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Private and social benefits of a pumped hydro energy storage with increasing amount of wind power

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Abstract

In this paper, we calculate the long-term profitability of a pumped hydro energy storage (PHES) plant that is planned to be built in an old mine. We model the optimal PHES operation for several scenarios with different wind power penetration levels. Our modelling approach first involves estimating wholesale electricity prices for the day-ahead, intraday and balancing market as a function of wind power penetration. The estimated price profiles are implemented in a dynamic programming model, where the PHES plant maximises its balancing market revenue given the optimal commitment in the day-ahead market. We show that increasing the wind penetration changes the optimal PHES operation and increases the PHES profits. Additionally, we quantify how the costs of wind power balancing are affected by the PHES investment. Policy implications are drawn based on the estimated private and social benefits from the investment.

Keywords: wind power, energy storage, dynamic programming, balancing costs, pumped hydro

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1. Introduction

The use of variable and intermittent renewable energy sources (RES)¹ such as wind and solar has increased rapidly during the last decade. This increase is a result of global climate policies aiming to slow down the climate change by cutting down CO₂ emissions. Because of the decreased investments costs of wind and solar power, they are increasingly displacing conventional fossil-fuelled thermal power generation technologies in the Nordic power market area. The main problem related to this development is that the wind and solar outputs are varying and intermittent by nature. In other words, solar power is available when the sun is shining, and wind power is available when the wind is blowing. Moreover, their output prediction involves weather forecasting errors. As a result, an increasing amount of backup and balancing power capacity is required to maintain the high security of supply in power grids with a higher RES share.

Demand and supply must be balanced at all times in the power grid. The system operator maintains the quality of electricity while minimising production costs. That is, power plants are dispatched based on their marginal costs; thus, the most expensive power plants are used to supply only the peak demand (peaker capacity). Therefore, in spot electricity markets, the spot prices reflect the scarcity of supply. In the long run, for a power plant to remain profitable, it needs prices above its marginal cost to cover the fixed costs if there are no capacity payment mechanisms.

The average wholesale electricity price, however, is shown to be a decreasing function of wind power penetration, at least in the spot electricity markets (Woo et al. (2011) and Clò et al. (2015)). As a consequence, conventional thermal power plants providing peak power capacity exit the market when they make negative profits. At the same time, more backup and balancing power capacity is needed to balance out the variability and intermittency of RES output. As a result, while RES supporting schemes have been successful in increasing the use of RES in electricity production, there are increasing concerns over the adequacy of backup and balancing power capacity (Norden, 2015).

The economic literature of wind power includes studies concerning the

¹We acknowledge that there are renewable energy sources with less variable and intermittent outputs such as geothermal energy and bioenergy. However, in this article, we specify the RES as having a variable and intermittent nature.

indirect system-wide integration costs resulting from integrating RES into power systems. These costs can be seen as additional social costs to the non-RES part of the power system (see, e.g., Gowrisankaran et al. (2016), Joskow (2011), Hirth (2013) and Hirth et al. (2015)). Due to these costs, the use of the levelised cost of electricity in determining a welfare-optimal generation mix has been criticised (Joskow, 2011). The integration costs are related to reinforcing the distribution and transmission networks, short-term balancing services and varying net electricity demand, reserve requirements, and cycling and ramping costs of conventional power plants (Hirth, 2013). Because of the system-wide effects, the integration costs must be included in evaluating the welfare effects of intermittent renewable energy sources to arrive at unbiased conclusions of a welfare-optimal generation mix (Hirth et al., 2015).

Different energy storage technologies have been proposed in solving the integration cost problem (Zhao et al., 2015). Energy storage provides a way to smooth out the RES generation profile and provide balancing power (for an energy storage literature review, see Hall (2008), Ayodele and Ogunjuyigbe (2013) and Rehman et al. (2015)). The excess RES output is stored in times of low demand and price, while it is discharged in times with low RES output and high demand and price. In the RES integration literature, it is shown that the balancing costs of RES can be reduced considerably with energy storage (Hedegaard and Meibom (2012), Deane et al. (2010) and Steffen (2012)). Furthermore, energy storage increases the market value of RES in power systems with low flexibility of other generating technologies (Connolly et al., 2012). Historically, the most successful form of energy storage has been pumped hydro energy storage (PHES), where water is exchanged between upper and lower reservoirs through a turbine and pump (IEA, 2014).

The majority of PHES were built under government-regulated entities, as only 5% of the global PHES investments have occurred in liberalised markets (Barbour et al., 2016). However, with increasing shares of RES, a renewed interest in PHES may arise in the liberalised electricity market areas. Similar to any other energy storage technology, the price variance has to be high enough to exploit price arbitrage possibilities covering the operational and capital costs. Even though the merit-order effect (Sensfuß et al., 2008) of RES may push the mean electricity price downwards, the price variance is shown to increase with RES penetration (Woo et al., 2011). Generally, a higher price variance and an increasing demand for balancing power may increase the economic attractiveness of investing in energy storage, such as

PHES, in the future.

The optimal operation of energy storage from the perspective of plant operators and power systems has been examined in multiple previous studies (for a literature review, see, e.g., Pérez-Díaz and Jiménez (2016) and Steffen and Weber (2016)). The first stream of energy storage models have been programmed as mixed-integer linear programming (MILP) problems. The total system costs are examined, for example, in Foley and Lobera (2013), who study the system effects of a compressed air energy storage facility in a power system with a large amount of renewable energy sources. Kazempour et al. (2009) examine the optimal behaviour of a price-taking PHES, which participates in the day-ahead market, spinning reserve and regulation markets. They include uncertainty in price forecasts and power delivery requests in the ancillary service markets in their model.

Pérez-Díaz and Jiménez (2016) construct a unit commitment MILP model and investigate the optimal PHES scheduling in a hydrothermal system. They show that PHES can reduce scheduling costs and allow for the retirement of some inflexible thermal generators. Sousa et al. (2014) investigate the benefits of PHES in wind power integration in a liberalised day-ahead market under the price-maker context. Their results show that wind power integration is less efficient if the PHES operator is more of a price-maker than a price-taker in the market. The main difference in these studies compared to our approach is that they do not model changing market conditions in terms of wind power affecting the electricity price. In other words, most of the previous studies examining optimal bidding strategies and profitability of storage have been simulated with realised electricity prices. Our contribution compared to the previous studies is that we compute the system-level impacts of a PHES over its expected techno-economic lifetime.

Other studies focus more on the storage-level analysis. For example, Kanakasabapathy and Shanti Swarup (2010) develop optimal bidding strategies for a PHES in a pool-based electricity market. They use forecasted hourly market clearing prices and maximise the profits by also considering both spinning and non-spinning reserve bids. Additionally, Lu et al. (2004) forecast the deterministic day-ahead market clearing price curve and maximise PHES profits by allowing for bidding to day-ahead and ancillary services markets. Similar to the studies described in the previous paragraph, in both of these studies, the focus is on optimal short-term bidding, and they do not investigate the long-term profitability in changing market conditions.

Connolly et al. (2011) examine three practical operation strategies of

PHES. They show that to remain profitable, the PHES operator must have very accurate price forecasts in the day-ahead market. With perfect foresight, the PHES profits exceed the annual investment repayments, but the variation in annual profits is significant. Thus, they conclude that even with a low investment cost and interest rate and a suitable power market, PHES is a risky investment because of the high variance in predicted profits. They do not, however, consider participation in ancillary service markets. Comparable to Connolly et al. (2011), we simulate the PHES operations in different market conditions while including the balancing power services in our model.

Steffen and Weber (2016) use optimal control theory to optimise the operation of energy storage in an environment with time-varying but deterministic electricity prices. The empirical part in their study indicates that the profit potential for storage plants decreased significantly from 2008 to 2011 in Germany. Although they perform an annual comparison, they do not specifically focus on examining the bidding behaviour and profits in future electricity markets with a higher amount of RES. Moreover, they assume that the electricity storage plant operates only in the day-ahead market. While they investigate the potential over time, their analysis is built on realised historical data that do not cover the entire expected lifetime of energy storage.

A few studies optimise the PHES operation by applying dynamic programming. Paine et al. (2014) examine how the rules of different independent system operators affect the operation and profitability of PHES. They develop a model for optimising the operation of PHES in two regions with different market rules. Their results show that different market rules determine the optimal PHES size, influence the optimal operational and bidding strategies, and affect the profits that a PHES operator is able to extract from the market. Other studies of this stream can be found in Zhao and Davison (2009), who propose a model of PHES operating in a power market with deterministic time-varying electricity prices and constant water inflows. In their model, the turbine efficiency depends on the hydraulic head and the water discharge. However, neither of these studies consider the different bidding deadlines in different markets or the price effects of wind power.

In this study, we compute the long-term market-based profitability of a PHES planned to be built in Europe's second deepest mine in Pyhäsalmi, Finland. Our modelling approach and application combines parts of the previous literature and contributes to it in many ways. The analysis starts from the investor's point-of-view and then turns to a system-wide perspective

by quantifying the effect of PHES on wind power balancing costs. The PHES operator may exploit three different markets in its operations. It acts as a price-taker in the day-ahead market and intraday market, whereas in the balancing market, it acts as a price-maker. Our model takes into account the different bidding deadlines in the three distinct markets. In the previous literature, optimal bidding strategies and the profitability of PHES have been simulated mainly with realised electricity prices (see, e.g., Paine et al. (2014)). Because of the long-term perspective, we estimate future price profiles in the three markets as a function of long-term wind power production targets. Optimal reservoir allocation, i.e., bidding strategy in the markets, is solved as a dynamic optimisation problem. Furthermore, we maximise profits over different turbine, pump and reservoir capacity combinations.

