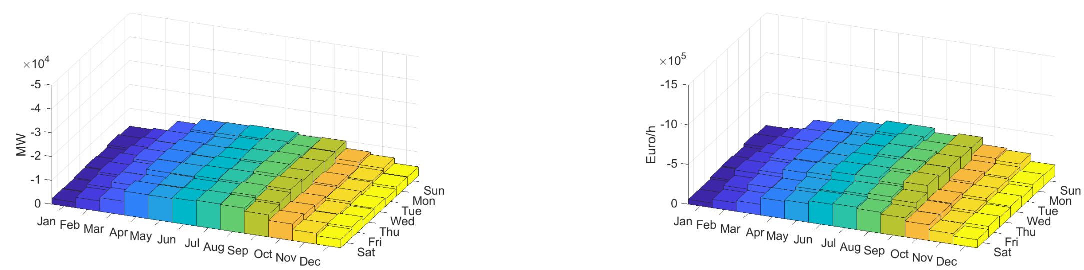
The self-generation of the residential sector, as driven by rooftop solar PV systems, by affecting the electricity withdrawal from the grid, represents the main source of load uncertainty for the retailers, who are unable to transfer this uncertainty to the final consumers. The results in this study imply higher retailers' load risk exposure to growing self-generation. Yet, the dynamics of this risk are linked to the peculiarities of the solar generation, which is weather-dependent and subject to the



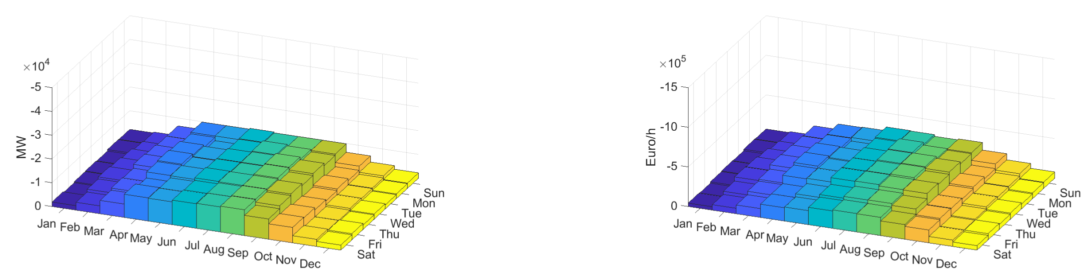
(a) h 5:00



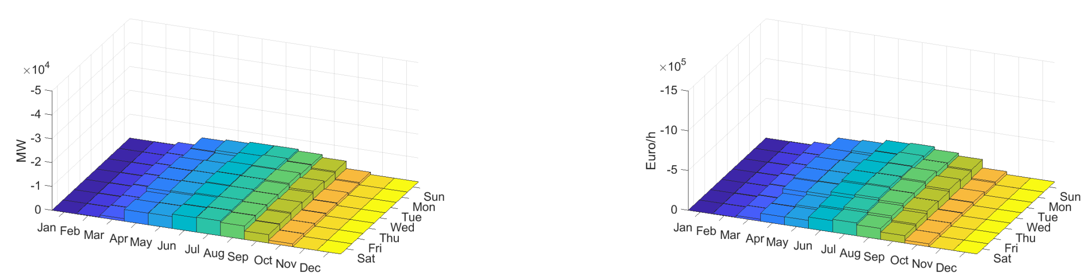
(b) h 8:00



(c) h 11:00

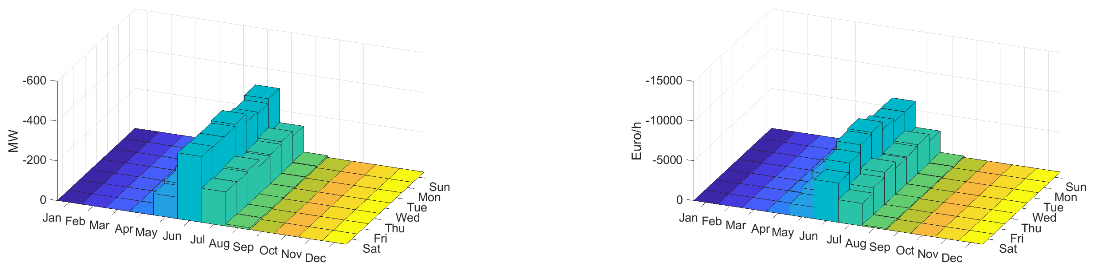


(d) h 14:00

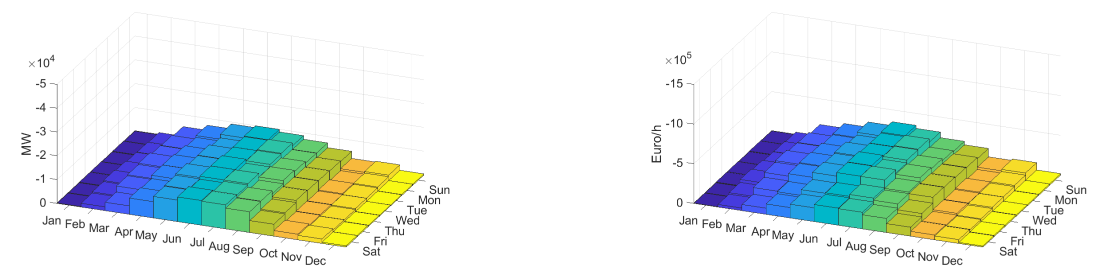


(e) h 17:00

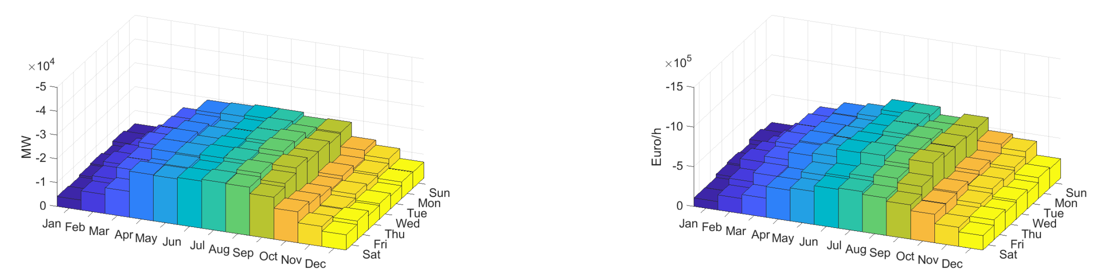
Figure 8: **Load (left) and revenue (right) CVaR(99%) at 10% self-sufficiency**



