Distributed allocation of a shared energy storage system in a microgrid

P. Dimitrov, L. Piroddi, M. Prandini

Abstract— **The economic management of a microgrid can greatly benefit from energy storage systems (ESSs), which may act as virtual load deferral systems to take advantage of the fluctuations of energy prices and accommodate for demand-production mismatches caused by the scarce predictability of renewable sources. In a distributed energy management scenario, an ESS may serve multiple users, a setting which calls for the development of suitable resource allocation policies for the storage capacity. In particular, distributed control policies are of interest, where each user operates independently with the least exchange of information with the other users. A methodology is developed in the paper for such purpose, based on an iterative resource allocation mechanism, realized by means of a negotiation process among users, resembling stock exchange dynamics. The resulting distributed strategy for the management of the shared resource comes close to optimality at a low computational cost, which is affordable in large scale practical applications. It is also robust to communication failures between users.**

I. INTRODUCTION

Electrical energy production and distribution systems are undergoing a dramatic revolution with a generalized increase in energy demand, and a shift towards a highly distributed generation scenario, where traditional big production plants are complemented by many medium/small-size energy production systems, geographically widely distributed at the consumers sites and directly used for their own energy needs. To further complicate the picture, the latter are often associated to renewable energy sources, such as solar and eolic, characterized by limited predictability. In this scenario, the users are not plain consumers anymore, but play also the role of energy providers, in that they can sell to the main grid the production in excess. The traditional distribution network, with a mono-directional energy flow from the production plants to the consumers is thus replaced by a network of bidirectional flows. In this framework, the energy management problem must be addressed in a distributed fashion, where each user actively operates to optimize its own economic benefit, limiting to a minimum the interaction and information exchange with the other users.

The users, with their loads and energy generators, are organized in entities called “microgrids” with a common connection to the grid. Given the high variability and the limited predictability of the loads and generators, an essential element of a microgrid is an energy storage system (ESS), which smooths the production/demand mismatch in the microgrid and can act as energy buffer or as a means of virtual load deferral, at the same time reducing network congestion [1]. For example, the advantages of integrating a battery with a wind farm facility have been investigated in [2], [3]. The ESS allows to store energy when the production exceeds the demand and subsequently consume the stored energy when production is insufficient to meet the demand. It can also be employed to reduce the overall energy cost, since energy need not be bought on load request, but when the price is lower, to be stored for later usage. For example, the optimal usage of the ESS for electricity trading with the grid is discussed in [4]. The importance of the ESS can be further appreciated in the presence of constraints on the load tracking error or on the energy exchange with the grid (in the form of hard or soft tolerance levels).

ESSs add flexibility to the energy management system, but are typically expensive resources, especially compared to their actual usage. From the perspective of a single user the energy storage is seldom charged at full capacity. A different consumer with different energy requirements could then benefit from it when not employed by the first user. More in general, a smart cooperation of multiple energy consumers with different needs would certainly decrease these usage inefficiencies and increase the return on investment of the energy storage resource. To this aim, it is however necessary to develop appropriate resource sharing strategies, to establish what fraction of the storage system to assign to the individual users depending on their consumption/production profiles, so as to use the resource efficiently and avoid excessive costs. This work fits in this scope and pursues the objective of developing a distributed algorithm for the sharing of an ESS.

The optimal solution to the optimal dynamical distribution of the storage resource can be obtained in a centralized, full information setting that takes into account all the users energy requirements. However, this is not necessarily the more convenient approach in practice, due to the high computational demand of centralized algorithms, especially in large scale problems, and considering also the implied loss of privacy (all users are required to release full information on their consumption profiles). Furthermore, implicit in a centralized scheme is that failure to provide such information even for a single user can impair the optimization algorithm. In other words, the centralized scheme relies on a faultless connection network.

We here seek a distributed solution to this problem, based on a Multi-Agent Resource Allocation mechanism [5], capable of ensuring fairness among the users [6] while

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aiming at the optimization of the overall system performance. Each user performs a separate optimization, exchanging only minimal information with the other users. This is achieved by an iterated negotiation process, whereby the users adapt their shares of the resource. This negotiation procedure involves pair-wise agreements between the users that result in a re-shaping of the respective storage capacity allocation profiles at each iteration. This distributed scheme breaks down the complexity of the optimization problem, by decomposing it into smaller ones associated to the individual users, and leaving it to the negotiation process to set individual bounds for the shared resource. The proposed method approaches the performance of the target centralized scheme, and provides a robust way to deal with information failures.