We show that wind power production lowers the day-ahead market prices and makes them more variable. However, the balancing market becomes a more important revenue source for the PHES as more wind power enters the market. The investor's and system's preferences are opposite to one another, considering the optimal choices of the power unit and storage capacity. Moreover, smaller power units with a sufficiently large storage capacity yield the best profitability from the investor's point-of-view. This is partly because the PHES operator is assumed to be a price-maker in the balancing market. In contrast, the larger power unit with a smaller storage capacity would be the best choice from the system's perspective. We simulate the positive system-wide externalities and quantify a support mechanism for the larger PHES capacity investment.

This paper is organised as follows: first, the case study, Pyhäsalmi mine, is introduced in Section 2. The price estimation model is presented in Section 3, and the dynamic programming model is defined in Section 4. The results are reviewed in Section 5 and discussed in Section 6. Conclusions finalise the paper in Section 7.

2. Nordic power market and case Pyhäsalmi in Finland

2.1. Nordic power market

Finland is a part of highly interconnected power market area consisting of the Nordic and Baltic countries. In this market area, wholesale electricity trade is organised through the Nord Pool power exchange, which is owned by the national transmission system operators (TSO). In the Finnish power market, over 80% of electricity demand is traded via the exchange market

Nord Pool Spot (Nord Pool Spot, 2017). Nord Pool Spot (Elspot) is a day-ahead forward auction market (DAM), where hourly system prices for the hours in the next day are determined by the submitted demand and supply bids.

Figure 1: Location of the planned PHEs.

Zonal pricing is applied in the Nordic power market area. For example, Finland is one price area, while Sweden is divided into four, and Norway is divided into five price areas. The existing inter-connector capacities from and

to Finland are presented in Figure 1. In recent years, Finland has usually been separated as its own price area. Thus, accepted Finnish supply offers of the day-ahead market area are typically paid the Finnish area price. The power exchange with Russia is more complicated since it is not a part of Nord Pool, and it is a capacity-based market rather than an energy-only market².

Besides the DAM, electricity is traded in other markets closer to the delivery hour. The intraday market (IDM) Elbas is a continuous³ market, which is opened two hours after Elspot closes, and it is closed one hour before the hour of delivery. Elbas is the primary market used to balance the mismatch between contracted and delivered supply (e.g., unexpected weather conditions or plant failures). The intrahour balancing market (BM) opens up after Elbas is closed. All resources whose output can be adjusted up (BM-UP) or down (BM-DOWN) by at least 10 MW within 15 minutes can be offered to the BM. The bids need to be submitted to the Fingrid (TSO in Finland) no later than 45 minutes before the hour of delivery. All scheduled bidders are paid the marginal price based on the bid price of the last scheduled generation unit.

The Nordic power market has a diverse portfolio of power generating technologies. It is a highly hydropower-dominated market area, where the amount of wind power is increasing rapidly. The Finnish production technology portfolio contains nuclear power, wind power, combined heat and power (CHP) and separate condensing thermal power. New nuclear power capacity is currently being built in Finland⁴. Wind power generation was 2.6% of total consumption in Finland in 2015. However, targets for wind output are 6 TWh in 2020 (6% of consumption) and 9 TWh in 2025 (10%) (Ministry of Economic Affairs and Employment, 2013). In recent years, 2500 MW of separate thermal power either has been decommissioned or acts only as a reserve capacity. Further investment decisions in CHP capacity have not been made. To date, Finland has managed to maintain its power balance by intensive use of its inter-connectors to Sweden, Russia and Estonia. For example, 19.8%

²A discussion of the challenges resulting from different market structures can be found in Viljainen et al. (2013).

³There can be multiple prices in an hour. The maximum within-hour difference between the lowest and highest price was 240 €/MWh in 2015. On average, the difference was 10 €/MWh with a standard deviation of 11.82 €/MWh.

⁴Olkiluoto 3, with a capacity of 1600 MW, is starting its production in 2020, and Hanhikivi 1, with a capacity of 1200 MW, is planned to be in operation in the late 2020s.

of consumption was supplied with imports in 2015. However, the demand for balancing power is expected to increase in the neighbouring countries, as wind power penetration is increasing there as well. For example, over 70% of up- and down-regulation in the Nordic power market area has been based on Norwegian and Swedish hydropower in recent years (Nord Pool Spot, 2017).

Almost all of the possible hydropower resources are already in use in Finland⁵. Approximately two-thirds of the Finnish hydropower can be considered reservoir hydropower with a limited possibility to shift production over short periods of time, typically from night to daytime. As pointed out in Huertas-Hernando et al. (2017), Finnish hydropower is not as flexible as that in Sweden and Norway. The rest is run-of-river hydropower whose production is determined fully exogenously by the river flows. Political debate over construction of two artificial lakes in Kollaja and Vuotos has continued for decades. However, building them would require changes to the Nature Conservation Act and the Act on the Protection of Rapids.

The adequacy of (flexible) generation capacity may be threatened in Finland in the years to come because of the above-mentioned reasons. Finland is currently barely self-sufficient, considering the overall generating capacity⁶. Even more critical is the situation of balancing the power capacity, as more inflexible wind and nuclear power is being built. For example, over 30% of the overall generation capacity is referred to as inflexible capacity when the wind and nuclear power investments currently under construction will become operational. However, in 2000, the percentage of inflexible capacity was 17%, which is also why Fingrid is concerned about the adequacy of the balancing power supply (Fingrid, 2016).

2.2. Case PHES in Pyhäsalmi, Finland

To test the developed model, we utilise the parameters of a PHES planned to be built in an old mine in Pyhäjärvi, Finland. There are multiple reasons why this case study was chosen. First, there is no PHES capacity currently installed in Finland. Second, the PHES would be built in Europe's second deepest metal mine, with a depth of 1,444 metres. In other words, the high

⁵However, the generation capacity could be increased by adding pumps and more efficient turbines to existing hydropower plants (European Commission, 2007).

⁶The peak consumption is estimated to be 3400 MW higher than the available peak capacity in winter 2015–2016 (Åf Consult, 2016).

head height ensures high generation efficiency regardless of the upper storage level. Third, most of hydro and wind power resources are located in the northern part of Finland, while the largest load centres are in the south. Line Cut P1 in Figure 1 represents the main bottleneck in the Finnish transmission network. Thus, the location of the PHES could also contribute to operating the power flow from the north to the southern load centres. Lastly, wind power penetration is rapidly increasing in Finland. Simultaneously, conventional separate thermal power capacity, capable of providing balancing power, is forced out of the market as being unprofitable.

To avoid regulatory obstacles, we assume that the closed-loop characteristic ensures that there is no uncertainty related to the water inflows or environmental effects related to rationing the water flows. This would be a considerable advantage over reservoirs built in river systems. The profits of the plant are simulated by using four estimated price profiles reflecting different wind share scenarios (see Section 3). An optimal price arbitrage rule is found through iteration for the day-ahead market, whereas dynamic programming is applied in optimising the bidding behaviour in the stochastic balancing market (see Section 4). We start by simulating the operation and profits in the current markets, and then adjust wind power production so that 5%, 10% and 15% of consumption is provided with wind power. According to Pöyry (2016) and Ministry of Economic Affairs and Employment (2016), we assume that electricity demand grows because of society's further electrification, such as the increasing number of electric cars and heat pumps. The assumed wind power generation and electricity consumption in the future are summarised in Table 1. The positive system-wide externalities and necessary investment subsidy mechanisms (if needed) are discussed after quantifying the market-based profitability.

Table 1: Future wind power generation and electricity consumption.

	Year 2015	Year 2020	Year 2025	Past 2025
Consumption (MWh)	81.13	86	89	92
Wind power (TWh)	2.09	4.30	8.90	13.80
Wind power (%)	2.57	5.00	10.00	15.00

The technical characteristics of the PHES and model parameters are given in Table 2. Simulations are run for different combinations of tur-

bine (C_T)/pump (C_P) capacity pairs⁷ (50/62.5 MW and 200/250 MW) and reservoir capacities (C_S) (5 and 10 hours of full generation/pumping)⁸. The available storage level is determined by the lower reservoir capacity down in the mine. Due to the high hydrological head, we assume that there are no considerable efficiency losses regarding the generation. Thus, the pump efficiency solely determines the assumed round-trip efficiency (η) of 80% (for efficiency literature, see Rehman et al. (2015)). We assume an annual discount rate (β) of 7%.

Table 2: Parameters.

Variable	Definition	Value
β	Discount rate	7 %
η	Pump efficiency	80 %
C_T	Maximum power output (MW)	50 and 200 MW
C_P	Maximum pump capacity (MW)	62.5 and 250 MW
C_S	Storage size (MWh) for small capacity	250 and 500
	Storage size (MWh) for large capacity	1000 and 2000

3. Effect of wind power on market prices and balancing power quantity

Examining the long-term profitability of a PHES in the Finnish power market requires us to carefully model the effect of wind power on the main revenue source of storage. In other words, we simulate future DAM, IDM and BM electricity prices in Finland as a function of wind power penetration.

Typically, the short-run marginal cost (excluding operation and maintenance costs (O&M)) of RES is considered near zero (De Jonghe et al., 2011). This implies that RES production replaces other generating sources with higher marginal costs in the power plant merit order. Furthermore, in case the RES supporting scheme guarantees a fixed price, it is always beneficial to produce when possible. The price of DAM electricity is expected

⁷Pump and generator capacities are set such that the effective capacities are symmetric.

⁸These alternatives follow the power and storage capacities proposed in the public discussion and by the consulting company in charge of the feasibility study.

to be decreasing with higher RES penetration (see, e.g., Keles et al. (2013)) because of this merit-order effect (see Sensfuß et al. (2008)).

Weron (2014) reviews the electricity price forecasting (EPF) methods, which are typically divided into two larger subgroups of structural and statistical models. A similar categorisation is used in Würzburg et al. (2013), who review literature investigating the effect of wind power production on electricity prices. As pointed out in Weron (2014), regression modelling techniques are still most widely utilised in EPF. Thus, for simplicity and transparency, we construct a semi-log multivariate regression model with autoregressive (AR) errors.

