Electricity Storage For Capacity Constrained Markets Under Demand-Side Management: Revenues And Management Options

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Introduction

This paper investigates the influence that the **Demand-Side Management (DSM)** programmes have on the economics of **Electricity Storage Systems (ESS)**. To assess the impacts of DSM, we built a linear optimisation model using dynamic programming for the net revenues maximization as the objective function. Profit maximization is reached through the optimization process of the allocation of *storage* and *generation* modes within time frames of *one-day* and *three-day* **management period (MP)** options. The allocation refers to the timings where each one of these modes should be placed.

The modelled DSM programme performs a hypothetical scenario of reducing load peaks and shifting it to off-peak hours. The involved ESS technologies as used for bulk storage (Pumped Hydro, Pumped-Hydro variable speed, CAES, Regenesys and Vanadium-Redox batteries) are simulated under several scenarios, regarding the choice of maximum discharging duration and the DSM impacts. The objective function of the deterministic model is subject to *profit-, time-* and *energy balance*-constraints which set the technical and economic limitations and requirements.

The paper proposes management options for maximization of profits when they are used for arbitrage services provision. It further examines the effects of the level of ESS power capacity in the network, on the achieved marginal net revenues and the potential for granting emissions allowances. Note that in this paper:

Profits=Capital costs-Net revenues and

Net revenues=Revenues –Variable operating costs, where Revenues denote the monetary value of selling electricity to the electricity pool with the **Market Clearing Price (MCP)**.

Background

ESS have multiple roles in the energy sector, generalised as ancillary and arbitrage services provision. Unlike the load levelling which requires tracking of the load profile, the purely profit making target makes use of the MCP profile. ESS operation, as we model it, is based on the MCP differences between the peak and off-peak hours and on the duration for which they occur, as well. Graves et al. (1999) suggest that the use of hourly MCP data, instead of blocked prices, can improve the achieved revenues [1]. We use hourly data, and we further propose hourly charge (store) and discharge (generation) thresholds. Graves et al. refer to levelized thresholds within a one-day period but we argue that this gives far less revenues than our approach, which gives the flexibility of committing one hour to combination of storage and generation modes.

The load and MCP values are linked with a statistical non-linear relationship of the form $P=aL^b$, where P explains the MCP, L the load, a the constant value and b the slope [2]. This formula explains that MCP is the dependent value on load changes. In our case, the factors able to alter the load profile are the DSM programmes and the power capacity of the ESS. As for the former, DSM, depending on the intensiveness of the programme, tends to flatten the load profile by reducing the demand spikes and increasing the low values during off-peak hours. The latter, affects only those load values which correspond to the charging hours, since during these hours the ESS power capacity is considered as additional load for the network operator. Conversely, during the times of dispatching electricity, the ESS do not affect the demand levels, but only serve fraction of it. Assessment of this statistical correlation, helps to calculate the transitions on MCP when load changes. This examination is important because the profitability of ESS in this case is based solely on the MCP difference between the peak and off-peak hours. Both factors mentioned, tend to reduce these differences and thus undermine the potential for profits.

Market competition level and Data

The data refer to hourly historical values for load and MCP for four years, from 2003 to 2006, from a UCTE (Union for the Co-ordination of Transmission of Electricity) electricity market which faces problems of capacity margins and low levels of competition [3]. The data for carbon prices refer to two-year period (2005-2006) for the European emissions trading scheme [4]. Data relevant to capital costs of the tested storage technologies have been acquired by [5 and 6]

In general terms, it is anticipated that in the majority of the unbundled electricity markets the level of competition affects the relationship of the demand and the wholesale electricity price [7]. Many unbundled markets like those of Alberta's (Canada), Northern California's, Spain's and Scandinavia's, show different behaviour of MCP against load. Possible explanations would be that the prolonged high price spikes at an early stage of one market's deregulation process, makes the deregulation easier. Other issues like

differences in generation mix or the price caps seem not enough to trigger the differences in MCP behaviour [7].
The market we model, shows low level of competition with the majority of energy supplied by one company. The high values of MCP are scattered throughout almost the whole range of load as indicated by Fig. 1, and calculations of the variability the prices show compared to the overall and daily average prices, place that specific market in a similar position as the Spanish one. For reference, we display the relevant figure for the markets of Spain and Scandinavia (Fig. 2).

