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A model for optimum prioritisation of energy storage use. I: Optimum local use of local generation

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Abstract. Modelling the operation of energy storage systems such as batteries in an energy model is challenging as it requires estimation of current and future imbalances between supply and demand and the value of energy stored and later returned to the system. Here, an approach is developed which optimally prioritises the provision of stored energy to the system according to a specified criterion such as time-of-use tariff. At this stage, the model assumes perfect knowledge of future supply and demand as well as a hierarchy of utility to the system operator. Such an operator would specify a ranked list of times of need from the energy storage. The model will then allocate available energy from earlier times while reserving necessary space in the available storage. By progressing through the times of need in ranked order, the model ensures best optimum use of the stored energy. The results show that the proposed method is very robust and can calculate reliably the potential of an energy storage system in any energy model based on time steps of balancing generation and demand with the mediation of storage.

Key words. Energy Storage System (ESS), Energy Model, Optimised Energy Storage Use

1. Introduction

Any energy system needs to balance supply and demand at each point in time, where imbalances can be resolved by many balancing mechanisms, from responsive generation and exchange with other systems to the use of energy storage systems to absorb surplus and meet a supply deficit at a later time. This is the well-established approach used traditionally by, for example, Pumped Hydro stations who fill a reservoir during off-peak hours to provide electricity during peak hours, and also by small hybrid systems such as domestic PV-battery installations.

An energy model using a time series modelling approach needs to mimic that action at the time discretisation level of the model (e.g., [1]). As soon as the value of energy varies over time, the energy storage system can supply stored energy at a time of high value and maximise its value by using cheap energy to charge the energy storage. In modern energy systems with increasing penetration of variable renewable generation and even local electricity trading by prosumers, the principle remains but the scheduling of energy storage becomes more challenging as not only demand varies but also supply [2,3], which in turn affects electricity price levels and volatility [4].

There is significant research in the literature evaluating methods to optimise battery scheduling, e.g. [5]. Some of these based charging and discharging decisions on optimisation methods using knowledge of generation and demand over the optimisation horizon, such as genetic algorithms [6] or Particle-Swarm optimisation (PSO) [7]. Others combine optimisation with forecasting, such as [8] combining persistence forecasting with linear programming, or more advanced forecasting methods [9], who highlight the challenge that any scheduling using forecasts will always be limited by forecasting errors.

The aim of this paper is to present a method to simulate optimum storage operation against a user's ranking as to when the stored energy is most useful to them. As such it does not try to predict the times of need or surplus but to quantify the best a storage device could provide given its design and performance characteristics. Its use would be in the optimum system design as well as a benchmark against which to evaluate scheduling methodologies.

2. Modelling methodology

The energy storage model was initially proposed by Früh et al. (2021) [10] within the context of a distillery using both, a PCM heat battery to provide heat for the distillation, and a standard battery to provide electricity for ancillary needs of the distillery. This model has now been developed further for integration of an energy storage system (ESS) into an energy model with a variety of renewable generation and variable energy tariffs. The particular target model for which this Energy Storage module was designed is the OnGen Expert System [11] but that does not preclude its implementation elsewhere.

The key storage technology parameters included here are

1. Installed energy capacity [kWh]
2. Maximum charging and discharging rates [kW]
3. Charging and discharging efficiencies
4. Minimum and maximum State of Charge (SoC)

One parameter already implemented in the model but not addressed here is the self-discharge. This is partly for clarity, to introduce and demonstrate the main principle, since self-discharge properties are not only very technology dependent, but can also be very complex for some technologies such as Li-Ion batteries [12,13]. Parameters not yet implemented but recognised to be potentially important are ramp rate limitations as well as minimum charging and discharging rates. The reason for not having them included at present is that the initial focus was for batteries as the ESS operating within a system model operating with a half-hourly time step. Incorporating these factors, however, pose no fundamental challenges to the algorithm introduced here but would obscure the main principle.

The algorithm for the storage action, which is shown in Algorithm 1, has three main stages,

1. Calculate the system balance prior to storage activation
2. Ranking of times of need
3. Operating the storage device to serve the need in rank order.

This algorithm operates within a time-series framework, where demand, local generation, and factors for the user such as time-of-use tariff information or import/export constraints are known at a specified time interval, δt, for a period of time, usually a calendar year.