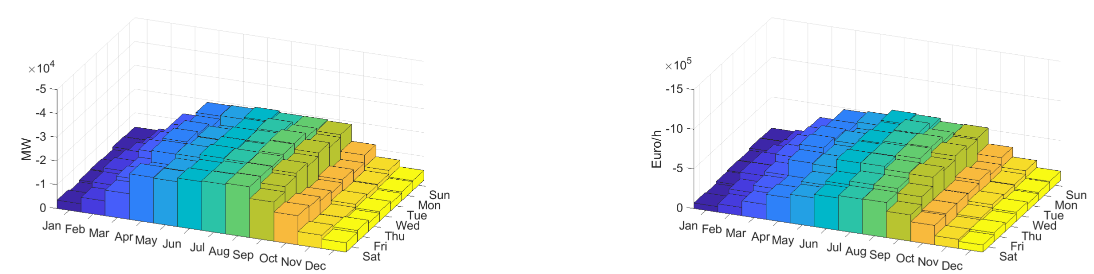
(a) h 5:00



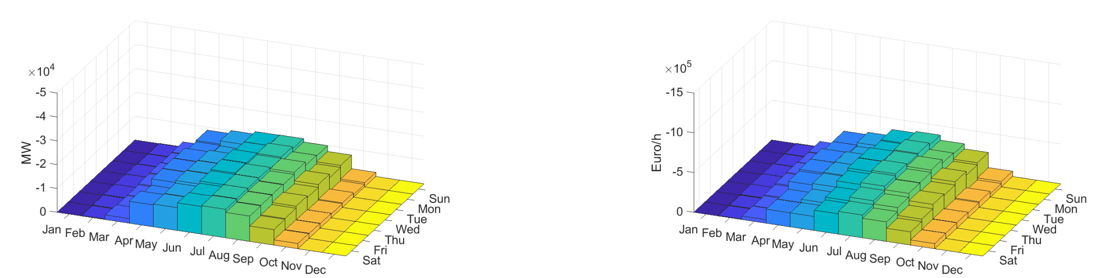
(b) h 8:00



(c) h 11:00

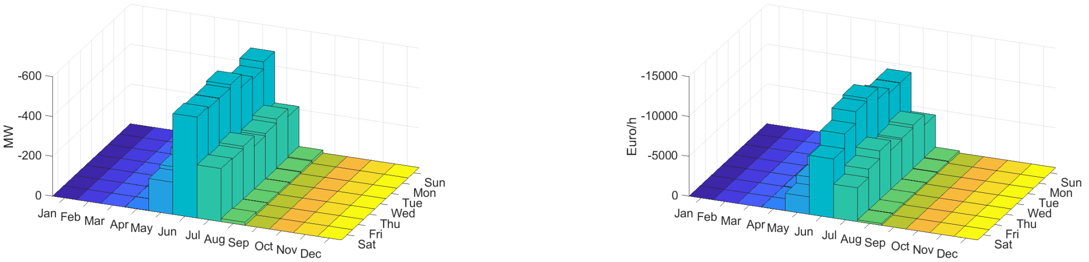


(d) h 14:00

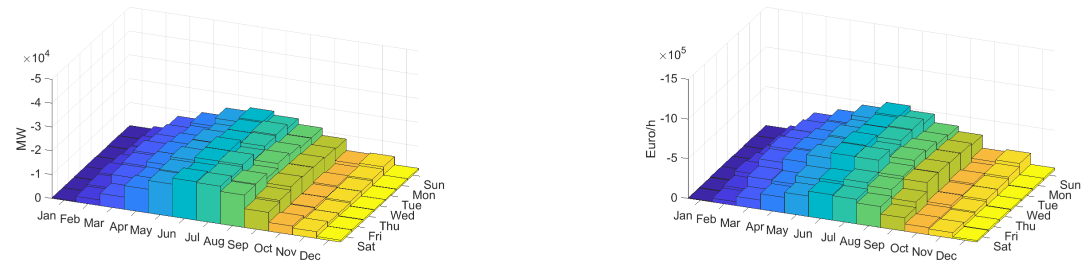


(e) h 17:00

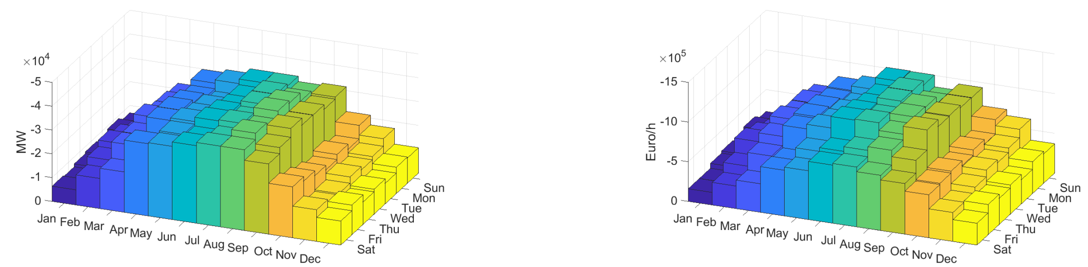
Figure 9: **Load (left) and revenue (right) CVaR(99%) at 20% self-sufficiency**



