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Abstract

Natural gas flows in pipelines as a consequence of the pressure difference at the inlet and outlet. Adjusting these pressures makes it possible to inject natural gas at one rate and withdraw at a different rate, hence using the pipeline as storage as well as transport. We study the value of using the so called pipeline linepack as a short-term gas storage and how this functionality may offset the discrepancy between the low flexibility in take-or-pay contracts and the high inherent flexibility of a gas fired power plant. To value the storage option, we consider a cycling power plant facing volatile power prices while purchasing gas on a take-or-pay contract. We estimate a Markov regime-switching model for power prices and a mean reverting jump diffusion model for gas prices. Applying Least Squares Monte Carlo simulation to the operation of the power plant, we find that the storage option indeed has significant value for the plant, enabling it to better exploit the sometimes extreme price fluctuations. Finally, we show how power price

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volatility and jump frequency are the main value drivers, and that the size of the storage increases the value up to a point where no additional flexibility is used.
Keywords: Linepack, Gas storage valuation, Regime-switching models, Natural gas prices, Electricity prices, Power plant

1. Introduction

Pipelines are the largest infrastructure investment in the natural gas value chain, accounting for 80 percent of midstream investments [1]. To provide both security of supply as well as a high standard of safety, the pressure of the pipelines must be kept within a certain range. By controlling the pressures, the stored gas in the pipeline (linepack) can increase or decrease as the withdrawal and injection rates differ from each other. We show that making part of the linepack available for the market as a storage volume can be a viable option to increase the flexibility of the energy system. Such increased flexibility is highly attractive in light of the intermittency of much of the future electricity generation sources [2].

We take the perspective of a German gas-fired power plant in order to analyse the value of using e.g. the North Sea pipeline system as a short term storage volume. This connection is not identified as congested [3], and has a reliability of "virtually 100%" [4]. The participant with the highest need for flexibility in its gas flows should be the one with highest willingness to pay for the storage. Arguably, a gas-fired power plant facing uncertainty in both electricity and gas prices can be such a participant. In Europe, the plant will often be committed to a long-term take-or-pay (TOP) contract, forcing the plant to buy a certain volume of gas per year. The high degree of uncertainty in prices with combined with a low degree of flexibility in the TOP contract makes additional flexibility valuable. Modern gas-fired power plants are able to ramp production up and down on short time notice. As most industrial processes that use gas as a primary input do not have the same degree of operational flexibility nor the same degree of participation in the gas spot market, we view a cycling gas-fired power plant as the agent with the highest incentive to pay for storage opportunities. Approximately 36 percent of the natural gas consumption in OECD Europe is consumed by power plants [5], implying that the sector should be vital in the demand for gas storage capacity. We estimate the additional value created by using the linepack to vary the power plant's output rate according to swings in the prices of power and natural gas, without violating the TOP contract.

Conventional storage capacity, consisting of depleted oil and gas reservoirs, aquifers, salt mines and LNG storage plants, are in most cases constrained by their geographical location and a rather low inflow and withdrawal rate. Furthermore, LNG plants have high storage costs since the gas needs to be cooled [6]. The pipeline exit point is usually situated at a major market hub. Considering the linepack as a separate storage volume placed at the receiving terminal, the high flexibility makes it a potentially valuable tool for short-term balancing of natural gas supply and demand.

We focus only on the value of the line pack, and ignore cost issues related to fuel consumption in compressor stations, or a possible loss of supply reliability, or pipeline capacity. That said, we note that linepack is highly flexible as long as it is within upper and lower bound based on the technical characteristics of the pipeline.

Midthun et al. [7] value the linepack as a natural gas storage facility, taking the perspective of a natural gas producer. They optimise the value of the gas sales for the producer both with and without the linepack, and quantify the size of a pipeline's possible linepack. Chaudry et al. [8] include linepack in optimisation of the GB gas and electricity network. Our paper shifts the focus on the value of linepack storage from that of a producer to that of a consumer of natural gas.

Keyaerts et al. [9] call for a change of the regulatory framework for natural gas pipeline capacity allocation in Europe, taking linepack into account. They point out value and cost components of linepack flexibility and identify the trade-off in its use as storage flexibility and transportation facility.

Storage valuation literature focus either on best practice power price simulation, gas price simulation or on valuing a general storage volume in the perspective of a commodity arbitrageur. Boogert and de Jong [10] apply the Least Squares Monte Carlo algorithm, developed by Longstaff and Schwartz [11], to value a natural gas storage contract. They show that the size of the effective storage volume as well as injection and withdrawal rates are the most important value-determinants. Lai et al. [12] value the option to store natural gas in the form of LNG using a heuristic that incorporates natural gas prices, LNG shipping models and inventory control. Bjerksund et al. [13] show that an advanced price process is of greater importance than a an advanced optimisation model, when valuing gas storage. Valuation of storage in connection with CO_2 capture plants is considered by [14, 15]. Finally, [16] value biomass storage in the context of a biomass supply chain.

Authors including de Jong [17], Janczura and Weron [18] and Schneider [19] agree that the power price exhibits mean reversion and spikes. Abadie and Chamorro [20] show that natural gas spot prices exhibit mean reversion. Secomandi [21] analyses the pricing of pipeline capacity based on the trading value of the gas, modeled as a mean reverting process. As an alternative, a nonstationary process such as geometric Brownian motion can be used for gas [22] or electricity prices [23], however, these are more suitable for a) long planning horizons (decades), or b) when analytical solutions are preferred [24].

The main contribution of this paper is the quantification of the value of linepack as storage of natural gas, from a gas consumer point of view. For power systems with increased use of intermittent renewable sources, pointing to ignored but potentially useful energy storage options is of high value. In addition, the Markov regime-switching model for electricity prices, incorporating spikes, mean reversion and possible negative prices, is state of the art. Finally, we introduce a gas price model with a mean level that depends on electricity prices, so that a realistic long-term relationship between prices of electricity and natural gas prevails.

The article is structured as follows: In Section 2 we describe the data used and estimate models that capture the joint dynamics of natural gas and power prices. We estimate a Markov regime-switching model with independent spikes for the power price, and a mean reverting jump diffusion model for the gas price, where the mean level is dependent on the power price. Simulating the two price series simultaneously, we essentially model the power plant's *dirty spread*[1]. In Section 3, we apply a real option approach and incorporate the price models in a Least Squares Monte Carlo algorithm to value the opportunity of storage. Our analysis is confined to valuing the storage option separately, disregarding the power plant's intrinsic value. We show numerical examples to illustrate how parameters such as storage capacity and price volatility affect the storage value in Section 4. In Section 5 we conclude.

