HydroCen
NORWEGIAN RESEARCH CENTRE
FOR HYDROPOWER TECHNOLOGY

CENTRE FOR ENVIRONMENT-FRIENDLY ENERGY RESEARCH

HydroCen Report nr. 15

Modelling batteries

Documentation of testing of using hydropower modules to model batteries in ProdRisk and EMPSW

Linn Emelie Schäffer

NTNU SINTEF NINA

HydroCen

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Schäffer, SINTEF 2020. Modelling batteries. HydroCen Report 15. Norwegian Research Centre for Hydropower Technology

Trondheim, August 2020

ISSN: 2535-5392 (digital publication Pdf)
ISBN: 978-82-93602-16-3

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COVER PHOTO
Pixabay.com

KEY WORDS
Batteries, hydro power models, EMPSW, ProdRisk

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Abstract

Schäffer, SINTEF 2020. Modelling batteries. HydroCen Report 15. Norwegian Research Centre for Hydropower Technology.

The report documents a test of how pumped storage functionality can be used to model batteries in SINTEFs long-term models. Firstly, optimal operation of a battery in a price taker setting is simulated using the ProdRisk model. The exogenous prices are taken from the Low Emission Scenario [3]. This first test was mainly done to build competence on the problem of modelling batteries. The results show that it functions very well being aware of the assumptions of the model, the most important being prices known for the whole week. In the second test, two batteries were put into our Low Emission dataset of Northern Europe 2030, with one battery in Germany and one UK. The dataset was simulated using the EMPSW model that uses formal optimization on individual plant level for the weekly marked clearing problem. EMPSW model gives reasonable results and show that batteries with relative short-term storage capacity can considerably reduce the number of price spikes. As for ProdRisk, EMPS also assumes everything known for the whole the week. In addition, the testes identified the weekly end value setting of battery storage as an improvement area. Especially, when the batteries are put into areas without regular hydro storages.

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1 Introduction

Technological developments have driven down costs of batteries in recent years[1], creating more optimistic business cases for using batteries in power systems. At the same time, the need for flexibility in the power system is increasing as large amounts of variable renewable energy sources are being integrated into the system. By investing in and utilising flexible resources in the power system, such as batteries and demand side flexibility, available power sources can be used more efficiently and costs of operating the power system can be reduced. For example, batteries can contribute to the system by increasing the load in surplus periods (charging) and discharge in hours with peak demand, making the balancing of supply and demand easier and increasing the value of intermittent renewables. Batteries and "new" types of flexibility can come to play a vital role in future energy systems and there is a high awareness of the potential of batteries if costs are reduced further. It is therefore likely that batteries will become part of more business models to provide flexibility in the future.

Batteries store electric energy and can be used in power systems to reduce the net power consumption in peak hours. Batteries do not produce energy but consume energy when charging and provide the energy back to the system when discharging. Hence, batteries can be used to reduce the hour to hour change in net power consumption by reducing the peaks. In addition, batteries can provide many other services ranging from grid services (e.g. voltage regulation, avoiding congestion and frequency control), market services (e.g. load shifting, energy arbitrage, primary frequency control and self-consumption of PV) and application stacking (combining the types of services provided) [1]. In a study based on Norwegian conditions and regulations, provision of balancing services was found to be the most feasible application for batteries when analysing at which investment cost large-scale batteries become economically feasible [1].

Given the wide range of use cases and possible business models, there is likely to be an increase in investments in batteries the following years. We already see different pilots in several European countries, such as Vattenfalls battery park close to the Pen y Cymoedd wind farm in Wales. The largest, and perhaps most economically successful, lithium-ion battery used in a power system today is the Tesla battery in South Australia. The battery was built to provide grid services and help avoid blackouts in the region[2] and has a power capacity of 100 MW and storage capacity of 129 MWh. The battery has been in operation for about two years and has played an important contribution to maintaining grid security, while also showing good economic results. Plans to expand the battery with 50 MW and 64.5 MWh was announced fall 2019[3]. Projects as the Tesla battery demonstrate that batteries can play a vital role in future markets, especially with increasing share of intermittent renewables. It is therefore becoming more important to include "new" flexibility sources, such as batteries and demand response, in power system analyses and power system models.