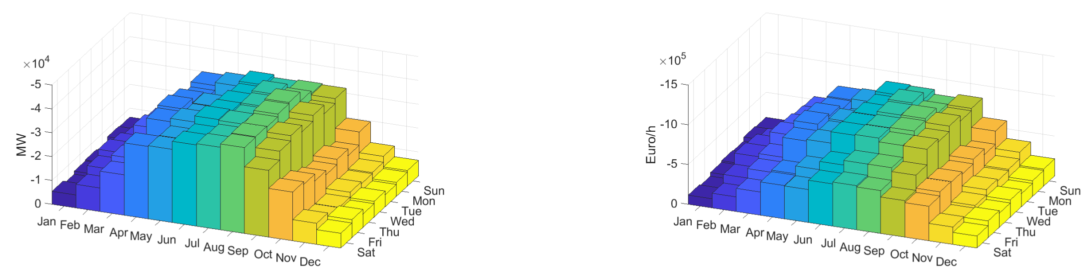
(a) h 5:00



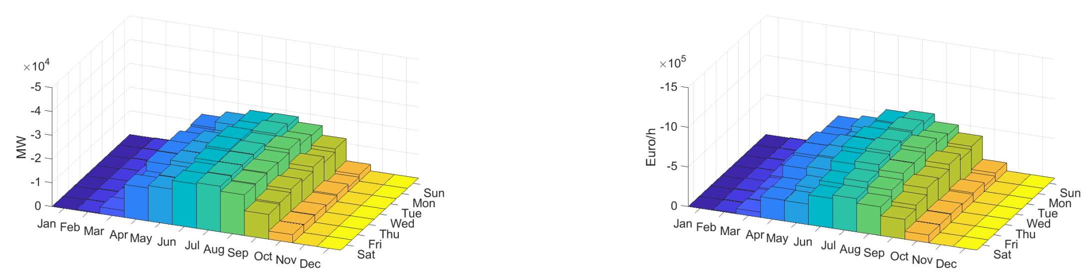
(b) h 8:00



(c) h 11:00



(d) h 14:00



(e) h 17:00

Figure 10: **Load (left) and revenue (right) CVaR(99%) at 30% self-sufficiency**

solar irradiation and hour of the day.

Overall, lower load and revenue losses are expected by the retailers at 5:00 and 8:00 and during the winter, from October to February (Fig.8-10, chart (a)-(b)). In contrast, a greater load risk is observed at 11:00 and 14:00 and during the period from April to September, i.e. when the solar irradiation is higher and the electricity demand of the residential sector is lower (Fig.6). During this period, the expected load loss at 11:00 and 14:00 hours is 10,000 MW, when considering a 10% degree of self-sufficiency (Fig.8, chart (c)-(d), left column). The load loss reaches 35,000 MW when considering a 30% self-sufficiency degree (Fig.10, chart (c)-(d), left column). This load loss corresponds to expected revenue losses of 100,000 Euro and 80,000 Euro per hour, at 11:00 and 14:00, respectively (Fig.10, chart (c)-(d), right column). These load and revenue losses represent the average expected load and revenue risks faced by the retailers in those specific hours of each day from April to September, when considering all residential households in Germany. Therefore, the retailers' risk exposure varies significantly across the day, which is in line with Boroumand et al. (2015) and Boroumand and Goutte (2017). Yet, compared to their research, in this study a quantification of both the load and revenue risks is allowed, which also accounts for the weekly periodicity and seasonal dynamics of the load and price series, thus further highlighting the time-varying behavior of such risks.

The distribution of load and revenue losses appears to be different and dependent upon the day of the week. The revenue losses are higher on weekdays, from Monday to Friday. In contrast, the load losses are observed to spread more homogenously during the week, reasonably reflecting the weather conditions and the availability of solar irradiation. This different behavior of the load and revenues losses is consistent across hours and adds further uncertainty to the amount of risk faced by the retailers' in the presence of high self-sufficiency.

In the past, the load variability was more predictable by aggregating a large number of consumers. Yet, an increasing self-generation from rooftop solar PV systems raises concerns about the reliability of households' standard load profiles, which are based on historical data, to capture the ongoing technological transformations of the retail electricity market. The results in this study are thus in line with previous research, raising concerns about the ability of aggregation and load profiling approaches to reduce the load variability (Hayn et al., 2014; McLoughlin et al., 2015; Sevlian and Rajagopal, 2018) and provide an estimate of the load unpredictability and its distribution in evolving retail markets.

For increasing degrees of self-sufficiency, the retailers' load risk is found to grow more than the associated revenue risk, thus implying the presence of some nonlinearities in the relationship between load and revenue risks, which are mainly evident at 11:00 and 14:00 and during the summer (Fig.8-10, charts (c)-(d)). Since the load-price correlation directly affects the hedging efficiency (Kettunen et al., 2010), risk management strategies assuming a time-invariant relationship between load and price risk can be inefficient against a multiplicative risk of load and price with increasing self-generation. This inefficiency has implications for the competitiveness in particular of small utilities. Whereas financial contracts such as futures, forwards, swaps and options, which are used for hedging, are settled against day-ahead prices and base, peak and off-peak loads, retail prices rely on time- and load-based fixed-price contracts and include congestion and network fees, which are defined by bidding zones and based on local supply and demand. This introduces a significant basis risk for electricity retailers, as substantial differences can emerge between wholesale day-ahead prices and retail fixed-price contract, depending upon the load variability. This basis risk can be further exacerbated by the increasing penetration of unpredictable self-generation from rooftop solar PV systems, thus implying a higher risk-premium required by the retailers from the final consumers as a compensation for bearing such a risk.

The self-generation affects the aggregated demand on a real-time basis, thus leading to greater load uncertainty in the retail electricity market. This uncertainty cannot be reduced through financial contracts, which assume constant price and volume across base, peak and off-peak time-windows. Despite the superior efficiency of the intraday options to manage the increasing uncertainty faced by the electricity retailers', their liquidity remains an issue (e.g. Boroumand et al., 2015; Newbery et al., 2018; Boroumand and Goutte, 2017). The lack of liquidity can increase the transaction costs, thus affecting the effectiveness of these financial instruments to manage the higher uncertainty faced by the electricity retailers', and may also imply a higher risk-premium paid by the consumers.

With increasing penetration of volatile renewable energy sources like rooftop solar PV systems, demand-side management (DSM) and distributed storage facilities may curb the load variability of the electricity demand in the residential sector, especially when facilitated by aggregators (Schill and Zerrahn, 2017; Saffari et al., 2018). By lessening peak loads and shifting loads from peak to off-peak time-window, these technologies can reduce the retailers' load risk exposure. Nonetheless, DSM and distributed storage technologies require investments whose returns are mainly driven by their opportunity costs and price variability, and by the consumers' behavior (Luthander et al., 2015; Wozabal et al., 2016; Schill and Zerrahn, 2017). Hence, they may ultimately increase the retailers' load risk exposure. Furthermore, in order to avoid grid congestions, time-of-use distribution network tariffs are adopted, as for instance in Spain and the UK, to facilitate the shift of the electricity demand from peak to off-peak hours (Li et al., 2016; Saffari et al., 2018). Yet, these tariffs are determined in advance and discriminated by rates (i.e. prices within different time-windows) and patterns (duration of each time-window) to reflect energy prices and system loads based on the information provided by the electricity retailers (Li et al., 2016). The retailers' load uncertainty due to increasing self-generation can affect the appropriateness of tariff structures reliant on historical system load profiles, with implications for the consumers' energy bill, which are of interest for policymakers and regulators.

