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The effect of energy storage on the Residual Load Duration Curve (rLDC) of a system with high Renewable Energy contribution

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Abstract. This paper evaluates how energy storage acting in a system with a very high contribution from variable Renewable source can reduce peak loads. The methodology uses observed demand and renewable generation data to construct scenarios of increasing renewable contribution complemented by energy storage. The analysis is based on the concept of creating load duration curves for the period over which a set of storage technologies can act to reduce peak loads by storing energy during low loads.

The models used here are developed on the premise that different types of storage are deployed for different purposes. For the scope of this work, three types were used. The first to manage loads within a day, the second acting over a period of a week, and the third at a much longer, seasonal scale.

Key words. Energy storage, Energy system, Load Duration Curve, Renewables integration.

1. Introduction

All models of energy systems are based on balancing supply and demand of power and/or energy. Detailed energy models, such as the TIMES model [1], are complex models balancing power for many selected time slices to scale those up to evaluating energy scenarios over time. As these models attempt to resolve as many individual components as possible, they are computationally extremely expensive and still struggle to represent the action of Demand Side Management (DSM) or Energy Storage (ES) well. The reason for this is that without DSM/ES the power balance needs to be achieved within a very short time period and resoled time slices in these models become effectively independent of each other if the slices are longer than the power balancing period. However, DSM and ES add a time constant to the balancing which may exceed the resolved time slices.

Simple models often rely on the bulk energy balances without much concern over ensuring power balancing at all times. In traditional power systems dominated by dispatchable generation, the energy and power balancing can indeed to a large degree be treated as separate problems – one addressing the problem of meeting peak demand and having sufficient flexible generation to match typical changes in the demand profile throughout the day; and the other considering the longer term use of the installed generation and the accumulated fuel consumption. As with the complex models, DSM and ES invalidate the assumptions by introducing a time constant over which energy can be stored to balance power over that time.

In future scenarios with substantial contribution from variable Renewable Energy sources, the power balancing becomes more critical, as does the need for DMS and ES.

The aim of this paper is to contribute to the development of a model for future energy scenarios which reflects the power balancing requirements explicitly while being, at present at least, as simple as possible. The proposed model is based on the concept of the Load Duration Curve (LDC) which has been used for many years as a diagnostic description of a power system [2]. This curve shows clearly not only the typical load and the total energy consumption but also clearly quantifies the maximum peak demands and how frequently they occur. The concept was developed in the early 1960's [3] but has recently received more attention again [4].

Extending the LDC to a duration curve of the residual load after incrementally meeting the load by the available generation types in merit order, leads to the concept of a hierarchy of residual load duration curves (*rLDC*) which show how each generation type contributes to the supply and affects the demand profile [4]. Previous work [4] has shown that the *rLDC* approach reflects very well the effect of variable renewable generation on the residual demand profile. That work highlighted the need to refine the representation of dispatchable generation and the representation of energy storage. The focus of this paper is to explore the effect of energy storage on the power profile and how this is reflected in the diagnostic *rLDC* curves resulting from that. This will be used to guide the development of an energy storage module for the *rLDC* model developed in [4] for future energy scenario studies.

2. Methodology

The methodology used here is to generate a year's time series of residual load, derived from observations of a transmission grid together with wind power and solar PV production fed into that grid. Combining the normalised demand with a scaled-up renewable generation creates a future residual load scenario on which the energy storage acts as a load-shifting device to shave peaks by filling valleys in the residual demand curve. The goal here is to make the residual load duration as flat as possible.

A. Energy storage assumptions and operation principle

The main assumptions are that a particular energy technology, with a prescribed round-trip efficiency, power rating and available energy capacity, has a specified cycling time horizon. Within each cycling period, the energy storage is recharged from the times of lowest demand and then, after accounting for losses, used to reduce the residual loads at times of high demand. Since the aim is to flatten the load curve, the charging and discharging aim to bring the residual load to the average value for that cycling period.

The entire process rests on the assumption that there are (fairly) regular load cycles into which the residual load time series can be sub-divided and that the load profile for a whole storage cycle is (perfectly) well known. Within the context of a typical daily demand cycle, this would usually be appropriate, and also with current wind and PV forecasting techniques, the anticipated wind and PV generation over a day are usually well enough predicted to satisfy these assumptions. At the other end, looking at seasonal storage, one might also expect to know that the entire storage cycle has to be a whole year to balance load and generation for the seasons from weather-dependent resources (such as wind and PV), and that any wind energy surplus from the winter would need to be stored until the summer or that any summer surplus from PV would need to be stored until the winter.

