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ORIGINAL PAPER

The natural hedge of a gas-fired power plant

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Abstract Electricity industries worldwide have been restructured in order to introduce competition. As a result, decision makers are exposed to volatile electricity prices, which are positively correlated with those of natural gas in markets with price-setting gas-fired power plants. Consequently, gas-fired plants are said to enjoy a "natural hedge." We explore the properties of such a built-in hedge for a gas-fired power plant via a stochastic programming approach, which enables characterisation of uncertainty in both electricity and gas prices in deriving optimal hedging and generation decisions. The producer engages in financial hedging by signing forward contracts at the beginning of the month while anticipating uncertainty in spot prices. Using UK energy price data from 2006 to 2011 and daily aggregated dispatch decisions of a typical gas-fired power plant, we find that such a producer does, in fact, enjoy a natural hedge, i.e., it is better off facing uncertain spot prices rather than locking in its generation cost. However, the natural hedge is not a perfect hedge, i.e., even modest risk aversion makes it optimal to use gas forwards partially. Furthermore, greater operational flexibility enhances this natural hedge as generation decisions provide a countervailing response to uncertainty. Conversely, higher energy-conversion efficiency reduces the

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natural hedge by decreasing the importance of natural gas price volatility and, thus, its correlation with the electricity price.

Keywords Electricity markets · Risk management · Stochastic programming

List of symbols

Indices

t	Time periods, $1, \ldots, N_T$
f	Power forward contracts, $1, \ldots, N_F$
h	Natural gas forward contracts, $1, \ldots, N_H$
ω	Scenarios, $1, \ldots, N_\Omega$

Real variables

P_f^F	Power sold via forward contract f (MW_e)
Q_h^F	Natural gas purchased from forward contract h (MWh)
$E_{t,\omega}^S$	Electricity sold in the spot market in period t and scenario ω (MWh_e)
$E_{t,\omega}^G$	Electricity generated in period t and scenario ω (MWh_e)
ζ	VaR (£)
η_ω	Auxiliary variable related to scenario ω and used to calculate CVaR (£)

Random variables

$\lambda_{t,\omega}^S$	Random variable modelling the spot price of electricity in period t of scenario ω $(£/MWh_e)$
$\mu_{t,\omega}^S$	Random variable modelling the spot price of natural gas in period t of scenario ω $(£/MWh)$

Constants

λ_f^F	Price of power forward contract f $(£/MWh_e)$
μ_h^F	Price of natural gas forward contract h $(£/MWh)$
$\overline{P}_f^F$	Upper quantity limit of power forward contract f (MW_e)
$\overline{Q}_h^F$	Upper periodic quantity limit of natural gas forward contract h (MWh)
$P^{G,max}$	Capacity of plant (MW_e)
e	Energy-conversion efficiency of plant (MWh_e/MWh)
L	Minimum percentage of energy produced during peak periods that must be produced during off-peak periods
d_t	Length of period t (h)
α	Quartile value used in CVaR calculation
β	Weighting factor for CVaR calculation
π_ω	Probability of occurrence of scenario ω

$W(t, t')$ Binary parameter equal to 1 if t and t' are two consecutive off-peak and peak periods, and 0 otherwise.

1 Introduction

Restructuring of the electricity industry worldwide has been motivated by both technological innovation and the desire to improve economic efficiency (Wilson 2002). Although the replacement of vertically integrated utilities with firms providing separate generation, retailing, and distribution services is still an ongoing process with varied outcomes (Hyman 2010), it has generally resulted in a paradigm with greater risk exposure stemming from volatile electricity prices. Consequently, decision support for generators, retailers, and industrial consumers alike needs to reflect variability in profits or costs (Deng and Oren 2006). At the same time, policymakers require a deeper understanding of how exposure to risk affects investment and operational decisions by industry in order to craft policy that may balance economic objectives with environmental ones.

Such tension between competing objectives is prominent in the UK. Starting with a largely coal-fired generation sector in the late 1980s, the UK has seen privatisation of its electricity industry lead to a "dash for gas" in the past twenty years. For a variety of reasons, e.g., lifting of government restrictions, historically low gas prices, and new combined-cycle technologies, the 1990s were favourable to investment in gas-fired generation. As a result, 40 % of the electricity generated in the UK during 2011 was from natural gas (DUKES 2012). Such herding behaviour stymies policymakers' promotion of renewable energy technologies and entrenches the position of gas-fired plants. Indeed, by being "price makers," gas-fired plants are less exposed to market risk as electricity and gas prices are strongly correlated, which renders renewable energy technologies less attractive to investors (Gross et al. 2010). Therefore, understanding the channels through which this natural hedge propagates is essential for policymakers in order to support the deployment of renewable energy technologies.

In this paper, we use a stochastic programming framework (Birge and Louveaux 1997) to explore the properties of a gas-fired power plant's natural hedge. Specifically, we assume that a price-taking producer facing uncertain electricity and gas spot prices seeks to maximise its expected profit from electricity sales over a representative month while controlling its risk. We find that such a producer is always better off purchasing all of its natural gas in the spot market as opposed to locking in its price at the mean forward price for the month. Thus, a natural hedge exists, but we discover that it is not a perfect hedge for even a slightly risk-averse producer, i.e., some gas forward contracting is always optimal, which necessarily alters the optimal power hedging strategy. Using these insights, policymakers may devise support schemes for making renewable energy technologies attractive from not only a levelised cost perspective but also a risk angle. For example, Gross et al. (2010) use levelised costs to examine how the natural hedge of gas-fired power plants in the UK puts wind and other renewable energy technologies at a disadvantage. In order to mitigate this undesirable outcome, feed-in tariffs and renewables obligation certificates have been proposed (Mitchell and Woodman 2011; Chronopoulos et al. 2014). The impacts of these proposals on the risk exposure for both dominant gas-fired and fringe renewable energy plants may be assessed using our framework. Moreover, as combined-cycle gas turbine (CCGT) plants rather than single-cycle ones become more prevalent, the nature of this hedge may change, and, thus, policymakers will have to anticipate how to adapt support schemes. Indeed, the installed capacity of CCGT plants has increased from 26 GW in 2007 to 32 GW in 2011, whereas single-cycle gas plant capacity has declined from 9 to 6.5 GW over the same period (DUKES 2012).

We use two sensitivity analyses to illustrate the effects of future technological innovation: greater operational flexibility and higher energy-conversion efficiency. Surprisingly, we find that they have opposing effects on the producer's hedging behaviour. More operational flexibility enables the plant to take further advantage of the positive correlation between electricity and gas prices. Consequently, less financial hedging occurs for relatively low levels of risk aversion. By contrast, improved efficiency mitigates the impact of natural gas price volatility on the producer's risk. Hence, the natural hedge is diminished, and forward contracting becomes more important.

The structure of this paper is as follows:

- Section 2 surveys the related literature on decision making under uncertainty in the energy sector, focusing on stochastic programming in order to provide context for our approach.
- Section 3 outlines our assumptions, formulates the deterministic equivalent of the plant's problem, and explains how we handle uncertainty.
- Section 4 consists of numerical examples based on UK data in order to distil managerial and policy insights.
- Section 5 summarises the paper, discusses its limitations, and outlines directions for future research.