The selected modelling approach can be found in few previous studies (Gelabert et al. (2011), Würzburg et al. (2013), Woo et al. (2011), Woo et al. (2016). Gelabert et al. (2011) study the ex post effects that renewable electricity and co-generation have had on the daily wholesale electricity prices in Spain. They show that an increase of 1 GWh of additional renewable generation reduced the average electricity prices by 2 €. Würzburg et al. (2013) analyse the daily price effect of RES in the Austrian-German power market area. Their conclusion is that the magnitude of the merit-order effect depends on the power market characteristics, but the effect is always a decrease in prices. Woo et al. (2011) utilise high-frequency 15-min data available in Texas. According to their results, wind power generation reduces the spot price level but increases the spot price variance. However, they do not separately model the DAM and IDM prices. Woo et al. (2016) examine the merit-order effect of wind and solar power in California's day-ahead and real-time electricity markets. Their main finding is that the day-ahead and real-time prices diverge with more RES production, and they conclude that more accurate day-ahead load and RES forecasts may enhance trading efficiency.

3.1. Econometric modelling of electricity prices

We contribute to this literature by modelling both the hourly DAM and IDM prices in a highly integrated international exchange-based market area with a diverse production technology portfolio and strong inter-connectors. In addition to controlling for different sources of production in Finland, we also control for price effects resulting from imports and exports. Our sample period extends from 1st January 2015 to 31st December 2015.

The hourly data are collected from various public sources, such as Nord Pool Spot, European Network of Transmission System Operators for Elec-

tricity (ENTSO-E) and the Finnish Energy. The data series used in the DAM price estimation are hourly day-ahead forecasts. The underlying assumption is that all market participants submit their supply and demand bids in the DAM based on these forecasts. In IDM price estimation, electricity consumption and wind power generation forecast errors are included in the estimation⁹.

Table 3 presents descriptive statistics of variables used in the estimations. The electricity price varies between 0.32 €/MWh and 150.6 €/MWh with a mean of 29.66 €/MWh and a standard deviation of 14.46 MWh. The average hourly load is 9,220.91 MWh with a peak of 13,628 MWh in the morning on the 22nd of January and a minimum load of 6,049 MWh in the summer. Approximately 2.6% of electricity consumption is supplied with wind power, but its output is highly variable with a range of 16.87–832.00 MWh.

The average wind power output in an hour was 238.29 MWh with a standard deviation of 166.45 MWh. The capacity factor of wind power was 23.85%, assuming a constant wind power capacity during 2015 (1000 MW). The maximum output variation between subsequent hours was 181 MWh, corresponding to 18.1% of the installed wind capacity. Because of low marginal costs and high fixed costs, nuclear output was below its maximum capacity (2776 MW) practically only when in maintenance. Thus, nuclear power output tended to be close to maximum at all times, which is demonstrated by the mean output of 2548.6 MWh and capacity factor of 91.8%.

Other fossil-fuelled generation can be adjusted more easily. This dispatchable characteristic could cause endogeneity with electricity price, which is why we control their price effect with the exogenously given daily oil, natural gas and coal prices (for similar approach see e.g., Clò et al. (2015) and Woo et al. (2011)). The impact of hydropower on electricity price must be controlled. To avoid endogeneity, this is accomplished by utilising exogenous daily water inflows (Finnish Environment Institute, 2018) to the largest lakes in the five main watersheds in Finland (for similar approach see e.g., Woo et al. (2016)). Last, inter-connectors are controlled by the day-ahead forecasted power flows between countries. These forecasts take into account the forecasted load, wind and other generation in the interconnected regions. The inter-connector uses are reported in terms of net imports. On average,

⁹Forecast error variables are constructed by utilising the day-ahead and realised loads and wind outputs obtained from ENTSO-E (2017).

Table 3: Descriptive statistics of the variables

Variable	Min	Max	Mean	SD
DAM price (€/MWh)	0.32	150.06	29.66	14.46
Load (MWh)	6049.00	13628.00	9220.91	1334.83
Wind (MWh)	16.87	832.00	238.29	166.45
Nuclear (MWh)	1641.69	2775.97	2548.63	329.73
Oil price (\$/barrel)	35.26	66.33	52.38	7.95
Natural gas price (\$/BTU)	1.63	3.32	2.63	0.35
Coal price (\$/ton)	35.55	50.95	43.04	3.56
Oulujoki, daily inflow (million m3)	100.36	994.17	356.87	152.56
Kemijoki, daily inflow (million m3)	61.94	2974.62	412.13	423.69
Kymijoki, daily inflow (million m3)	36.19	371.62	176.63	81.70
Kokemaenjoki, daily inflow (million m3)	82.53	581.12	246.54	95.20
Vuoksi, daily inflow (million m3)	133.71	1548.91	707.57	291.32
EST Interconnector (MWh)	-738.00	1000.00	583.60	263.57
SE1 Interconnector (MWh)	-1560.00	61.7	-1171.27	432.85
SE3 Interconnector (MWh)	-1200.00	1163.40	-953.55	357.69
RUS Interconnector (MWh)	-1300.00	320.00	-378.27	467.00
IDM price (€/MWh)	-6.31	153.51	28.46	14.39
Load forecast error (MWh)	-1148.00	2197.00	-61.59	269.76
Wind forecast error (MWh)	-346.18	212.59	-27.39	57.69
Price P_t^{BM-UP} (€/MWh)	5.80	2000.00	52.98	84.98
Price $P_t^{BM-DOWN}$ (€/MWh)	-5.00	40.00	17.28	7.63
Load Q^{BM-UP} (MWh)	0.83	435.17	63.60	58.79
Load $Q^{BM-DOWN}$ (MWh)	-457.67	-1.67	-70.67	61.19

Finland imports electricity from Sweden and Russia but exports to Estonia.

We also control for time dependence in residuals after controlling for other factors. Full sets of binary indicators for months ($Month_{it} = 1$ for $i = 1, \dots, 11$, and 0 otherwise), weekday ($Day_{it} = 1$ for $i = 1, \dots, 6$, and 0 otherwise) and hour-of-day ($Hour_{it} = 1$ for $i = 1, \dots, 23$, and 0 otherwise) are included, where the references of the time indicators are December, Sunday

and the hour ending at midnight, respectively. The model is written as

$$\begin{aligned} \log(p_t^{DAM}) = & \beta_0 + \beta_1 Wind_t + \beta_2 Load_t + \beta_3 Nuclear_t \\ & + \sum_{k=1}^{12} \gamma_k X_{kt} + \sum_{i=1}^{11} \alpha_i Month_{it} + \sum_{j=1}^6 \delta_j Day_{jt} + \sum_{h=1}^{23} \phi_h Hour_{ht} + \varepsilon_t \end{aligned} \quad (1)$$

where X_{kt} includes fuel prices, water inflows and inter-connectors ($k = 1, \dots, 12$) and ε_t is a normally distributed error term. We are mostly interested in the coefficients for wind power production and load since those are assumed to change in the long term. Our first hypothesis is that wind generation reduces market price, so that $\beta_1 < 0$. This is because of the low marginal production costs, and wind producers in Finland receive a fixed feed-in tariff of 83.5€/MWh that is nearly three times higher than the mean price during the sample period. Since most customers have fixed-tariff contracts, it is assumed that electricity consumption is fully price-inelastic (for a literature review of price-elasticity of electricity demand see, e.g., Bernstein and Griffin (2006))¹⁰. Therefore, we treat load as exogenous, include it as an independent variable, and hypothesise that $\beta_2 > 0$.

Hourly average IDM prices are estimated in a similar fashion to the DAM prices. Forecasting errors of load ($Loaderror_t = Load_t^{DAM} - Load_t^{REAL}$) and wind power production ($Winderror_t = Wind_t^{DAM} - Wind_t^{REAL}$) are added into Equation (2). The IDM price model is written as follows:

$$\begin{aligned} \log(p_t^{IDM}) = & \beta_0 + \beta_1 Wind_t + \beta_2 Load_t + \beta_3 Nuclear_t \\ & + \beta_4 Loaderror_t + \beta_5 Winderror_t \\ & + \sum_{k=1}^{12} \gamma_k X_{kt} + \sum_{i=1}^{11} \alpha_i Month_{it} + \sum_{j=1}^6 \delta_j Day_{jt} + \sum_{h=1}^{23} \phi_h Hour_{ht} + \varepsilon_t \end{aligned} \quad (2)$$

¹⁰To provide further evidence of the demand inflexibility, we estimated hourly price elasticities in January 2017 from the demand bid data provided by the Nord Pool. The results show that the hourly elasticities vary from 0.006 to 0.011. The bid data are available for the entire Nord Pool market area; thus, the elasticities in Finland cannot be specifically modelled. However, to the authors' knowledge, there are no clear factors stating why the elasticities would be any higher or lower than in the whole market area. More detailed results of the estimation are shown in Appendix A.

where ε_t is a normally distributed error term. Intuitively, in case the realised load is higher than forecasted (negative value), the price would become higher and vice versa. Accordingly, if the forecasted wind power production is higher than realised (positive value), the price would increase. Thus, we hypothesise that $\beta_{10} < 0$ and $\beta_{11} > 0$.

To endogenise the price effect from operating in the BM, we estimate models for balancing prices p_t^{BM} (price-maker assumption in the dynamic optimisation model). The only explanatory variables are demand for balancing Q_t^{BM} and day-ahead market spot price¹¹ for that hour p_t^{DAM} . We assume the balancing quantity to be fully inelastic since the system operator wants to maintain the power balance at all times, even if the balancing power price would be high¹². The BM price models for up- and down-regulation are written as follows:

$$p_t^{BM-UP} = \beta_0 + \beta_1 Q_t^{BM-UP} + \beta_2 p_t^{DAM} + \varepsilon_t \quad (3)$$

and

$$p_t^{BM-DOWN} = \beta_0 + \beta_1 Q_t^{BM-DOWN} + \beta_2 p_t^{DAM} + \varepsilon_t \quad (4)$$

where ε_t are normally distributed error terms. The time-series unit roots were tested with the augmented Dickey-Fuller test, and the results are given in Table B.1 in Appendix B. Nuclear power generation, fuel prices and water inflows are first-differenced to ensure their stationarity and to avoid any spurious regression problems. After differencing, all variables are stationary at the 1 % significance level.

