Energy Economics 51 (2015) 503–509

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Hedging strategies in energy markets: The case of electricity retailers

Raphaël Homayoun Boroumand [a,*], Stéphane Goutte [b,1], Simon Porcher [c], Thomas Porcher [a]

[a] Department of Applied Economics, PSB Paris School of Business, 59 rue Nationale 75013 Paris France
[b] Université Paris 8 (LED), 2 rue de la Liberté, 93526 Saint-Denis Cedex, Paris, France
[c] London School of Economics and Political Science, Houghton Street, WC2A 2AE, London, UK

ARTICLE INFO

Article history:
Received 22 October 2014
Received in revised form 25 June 2015
Accepted 28 June 2015
Available online 29 July 2015

JEL classification:
C02
L94
G11
G32

Keywords:
Electricity
Risk
Retailer
Hedging
Portfolio
Intra-day
VaR
CVaR

ABSTRACT

As market intermediaries, electricity retailers buy electricity from the wholesale market or self-generate for re(sale) on the retail market. Electricity retailers are uncertain about how much electricity their residential customers will use at any time of the day until they actually turn switches on. While demand uncertainty is a common feature of all commodity markets, retailers generally rely on storage to manage demand uncertainty. On electricity markets, retailers are exposed to joint quantity and price risk on an hourly basis given the physical singularity of electricity as a commodity. In the literature on electricity markets, few articles deal on intra-day hedging portfolios to manage joint price and quantity risk whereas electricity markets are hourly markets. The contributions of the article are twofold. First, we define through a VaR and CVaR model optimal portfolios for specific hours (3 am, 6 am,. . . ,12 pm) based on electricity market data from 2001 to 2011 for the French market. We prove that the optimal hedging strategy differs depending on the cluster hour. Secondly, we demonstrate the significantly superior efficiency of intra-day hedging portfolios over daily (therefore weekly and yearly) portfolios. Over a decade (2001–2011), our results clearly show that the losses of an optimal daily portfolio are at least nine times higher than the losses of optimal intra-day portfolios.

© 2015 Elsevier B.V. All rights reserved.

1. Introduction and literature review

In competitive wholesale and retail electricity markets, electricity retailers buy electricity from producers through long-term contracts, on the day-ahead/spot market, or self-generate, for (re)sale on the retail market. On the residential segment, retailers have to serve fluctuating load at usually fixed predetermined prices (Boroumand and Zachmann, 2012; Bushnell et al., 2008). As market intermediaries, retailers have the contractual obligation to harmonize their upstream (sourcing) and downstream (sales) portfolios of electricity (Boroumand, 2015). Demand uncertainty is a common feature of all commodity markets and is traditionally managed through inventories. For all commodity retailers, inventories enable intertemporal arbitrages and facilitate matching between sourcing and selling portfolios in accordance with supply/demand variability. However, in electricity markets, retailers are uncertain about how much electricity their customers will consume at any hour of the day until they actually turn switches on. In standard electricity retail contracts, retailers operate under an obligation to serve and cannot curtail delivery (except in the case of the so-called ‘interruptible contracts’). On the supply side, the economic non-storability of (large) electricity volumes contributes to make electricity markets very specific. Consequently, electricity needs to be generated and consumed simultaneously. This non-storability contributes to the exceptionally high volatility of electricity wholesale prices in most spot markets around the world (Geman, 2008). The crucial dimension of price formation in electricity markets is the instantaneous nature of the product (Bunn, 2004) leading to structural price jumps (Goutte et al., 2013, 2014). Regardless of how retailers hedge their expected load, they will inevitably be short or long given demand stochasticity. Any corresponding adjustment on the spot market will be made at volatile hourly prices whereas retail prices are generally fixed for a significantly longer period given consumers' risk aversion (generally 1 year minimum with tacit conduction). This asymmetry of price patterns combined to demand variability can generate very high losses for retailers which are not efficiently hedged (Boroumand, 2009). Indeed, retailers cannot pass through increases of

* Corresponding author. Tel: +33153364400.
E-mail address: raphaelboroumand@gmail.com (R.H. Boroumand).

[1] This paper has benefited from the support of the Chaire European Electricity Markets of the Paris Dauphine Foundation, supported by RTE, EDF and EPEX Spot. The views and opinions expressed in this Working Paper are those of the authors and do not necessarily reflect those of the partners of the CEEM.

http://dx.doi.org/10.1016/j.eneco.2015.06.021
0140-9883/© 2015 Elsevier B.V. All rights reserved.