For intermediate periods, these assumptions are less secure. However, for the purpose of this paper, we proceed under these assumptions.

B. Storage hierarchies

To evaluate the effectiveness of storage cycles for different time horizons, a set of three technology types are operating successively on the residual load, starting with the residual load rL_0, after demand has been balanced with all PV and wind power. Initially an installed storage capacity is operating at a daily cycle. Once this has reduced peak loads from available valleys in that day, a new residual load, rL_d, is constructed. This is then used as the input for the next level of storage which operates on a weekly cycle to construct a new residual load, rL_w. A third level of storage then operates on a longer time scale. Two different time scales were used in this final step to test the sensitivity of the approach to the chosen time scale: one a monthly cycle and secondly using the full year as a single cycle. These then resulted in the final residual load time series, rL_m and rL_y, respectively.

C. Storage module validation

After each stage of applying the load shifting within the time horizon of that stage, the energy storage State of Charge, *SoC*, is calculated based on the difference between the input time series, rL_{j-1}, and the output time series, rL_j, from the load-shifting module with a storage SoC model given by Eq.(1) (for storage stage j at time step i)

$$\boldsymbol{SoC_i} = \begin{cases} \boldsymbol{SoC_{i-1} + \eta_{ch} \left|\Delta P_{j,i}\right|} & , \quad \boldsymbol{\Delta P_{j,i} < 0} \\ \boldsymbol{SoC_{i-1} - \frac{1}{\eta_{dis}} \left|\Delta P_{j,i}\right|} & , \quad \boldsymbol{\Delta P_{j,i} > 0} \end{cases} \tag{1}$$

With the storage power $\boldsymbol{\Delta P_{j,i} = Lr_{j-1,i} - Lr_{j,i}}$ defined as positive when it is supplying power to the grid and negative when it acts as a load. This allows to check that the load-shifting across arbitrary times within the charging time horizon can be accurately reproduced by the storage acting in time.

D. System configuration

The analysis is illustrated on a year's worth of residual load data at a 5-minute interval, derived from observations of the UK National Grid of transmission level demand, wind power production and solar PV production for the year 2017 ([4], the same data set as used by [3]. The demand data are normalised by the peak demand, the PV generation is normalised by the maximum PV output, and the Wind generation is normalised by the maximum wind output. For the record used here, the capacity factor of the PV was 13%, and that of the wind power was 39%. The average demand was 63% of peak demand.

For future energy scenarios, the PV and Wind power are each multiplied by a scale factor to represent how an increased installed capacity under the same resource conditions would perform. For the purpose of illustrating the load-shifting module and its effect on the residual load, both the PV and the Wind capacity were doubled compared to 2017. This ensured that the Renewable capacity would produce a sufficiently more energy than was consumed in that year to allow for losses. The resulting residual load is shown in Figure 1, with demand at the top, followed by PV generation, then by Wind generation, and the residual load, rL_0, in the bottom panel. Given the higher PV output during summer and the higher wind speeds in winter, the residual load does not show a pronounced seasonal cycle in this particular case.