The model in Equation (2) is estimated first as an ordinary least squares model, but the estimated residuals turn out to be serially correlated. The autocorrelation is corrected by following (Woo et al., 2011) and (Clò et al., 2015), assuming that residuals follow a stationary AR(1) process $\varepsilon_t = \rho\varepsilon_{t-1} + v_t$ with $|\rho| < 1$ and v_t is white noise. Heteroskedasticity-robust standard errors are shown in the parentheses.

The estimation results are presented in Table 4. Model 1 presents generalised least squares results in levels, while the dependent variable in Model 2

¹¹The minimum up-regulation price is at least the corresponding spot price, and the maximum down-regulation price is the corresponding spot price.

¹²The value of lost load (VOLL) estimates differs between residential, industrial and service sectors and ranges from a few €/kWh to more than 250€/kWh (Schröder and Kuckshinrichs, 2015).

is log-transformed. The price reducing effect of wind power is verified by the statistically significant negative estimate. Model 1 shows that wind power reduces the day-ahead spot prices by 13.079 €/GWh, *ceteris paribus*. A higher load increases prices as expected. In addition, IDM prices (Model 3) decrease because of wind power. Both forecast errors are statistically significant and have expected signs. For example, the IDM price increases by 0.0295% if wind power production is 1 MWh lower than forecasted in the DAM. If the load is forecasted to be higher than the realisation, the excess production needs to be consumed anyway. Thus, the IDM price becomes 0.0355 %/MWh lower so that someone would be willing to consume more than that committed in the DAM.

To avoid negative prices when simulating future DAM and IDM prices as a function of wind power penetration, we use natural logarithms of the dependent variable. In other words, we want to avoid speculating on whether or not the higher number of negative prices would occur as a result of increasing RES penetration. Moreover, it is more important how much the price variance would be increased with wind power penetration. The estimated models are used to simulate out-of-sample prices in the future, assuming the expected wind power production and electricity consumption presented in Table 1, *ceteris paribus*. This issue is not present in the balancing power price estimations; thus, they are estimated as levels.

The balancing power models (4) and (5) show the relationship between price and quantity. Both quantities are significant at the 1% level, and the explanatory power of both simple models is acceptable. The up-regulation price is increased by 0.424 €/MWh with respect to quantity, whereas the down-regulation price is decreased by 0.128 €/MWh with respect to quantity.

3.2. Wind power-related increase in the balancing power quantity

In the wind power integration cost literature, it has been shown that balancing costs increase with wind power penetration (Hirth, 2013). Therefore, the balancing quantities in our sample period data are scaled according to the wind power penetration in different wind power scenarios. Fingrid has estimated that the maximum balancing power requirement of wind power is a constant 16% of the installed capacity (Åf Consult, 2012). This estimate is used to scale the balancing market quantities as a function of the installed wind power capacity in the system. The installed wind power capacity was 1000 MW in 2015, which corresponds to 160 MW of the balancing

Table 4: Regression results

	<i>Dependent variable:</i>				
	p_t^{DAM}	$\log(p_t^{DAM})$	$\log(p_t^{IDM})$	p_t^{BM-UP}	$p_t^{BM-DOWN}$
	(1)	(2)	(3)	(4)	(5)
Constant	-72.169*** (3.942)	-0.541*** (0.146)	-0.680*** (0.209)	-8.510*** (0.873)	2.914*** (0.162)
Load (GWh)	13.079*** (0.385)	0.473*** (0.014)	0.410*** (0.021)		
Wind (GWh)	-13.272*** (1.789)	-0.514*** (0.075)	-0.465*** (0.073)		
Δ Nuclear (GWh)	0.744 (2.409)	-0.039 (0.075)	-0.037 (0.180)		
Load forecast error (GWh)			-0.355*** (0.037)		
Wind forecast error (GWh)			0.295* (0.151)		
P_t^{DAM}				1.284*** (0.026)	0.825*** (0.005)
Up-regulation Q				0.424*** (0.010)	
Down-regulation Q					0.128*** (0.002)
Fuel price controls	Yes	Yes	Yes	No	No
Water inflow controls	Yes	Yes	Yes	No	No
Month indicators	Yes	Yes	Yes	No	No
Weekday indicators	Yes	Yes	Yes	No	No
Hour-of-day indicators	Yes	Yes	Yes	No	No
Observations	8,760	8,760	8,760	8,760	8,760
Residual standard error	9.116	0.370	0.476	35.37	6.652
Adjusted R ²				0.330	0.765
Log likelihood	-26883.22	3206.78	-3605.84		

Note:

*p<0.1; **p<0.05; ***p<0.01

power demand related to wind power. Figure 2 illustrates that this is a reasonable assumption, when compared with the wind power forecasting error ($Winderror_t$) in 2015. More specifically, the forecasting error varied between -346.18 MWh (34.62% of the installed capacity) and $+212.59$ MWh (21.26%). On average, the forecast error is slightly negative (-23.79 MWh). The negative and positive forecast errors exceeded the $+160$ MWh and -160 MWh limits in Figure 2 in 0.001% and 2.123% of the hours in 2015, respectively.

Figure 2: Wind power forecast error ($Winderror_t$) with 1000 MW of installed capacity in 2015.

According to the balancing market data in 2015, the probability of $Q_t^{BM} = 0$ was 46.0%, that of $Q_t^{BM} > 0$ was 22.4% and that of $Q_t^{BM} < 0$ was 31.6% over all hours. Thus, in the PHES operation model (see Section 5), during 46% of the hours, no balancing is needed, and the remaining probability mass is divided evenly for up- and down-regulation¹³. Figure 3 presents the up-

¹³As the balancing market is used to correct the deviations between the forecasted and

and down-regulation power distributions in 2015. In the PHES operation model, the demand for the balancing power is randomly drawn from these distributions. For the higher wind share scenarios, the balancing quantities are scaled with 16% of the installed wind power capacity estimates.

Figure 3: Up- and down-regulation quantity distributions.

In the next section, we present the PHES operation model. The simulated future prices for the day-ahead market (p_t^{DAM}), intraday market (p_t^{IDM}) and balancing market (p_t^{BM}), as well as the balancing market quantities (Q_t^{BM}), are used as inputs in the PHES operation model.

4. The PHES operation model

The PHES operator acts as profit maximiser and operates in a DAM, IDM and BM. The PHES operator submits its bids into the DAM twelve to thirty-six hours before the delivery hour and adheres to the following price arbitrage strategy in its day-ahead unit commitment: 1) pump water at full capacity up to the upper reservoir when the hourly price is below the daily mean DAM price by a threshold limit T_p and 2) generate electricity at full capacity when the hourly price is above the mean daily DAM price by a threshold limit T_g .

realised supply and demand, the occurrence of up- and down-regulation directions should be symmetric in the long run.

As these bids are set on a day-ahead basis, uncertainty exists regarding the storage level when the operating hour arrives. If the PHES operator cannot fulfil the DAM commitment at the operation hour due to reservoir limits, IDM is used to balance the difference between the DAM commitment and the current reservoir level. In other words, the PHES operator buys energy from IDM if it cannot generate the committed energy to the DAM and sells energy to IDM if it cannot pump the committed energy from the DAM¹⁴. After the DAM and IDM balances are set, the PHES operator is able to offer its free capacity to the BM. The optimal bidding behaviour of the PHES operator in the BM is solved as a dynamic optimisation problem.

The utilisation of the PHES is limited by the pump C_P and turbine C_T capacities (MW) and by the storage size C_S (MWh). The upper reservoir energy content is marked by $S_t \in [0, C_S]$ (MWh), and the lower reservoir energy content is the mirror image of S_t . The profits of the PHES are determined by the interaction between the offered quantities to the three markets x_t^{DAM} , x_t^{IDM} and x_t^{BM} (MWh) and the market prices in them p_t^{DAM} , p_t^{IDM} and p_t^{BM} (€/MWh), respectively. It is assumed that the PHES operator acts as a price-taker in the DAM and IDM because of its relatively small capacity. Conversely, the PHES operator acts as a price-maker in the BM since volumes in it are smaller. Its actions affect the BM prices through Q_t^{BM-UP} and $Q_t^{BM-DOWN}$ in Equations (4) and (5), respectively. Thus, the PHES operator takes its own price effect into account as it bids into the BM.

The model for the PHES operations is as follows:

1. *Set discharge/pump schedule in the day-ahead market: $x_t^{DAM}(p_t^{DAM})$*
 - Calculate the next day's ($D = 1, 2, \dots, 365$) average DAM price $\hat{p}_D^{DAM}$ based on the DAM price forecasts and act by the rules:
 - If $p_t^{DAM} < T_p * \hat{p}_D^{DAM}$, pump at full capacity $x_t^{DAM} = -C_P$.
 - If $p_t^{DAM} > T_g * \hat{p}_D^{DAM}$, generate at full capacity $x_t^{DAM} = C_T$.
2. *Use the intraday market to correct imbalances between day-ahead market commitment and realised reservoir situation before the hour of delivery: $x_t^{IDM}(x_t^{DAM}, S_t)$*

¹⁴Behaviour in IDM is not optimised further because of its complex nature of being a continuous market with multiple hourly prices (for a more detailed discussion regarding the trading behaviour in Elbas, see, e.g., Scharff and Amelin (2016)).