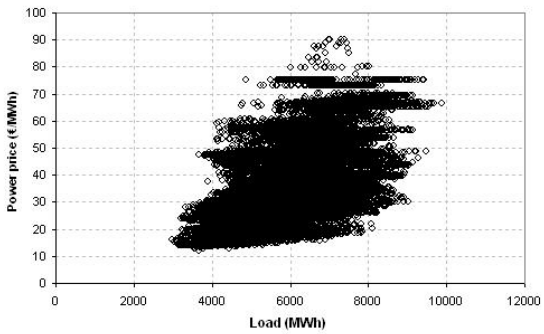

Fig. 1. Hourly MCP against load for the market of Greece for years 2003-2006

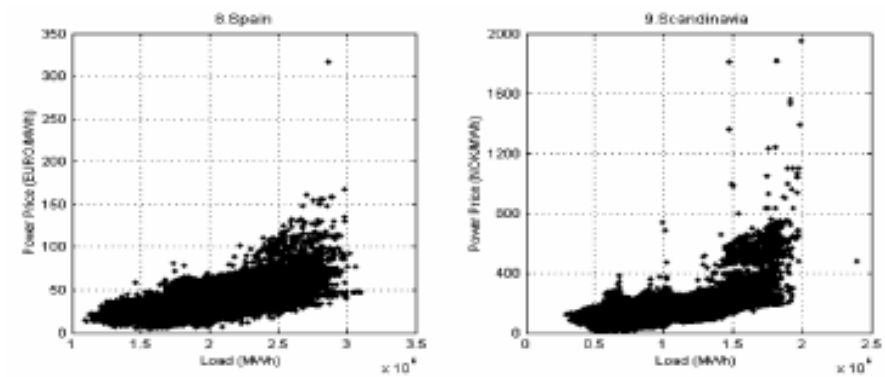

Fig. 2. Hourly MCP against load for the markets of Spain and Scandinavia
Source: [7]

Method

The first requirement is to correlate the load and MCP values in a statistical model in order to find the response of MCP

- *to load changes due to DSM and*
- *to the participation of the ESS power capacity on the network's load.*

Their statistical relationship is found by a linear regression model, dividing each day into the same temporal five parts based on the load profile slope, for which five different regression coefficients are produced.

Once this is done, we model the operation of the ESS technologies used for arbitrage services provision, but not related to load management purposes. The MCP profile is used to determine the optimal combination of timings that the storage and generation modes should get, targeting the maximization of profits. This is structured following a linear programming approach, of which the objective function describes the maximization of the net revenues (Eq. 1.1), where $\boldsymbol{p_i x_{i,i}}$ explains the revenues from dispatching electricity for one hour $\boldsymbol{i}$ with MCP equal to $\boldsymbol{p_i}$ and $\boldsymbol{p_i x_{i,j}}$ denotes the variable operating costs for storing the electricity with MCP equal to $\boldsymbol{p_j}$ meant to be dispatched at the hour $\boldsymbol{i}$.

$$\text{Net Revenues} = P \cdot \sum \left(p_i x_{i,i} - \sum p_j x_{i,j} \right) \; for\; i : i \in [1, H],\; j : j \in [1, H]$$

with ***H*** *denoting the maximum hours of the MP (i.e. 24 or 72)*

Eq. 1. Objective function of the linear optimization model

Net revenues depend on the power capacity ***P*** and on the duration in hours of the MP with maximum ***H***. The maximisation of profits is not described by the objective function as its difference from the net revenues is the fixed element of the annual amortization costs, which does not affect the timings allocation of the storage and generation modes. Amortization costs are calculated in equal daily payments as:

$$A_d = \frac{1}{365} \cdot P \cdot r \cdot \frac{\left[\frac{1}{\eta} \cdot C_e \cdot MDD\right] + \left[\frac{1}{\eta} \cdot C_{BoP} \cdot MDD\right] + \left[\left(\frac{n}{k} - 1\right) \cdot \frac{1}{\eta} \cdot C_R \cdot MDD\right] + C_P}{\left[1 - \frac{1}{(1+r)^n}\right]}$$

Eq. 2. Formula for the calculation of the amortized daily payments of the capital costs

The Energy, Balance of Plant (BoP) and Replacement costs *(C_e, C_{BoP}, and C_R)* refer to the energy storage capacity *($MDD*\eta^{-1}$)*, where *MDD* denotes the Maximum discharging duration and η the round trip efficiency. The replacement period ***(k)*** of the ESS and the amortization period ***(n)*** complete the description of the formula. The amortisation period ***(n)*** is set equal for all technologies, otherwise, the calculation assumes different active operation period for the compared technologies, equal to their life expectancy. The selected interest rate is 2.5%, considered fixed over a 30-year period.