2 Related work

Methods for decision making under uncertainty in the electricity industry are widespread. Some use the real options approach (Dixit and Pindyck 1994), which is able to handle uncertainty, discretion over timing, and multi-stage problems. However, in order to obtain quasi-analytical solutions, simplifying assumptions are usually made about the underlying uncertainties (Siddiqui and Maribu 2009). Furthermore, risk is not directly addressed in the objective function even in simulation-based studies that accommodate more realistic price processes because the objective is still to maximise expected profit (Abadie and Chamorro 2008). An alternative is to use portfolio optimisation (Liu and Wu 2006), but while it addresses risk management for a generator by considering uncertain electricity and fuel prices, the risk measure used, i.e., variance, punishes exposure to both upside and downside risk.

More amenable to problems in the power sector, especially short- to medium-term operational ones, is stochastic programming since it accounts for technical constraints as well as coherent risk measures in the formulation. Typically, two-stage stochastic programming involves here-and-now decisions, e.g., forward contracting, without knowledge of uncertainty and wait-and-see ones, e.g., generation and spot sales, after uncertainty has been revealed (Conejo et al. 2010). Yet, without simplifying assumptions about the underlying sources of uncertainty (Oum and Oren 2008), this framework is also unable to deliver closed-form solutions. Thus, discrete scenarios generated from time-series models (Escudero et al. 1996; Contreras et al. 2003) that approximate the underlying continuous stochastic processes fitted to the data are usually employed to arrive at tractable problems (Dupačová et al. 2000).

Applications of stochastic programming to the electricity industry typically focus on the problem of a single decision maker, e.g., producer, retailer, or consumer. Notably, Fleten and Kristoffersen (2007) examine the bidding and production strategies of a Nordic hydropower plant under uncertain electricity prices. They find considerable value to accounting for stochastic prices as opposed to replacing them with their means. Closer to our effort is the two-stage model of Conejo et al. (2008), which determines the optimal year-long futures contracts to be signed by a power producer facing uncertain spot prices and fixed generation costs. They demonstrate that futures sales increase with risk aversion as the producer prefers to avoid exposure to uncertain spot prices. However, such a strategy may be problematic for unreliable generators prone to forced outages as they would be liable to procuring electricity at possibly very high spot prices in order to meet their contractual obligations. Pineda et al. (2010) and Pineda and Conejo (2012) address such unit failures and illustrate how insurance contracts and options, respectively, may be purchased by such risk-averse producers. Analogously, Pousinho et al. (2011) use stochastic programming to examine the trading strategy for a risk-averse wind producer facing uncertainty in both electricity prices and wind speeds. Modelling correlated electricity prices and loads, Kettunen et al. (2010) address the risk-management problem of a retailer. Besides multiple sources of uncertainty, they also incorporate inter-temporal cash-flow constraints. A multi-stage model for an electricity retailer based on the scenario-free stochastic programming approach is implemented by Rocha and Kuhn (2012) using linear decision rules. Finally, Carrión et al. (2007) take the perspective of an industrial consumer facing uncertain spot prices while having recourse to self generation and purchasing various forward contracts. Implementing a multi-stage framework, they show that a more risk-averse consumer increases its forward contracting and reduces both spot purchases and self generation. Carrión et al. (2009) model the analogous hedging problem of a retailer.

Analysis of risk for producers with uncertainty in both electricity and fuel prices has been rare. This would be particularly pertinent for policymakers in terms of understanding the drivers of producers' risk exposure. Extant work examining risk typically focuses on expected profit maximisation of an investor (Roques et al. 2006) or the expected cost minimisation for CO_2 abatement (Blyth et al. 2009). Although risk may be quantified *ex post* given uncertain energy and CO_2 prices along with technology costs, it is not directly tackled in the decision-making objective. An exception is Kettunen et al. (2011), who use a stochastic programming framework to illustrate how uncertain CO_2 prices promote market concentration as less risk-averse firms leverage their existing plants to make more investments of the same kind. Following in a similar spirit but focusing on a producer's operations with both electricity and fuel price risk, we seek to understand the behaviour of the built-in hedge for gas-fired power plants with current and future versions of the dominant CCGT technology.

3 Problem formulation

3.1 Assumptions

We consider the profit-maximisation problem of a gas-fired power plant over a representative month with daily generation and spot market decisions after spot price scenarios are realised. For simplicity, we ignore the interaction of this plant's operations with other generation assets that the producer may hold. In reality, a combined offering strategy for the producer's portfolio of plants may be quite different from that of a single plant. Furthermore, auction rules, market power, transmission congestion, ramping constraints, unit failures, and unit-commitment issues also influence generation output but are not explicitly modelled here. Finally, although CO_2 emissions are relevant for gas-fired power plants, we ignore them due to relatively low CO_2 prices at the time of this analysis.

In abstracting from these details, we seek to distil the risk-management incentives for a gas-fired power plant. Towards that end, we use a two-stage model in which the here-and-now decision at the first stage ($t = 0$) is the amount of forward contracting, which is made without knowing the realised spot prices (Fig. 1). We assume that only monthly contracts are available for both types of energy, and they must be selected at the beginning of the month. Subsequently, second-stage decisions (at $t = 1, \ldots, N_T$) about spot transactions and power production are made daily given the spot price realisation. In effect, the producer knows the spot price with greater certainty a day in advance than several weeks ahead when forward contracts are signed. Therefore, we treat spot prices as known after the first stage, and the producer is able to make wait-and-see generation decisions given complete certainty. A more realistic multi-stage formulation with weekly contracts could also be implemented.

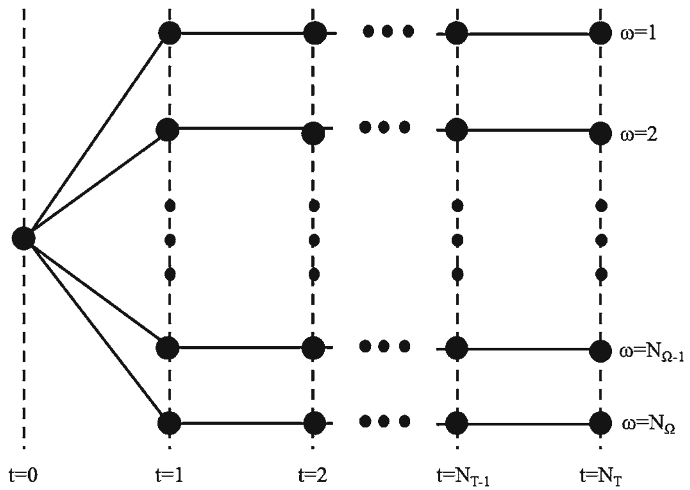

Fig. 1 Two-stage decision-making framework

Although we similarly assume that the producer is a price taker in the forward markets, there is no uncertainty about forward prices at any stage. Thus, spot prices are taken to be stochastic and exogenous, while forward prices are deterministic. We also approximate the plant's ramping and start-up constraints by restricting its generation from changing too quickly from a pre-defined off-peak day to a peak day. While modern gas-fired power plants can ramp up to full capacity in a matter of hours, they also incur start-up costs, which may preclude several start-up and shut-down cycles per day. For example, 1,200 GJ of fuel are burned for a "hot start" (immediately one hour after the unit is shut down), which leads to a start-up cost of £6k assuming a fuel price of £18/MWh. These calculations are based on a CCGT plant installed in 2010 in Aghada, Republic of Ireland (Šumbera 2013). Furthermore, according to the same source, CCGT plants have constraints on minimum up- and down-times (typically four hours each). Combined with the fact that UK intra-day peak and off-peak half-hourly electricity spot prices for January 2014 averaged £53.36/MWh$_e$ and £39.32/MWh$_e$, respectively, it is rather unlikely that prices during peak hours would drop sufficiently below the average operating cost of £40.47/MWh$_e$ for long enough to warrant shutting down the plant during peak hours. Thus, our compromise is to consider daily generation decisions with a constraint when going from an off-peak day to a peak one.