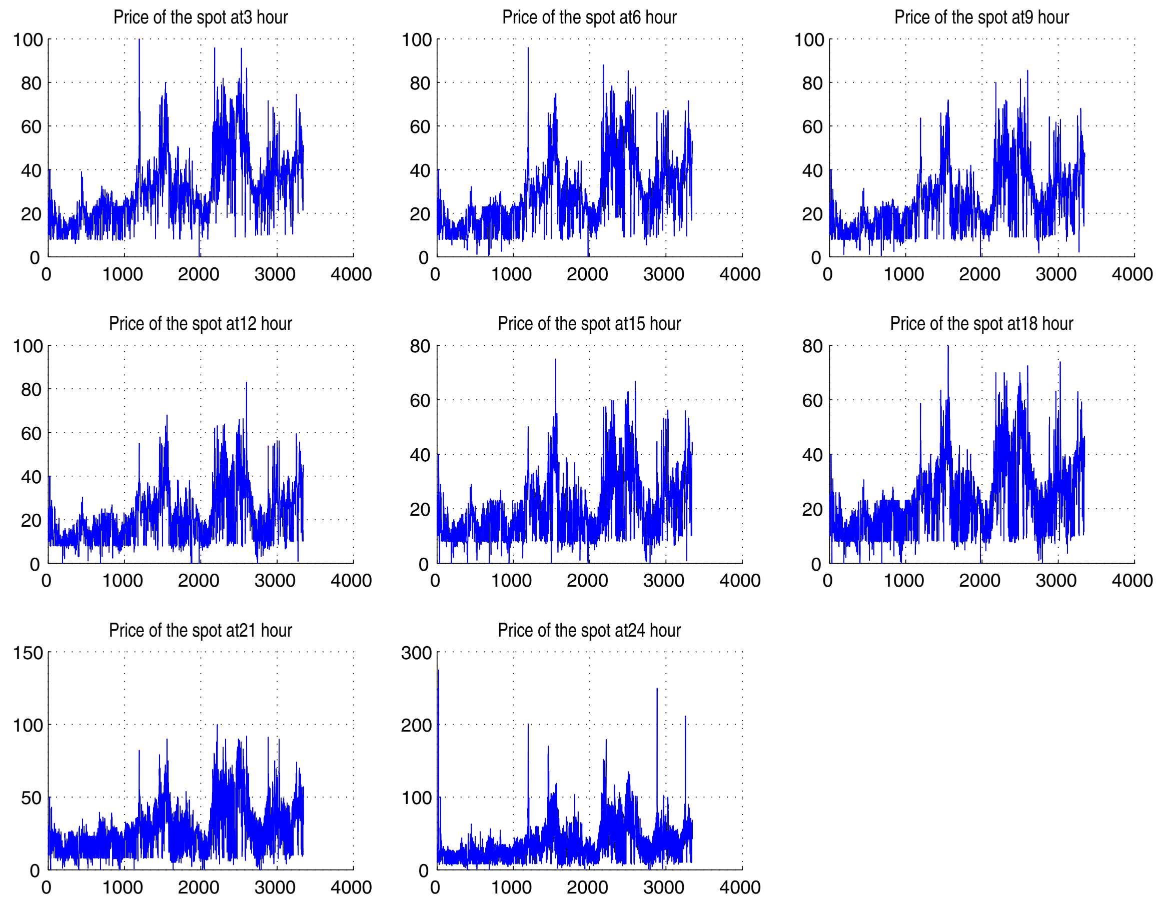

Fig. 1. Spot electricity price for each cluster hour from 27 Nov 2001 to 8 March 2011.

wholesale prices to their customers either because of potential losses of market shares on a longer run or because electricity prices are frozen (like in most US states). Given the strong positive correlation and multiplicative interaction between load level and spot price (Stoft, 2002), any under- or over-contracted position will be settled at the most unfavorable times. Most likely, when retailers are short (consumption exceeds demand forecasts), spot prices are high and above retail prices. Reversely, when retailers are long, spot prices will most likely be lower than their average sourcing cost. To sum up, the hourly variability of demand, its inelasticity, and the rigidity of supply (non-storability and plant outages) expose retailers' net profits to hourly volumetric and price risks, both correlated with weather conditions (Stoft, 2002). Price and quantity risks can bess very severe given that supply and demand conditions usually shift adversely (Stoft, 2002). Suppliers' profits depend on electricity demand, spot price, and retail price. Since retail prices are usually fixed for residential customers (Henney, 2006), profit is strongly impacted by hourly spot price variations. Consequently, retailers are unable to hedge their electricity sales by only trading in forward and spot markets on a monthly, weekly, or daily basis. They need to engage in risk management strategies on an hourly basis to mitigate the exposure of their profits or their opportunity cost (if they self-generate) exposed to joint price and volumetric risk. As a consequence of electricity liberalization, a wide variety of hedging instruments have emerged to enable economic agents to manage their risks (Geman, 2008; Hull, 2005; Hunt, 2002; Hunt and Shuttleworth, 1997). Since quantity risk is non-tradable (i.e. cannot be transferred by a retailer to another economic agent), hedging consists in price-based financial instruments (Brown and Toft, 2002). In electricity markets, efficient hedging should be against variations in total costs (quantity times price), which is complex with hourly demand variability. A retailer profit facing a multiplicative risk of price and quantity is nonlinear in price. Therefore, hedging with linear payoff instruments (forward and futures contracts) is not efficient (Boroumand and Zachmann, 2012). Conventional hedging strategies deal with one source of uncertainty. Methodologies to hedge price risk have been studied by the literature. However, hedging joint price and quantity risk for electricity retailers remains an outstanding issue. The literature on risk management within electricity markets adopts usually the perspective of electricity producers (Conejo et al, 2008; Paravan et al., 2004; Pineda and Conejo, 2012; Roques et al, 2006). Chao et al. (2008) deals with the vertical allocation of risk bearing within the electricity value chain. On retailers' perspective, Boroumand and Zachmann (2012) compare the risk profiles of different financial and physical hedging portfolios according to the Value at Risk (95%). By defining optimal annual hedging portfolios, they show the risk management benefits of relying on financial options and physical assets with different marginal costs (base, semi-base, and peak plants). Chemla et al (2011) show the superior efficiency of vertical integration over forward hedging when retailers are highly risk averse. Xu et al. (2006) present a midterm power portfolio optimization and the corresponding methodology to manage risks. Oum et al (2006) and Oum and Oren (2010) obtain the optimal hedging strategy with electricity derivatives by maximizing the expected utility of the hedged profit (Oum et al, 2006) and the expected profit subject to a VaR constraint (Oum and Oren, 2010). The authors explore optimal procurement time of the hedging portfolio. VehvilŠinen and Keppo (2003) study the optimal hedging of price risk using a mix of electricity derivatives. Carrion et al (2007) develop a risk-constrained stochastic programming framework to decide which forward contracts the retailer should sign and at which price it must sell electricity in order to maximize its expected profit for a given risk exposure. Carrion et al (2009) propose a bilevel programming approach to solve the medium-term decision-making problem of an electricity retailer.