2. Model description

To be able to value a gas storage facility, we need to accurately model the power price and the gas price. The models must capture the seasonal patterns, its stochastic behaviour and the way gas and power prices move together. We first model the power price, and then use it as an explanatory variable in the gas price model. These two models will be used in the simulation based valuation algorithm in Section 3.

2.1. Power price model

The data set used for power prices consists of hourly data from the EPEX commodity exchange in Germany, from 2011-01-03 until 2011-10-23; a total of 7056 data points. In general, the prices exhibit a strong degree of hour-of-day effects and weekday effects. In addition, sudden spikes are clearly visible in Figure 1, but they seem to disappear just as soon as they arrive. There also seems to be a certain degree of clustering of spikes.

[1] The dirty spread is the spread between the power price and the price of the gas needed to produce the power before subtracting the CO_2 price.

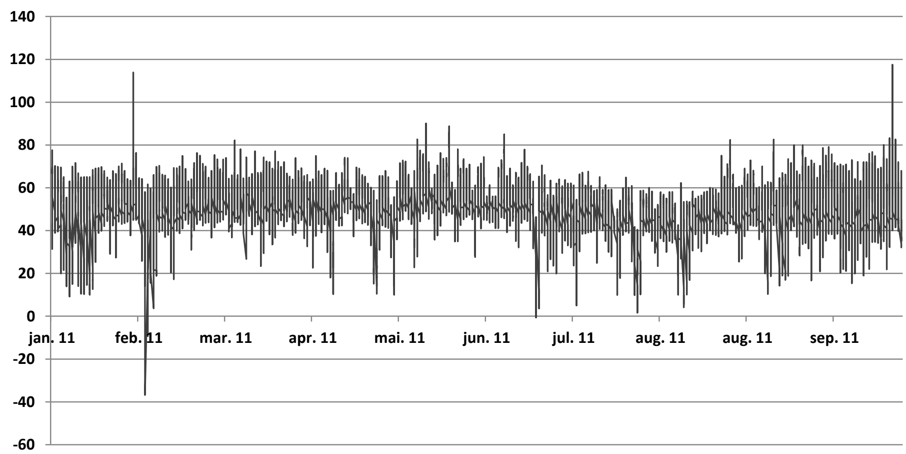

Figure 1: The time series of hourly power prices at EPEX.

To analyse the stochastic part of the data, we first filter out the deterministic effects by simple dummy variables for hours and weekdays and store the residuals. The typical daily and weekly pattern of power prices are apparent in the dummy coefficients given in Figure 2, all of which are significant at the 5% level. In mathematical terms:

$$S_t^{el} = \mu_0^{el} + \sum_{i=1}^{6} \delta_i^{weekday} \theta_i^{el} + \sum_{j=1}^{23} \delta_j^{hour} \gamma_j^{el} + q_t^{el} \tag{1}$$

where S_t^{el} is the electricity price, μ_0^{el} is a constant, θ^{el} are coefficients for weekdays and γ^{el} are coefficients for hours. The δs are binary variables that indicate whether a price observation is from a certain weekday or hour. Note that one day and one hour is left out of the regression to avoid multicollinearity.

After filtering out the deterministic effects, we are left with what we will denote the stochastic component q_t^{el}. It has several spikes, and seems to be mean reverting. We wish to dampen the extreme values through a

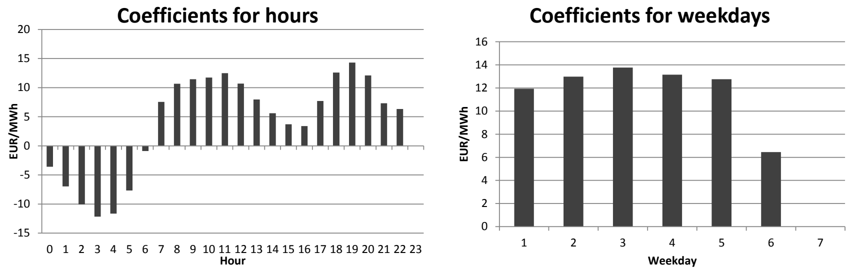

Figure 2: Coefficients for hour- and weekday effects.

simple transformation, but since q_t^{el} is often negative, taking log returns is not possible. Following Schneider [19], we take the inverse hyperbolic sine of a transformation of the prices:

$$x_t = \sinh^{-1}(z_t) = \sinh^{-1}(\frac{q_t^{el} - \xi}{\phi}) \tag{2}$$

Here, ξ is a shifting and ϕ is a scaling of q_t^{el}. For large positive and negative values of q_t^{el} this function behaves approximately like the logarithm, and it has an almost linear part around zero. This means that it will dampen the extreme values like the logarithm does, but still allows for negative values. Instead of choosing the parameters ξ and ϕ graphically to get a good fit, as in Schneider [19], we estimate them using Expectation Maximisation as described below.

Figure 3 shows the distribution of x_t within two standard deviations of the mean compared to a normal distribution, and justifies a regime switching model for x_t where the mean regime follows a normal distribution. The series is stationary, suggesting that x_t may, except from the spiky extreme values, follow a mean reverting price process with white noise residuals.

The tail values excluded in Figure 3, or the spikes, seem to occur independently of the "regular" price process. We therefore choose a Markov regime-

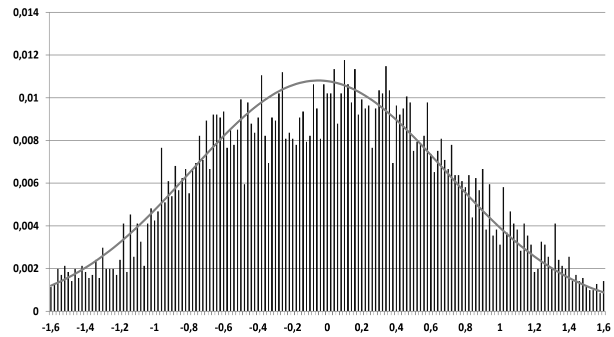

Figure 3: The empirical distribution of the capped prices compared to a normal distribution.