As for risk control, variance, shortfall probability, expected shortage, value-at-risk (VaR), and conditional value-at-risk (CVaR) are widely used as risk measures. While variance is appealing for its ease of implementation, it penalises the decision maker equally for upside as well as downside risk. The shortfall probability and the expected shortage are also straightforward to implement but require the specification of an arbitrary target value for profit (Conejo et al. 2010). Getting around this arbitrariness, for a given level of $\alpha \in (0, 1)$, the VaR is defined as the largest value ensuring that the probability of obtaining a profit less than this value is lower than $(1-\alpha)$ (Oum and Oren 2008). However, a shortcoming of VaR is that it provides no information about the extent of the losses that might be suffered beyond the threshold amount (Rockafellar and Uryasev 2002). As an alternative, the CVaR is proposed, which is a coherent risk measure (reflecting translation invariance, subadditivity, positive homogeneity, and monotonicity) and can also be expressed using a linear formulation to indicate the expected value of the profit smaller than the $(1-\alpha)$-quartile of the profit distribution (Fig. 2).

3.2 Deterministic-equivalent problem

In a medium-term planning horizon, e.g., 1 month to a year, the objective of the power producer is to determine its generation and trading strategies to maximise its expected profit, while controlling the risk of profit variability. Compared to the stochastic programming literature, our two-stage formulation is closest in spirit to that of (Conejo et al. 2008): we have a power producer taking here-and-now decisions about forward contracting with wait-and-see decisions about spot transactions. The main difference is that we assume that the spot price of natural gas is also stochastic and may be hedged via forward contracts as well. As in Carrión et al. (2007) or

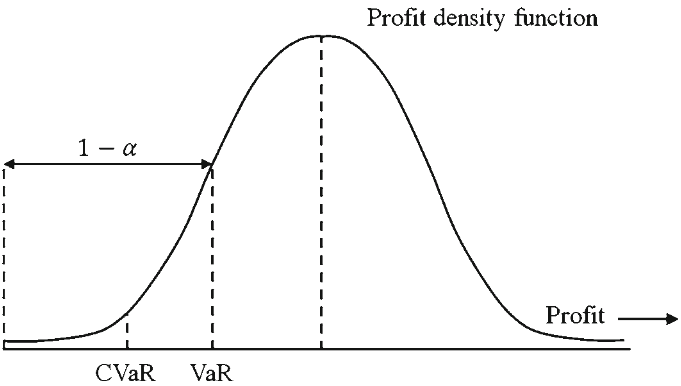

Fig. 2 Conditional value-at-risk

Kettunen et al. (2010), we could also have a multi-stage model with weekly contracts, which would be a more realistic representation of the hedging opportunities available to a power producer. Nevertheless, our objective is to gain insights about the natural hedge rather than to devise a risk-management strategy for a producer.

As we consider a decision horizon of 1 month, forward contracting positions are taken at the beginning of the month and are in force for each day thereafter. Given the forward positions, the set of daily decisions in the spot market are made throughout the month with knowledge of the spot prices. While decisions based on representative hours could also be implemented, natural gas prices are available only on a daily basis. Thus, the deterministic-equivalent formulation is as follows (see "List of symbols" for the notation):

$$\begin{aligned}\text{Maximise}_{P_f^F, Q_h^F, E_{t,\omega}^S, E_{t,\omega}^G, \zeta, \eta_\omega} & \sum_{\omega=1}^{N_\Omega} \pi_\omega \sum_{t=1}^{N_T} \left(\sum_{f=1}^{N_F} \lambda_f^F P_f^F d_t \right. \\ & \left. + \lambda_{t,\omega}^S E_{t,\omega}^S - \sum_{h=1}^{N_H} \mu_h^F Q_h^F - \mu_{t,\omega}^S \left(\frac{E_{t,\omega}^G}{e} - \sum_{h=1}^{N_H} Q_h^F \right) \right) \\ & + \beta \left(\zeta - \frac{1}{1-\alpha} \sum_{\omega=1}^{N_\Omega} \pi_\omega \eta_\omega \right) \end{aligned} \tag{1}$$

s.t.

$$0 \leq P_f^F \leq \overline{P}_f^F, \quad \forall f \tag{2}$$

$$0 \leq Q_h^F \leq \overline{Q}_h^F, \quad \forall h \tag{3}$$

$$0 \leq E_{t,\omega}^G \leq P^{G,max} d_t, \quad \forall t, \forall \omega \tag{4}$$

$$E_{t,\omega}^G \geq L E_{t',\omega}^G, \quad \forall \omega, \forall t, t' | W(t, t') = 1 \tag{5}$$

$$E^G_{t,\omega} = E^S_{t,\omega} + \sum_{f=1}^{N_F} P^F_f d_t, \quad \forall t, \forall \omega \tag{6}$$

$$\zeta - \sum_{t=1}^{N_T} \left(\sum_{f=1}^{N_F} \lambda^F_f P^F_f d_t + \lambda^S_{t,\omega} E^S_{t,\omega} - \sum_{h=1}^{N_H} \mu^F_h Q^F_h \right.$$
$$\left. -\mu^S_{t,\omega} \left(\frac{E^G_{t,\omega}}{e} - \sum_{h=1}^{N_H} Q^F_h \right) \right) \le \eta_\omega, \quad \forall \omega \tag{7}$$

$$\eta_\omega \ge 0, \quad \forall \omega \tag{8}$$

$$E^S_{t,\omega} \ge 0, \quad \forall t, \forall \omega \tag{9}$$

$$\frac{E^G_{t,\omega}}{e} - \sum_{h=1}^{N_H} Q^F_h \ge 0, \quad \forall t, \forall \omega \tag{10}$$

The producer's objective function is to maximise the expected profit plus a weighted CVaR term as captured by Eq. (1). Here, the first two terms consist of the revenues from forward and spot sales of power and electricity, respectively. Next, the remaining portion of the second line reflects the cost of generation from both forward and spot purchases of natural gas. Without loss of generality, we neglect fixed operating and maintenance costs. Finally, the third line of Eq. (1) is the weighted CVaR term (Rockafellar and Uryasev 2002), where $\beta \in [0, \infty)$ is a factor that represents the trade off between risk and return.

