Optimal Sizing of an Energy Storage Portfolio Considering Multiple Timescales

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***Abstract*—Energy storage is likely to play a key role in future power systems relying primarily on renewable generation. Appropriate sizing of these systems is vital for a reliable future power system. A variety of energy storage technologies exist, some of which are suited to store energy across different timescales than others. It is necessary to co-optimize all energy storage technologies to ensure that there is sufficient generation to utilise all devices. This requires considering both short and longer timescales simultaneously. This paper proposes a stochastic optimization algorithm for sizing of a portfolio of energy storage technologies that operate across a variety of timescales. Its application is demonstrated using a case study of the UK's transmission level demand, but with renewables scaled to meet the majority of energy demand.**

***Index Terms*—Energy storage, Optimization, Power system planning, Power system reliability, Stochastic systems**

I. Introduction

This paper presents a convex formulation for optimal sizing of a portfolio of different energy storage technologies, considering operation over multiple timescales.

Renewable electricity generation has been increasing rapidly over the last decade. At the end of 2019, there was an estimated 2.5 TWh of renewable electricity generation installed globally – an increase of 107% from 2010 [1]. Increasingly, governments are making commitments to move towards a zero-carbon electricity system (e.g. [2]), where it is likely the majority of electricity will be generated from renewables. Due to their low cost, the majority of the increased renewable supply is expected to come from wind and solar power [3].

One barrier to the integration of renewable electricity is its intermittency; solar and wind generation depend on the weather and are therefore subject to local and seasonal variations. Energy storage provides a potential solution, by storing energy at times of surplus and discharging at times of shortfall. In a system relying primarily on renewable generation, appropriately sizing the energy storage will be vital to ensure a reliable power supply.

Previous research has addressed the sizing of energy storage systems. For example, using two-stage model predictive control [4], a bounded problem [5], mixed integer linear programming [6], iterative optimal power flow [7], and robust stochastic optimization with an optimal value function [8]. However these all considered only a single type of energy storage, with a heavy focus on Lithium Ion (Li-ion) batteries. Battery energy storage is attractive because of its high efficiency and fast response time, however the high cost and non-negligible self-discharge rates means it is ill-suited for long-term energy storage.

It has been shown that a single energy storage technology is sometimes inadequate to meet energy requirements [9]. A cheaper and more reliable system can be obtained by incorporating multiple forms of energy storage. For example, hybrid battery-hydrogen [10], battery-supercapacitor [9], [11], [12], battery-thermal [13], and battery-pumped hydro [14], [15] have been proposed. A more detailed review of existing energy storage methods and the sizing methods that have been proposed is presented in [16].

Sizing such a system is difficult, because the different technologies are suited for operation over different timescales. For example, Li-ion batteries are suited to short duration energy storage, while hydrogen is better suited to inter-seasonal storage [17]. This makes it challenging to co-optimize multiple storage assets, as the more time steps that must be considered, the higher the computational complexity. However, the individual storage technologies can not be sized independently, because the available generation needs to be allocated between the devices – without a day-to-day energy surplus, there will be insufficient energy available to charge longer term storage.

Some algorithms have been proposed which aim to size systems over multiple time scales. Both hourly and intra-hour timescales are included in [18], [19], however these both focus on a small number of near time-steps. In [20] the authors propose a method for optimizing the use of battery energy storage in both the frequency (short-term) and energy (long-term) markets. However, the problem is defined in terms of the battery health and revenue, rather than the cost of the electricity system.

Other work attempts to simplify the problem in order to approximately solve an optimization with a large number of time steps. In [14] they split the time horizon into subproblems that are solved using alternating direction method of multipliers, however this method requires perfect knowledge of the generation and demand. In [15] clustering is used to group similar hours, in order to reduce the number of time steps considered, which they show achieves a reasonable approximation of the full problem.

One of the limitations of many of the existing methods is that they scale badly with the number of decision variables, hence limiting the number of time steps that can be considered. The majority of the algorithms discussed used non-convex formulations, which typically scale significantly worse than their convex counterparts. This effect is demonstrated by the case studies in the papers discussed, which used time horizons of one hour [4], one day [5], [8], and ten days [7].

In this paper we formulate sizing of multiple storage assets over multiple timescales as a stochastic linear programming problem. This formulation differs from the aforementioned literature because it takes into account *both* multiple modes of storage and multiple timescales, and because of its convexity – allowing a comparatively large number of time steps and modes of storage to be considered simultaneously. We demonstrate the performance of this algorithm through a case study of the Great British (GB) transmission system with solar and wind power scaled to meet the majority of demand.