From a Norwegian point of view, it is interesting to quantify how batteries may affect prices and price variation in Norway and Europe. Forecasts for future prices are often calculated with fundamental based market models that include detailed representation of flexible hydro but lack specific functionality for modelling of batteries. This report documents testing that is done to find out whether the general hydro functionality in some of these models can be used to model batteries also. Tests are done using the hydro scheduling model ProdRisk and the protype market model EMPSW. Other projects also focus on the use of batteries in power systems[4] and on operational models for batteries in power systems with high share of renewables [2].

[1] http://publikasjoner.nve.no/faktaark/2019/faktaark2019_14.pdf
[2] It can be questioned if the battery was built more as a PR-stunt than of other reasons
[3] https://www.powerengineeringint.com/2019/11/20/australias-tesla-battery-to-undergo-a-50-mw-expansion/
[4] https://www.sintef.no/en/projects/integer-integration-of-energy-storage-in-the-distribution-grid/

2 Modelling of batteries using hydropower modules

The operational problem for batteries is a planning problem of when to charge and discharge the battery to maximize socioeconomic surplus from a system perspective or to maximise the profit from the battery owner's perspective. Given that the battery operates in an open market the operator will try to maximise profit by offering the most profitable products at the most profitable times. Batteries can provide a range of services (products) and can contribute both into balancing and energy markets. We will in this report only focus on energy markets and more specific income from energy arbitrage.

Assuming that the battery only participates in an energy market (e.g. day ahead/spot), the battery should be charged when the power price is low (buying electricity) and discharged when the power price is high (selling electricity). Assuming uncertainty about future power prices, an expectation of future power prices is needed to evaluate the value of the energy stored in the battery. The operator will decide when to charge and discharge the battery based on the current power price and the expected development in the power price, as well as the state of the battery (fully charged/discharged etc.).

Operation of hydropower units with pumping capabilities follow the same principles as batteries but often at a larger scale. They pump water for storage when the power price is low and produce electricity when the power price is high. Hydropower units with pumps can therefore be used to model batteries in hydro-thermal power system models.

To set up a hydropower unit to simulate a battery, the unit should be set up as a closed loop cycle with a generation unit, a pump, an upper reservoir and a lower reservoir. The turbine capacity, reservoir size and available water should be set to give the wanted power and storage capacities of the battery. The PQ-curve and energy equivalent should be used to achieve the wanted efficiency (e.g. the power output capacity (MW), the storage capacity (GWh) and the round cycle efficiency).

3 ProdRisk test case

Mid-term optimisation model for operation of cascaded hydropower systems. ProdRisk optimise operation of the hydro system towards a given power price under uncertainty in power price and inflow. The pumping functionality in the ProdRisk model can also be used to simulate a battery and optimise operation of the battery towards stochastic power price series. Simulations of battery operation using the ProdRisk model can be used to evaluate how the battery will be used, i.e. the operational pattern of the battery. Information about the operational pattern can be used to evaluate the design of the battery, for example the storage, charging and discharging capacity. Furthermore, the model can be used to assess income potential from the spot market and economic feasibility.

An important assumption when using the ProdRisk model is that the battery is a price taker, e.g. decisions on how to best operate the battery do not impact the power price in the area. To evaluate how batteries can affect the price in a region, a fundamental market model that models both demand and supply should be used.

3.1 Design of the battery and implementation

Table 1. Values of input used to simulate a battery in ProdRisk.

Input	**Value**	**Comment**
Reservoir size	20 mm^3	
Maximum reservoir filling	18 mm^3	Not necessary if reservoir size is set to the wanted size
Energi equivalent	0.2778 kWh / (m^3)	
Minimum production	0	Given as part of PQ- curve
Maximum production	1000 MW	Given as part of PQ- curve
Minimum discharge	0	Given as part of PQ- curve
Maximum discharge	1000 m^3/s	Given as part of PQ- curve
Pump capacity	1000 MW	
Pump capacity	800 m^3/s	Max and min given together with max and min pumping head.
Head	100m (max 100, min 99.9)	Required because of pumping. Max and min head set close to equal (0.1) since there is no head difference in an electrical battery

A testcase has been done using a hydropower module to simulate a battery using ProdRisk. The characteristics given in Table 1 describe a large battery with 80% round-cycle efficiency. The efficiency can be increased by increasing the pumping capacity (m^3/s). The maximum filling of the reservoir, the maximum discharge and the energy equivalent decides the energy storage capacity of the battery. In the example the storage capacity is 18 mm^3 and the discharge capacity is 1000 m^3/s. It takes 5h at maximum production to empty the reservoir, giving 5 GWh of energy. Hence, the battery is designed to store 5 GWh of energy and requires 5 hours to discharge from full to empty. Since the pumping capacity in m^3/s is 20% lower, accounting for the round cycle efficiency, the reservoir requires 6.25 hours of maximum pumping to fill from empty to full, using 6.25 GWh of energy.