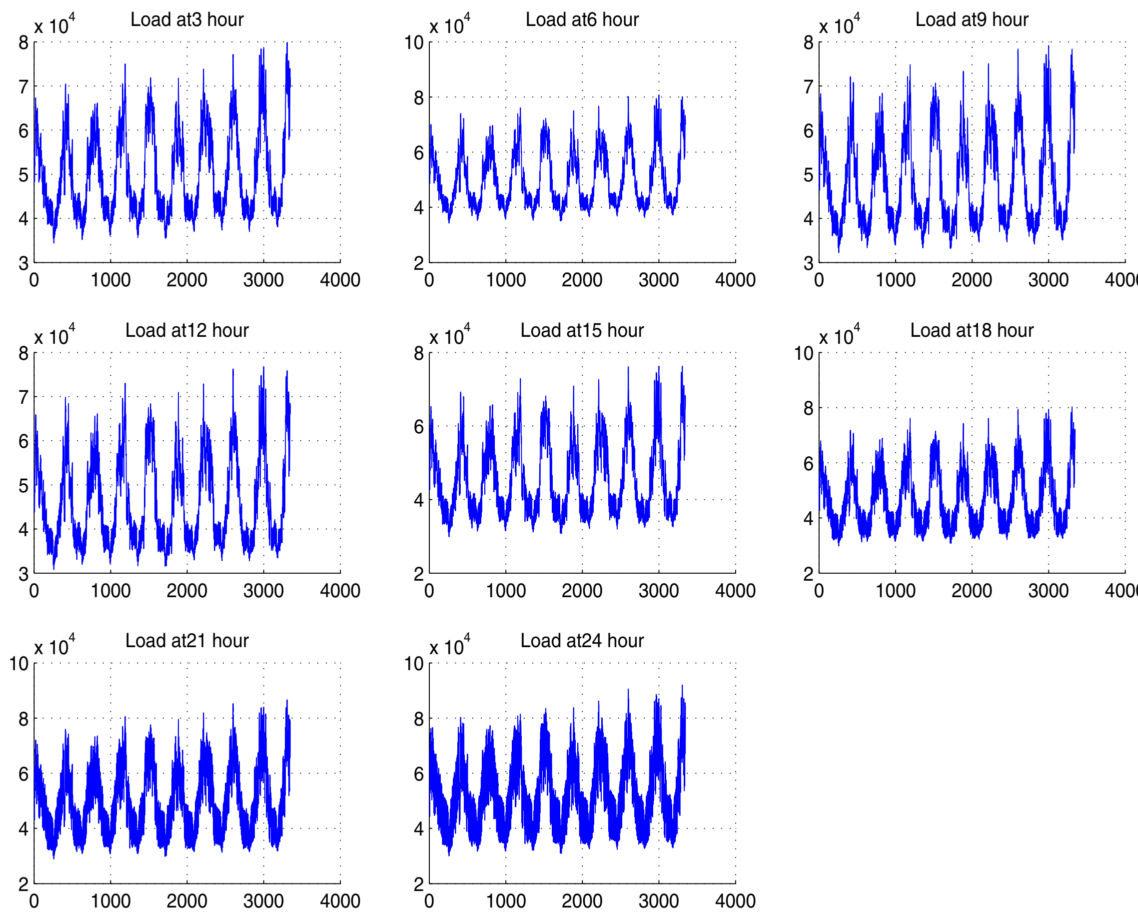

Fig. 2. Electricity load for each cluster hour from 27 Nov 2001 to 8 March 2011.