- If $x_t^{DAM} > 0$ and $x_t^{DAM} > S_t$ (overgeneration), buy $x_t^{IDM} = x_t^{DAM} - S_t$ from IDM at price p_t^{IDM} .
- If $x_t^{DAM} < 0$ and $S_t - \eta x_t^{DAM} > C_S$ (overpumping), sell $x_t^{IDM} = -x_t^{DAM} - (C_S - S_t)/\eta$ to IDM at price p_t^{IDM} .

3. *Schedule the balancing market bidding x_t^{BM} as a discrete time ($t = 1, 2, \dots, 8760$) dynamic optimisation problem.* The state variables are water energy stored in the upper reservoir S_t and the total quantity required in the balancing market Q_t^{BM} . The policy variable x_t^{BM} is the amount of balancing services offered by the PHES operator to the BM. The hourly discount factor¹⁵ is marked as β . The Bellman equation is as follows:

$$V_t(S_t, Q_t^{BM}) = \max_{x_t^{BM}} \{f_t(Q_t^{BM}, x_t^{BM}) + \beta E(V(S_{t+1}, Q_{t+1}^{BM}))\}. \quad (5)$$

The operation limits are the reservoir size C_S (MWh), turbine capacity C_t (MW), pump capacity C_p (MW) and pump efficiency rate η (%). The transition equation of the state variable S_t is

$$S_{t+1} = \begin{cases} S_t - x_t^{NET}, & \text{if } x_t^{NET} \geq 0 \\ S_t - \eta x_t^{NET}, & \text{if } x_t^{NET} < 0 \end{cases} \quad (6)$$

where x_t^{NET} is the sum of day-ahead, intraday and balancing market operations:

$$x_t^{NET} = x_t^{DAM}(E(p_t^{DAM})) - x_t^{IDM}(S_t, x_t^{DAM}) - x_t^{BM}. \quad (7)$$

The state variable Q_t^{BM} is stochastic, and the hourly realisation follows the logic explained in Section 4. The balancing power probability distribution and quantities as a function of wind power penetration are presented in Appendix C.

The control variable x_t^{BM} is limited by the realisation of Q_t^{BM} , DAM commitment x_t^{DAM} and reservoir level S_t :

- In case of $Q_t^{BM} = 0$, the PHES operator may offer no balancing power

$$x_t^{BM} = 0$$

¹⁵ $\beta = \frac{1}{r}^{(1/T)}$, where r is the annual discount rate and $T = 8760$.

- In up-regulation hours ($Q_t^{BM} > 0$) the balancing limits are

$$0 \leq x_t^{BM} \leq \min\{Q_t^{BM}, S_t - x_t^{DAM} - x_t^{IDM}, C_T - x_t^{DAM} - x_t^{IDM}\}$$

- In down-regulation hours ($Q_t^{BAL} < 0$) the balancing limits are

$$\max\{Q_t^{BM}, 1/\eta(S_t - C_S) - x_t^{DAM} - x_t^{IDM}, -C_P - x_t^{DAM} - x_t^{IDM}\} \leq x_t^{BM} \leq 0$$

The reward function is the sum of revenue collected from the three markets:

$$f_t(Q_t^{BM}, x_t^{BM}) = p_t^{DAM} x_t^{DAM} + p_t^{IDM} x_t^{IDM} + p_t^{BM} x_t^{BM} \quad (8)$$

The operation is simulated over an annual period with the hourly discrete time steps $n_t = 8760$. The reservoir is half-full at the beginning of the optimisation period. The reservoir level S_t is discretised into $n_S = 11$ evenly spaced grid points¹⁶ and the balancing quantity Q_t^{BM} into $n_Q = 13$ evenly spaced grid points. The resulting value and policy vectors are $[n_t, n_S, n_Q]$ -sized matrices. Monte Carlo simulations are run for different balancing market realisations. The results presented in Section 5 are the mean values over these runs.

5. Results

The optimal DAM price arbitrage strategy is searched by combining five generating thresholds $T_g = [1.1 \ 1.2 \ 1.3 \ 1.4 \ 1.5]$ and five pumping thresholds $T_p = [0.9 \ 0.8 \ 0.7 \ 0.6 \ 0.5]$. Only symmetric threshold combinations are simulated for each wind and PHES size scenario to minimise the computational burden. The other parameters are given in Table 2.

The validation of price simulations is performed in Section 5.1. The optimal operation of the largest PHES option (200 MW + 2000 MWh) is presented in Section 5.2, and the balancing market effect of this option is presented in Section 5.3. The optimal PHES size and net present values (NPV) of different PHES investment alternatives from the investor's and system's point of view are presented in Section 5.4.

¹⁶A tighter reservoir grid was tested. The results did not deviate significantly from the original results.

5.1. Simulated prices in DAM, IDM and BM

To illustrate the effect of wind power on market prices and to validate the regression models in Section 4 (Table 4), first and second moments of the simulated DAM and IDM prices are given in Table 5. Whereas the DAM and IDM prices change exogenously as a function of given wind share and electricity consumption, the BM prices are affected by the wind share and the PHES operation. In other words, the DAM and IDM prices apply for all scenarios, whereas the BM prices are endogenously set by the optimal operation. The comparison between the simulated price moments in the 2.5% wind share scenario and the moments listed in Table 3 shows that the model is able to mimic the mean value of prices to the data rather well in all marketplaces. The standard deviations of the DAM and IDM prices are somewhat higher than that of the actual data. The standard deviations of the simulated up- and down-balancing prices differ clearly from the data mainly because the balancing market quantities are drawn from a discretised grid in the simulations¹⁷.

Table 5: Average and standard deviation of the DAM, IDM and BM prices without the PHES (€/MWh).

Wind share	DAM		IDM		BM: down / up	
	mean	std	mean	std	mean	std
2.5%	31.16	16.75	30.31	15.03	18.75 / 60.56	15.58 / 31.96
5%	37.45	22.81	35.49	19.72	20.00 / 80.56	21.32 / 44.23
10%	35.72	25.63	33.26	21.79	10.98 / 103.05	26.89 / 63.06
15%	34.44	29.09	31.55	24.57	1.487 / 127.46	32.81 / 84.18

Based on the results in Section 3, higher wind power output lowers the average prices in the DAM and IDM. The spread between up- and down-balancing prices becomes wider with a larger wind share in the BM. The price variance increases with the wind penetration in all three markets. Essentially, both the DAM and BM become more appealing to the PHES operator, as price variance in the DAM increases and price spread in the BM expands. However, the more the PHES operator commits to the DAM, the more its

¹⁷A tighter discretisation of the grid would provide a better match for the standard deviation of the BM prices, but this would considerably increase the computational time of the simulations.

operational possibilities become restricted in the BM. It follows that there exists an optimal allocation between the DAM and BM operations for the PHES operator.

5.2. An example of the PHES operations

This section presents the optimised operation of the largest PHES option, 200 MW generation and 250 MW pump capacity with 2000 MWh reservoir size. An example of PHES scheduling in the DAM, IDM and BM and the resulting upper reservoir level are given in Figure 4. The PHES operator bids into the DAM (second from the top) according to the DAM price arbitrage thresholds (top figure). The reservoir level (middle) and the DAM commitment are balanced using the IDM (fourth figure) before entering into the BM (bottom figure).

Figure 4: Scheduling in the DAM, IDM and BM in one week in the winter.

The PHES operator makes the DAM scheduling in advance (+12...+36 hours before delivery), and the BM operation is determined stochastically. Therefore, there might be mismatches between the storage level and DAM commitment in the hour of delivery. From Figure 4, it can be seen that in some hours, the PHES operator has committed too much in the DAM relative to its available reservoir level in that hour. These situations are shown by the non-zero IDM operations. In other words, in some hours, the PHES operator needs to buy energy from the IDM because in the DAM, it has committed to producing 200 MWh; however, the upper reservoir cannot provide the required energy. On the other hand, in some hours, the PHES operator needs to sell energy to the IDM because its upper reservoir is close to full, but it has committed to buy (pump) 250 MWh in the DAM. The DAM commitment x_t^{DAM} together with the state variables storage level S_t and the balancing market quantity Q_t^{BM} set the limits for the optimal balancing market scheduling of the PHES.

The profits in the DAM, IDM and BM with different price arbitrage threshold combinations are shown in Table 6. The optimal DAM bidding rules are $T_p = 0.8$ and $T_g = 1.2$ in wind scenarios of 2.5% and 5%, but the thresholds change to $T_p = 0.7$ and $T_g = 1.3$ in wind scenarios of 10% and 15%, respectively. In other words, the PHES operator sets tighter DAM price arbitrage limits in the two latter wind scenarios. This is because the revenue stream that the PHES operator is able to collect from the BM increases with higher wind shares. Consequently, it is profitable for the PHES operator to commit less in the DAM and, accordingly, to have more flexibility in its BM operation.

Table 6: Total PHES revenue for wind scenarios with different price arbitrage limits.

Threshold: down / up	Wind 2.5%	Wind 5%	Wind 10%	Wind 15%
0.9 / 1.1	11.34	16.03	20.85	27.87
0.8 / 1.2	11.78	16.74	22.22	29.71
0.7 / 1.3	10.72	15.89	22.27	30.70
0.6 / 1.4	7.94	13.37	20.80	29.95
0.5 / 1.5	5.36	10.16	18.72	29.15

Figure 5 shows the revenue distribution from the DAM, IDM and BM for the wind share scenarios given the optimal DAM threshold strategies. In

low wind power scenarios with 2.5% and 5% wind share, the PHES operator collects most its revenues in the DAM. Correspondingly, revenues from the BM are relatively low, accounting for only 13.2% and 18.1% of all revenues. However, this changes with higher wind power penetration levels. Under the 10% wind power level, 48.5% of total revenues are collected from the BM. Under the 15% wind power level, the BM becomes the most important revenue source for the PHES operator, as 55.1% of total revenues are collected from there.

Figure 5: Revenue from the DAM, IDM and BM as a result of the optimal PHES operation.