Tariffs are relevant factors for the profitability of investment in RES. RES generation entails a load forecasting challenge, which has a crucial role in the transition towards a sustainable power system (Punda et al., 2017). Load variability, in both supply and demand, has always been present in power systems. Yet, the integration of RES has increased it, setting new technical and economical requirements to guarantee the system flexibility and maintain the supply-demand balance. Capital intensive and variable RES investments need reliable price signals to enhance efficiency. In this respect, price-based support schemes, such as feed-in-tariffs (FIT), play a key role in stabilizing the generators' revenue flow and reducing their investment risks (Tietjen et al., 2016; Pineda et al., 2018). Nonetheless, the choice of the optimal renewable support schemes has been driven mainly by the objective of reducing the generators' load and revenue risk (Pineda et al., 2018). While eligible generators can transfer the cost (and risk) of renewable generation to the retailers in the wholesale market, in the retail market the regulatory body determines the cost to be transferred to the final consumers (Punda et al., 2017). Renewable support schemes can thus entail a regulatory risk, which depends upon the renewable load variability, and can affect the revenue and load risk faced not only by generators and equity investors in long-term capital intensive projects, but also by retailers when increasing levels of self-generation in the residential sector are considered. Uncovering the retailers' risk exposure to rooftop solar PV systems has thus implications for consumers, investors, generators and policymakers.

6 Conclusions

In this paper, an assessment of the electricity retailers' risk exposure to increasing degrees of self-generation from rooftop solar PV system is presented, which is based on the Monte Carlo simulations and the CVaR(99%) risk metric. The German market is considered, since Germany is at the forefront of solar PV installations.

Notwithstanding the considerably high economic value of solar PV for the energy system, the risk assessment in this paper implies greater uncertainty faced by the retailers in the presence of an increasing penetration of rooftop solar PV systems, especially when accounting for their inability to transfer load and revenue volatility risks to the consumers. Traditional financial derivatives are mainly devoted to long-term hedging. The increasing need of shorter-term flexibility, while highlighting the importance of intraday and balancing markets, questions the suitability of the traditional financial products, in particular standard futures and forward contracts, in providing this flexibility, and suggests the need of different derivatives products for mitigating risks in evolving electricity markets. This would imply a shift in the hedging approach, which is of relevance for market-players and policymakers and is thus left for future research.

The increasing need of the retailers for real-time portfolios re-balancing has implications when considering the efficiency and cost of different risk mitigation options - i.e. financial derivatives, physical hedging, tariffs - in the context of a rapidly evolving decentralized electricity market. These options affect investment decisions and thus the power system availability of ensuring adequate flexibility and reliability. Their assessment is thus left as an avenue for future research.

Whilst the use of a robust simulation technique in this paper has provided useful insights, there are some limitations to the analysis undertaken. A time-invariant price-load relationship has been assumed on an hourly basis, which does not account for adjustments in the link between load and price risk over time due to wholesale and retail price differentials. Furthermore, our analysis does not consider distributed storage or demand response technologies. Such technologies affect households' grid load profile and, therefore, if uncontrolled, may exacerbate the unpredictability of the retailers' load profile. It is therefore important to address this issue in future research.

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A Appendixes

A.1 Cross-correlation analysis

A cross-correlation analysis is performed to support the assumption of independence between the residual load and price stochastic components. The results are shown in Fig.11, where the cross-correlation functions, along with their 90% confidence intervals for each hourly residual load-price pair are depicted. Overall, the majority of the empirical cross-correlations are within the 90% confidence interval, thus supporting the assumption that the stochastic component of the residual load and day-ahead prices can be calibrated independently.