switching (MRS) model with independent spikes, due to de Jong [17]. The x_t from eq. (2) follow a mean reverting process in one regime, and switches to either a high-spike or a low-spike regime. The independence of regimes means that if the price at $t-1$ was generated by the low-spike regime, and at t it is generated by the mean reverting regime, the price in time t will not be influenced by how low it was in the previous period. What regime the process is *actually* in is not observable, but we assume that the switching between regimes is governed by a Markov transition matrix, Π. Recall that $x_t = \sinh^{-1}(z_t) = \sinh^{-1}(\frac{q_t^{el}-\xi}{\phi})$, to handle negative prices. This renders the model:

$$x_t^M = x_{t-1}^M + \alpha^{el}(\mu^{el} - x_{t-1}^M) + \sigma_M^{el}\epsilon_t^{el}, \quad \epsilon_t^{el} \sim N(0,1) \tag{3}$$

$$x_t^H = \mu^{el} + \sum_{i=1}^{n_t^{el,H}} Z_t^{el,H}, \quad n_t^{el,H} \sim POI(\lambda_H^{el}), \quad Z_t^{el,H} \sim N(\mu_H^{el}, \sigma_H^{el}) \tag{4}$$

$$x_t^L = \mu^{el} + \sum_{i=1}^{n_t^{el,L}} Z_t^{el,L}, \quad n_t^{el,L} \sim POI(\lambda_L^{el}), \quad Z_t^L \sim N(\mu_L^{el}, \sigma_L^{el}) \tag{5}$$

$$\Pi = \begin{bmatrix} 1 - p_{MH} - p_{ML} & p_{HM} & p_{LM} \\ p_{MH} & 1 - p_{HM} & 0 \\ p_{ML} & 0 & 1 - p_{LM} \end{bmatrix} \tag{6}$$

where entry $p_{i,j}$ in Π represents the probability of going from state j at time t, to state i at time $t+1$, $(i,j) \in \{1,2,3\}$ and $1, 2$ and 3 representing regimes M, H and L respectively. As can be seen from the Markov transition matrix, it is assumed that a transition from either a high spike to a low, or the opposite, is impossible. The average x_t is denoted μ^{el} and the speed of mean reversion back to this level is α^{el}, while the standard deviation of residual variation is σ_M^{el}. Note that the x_ts in the high spike regimes consist of $n_t^{el,H}$ jumps, where each jump is normally distributed with mean μ_H^{el} and standard deviation σ_H^{el}. The number of jumps is assumed to follow a poisson process with rate parameter λ_H^{el}, and correspondingly in the low spike regime. The parameters above are estimated via the Expectation Maximisation (EM) algorithm, largely following the original approach in Hamilton [25]. As the spike regimes are independent of the mean reverting regime, the expected price in the latter regime at time t is cumbersome to calculate. This is because we can not observe how many of the previous observations that are created by spike regimes, so all possible paths between times 0 and t should be considered, a significant computational burden. To save computational effort, we adopt the improvements proposed by Janczura and Weron [18] and

Table 1: Table of estimated parameters.

	MRS model		
Regime	1	2	3
α^{el}		0.036	
ϕ		7.599	
ξ		38.460	
μ^{el}	-0.038	0.311	-0.373
σ^{el}	0.210	0.010	0.026
λ^{el}	1.842	-	1.899
p_{MH}		0.009	
p_{HM}		0.129	
p_{ML}		0.044	
p_{LM}		0.409	

recursively approximate the expected price using the equation

$$\mathbb{E}[x_{t-1}^M|x_{t-1}] = \zeta_{1,t|t}x_t + (1-\zeta_{1,t|t})\{\alpha^{el}\cdot\mu^{el} + (1-\alpha^{el})\mathbb{E}[x_{t-2}^M|x_{t-2}]\} \qquad (7)$$

Here, $\zeta_{1,t|s}$ is the conditional probability of being in regime $1(=M)$ at time t given the information available at time $s \leq t$ (see [18] for details). The results of the estimation is displayed in Table 1.

This model was compared to a similar model with dependent spikes, several GARCH-specifications and a parameter-switching model (Janczura and Weron [18]), and outperformed all in terms of likelihood. Table 2 shows the average descriptive statistics of 5000 simulations. Our valuation method is based on Monte Carlo simulation, and the most important trait of our model

Table 2: Comparison of descriptive statistics from simulation with the actual values.

	Actual	Simulation
Mean	37.38	37.80
Standard Deviation	8.26	8.47
Skewness	-1.22	-0.24
Kurtosis	8.79	9.01

is that the deterministic and stochastic patterns replicate the observed prices well. We conclude that the MRS-model captures the dynamics in hourly power prices well enough for our purposes, and that we will continue using it in the valuation.

2.2. Gas price model

In modelling the gas price, we have used daily data for natural gas day-ahead prices both in the German and the UK market. Although our modelling is performed on the German market, we have used prices from UK's National Balancing Point as this time series has a history back to 1996. NetConnect Germany (NCG), Germany's most liquid gas market, only has data from 2007 onwards. Due to physical connections, gas prices in Northern Europe are closely integrated, and the NCG and NBP prices usually move in tandem. To be sure that this is correct, we estimated the following model:

$$S_t^{NBP} = \beta_0 + \beta_1 S_t^{NCG} + \epsilon_t^{NBP} \tag{8}$$

where β_0 is the difference in price between NBP and NCG and β_1 is the factor explaining how much of the NBP price that can be explained by the price level of the NCG price. The results show that the coefficient β_1 is not significantly different from one on the 1% level, and that the NBP price is on average 0.51 EUR/MWh higher than the NCG price. We will in the following assume that the relationship $S^{NBP} = S^{NCG} - 0.51$ holds for all points in time. Analysing the NBP price series in Figure 4, we first note that there seems to be some trend, or price inflation, in the gas price. We can also observe higher prices during winter and lower prices during summer.

As can be seen in Figure 4, the natural gas price exhibits mean reversion and spikes that seem to arrive at random. Supply and demand imbalances can cause the price to spike up or down, and return to the mean level during the following days.

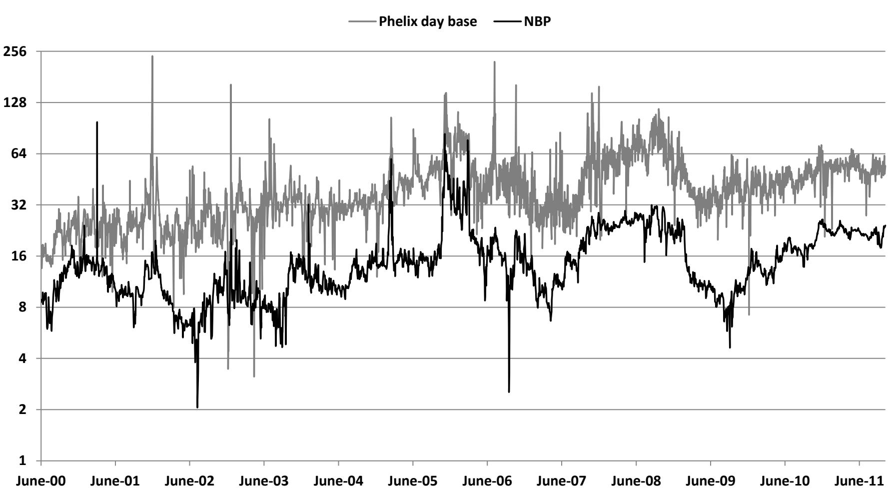

Figure 4: The NBP day-ahead gas price seems to fluctuate along with the Phelix day-ahead power price. Note the occurrence of spikes in the NBP price. Price axis in log scale.