The formulation presented here is for economic dispatch, and therefore does not include placement of storage assets, or power flow analysis. For sizing of the total storage system it is assumed that the network configuration will not affect the total amount of storage required. However, the constraints of the network may limit the total amount of storage which can be put onto the system, and so power flow analysis should be done separately.

II. Problem Formulation

In this section, the energy storage sizing problem is formulated as a stochastic linear program. First, the parameters used to describe each storage asset are described, then multi-timescale optimal sizing is formulated as a linear programming problem, and finally a scenario-based approach is used to incorporate stochasticity into the problem.

A. Energy Storage Model

A variety of energy storage models have been proposed, ranging from those that only consider round-trip efficiency (e.g. [6]) to detailed models which capture the life-time behavior of a device (e.g. [21]). Here we attempt to maximize the model's expressivity, while allowing a convex formulation of the optimization problem. A technology neutral approach is taken, meaning that the parameters chosen can be derived for any energy storage technology. The specific parameters used are as follows:

(1) charging efficiency: the percentage of the energy extracted from the grid that is put into storage. This is assumed to be constant, although in reality it may be a function of the state of charge of the storage.

(2) discharging efficiency: the percentage of the energy extracted from storage that is exported to the grid (also assumed to be constant). Separating discharging and charging efficiency is important, as some technologies have disproportionate losses on one side, and this affects the required storage capacity.

(3) self-discharge rate: the rate at which charge will naturally dissipate if left in storage. Including this parameter is particularly important for thermal storage systems, which have higher self-discharge rates. In reality the self-discharge rate is likely to be a function of many external and internal parameters – e.g. for thermal storage the ambient temperature. However, here we make the simplification that self-discharge is linear with state of charge.

(4) fixed cost: the cost per MWh of installed capacity. This includes the capital cost and any fixed maintenance costs. It is assumed that all considered storage technologies have similar life-times, however if this is not the case then the fixed cost per annum could be used instead.

(5) operational cost of charging: the variable cost associated with charging the storage, or the cost per MWh of inflow. This could include variable operation and maintenance costs, or use-dependant degradation costs.

(6) operational cost of discharging: the cost per MWh of outflow. This is separated from the operational cost of charging because it may affect the order in which stored assets are discharged.

The optimization problem is formulated in terms of these generic parameters, but the case study in Section III considers three specific technologies: Li-ion battery, hydrogen, and compressed air storage.

B. Deterministic Formulation

Consider N_s methods of energy storage, each denoted by a superscript (i) over N_t time intervals, t, each of length δ_t hours. The (grid-side) charging power of storage i at time t is given by $c_t^{(i)}$ and the discharging by $d_t^{(i)}$. Note that it is necessary to define separate variables for charging and discharging in order to incorporate conversion losses into the formulation in a convex manner. Although simultaneous charging and discharging is not explicitly disallowed, there are cost terms associated with both charging and discharging, meaning it will never occur in the minimum cost solution. The charging and discharging at each time interval are limited according to the rate limits of the storage technology, such that:

$$0 \leq c_t^{(i)} \leq \bar{c}^{(i)}\Theta^{(i)}\delta_t \quad \text{and} \tag{1}$$

$$0 \leq d_t^{(i)} \leq \bar{d}^{(i)}\Theta^{(i)}\delta_t \quad \forall t, i\,, \tag{2}$$

where $\bar{c}^{(i)}$ is the maximum charging rate in % per hour, and $\Theta^{(i)}$ is the total *usable* storage capacity in MWh – it is necessary to distinguish between usable and nameplate capacity, because some storage technologies must stay within tighter bounds of charge. The amount of usable energy stored in asset i at time t is written as $C_t^{(i)}$, and can be related to the amount of energy stored at time $t-1$ as:

$$C_t^{(i)} = C_{t-1}^{(i)}(1 - s^{(i)}\delta_t) + \eta_c^{(i)}c_t^{(i)}\delta_t - \frac{1}{\eta_d^{(i)}}d_t^{(i)}\delta_t\,, \tag{3}$$

where η_c, η_d are the charging and discharging efficiencies respectively, and $s^{(i)}$ is the self-discharge rate. Given some known value for initial state of charge, $C_0^{(i)}$, the energy stored at each time step can be formed as linear functions of the