The ESS power capacity has to be considered in the demand profile of the interconnected network, only at times when it stores electricity. The impacts on the load and indirectly on the MCP profile lead to possibly a reduced marginal profit for storage investments. The assessment of the impacts uses dynamic programming to calculate and test various allocations of the storage and generation modes per MP. The model starts assuming there is no influence of the ESS power capacity on the network's demand profile, because there are no data for and it is out of the scope of this research to model the auction process of the electricity pool. In other case, it would be feasible to calculate the exact storage and generation allocations.
As indicated by Fig. 3 the model follows steps of different allocations each time. Each step realizes the linear optimisation of allocation, using the MCP profile of the previous step as a pattern. The process for every MP is terminated when the difference of the net revenues between two consecutive steps of the dynamic programming is minimised.

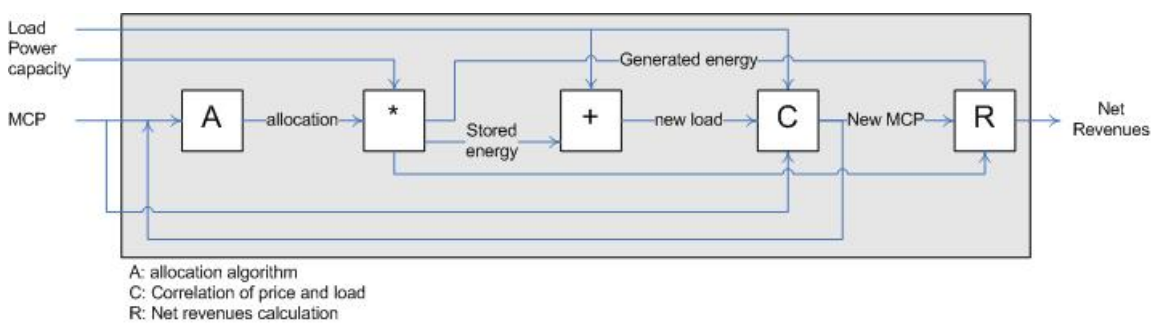

Fig. 3. Dynamic programming flowchart

Results

The outcomes refer to the four years collectively and are affected by a series of parameters, like the:

- *maximum discharging duration (from 2 to 10 hours daily or 6 to 30 hours in the three-day MP),*
- *round trip efficiency (depending on the technology),*
- *DSM (DSM and No-DSM scenarios),*
- *duration of the management period (one-day and three-day) and*
- *participation of the power capacity on the load profile.*

Even though all of them influence the total and marginal (per MW) profits, the way the results are displayed has only two key decision parameters, the maximum discharging duration and the round trip efficiency. All the other parameters, either solely or in combinations between them, will constitute management options.

Duration of the Management Period (MP)

The assumption for the MP, is that the energy is not transferable to the next MP. For tackling that, the research examines an extended period which consists of 72 hours within which the energy is transferable between the included days. This development, gives the flexibility to the model to exploit more possible hours for storage operation. Hours which would be useless in the one-day MP, now can be used. For example, in the one-day MP, the first and last hours during which the ESS is activated have to be charging and discharging respectively. For the hours prior the first active one and the hours after the last active one, the ESS remains idle. With the three-day MP, it is possible that these idle hours are available to be used for charging or discharging. Further, the probability of capturing lower and higher MCP values increases. The extended MP from 24 to 72-hour shows improved net revenues by around 20% and 19% for the DSM and NoDSM scenarios respectively. The figures refer to all technologies with small variations between them.

Demand-Side Management scenarios

The initial hypothesis that the DSM can have significant effects on storage economics was proven right. While energy cuts from the peaks due to DSM programmes account for only 0.74% of the total energy dispatched in the network, this is adequate to reduce net revenues by an average of around 11.4% for the 24-hour MP, for all the tested technologies with small variations. The relative number for the 72-hour MP is around 9.8% with small variations. The following Fig. 4 indicates the net revenues behaviour as the maximum discharging duration gets higher values, for the DSM scenario in the one-day MP. For the NoDSM scenario, the image is similar with the only difference that it should be scaled up by 11.4% in average.

