A novel control strategy for optimized multi-objective operation of energy storage devices

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***Abstract*—In this work, we present a novel approach for the control of energy storage, which makes it possible to optimize the control of the device towards multiple objectives simultaneously. The proposed control method is explained and demonstrated. Future work includes an implementation of the proposed control strategy in our simulation toolkit (DEMKit) and a validation using real energy storage devices.**

I. Introduction

Energy storage devices can be deployed for various applications, like e.g. peak-shaving, load-shifting (i.e. energy management) and grid frequency stabilization (i.e. power management). Each of these applications requires the energy storage device to operate on different time-scales, steering signals and under different conditions. Energy Management Systems (EMS) and simulation tools (e.g. DEMKit [1]) can be used to optimize control actions for the energy storage device for given applications. However, the use of a storage device for one application limits (or prevents altogether) the utilization of the storage device for other applications. Therefore, optimizing for only one application could leave part of the *storage potential* of the energy storage device untapped. Tapping into this unused storage potential is possible [2], however this requires a (highly) complex control structure and a larger level of customization towards specific applications.

In this paper we introduce a novel approach which makes it possible to control an energy storage device in a way that optimizes its operation towards multiple applications simultaneously. In the proposed control strategy we split up the storage device in multiple virtual storage devices (*VSD*s). The capacity of the VSDs is flexible over time, to ensure an optimal composition of VSDs for the current situation. Each of these VSDs can be controlled by its own, application specific, controller, such that we can make use of existing device models and device controllers. All VSDs are governed by one over-all controller which ensures that there is one over-all optimal result for all VSDs combined, rather than competitive optimal results for each individual VSD. Hereby, we reduce the complexity of the over-all storage device control. Additionally, we increase the flexibility of the over-all storage device control as existing models for different energy storage devices can be included and replaced as needed. An overarching controller translates the results of the virtual controllers to feasible control instructions for the real storage device.

II. Proposed control strategy

In the proposed control strategy we consider an actual storage device (*ASD*), e.g. a battery or super-capacitor, with capacity C. A schematic overview of the proposed control strategy is presented in Figure 1. The ASD, represented by the grey rectangle in Figure 1, is divided in n virtual storage

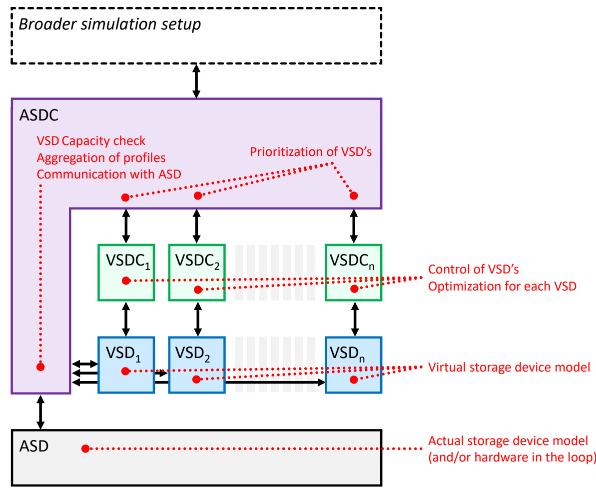

Fig. 1. Schematic representation of the proposed storage device control.

devices VSD_i, for $i = 1, 2, ..., n$, represented by the blue squares in that figure. Each VSD$_i$ has its own characteristics (e.g. (dis)charge speed and (dis)charge time regime), which are used in the optimization. However, these characteristics must be within the limitations of the ASD. For each VSD$_i$ a different device model can be used to control the storage device (for example VSD$_1$ could be modelled as a non-ideal battery, e.g. using the DiBu-model [3], while VSD$_2$ is modelled as an ideal battery e.g. using the coulomb counting method [4]). Each VSD$_i$ has its own capacity C_i. The capacity for each VSD$_i$ is flexible but limited by upper boundaries ($BU_{i,t}$) and lower bounds ($BL_{i,t}$) which are set per VSD$_i$ and per time interval. The boundaries are time-dependent to allow for a different set-up of the VSDs at different times. At the start of the simulation the bounds ($BU_{i,t}$) and ($BL_{i,t}$) for all time intervals (t) should be given.

Note, that in this control strategy the sum of the capacities C_i of all VSD$_i$s may be larger than the capacity C of the ASD. The reason for this is that the probability of all VSDs to be at their upper limits is expected to be small.

For each VSD$_i$ there is a controller ($VSDC_i$) represented by the green squares in Figure 1, which optimizes and plans the desired operation for each time-interval of the virtual storage device, i.e. it decides when to charge and discharge and by how much power. The control and optimization of the virtual storage device is handled in the same way actual storage devices are already optimized and controlled in simulation and optimization tools, e.g. DEMKit. The *cost* ($F_{i,t}$) of using a specific VSD$_i$ at a specific time t, while also taking into account the relevant boundaries ($BL_{i,t}$, $BU_{i,t}$) is also included. The *cost* could also be negative, i.e. using a specific VSD_i at that time is encouraged. In short, for every time-interval t, each VSDC_i first checks if $BL_{i,t} \leq C_{i,t} \leq BU_{i,t}$, if this is true, then each VSDC_i optimizes the SoC for the associated virtual storage device, VSD_i while taking into account $F_{i,t}$. The desired optimized battery State of Charge (SoC_i) is then sent to the actual storage device controller (*ASDC*).