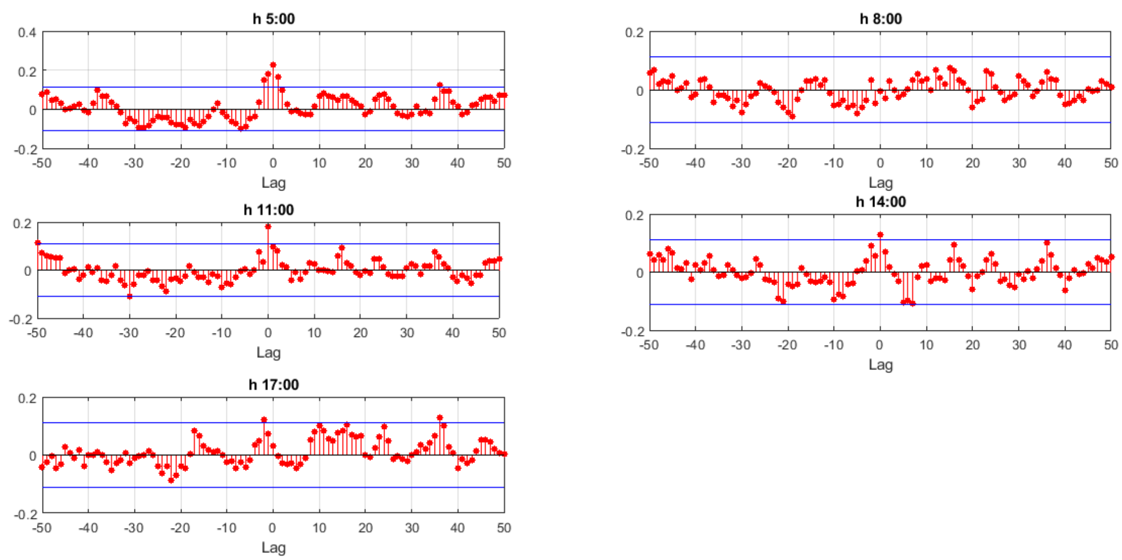
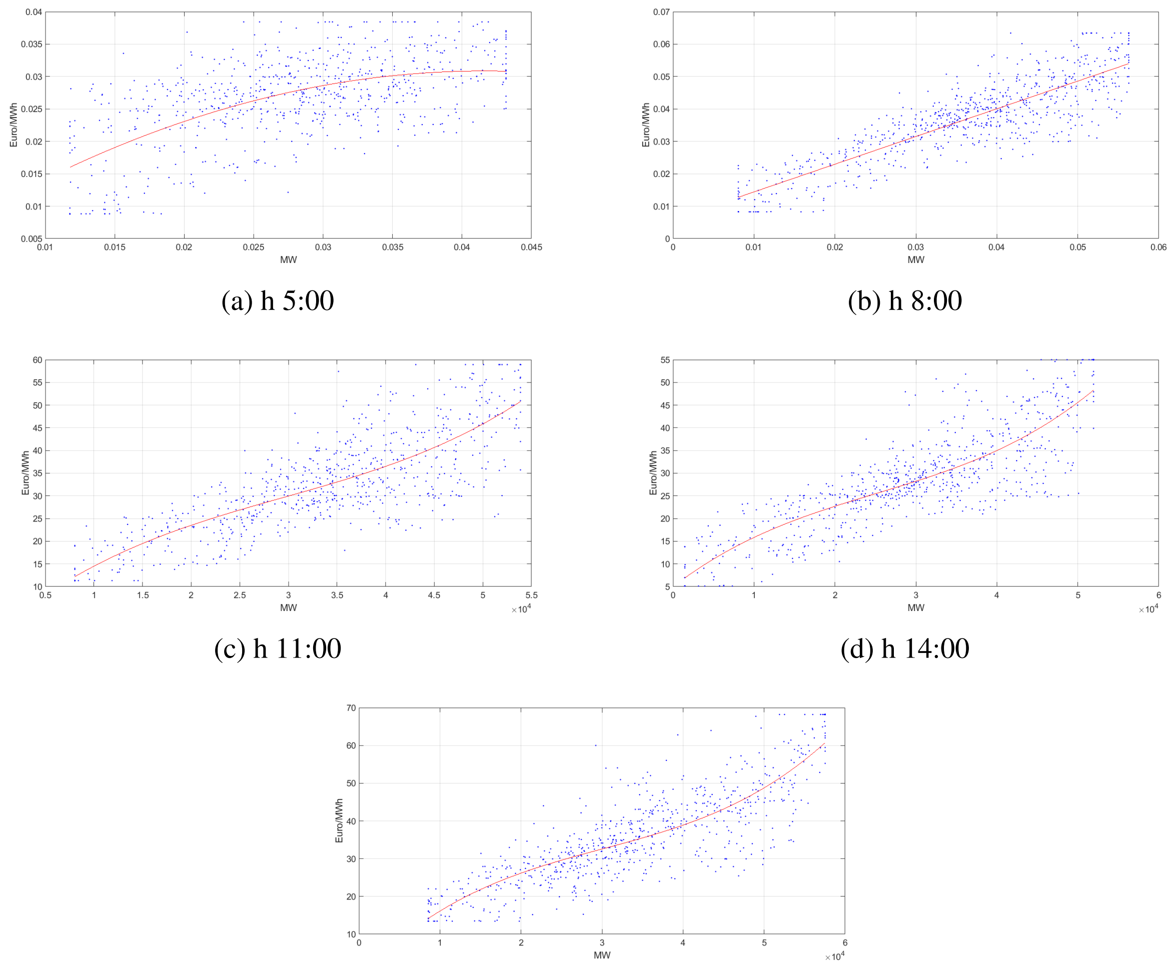


Figure 11: **Cross-correlation functions of the stochastic components of the residual load and day-ahead prices (red dot) and 90% confidence interval (blue bands)**

A.2 Fitted seasonal and deterministic components of the residual load and day-ahead prices

The polynomial function provides a reasonable fit of the deterministic function $f(L_{h,t})$ in Eq.8, which appears to take a concave-convex shape at 11:00, 14:00, 17:00. A third-degree polynomial is thus assumed at these hours. In contrast, a two-degree polynomial is found to better fit the load-price relationship at 5:00; finally, a linear relationship is observed at 8:00. In Fig.12, the day-ahead prices against the residual load are plotted (blued dot), along with the fitted polynomial functions of the residual load (red line).