To provide a common and consistent unit base, all power quantities (kW) are expressed as energy units consumed, produced, or exchanged during a time interval (kW δt). This enables a clear and simple balancing of energy in storage in the ESS and energy absorbed or delivered by the ESS during a particular time slot. For example, with a half-hourly time stepping, a 1 MW wind turbine operating at its rated power provides 500 kWh during one time slot.

A. System balance without storage

From the known load, *L*, and local generation, *G*, three balance quantities are calculated at each time step, *t*, namely the amount of the demand met *directly* by the local generation, *D*, any *surplus* generation, *S*, and any *residual* deficit, *R*, which still needs to be met or would result in loss of supply.

$$\begin{aligned} \boldsymbol{D_t} &= \mathbf{min}(\boldsymbol{L_t}, \boldsymbol{G_t}) \\ \boldsymbol{S_t} &= \boldsymbol{G_t} - \boldsymbol{D_t} \\ \boldsymbol{R_t} &= \boldsymbol{D_t} - \boldsymbol{G_t} \end{aligned} \tag{1}$$

These are lines 1 to 3 of Algorithm 1.

B. Ranking

Lines 9 to 14 of Algorithm 1 summarise the ranking action. As the ranking depends on the user's wishes, the details are not included in that algorithm but need to be defined for each application.

Algorithm 1. Formal algorithm of the basic energy storage model designed to meet local demand.

Algorithm 1 Basic storage model

Require: Time step δt
Require: Load L [kWδt], Generation G [kWδt]
Require: Value information, e.g., electricity tariffs T [£/kWh]
1: Demand met from generation $\forall t: \ D \leftarrow \min\{L,\ G\}$
2: Surplus $S_0 \leftarrow G - D$
3: Residual $R_0 \leftarrow D - G$
4: **procedure** Initialise Storage(C, B_c, B_d)
5: Charge level [kWh] $\forall t: \ C = C_{\min}$
6: Charging [kWδt] $\forall t: \ B_c = 0$
7: Battery discharging [kWδt] $\forall t: \ B_d = 0$
8: **end procedure**
9: **procedure** Prioritise(R_0, T)
10: Select indices I from all $\{i\}$ which satisfy criterion
11: rank indices I: sort I by value T in descending order
12: Residual to be met by ESS $\forall I$: $\tilde{R}$
13: **return** $\left\{I, \tilde{R}\right\}$
14: **end procedure**
15: **procedure** Storage$(\tilde{R}, S_0, C, B_c, B_d, I)$
16: **Initialise** $R_1 \leftarrow \tilde{R}; S_1 \leftarrow S_0$
17: **for** $i \in I$ **do**
18: How much is missing: R_1^i/η_d
19: Available capacity at time i: $C_{av} \leftarrow C_{\max} - C^i$
20: Discharging capacity at i: $P_{d,av} \leftarrow P_{d,\max} - P_d^i$
21: How much to bid for: $Bid \leftarrow \min\{R_1^i/\eta_d,\ C_{av},\ P_{d,av}\}$
22: $j \leftarrow i$
23: **while** $Bid > 0 \ \wedge \ j > 1$ **do**
24: Available capacity at time j: $C_{av} \leftarrow C_{\max} - C^j$
25: Available discharging potential at time i: $P_d \leftarrow B_{d,\max} - B_d^i$
26: Revise Bid: $Bid \leftarrow \min\{Bid,\ P_d/\eta_d,\ C_{av}\}$
27: Available charging potential at time j: $P_c \leftarrow B_{c,\max} - B_c^j$
28: Offered charge at time j: $\Delta C \leftarrow \min\{Bid,\ \eta_c P_c,\ \eta_c S_1^j\}$
29: **if** $\Delta C > 0$ **then**
30: Take offer from surplus: $S_1^j \leftarrow S_1^j - \Delta C/\eta_c$
31: Move into storage: $P_c^j \leftarrow P_c^j + \Delta C/\eta_c$
32: Carry charge forward to i: $C^{j+1,\dots,i} \leftarrow C^{j+1,\dots,i} + \Delta C$
33: Discharge from storage at i: $P_d^i \leftarrow P_d^i + \eta_d \Delta C$
34: Reduce residual load: $R_1^i \leftarrow R_1^i - \eta_d \Delta C$
35: Revise available charge: $C_{av} \leftarrow C_{\max} - C^{j+1}$
36: **end if**
37: Reduce bid: $Bid \leftarrow \min\{Bid - \Delta C,\ C_{av}\}$
38: Step one time step further into past: $j \leftarrow j - 1$
39: **end while**
40: **end for**
41: **return** R_1, S_1, C, B_c, B_d
42: **end procedure**
43: Consolidate residual R: $R \leftarrow R_1 + \left(R_0 - \tilde{R}\right)$