How the battery is designed differ depending of the intended use of the battery. Especially, the size of the battery (the scale) and the ratio between power capacity and storage capacity are important criteria which needs to be adapted to the needs (services required) and size of the market where the battery is to operate. Comparing with the Tesla battery in Australia, the discharge capacity of the example battery is 10 times higher and the battery is designed to store a much larger amount of energy. While the Tesla battery in Australia can deliver at maximum capacity in about 1.3 hours, the battery described here is designed to deliver energy for 5 hours. The differences in design makes the example battery better suited to deliver energy services and profit on energy arbitrage, while the Tesla battery mainly is designed to provide grid services, operating for shorter time periods

3.2 Simulation results

In ProdRisk, there is no impact on the price from the battery. The planning strategy should therefore be to discharge at high price and charge at a low price. Based on this it could be easy to assume that the battery always is fully charged or empty, however, this is not necessarily the case. Optimal operation depends on the price, but also of the state of the battery and the design. With the charging and discharging capacity of the battery in the test case it takes 6.25h to fully charge an empty battery and 5h to discharge the battery from full to empty. With a temporal resolution of 3h per time step, the battery cannot always operate at maximum charging capacity or maximum discharge capacity and it takes several time steps to complete a full cycle of the battery. Because of this, optimal operation of the battery is not always to completely fill up or completely empty the battery. Evaluating the reservoir filling when the battery change from charging to discharging or opposite we see that the battery most often is charged to 100% or discharged to 0%, but that there also are some typical "in-between" levels. Such levels are for example 4%, which lets the battery be fully charged again in only 2 time-steps with full charging. This is illustrated in Figure 1 which shows the probability density of the state of the battery (percent of fully charged) when changing from charging to discharging (max charge) and from discharging to charging (min charge).