The operation hours and energy allocation in different markets are presented in Table 7. The energy allocated to the BM increases with wind power penetration. The generation and pumping hours and amounts of energy remain relatively stable, with 2.5–5% wind power in the DAM, as implied by the optimal bidding rules in Table 6. However, when wind power penetration increases further to 10–15%, generation in the DAM is decreased and shifts

to the BM. This result is mainly because the own-price effects are diluted when the overall balancing power demand increases further.

Table 7: PHES operation in DAM, IDM and BM.

Wind 2.5%	DAM			IDM			BM		
	Pump	Gen	Idle	Buy	Sell	Idle	Down	Up	Idle
Operating (% of hours)	28.3	27.2	44.5	1.6	2.5	96.0	19.1	18.7	62.0
Energy (GWh)	620.5	476.0	0	17.7	37.9	0	39.7	46.6	0

Wind 5%	DAM			IDM			BM		
	Pump	Gen	Idle	Buy	Sell	Idle	Down	Up	Idle
Operating (% of hours)	29.3	28.4	42.3	1.7	2.4	95.9	18.6	19.0	62.4
Energy (GWh)	641.5	497.4	0	20.0	35.0	0	59.6	65.8	0

Wind 10%	DAM			IDM			BM		
	Pump	Gen	Idle	Buy	Sell	Idle	Down	Up	Idle
Operating (% of hours)	24.0	20.7	55.4	0.5	2.6	96.9	20.1	21.2	58.7
Energy (GWh)	525.3	361.8	0	6.3	39.3	0	101.8	126.5	0

Wind 15%	DAM			IDM			BM		
	Pump	Gen	Idle	Buy	Sell	Idle	Down	Up	Idle
Operating (% of hours)	26.1	22.7	51.1	0.8	3.2	96.0	19.5	20.6	59.9
Energy (GWh)	572.3	398.4	0	9.2	49.8	0	144.9	163.1	0

Finally, Figure 6 illustrates how the revenue is collected over the annual period. The PHES operator makes higher revenue during the autumn and winter months than during the summer months. The main reason for this is that DAM prices tend to be more variable during seasons with high demand in the winter than with low demand in the summer. As a reminder, the PHES operator can better utilise the price arbitrage strategy in the month with a higher price variance. This result underlines the importance of simulating PHES operations over the annual period to take into account the seasonal variation in demand and supply. Extrapolating from short-period simulations may yield upward- or downward-biased profit estimates.

5.3. Wind power balancing costs and PHES

Our assumption is that the PHES provides fast balancing power in the balancing market and affects the balancing price with its actions (see Figure 7). When PHES provides up-regulation (x_t^{UP}), less other up-regulation supply ($Q_t^{UP} - x_t^{UP}$) is needed. Consequently, the up-regulation price is reduced by ΔP_t^{UP} compared to a situation with no PHES (see Equation (4)). When PHES provides down-regulation (x_t^{DOWN}), less other down-regulation supply

Figure 6: Revenue from the DAM, IDM and BM under optimal DAM bidding rules.

$(Q_t^{DOWN} - x_t^{DOWN})$ is needed. Thus, the down-regulation price is increased by ΔP_t^{DOWN} compared to a situation with no PHES (see Equation (5)). In other words, the PHES may lower the balancing costs by decreasing the gap between the balancing price and spot price.

The balancing market prices with (200 MW + 2000 MWh) and without the PHES are shown in Table 8. The gap between the average down-regulation and up-regulation prices reduces clearly when the PHES enters the market. With 2.5% wind share, the gap reduces from 41.81 €/MWh to 31.30 €/MWh. More importantly, the gap reduces from 127.46 €/MWh to 88.88 €/MWh in the highest wind share scenario.

Table 8: Mean BM prices (down / up) and the gap between the two (in €/MWh).

Wind share	No PHES		With PHES	
	mean	diff	mean	diff
2.5%	18.75 / 60.56	41.81	20.91 / 52.21	31.30
5%	20.01 / 80.56	60.55	23.22 / 68.77	45.55
10%	10.98 / 103.05	92.07	16.45 / 80.35	63.90
15%	1.49 / 127.46	125.97	9.27 / 98.15	88.88

Figure 7: Price setting in the balancing power market.

Balancing costs with and without the PHES investment are calculated by utilising the results in Table 8. In other words, the effects of the PHES on the balancing costs related to wind power are quantified in Table 9. The balancing costs with PHES represent the costs under optimised bidding rules from the investor's point of view. The starting point is that higher wind power penetration significantly increases the balancing costs with and without the PHES. However, as Table 9 illustrates, the balancing costs per additional wind power production are clearly reduced by the PHES. That is, without PHES, the balancing costs increase by 4.95–10.40 euros per increased MWh of wind power, while with PHES, they increase only by 3.61–7.84 euros per increased MWh of wind power. To summarise, the PHES reduces the balancing costs related to wind power by over 25% in all wind power scenarios.

From a power system-wide perspective, the PHES investment would therefore be an extremely beneficial investment because it allows for more efficient integration of variable RES into the power system at a lower cost. A higher balancing power supply would partly ensure a high security of electricity supply, and the resulting lower balancing costs should eventually lower cus-

Table 9: Balancing costs of wind power without and with PHES

	Wind 2.5%	Wind 5%	Wind 10%	Wind 15%
Wind power generation (TWh)	2.09	4.30	8.90	13.80
Δ Wind power generation (TWh)	—	2.21	4.60	4.90
Balancing costs (no PHES) (M€)	10.323	21.270	54.061	105.035
Wind induced increase in balancing costs (no PHES) (M€)	—	10.947	32.791	50.974
Wind induced increase in balancing costs (no PHES) (€/ΔMWh wind)	—	4.953	7.128	10.403
Balancing costs (with PHES) (M€)	7.168	15.141	36.899	75.299
Wind induced increase in balancing costs (with PHES) (M€)	—	7.973	21.758	38.400
Wind induced increase in balancing costs (with PHES) (€/ΔMWh wind)	—	3.607	4.730	7.837
Total reduction in balancing costs with PHES (M€)	3.156	5.453	17.162	29.735
Total reduction in balancing costs with PHES (€/ΔMWh wind)	—	2.467	3.730	6.068

tomers' electricity bills.

5.4. Long-term profitability and system effect of PHES investment

The long-term profitability and system benefits of the PHES investment are calculated for two possible capacity combinations (50 MW turbine with 62.5 MW pump, and 200 MW turbine with 250 MW pump) and two possible reservoir sizes (5 and 10 hours full generation/pumping). Three possible lifetimes are compared: 40, 50 and 60 years¹⁸. The discount rate is assumed at 7%, as in the dynamic optimisation model.

The capital cost estimates used in the investment profitability analysis are received from Pöyry¹⁹. The power output cost of 630 €/kW is used for the 50 MW option, and 507 €/kW is used for the 200 MW option. The same cost estimates are used for the turbine and pump. The energy storage cost of 25 €/kWh is used for the 250 MWh and 500 MWh options, and 22 €/kWh

¹⁸For example, Connolly et al. (2011) states that the typical PHES lifetime is 40 years. Our results show the sensitivity to this assumption by also computing the profitability over 50 and 60 years.

¹⁹Pöyry is in charge of the feasibility study of the Pyhäsalmi PHES project.

is used for the 1000 MWh and 2000 MWh options. These values are in line with the capital costs estimates in the energy storage literature²⁰ and take into account the economies of scale. No operational costs other than the cost of the electricity that is needed to operate the pump are assumed²¹.

Based on the wind power scenarios presented in Table 1, for the first five years, the PHES is operated in a power system with 5% wind share, in a power system with 10% wind share for the next five years, and in a power system with 15% wind share thereafter. The total annual revenues for different PHES size options are presented in Appendix D. The strategy with the largest annual revenue is chosen for each wind power scenario.

Under these assumptions, the PHES investment is profitable in all alternatives (see Table 10). However, the ranking of the alternatives depends on the analysed metric. By considering the net present values (NPV), the investor would choose the alternative with the higher power output and larger storage capacity. On the other hand, by looking at the internal rates of return (IRR), the investor would likely choose the smaller power unit with a larger storage capacity. This result highlights the endogeneity effect of PHES operations on the BM prices. A larger power capacity option “cannibalises” part of its own profits available from the BM scheduling by having a stronger impact on the BM prices. This effect is weaker if the investor chooses the alternative with a smaller power unit. These results rest on the assumption that the marginal effect of an increase in the BM capacity is linear with respect to the BM prices, i.e., we have excluded the possibility of strategic bidding by the PHES operator in the model.

The larger reservoir is a better choice from the investor’s point of view in both smaller and larger power capacity options. The PHES operator obtains far more operational flexibility by investing in the larger storage capacity. For example, under the 5% wind scenario with 50 MW power capacity and a storage size of 250 MWh, the upper storage constraint is binding in 13.0%, and the lower constraint in 4.9% of all hours, while the corresponding figures for larger storage are only 0.2% and 1.3%. As shown in Table 10, the benefits

²⁰Cost estimates in Schoenung and Hassenzahl (2003) are 10 \$/kWh for energy and 1000 \$/kW for power. Cost assumptions in Connolly et al. (2011) vary between 235 and 1085 €/kWh for pump and turbine investments and between 7.9 and 15.8 €/kWh for storage investment.

²¹One could consider for instance taxation. However, our analysis includes only the market prices, as future public policies remain unknown at this point.