However, to our knowledge, few articles propose portfolio optimization based on intra-day hedging for electricity intermediaries, despite the well-known structural electricity price spikes subsequent notably to the non-storability of electricity. The frequency of spot hourly price spikes reinforces the necessity of intra-day hedging strategies.

Our results clearly demonstrate that the optimal hedging portfolio varies in relation with the hours of the day. The contribution of the article is twofold. First, our model demonstrates that the average of the cumulated hourly losses [as measured by the average VaR and CVaR] of the eight homogeneous group of hours is lower than the VaR (95%) and the corresponding CVaR of a single daily optimal portfolio. Therefore, we propose several optimal hedging portfolios per day. Secondly, for any group of hours, we demonstrate that the optimal portfolio is specific.

The article is structured as follows: Section 1 presents the statistical features of the simulated data. Section 2 presents our methodology. In Section 3, we present the results of our simulations. The last section concludes and provides policy recommendations.

2. Data

The methodology is an extension of Boroumand and Zachmann (2012) with two key differences. First, we realize simulations on electricity price and volume data over a 10-year period (2001–2011). The extensive data simulation contributes to the high robustness of our results. Second, we test intra-day portfolios rather than annual portfolios. Therefore, we calculate intra-days VaR for each hourly cluster. We take the French spot electricity price from 27 Nov 2001 to 8 March 2011.

Our model relies on data from the French spot electricity market from 27 Nov 2001 to 8 March 2011. This market is relevant for several reasons. First, the spot price is the reference price of the French wholesale market. Indeed, many retailers index their price on the referential spot price. Overall, the EPEX spot auction represents 70% of all day-ahead transactions. Admittedly, the size of the market in 2001 was smaller but it has never been an extension of the incumbent, which is an actor among others. Indeed, EDF uses mainly its production for its own portfolio of clients. The French spot market is the 3rd biggest market in Europe in terms of volume (687 TWh in 2011), the HHI index is low (691 for the last semester of 2011), and the liquidity is high with 57858 transactions for the first semester of 2011 (CRE,[2] 2011).

We define eight different hourly prices, namely, our cluster hours, which are 3 am, 6 am, 9 am, 12 am, 3 pm (15), 6 pm (18), 9 pm (21), 12 pm (24).

Fig. 1 clearly exhibits spot price spikes. Fig. 2 shows the different levels of consumption volume and variability for each cluster hour.

3. Hedging strategies

We demonstrate that a retailer cannot reproduce the risk-reducing benefits of physical hedging by pure contractual portfolios. For this purpose, we compare the risk profiles of different portfolios of hedging with the traditional Value at Risk (VaR) indicator. The Value at Risk (VaR) is an aggregated measure of the total risk of a portfolio of contracts and assets. The VaR summarizes the expected maximum loss (worst loss) of a portfolio over a target horizon (10 years in this article) within a given

[2] Observatoire des marchés de l'électricité et du gaz.

Table 1
Payoffs of different contracts/assets given the spot price P_t.

Contract	Payoff
Retail contract	$\pi_{retail,t} = -P_t.V_t + \mathbb{E}[P_t.V_t]$
Forward	$\pi_{forward,t} = V_{forward}.P_t - \mathbb{E}[V_{forward}.P_t]$
Power plant	$\pi_{plant,t} = V_{plant}\times\ ,\max(P_t - mc, 0) - \mathbb{E}[V_{plant}\times\ ,\max(P_t - mc, 0)]$
Call option	$\pi_{call,t} = V_{call}\times\ ,\max(P_t - K, 0) - \mathbb{E}[V_{call}\times\ ,\max(P_t - K, 0)]$
Put option	$\pi_{put,t} = V_{put}\times\ ,\max(K - P_t, 0) - \mathbb{E}[V_{put}\times\ ,\max(K - P_t, 0)]$

confidence interval (generally 95%). Thus, VaR is measured in monetary units, Euros in our article. As the maximum loss of a portfolio, the VaR(95%) is a negative number. Therefore, maximizing the VaR is equivalent to minimizing the portfolio's loss. We rely on the Value at Risk because it is a good measure of the downside risk of a portfolio and is for example used as preferred criteria for market risk in the Basel II agreement. We strengthen the robustness of our results with the CVaR.

The Conditional Value at Risk, CVaR, is strongly linked to the previous risk measure (i.e. VaR) which is, as mentioned above, the most widely used risk measure in the practice of risk management. By definition, the VaR at level $\alpha \in (0,1)$, $VaR(\alpha)$ of a given portfolio loss distribution is the lowest amount not exceeded by the loss with probability α (usually $\alpha \in [0.95,1]$). The Conditional Value at Risk at level α $CVaR(\alpha)$ is the conditional expectation of the portfolio losses beyond the $VaR(\alpha)$ level. Compared to VaR, the CVaR is known to have better mathematical properties. It takes into account the possible heavy tails of portfolio loss distribution. Risk measures of this type were introduced by Artzner et al. (1999) and have been shown to share basic coherence properties (which is not the case of $VaR(\alpha)$.