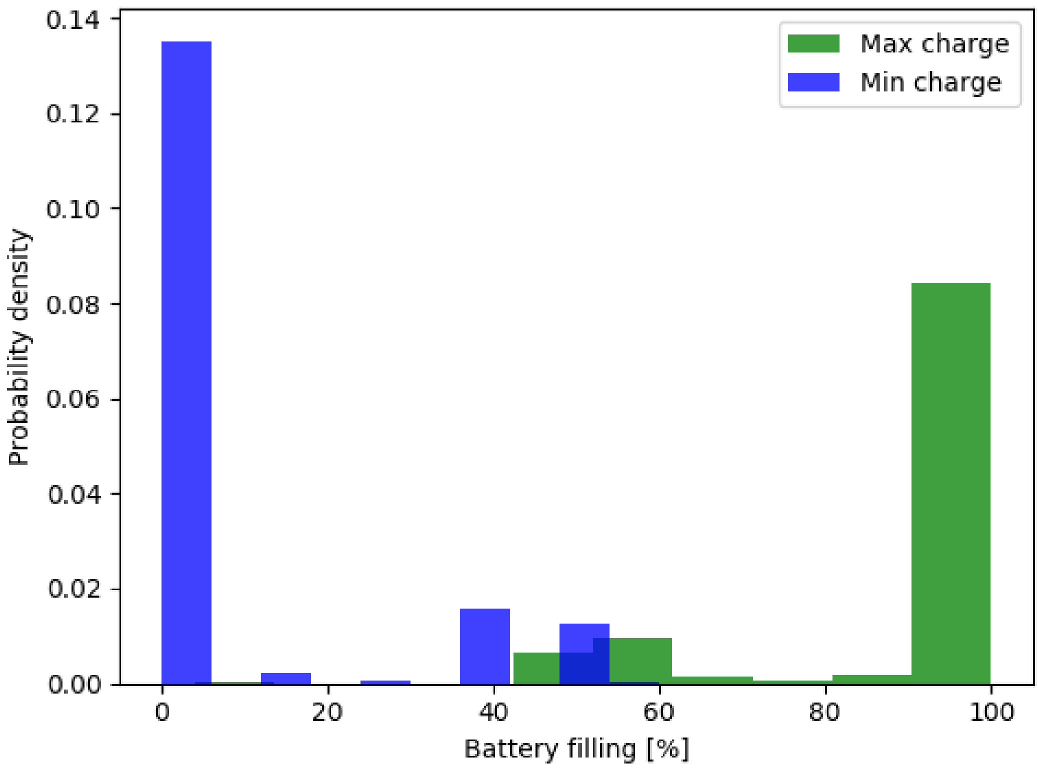

Figure 1. Histogram of the probability density of different battery charge levels when changing from charging to discharging (max charge) and discharging to charging (min charge).

Table 2 gives the levels of battery charges that occurs the most often when changing charging state and a comment of why this level regularly occurs. The levels are either a result of having utilised a good operational opportunity (i.e. discharging at maximum in two time-steps with a high price) or partly utilising an ok opportunity and at the same time preparing for a good future opportunity (i.e. discharging at ok price, but only so that the battery can be fully charged again in two time-steps instead of fully discharging and then using three time steps to fully charge the battery again). This behaviour indicates that it can be quite complex to evaluate operational patterns of batteries in the power system, and hence also to analyse tear and associated costs, without using simulation models.

Table 2. The four most common battery charge levels, the number of occurrences and the share of all occurrences over 58 simulation years.

	Battery level	Number of occurances	Occurances [%]	Comment to battery level
From charging to disharging (max)	100 %	5732	65 %	fully charged battery
	96 %	1439	16 %	2 x time step of maximum charging above empty battery
	60 %	797	9 %	1 x time step with maximum discharging above empty battery
	48 %	553	6 %	1 x time step with maximum charging above empty battery
From discharging to charging (min)	0 %	5757	65 %	empty battery
	4 %	1418	16 %	2 x time step of maximum charging below full battery
	40 %	697	8 %	1 x time step of maximum discharging below full battery
	52 %	673	8 %	1 x time step with maximum charging below full battery

Figure 2 and Figure 3 illustrates the operational pattern of the battery for two different weeks simulated for two different weather years. The battery is often at 100% or 0% battery charge level, but there are also several cycles where the battery is charged or discharged to a different level.

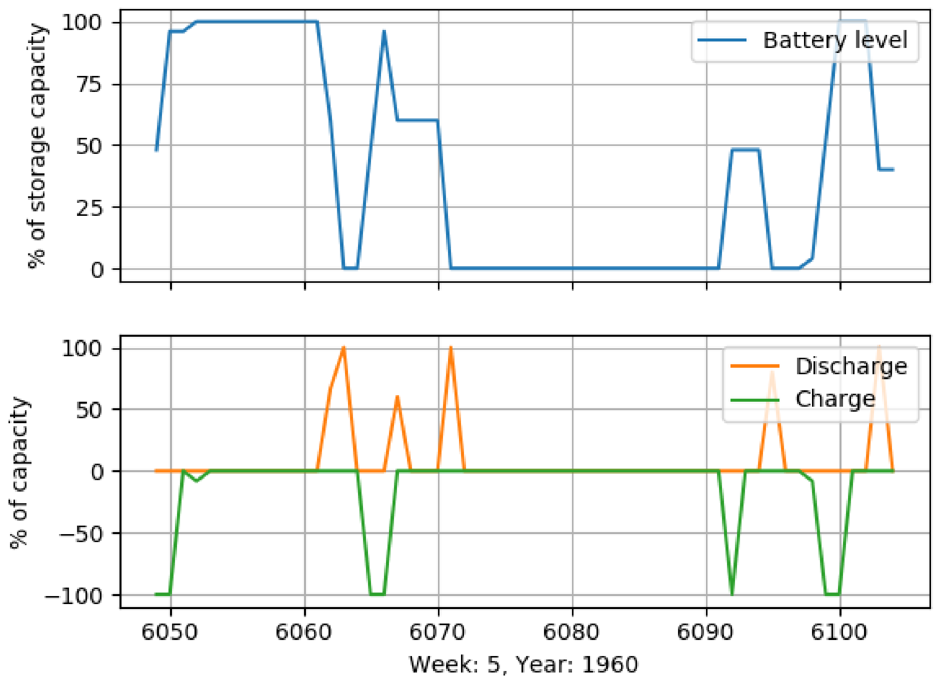

Figure 2. The battery charge level over time (top) and the operational charging/discharging pattern (bottom) for week 5, weather year 1960.