(a) h 5:00

(b) h 8:00

(c) h 11:00

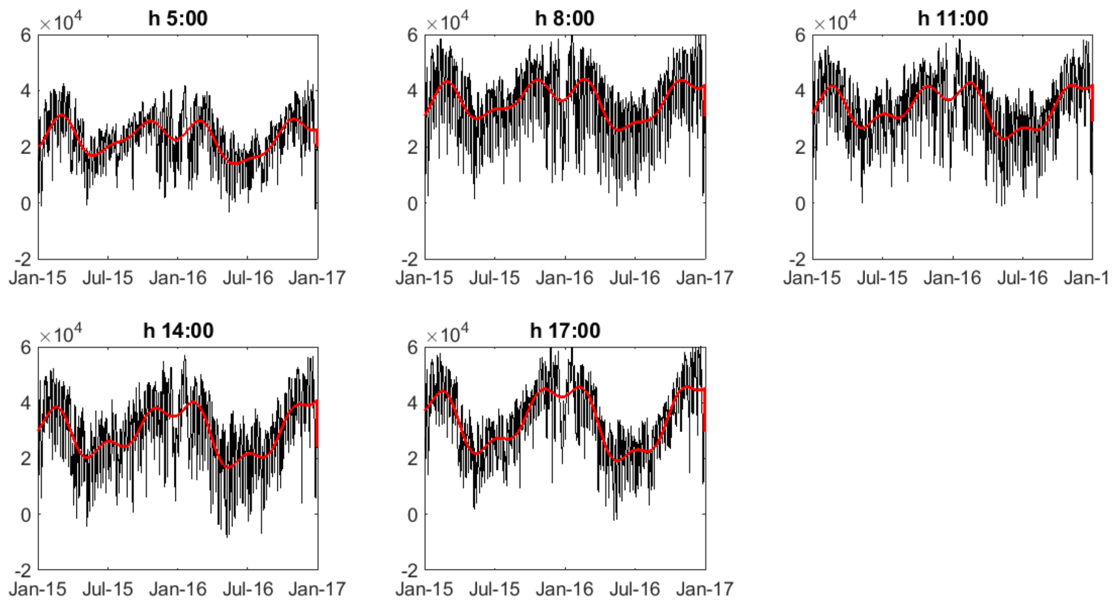
(d) h 14:00

(e) h 17:00

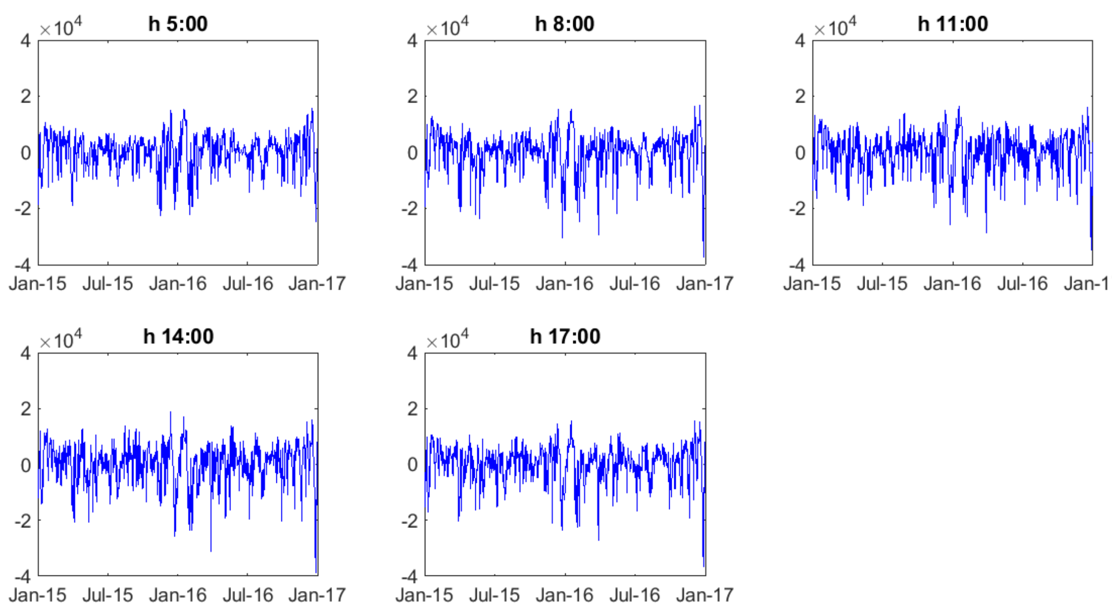
Figure 12: **Prices vs. residual load (blue dot) and polynomial function (red line)**

Fig.13 - chart (a) shows the residual load time series (black line) and its estimated long-term seasonal component (LTSC, red line) at different hours. Chart (b) depicts the stochastic component of the residual load ($X_{h,t}$ in Eq.7) after removing the long- and short-term seasonal components and suggests a mean-reverting behavior of the series, likewise the presence of jumps. The residual component of the day-ahead price time series, after removing the deterministic function of the residual load, is shown in Fig.14 - chart (a) (black line), along with the estimated long-term seasonal

component (LTSC, red line). Chart (b) of Fig.14 shows the stochastic component of the residual price after removing the long- and short-term seasonal components ($Y_{h,t}$ in Eq.10) and implies a mean-reverting behavior.

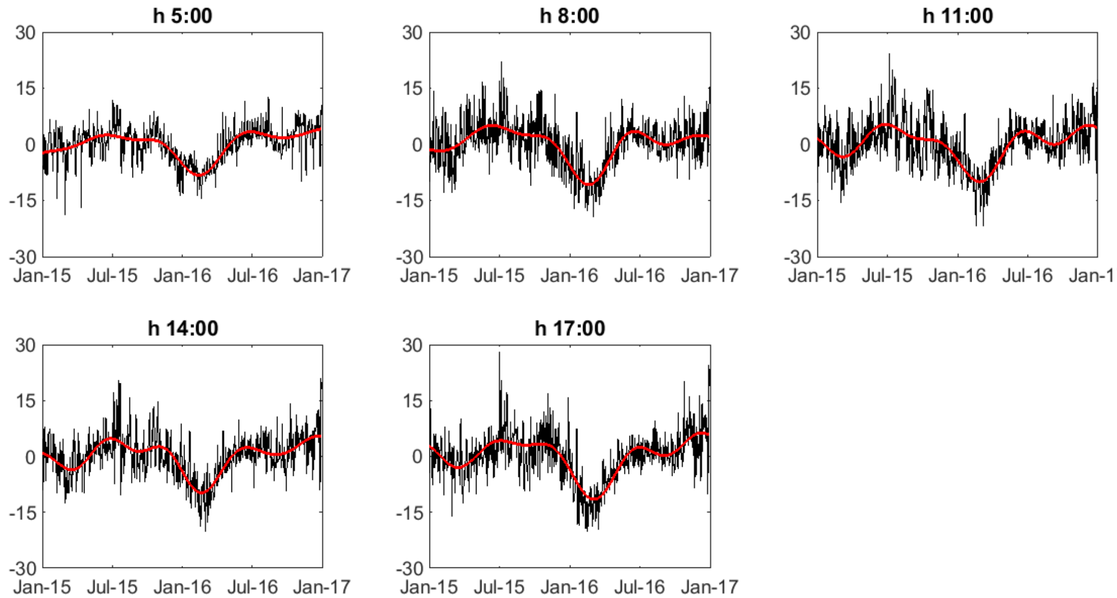


(a) Actual residual load (black line) and LTSC (red line)