the decision variables [$c_t^{(i)}, d_t^{(i)}$] in terms of the storage parameters [$s^{(i)}, C_0^{(i)}, \eta_c^{(i)}, \eta_d^{(i)}$]. Constraints must be placed on the charge of each asset at each time, to ensure that it always stays between 0 and 100%:

$$0 \leq C_t^{(i)} \leq \Theta^{(i)} \quad \forall t, i\,. \tag{4}$$

Additionally a final energy constraint should be placed on the state of charge at the end of the optimization horizon:

$$C_{N_t}^{(i)} \geq C_0^{(i)} \quad \forall i\,. \tag{5}$$

This is necessary to avoid initially stored energy being used as generation rather than storage. The final constraint is on the energy balance at each time step:

$$p_t + \sum_i c_t^{(i)} - \sum_i d_t^{(i)} \leq \sigma_t \quad \forall t\,, \tag{6}$$

where p_t is the net demand (i.e. the demand minus the renewable generation) and σ_t is a nonnegative slack variable. If $\sigma_t = 0\ \forall t$ then the storage is sufficient to satisfy demand at all times, however the inclusion of this variable allows some flexibility in demand to be modelled, and prevents computational infeasibility in the optimization problem. Note that this is defined as an inequality rather than an equality constraint because it is assumed that excess renewable generation could be curtailed.

The total cost of the storage system, f, that is to be minimized can be decomposed into three distinct components:

$$f(c, d, \Theta, \sigma) = f_{op}(c, d) + f_{cp}(\Theta) + f_d(\sigma)\,, \tag{7}$$

where f_{op} represents the cost of operating the storage assets, f_{cp} represents the capital purchase price, and f_d is the cost associated with demand flexibility. These can each be defined as follows:

$$f_{op}(c, d) = \sum_i \alpha_i \sum_t c_t^{(i)} \delta_t + \sum_i \beta_i \sum_t d_t^{(i)} \delta_t\,, \tag{8}$$

$$f_{cp}(\Theta) = \sum_i \gamma_i \Theta^{(i)}\,, \tag{9}$$

$$f_d(\sigma) = \sum_t k_t \sigma_t \delta_t\,, \tag{10}$$

where α_i, β_i represent the cost of charging or discharging a storage asset respectively, γ_i represents the cost per unit of capacity, and k_t represents the cost per unit of demand reduction. The deterministic optimal sizing problem can then be formulated as: minimize (7), subject to (1-6).

C. Stochastic Formulation

The previous section assumes that the net demand p_t is know with certainty. However, high levels of uncertainty are present in both the demand and the renewable supply. Capturing this variability is essential for sizing energy storage systems, because the system must be large enough to provide a reliable power supply with some degree of confidence, rather than just in a single case.

Here we adopt a scenario based approach to incorporate stochasticity, such that we consider N_{sc} discrete scenarios for p_t that are each considered to be equally likely. Additional decision variables are defined for the charging and discharging of each storage asset, and demand suppression in each scenario. However a single set of variables are used for storage capacity, as the system must be sufficient size for all scenarios. The constraints are therefore re-written as:

$$0 \leq c_{t,sc}^{(i)} \leq \bar{c}^{(i)} \Theta^{(i)} \delta_t \qquad \forall t, sc \tag{11}$$

$$0 \leq d_{t,sc}^{(i)} \leq \bar{d}^{(i)} \Theta^{(i)} \delta_t \qquad \forall t, sc \tag{12}$$

$$0 \leq C_{t,sc}^{(i)} \leq \Theta^{(i)} \qquad \forall t, sc, i \tag{13}$$

$$C_0^{(i)} \leq C_{N_t,sc}^{(i)} \qquad \forall sc, i \tag{14}$$

$$\sigma_{t,sc} \geq p_{t,sc} + \sum_i c_{t,sc}^{(i)} - \sum_i d_{t,sc}^{(i)} \quad \forall t, sc \tag{15}$$

where the subscript sc denotes the scenario specific variables.

The objective function is replaced with the expected value of the objective across all of the scenarios. If the likelihood of individual scenarios were known, then the objectives could be weighted by their probability. However, this formulation assumers all scenarios to be equally likely, and so the average objective is used:

$$f(.) = f_{cp}(\Theta) + \frac{1}{N_{sc}} \sum_{sc} \Big(f_{op}(c_{sc}, d_{sc}) + f_d(\sigma_{sc}) \Big)\,. \tag{16}$$

Given that the objective and constraints are all linear functions of the decision variables [$c_{t,sc}^{(i)}, d_{t,sc}^{(i)}, \Theta^{(i)}$], the optimization problem takes the form of a linear programming problem – which are convex and can be solved using commercial solvers such as cvxopt.