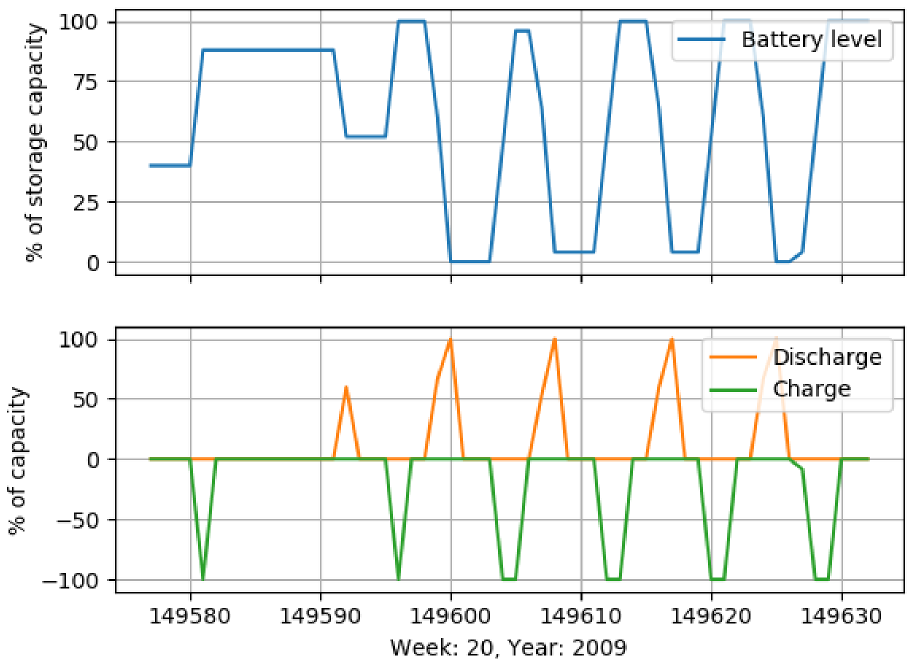

Figure 3. The battery charge level over time (top) and the operational charging/discharging pattern (bottom) for week 20, weather year 2009.

4 EMPSW test case

Simulating operation of a battery towards a given power price can give important information on how a battery should be operated into a market, assuming that we have good price forecasts and the battery is small enough to not have a significant impact on the market. However, this is often not the case when analysing future power systems. Firstly, most power systems are going through large changes making future prices more uncertain, and secondly, batteries can have a significant impact on the power systems depending on the design and scale. Since batteries can have a significant impact on future power systems, they should also be included in fundamental power system modelling. EMPSW is a fundamental power system model that optimise operation of the power system with the objective to minimize the total socioeconomic costs of meeting electricity demand given the constraints of the system. By including different levels of battery capacity, the impact of batteries on the system, security of supply and the power price can be evaluated.

As previously discussed, batteries can be added to power systems for several reasons, such as to ensure security of supply through grid services or as back-up capacity, save infrastructure costs by resolving bottle-necks and provide load-shifting or frequency control services to the power market. In EMPSW the impact of batteries providing power and energy services to the energy markets, e.g. load-shedding and energy arbitrage, can be analysed.

4.1 Design of the battery and implementation

We have implemented two batteries into the HydroCen Low emission dataset [3]. A large battery, equal to the one used in ProdRisk is added into the German power market, while a small battery with 1/10 of the size of the large battery, is added to the Great Britain market. The two batteries have the same ratio between power capacity and storage capacity and therefore use the same number of hours to discharge (empty) or charge (fill up) the battery. The characteristics of the small battery is given in Table 3 and for the large battery in Table 1 in the previous chapter. The areas where the batteries are added have large shares of intermittent renewable energy sources and high variability in the power price. In other words, these areas could be good candidates for investments in technologies such as batteries.

Table 3. Values of input used to simulate the little battery in EMPSW.