We also note that the gas price moves along with the price of electric power (see Figure 4).[2] For the valuation of our gas storage, it is important that we incorporate the covariation in the gas and power prices, ensuring that the gas price does not move unrealistically high or low when compared to the power price, as market forces likely would take effect and drive the prices back to a long-term equilibrium. A price disequilibrium should result in gas-fired power plants either ramping up or scaling down activity, and thereby providing a counteractive force on the gap between gas and electricity prices. We propose a process for the natural gas price, taking into account both the spikes, mean reversion and the price level of electricity. Here, the mean level for the gas price S_t^g is $\mu_t^g = \mathbb{E}[S_t^g | S_t^{el}]$, where S_t^{el} is the electricity price. In contrast to the power price, the gas price reverts more slowly from spikes, i.e., they are not independent. Two spike functions are therefore added to the price process with Poisson arrival rates λ_H^g and λ_L^g for the high and the low spike process:

$$\Delta S_t^g = \alpha^g(\mu_t^g - S_{t-1}^g) + \sum_{i=1}^{n_t^{g,H}} Z_t^{g,H} + \sum_{j=1}^{n_t^{g,L}} Z_t^{g,L} + \sigma^g \mu_t^g \epsilon_t^g, \quad \epsilon_t^g \sim N(0,1) \tag{9}$$

$$\mu_t^g = \mu_0^g + \kappa S_t^{el} + \sum_{k=1}^{11} \delta_k^{month} \theta_k^g \tag{10}$$

Here S_t^g and S_t^{el} are the prices of gas and power at time t, μ_t^g is the

[2] One would expect that in situations of cold weather, both electricity and gas demand is high, and gas might be used as the marginal source of electricity. In such a situation, one should expect a strong relationship between gas and electricity prices. In other market conditions where demand is lower, one would expect prices of natural gas and electricity to be less dependent on each other.

expected gas price and α^g is the mean reversion rate. The expected gas price consists of μ_0^g, a constant, the influence of the power price κS_t^{el} and the seasonal effect θ_k^g if the binary variable δ_k^{month} is one for month k. The spike terms in eq. (9) are constructed exactly like in the power price model of equations (4) and (5). Finally, the residual ϵ_t^g is assumed standard normally distributed and σ^g is a volatility parameter.

We thus allow the gas price to fluctuate as a mean reverting process with spikes, but we set the mean level to be dependent on the level of the electricity price. This is consistent with the results of de Jong and Schneider [26]. We allow for high and low spikes, and we also allow for seasonal effects in the gas price that are not explained by the seasonality of the power price. If these seasonal variation parameters θ_k^g are found to be statistically significant (which we find that most of them are), the seasonal patterns in natural gas differ from those of electricity.

This model is estimated in two steps: we first estimate the relationship between the gas price and the electricity price, and in the second step we estimate the mean reversion in the residuals q_t^g that is not explained by the power price. The residual q_t^g is defined as:

$$q_t^g = S_t^g - \mu_t^g \tag{11}$$

where μ_t^g is the expected mean level for the gas price. The first step is a regression of the gas price on the power price and seasonal dummy variables to find μ_t^g, according to

$$S_t^g = \mu_0^g + \kappa S_t^{el} + \sum_{k=1}^{11} \delta_k^{month} \theta_k^g + q_t^g \tag{12}$$

Here we find the long-term relationship between the gas price and the power price by determining μ_0^g, κ and the different θ_k^g. But as we wish to model daily gas prices and hourly power prices for the valuation in Section 3, we need to convert hourly power prices to a daily average given as S_t^{el} in eq. (12). This was done by weighing 24 hourly power prices with the load curves in Germany[3]. Also, this average day price is affected by price spikes that seem to occur independently of the gas price—we therefore use the arithmetic average of one week as S_t^{el}.

We now have an estimate of the expected gas price, $\mathbb{E}[S_t^g|S_t^{el}] = \mu_t^g$, as a function of the power price and the time of year, defined by the monthly effects. The results are given in Table 3, with seasonal parameters θ_k^g omitted. The second step involves estimating the mean reversion model, where μ_t^g enters as the expected price:

$$\Delta S_t^g = \alpha^g(\mu_t^g - S_{t-1}^g) + \sigma^g \mu_t^g \epsilon_t^g, \quad \epsilon_t^g \sim N(0,1) \tag{13}$$

The results of the regression are shown in Table 3, and the residuals q_t^g in Figure 5. The reason for allowing the variance to be proportional to the expected gas price instead of the realised price is that the realised price will have an added spike element that may cause unrealisticaly high volatility in the days following a spike. We therefore add the spike processes as given in eq. (9).

To estimate the occurrence of spikes, we need to find the parameters

[3]The load of each hour is the average consumption for that hour as a percentage of the daily total. The load curves are given for each month of the year.

Table 3: Results from the two regressions performed to estimate the gas price model.

Results from the regression of eq. (10)				
Name	Coefficient	Std.Error	t-value	t-prob
μ_0^g	1.9280	0.2999	6.43	0
κ	0.3236	0.0052	62.0	0
Results from the regression of eq. (13)				
Name	Coefficient	Std.Error	t-value	t-prob
α^g	0.2697	0.0178	15.2	0

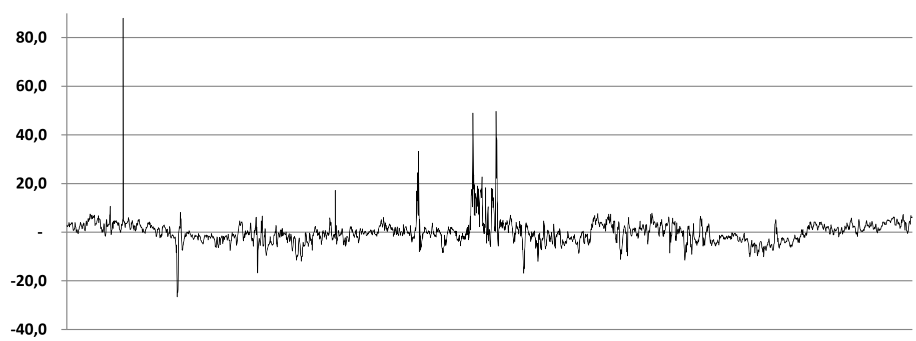

Figure 5: q_t^g. Residuals of the price of gas after subtracting the deterministic component given by eq. (10).