The rest of the paper is organized as follows. A description of the system under consideration is provided in Section II. The centralized problem setting is discussed in Section III. The proposed decentralized control scheme for solving the shared resource allocation problem is formulated and addressed in Section IV. Section V is devoted to the analysis of some case studies. Finally, Section VI presents some conclusions and discusses possible implications of the presented results.

II. SYSTEM DESCRIPTION

A. Batteries

A battery energy storage system (BESS) is made up of a set of interconnected small-power battery modules to achieve a desired electrical characteristic. In conventional microgrids, the BESSs are "charged" when the supply from the distributed generation sources exceeds the load demand. They deliver the absorbed energy, or "discharge" when the supply to the microgrid is insufficient. They can also be used to curtail the energy cost by buying and storing energy during light-load periods (when the price is typically lower), and making it available later at peak-load times. Such economic benefit can be achieved provided that the BESS efficiency η_B exceeds the energy cost ratio:

$$\eta_B > \frac{C_{low}}{C_{high}},$$

where $\eta_B = \frac{E_d}{E_c}$, E_c and E_d representing respectively the total energy supplied to the BESS during charging and the total energy delivered back when fully discharging the BESS, and C_{low} and C_{high} are the minimum and maximum energy cost, respectively.

A BESS is essentially characterized by the following set of parameters [7]:

P_B^{max}	maximum charging/discharging power
T_B	maximum discharging time under power P_B^{max}
Q_B	maximum discharging capacity ($= P_B^{max} T_B$)
η_B	round-trip efficiency
CL	life span (in cycles)

The level of charge in the battery is measured by the *State Of Charge* (SOC), that takes values in $[0,1]$. The SOC is updated periodically by accumulating electrical energy flowing through the battery stack:

$$SOC(t+1) = SOC(t) + \Delta SOC,$$

where t is a time index and ΔSOC is the variation of the SOC during one time period.

Besides the capital cost, associated to the one-time investment required to bring the BESS into an operative status, other operating costs must be taken into account when purchasing a battery. These are connected to the energy losses due to battery inefficiencies (η_B ranges from 65% to 85%), as well as system operation, maintenance and replacement costs.

The BESS costs can be reduced for each energy consumer by sharing the BESS amongst several users. This operation will not only decrease the investment amount, but also increase the return on asset acquisition. Indeed, in a multi-user setting it is more convenient to invest on a single large shared BESS, rather than multiple private ones (with an overall equal storage capacity), provided that each user's share of the BESS is dynamically adapted to its current actual needs (compatibly with those of the other users). To achieve this result, however, a dynamical resource allocation problem must be solved, in order to optimally distribute the storage capacity among the users over time.

Regarding the storage allocation problem among the users, we are interested in solutions that guarantee both *efficiency* and *fairness*. Efficiency requires that the resource should not, at any moment, be under-exploited. This implies that: a) the chosen allocation should be such that there is no alternative arrangement that is improving for some users and not worsening for the others (Pareto optimality), and b) the sum of all payoffs is maximal (utilitarianism). The fairness property requires that all users should get returns in proportion to their investments.

B. Microgrid configuration and user characterization

In this work, we consider a system that consists of a grid providing electrical energy to several buildings which have different energy requirements to fulfill, *i.e.* a number of commercial and residential buildings that need electrical energy to implement the daily demands of energy consumers, and an energy storage facility available to all users (see Fig. 1). The power generated by the power plant (or bought from the grid) can be directly absorbed by the end users or employed to charge the energy storage. Accordingly, the energy consumers can obtain electricity from either the power plant or the energy storage system.