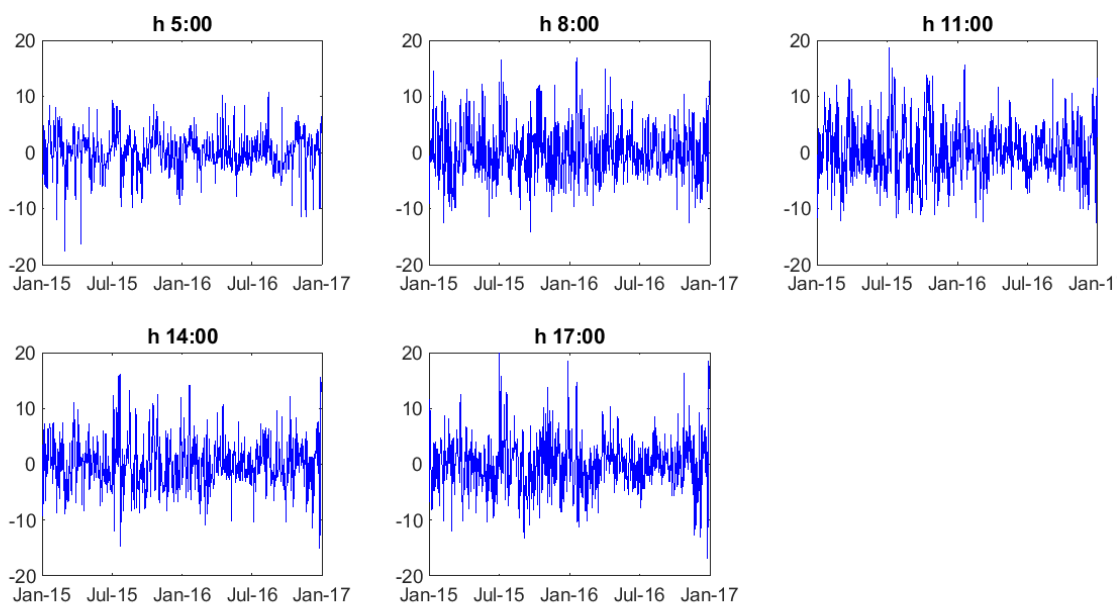


(b) Stochastic component

Figure 13: **Residual load: LTSC and stochastic components (in MW)**



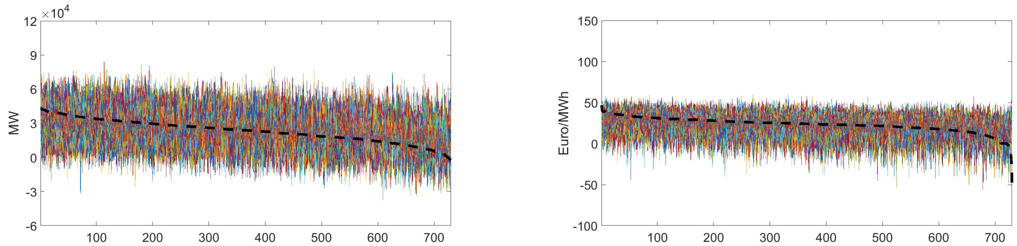
(a) Residual component (black line) and LTSC (red line)



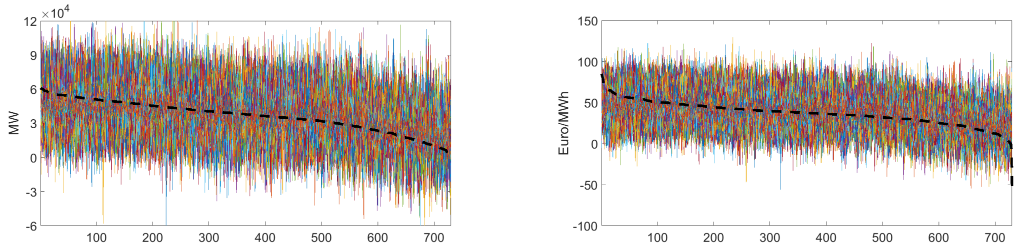
(b) Stochastic component

Figure 14: **Residual day-ahead prices: LTSC and stochastic components (Euro/MWh)**

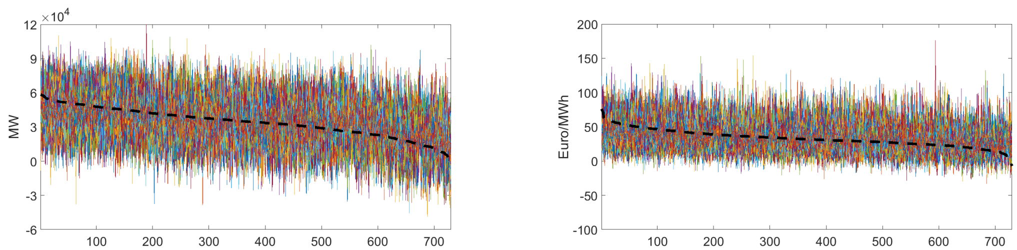
A.3 Simulated residual load and day-ahead prices at different degrees of self-sufficiency