3.1. Payoff of the assets and contracts within a hedging portfolio

A retailer is assumed to have concluded a retail contract (the retail contract is given ex ante and is therefore not a portfolio's parameter of choice) with its customers that imply stochastic demand V_t for $t = 1{:}T$. The demand distribution is known to the retailer and the uncertainty about the actual demand V_t is completely resolved in time t. To fulfill its retail commitments, the retailer can buy electricity on the spot market at the ex ante uncertain spot market price P_t. The spot market price distribution is known by the retailer. To reduce its risk from buying an uncertain amount of electricity at an uncertain price, the retailer can conclude financial contracts and/or acquire physical generation assets. All contracts (including the retail contract and the physical assets generation volumes) are settled on the spot market that is assumed to be perfectly liquid. Thus, the payoff streams depend on a given number of hourly spot market realizations.

Table 2
Descriptive statistics of the simulated data for each cluster hour.

Clusters hours	3 am	26 am	9 am	12 am
Mean price ($\mathbb{E}[P_t]$)	24.11	23.97	46.66	57.99
Median price (mc)	21.77	21.94	42.01	49.87
Mean load	46978.33	46970.76	57137.90	59106.19
Median load	45428.00	45383.00	55431.00	57793.00
Variance price	158.03	153.92	2790.30	4473.27
Variance load	36966692.94	37830907.83	41246907.38	28520369.27

Clusters hours	3 pm	6 pm	9 pm	12 pm
Mean price ($\mathbb{E}[P_t]$)	48.50	44.08	45.17	35.76
Median price (mc)	42.52	39.33	40.52	32.99
Mean load	56482.52	54875.10	55260.57	53092.89
Median load	55659.00	52932.00	54308.00	51468.00
Variance price	1047.84	619.90	1268.30	252.82
Variance load	24607724.92	40756544.24	39911753.29	29013300.90

Table 3
Optimal hedging portfolio for each cluster hour, and for a day. The values of the corresponding VaR and CVaR are also given.

Hour	VaR		CVaR	
	Optimal hedging portfolio	Value	Optimal hedging portfolio	Value
3 am	Forward and 3 plants	−676.94	Forward and 3 plants	−954.53
6 am	All possible contracts	−782.23	Only forward	−1073.72
9 am	Forward and $V_{plant,75}$	−1615.48	Without options	−2692.99
12 am	Forward and 3 plants	−1449.12	$V_{plant,25}$ and $V_{plant,75}$	−2499.38
3 pm	Forward and 3 plants	−1353.29	Forward and 3 plants	−2295.76
6 pm	$V_{plant,25}$ and $V_{plant,75}$	−1496.32	$V_{plant,25}$ and $V_{plant,75}$	−1872.97
9 pm	Forward and 3 plants	−1210.55	Forward and 3 plants	−1979.57
12 pm	Forward and 3 plants	−943.84	Forward and 3 plants	−1687.96
Daily	Only options	−16095.31	Forward and $V_{plant,75}$	−21917.63

3.1.1. Portfolios' structures

Let denote by $\pi_{i,t}$, the price at time $t = 1{:}T$ of a particular contract with name i. We consider five different contracts/assets Đ, namely, a retail contract, a forward contract, a power plant, a call option on the spot price, and a put option on the spot price given the spot price. In Table 1, we recall the payoff of these five contracts.

If for example, the electricity spot price (P_t) is above the strike price of the options (K), there is a positive payoff of the call option, while the payoff of the put option is zero. The payoff of the power plant depends on the installed capacity of the plant (V_{plant}) and its marginal cost (mc) and only the payoff of the retail contract depends on the stochastic demand V_t. We subtract the expected value $\mathbb{E}(.)$ from the gross payoff all contracts/assets to obtain a zero expected value. That is, we assume to be in a perfect and complete market (no market power, no transaction costs, full transparency, etc.). Consequently, arbitrage would not allow for the existence of systematic profits.

Without this assumption, the method for the evaluation of contracts and assets would drive our results. Indeed, the net loss calculated for each portfolio would be strongly determined by the valuation method of the assets or contracts within each portfolio.

3.2. Methodology of numerical simulations

The marginal generation cost of the power plant is set to the median of the simulated spot prices mc Euro/MWh (second line of Table 2), thus representing a peak load power plant. The strike price of the options is set to the expectation value of the spot price $K = \mathbb{E}[P_t]$ Euro/MWh (first line of Table 2).

We clearly see in Table 2 that all statistical indicators on a 10-year basis vary considerably depending on the cluster. For instance, the variance price for cluster 3 am is 158.03, whereas it is 2790.30 for cluster 9 am. In the same vein, the mean price of cluster 3 am is 24.11 whereas it is 57.99 for cluster 12 am. This is related to the fact that electricity markets are hourly markets. Price and demand variability are on an hourly basis. This hourly feature and the presence of price spikes justify an intra-day hedging approach rather than a daily approach.