To characterize the users' energy requirements we make here reference to data on building loads collected by the US Department of Energy for their System Advisor Model (SAM) program [8]. The energy request of a building varies widely depending on its category. For example, a household usually has more devices on early in the morning, in the evening, and during the weekend, while an office is commonly running during the day and only five days per week. In other words, two users of these categories would typically have out-of-phase load requests. It is precisely this

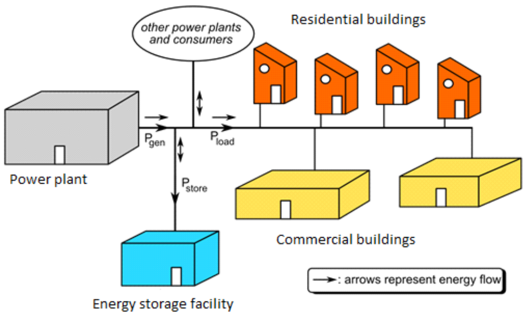

Fig. 1. Configuration of the microgrid system.

difference that can be exploited by the approach proposed here. For this reason, we will consider users of three different typologies, namely residential buildings, small hotels and office buildings. The corresponding energy requirements [8] are depicted in Fig. 2 over a period of 3 days (data have been rescaled to be of comparable amplitudes). Most of the energy consumption of the residential building occurs in the afternoon with a peak around hour 17 and the lowest point at night. The energy consumption of the small hotel typically presents one smaller peak in the mornings and a larger one in the evenings. Finally, the office building has a more uniform consumption profile during working hours and displays a reduced energy consumption throughout the whole weekend. With such different profiles it is expected that these buildings should present very different requirements for the storage capacity.

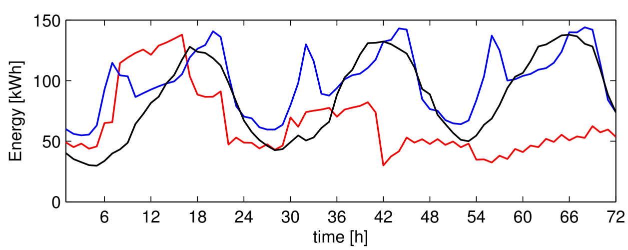

Fig. 2. Energy requirement profiles for a residential building (black), a small hotel (blue), and an office building (red).

Finally, the energy cost is assumed variable according to the graph of Fig. 3, [9].

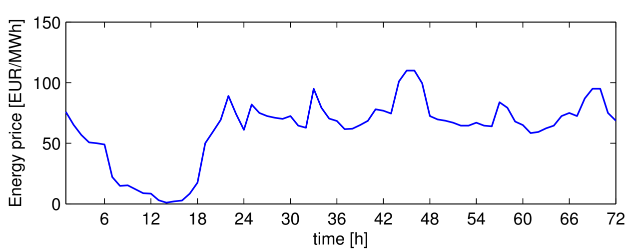

Fig. 3. Daily variation of energy prices.

III. THE CENTRALIZED CONTROL CASE

Prior to formulating the distributed control problem, it is convenient to address a centralized problem setting, in which the storage facility manager operates in the interest of the community of consumer buildings as a whole, minimizing the overall cost. In the centralized framework fairness among the individual users is not necessarily a concern, the overall benefit of the community being the objective. Nevertheless, it is always true that the optimal centralized solution can also enforce fairness if a suitable revenue redistribution strategy is adopted *a posteriori*. Therefore, it provides a consistent benchmark for the distributed design.

The optimal economic management of the microgrid can be achieved by minimizing the following cost function

$$J = \sum_{t=1}^{T} \sum_{i=1}^{N} c_i(t)(G_i(t) + C_i(t)), \tag{1}$$

where $G_i(t)$ is the direct energy transfer from the grid to the ith user at time t and $C_i(t)$ is the energy taken from the grid to charge the battery share of the ith user at time t, all expressed in kWh, so that $G_i(t) + C_i(t)$ is the total energy bought from the grid by the ith user at time t, at price $c_i(t) \geq 0$. Notice that the energy cost is not only a function of time, but may vary also with the consumer category.

In expression (1) time t is measured in hours, T denoting the optimization horizon, and N is the number of users involved in the decision process. In the following we will assume that energy can only be bought from the grid ($C_i(t) \geq 0$ and $G_i(t) \geq 0$).

The following constraints must be fulfilled in the optimization process. First of all, the energy $S_i(t) \geq 0$ stored in the BESS for the ith user at each time step t must respect the following dynamic equation:

$$S_i(t+1) = S_i(t) + C_i(t) - D_i(t),\ i = 1, \ldots, N, \tag{2}$$

where $D_i(t) \geq 0$ is the energy discharged from the battery to the ith user at time t. The stored energy must also respect the following bound at every time t:

$$S_i(t) \leq \bar{S}_i(t),\ i = 1, \ldots, N, \tag{3}$$

where $\bar{S}_i(t)$ is the storage share of the ith user for time slot t. At each time instant the following equality constraint holds:

$$\sum_{i=1}^{N} \bar{S}_i(t) = \bar{S}, \tag{4}$$

$\bar{S}$ denoting the maximum battery capacity.