Input	Value	Comment
Reservoir size	2.0 mm3	
Maximum reservoir filling	1.8 mm3	Not necessary if reservoir size is set to the wanted size
Energy equivalent	0.2778 kWh / (m3/s)	
Minimum production	0	Given as part of PQ- curve
Maximum production	100 MW	Given as part of PQ- curve
Minimum discharge	0	Given as part of PQ- curve
Maximum discharge	100 m3/s	Given as part of PQ- curve
Pump capacity	100 MW	
Pump capacity	80 m3/s	Max and min given together with max and min pumping head.
Head	100m (max 100, min 99.9)	Required because of pumping. Max and min head set close to equal (0.1) since there is no head difference in an electrical battery

4.2 Simulation results

Operation of the batteries in the power system model follows a similar pattern as in ProdRisk. However, in the power system model a wider range of charging levels for the battery can occur, as the battery has an impact on the system and therefore also on the power price. Figure 4 gives the probability density of the charge state of the battery (percent of fully charged) when changing from charging to discharging (max charge) and from discharging to charging (min charge).
Table 4 and Table 5 give the levels of battery charges that occurs the most often for the two batteries when the batteries changing charging state and a comment of why this level regularly occurs. The levels are mostly the same as in the simulation results in ProdRisk given in Table 2. From the number of occurrences given for the levels in Table 4 and Table 5, we see the most repeated maximum and minimum charge levels constitute a smaller share of all occurrences than in the ProdRisk simulation. This can be a result of other battery levels being optimal, since the operation of the batteries has an impact on the system and not only optimise towards a given price.

It should also be mentioned that the charge level distribution shown in Figure 4 depends on the model time resolution, it only takes about two model periods to go from fully charged to empty. A model with a finer time resolution might have given different results.

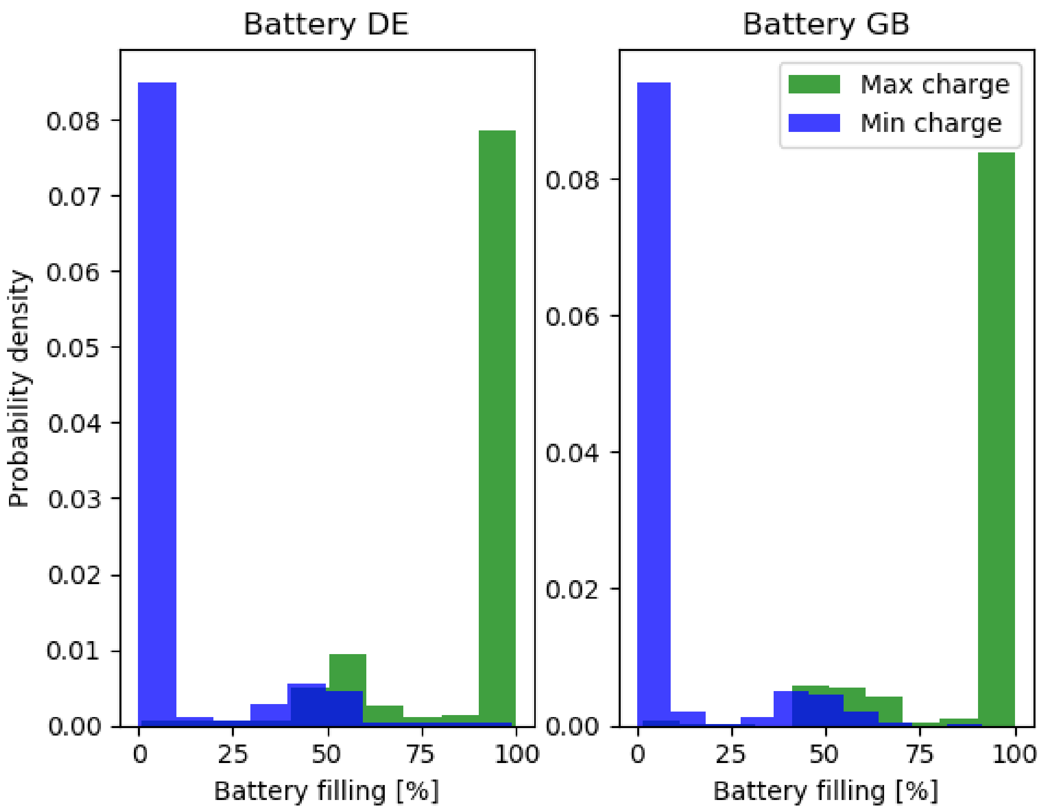

Figure 4. Histogram of the probability density of different battery charge levels when changing from chargin to discharging (max charge) and dischargin to charging (min charge).