III. Case Study

In this section we demonstrate the application of the proposed algorithm using a case study of the UK power system with significantly increased renewable generation. Scenarios for net demand were constructed from historic data. Existing demand and nuclear generation were assumed to remain unchanged, and the renewable generation was scaled until sufficient energy was available to satisfy all demand.

Three mediums of energy storage were investigated: Li-ion batteries (Li-ion), compressed air energy storage (CAES), and power-to-hydrogen-to-power (H_2). These were chosen to represent short, medium and long-term storage respectively. The assumed model for each of these technologies are displayed in Table I, and the assumptions behind them are described in the Appendix. The units of s are in % self-discharge per hour, α and β are measured in \$/MWh of charge or discharge, and γ is measured in \$/MWh of installed capacity.

TABLE I: The storage parameters used in the simulation

Storage	η_c	η_d	$\bar{c}$	$\bar{d}$	s	α	β	γ
Li-ion	0.92	0.92	0.25	0.25	$2.8e^{-5}$	0.1	0.1	$2.0e^5$
CAES	0.92	0.71	0.095	0.2	0	33	33	$1.2e^5$
H_2	0.80	0.58	0.001	$3e^{-3}$	0	60	40	4.3e4

TABLE II: The demand parameters used for the simulation. The $t = 1$ dates correspond to the first day of historic data used for the year long simulation in the scenario.

t	δ_t	k_t
$1 - 96$	1	10^5
$97 - 127$	24	10^5
$128 - 164$	168	10^5

N_s	$t = 1$
1	1-Jan-17
2	1-Feb-17
3	1-Mar-17
4	1-Jan-18
5	1-Feb-18

N_s	$t = 1$
6	1-Mar-18
7	1-Jan-19
8	1-Feb-19
9	1-Mar-19

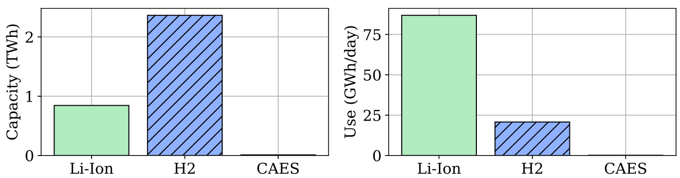

Fig. 1: Optimal sizing and throughput of the storage assets.

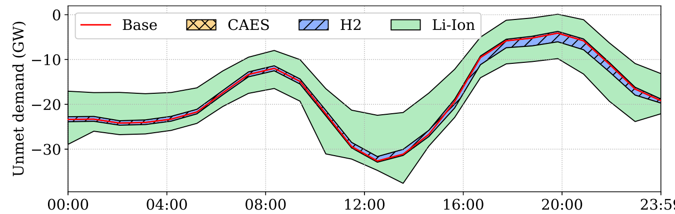

Fig. 2: Average deployment of storage throughout 24 hours.

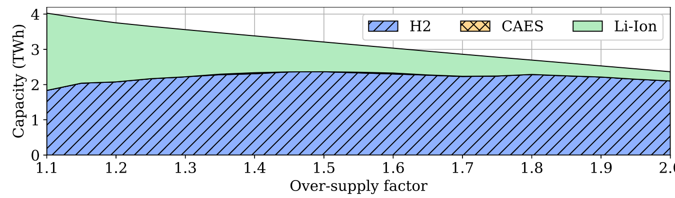

Fig. 3: Variation in storage sizing with amount of supply.

The demand related parameters are displayed in Table II. Three different timescales are included: hourly, daily, and weekly. The simulation has a time horizon spanning one year which is split into: 96 hours, 31 days, and 47 weeks. Nine scenarios are considered, using the years 2017-2019 and considering three different start points for each year. This means that the scenarios capture both seasonal and day-to-day variability. For all timescales, the price of unmet demand is taken to be $100,000\$/\mathrm{MWh}$ – chosen such that demand suppression is only practically employed to prevent computational infeasibility. In reality, demand suppression may be cost competitive with energy storage, but as this could significantly effect the sizing of the system, this option was not included for this case study.