In addition, the charging and discharging variables are bounded from above by the maximum energy quantities that can be charged and discharged in a time period, denoted respectively $\bar{C}$ and $\bar{D}$. For simplicity and fairness we will assume equal bounds for all the users:

$$C_i(t) \leq \bar{C}/N,\ i = 1, \ldots, N \tag{5}$$

$$D_i(t) \leq \bar{D}/N,\ i = 1, \ldots, N \tag{6}$$

The more general case where the individual bounds appearing in the previous equation are also subject to adaptation will be considered in a subsequent work.

Finally, we will assume that the energy request $L_i(t) \geq 0$ of each user is exactly met at each time step t, taking the necessary energy either from the grid or the BESS, which implies that $G_i(t)$ equals:

$$G_i(t) = L_i(t) - D_i(t),\ i = 1,\dots,N. \tag{7}$$

Notice that the non-negativity conditions on all the involved energy variables imply that $D_i(t) \le L_i(t)$ and $G_i(t) \le L_i(t)$, $i = 1,\dots,N$.

The equality constraint (7) just defined allows one to eliminate variable $G_i(t)$ from the formulation, leaving $C_i(t)$ and $D_i(t)$ as the decision variables. Indeed, the basic decisions that the control system has to take concern when and at what rate to charge the BESS, given the battery constraints, the SOC, and the energy cost. Notice finally that $C_i(t)$ and $D_i(t)$ should never be simultaneously strictly positive, which can be enforced *a posteriori* by subtracting $\min(C_i(t), D_i(t))$ from both variables in the optimal solution (the value of the cost function is not modified since it depends on the difference $C_i(t) - D_i(t)$).

Notice that the formulation can be easily extended to account for the users selling energy to the grid, or to include distributed and/or renewable energy generators. However, the focus is here on the allocation of the shared resource, so these extensions have been overlooked for the time being.

IV. THE DISTRIBUTED SETTING

The distributed setting formulates the energy management problem in a slightly different way, in that each individual user is in charge of its own energy management and has a pre-assigned share of the battery, proportional to its investment in that facility. Some flexibility is allowed in the use of the battery, in that one user can rent part of its storage share to other users provided that a suitable compensation is obtained in return.

This requires a two-layer optimization scheme, where the lower layer is devoted to the economic optimization of each individual user for some given battery shares, and the upper layer modifies the battery shares based on a negotiation process.

A. Individual economic optimization

Let us first assume that the battery shares (in terms of maximum storage availabilities) $\bar{S}_i(t)$, $i = 1,\dots,N$, $t = 1,\dots,T$, are assigned. Obviously, such assignments must comply with condition (4). Then, the individual economic optimization problem for the ith user can be formulated as follows:

$$\min J_i = \sum_{t=1}^{T} c_i(t)(L_i(t) + C_i(t) - D_i(t)) \tag{8}$$

subject to:

$$S_i(t+1) = S_i(t) + C_i(t) - D_i(t)$$
$$S_i(t) \le \bar{S}_i(t)$$
$$C_i(t) \le \bar{C}/N$$
$$D_i(t) \le \bar{D}/N$$

where, as before, variables $C_i(t)$, $D_i(t)$, and $S_i(t)$, are nonnegative. Notice that problem (8) relative to user i is completely decoupled from the other users, once $\bar{S}_i(t)$ is assigned for $t = 1,\dots,T$.

Let J_i° denote the optimal value of J_i. Then, the sum $\sum_{i=1}^{N} J_i^\circ$ can be interpreted as the optimal overall cost associated to the battery sharing distribution defined by coefficients $\bar{S}_i(t)$, $i = 1,\dots,N$, $t = 1,\dots,T$. A second optimization layer must therefore be added to establish the optimal distribution of the shared resource.

B. Negotiation process for the optimization of the resource shares

In the interest of achieving a distribution of the shared resource among the users without having to resort to a super-user responsible of managing the storage facility based on full information on the users' load requirements, some kind of communication between the actors is needed. The objective is to find a communication protocol that can lead the different agents to behave so as to reach the most efficient redistribution of the resource and maximize the savings for the entire system. A secondary, but not less important objective, consists in solving the problem with the least possible information exchange between the agents.