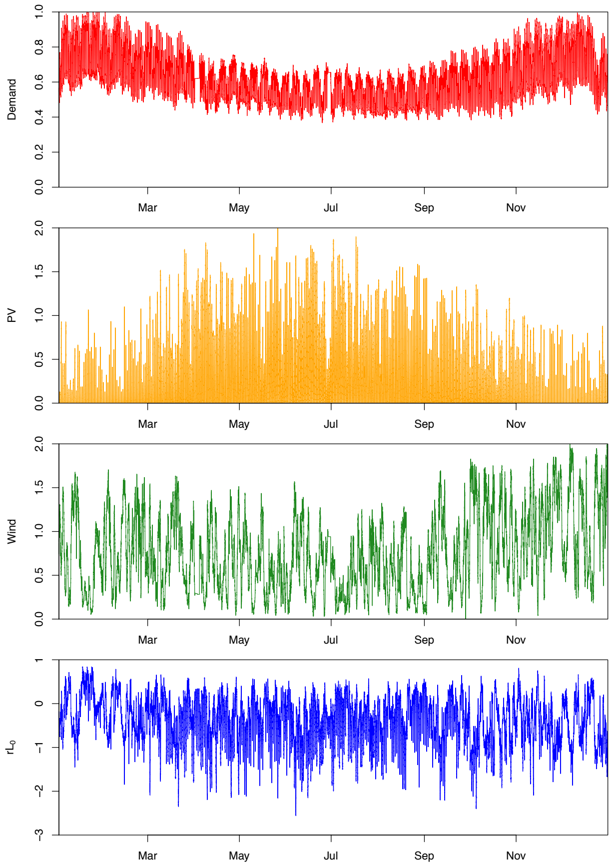

Fig.1. Time series of (from top to bottom): normalised demand, PV generation, wind generation, residual demand.

The normalisation of the load and generation by the peak demand means that all power quantities are dimensionless in the following while the energy is expressed in units *hours*, where 1 h reflects one hour load at peak demand.

3. Model implementation

The charging procedure is a successive 'filling of the valley'. For the time of lowest residual load, the storage starts with raising this level to the second-lowest value and absorbing the energy given by product the load difference and the time step. This is then repeated by raising the residual load of those two time points to the third-lowest and absorbing the energy represented by that power difference and the two time intervals. This is repeated either until the valley is filled up to the average or until the storage capacity is reached. This process is illustrated at the right side of Figure 2 by the dark-green dashed lines. This figure shows the input residual load values for a storage cycle sorted in descending order. The green lines on the right-hand side show the possible successive layers of load filling, the dark green part is the load filling which was achieved within the storage capacity. At some point in the process, the new residual load level reached might exceed the initial lowest load levels by more than the power rating of the storage capacity. In this case, these affected time slots are no longer available for further load increase and are eliminated from the process. This is evident by the limiting green line which has the same shape as the residual load curve but is shifted up by the power rating of the storage.

Once the charging process is completed, the energy absorbed is multiplied by the round-trip efficiency to set the energy available for the peak shaving, which is carried out in the same manner as the load filling, starting from the highest residual loads and gradually reducing them until the available energy is used up. This is illustrated by the dark orange lines on the left-hand side of Figure 2.

The required storage action for this load levelling and the resulting new residual load is then rearranged into time order, and is shown in the Figure 3, with the residual loads and storage power delivery or absorption in the upper panel and the resulting state of charge of the storage in the lower panel.

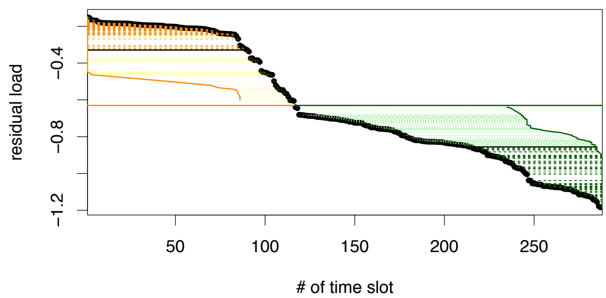

Fig.2. Illustration of load-shifting by valley filling and peak shaving.

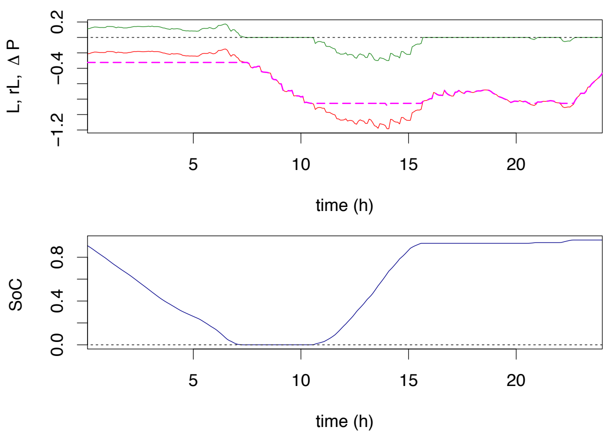

Fig.3. Resulting new residual load after storage action (upper panel), and corresponding SoC of storage (lower panel) for a typical load-shifting period of 24 hours

4. Results

In this section, the results of the load shifting outlined in §3 are shown for the selected case, following the succession of increasing time horizons, starting with the daily cycle. Over the section, the full residual load picture is gradually developed, highlighting the effect of each successive time horizon of storage operation.