Table 4: Parameters used in modelling natural gas prices.

Fitted parameters	
λ_H^g	0.003
λ_L^g	0.003
σ_H^g	19.9
σ_L^g	10.0
μ_H^g	40.1
μ_L^g	0.0
σ^g	0.065

$\lambda_H^g, \lambda_L^g, \sigma_H^g, \sigma_L^g, \mu_H^g$ and μ_L^g. We also get a very high estimate of σ^g from the regression in (13), so we vary these parameters as well as σ^g in order to get as close a replication of the mean, variance, kurtosis, skewness and percentiles of the gas price series as possible. The best fit parameters are shown in Table 4. Table 5 shows how the first four moments from a simulation compared to the actual data set.

3. Valuation of the linepack

We have developed models for the day-ahead gas price and the hourly power price, and shown how they capture the observed dynamics. We now proceed to use these models in a valuation of the linepack, through its economic use by a gas fired power plant, as described in the Introduction. The plant is committed to a long-term gas contract for its input, and depending on the built-in flexibility of the contract, a plant might find itself in a posi-

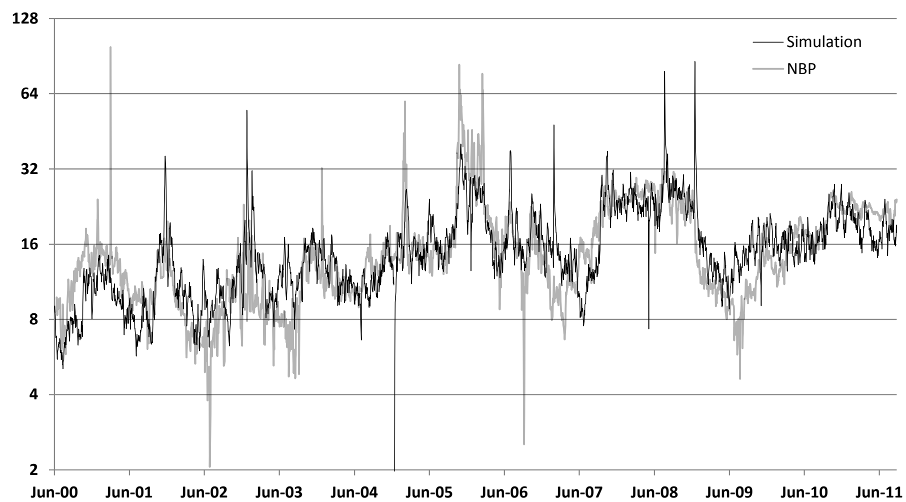

Figure 6: Simulation of gas price compared to the actual gas price. Note that the simulation only depends on the power price and the previous simulated price, but it still follows the actual price closely because of the cointegration with the power price.

Table 5: Results of 100 simulations of NBP natural gas prices. The last row, *Correlation*, indicates the correlation of the gas price to the 1-week average of the power price.

Period	2000-2011	
	Actual	Simulated
Mean	15.60	16.02
Standard dev.	7.69	7.00
Skewness	2.37	2.14
Kurtosis	12.83	14.72
5% quantile	6.85	7.73
95% quantile	27.4	28.43
Correlation	0.744	0.770

tion where there is little flexibility left. It will have to either produce power with the committed gas volume or sell it in the spot market. We assume a scenario where the power plant has little flexibility under the TOP contract. The situation is the same for a plant that has bought gas on a forward contract. In this scenario, a short-term storage facility such as the linepack may add value to the power plant. It enables the plant to ramp down production when the dirty spread becomes negative and ramp up again when it gets positive—without violating the take obligation. The decision at every point in time is thus whether to produce power, to sell gas in the market, or to store it for an a priori unknown time period. The price paid for the gas is considered a sunk cost, so the gas price used in the decision problem is the actual spot price at the time of the decision. The stored gas will later be sold for an a priori unknown price, either as gas or converted to electric power. The choice between the first two options is simple when the efficiency of the plant is known: If the dirty spread is positive, a unit of gas has higher value if converted to power, and vice versa. The third option is more complex, as we discuss below.

In our setup, we assume that the power plant has a fixed, maximum power output. We assume that the plant can sell all of its power or gas without influencing prices in the market, disregarding transaction costs and bid-ask spreads. We discretise time into hours, and assume that the plant can alter its production instantanously to respond to hourly price changes. In reality there will be a short period of continuously increasing or decreasing output while ramping up or down, and there will be costs related to doing this. We omit these factors to simplify our analysis. If the plant in one specific hour wishes to sell gas in the market, we will use the settlement price for that day, modelled in Section 2.2. The settlement price is the weighted average price for the day, and in absence of rich data on intraday trading we believe this is a reasonable approximation. Note that this implies a constant gas price throughout each 24 hour period. We further assume continuous trading of natural gas contracts also during weekends. We omit any CO_2 emission costs, because this cost will only weakly influence the value of the storage; assuming that all stored gas will be converted to electricity at some point in time, the CO_2 cost will be paid for all the gas volumes received regardless of the option of storage.

The linepack has some maximum injection and withdrawal rate, Δv_{in} and Δv_{out}, as well as a maximum and minimum storage capacity, v_{max} and v_{min}.

Taking a real options approach, the value of the option to store gas can be viewed as a dynamic program. In the Bellman equation (Dixit and Pindyck [27, p.100]), eq. (14), each state corresponds to a certain point in time, having a certain volume of gas in the storage, with the prices of gas and power at a certain level. The control variable is how much to inject or withdraw in the present state—leading to profits from selling gas or producing power. For the decision problem of the gas fired power plant, we define the Bellman equation for the value of the linepack:

$$\begin{aligned} V_t(P_t, v_t, \Delta v_t) = & - \Delta v_t P_t + e^{-\rho}\mathbb{E}[V_{t+1}(P_{t+1}, v_{t+1}, \Delta v_{t+1})] \\ P_t \equiv & \max\{\eta \cdot S_t^{el},\ S_t^{g}\} \end{aligned} \tag{14}$$

where V_t denotes the value of the storage volume at time t, Δv_t the injection/withdrawal of gas per hour, ρ the discount rate, and η the efficiency of the plant. The variable P_t, is defined as the maximum of the electricity price times the plant efficiency and the gas price, i.e., the most profitable utilisation of the gas. Note that a positive injection to the storage implies *not* producing or selling, thereby incurring an alternative cost of $\Delta v_t P_t$.