This objective function is maximised by selecting the forward positions for both power, P^F_f, and natural gas, Q^F_h, as well as daily generation decisions, $E^G_{t,\omega}$, and spot transactions, $E^S_{t,\omega}$, under each scenario. Additional auxiliary decision variables, ζ and η_ω, are needed to implement the CVaR constraint. The constraints for the producer's problem include Eqs. (2) and (3), which are the contracting constraints for the forward sales of power and forward purchases of natural gas, respectively. As per Conejo et al. (2008), these constraints reflect market liquidity in the form of a limited amount of energy available for trade. Eq. (4) is the capacity constraint for generation, while Eq. (5) approximates the limited operational flexibility for the power plant. Here, $W(t, t') = 1$ if t is an off-peak day that immediately precedes a peak day, t'. In effect, the plant is not able to adjust generation as much as it would ideally like due to physical characteristics that are not directly modelled here, e.g., minimum up-times or start-up costs. Thus, L is a parameter that captures the extent of the plant's inflexibility, e.g., $L = 0$ means complete flexibility. Eq. (6) simply states that all electricity generated has to be sold in either the forward or the spot market, while Eqs. (7) and (8) implement the CVaR constraint in a linear manner. Intuitively, a risk-averse producer would like to maximise its CVaR in Eq. (1), which is equivalent to forcing the η_ω variables to be as small as possible for a given ζ. Now, since Eq. (8) restricts η_ω to be non-negative, the smallest value that this auxiliary variable can assume is zero. Next, from Eq. (7), η_ω will be either zero if the profit in scenario ω exceeds ζ or the shortage level if the profit in scenario ω is less than ζ. Consequently, after η_ω is weighted by the probabilities π_ω and summed up over all scenarios before being scaled by $1 - \alpha$ in the objective function, the resulting term, i.e., $\frac{1}{1-\alpha}\sum_{\omega=1}^{N_\Omega}\pi_\omega\eta_\omega$, represents the expected profit shortage relative to ζ. Finally, the non-negativity of electricity spot sales and natural gas spot purchases is enforced via Eqs. (9) and (10). In general, these constraints may be relaxed to allow for arbitrage between markets, but our focus is on understanding the natural, i.e., physical, hedge of a gas-fired power plant.

3.3 Representation of uncertainty

In order to solve the problem in Eqs. (1) through (10), we need an adequate representation of the uncertain electricity and natural gas spot prices. These are obtained by generating a suitably large number of scenarios, $\lambda^S_{t,\omega}$ and $\mu^S_{t,\omega}$, for each day, t, of a given month. Time-series analysis is used as the basis for scenario generation, and autoregressive integrated moving average (ARIMA) models are usually sufficient to capture salient features of energy prices, viz., high frequency, non-constant variance and mean, weekly seasonality, and high volatility (Contreras et al. 2003).

The non-constant mean is alleviated by differentiating the series by using factors $(1-B^s)$, where B is the backshift operator and s is the number of steps, i.e., $B^s(y_t) = y_{t-s}$, where y_t is the price on day t. Weekly seasonality is often taken into account by using lags of order 7. In order to obtain constant variance, applying logarithmic transformation to the original process is widely used. If the mean and variance of the process do not change over the observed time period, then we can regard the time series as a stationary process.

After making these transformations, the general form of a seasonal ARIMA model with parameters $(p, d, q) \times (P, D, Q)_s$ is

$$\phi(B)\Phi(B^S)(1-B)^d(1-B^S)^D y_t = \theta(B)\Theta(B^S)\epsilon_t \tag{11}$$

where y_t is the price on day t and ϵ_t is the error term. In this model, there are p autoregressive parameters, $\phi_1, \phi_2, \ldots, \phi_p$, q moving average parameters $\theta_1, \theta_2, \ldots, \theta_q$, and d is the differentiation order. This model also includes seasonal components of P autoregressive parameters $\Phi_1, \Phi_2, \ldots, \Phi_P$, Q moving average parameters $\Theta_1, \Theta_2, \ldots, \Theta_Q$, and the differentiation order D. $\phi(B)$, $\Phi(B)$, $\theta(B)$, and $\Theta(B)$ are polynomial functions of backshift operator B, e.g., $\phi(B) = 1 - \sum_{j=1}^{p}\phi_j B^j$ and $\theta(B) = 1 - \sum_{k=1}^{q}\theta_k B^k$.

From suitable ARIMA models for the price processes, scenarios may be generated using the general form of Eq. (11) (Contreras et al. 2003). Unlike most of the stochastic programming literature that we have discussed, our work involves generating scenarios for two dependent processes. Given that electricity and natural gas prices are likely to be correlated in a non-contemporaneous manner, we cannot simply use independent ARIMA models of the form in Eq. (11) to generate scenarios. Rather, we consider transfer functions or dynamic regression models to link the two price processes. Intuitively, the latter approach includes lagged terms of the dependent and independent processes in the model for the dependent one, whereas the former uses only the lagged terms of the independent process plus lagged terms of a function of the error terms. For example, Nogales and Conejo (2006) relate electricity demand and price, and Conejo et al. (2005) compare transform functions with dynamic regression by applying them to model electricity prices of the PJM (Pennsylvania–New Jersey–Maryland) Interconnection to show that they are more effective than ARIMA models alone.

In our case, the transfer function seems to work better, and the general form for it is:

$$y_t = w(B)x_t + \gamma_t \tag{12}$$

where y_t and x_t are the two correlated time series assumed to be stationary. $w(B)$ is the polynomial function of backshift operator, i.e.,

$$w(B) = \sum_{m=0}^{M} w_m B^m \tag{13}$$

The coefficients w_m describe the dynamic relationship between y_t, i.e., natural gas spot price, and the explanatory variable x_t, i.e., electricity spot price. The part of y_t not explained by x_t is a disturbance term that follows an ARMA model of the form:

$$\gamma_t = \frac{\theta(B)}{\phi(B)}\epsilon_t \tag{14}$$

where $\theta(B)$ and $\phi(B)$ are polynomial functions of backshift operator B and ϵ_t is assumed to be white noise.

4 Numerical examples

In order to explore the natural hedge, we use data from the UK Automated Power Exchange (APX) to generate scenarios for electricity and natural gas spot prices as indicated in Sect. 3.3. Next, we use these scenarios as inputs to the deterministic-equivalent formulation from Sect. 3.2 of a gas-fired plant's medium-term risk-management problem. Finally, we run the problem under various settings to extract policy insights.

4.1 Data

For the time-series analysis, a total number of 2,191 daily spot prices for electricity and natural gas are available from the APX (Fig. 3). The time period begins on 1 January 2006 and ends on 31 December 2011. The daily electricity spot prices are the average of the reference price data (RPD) for all 48 half-hour periods, while the gas spot prices are the weighted-average prices with the weight provided by APX of all trades for the relevant day on the on-the-day commodity market (OCM). A summary of the descriptive statistics of electricity and gas spot prices as well as their logarithms is provided in Table 1. It shows that the electricity and gas spot prices are highly volatile, and after logarithmic transformation, the data become more stable. Ultimately, we

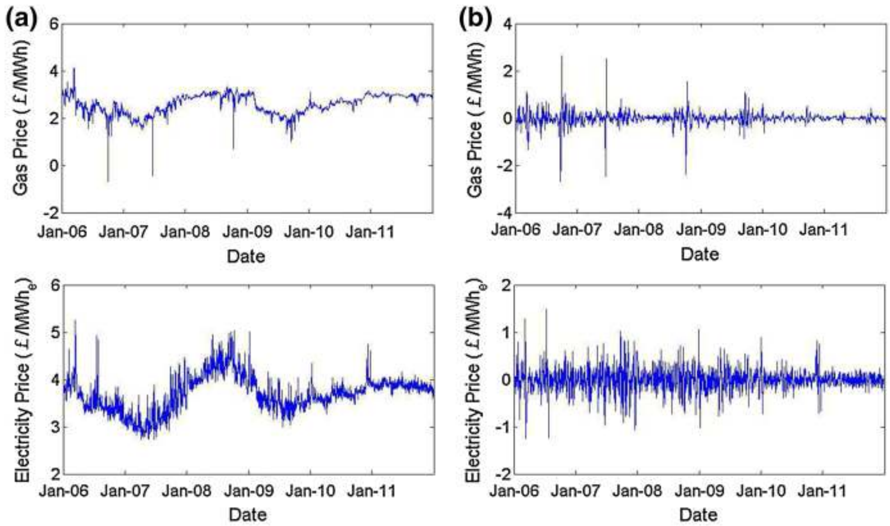

Fig. 3 Logarithms of UK APX electricity and natural gas prices before (**a**) and after (**b**) weekly differentiation