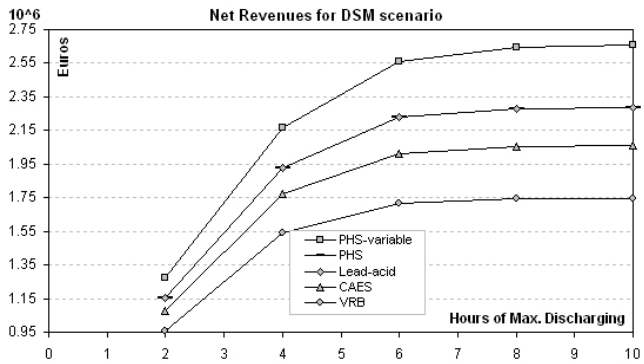

Fig. 4. Net Revenues for all tested technologies under the DSM scenario in the one-day MP

It is interesting to see that the development of the net revenues curves show a tendency for stabilisation after the 6 hours of maximum discharging duration even though the higher net revenues are gained at the end of the scale. These findings are further verified by Fig. 5 where the 10 hours of max discharging and the highest value of the round trip efficiency corresponding to the PHS-variable show the highest potential. However, the gains after the 6 hours are minimal. One more point to note, is that as the net revenues grow for higher efficiencies, the growth rate increases for higher values of hours of max. discharging. For 2 hours of MDD the growth rate is 32% while for 6 hours gets 50%. The rate's growth almost stops evolving after the 6th hour.

The almost identical performance achieved by PHS and Lead-acid technologies can be explained by the fact that the optimal allocation of the charge and discharge operations depends solely on the MCP profile and the round trip efficiency, and these technologies have been tested as if they had the same AC-AC efficiency.

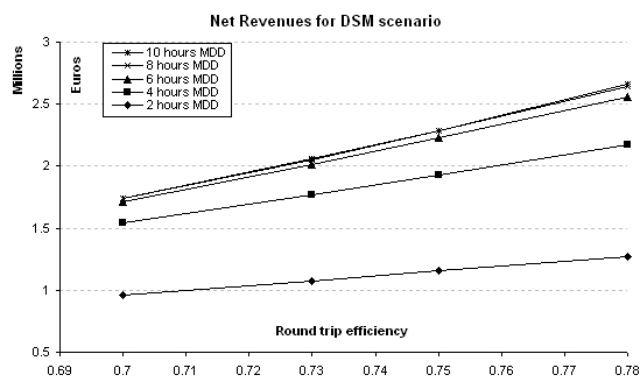

Fig. 5. Net Revenues against efficiency under the DSM scenario in the one-day MP

Apart from the net revenues, the other parameter affecting the profits is the capital costs. Due to their very high values compared to the achieved net revenues, they dominate the storage economics. For the examined 30-year period, these costs have been amortized in an annual basis. The amortized annual payments, as in Eq. 2, show a proportional relationship with the MDD, and are not influenced by the duration of the MP. The following table summarises the annual capital costs for all technologies.

Table 1. Annual amortization payments for a payback period of 30 years.

MDD per MP (hours)	Annual amortization payments for all technologies (million Euros)				
	Lead-acid	VRB	CAES	PHS	PHS-variable
2 (and 6)	3.57	5.02	0.81	1.47	1.53
4 (and 12)	6.96	9.86	1.01	1.52	1.58
6 (and 18)	10.35	14.70	1.22	1.57	1.64
8 (and 24)	13.73	19.55	1.42	1.62	1.69
10 (and 30)	17.12	24.39	1.63	1.68	1.74

From Table 1, it seems that the Lead-acid and VRB technologies have the highest capital costs and the CAES the lowest. The significant difference between the CAES and the Lead-acid and VRB is because the former has substantially lower energy related and BoP costs even if it has over three times higher power related costs. Further the lifetime of the two latter technologies is shortly limited and replacement costs add up. Although the PHS technologies have comparable amortization payments, the gap with the CAES closes as the MDD gets higher values. This happens because CAES has higher energy related and BoP costs which gain importance as the MDD increases.
The capital costs for the three-day MP are calculated under the assumption that the MDD is evenly distributed across the three days. However, there is tendency of more frequently occupying the first 7-9 hours of the first of the three days, compared to the last day. The occupation density difference is 8 to 9% on average between the first and the third day for the lowest and the highest MDD respectively. When coming to the hours in the middle of the day, these differences become 7 and 3% respectively. This means that for higher MDD, the margins for unused hours are getting smaller, thus the model occupies almost the same intermediate hours of the three days.

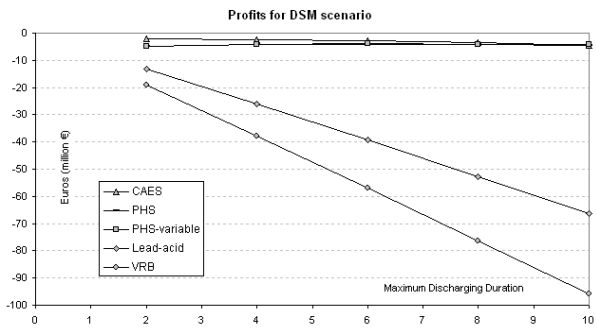

Fig. 6. Profits for all technologies for the DSM scenario. and separately for the CAES, PHS and PHS-var.