The basic negotiation process involves a pair of users and focuses on adapting the storage capacity $\bar{S}_i(t)$ at each time step, with the objective of improving the overall solution. As explained later, this basic negotiation scheme provides the cornerstone for devising multi-user negotiation processes.

1) Negotiation involving a pair of users: In a negotiation between users i and j, user i bids for a portion of storage of user j at some given time instants. The following scheme is adopted to establish if the transaction has to take place. Both users perform an initial optimization with the original storage capacity shares, resulting in costs J_i° and J_j°. Then, the ith agent repeats the evaluation with an increase in the storage capacity bound

$$\bar{S}_i^{new}(t) = \bar{S}_i(t) + \Delta S,\ \forall t$$

where ΔS represents a fixed small portion of the storage. We denote the updated cost $J_i^{\circ\,new}$. By construction, $J_i^{\circ\,new} \le J_i^\circ$. If there is a strict gain, let $T_i^{bid} = \{t \in \{1,\dots,T\} \mid S_i^{new}(t) > \bar{S}_i(t)\}$ be the set of time steps where the original storage bound of user i has been exceeded by the solution S_i^{new} of the updated problem with increased storage capacity. Then, T_i^{bid} is communicated to user j, that repeats the optimization with less capacity wherever requested by agent i. More precisely,

$$\bar{S}_j^{new}(t) = \bar{S}_j(t) - \Delta S,\ \forall t \in T_i^{bid}.$$

The resulting cost $J_j^{\circ\,new}$ is communicated back to user i.

Briefly, the bid results in an increase in $\bar{S}_i(t)$, $t \in T_i^{bid}$ and a corresponding equivalent decrease in $\bar{S}_j(t)$. This modification is acceptable if the gain that user i can realize thanks to this bound relaxation exceeds the loss of user j resulting from the tightening of its bound, *i.e.*:

$$-\Delta J_i^\circ > \Delta J_j^\circ,$$

where $\Delta J_i^\circ = J_i^{\circ\,new} - J_i^\circ \le 0$ and $\Delta J_j^\circ = J_j^{\circ\,new} - J_j^\circ \ge 0$ are the performance variations induced by the modifications in the storage shares. To make the bargain advantageous for both users, user j is compensated of its loss, and both users share equally the residual economic benefit. In other words, the following corrections are applied to the individual cost functions:

$$\tilde{J}_i^{\circ\, new} = J_i^{\circ\, new} + c_{ij}$$
$$\tilde{J}_j^{\circ\, new} = J_j^{\circ\, new} - c_{ij}$$

where
$$c_{ij} = \frac{\Delta J_j^\circ - \Delta J_i^\circ}{2}.$$

It is easy to verify that both $\tilde{J}_i^{\circ\, new} < J_i^\circ$ and $\tilde{J}_j^{\circ\, new} < J_j^\circ$ hold. Also, the benefits for both users are equal, *i.e.* $\tilde{J}_i^{\circ\, new} - J_i^\circ = \tilde{J}_j^{\circ\, new} - J_j^\circ$. Notice that the compensation term c_{ij} does not influence the underlying optimization process (*i.e.*, repeating the optimization with $J_i + c_{ij}$ instead of J_i as a cost function, yields the same solution). Also, the presence of the compensation terms does not affect the overall cost ($\tilde{J}_i^{\circ\, new} + \tilde{J}_j^{\circ\, new} = J_i^{\circ\, new} + J_j^{\circ\, new}$).

2) Negotiation involving multiple users: In the case of multiple users all possible pair-wise bids are evaluated in terms of the net economic advantage achievable. The corresponding values are stored in a matrix:

$$G = \begin{bmatrix} 0 & g_{12} & \cdots & g_{1,N} \\ g_{21} & 0 & \cdots & g_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ g_{N,1} & g_{N,2} & \cdots & 0 \end{bmatrix}$$

where $g_{ij} = \tilde{J}_i^{\circ\, new} - J_i^\circ$ denotes the net gain that both users i and j would have as a consequence of user i bidding for some storage capacity of user j. Notice that to calculate matrix G one has to make one first round of $2N$ optimizations, *i.e.* two for each user: one with the original individual storage bounds first and then one with the increased bounds. Then, for each possible bid ($N(N-1)$) the optimization has to be recalculated for the bidded user, taking into account the decreases in the storage capacity bounds at specific time instances requested by the bidding user. This amounts to a total of $N(N+1)$ optimization runs. In the logic of the distributed approach these can be calculated in parallel by the N users (each being required to perform $N+1$ optimizations). Then, each user broadcasts its best result, and the most convenient bid is actually implemented, and the storage shares are updated for the agents involved.