Table 4. The four most common battery charge levels for the German (DE) battery. The table also provides the number of occurrences and the share of all occurrences over 58 simulation years.

	Battery level	Number of occurances	Occurances [%]	Comment to battery level
From charging to disharging (max)	100 %	8371	60 %	fully charged battery
	96 %	2290	16 %	2 x time step of maximum charging above empty battery
	60 %	1158	8 %	1 x time step with maximum discharging above empty battery
	48 %	562	4 %	1 x time step with maximum charging above empty battery
From discharging to charging (min)	0 %	10019	71 %	empty battery
	4 %	1011	7 %	2 x time step of maximum charging below full battery
	40 %	659	5 %	1 x time step of maximum discharging below full battery
	52 %	545	4 %	1 x time step with maximum charging below full battery

Table 5. The four most common battery charge levels for the battery in Great Britain (GB). The table also provides the number of occurrences and the share of all occurrences over 58 simulation years.

	Battery level	Number of occurances	Occurances [%]	Comment to battery level
From charging to disharging (max)	100 %	4842	62 %	fully charged battery
	96 %	784	10 %	2 x time step of maximum charging above empty battery
	48 %	204	3 %	1 x time step with maximum charging above empty battery
	60 %	192	3 %	1 x time step with maximum discharging above empty battery
From discharging to charging (min)	0 %	3899	50 %	empty battery
	4 %	644	8 %	2 x time step of maximum charging below full battery
	40 %	260	3 %	1 x time step of maximum discharging below full battery
	48 %	204	3 %	1 x time step with maximum charging above empty battery

The battery located in Germany is operated actively and has a large number of charging/discharging cycles over the 58 simulating years. The battery is connected to the middle of Germany. The average price in this area is reduced from 88.12 EUR/MWh in the simulation without batteries to 81.81 EUR/MWh in the simulation with batteries. The average price in this area is very high because of a few hours with extremely high prices up to 3000 EUR/MWh. The median of the power price over all time steps over 58 simulation years is 42.76 EUR/MWh and is equal in the two simulations. Figure 5 shows the operational pattern of the battery in German for an example week, and the according change in battery charge level. Figure 6 plots the operational pattern (charging and discharging) for the same week and weather scenario and the simulated power price with (Power price) and without (Power price old) batteries. The plot illustrates how the battery is charged at low prices and discharged at high prices. For the second discharge peak, the power price is significantly reduced in the simulation with batteries compared to the price in the simulation without batteries.