This development decisively alters the image we have up to this point of analysis for the best performing technology. Based on the net revenues, PHS-var had the highest score and CAES was the second worst; but considering the capital costs, the profit-wise ranking of technologies places the CAES on top, apart from the 10 hours of MDD where the PHS-var . Higher values of MDD are interpreted to need for higher storage capacity with greater capital costs. These, influence the profits which go decreasing quite fast for the Lead-acid and VRB, as indicated by Fig. 6. It indicates the profit behaviour for the DSM scenario in the one-day MP. However, as shown in Fig. 7, the CAES, PHS and PHS-var technologies are very close to the threshold of zero profits with much more flat average patterns compared to Lead-acid and VRB. The profits for the NoDSM and three-day MP do not show noticeable differences because the capital costs which are stable are far higher than the net revenues.

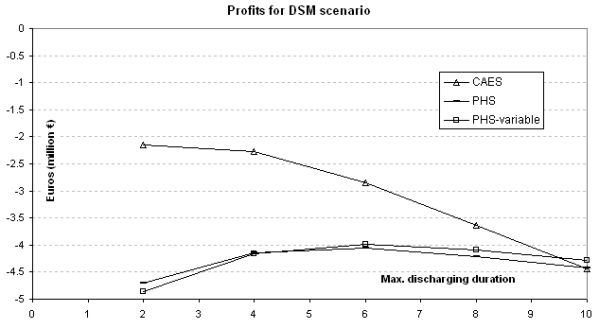

Fig. 7. Profits for for the DSM scenario, separately for the CAES, PHS and PHS-var.

The fact that the profits are negative throughout the whole range of MDD reveals the poor income sources available to all technologies. They can only exploit the MCP differences between the peak and off-peak hours without accepting support from any kind of subsidy such as capital cost funds and special rates for dispatching electricity. Therefore it is probably misleading to assume that it is more profitable to retain low MDD values, because it is quite likely such storage systems to receive governmental support, especially at the beginning of their deployment in the market. For all technologies apart from the two PHS, there is a

constant declination of profits. For PHS and PHS-var, the relative combination of high net revenues and low annual amortization costs gives the best profit-wise performance at 6 hours of MDD.
Likewise, the performance of CAES is principally based on the relatively more profitable combination of energy and power capital costs, where the low amortization expenditures dominate. The technology being able to capture more value out of the MCP and to show greater net revenues is the PHS-variable speed due to its higher efficiency; CAES is well behind that, with approximately 15-28% lower net revenues for both MPs and both DSM and NoDSM scenarios. However, CAES show the best economic performance, especially for low MDD, which should not be perceived as a clear image of the reality as subsidies for higher energy capacity systems could add more value to intermediate or high MDDs.

Participation of the power capacity on the load profile

A big issue to examine is the influence of the ESS power capacity on the marginal net revenues, i.e. which is that power capacity that the specific electricity market can hold so that the net revenues for every installed MW are positive. The background logic is that the ESS power capacity should be considered in the load profile at the hours of the charging mode. At these hours, the load is increased by the energy dispatched per hour, because it physically imposes growth of the electricity demand of the grid. During the discharging mode, the grid's demand is not altered and thus the power capacity has no influence on load profile.

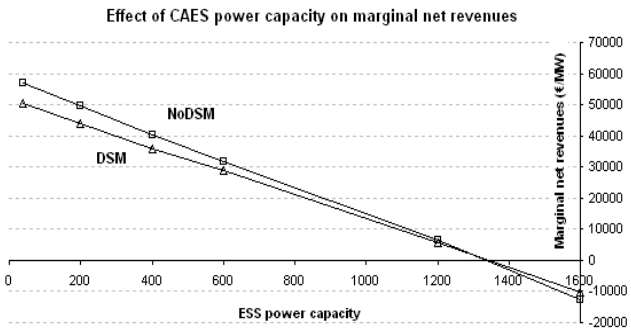

Fig. 8. Declination of the marginal profits of CAES.

Fig. 8 is indicative of the CAES case, showing that at around 1600 MW of installed power capacity the net revenues per installed MW get zero. However, it is quite unlikely for the specific market to reach this amount of installed power capacity of storage systems, at least in the foreseeable future. The rate with which the marginal profits drop for every additional MW of installed power capacity, is 34.42 € for the DSM scenario and 42.73 for the NoDSM scenario. These numbers account for 0.068% and 0.075% of the highest marginal net revenues, respectively.

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