At each subsequent step, the elements of matrix G associated to any of the users involved in the bid implemented at the previous step are updated and the best current bid is actually implemented. The process ends when no further element of G is strictly negative.

To avoid the full calculation of all possible pair-wise bids, various heuristic policies can be enforced. For example, only the user with greatest gain potential can be analyzed for possible advantageous bids. Notice also that the proposed scheme is robust to failures of the communication networks. Indeed, the bid optimization phase can still be carried out using the available entries of matrix G, though obviously to a suboptimal outcome. Also, an isolated agent can still operate based on the pre-assigned storage share.

V. EXAMPLES AND SIMULATION STUDIES

A. The 2-user case

We first consider a simple 2-user case to analyze in detail the negotiation process. In this example, user 1 is a hotel and user 2 an office building (refer to Fig. 2). Both have a charging bound of $\bar{C}_i = 25$ kW, $i = 1,2$ and a maximum initial storage capacity of $\bar{S}_i = 200$ kWh (the storage unit has an overall capacity of 400 kWh). The optimization problem is set over a 3-day horizon and the sampling time is 1 h. For better readability, storage usage will be graphically represented using antagonistic plots, in which user 1 is shown from bottom to top while user 2 is represented from top to bottom. The distance between the two lines indicates the non-used portion of the storage.

Consider first the centralized control setting. With fixed storage shares the optimal solution (see Fig. 4.top) indicates that the storage unit has not be exploited to its full extent. Both users at some point saturate their share, and in most of these situations when one user saturates its storage capacity the other agent is using very little of its own share. A dramatic modification of the usage of the storage unit occurs if flexible shares are allowed and the centralized solution is computed (see Fig. 4.bottom). During the first 2 days the storage is prevailingly allocated to user 1 (occasionally, the entire storage capacity is allocated to user 1), with a storage share that never goes below 40 %. In various occasions the storage is fully used by the users (the 2 SOC levels sum up to 100 % of the storage capacity). This occurs in particular in the first 2 days (from hour 14 to hour 31) where the storage usage rises from about 50 % to about 100 %.

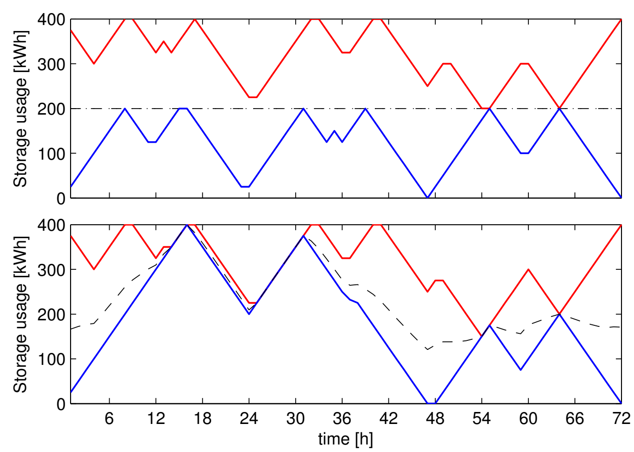

Fig. 4. Antagonistic plot of the SOC levels of the 2 users (centralized control): fixed (top) and variable storage shares (bottom). In both graphs, user 1 (blue line) is from bottom to top, and user 2 (red line) from top to bottom. The black dashed line indicates the storage bound for both users.

In the distributed case the storage levels are adjusted as a result of the negotiation process. Fig. 5 reports three different stages of the negotiation process. Initially, user 1 bids for an increase in its storage share in two different periods (around $t = 15$ and $t = 30$). At the same time user 2 makes a bid at time 54. Then the negotiation process continues (recall that finite variations of the storage levels are applied), essentially enlarging the previously accepted bids. The final solution is apparently not dissimilar from the centralized one.