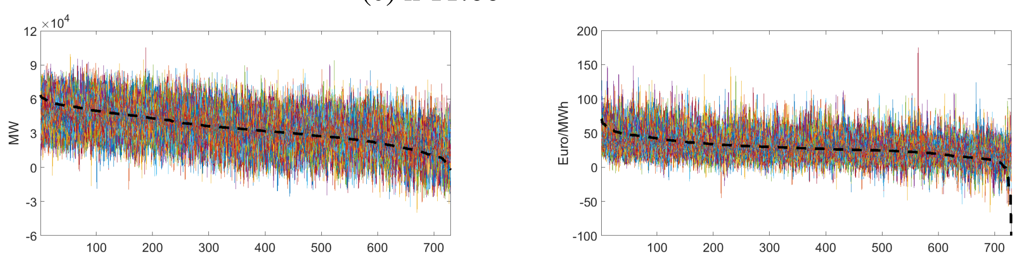
(a) h 5:00



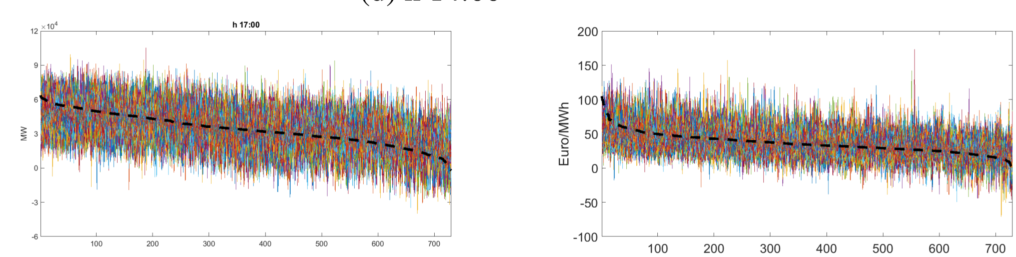
(b) h 8:00



(c) h 11:00

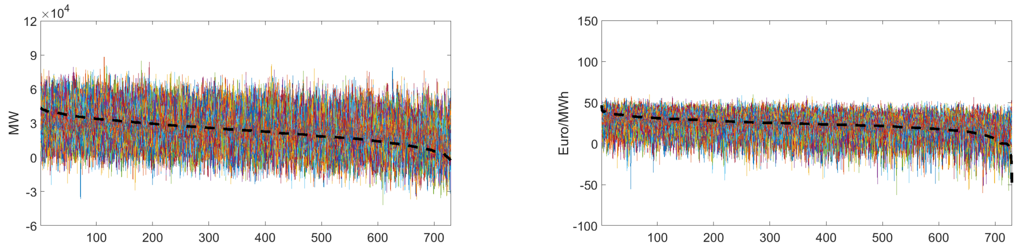


(d) h 14:00

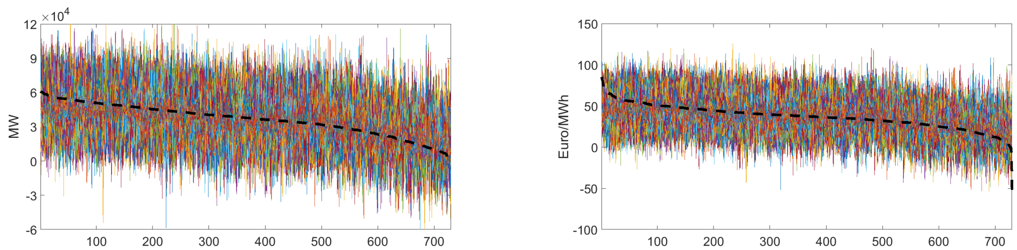


(e) h 17:00

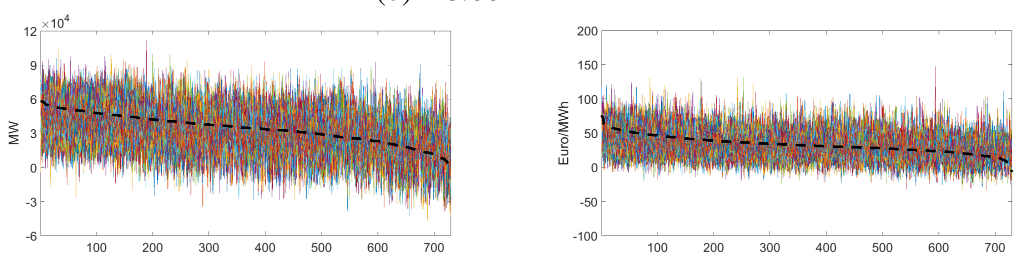
Figure 15: **Actual (black dot) vs simulated residual load (left) and day-ahead price (right) duration curves: 10% self-sufficiency**



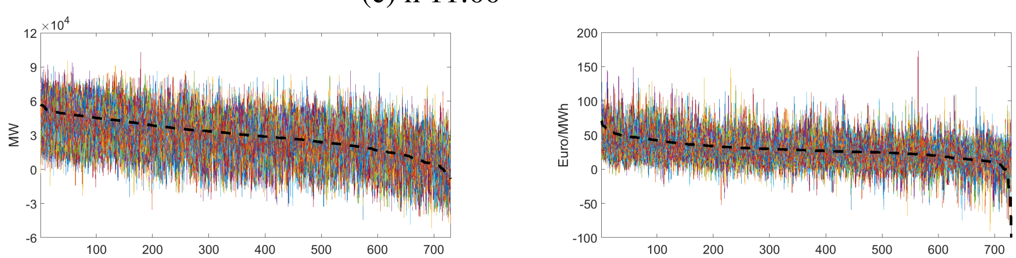
(a) h 5:00



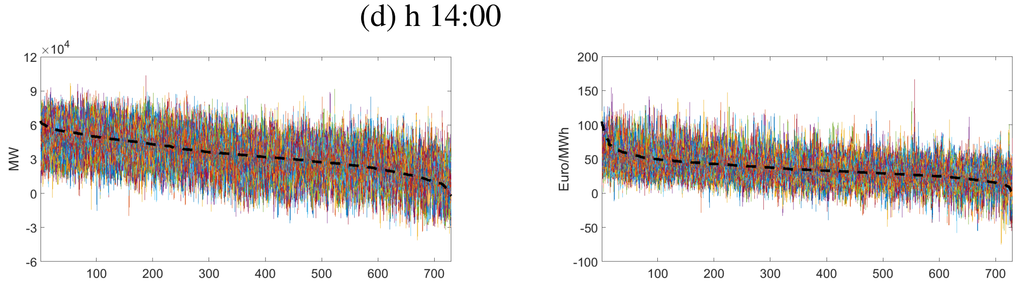
(b) h 8:00



(c) h 11:00



(d) h 14:00



(e) h 17:00

Figure 16: **Actual (black dot) vs simulated residual load (left) and day-ahead price (right) duration curves: 20% self-sufficiency**

A.4 Performance evaluation Monte Carlo simulations

Tab.6 and Tab.7 present some error measures comparing the observed and simulated residual load and price time series. The average root mean square error (RMSE) and the average mean absolute percentage error (MAPE) are reported in columns two and three. Column four shows the average linear pairwise correlation coefficient R. The last two columns of the tables show the median values of the first and third quartile of the simulated series (P_{25}, P_{75}). While the RMSE, MAPE and R measures are parametric pairwise measures, the quartiles are non-parametric statistics, thus capturing dynamics in the distribution of the simulated series.

Table 6: **Error Measures: Residual Load**

	RMSE	MAPE (%)	R	P_{25}	P_{75}
5:00	9301	80.08	0.519	17650	30088
8:00	10571	35.30	0.672	28722	45735
11:00	10534	59.95	0.617	26540	42674
14:00	10499	69.58	0.684	21238	39245
17:00	9592	33.46	0.731	25065	43861

Table 7: **Error Measures: Day-Ahead Prices**

	RMSE	MAPE (%)	R	P_{25}	P_{75}
5:00	9.09	620.7	0.38	19.05	28.79
8:00	12.69	148.8	0.56	29.44	46.42
11:00	12.29	232.1	0.44	25.72	40.55
14:00	13.38	190.1	0.48	21.66	36.08
17:00	11.91	33.49	0.61	27.42	44.36

Year	Number	Title/Author(s)
2018		
	596	VAT revenue elasticities: an analytical approach *Jean Acheson, Yota Deli, Edgar L. W. Morgenroth, Derek Lambert and Martin Murphy*
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