3.3. The risk minimization

We can calculate the cumulated annual payoffs of the N = 3347 hourly price/volume combinations for all 2000 simulations given the portfolio ($V_{forward}$,V_{plant},V_{call},V_{put},):

$$\pi^i = \sum_{t=1}^{N}\left[\pi_{retail,t}\left(P_t^i, V_t^i\right)\right] + \left[V_{forward} \times \pi_{forward,t}\left(P_t^i\right)\right] + \left[V_{plant} \times \pi_{plant,t}\left(P_t^i, mc\right)\right] + \left[V_{call} \times \pi_{call,t}\left(P_t^i, K\right)\right] + \left[V_{put} \times \pi_{put,t}\left(P_t^i, K\right)\right]. \quad (2.1)$$

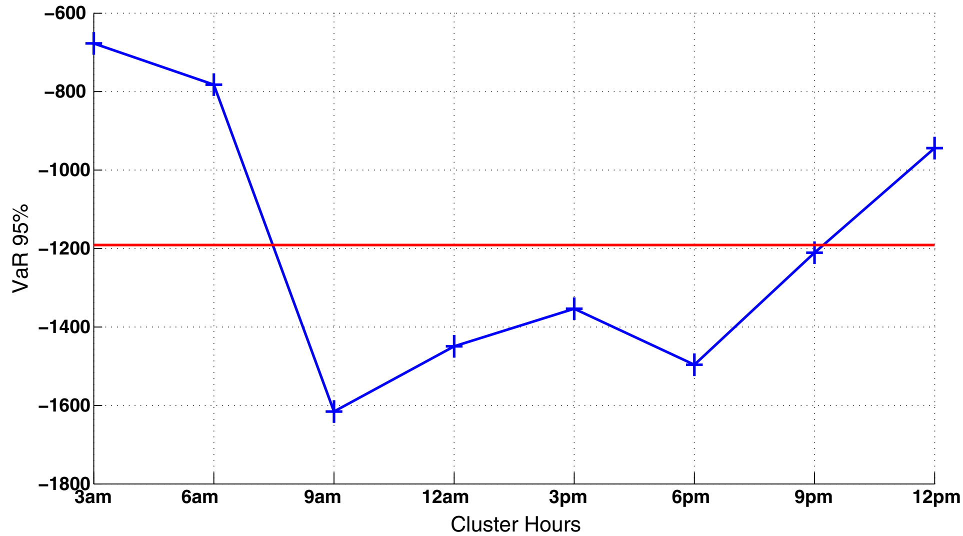

Fig. 3. VaR values obtained by the optimal hedging portfolio for each cluster hour on a 10-year basis (in blue). Corresponding mean in red.

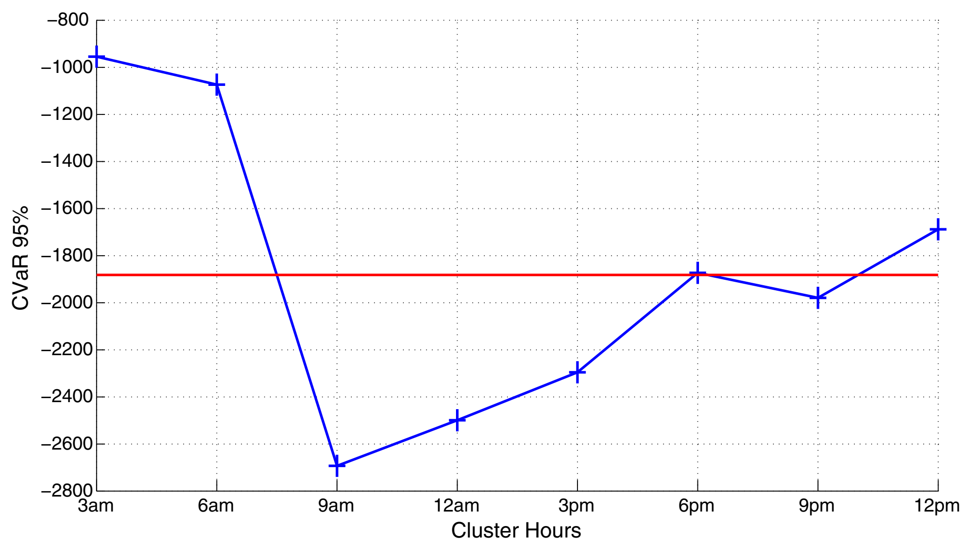

Fig. 4. CVaR values obtained by the optimal hedging portfolio for each cluster hour on a 10-year basis (in blue). Corresponding mean in red.

Thus π^i is the global payoff of the ith hourly price and volume simulation of a day given the portfolio defined by ($V_{forward}$, V_{plant}, V_{call}, V_{put}). Using an optimization routine,[3] the portfolio that produces the lowest VaR(95%) can be identified. As the routine does not necessarily converge for this nonlinear problem (especially for the three and four assets case), we rerun the optimization for each case with 100 different randomly drawn starting values. The result of the best run can be considered sufficiently close to the global optimum, as all results tend to be within a fairly narrow range.