One example would be to minimise the money spent on buying electricity. This would be achieved by first selecting all periods of deficit, and then sorting those periods in descending order of electricity tariff. The task of the ESS would be to reduce the most expensive electricity residual within its operating constraints.

Another example could be that a user has a contract with a maximum electricity import limit. Exceeding this could either lead to loss of supply or incur a penalty charge each time the electricity bought from the grid exceeds some threshold, R_{cap}. An ESS with a discharging rating of $P_{d,max}$ could avoid such events where the residual demand exceeds that cap by not more than its rating. Furthermore, an ESS could use its available charge to either avoid many events which would exceed the cap only by a small amount, or it might use the same charge instead for very few events which exceed the cap by a large amount. Clearly, it is better to avoid a penalty often and, as a result, the ranking would first select only those time slots where the residual demand is within the band from R_{cap} to $R_{cap} + P_{d,max}$ but not those with even higher residual. In a second step, the selected time slots would be sorted by increasing residual demand. In addition to the ranked list of 'when', one would specify the amount needed, $\widetilde{\boldsymbol{R}}$, to reduce the residual demand not to zero but just to below the cap. This ensures that the charge available in the ESS is used for the largest number of time slots.

A further example would be 'peak shaving' to reduce the volatility of the residual demand. Here, local residual demand maxima would be identified and, the ESS would be tasked to reduce them to the average residual of the two adjacent time slots. To maximise peak shaving, the algorithm would be invoked repeatedly to gradually reduce peaks until the ESS is fully utilised.

C. Storage operation

The underlying principle of the ESS operation is to start each time slot i by identifying how much would be asked from the ESS considering its discharging efficiency (line 18) and how much 'space' (spare capacity) is in the ESS at that time slot, given the constraints of space in the ESS available for that slot (line 19) and maximum discharge rate (line 20). Only the smallest of the three can be expected from the ESS (line 21).

Then the algorithm will search for opportunities to charge the battery going backwards in time, one time slot at a time. If it finds available charge at some earlier time j (lines 28 and 29), this is added to the ESS at that earlier time j (lines 30 and 31) and carried forward to the time of need i (line 32) where it is then released (line 33) to reduce the required residual (line 34). Once the ESS space has been used, that space and charging/discharging capacity is reserved for all future calculations. This searching is continued until the ESS is full. After this, the algorithm continues to the next time of need.

Since the times of need $\{i\}$ are sorted in decreasing importance, it is guaranteed that a more costly or urgent need is considered before others. Conversely, this ensures that any available charge should be considered within the searching loop without running the risk of using up any ESS unnecessarily. To ensure that all available space is utilised but not more than that, it is important to initialise the state of the ESS as minimum SoC and zero charging/discharging at all times (lines 4 to 8).

D. Results from the ESS operation

Once all selected time slots in the set I have been considered, the battery procedure returns a reduced residual demand, R_1, which is remaining after the ESS has tried to meet as much of the requested demand, $\widetilde{\boldsymbol{R}}$. This is balanced by a similarly reduced surplus which remains after that taken up by the ESS, and the balance of charging/discharging of the ESS and its SoC at all times.

If the requested demand is the full residual demand, then R_1 is the actual new residual demand after the ESS action. However, if only some charge was requested, as would be the case for avoiding excess charge or for peak shaving, then the remainder, $\boldsymbol{R_0} - \widetilde{\boldsymbol{R}}$, was put aside before the ESS consideration and needs to be added again at the end (line 43).

E. Recursive application

If a user has several functions of the ESS in mind, or for peak shaving, then one application of the Storage procedure only deals with one intended function, or only with the 'tops of the peaks'. For a full set of functions or for maximum peak shaving, the pair of Prioritise and Storage procedures (lines 9 to 43) needs to be repeatedly applied, where the consolidated residual, R, has to be the input to the Prioritise procedure instead of R_0, and the updated S_1 instead of S_0 is the input to the Storage procedure alongside the updated ESS state variables, C, B_c, B_d. The latter ensures that battery charge or operation already reserved in an earlier run of the procedure is not released for use again.