3.1. Valuation method: Least Squares Monte Carlo simulation

Following Boogert and de Jong [10], we use LSMC simulation to compute the value of the linepack. Boogert and de Jong consider a gas storage facility with large capacity (250,000 MWh) that exploits seasonal and day-to-day arbitrage opportunities. Our case, on the other hand, has lower storage capacity, two ways to convert gas withdrawals to money, more complex price processes, and the opportunity to exploit hourly price patterns. We also perform the storage valuation on the linepack, a volume with more flexible characteristics than a conventional storage, as discussed in Section 1. We define a finite period of T hours over which to value the storage. The idea of LSMC is to simulate M price paths, and at each step along each path *approximate* the expected continuation value $\mathbb{E}[V_{t+1}(P_{t+1}, v_{t+1}, \Delta v_{t+1})]$ with a least squares regression. At time $t = 0$ and $t = T$, there must be defined boundary conditions, for example the volume of gas in the storage at $t = 0$ and the value of having a certain volume of gas at $t = T$. To start the iteration, the values V_t are regressed across all scenarios on the state variables in the period before. Based on this estimate, the choice is made whether to inject or withdraw gas, resulting in some realised value V_{t-1}. The regression is then repeated for the previous time period.

The regressions used to approximate eq. (14) may have several forms. In their introduction of the LSMC, Longstaff and Schwartz [11] suggest power functions, Laguerre polynomials and several other functions of all the state variables, as well as their cross products. In our application, this would lead us to regress the values V_{t+1} on various terms involving P_t and v_t, across the M price scenarios. However, Boogert and de Jong further discretise the state space into volume levels, so that P_t is the only independent variable in the regression. Applying this principle, we are left with a three-dimensional grid with time t, volume level v and scenario m as the three axes. For a further discussion of reducing the dimensionality, see Boogert and de Jong [10]. Based on scatter plots of V_{t+1} and P_t for all scenarios, we choose a polynomial form of order three in the regression.

A Matlab algorithm was written to calculate the value from all allowed injections or withdrawals of gas, and the expected value in eq. (14) is approximated with the regression. It starts at time T and moves backwards, where the allowed injections and withdrawals are constrained by the maximum and minimum volume allowed in the storage. Given the boundary condition that the linepack must be empty at time T and time 0, the value of the linepack is the average value at time 0 across all simulated price scenarios. When choosing the optimal injection rate Δv_t, it will often be the case that $v_t + \Delta v_t$ is not a defined point in the grid. In such a case, the expected option value will be computed as an interpolation between the two closest defined points.

4. Results and discussion

In this section we will use the models developed in Sections 2 and 3 to create some numerical valuation examples. We will first present a reference case and analyse the results. The reference case will give an indicative value on which we can base sensitivity analyses. We proceed to demonstrate how sensitive the value is to various parameters, and how the optimal dispatching change when the parameters vary. Consider a medium sized combined cycle plant with a maximum power output of 300MW and efficiency of 53.8%[4]. We assume it receives 200MWh of gas per hour, corresponding to the parameter v_{in}, and that it is allowed to store gas in the linepack for up to 10 hours, i.e., v_{max} is 2000MWh. The maximum gas withdrawal v_{out} is -100MWh, such that all the incoming gas and the withdrawals total to the maximum output of 300MW. We simulate 1000 price scenarios of three weeks length, and use

[4]The efficiency corresponds to a General Electric LMS100 combined cycle gas turbine.

Table 6: Parameters used in reference case.

v_{max}	2000 MWh
v_{min}	0 MWh
η	53.8 %
v_{in}	200 MWh
v_{out}	-100 MWh
T	504 hours (= 3 weeks)
ρ	6%
M	1000 simulations

an annual, exogenous discount rate of 6%. These parameters are summarised in Table (6).

Recall the assumption that the power plant is in a situation with little or no flexibility left in the take-or-pay contract, meaning that without any storage option it has to use or sell all the incoming gas. The prices are simulated over three weeks, as it is unlikely that a power plant will be in this situation for very long periods of time. We use a discretisation of $N = 100$ volume levels, meaning that each volume step will be 20 MWh for $v_{max} = 2000$. We first show how the production and storage decisions vary with the prices of the input variables. Consider Figure 7. We see that whenever the price is low, production ceases and gas is stored. When either the gas price is higher than normal or the storage volume is full, gas is sold on the market. Notice that at around $t = 175$ hours, the power price spikes downwards while the storage volume is full. The power plant will sell no more than the gas received each hour, as the probability of higher power prices in the future makes it suboptimal to empty the storage.