The objective is to find the portfolio consisting of one 1 MWh baseload retail contract and a linear combination of financial contracts as well as physical assets that reduces the retailers risk. Thus, the factors for the other contracts/assets are also measured in MWh. The next tables give the results given by two types of portfolios that maximize the VaR(95%).

- portfolios containing one retail contract.
- portfolios containing one retail contract and different power plants.

[3] We proceed under constrained nonlinear optimization or nonlinear programming using the function *fmincon* in Matlab.

3.4. Optimization results

All hourly optimization results are given in Appendix (Tables 6–13). To present more complete results, we give the corresponding daily optimization results in Table 14.

As shown by Table 3, the simulations show that the optimal hedging varies considerably for each cluster.

A critical result of this Table is that this variation of optimal hedging strategy is not only in terms of VaR or CVaR values (i.e. we obtain results in the range of −1615.38 to −676.94 for the VaR (Fig. 3) and −2692.99 to −954.53 for the CVaR (Fig. 4)) but also in terms of hedging portfolio: 5 (resp. 4) out of 8 optimal portfolios for the VaR (resp. CVaR) criteria are composed by a combination of a forward contract and 3 powerplants.

Remark 2.1. The complementarity and the non-correlation between the payoff and the risk level of a forward and 3 different powerplants (baseload, semi-peak, and peak) portfolio enable more flexibility given the hourly variability of electricity demand.

Therefore, if a retailer is hedged on a daily basis given its liquidity or cost constraints, it should at least choose this portfolio (i.e. forward contract and 3 powerplants) to minimize its losses.

Table 4
Increasing differential loss between the single forward hedging portfolio and optimal hedging one given in Table 3.

Hour	Increasing loss in percentage	
	VaR	CVaR
3 am	105.64%	6.37%
6 am	102.22 %	0.00%
9 am	61.72%	5.71%
12 am	27.81%	22.45%
3 pm	21.97%	18.19%
6 pm	106.35 %	59.12%
9 pm	116.92%	11.75%
12 pm	35.80%	10.56%
Daily	46.87%	24.48%

Moreover, we show that a daily hedging optimization is worst than any hourly hedging optimization (we obtain a VaR of −16095.31 and a CVaR of −21917.63). This implies that intra-day hedging portfolios are much more appropriate than single daily portfolios to manage joint volumetric and price risks on electricity markets.

Confirming on a 10-year period and on an hourly basis, one of the results in Boroumand and Zachmann (2012), a single forward hedging is not only never optimal but also inefficient given that electricity demand is not constant. Table 4 gives the increasing loss using a single forward hedging instead of the optimal hedging portfolio given in Table 3.

Indeed, forward hedging is not relevant within markets where demand is stochastic and correlated to the spot price.

Over a decade (2001–2011), our results show that the losses of an optimal daily portfolio are ten times higher for the VaR criteria (resp. nine times higher for the the CVaR criteria) than the losses of any optimal intra-day portfolio. We obtain for the optimal daily hedging portfolio a VaR value of −16095.31 (resp. a CVaR value of −21917.63) against −1615.48 for the worst one in cluster hour optimization (9 am) (resp. −2692.99 for the worst one again in cluster hour optimization (9 am).

3.4.1. In and out of the money case

An interesting extension of our hedging portfolio optimization is to test the case of in and out of the money option. We run our optimization process for the cluster hour 6 pm (peak demand) with different strike values for the call option. As mentioned in Section 3.2, the strike price of the options is set to the expectation value of the spot price $K = \mathbb{E}[P_t]$ Euro/MWh. Thus, regarding the first line of Table 2 for the cluster hour 6 pm, we have a value of at the money strike equal to $K = 44.08$ euros. In Table 5 we take a range of strike price values of −10 to +10 of K with step of 5 (Table 5).

The more a call option is in the money, the higher is its intrinsic value. Thus, the spread between *all possible contracts* and *only options* portfolio increases (Table 5). To the contrary, this spread vanishes in the out of money case.

Table 5
Optimal VaR obtained with respect to the strike $K + \alpha$ of the call option.

Portfolio	Values of α				
	−10	−5	0	5	10
All possible contracts	−1842.64	−1842.64	−1757.36	−1633.56	−1467.77
Only options	−1928.39	−1848.05	−1760.97	−1633.56	−1467.77

4. Conclusion and policy recommendations

Our article contributes to the literature on electricity retailers' risk hedging. We simulate optimal intra-day portfolios given that electricity markets are hourly markets. First, we demonstrate that the optimal hedging strategy differs depending on the cluster hour with respect to VaR and CVaR risk indicators. Second, we prove the significantly superior efficiency of intra-day hedging portfolios over daily (therefore weekly and yearly) portfolios. Over a decade (2001–2011), our results clearly show that the losses of an optimal daily portfolio are at least nine times higher than the losses of optimal intra-day portfolios (Table 3). A clear understanding of risk management strategies within electricity markets is crucial for market players, energy regulators, and financial investors. Without appropriate risk management instruments, the contribution of electricity retail markets to the global performance of the electricity industry will remain uncertain (Boroumand, 2015). We believe that this article contributes to a better understanding of risk management issues in electricity markets. The challenge for energy regulators is to enhance the liquidity of risk management instruments such as intra-day options. A relevant research extension is to propose a dynamic framework for hedging strategies with distinct and/or additional financial derivatives.