3. Case study

The case study used here to demonstrate the algorithm is a medium-sized demand node operating a variable electricity tariff located in a mid-latitude climate with moderate to good PV and wind resources. The key characteristics of the system are listed in Table I. Of the total annual consumption of 6640 MWh, 4554 MWh are met directly by the wind and PV production of 8021 MWh, leaving an initial residual total demand of 2086 MWh and an initial surplus of 3468 MWh.

The ESS model is applied for a range of energy storage capacities, from 0.5 MWh to 100 MWh. The size of one 'unit' of 500 kWh was chosen arbitrarily to provide a fine enough resolution when exploring the 'number of units' while keeping the number of simulations reasonably small. In all cases, the algorithm is applied twice, first to avoid excess charges when electricity import exceeds 500 kWh, and secondly to reduce as much of the residual demand as possible, ranked in order of tariff to minimise the annual electricity bill.

Table I. – System characteristics for the Case study

Time step	(h)	0.5
Demand Minimum	(kWh per time step)	81
- Mean		378
- Maximum peak		1112
Wind capacity	(kW)	2000
Wind capacity factor	(%)	29
PV capacity	(kWp)	4000
PV capacity factor	(%)	11
ESS unit storage	(kWh)	500
Min - Max SoC	(%)	20 – 80
Max charge/discharge	(kWh per time step)	400
Charging efficiency	(%)	95
Discharging efficiency	(%)	95
No. of storage units		1 to 200
Maximum export	(kWh per time step)	250
Electricity tariff Minimum	(p/kWh)	1
- Mean		40
- Maximum		399
Additional charge if demand > 500 kWh	(£)	10
Gross annual electricity cost	(thousand £)	1694
Gross annual electricity income	(thousand £)	328

4. Results

The results are presented in three sections. The first illustrates the storage action and its effect on the system balance for three example configurations, from a very small to a very large ESS. Then the overall performance for all ESS sizes is presented, before the computational effort is considered.

A. System performance examples

Figures 1 to 3 show a selected week in mid-summer, starting on a Friday, for storage capacities of 1, 10, and 100 MWh, respectively. The top panel in each shows, as the grey line, the initial deficit (positive) and surplus (negative) before any ESS action (best seen in Fig.3). The red line overlays the residual demand after the first round of ESS action and the blue line the remaining surplus. That week starts with moderate residuals and significant surplus for three consecutive days, then a day with very little surplus followed by another day with significant surplus and followed by two days with no surplus, including a 12-hour period on Wednesday where the initial deficit exceeds the penalty threshold of 500 kWh. The second panel shows the ESS state of charge after the first round of operation (light green dashed) and after the second and final round (dark green solid). The third panel overlays the final residual and surplus over the initial balance. The bottom panel shows the electricity tariff for each time slot and highlights (in red) those time slots where electricity has to be bought to meet the final residual.

One can see that the small ESS in Figure 1 only manages to eliminate a few events by fully charging on Tuesday, while the 10 MWh ESS in Figure 2 eliminates all of the excess residual through charging the battery from its minimum to around 60% SoC. In the second round, where the ESS shifts surplus generation to times of most expensive electricity, the small ESS charges up rapidly early in the week and discharges soon after, resulting in a clear daily cycling of the ESS. However, on Sunday the available charge is kept in storage until the weekday tariffs resume on Monday. As all the storage capacity was needed to reduce the excess charge, there is no spare capacity for peak-tariff avoidance left. The intermediate ESS in Figure 2 has sufficient capacity to avoid all tariffs until Tuesday and then only using the cheapest night tariff.

The largest ESS, in Figure 3, only uses a small fraction of its potential in the first round but has been gradually building up charge in the days leading up to the selected week and reaching full capacity on Sunday afternoon and again on Tuesday afternoon. Given that it was possible to reach full charge even while maximising its discharge before Sunday afternoon, the ESS is used to meet all residual demand leading up to that point, even at the cheapest night-time tariff. However, the maximum charge limit does restrict the use of the stored energy after that time and reserves the stored energy for the day-time and evening peak. Instead the charge accumulated by Tuesday evening is manged to last until the evening peak of the Wednesday in the following week.