Table 1 Descriptive statistics, UK APX energy prices (£$/MWh_e$ and £$/MWh$), 2006–2011 (APX Group)

Statistic	Electricity	Ln electricity	Gas	Ln gas
Mean	43.350	3.696	14.500	2.594
SD	17.950	0.378	5.497	0.423
Minimum	15.290	2.727	0.493	−0.707
1st Quartile	31.270	3.443	9.857	2.288
Median	40.820	3.709	14.430	2.669
3rd Quartile	50.340	3.919	18.980	2.944
Maximum	190.500	5.250	61.350	4.117

will use these data in Sect. 4.2 to generate scenarios for the representative month of January. Similar analysis for a representative month of July indicates that the findings are qualitatively similar and are, thus, not presented here.

We consider a single gas-fired plant with capacity $P^{G,max} = 100$ MW$_e$ and an energy-conversion efficiency of $e = 0.45$. As for the technical parameters, we set the peak/off-peak factor to $L = 0.33$, which is in line with that used by Conejo et al. (2008). The peak/off-peak periods are determined by the average daily prices among the 31 days in January, i.e., the days with the 22 highest daily average prices are the peak periods (Table 2). For reference, if the plant were operated at its rated capacity for the entire month, then it would generate $100 \times 24 \times 31 = 74.4$ GWh$_e$ of electricity and consume $74.4/0.45 = 165.33$ GWh of natural gas.

Two types of forward contracts spanning each day of the next month are available. Carrión et al. (2007) provide several examples of contracts for the Spanish electricity market. Similarly, we use data from the Intercontinental Exchange (ICE) on January

Table 2 Peak and off-peak periods during January

Peak periods	Off-peak periods
2-6, 9-13, 16-20, 23-27, 30, 31	1, 7, 8, 14, 15, 21, 22, 28, 29

Table 3 Power forward contracts

Contract	λ_f^F	$\overline{P}_f^F$
f	(£/MWh$_e$)	(MW$_e$)
1	42.15	40
2	42.85	20

Table 4 Natural gas forward contracts

Contract	μ_h^F	$\overline{Q}_h^F$
h	(£/MWh)	(MWh)
1	18.35	1,000
2	18.65	2,000

2012 prices as of 31 December 2011 in order to introduce two different types of forward contracts for each energy type.

The parameters defining each contract are provided in Tables 3 and 4. For reference, the mean January electricity and natural gas spot prices during this time period are £45.23/MWh$_e$ and £16.85/MWh, respectively. Furthermore, if the plant were operating at capacity, then it would be able to sell forward a maximum of 60 % of its power. Similarly, it would be able to hedge a maximum of 56 % of its natural gas purchases, i.e., a total of 31 $\times$ 3,000 MWh = 93 GWh.

4.2 Time-series analysis and scenario generation

Figure 3 plots the logarithms of electricity and gas spot prices before and after weekly differentiation. It is apparent that the time series of daily prices are not stationary. For this reason, we will consider differentiating the original series using factors $(1 - B^s)$. After weekly differentiation, the non-constant mean and variance are alleviated, and the time series seem to be stationary.

On these transformed data, we carry out the procedure described in Sect. 3.3. According to the model identification method described by Box and Jenkins (1976), the terms of $\theta_7 B^7$ and $\theta_8 B^8$ should be included in the polynomial $\theta(B)$ because in Fig. 4, there are peaks at 7 and 8 in the ACF and PACF damped sinusoid at the same value. We start from an initial model and select one with the lowest AIC and standard deviation of the error term after trying several different models. The final ARIMA model for electricity and natural gas prices is as follows:

$$(1 - \phi_1 B - \phi_2 B^2)(1 - B^7)\log(y_t) = (1 - \theta_1 B - \theta_7 B^7 - \theta_8 B^8)\epsilon_t \qquad (15)$$

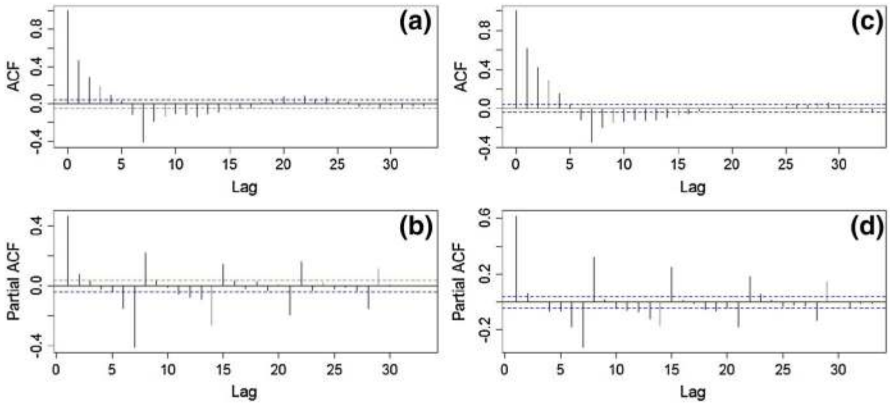

Fig. 4 ACF and PACF after differentiating: **a** ACF of the logarithm of the electricity price, **b** PACF of the logarithm of the electricity price, **c** ACF of the logarithm of the natural gas price, **d** PACF of the logarithm of the natural gas price

Table 5 Estimated Parameters of ARIMA model for energy spot prices

Electricity	Natural gas
$\phi_1 = 1.42942$	$\phi_1 = 1.46055$
$\phi_2 = -0.43126$	$\phi_2 = -0.47436$
$\theta_1 = 0.89485$	$\theta_1 = 0.78316$
$\theta_7 = 0.98103$	$\theta_7 = 0.98227$
$\theta_8 = -0.8759$	$\theta_8 = -0.78177$
$\sigma^E = 0.151$	$\sigma^G = 0.142$

In Eq. (15), the prices of electricity and natural gas on day t depend on previous values of two terms: 1- and 2-day lags and weekly differentiation. They also depend on error terms with lags of 1, 7, and 8 days. Next, SAS 9.2 is used to estimate the parameters, which are shown in Table 5. All the parameters have passed the t-test at the 95 % significance level.

Using the scenario-generation procedure described in Sect. 3.3 for both electricity and natural gas prices, a set of 1,000 scenarios for January is obtained from independent ARIMA models. In Fig. 5, crosses represent pairs of historical gas-electricity prices, whereas circles correspond to generated scenario pairs. Although historical data are almost within the area covered by the generated scenarios, some generated points are far away from the historical data, especially for the natural gas prices. This result indicates that the correlation between electricity and natural gas prices should be taken into consideration. Indeed, Fig. 6 shows non-contemporaneous correlation between the residuals from the independent ARIMA models. Hence, it is necessary to account for the non-contemporaneous correlation between electricity and natural gas prices by means of a transfer function described in Sect. 3.3.