Table 10: Net Present Value of the PHES Investment [M€]

Capacity gen/pump (MW) + Reservoir (MWh)	Cost (M€)	TECHNO-ECONOMIC LIFETIME (YEARS)		
		40	50	60
NET PRESENT VALUES OF THE INVESTMENT (M€)				
50/62.5 + 250	77.13	32.69	37.77	40.35
50/62.5 + 500	83.38	44.34	50.16	53.12
200/250 + 1000	250.15	18.38	30.59	36.76
200/250 + 2000	272.15	55.25	69.65	76.98
INTERNAL RATE OT RETURN OF THE INVESTMENT (%)				
50/62.5 + 250		9.77	9.94	10.00
50/62.5 + 500		10.46	10.60	10.65
200/250 + 1000		7.52	7.79	7.91
200/250 + 2000		8.44	8.66	8.75
NET PRESENT VALUE OF THE REDUCED BALANCING COSTS (M€)				
50/62.5+ 250		113.51	119.04	121.86
50/62.5 + 500		120.62	126.58	129.61
200/250 + 1000		257.11	270.95	277.98
200/250 + 2000		262.88	276.82	283.91

from having a less restricted storage capacity exceed the investment costs of choosing the larger storage capacity. To summarise, the highest IRR is achieved with a combination of a 50 MW turbine, 62.5 MW pump and 500 MWh reservoir. The IRR of the optimal investment varies between 10.46 and 10.65%, depending on the assumed techno-economic lifetime. The larger power unit options yield clearly lower IRRs irrespective of the assumed lifetime.

The power system-wide benefits resulting from the PHES investment are shown by the NPV of the reduced balancing costs. As the lower part of Table 10 illustrates, the system benefits are higher with the larger power unit options. More specifically, the average NPV of the reduced balancing costs increases from 122 to 272 million euros if the larger PHES power unit option is chosen instead of the smaller one. Based on the results, a support policy can be estimated that would make the private investor to choose the

larger PHES capacity option. In other words, an investment subsidy of 54.45 M€ would be required to achieve similar IRR than in the 50 MW + 500 MWh case, assuming a 60-year lifetime. In this example, in total of 154.30 M€ worth of balancing costs are avoided with the subsidy. The avoided costs and amount of subsidy yield a social IRR of 9.73%.

6. Discussion

Our results indicate that a PHES plant could be profitable from the investor's point of view under certain assumptions regarding the discount rate, investment costs and economic lifetime. This finding is mainly because the price variance increases with the wind power penetration that allows for higher operating profits. It should be noted that the results are especially sensitive to the choice of discount rate. However, the problem related to this sensitivity is diluted by analysing the profitability in terms of the internal rates of return.

The optimal operating thresholds in the DAM differ in the simulated scenarios, reflecting the fact that the BM becomes more appealing with higher wind power penetration levels. If the PHES operator decides not to produce in the DAM, it can produce/pump more in the BM in case there is a need for up-regulation or down-regulation power. By optimising the DAM bidding thresholds, our model takes the day-ahead/balancing market capacity allocation into account. The results shown in Tables D.1-D.4 illustrate the market participation decision. First, because the revenue potential from the BM increases with higher wind shares, the PHES operator chooses tighter DAM participation thresholds. Second, the PHES operator chooses looser DAM participation thresholds as the larger storage capacity allows the PHES a wider operation range in the BM.

From the social perspective, wind power integration costs, such as balancing costs, can be considered as social costs paid by the consumers (Gowrisankaran et al., 2016). Our results indicate that the investment would also be socially profitable by decreasing these costs. In the previous literature, the estimated balancing costs have varied between 0 and 12.6 €/MWh (Hirth et al., 2015) and between 0.3 and 2.1 €/MWh in the Nordic hydro-dominated power system (Holtinen et al., 2011)²². In our base scenario with no PHES investment,

²²However, in Finland, there is much less hydropower capacity than in Sweden and Norway.

the balancing costs rise from 4.953 €/MWh to 10.403 €/MWh when the wind power share increases from 5% to 15%. Assuming the largest PHES investment option, the balancing cost increase is 3.607 €/MWh with a wind share of 5% and 7.837 €/MWh with a wind share of 15%. However, as shown in Table 10, the profitability of the investment from the investor's perspective is decreased with the larger power unit. This result implies that the profitability worsens with a higher amount of new capacity in the balancing power market. Thus, even though the balancing costs can be eventually reduced to the upper level found in the previous Nordic studies, it may be that not all of the new capacity would remain profitable. Furthermore, the balancing costs might be lowered by optimising the Finnish hydropower production with a target to minimise the balancing costs.

Although the results are encouraging, there are some simplifying assumptions that need to be considered. The most crucial one is the assumption that only wind power penetration and electricity consumption change. The best knowledge of the capacity development of other technologies is used. For example, there is uncertainty related to the commissioning of new nuclear power plants and decommissioning the old reactors. The combined heat and power capacity is expected to remain relatively stable, and most of the hydropower resources are already in use. There is also high uncertainty related to solar power capacity development in Finland and electricity imports from neighbouring countries.

Similarly, it might be that investments in other balancing power sources are made during the assumed PHES lifetime. Especially in the case of excess returns, it is likely that other investments may enter the market. Sources of additional emissions-free balancing power capacity in the Finnish power market could arise from increasing the capacities of existing hydropower plants and the construction of new water reservoirs such as Kollaja and Vuotos. Nevertheless, the power increases are expensive, and nature conservation legislation prevents building new capacity locations with the highest hydropower potential. The entry decisions of other balancing power sources such as batteries and flexible gas turbines are a potential avenue for further study.

Additionally, the larger use of demand response as a balancing power source is still under-examined. All Finnish households are equipped with a smart-metering technology, which could be used to remotely and automatically optimise electricity usage/heating (for a literature review, see, e.g., Haider et al. (2016)). By aggregating the demand flexibility and offering it in

power markets through aggregators (Campagne and Oren, 2016), both up-regulation and down-regulation could be provided by altering the consumption patterns. Demand-side flexibility could turn out to be more cost- and emission-efficient than investments in supply-side flexibility (Faruqui et al., 2010).

The price estimations verify the price effect of wind power production found in the previous literature (see, e.g., Wrzburg et al. (2013)). Similar to Woo et al. (2016), we show that wind power also decreases prices in the IDM. Moreover, the price effects of forecasting errors of electricity consumption and wind power production are quantified. Furthermore, we contribute to this branch of literature by including a large set of exogenous watershed inflow data to control for the price effect of dispatchable hydropower. This is a unique dataset that has not been previously utilised for this purpose. Based on our results, we argue that more precise day-ahead wind power forecasting would contribute to minimising the balancing costs and maximising the social welfare.

The feed-in tariff of wind power has been successful in increasing wind power production in Finland. However, what has not been realised *ex ante* is how strong the market disturbances would be that it could create. Instead of simply planning new support schemes for increasing the use of RES, it should be taken into account that the balancing power demand is expected to be increasing simultaneously. This perspective has been vaguely commented on in the updated Finnish Energy and Climate Strategy (Ministry of Economic Affairs and Employment, 2016). Our model offers a way to estimate possible storage power support policy requirements. Naturally, the results are highly sensitive to aforementioned assumptions given the long time perspective of the analysis.

7. Conclusions

In this paper, we investigated the optimised behaviour of a planned pumped hydro energy storage investment in the Finnish power system. We contribute to the existing energy storage literature in several ways, combining three branches of literature related to electricity price forecasting, optimal use of energy storage and wind power integration costs. The analysis starts from the investor’s point of view and then turns to the social benefits. First, the long-term profitability of the storage is examined as a function of wind power penetration. Electricity prices in the day-ahead, intraday and balanc-

ing markets are simulated to represent different wind power penetration levels in the future. A dynamic programming model with a combination of features from the earlier literature is used to optimise the use of storage. Last and most important, we contribute to the wind power integration cost literature by quantifying the effect of energy storage on the balancing power costs. A possible support scheme policy for pumped hydro energy storage is discussed based on the identified difference between private and social benefits from the investment.

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Appendix A

To provide more evidence on the inflexibility of electricity demand, we utilized the bid data from the Nord Pool. Data reports of Elspot system price bid curves for each hour are provided by the Nord Pool. Bid information contains the volumes and corresponding prices of supply and demand bids. Only single hourly orders are represented in the datasets so that block order volumes and net imports must be added to achieve the correct intersection point of demand and supply curves in the equilibrium.

We fit a constant elasticity demand function to each bid dataset. In other words, following model was estimated for all hours in January 2017 ($t = 1, \dots, 744$) as an OLS model by regressing the demand bid volumes on corresponding bid prices. Demand bids are treated as exogenous as they are submitted based on forecasted future consumption dependent on e.g., exogenous weather conditions. In other words, resulting equilibrium price is unknown to the bidders before the market is closed. By taking the logarithms of both variables, the δ_1 can be interpreted directly as price elasticity of demand. Formally,

$$\log(q_{i,t}^{buy}) = \delta_{0,t} + \delta_{1,t} \log(p_{i,t}^{buy}) + \varepsilon_t \quad (\text{A.1})$$

where $q_{i,t}^{buy}$ is purchase bid volume i for hour t in the next day, $p_{i,t}^{buy}$ is the corresponding price of bid i for hour t in the next day and ε_t is a normally distributed error term. Examples of realised market equilibria and model fits are shown in Figure A.1 where six hours (4th, 8th, 12th, 16th, 20th and 24th) in four days (1st, 11th, 18th and 25th) of January 2017 are plotted.

At first, it is evident that the demand curves have relatively similar shape in different days and hours. On the other hand, the demand levels vary a lot reflecting the diurnal electricity consumption pattern. Overall, based on these figures low elasticities estimates are expected. Supply curves have highly elastic parts starting from 30 000 MWh and extending to 50 000 MWh. Figure indicates that the price volatility in system prices is relatively low as demand rarely gets to the steep part of the supply curves. On the supply-side there is a lot of flexible hydro power capacity that can shift the supply curve

Figure A.1: Examples of market equilibria in January 2017

to the right by bidding low prices. However, the flexibility is limited in the spring when snow is melting to the reservoirs.