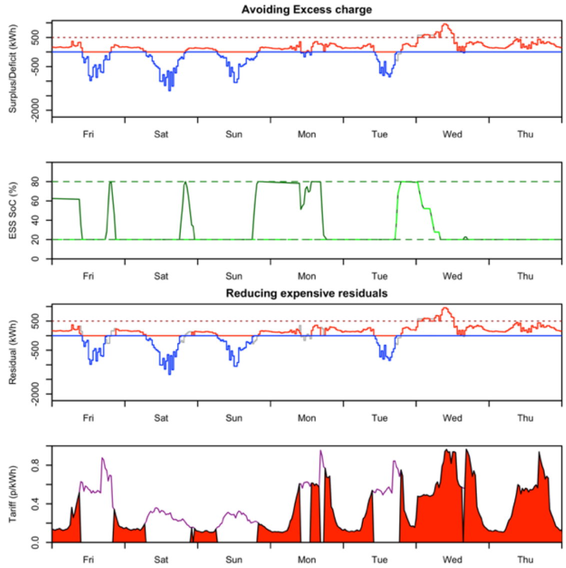

Fig.1. A selected week with a 1 MWh ESS. Top: initial balance (grey) and after eliminating excess demand , red: residual demand, blue: remaining surplus. 2nd: ESS SoC: light green after eliminating excess and dark green at end. 3rd: initial final residual in red/blue. Bottom: electricity tariff as the line. Areas filled in are those where electricity was imported.

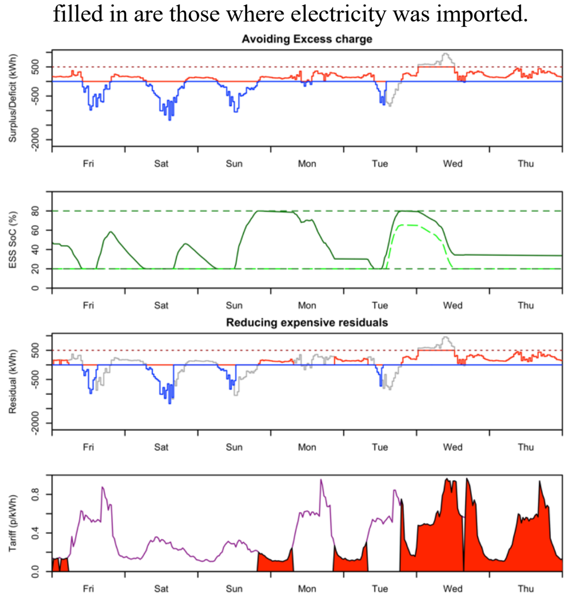

Fig.2. As for Figure 1 but with 10 MWh storage.

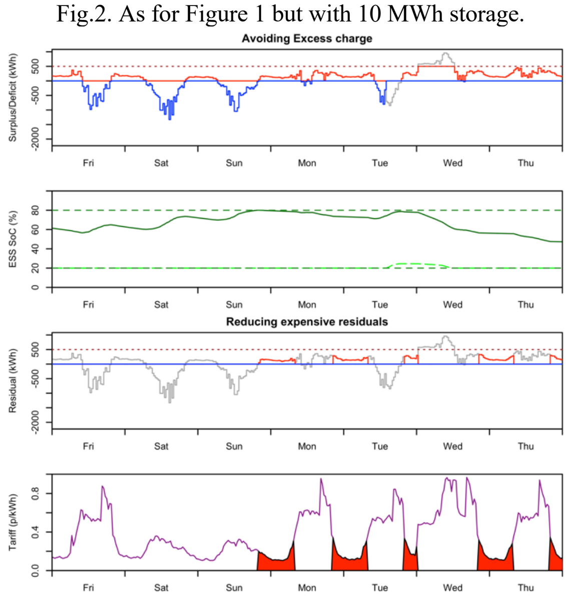

Fig.3. As for Figure 1 but with 100 MWh storage.