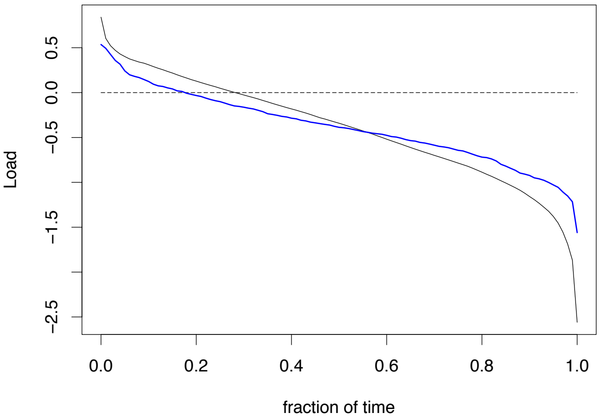

Fig.4. residual LDC_d (blue) derived from daily load-shifting acting on the initial $rLDC_0$ (black line).

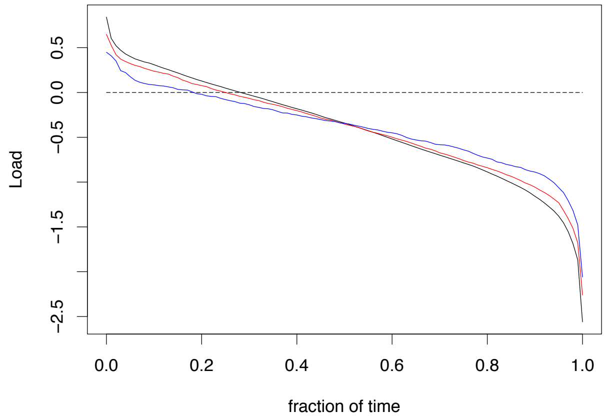

Fig.6. residual LDC_w (blue) derived from weekly load-shifting acting on $rLDC_d$ (red line); (black line: initial $rLDC_0$).

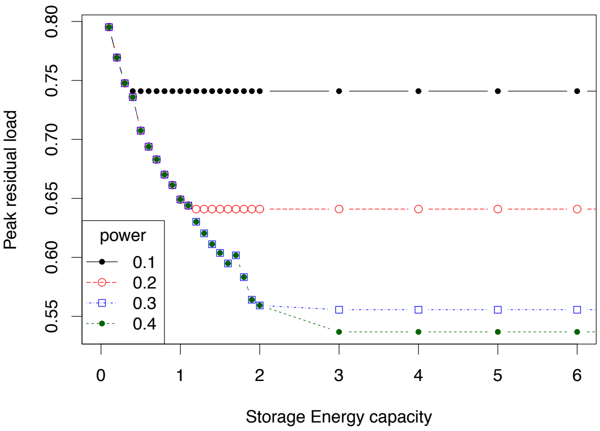

Fig.5. Peak residual load occurring after daily load shifting against energy capacity of the storage for a set of power ratings of the storage.

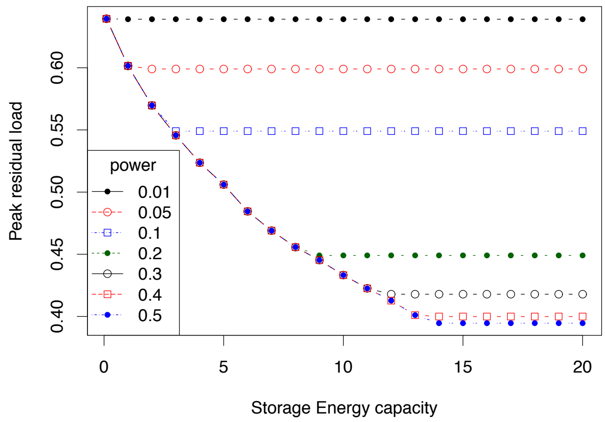

Fig.7. Peak residual load occurring after weekly load shifting against energy capacity of the storage for a set of power ratings of the storage.

A. Daily Cycling

Figure 4 summarises the effect of daily load shifting on the initial residual load, $rLDC_0$, for an installed storage capacity of 2 h and power rating of 0.3.