Figure 1 shows the optimal sizing (left) and usage (right) of each storage asset in the minimum cost case. The H_2 storage has the largest capacity, however the Li-ion has a much higher throughput. This result makes sense given the parameters in Table I; H_2 has a low cost and a low self discharge rate, so it is suited for storing large amounts of energy for long periods, while Li-ion has a low marginal cost and high efficiency, making it suited for high-cycle use. CAES has a comparatively small capacity and throughput, suggesting that, with the chosen parameters, it is rarely cost competitive with the other two storage modes.

The deployment of the individual assets can be further understood by considering the average charging and discharging profiles throughout a typical day. Figure 2 shows the average 24 hours across all the time and scenarios. The red line shows the net demand (the demand minus the energy generation). Shading above the red line indicates charging, while shading below indicates discharging. In practice, a single storage asset will never be simultaneously charging and discharging, however this figure looks at an average over multiple days. Similarly, discharging will only occur when the net demand is positive. Li-ion can be seen to both charge and discharge throughout the day, with the most significant charging happening to coincide with the solar peak. Whereas, H_2 charges slowly throughout the day and occasionally discharges to meet the evening peak demand.

Naturally the results of this case study will depend significantly on the storage parameters selected. However, they will also depend on the assumed generation profile, and the remains of this section explores the effect of generation choices on optimal storage requirements.

Conversion losses mean that, in order to meet demand with variable generation and storage, an oversupply of energy is required. The amount of excess energy will effect the minimum cost storage solution. Figure 3 shows the change in optimal storage capacity as the over-supply factor (i.e. the ratio of supply to demand) increases. As expected, the total storage requirement decreases as the over-supply factor increases. This decrease is dominated a the reduction in Li-ion, likely due to the decreasing need for intra-day storage. H_2 requirements do not change significantly with the over-supply factor. This could be because the requirement for this storage is driven by rare renewable droughts (e.g. long dark still periods) which are not corrected by scaling up generation. CAES is installed in small amounts between an over-supply of 1.4 and 1.6, but in amounts difficult to see on this scale, zero CAES is installed outside of these bounds.

The previous results all assumed a uniform scaling of the UK's existing renewables. However, wind and solar have very different diurnal and seasonal profiles, and so their relative size is also likely to effect the optimal mix of energy storage. Figure 4 shows the variation in optimal storage capacity with ratio of wind to solar generation, assuming a constant over-supply ratio of 1.5. The total energy storage requirement decreased very slightly as wind becomes more dominant, but the share of Li-ion increases significantly. This could be explained by the fact that the UK has a stronger seasonal variation is solar irradiance than wind speed, increasing the need for long-term storage.

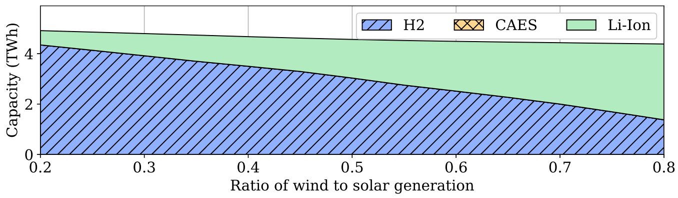

Fig. 4: Variation in storage sizing with ratio of wind to solar generation.

IV. Conclusion

In this paper we proposed a convex formulation for optimal sizing of a portfolio of energy storage which includes multiple timescales of storage. Using simplifications for the self-discharge, charging, and discharging rates, the deterministic problem was formulated as a linear programming problem, and then extended to a stochastic optimization problem using a scenario based approach.

The algorithm was demonstrated using a case study of the GB electricity system, with renewables scaled to meet the majority of demand. Three specific storage technologies were considered: Li-ion battery, hydrogen, and compressed air storage, over three timescales: hourly, daily, and weekly. With the parameters considered, the optimal system was formed of a large long-term hydrogen storage and smaller high-use Li-ion store. Compressed air was only found to be cost-competitive in small amounts and specific circumstances. A sensitivity analysis revealed that the size of the battery storage was highly dependent on the sizing of the renewable generation, and the ratio between the hydrogen and battery storage depended strongly on the ratio of wind and solar generation.

Appendix

This section describes the assumptions used to derive the parameters in Table 1. Note that electricity costs have been ignored as the source of electricity is common between the storage technologies. For Li-ion the parameters were selected according to the four hour grid-scale system in [22]. The CAES system was based on the A-CAES system in [23] it was assumed that the variable costs were split evenly between charging and discharging. For hydrogen storage the costs depend heavily on the sizing of the respective components. The one in this paper used an electrolyser [24], salt cavern [25], and turbine [26] with a 1 kW : 80 kWh : 1.9 kW size ratio, resulting in a slow but cheap system.

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