B. *Effect of storage size*

The overall performance of the ESS in the system can be measured by the total amount of energy supplied to the system in the sample year. Figure 4 shows how the energy managed by the ESS rapidly increases with its size while reducing both, surplus and residual demand. That initial rapid change gradually reduces suggesting that the marginal benefit of increasing the storage tails off rapidly at around the 10 to 20 MWh storage size. With the mean half-hourly consumption (Table I), this equates to a time scale of 13 to 26 hours, confirming a common observation [2,14] that much of an ESS addresses the daily demand and generation cycle. Addressing imbalances across several days or weeks requires significantly larger capacities. This observation is also reflected in the annual electricity bill shown in Figure 5. In this sample system, where up to 250 kWh could be exported per half hour time slot, the income opportunities lost by using surplus to charge the ESS reduces less rapidly than the savings from avoiding import. Despite losses, measured by the round-trip efficiency of the ESS, the strategy to avoid the most expensive residuals more than outweighs losses, reducing the net costs to zero for the largest ESS included here.

Given that the scheduling has to work around the minimum and maximum SoC, the operation of the ESS can also be illustrated in the typical time between being successively 'full' or 'empty'. Figure 6 shows both, mean and the median of the time between the ESS reaching each extremum SoC. While the mean or average time between the ESS reaching successive maximum SoC appears to increase almost linearly with storage capacity, the other three measures show a levelling off. It is worth to note that the mean and median are very close to each other for the smaller ESS, up to about 20 MWh. This again suggests that the storage size up to 20 MWh is regularly used to meet the daily and weekly cycles but capacities beyond that are used less frequently to cover more variable periods of persistent deficit. The median of the cycling limited by the maximum SoC levels off at around 7 days, suggesting that the larger ESS exploit their capacity for half the time to carry over spare weekend capacity into the week. In stark contrast, the ESS being exhausted to its minimum SoC limits both, the average and median times to much shorter periods, 3 to 4 days on average, with half of the periods only around a single day.

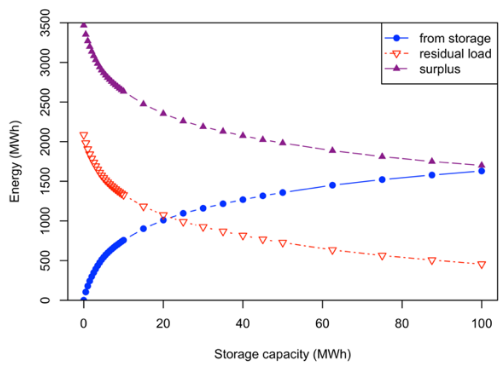

Fig.4. ESS performance against storage capacity: Annual electricity supply to the demand from storage (blue dots), remaining surplus (filled upward triangles) and residual demand (open downward triangles)

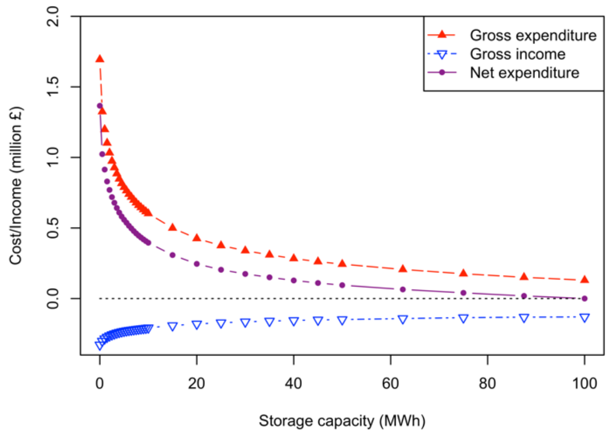

Fig.5. Annual electricity expenditure and income against storage capacity.

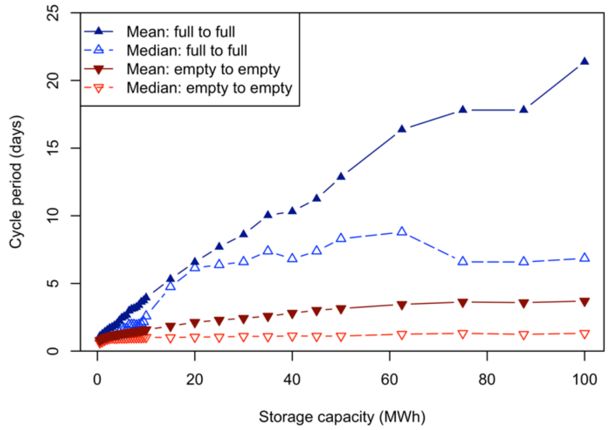

Fig.6. Mean and median period between the ESS reaching its minimum or maximum capacity against storage size.