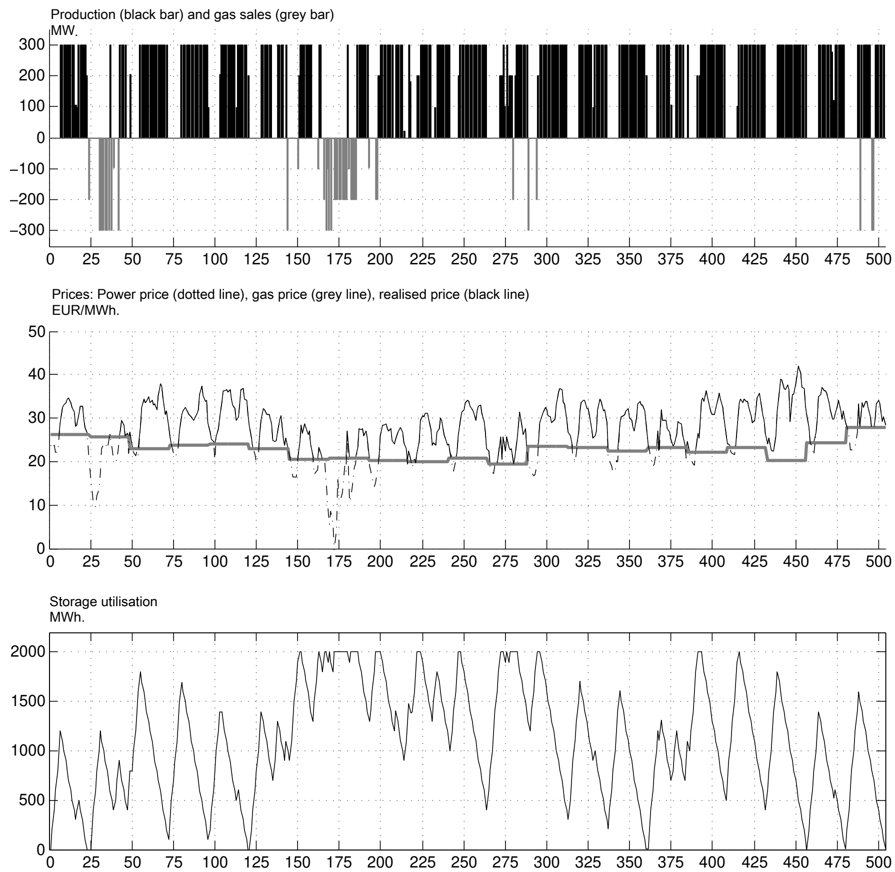

Figure 7: Simulation of three weeks of storage and production. Top: Production and gas sales in MW. Positive values imply production, negative (grey) values imply that gas is sold in the market. Middle: Price series of power and gas. The grey series is the daily gas price, the dashed line is the hourly power price corrected for efficiency, and the continuous line is the $P(t)$, meaning the maximum of these two. Bottom: Storage volume in MWh. Horizontal axis in hours.

The value of a license to use the linepack over a period of three weeks is estimated to 249,234 euro. This reference case scenario value is computed taking the average of ten runs of $M = 1000$ simulations each run. The standard deviation of the ten computed values is 427 euro. If we assume no access to linepack storage, the plant would have to produce power or sell gas at market prices every hour. Computing the revenue of the same period without a storage option reveals that the linepack value is about 8.5% of this revenue. Even more interesting is the increase in profitability. The cost of gas in take-or-pay contracts is usually confidential, but if we assume a constant gas price of 22 EUR/MWh and that the plant has no other costs, its profit would increase by 34% during the period of time in which the plant has a low flexibility due to commitment to a TOP or forward contract. Converted to power price terms, this corresponds to an increase of 2.51 EUR/MWh over the simulated period. The reference case assumes no trading, ramp-up or ramp-down costs for the power plant. As the algorithm calculates the isolated value of being able to store gas, we conclude that the increased flexibility indeed can be considered valuable to a plant in a situation of low initial flexibility. The storage option allows for better utilisation of gas and increased profits to the owners of the plant. The results shown imply that a broader utilisation of the linepack in the pipeline network would enable more efficient operation of power plants; potentially even dampening the extreme spikes seen in today's power prices. By a no-arbitrage argument, if every plant had the same flexibility, some of the variation in prices could be eliminated. The price volatility is the primary source of profits for the storage volume as a separate entity, so an increased use of the linepack would also reduce the marginal value of each MWh of storage volume. However, it may be a valuable tool for the energy system as a whole.

Below we show some examples of how sensitive the value of the linepack is to changes in parameters of the storage volume or the price processes. In each simulation we use $M = 250$ simulations.

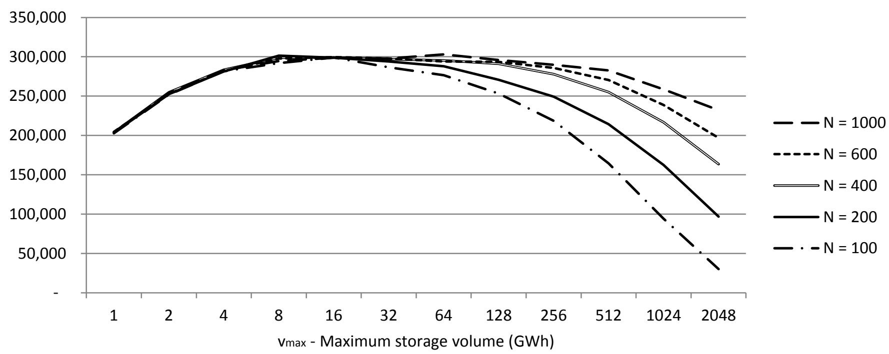

Figure 8: A higher storage volume (v_{max}) requires a higher volume discretisation (N) to provide a good estimate. For $N = 100$, the value of a 64 GWh storage volume is estimated to be lower than for a 32 GWh volume. For $N = 1000$, the value is equal, as one would expect.

We now analyse how the value changes with increased storage capacity. When evaluating how the value of the linepack varies with the maximum storage capacity v_{max}, one would expect that the value at first increases rapidly with higher capacity, but that it eventually flattens out as the capacity goes to infinity. One could say that when value goes to infinity, flexibility only goes to 100%, and asymptotically the value should also reach a maximum. We find that for low values of volume levels N with high values of v_{max}, the asymptotic value of the storage volume actually falls (Figure 8). This is caused by the error of interpolation increasing with higher capacity as the

LSMC algorithm divides the maximum volume into $N+1$ levels. An interpolation is a linear function while our model estimates the value of continuation by a polynomial function of power 3, rendering the interpolation inaccurate for large intervals. We observe that for higher volume discretisation (higher N), the accuracy improves and the value goes asymptotically to a stable level as the volume rises. We can see from Figure 8 that for $N = 100$ and $v_{max} = 4000$ the error of estimation is small, while for $v_{max} = 8000$ it is visible. We can conclude that the size of N relative to v_{max} should be around $\frac{1}{40}$.

In Section 2, we estimated the parameters of our price models and noted some potential estimation errors, most notably in the gas price model. We now address the sensitivity of the value estimate to changes in different parameters. None of the parameters in the gas price model showed significant effect on the value, as it is seldom optimal to sell gas in the market. The results from gas price sensitivity analyses is therefore omitted. However, Europe may expect a larger fraction of renewable power generation in the future. Germany is phasing out its nuclear power plants and the UK has ambitious goals for wind power. Both solar and wind power has relatively unpredictable and volatile output, and we therefore analyse how changes in power price volatility and spike occurences affect the linepack value. This corresponds to the parameters σ^{el}, λ_H^{el} and λ_L^{el}, as well as p_{ML} and p_{MH} (the last two representing the frequency of the power price entering the spike regimes).