Acknowledgments

The authors would like to thank the participants of the ICCM January 2014 workshop, specially Professor Helyette Geman, Professor Derek Bunn, and Professor Ehud I. Ronn. The authors are also grateful to the members of the Department of Economics, City University London, for their suggestions.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2015.06.021.

References

Artzner, P., Delbaen, F., Eber, J.M., Heath, D., 1999. Coherent measures of risk. Mathematical Finance. 9 p. 203Ð228.

Boroumand, R.H., 2015. Electricity markets and oligopolistic behaviors: The impact of a multimarket structure. Research in International Business and Finance. 33, 319–333.

Boroumand, R.H., Zachmann, G., 2012. Retailers' risk management and vertical arrangements in electricity markets. Energy Policy 40 (1), 465–472.

Boroumand, R.H., 2009. Les fournisseurs non intégrés d'électricité: l'échec d'un modèle organisationnel. Rev. Energ. 590, 231–240.

Brown, Toft, 2002. Rev. Financ. Stud. 15 (4), 1283–1324.

Bunn, D. (Ed.)2004. Modelling Prices in Competitive Electricity Markets (Wiley finance) (358 pages).

Bushnell, J., Mansur, E., Saravia, C., 2008. Vertical arrangements, market structure, and competition: an analysis of restructured US electricity markets. Am. Econ. Rev. 98 (1), 237–266.

Carrion, M., Conejo, A.J., Arroyo, J.M., 2007. Forward contracting and selling price determination for a retailer. IEEE Trans. Power Syst. 22 (4), 2105–2114.

Carrion, M., Arroyo, J.M., Conejo, A.J., 2009. A bilevel stochastic programming approach for retailer futures market trading. IEEE Trans. Power Syst. 24 (3), 1446–1456.

Chao, H.P., Oren, S., Wilson, R., 2008. Reevaluation of vertical integration and unbundling in restructured electricity markets. In: Sioshansi, F.P. (Ed.), Competitive Electricity Markets: Design, Implementation, and Performance. Elsevier, London.

Chemla, G., Porchet, A., A•d, R., Touzi, N., 2011. Hedging and vertical integration in electricity markets. Manag. Sci. 57 (8), 1438–1452.

Conejo, A.J., Garc'a-Bertrand, R., Carri—n, M., Caballero, A., de AndrŽs, M., 2008. Optimal involvement in futures markets of a power producer. IEEE Trans. Power Syst. 23 (2), 703–711.

Geman, H., 2008. Risk Management in Commodity Markets: From Shipping to Agricultural and Energy. Wiley Finance, WestSussex, England.

Goutte, S., Oudjane, N., Russo, F., 2013. Variance optimal hedging for discrete time processes with independent increments. Application to electricity markets. J. Comput. Finance 17 (2).

Goutte, S., Oudjane, N., Russo, F., 2014. Variance optimal hedging for exponential of additive processes and applications. Stochast. Int. J. Prob. Stochast. Process. 86 (1), 147–185.

Henney, A., 2006. An international assessment of competitive electricity mass markets, a multiclient study. EEE Limited.

Hull, J., 2005. Options, futures, and other derivatives. 4th ed. Prentice Hall, Englewood, NJ.

Hunt, S., 2002. Making Competition Work in Electricity. Wiley.

Hunt, S., Shuttleworth, G., 1997. Competition and Choice in Electricity. Wiley.

Oum, Yumi, Oren, S., 2010. Optimal Static hedging of volumetric risk in a competitive wholesale electricity market. Decis. Anal. 7 (1), 107–122 (Special issue Êin memory of Michael H. Rothkopf).

Oum, Yumi, Oren, S., Deng, S., 2006. Hedging quantity risk with standard power options in a competitive wholesale electricity market. Nav. Res. Logist. 53, 697–712.

Paravan, D., Sheble, G.B., Golob, R., 2004. Price risk and volume risk management for power producers. International conference on probabilistic methods applied to power systems.
Pineda, S., Conejo, A.J., 2012. Managing the financial risks of electricity producers using options. Energy Econ. 34 (6), 2216–2227.
Roques, F., Newbery, D., Nuttall, W., 2006. Fuel mix diversification incentives in liberalized electricity markets: a Mean-Variance Portfolio Theory Approach. EPRG Working Paper (www.electricitypolicy.org.uk).
Stoft, S., 2002. Power System Economics: Designing Markets for electricity. IEEE Press/ Wiley-Interscience.
VehvilŠinen, I., Keppo, J., 2003. Managing electricity market price risk. Eur. J. Oper. Res. 145 (1), 136–147.
Xu, Jun, Luh, Peter B., Fellow, I.E.E.E., White, F.B., Ni, Ernan, Kasiviswanathan, K., 2006. Power portfolio optimization in deregulated electricity markets with risk management. IEEE Trans. Power Syst. 21 (4).