The ASDC, represented by the purple shape in Figure 1, controls the behaviour (i.e. desired State of Charge) of the actual storage device, by aggregating the desired SoC_i for all VSDs. In the ASDC also a prioritization of the VSDs is also handled. This is implemented by a priority list; e.g. for 3 VSDs we may have VSD_i is $2 < 1 < 3$, meaning that the highest priority should be given to achieve the desired SoC for VSD_3, when that is achieved the desired SoC for VSD_1 gets priority and so on. For this, the ASDC first checks if $\sum_{i=1}^{n} SoC_i \leq C$. Similarly, the ASDC also checks whether the aggregated charging/discharging request fits within the physical constraints of the storage device.

If this is true, the desired SoC is communicated to the ASD. If this is not true the prioritization is taken into account. In this case, the aggregated planned power profile, that of all VSDCs combined, may be adapted by minimizing the difference between the desired power of a VSDC and the feasible power to be charged/discharged. In practice, this means that the planned charging/discharging power of the VSDC with highest priority can be executed, but for lower prioritized VSDs adaptations may be required. Take for example $SoC_3 + SoC_1 < C$ but $SoC_3 + SoC_1 + SoC_2 > C$ with the same prioritization as given above. In this case desired SoC_3 and SoC_1 are included in the aggregated SoC that is applied to the ASD, but the desired SoC_2 is not included. Instead ($SoC_{2,new}$) is calculated, which is the capacity still available after the other desired SoC_is are subtracted from the ASD capacity (C), i.e.

$$SoC_{2,new} = C - \left(\sum_{i=1}^{n} SoC_i - SoC_2 \right). \tag{1}$$

The value of $SoC_{2,new}$ is then included in the aggregated SoC that is applied to the ASD. The value is of $SoC_{2,new}$ is also communicated to the relevant VSD (in this case VSD_2) for the next iteration.

III. Example

To demonstrate the proposed control strategy, we present a simple example. For simplicity, the sum of the capacities of all virtual storage devices is equal to the ASD capacity. Additionally, it is assumed that the ASD can react to steering signals very fast. For the control the ASD is divided in two virtual devices: VSD_1 and VSD_2, with different characteristics:

VSD_1: Peak shaving goal with 80% of ASD capacity

VSD_2: Grid stabilization goal with 20% of ASD capacity

As discussed in Section I the virtual storage device controllers (VSDCs) determine the desired (dis)charge power of each VSD at any time. The desired SoC, resulting from the (dis)charge power of the two VSDs in the example is displayed, as a fraction of the ASD capacity, in Figure 2. The desired state of charge for VSD_1 (SoC_1) is optimized to peak-shave the energy usage of a device that uses energy periodically (e.g. an electric space-heater). The desired state of charge for VSD_2 (SoC_2) is to stabilize the grid by reacting to randomly occurring fluctuations.

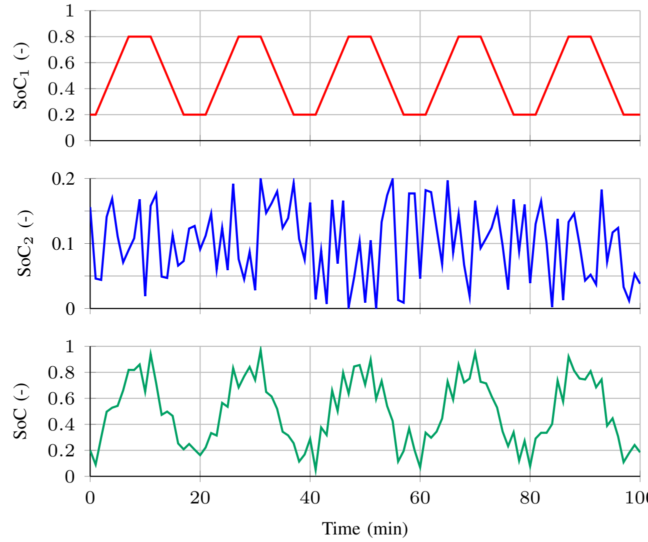

Fig. 2. Example of the application of the proposed control strategy. SoC_n is associated with VSD_n, for $n = 1, 2$ and SoC is associated with ASD. All SoCs are expressed as a fraction of the ASD capacity.

The desired SoC for the actual storage device (ASD) is the calculated from the two optimized SoCs by the actual storage device controller (ASDC). We assume that the time-step used for the desired SoC of the ASD is 1 minute, this accommodates the time regime of VSD_2 and is within the limitations of the ASD. Note, that is this example the capacities of both VSDs have been constant over time, however if the capacities can be changed over time by the ASDC, an improved desired SoC may be determined for both VSDs. Hence, in that case the usage of the ASD can be further improved.

IV. Conclusion & Outlook

The used example in Section III is somewhat trivial and the results could also be achieved without the proposed control strategy. However, it would be difficult to achieve results for non-trivial examples, like e.g. introduced by Nykamp et al [2], without the proposed strategy. Here the available capacity for the VSDs changes over time and different parties have control over the storage device while maintaining strict constraints to guarantee available capacity for the primary objective of the asset. Currently, the algorithm governing the operation of the ASDC block is under development. We intend to include time-dependent capacities, and prioritization for VSDs.

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