Figures 9 and 10 show the effect of the variation in parameters on the estimate of the value. Higher values of both σ^{el} and the arrival rates of spikes increase the overall volatility of the power price, implying that power price volatility is the main value driver for the linepack. Analysing Figure 11, the effect from changes in p_{ML}, one can see that more spikes to the low regime increases the value of the linepack more than λ_H and λ_L. The implicit price increase from increases in p_{MH} is not that relevant, because high spikes increase revenue along with the linepack value.

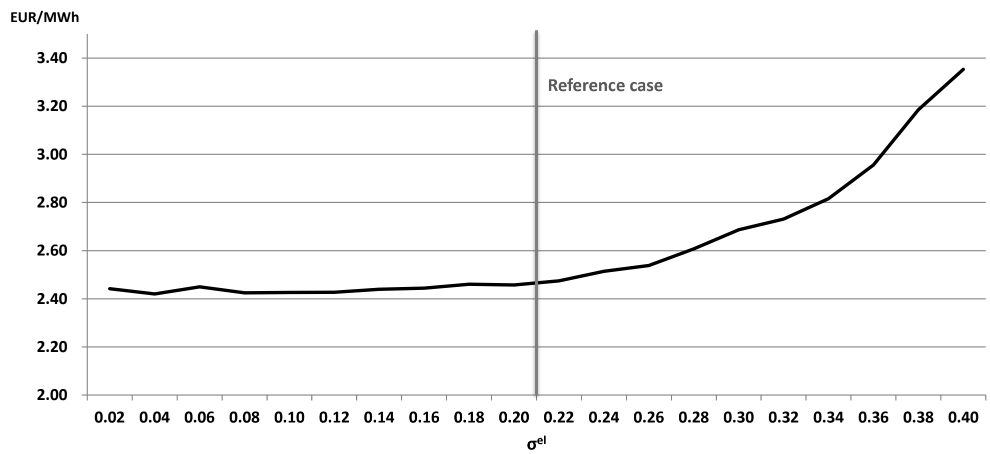

Figure 9: Implicit power price increase when varying volatility σ^{el} in the power price. In the reference case, $\sigma^{el} = 0.21$.

5. Conclusion

Linepack is an under-utilised and under-communicated short-term energy storage option. Since it uses existing natural gas pipeline infrastructure, it is cost efficient and environmentally sound. In this article we have analysed its value for a participant in the natural gas value chain. We exemplified the idea through a gas fired power plant, facing both gas price and electricity price volatility. We developed models for power and gas prices that can accurately

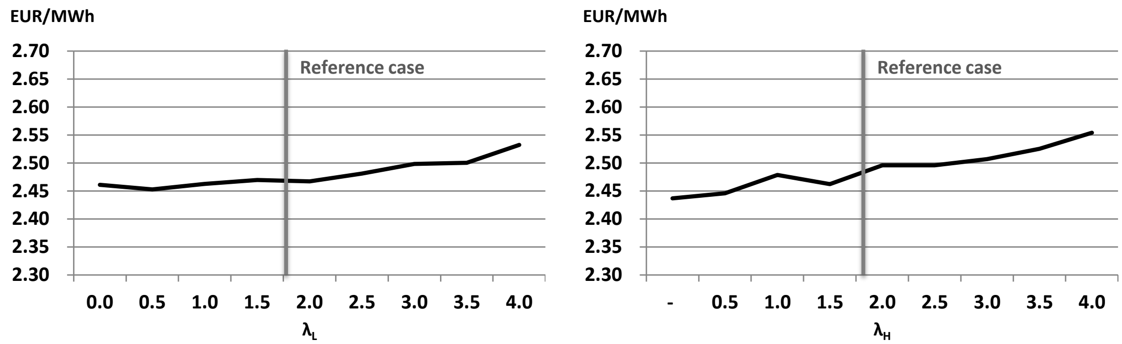

Figure 10: Implicit power price increase when varying arrival rates λ_H^{el} and λ_L^{el} for high and low spikes in the power price. In the reference case, $\lambda_H^{el} = 1.89$ and $\lambda_L^{el} = 1.84$.

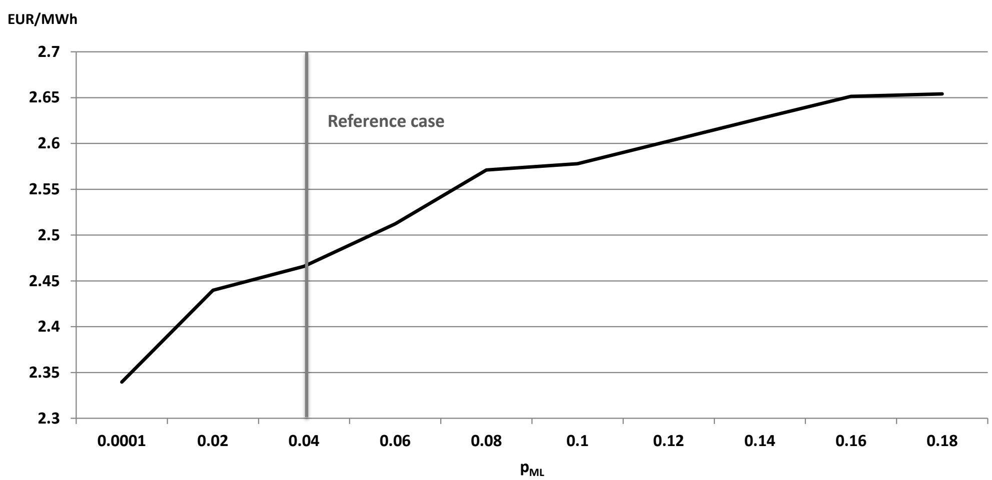

Figure 11: Implicit power price increase when varying p_{ML} in the power price. In the reference case, $p_{ML} = 0.044$.

capture both regular variations, irregular spikes, and the covariation in the two prices. The Least Squares Monte Carlo algorithm was employed in the valuation, and we conclude that the flexibility of having a storage opportunity was indeed beneficial for the power plant. Specifically, when committed to a take-or-pay contract, the plant in the reference case could increase the value of the gas by 34% with the option to store gas for up to ten hours. This is equivalent to receiving a power price that is 2.51 EUR/MWh higher than market prices, over the three week period simulated. Further, we showed that the volatility and spike arrival rates of the power price are the most significant value drivers, because in most cases storing gas to produce power later is more profitable than selling gas in the market. The gas price parameters are therefore of smaller importance. The capacity of linepack storage increases value up to a limit where no more flexibility is used. In a future with more output from unpredictable renewable power sources, such as solar and wind power, the linepack may enable participants in the natural gas value chain to more efficiently utilise its gas.

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