Nuclear power capacity in Finland and Sweden is typically considered as a baseload capacity and producers do not want to ramp generation up and down. Thus, nuclear generators bid low enough that they are always scheduled for production. This is backed up by the fact that the capacity factors for the Nordic nuclear plants have typically been over 90%. However, with expected maintenance and unexpected failures the supply curve is shifted to the left. Wind power is exogenously determined by the weather conditions. As some kind of subsidy is paid for wind generation, wind producers want to produce when even possible. Therefore, also wind producers bid such low prices that they are always scheduled for production. In case of high wind the supply curve is shifted to the right, and vice versa. For instance, wind power output was at its highest at 11th day in January that can be also seen from the supply curves far right in the up-right plot in Figure A.1.

A constant elasticity demand function was fitted to data for each hour in January 2017. Model fits were good as they ranged from $R^2 = 0.8$ to $R^2 = 0.95$. Results are presented in Figure A.2 that shows very low elas-

ticities with some variation across hours and weekdays. As shown by the Figure 2, the price elasticities are fairly low. This implies that there is a limited amount of flexible consumers reacting to day-ahead market price signals. Furthermore, it is likely that a consumer with capability to shift large amounts of consumption, such as industrial consumers, attend other short-term markets where the possible compensations of demand response are higher.

Figure A.2: Hourly price elasticities in January 2017.

Appendix B

Table B.1: Tests for unit roots in the time series.

Variable	Augmented Dickey-Fuller	Significance level
Price P_t^{DAM} (€/MWh)	-11.2798	1 %
Load (MWh)	-2.8082	1 %
Wind (MWh)	-7.4011	1 %
Δ Nuclear (MWh)	-58.9542	1 %
Δ Daily oil price (\$/barrel)	-13.6952	1 %
Δ Daily natural gas price (\$/BTU)	-14.0362	1 %
Δ Daily coal price (\$/ton)	-10.4344	1 %
Δ Oulujoki, daily water inflow (miliion m3)	-10.9636	1 %
Δ Kemijoki, daily water inflow (miliion m3)	-9.4570	1 %
Δ Kymijoki, daily water inflow (miliion m3)	-19.4459	1 %
Δ Kokemaenjoki, daily water inflow (miliion m3)	-14.8819	1 %
Δ Vuoksi, daily water inflow (miliion m3)	-12.0054	1 %
EST Interconnector (MWh)	-7.932	1 %
SE1 Interconnector (MWh)	-9.9007	1 %
SE3 Interconnector (MWh)	-7.9481	1 %
RUS Interconnector (MWh)	-14.4276	1 %
Price P_t^{IDM} (€/MWh)	-11.2445	1 %
Load prediction error (MWh)	-14.1294	1 %
Wind prediction error (MWh)	-22.4426	1 %
Price P_t^{BM-UP} (€/MWh)	-32.5158	1 %
Price $P_t^{BM-DOWN}$ (€/MWh)	-14.2647	1 %
Load Q^{BM-UP} (MWh)	-37.3659	1 %
Load $Q^{BM-DOWN}$ (MWh)	-29.9968	1 %

Note: Δ refers to first-differenced variable.

Appendix C

- The probability for $Q_t^{BM} = 0$ is 46.0%.
- The probability for $Q_t^{BM} < 0$ is 27.0%. Table B.1. presents the down-regulation probability distribution for Q_t^{BM} .

Table C.1: Discretized down-regulation quantities [MW] and probability distribution

Grid point	1.	2.	3.	4.	5.	6.
Wind 2.5%	-420	-344	-268	-192	-116	-40
Wind 5%	-580	-475	-370	-265	-160	-55
Wind 10%	-914	-749	-583	-417	-252	-87
Wind 15%	-1270	-1040	-810	-580	-351	-121
Probability	0.04%	0.50%	1.56%	9.23%	23.80%	64.89%

- The probability for $Q_t^{BM} > 0$ is 27.0%. Table B.2. presents the up-regulation probability distribution for Q_t^{BM} .

Table C.2: Discretized up-regulation quantities [MW] and probability distribution

Grid point	1.	2.	3.	4.	5.	6.
Wind 2.5%	37	110	182	254	327	399
Wind 5%	52	153	255	356	458	559
Wind 10%	83	245	407	569	731	892
Wind 15%	116	343	569	795	1021	1248
Probability	68.28%	23.73%	5.14%	1.78%	0.81%	0.25%

Appendix D

Table D.1. PHES size: Turbine 50MW, pump 62.5MW, storage 250MWh.

Annual total revenue (million euros) and revenue (million euros) from [DAM/IDM/BM] with different DAM price arbitrage strategies (optimal strategy bolded).

Threshold [down/up]	Wind 2.5%	Wind 5%	Wind 10%	Wind 15%
0.9 / 1.1	2.75 [3.55/-1.37/0.56]	4.22 [4.62/-1.71/1.31]	6.69 [4.77/-1.62/3.54]	9.66 [4.90/-1.60/6.35]
0.8 / 1.2	2.98 [2.60/-0.51/0.89]	4.59 [3.56/-0.74/1.77]	7.08 [3.85/-0.82/4.05]	10.28 [4.17/-1.01/7.13]
0.7 / 1.3	3.08 [2.04/-0.14/1.18]	4.76 [2.76/-0.27/2.27]	7.53 [2.97/-0.34/4.90]	10.47 [3.39/-0.52/7.59]
0.6 / 1.4	2.97 [1.02/0.06/1.90]	4.71 [1.78/-0.04/2.98]	7.54 [2.21/-0.10/5.43]	10.83 [2.65/-0.26/8.43]
0.5 / 1.5	2.71 [0.22/0.11/2.39]	4.55 [0.74/0.07/3.74]	7.39 [1.34/-0.02/6.08]	10.77 [1.88/-0.13/9.03]

Table D.2. PHES size: Turbine 50MW, pump 62.5MW, storage 500MWh.

Annual total revenue (million euros) and revenue (million euros) from [DAM/IDM/BM] with different DAM price arbitrage strategies (optimal strategy bolded).

Threshold [down/up]	Wind 2.5%	Wind 5%	Wind 10%	Wind 15%
0.9 / 1.1	3.70 [3.55/-0.49/0.64]	5.49 [4.62/-0.57/1.44]	8.15 [4.77/-0.54/3.92]	11.63 [4.90/-0.56/7.29]
0.8 / 1.2	3.88 [2.60/-0.01/1.29]	5.77 [3.56/-0.10/2.32]	8.52 [3.85/-0.14/4.82]	12.07 [4.17/-0.21/8.11]
0.7 / 1.3	3.76 [2.04/0.04/1.68]	5.76 [2.76/0.01/2.99]	8.81 [2.97/0.00/5.84]	12.42 [3.39/-0.07/9.10]
0.6 / 1.4	3.39 [1.02/0.05/2.32]	5.48 [1.78/0.03/3.67]	8.78 [2.21/0.02/6.55]	12.33 [2.65/0.01/9.67]
0.5 / 1.5	2.97 [0.22/0.05/2.70]	5.07 [0.74/0.05/4.28]	8.31 [1.34/0.04/6.94]	12.17 [1.88/0.01/10.28]

Table D.3. PHES size: Turbine 200MW, pump 250MW, storage 1000MWh.
Annual total revenue (million euros) and revenue (million euros) from
[DAM/IDM/BM] with different DAM price arbitrage strategies (optimal strategy
bolded).

Threshold [down/up]	Wind 2.5%	Wind 5%	Wind 10%	Wind 15%
0.9 / 1.1	7.64 [14.20/-7.09/0.53]	11.20 [18.48/-8.70/1.42]	15.51 [19.07/-8.02/4.46]	21.88 [19.61/-7.52/9.81]
0.8 / 1.2	8.47 [10.41/-2.91/0.99]	12.38 [14.24/-4.00/2.15]	16.97 [15.40/-4.03/5.60]	23.79 [16.66/-4.18/11.32]
0.7 / 1.3	8.58 [8.17/-0.86/1.28]	12.64 [11.05/-1.31/2.92]	17.97 [11.87/-1.33/7.44]	24.88 [13.56/-1.82/13.15]
0.6 / 1.4	7.16 [4.07/0.61/2.50]	11.68 [7.11/0.20/4.39]	17.88 [8.82/-0.07/9.14]	26.03 [10.60/-0.58/16.02]
0.5 / 1.5	5.13 [0.88/0.84/3.41]	9.58 [2.96/0.68/5.93]	16.64 [5.34/0.28/11.02]	25.71 [7.50/0.03/18.19]

Table D.4. PHES size: Turbine 200MW, pump 250MW, storage 2000MWh.
Annual total revenue (million euros) and revenue (million euros) from
[DAM/IDM/BM] with different DAM price arbitrage strategies (optimal strategy
bolded).

Threshold [down/up]	Wind 2.5%	Wind 5%	Wind 10%	Wind 15%
0.9 / 1.1	11.34 [14.20/-3.36/0.52]	16.03 [18.48/-3.84/1.41]	20.85 [19.07/-3.21/5.01]	27.87 [19.61/-2.47/10.76]
0.8 / 1.2	11.78 [10.41/-0.16/1.56]	16.74 [14.24/-0.51/3.03]	22.22 [15.40/-0.49/7.34]	29.71 [16.66/-0.39/13.46]
0.7 / 1.3	10.72 [8.17/0.38/2.20]	15.89 [11.05/0.29/4.58]	22.27 [11.87/0.34/10.08]	30.70 [13.56/0.25/16.91]
0.6 / 1.4	7.94 [4.07/0.67/3.20]	13.37 [7.11/0.42/5.85]	20.80 [8.82/0.35/11.63]	29.95 [10.60/0.32/19.04]
0.5 / 1.5	5.36 [0.88/0.68/3.79]	10.16 [2.96/0.52/6.66]	18.72 [5.34/0.35/13.03]	29.15 [7.50/0.26/21.39]

Highlights

- Examine energy storage's profitability when wind power production is increasing.
- Examine energy storage's profitability when wind power production is increasing.
- Wind power balancing costs are computed with and without the energy storage.
- Investor's and system's capacity preferences are shown to be opposite.
- Optimal operating strategy changes with wind power penetration.