Although the standard deviations of the electricity and natural gas error terms are similar, the generated scenarios for electricity prices look better than those for natural

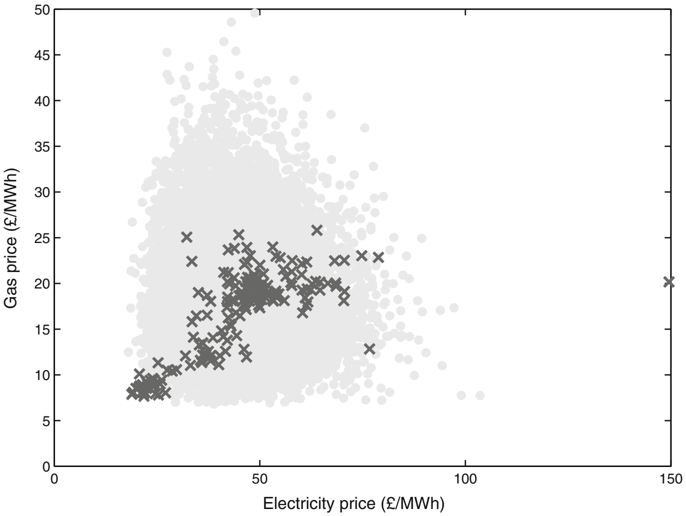

Fig. 5 Generated scenarios for January by independent ARIMA models

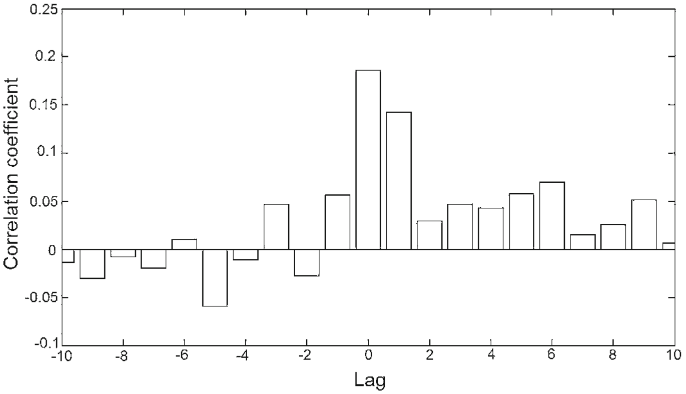

Fig. 6 Residual cross-correlation

gas prices. Plus, transfer functions linking electricity prices and demand usually have the latter as the independent variable, i.e., exogenous demand drives the price (Nogales and Conejo 2006). Similarly, it is plausible that the electricity industry's demand for natural gas drives the price of natural gas rather than the other way around. For these reasons, we build a transfer function to model natural gas prices by using the electricity price (reflecting demand for natural gas) as an explanatory variable. As for the transfer function, we take differentiation of order 7 at first because one assumption of the transfer function is that the two time series are stationary. The final transfer function model for natural gas prices is:

$$\log(y'_t) = (w_0 + w_1 B)\log(x'_t) + \frac{\left(1 - \theta_1 B - \theta_7 B^7 - \theta_8 B^8\right)}{\left(1 - \phi_1 B - \phi_2 B^2\right)}\epsilon_t \tag{16}$$

where y'_t and x'_t are the natural gas and electricity prices after differentiation in day t, respectively. Since it is necessary to know the value of electricity prices to model natural gas prices, when using transfer function models, an additional model is required to generate scenarios of the explanatory variable. We use the ARIMA model in Eq. (15) to generate scenarios of electricity prices. Table 6 shows the estimated parameters of the transfer function, which have all passed the t test at the 95 % significance level.

The diagnostic check of the ARIMA model for the electricity prices and the transfer function model for the natural gas prices indicates that the standard residuals are fairly random (Fig. 7). Furthermore, the ACF plot and the p-values of the Ljung-Box test (for which the null hypothesis is that there is no autocorrelation between the residuals under this lag) indicate that the residuals are not statistically significantly autocorrelated. Finally, Fig. 8 depicts the set of natural gas price scenarios versus the set of electricity price scenarios (circles) together with historical data (crosses). Notice that the correspondence between scenarios and historical data is much better than that with independent ARIMA models.

4.3 Results

Using the formulation from Sect. 3.2 and 1,000 equiprobable scenarios generated for the month of January from Sect. 4.2, we solve the problem under the following three cases:

Table 6 Estimated parameters of the transfer function

$\phi_1 = 1.40887$	$\theta_1 = 0.77283$
$\phi_2 = -0.42737$	$\theta_7 = 0.98262$
$w_0 = 0.18456$	$\theta_8 = -0.77247$
$w_1 = 0.08751$	$\sigma^D = 0.139$

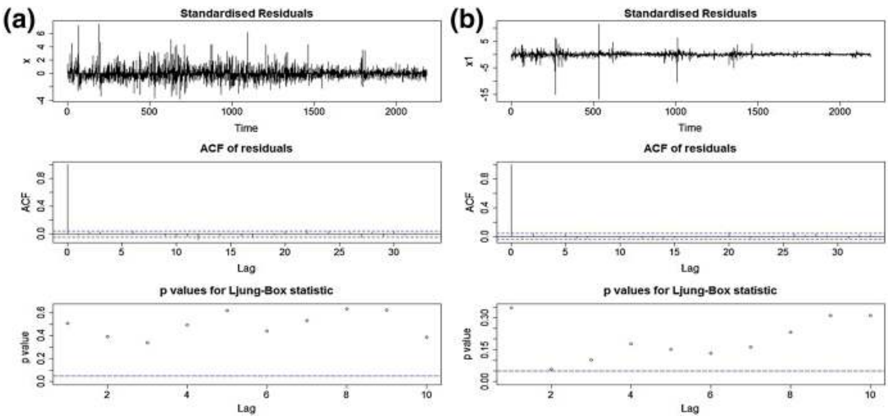

Fig. 7 Diagnostic plots **a** ARIMA model for the electricity price and **b** transfer function for the natural gas price

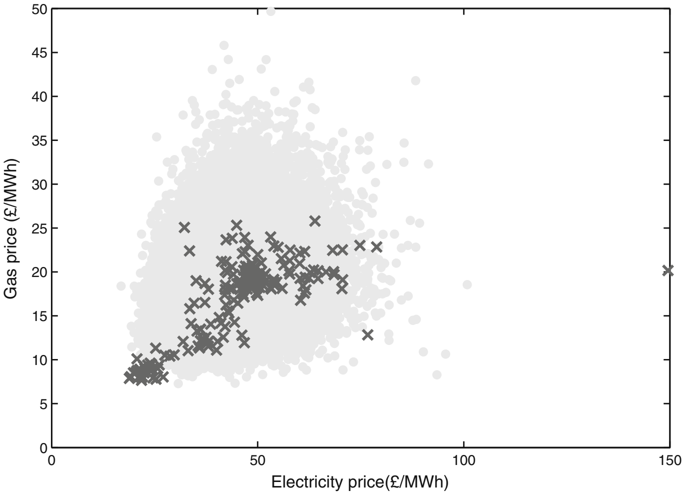

Fig. 8 Generated scenarios of electricity and natural gas prices using the transfer function