Figure 4 highlights that not only a bulk of residual load is reduced by the storage but also that the maximum peak is significantly reduced. Figure 5 summarises how effectively different combinations of power rating and energy storage can reduce that peak. At very low energy capacities, the ability to reduce the peak is limited by that capacity irrespective of the power rating. However, as the capacity increases, the power rating becomes the limiting factor at a certain storage capacity. Beyond that capacity, the limit in power rating caps any further peak reduction, shown by the horizontal lines for the different power rating. While substantial reductions can be made at low power ratings, almost proportional to the power rating, that gain becomes small above a power rating of 0.3 (30% of peak demand), with no further improvement possible above an installed power capacity of 0.4.

B. Weekly cycling

Taking the residual load after daily cycling with energy storage with capacity 1h and power rating 0.3 results in an $rLDC_w$ shown in Figure 6.

The effect on the peak residual demand, in Figure 7, shows a very similar patter to that of the daily load shifting, except that the ultimate limit of managing the residual load occurs for a storage capacity of 14 h with an additional storage power rating of 0.4.

C. Monthly cycling

Completing the set of storage installations with a third set operating over a month shows an equivalent effect as the previous two. Using a daily load-shifting capacity of 1 h / 0.3 and a weekly capacity of 9 h / 0.2, results in the peak residual demand shown in Figure 8. Using a power rating of 0.4 gets close to meeting all remaining demand but to close the final cap, a power capacity of between 0.7 and 0.8 is required. The system is fully balanced with a storage capacity of 110 h.

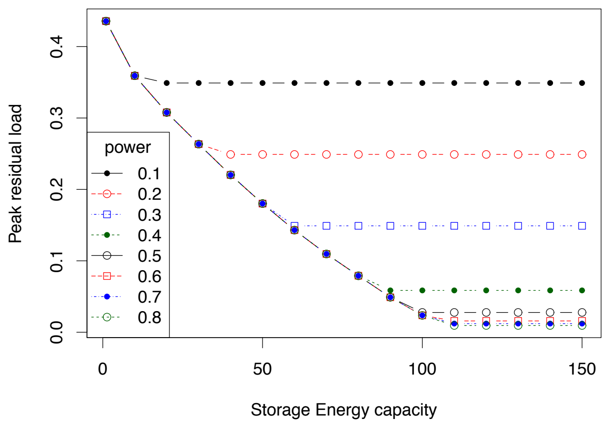

Fig.8. Peak residual load occurring after monthly load shifting against energy capacity of the storage for a set of power ratings of the storage.

A qualitatively similar result is also found when the weekly load-shifting capacity is increased to 15 h / 0.5. As one might expect, the system is now balanced with a slightly lower monthly capacity, namely 90 h / 0.5.

5. Conclusion

The results show clearly that both, energy storage capacity and power rating impose firm limits on the load-shifting capability at all time horizons. At the same time, they show that a hierarchy of different storage capacities, each designed to operate on a different time horizon, is both needed and able to balance the system over the entire year.

However, they also show that these limits follow a clear systematic pattern which provides a guideline for optimum planning of energy storage requirements and their capability in future energy systems. The results for the particular load and renewable resource profiles, with the chosen generation portfolio also show that assessing load-shifting over a month achieves full load balancing.

The systematic nature of the performance with varying storage capacities can be taken as evidence that it should be possible to develop an energy storage module for an *rLDC*-based energy systems model. Continuing research will be aimed at consolidating the observed response of the system for different generation portfolios and demand-resource profiles.

A. Further work

Given that this study used a renewable portfolio which balanced PV and wind to a degree across the seasons, a key uncertainty is how the longer-term load-shifting across months or seasons would perform in less balanced situations. This is clearly the first step to be carried out. As a result, it is proposed to explore the sensitivity of the balancing for a range of different PV and wind capacities. As part of this, it should also be assessed how much overproduction is needed to allow for the roundtrip efficiency of the storage technologies.

Once the sensitivity of the storage performance to the residual load profiles has been quantified, the information is available to propose and test formulations of the *rLDC* storage module to be developed. This will have to answer questions as to whether such a model can be based on a relatively simple closed additive or multiplicative function. If that is shown to be possible, then the module would consist of a function of the resulting residual load duration curve using the input load duration curve as the input variable, and using the storage characteristics as module parameters. An alternative approach to explore would be to base the resulting *rLDC* on the joint probability of the input *LDC* and a statistical description of the storage action.

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