C. *Computational considerations*

The computational costs involved in implementing this algorithm are considered. The average total number of iterations of the loop in lines 23 to 39 is shown against the storage size in Figure 7, showing the number of iterations during the first round to try to reduce the excess charge (red open circles) and the total number of both rounds together (filled blue circles). Initially, the first round completes more iterations than the first: the first round reserves a significant amount of the available storage, leaving fewer opportunities for the second round. At around 3 MWh, both rounds spend an equal amount of iterations charging and discharging the ESS, after this the second round always has more scope for using the ESS. Above a storage capacity of 20 MWh, all opportunities to reduce the excess in the first round have been addressed, and the number of iterations levels off. In contrast, the number of iterations in the second loop appears to continue to increase fairly linearly without showing any sign of levelling off, even though the resulting energy transfer (Figure 4) increases less and less. This suggests that the algorithm spends an increasing amount of work finding and transferring available electricity. This can be measured in the number of iterations needed for each MWh provided to the load by the ESS, shown in Figure 8. This indeed shows a range where the operation is most effective in the 15 to 40 MWh range.

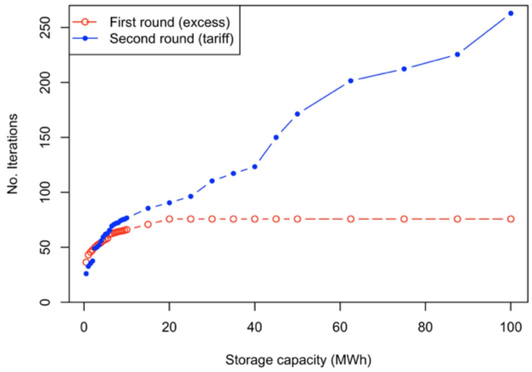

Fig.7. Average number of storage iteration loops per time slot selected against storage capacity for 2 rounds of ESS procedure.

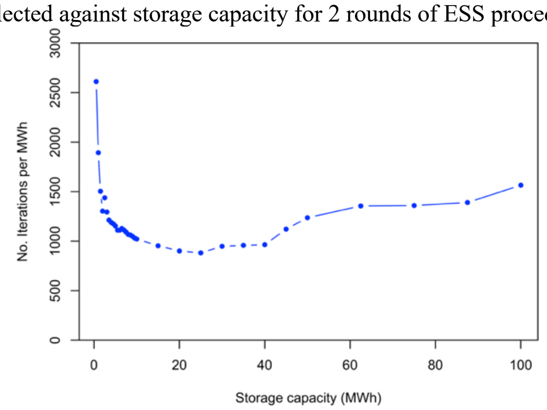

Fig.8. Number iterations needed per MWh of electricity delivered by the ESS, against storage capacity.

Translating the number of iterations into actual computing time, the CPU time needed by a relatively low-spec laptop (Macbook Air from 2015, 1.6. GHz Dual-core i5), even the largest ESS capacity used here on a data set of half-hourly data (17 568 slots) was completed in less than 20 s.

4. Conclusions

This paper has introduced a simulation tool to model the optimum operation of an energy storage system in a time series energy model using known or prescribed load and generation data. As such it implicitly assumes perfect knowledge which can be used to simulate the optimum or benchmark performance of an ESS. This model has been demonstrated in a case study to work reliably and produce results fully consistent with expectations.

As such, the model can be implemented for a broad range of energy systems models which are commonly used to understand the system dynamics as well as to provide a guide in the systems design process. It could be used in in conjunction with forecasts of generation and demand. In this case, it would show the optimum scheduling for the estimated prediction horizon. The only change to implement the model in predictive scheduling would be to initialise the ESS not at its minimum SoC but at the actual SoC at the beginning of the predicted period (line 5).

Currently, the ESS is represented by a small number of typical performance characteristics and is therefore flexibly to be applied across a large range of energy storage technologies. Given the transparent nature of the algorithm, it is easy to incorporate technological constraints, such as ramp rates. The most challenging, but not insurmountable, aspect appears so far to be complex self-discharge characteristics if they depend on current state factors as well as its history, as found with Li-Ion batteries [12,13], which show an initial rapid loss after charging followed by a more gradual self-discharge, as well as a degradation of capacity over time and use.

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