- *Case 1* Stochastic electricity spot prices, fully hedged gas purchases equal to the quantity-weighted mean natural gas forward price, i.e., $C^G = \frac{\sum_{h=1}^{N_H} \overline{Q}_h^F \mu_h^F}{e \sum_{h=1}^{N_H} \overline{Q}_h^F} =$ £41.20/MWh$_e$, and only power forward contracts for financial hedging
- *Case 2* Stochastic energy spot prices but only power forward contracts for financial hedging
- *Case 3* Stochastic energy spot prices with both power and natural gas contracts for financial hedging

Each case is run for $\alpha = 0.95$ and increasing β starting from zero until the financial hedging does not change. It should be noted that while β has no physical meaning, we are able to compare decision making among cases by examining the outcomes for completely risk-neutral and fully contracted producers. We consider three settings: a base setting, one with complete operational flexibility, i.e., $L = 0$, and one with a higher energy-conversion efficiency of $e = 0.60$. The generated scenarios yield mean January 2012 electricity and gas spot prices of £43.19/MWh$_e$ and £18.21/MWh, respectively. The problem of the gas-fired power plant in Eqs. (1)–(10) may be solved numerically using CPLEX in GAMS 23.0.2. The solution time is around ten seconds on a desktop PC with a quad-core 2.9 GHz processor and 8 GB of RAM. We check the stability of the scenarios by increasing their number from 1 to 1,000 and find that the solutions in all cases and with various levels of risk aversion are stable after about 800 scenarios (Figs. 9, 10). Except for the setting with a higher energy-conversion efficiency, the solution for Case 2 for all levels of risk aversion is equal to that for Case 3 with a risk-neutral producer.

4.3.1 Base setting

By solving the problem for various levels of β, we sketch out the power plant's efficient frontier. Figure 11 illustrates this for the base setting. In Case 1, the power plant

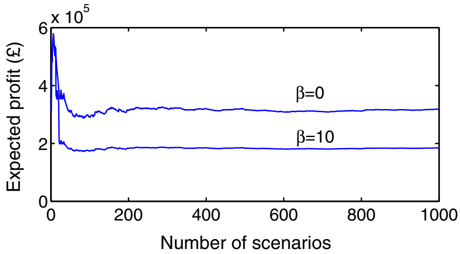

Fig. 9 Stability of the solution with the number of scenarios (Case 1)

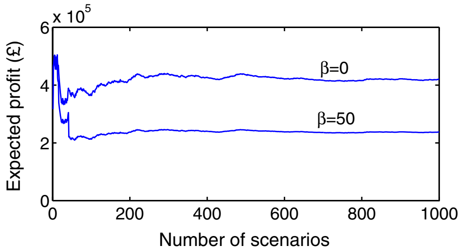

Fig. 10 Stability of the solution with the number of scenarios (Case 3)

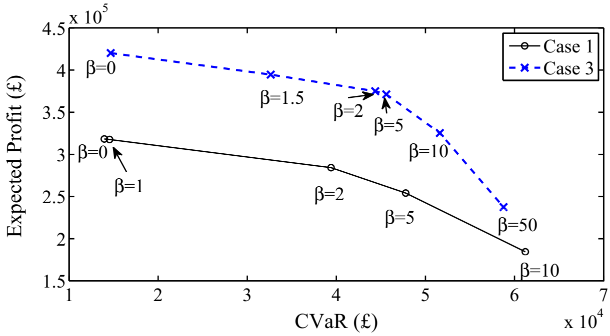

Fig. 11 Efficient frontiers in base setting

hedges its natural gas costs completely at the quantity-weighted mean forward price. For $\beta = 0$, the producer is risk neutral and makes an expected monthly profit of £320k with a CVaR of just under £13.9k without any forward sales. As the producer becomes more risk averse, it gives up some expected profit for a higher monthly CVaR via forward sales, viz., ending up with an expected profit of £184k and a CVaR of £61k when $\beta = 10$.

Once spot transactions at stochastic natural gas prices are allowed, the producer's situation improves in Case 3. Indeed, the positive correlation between electricity and natural gas prices does constitute a natural hedge, i.e., the producer's expected profit and CVaR are higher as a consequence of facing the stochastic fuel price, which reduces the net exposure to uncertainty. For $\beta = 0$, the expected profit and CVaR increase to £420k and £14.7k, respectively, relative to Case 1. However, this natural hedge is not a perfect hedge as the producer can mitigate its risk further by holding natural gas forwards in Case 3. Case 2 in this setting results in no forward contracting

Table 7 Base setting trading strategies for Case 1

β	Expected generation (GWh_e)	Proportion of powersold forward
0	42.133	0.000
1	42.243	0.007
2	48.148	0.309
5	52.187	0.470
10	61.139	0.730

Table 8 Base setting trading strategies for Case 3

β	Expectedgeneration (GWh_e)	Proportion of power sold forward	Proportion of gas purchased forward
0	45.677	0.000	0.000
1.5	48.605	0.167	0.167
2	50.816	0.274	0.274
5	51.168	0.291	0.291
10	54.823	0.448	0.448
50	61.617	0.679	0.679

regardless of the level of risk aversion and, thus, provides a solution that is equal to the one in Case 3 with a risk-neutral producer.

In order to explain the differences between the cases, we next break down the producer's generation and hedging strategy further. Table 7 indicates that the risk-return trade off in Case 1 is facilitated by financial hedging, which also allows more generation to take place. Specifically, forward sales increase from nothing to over 70 % of the output for an extremely risk-averse producer, which uses both power contracts fully. In effect, by locking in most of its revenues, a risk-averse producer is committed to generating more than a risk-neutral one. By contrast, the availability of the natural hedge in Case 3 means that more generation is possible and less financial hedging is needed (Table 8).

Higher risk aversion requires forward purchases of natural gas for optimal risk management, which also modifies the hedging of power sales. Finally, the power sold forward seems to use gas purchased through forwards, thereby eliminating exposure to cross-commodity risk.

4.3.2 Operational flexibility

With complete operational flexibility, the expected profit and CVaR increase in all cases except for the extremely risk-averse ones (Fig. 12). This is because the producer is now able to generate only on those days when the spark spread is sufficiently high. In Case 3, such flexibility drastically mitigates the risk of even risk-neutral producers compared to the base setting. However, it is not clear how the natural hedge is affected.

Scrutinising the generation and trading strategies, we find in Case 1 that although a relatively more risk-neutral producer's generation and hedging are reduced compared

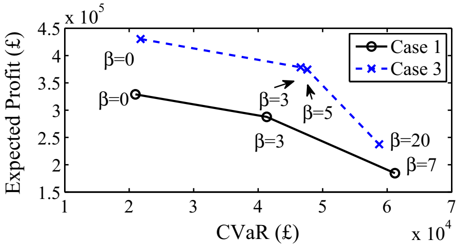

Fig. 12 Efficient frontiers with operational flexibility

Table 9 Operational flexibility trading strategies for Case 1

β	Expected generation (GWh_e)	Proportion of power sold forward
0	41.246	0.000
3	47.877	0.311
7	61.139	0.730

Table 10 Operational flexibility trading strategies for Case 3

β	Expected generation (GWh_e)	Proportion of power sold forward	Proportion of gas purchased forward
0	45.182	0.000	0.000
3	50.661	0.275	0.275
5	51.026	0.292	0.292
20	61.617	0.679	0.679

to the base setting, they are unchanged as β increases (Table 9). The explanation for this behaviour is that without operational constraints, a more risk-neutral producer is able to increase its expected profit by being more selective about generation. Thus, there is less need for forward sales at low levels of β. However, as risk aversion increases, most of the power is sold forward as in the base setting, which renders operational flexibility less relevant. Exposure to stochastic natural gas prices in Case 3 reduces the need for financial hedging relative to Case 1 as in the base setting (Table 10). Compared to the results in Table 8, operational flexibility increases the effect of the natural hedge as the producer is able to use the positive correlation between the two spot prices to its advantage to a greater extent by not hedging financially until $\beta = 3$. Nevertheless, the natural hedge by itself is still not optimal for a more risk-averse producer. As in the base setting, power sold forward seems to be generated via contracted natural gas.