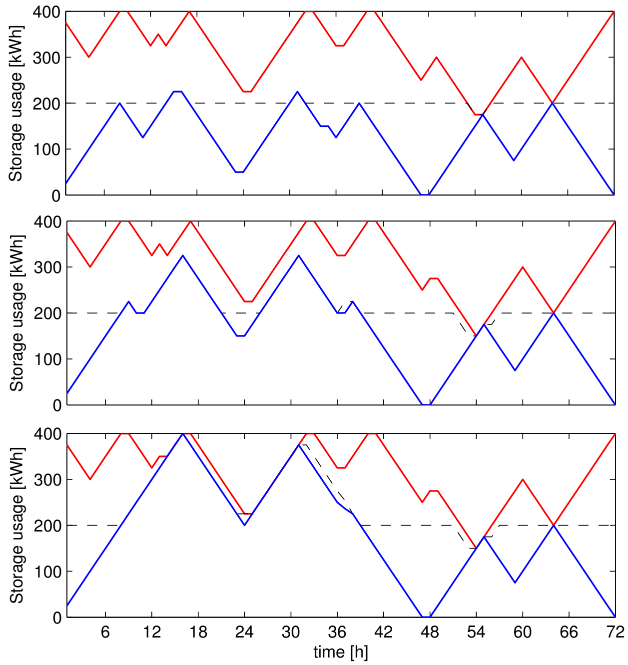

Fig. 5. Antagonistic plot of the 2 users SOC levels (distributed control) at various negotiation stages: initial stage (top), intermediate stage (middle) and final solution (bottom). Color code as in Fig. 4.

Notice that while the shares (see the black dotted lines in Fig.s 4.bottom and 5.bottom) appear to be rather different, the two solutions in terms of actual storage occupancy are almost identical.

B. The 6-users case

We also considered a larger example with 6 users, all with different load profiles. As in the previous example, all users have a charging limit of $\bar{C}_i = 25$ kW, $i = 1, \ldots, 6$ and a maximum initial storage capacity of $\bar{S}_i = 200$ kWh, $i = 1, \ldots, 6$ (the storage unit has an overall capacity of 1200 kWh). Fig. 6 depicts the overall usage of the storage by the 6 agents. Again the difference between the centralized and distributed solutions is neglectable.

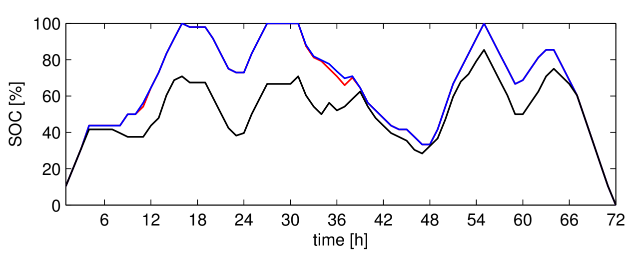

Fig. 6. Overall storage usage in the 6-users case: fixed shares (black line), variable shares - centralized control (blue line), and variable shares - distributed control (red line).

VI. CONCLUSIONS AND FUTURE WORK

This paper presents an algorithm to achieve multi-agent resource allocation in a distributed scheme, with the least amount of information exchange between the users. The method is based on a pair-wise negotiation scheme, whereby users bid for a portion of the storage capacity allotted to another user. Bids are successful when the gain of the bidder is larger than the loss incurred by the other agent, so that by equally dividing the difference both users can improve with respect to their previous situation. Various policies can then be enforced to find a successful bid. In this endeavor, we envisaged a full bid assessment, where all possible pair-wise bids are evaluated and only the best is implemented. Solutions involving less computational effort can also be applied.

In the provided scenarios, the presented method was able to retrieve almost the same solution as the centralized control, thus demonstrating its effectiveness.

Current research focuses on the elimination of the simplifying assumptions regarding the charging/discharging variables made here to reduce the coupling between the individual optimization problems. It is also of interest to investigate alternative bid choice policies, in order to reduce the overall computational effort and information exchange.

An interesting extension, that is a topic for future research, concerns time-varying storage units, as in the case of a parking lot of electric vehicles (EVs). Indeed, EVs can be employed as a responsive load capable of delivering energy back to the grid [10]. More in general, let us note that, although the distributed algorithm for resource allocation has been developed for a shared energy storage system, it can be as well applied in other contexts where one or more resources are shared by multiple agents.

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[10] R. Verzijlbergh, M. Ilic, and Z. Lukszo, "The role of electric vehicles on a green island," in *North American Power Symposium*, pp. 1–7.