4.3.3 Higher energy-conversion efficiency

With a higher energy-conversion efficiency of $e = 0.6$, both the expected profit and the CVaR increase dramatically in all cases relative to the base setting (Fig. 13). With effectively a 25 % lower average cost of generation, the plant is able to turn

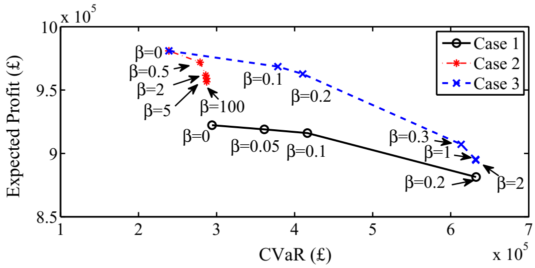

Fig. 13 Efficient frontiers with higher energy-conversion efficiency

Table 11 Higher energy-conversion efficiency trading strategies for Case 1

β	Expected generation (GWh_e)	Proportion of power sold forward
0	70.700	0.000
0.05	70.936	0.114
0.1	71.204	0.209
0.2	72.720	0.614

Table 12 Higher energy-conversion efficiency trading strategies for Case 2

β	Expected generation (GWh_e)	Proportion of power sold forward
0	68.623	0.000
0.5	69.549	0.214
2	70.062	0.323
5	70.190	0.350
100	70.343	0.375

Table 13 Higher energy-conversion efficiency trading strategies for Case 3

β	Expected generation (GWh_e)	Proportion of power sold forward	Proportion of gas purchased forward
0	68.623	0.000	0.000
0.1	69.549	0.214	0.214
0.2	69.796	0.266	0.266
0.3	71.887	0.621	0.621
1	72.787	0.613	0.760
2	72.829	0.613	0.766

an operating profit on more days, which also mitigates its risk. Moreover, the higher efficiency means that the natural gas price is less important than in the base setting. This suggests that the natural hedge is now weakened, which is picked up by the appearance of financial hedging during Case 2.

An investigation of the generation and hedging strategies in Tables 11, 12 and 13 confirms that higher efficiency reduces the natural hedge relative to the base setting. In Case 1, the impact of higher efficiency is more obvious as it simply reduces the deterministic generation cost. Still, this has consequences for risk management as fewer unprofitable days lead to a higher expected profit even in the lowest 5 % of scenarios, thereby reducing the need for hedging (Table 11). Next, Case 2 illustrates that the natural hedge diminishes, which leads to more financial hedging (Table 12) than in the base setting. Finally, Case 3 reveals that the fractions of power sold forward and natural gas purchased forward are higher than in the base setting (Table 13). Another intriguing difference from the results in the previous two settings is that a highly risk-averse producer now hedges even natural gas purchases that are used for some spot sales of electricity. In effect, the natural hedge has diminished to the extent that the producer no longer finds it beneficial to use the positive correlation between the spot prices to its advantage. Consequently, the natural hedge is less relevant in a future with a more efficient CCGT technology, and the forward contract limit for electricity is reached with $\beta = 0.3$. After this point, greater risk aversion leads to more generation by the producer sold into the spot market using gas bought on the forward market, i.e., the low cost of generation offsets the absence of the natural hedge and leads to a decoupling in the hedging ratios unlike in the base setting.

We have assumed in our example that the relationship between electricity and natural gas prices does not change as a result of the higher energy-conversion efficiency. In other words, the time-series analysis used to generate scenarios for the energy prices is still valid. However, it may be the case that decoupling of electricity and natural gas markets because of higher efficiency leads to prices (and, thus, generated scenarios) that are not as positively correlated as in Fig. 8. Taking this shift into account could either strengthen or weaken our conclusions. For example, less correlated energy prices would weaken the natural hedge, thereby leading to an even greater increase in financial hedging in Case 3. Alternatively, the plant may reduce its operations, which would obviate the need for contracting. Hence, the overall effect of decoupled markets may be ambiguous and could be the subject of additional research that treats energy prices as being endogenous to the model.

5 Conclusions

The coupling of the UK's electricity and natural gas markets has been perhaps an unintended consequence of the restructuring of its power sector in the early 1990s. As gas-fired power plants are effectively price setters in UK electricity markets, they are also hedged to a greater extent than renewable energy technologies, which are needed for the UK to meet its policy objectives. Due to their relatively higher risk, such renewable energy technologies will not be readily adopted by private producers. Since other industrialised economies face similar predicaments, lessons learned for the UK may be relevant for their policymakers as well. Thus, in order to devise incentives to facilitate investment in renewable energy technologies, policymakers need to understand better the channels through which the so-called natural hedge of gas-fired producers propagates.

Taking a stochastic programming perspective to tackle risk directly, we find that such a natural hedge does exist for a typical UK producer. Indeed, the positive correlation between electricity and natural gas spot prices is advantageous for the producer both in terms of increasing expected profit and controlling risk. Nevertheless, it is not a perfect hedge as some natural gas forward purchases may be necessary for even a moderately risk-averse producer. With future evolution of CCGT technologies, the behaviour of this natural hedge may be of interest to policymakers. If a gas-fired plant could be operated in a more flexible manner, then the extent of the natural hedge increases while forward contracting diminishes for a risk-averse producer. In effect, the plant itself becomes a more effective physical hedge by taking advantage of periods of high spark spreads to generate. Consequently, expected generation also decreases. On the other hand, if the energy-conversion efficiency of CCGT is likely to increase, then the natural hedge actually diminishes as exposure to natural gas prices is lower. It should be noted that these results hold for the UK using data from 2006 to 2011 and under the assumption that a single daily dispatch decision is valid, which is appropriate given the observed spark spreads, e.g., in January 2014. Unlike the extant literature on the UK power sector, our work directly addresses risk and the behaviour of this natural hedge rather than relying on levelised cost calculations. Hence, assessments of support schemes (such as feed-in tariffs and renewables obligation certificates) for promoting renewable energy technologies could use our case studies to examine how coupled electricity and gas prices may affect the natural hedge of CCGT technologies, which are currently favoured by investors.

For future work, relaxation of some of our assumptions would be warranted. In particular, the inclusion of a competing producer (either based on natural gas or a renewable energy) could shed additional light on the natural hedge by capturing the market power that is present in most electricity industries. Another direction of research could involve generation of more realistic scenarios that capture the tail dependencies between electricity and natural gas prices, e.g., via copulas. This link is especially pertinent because of the significance of risk control in our setting. Similarly, more realistic forward contracts reflecting the market's liquidity and operational constraints would allow us to generalise the insights further.

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