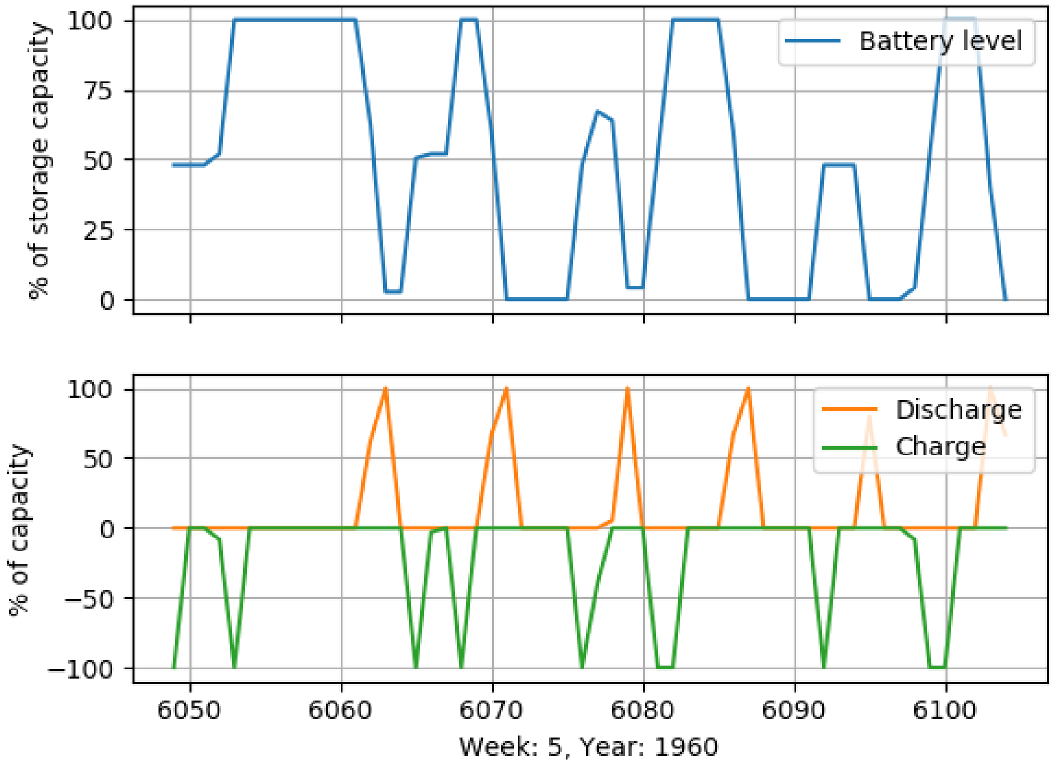

Figure 5. The battery charge level of the battery added in Germany over time (top) and the operational charging/discharging pattern (bottom) for week 5, weather year 1960.

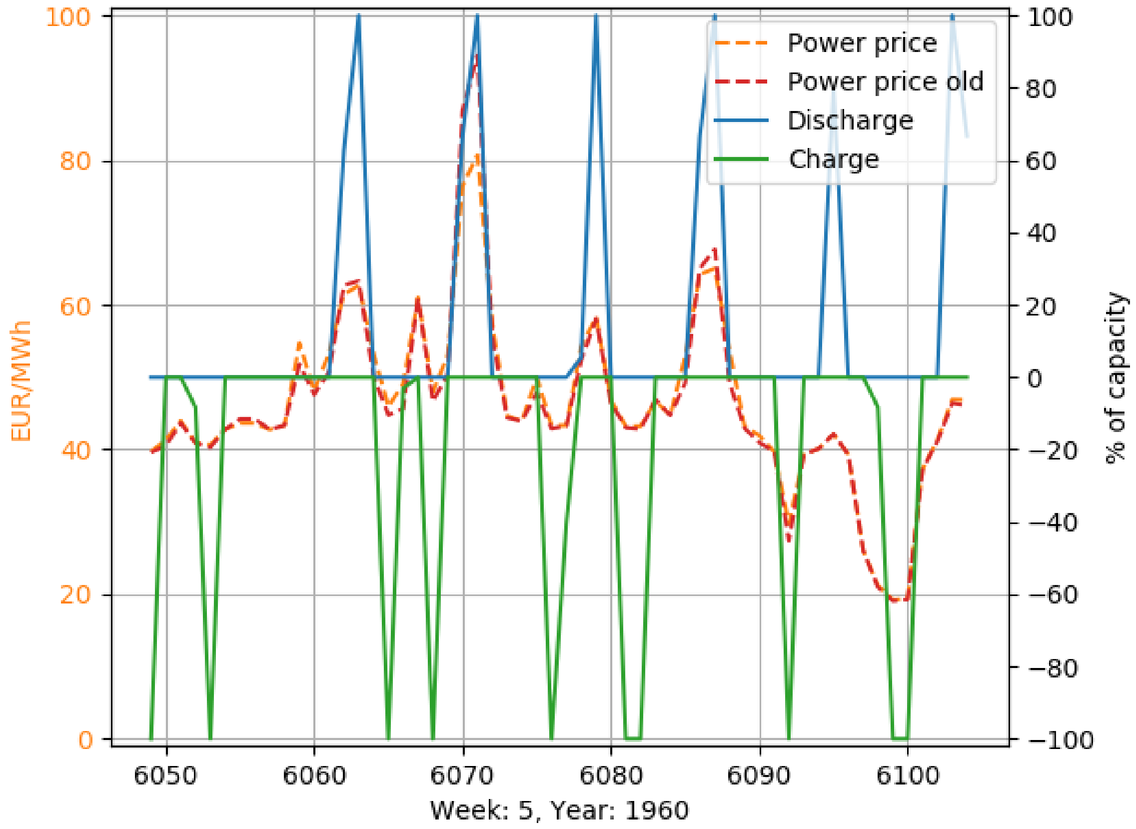

Figure 6. The operational pattern (charging and discharging) of the battery added in Germany, plotted for week 5 of weather year 1960, and the resulting power price in the simulation with batteries (Power price) and in the simulation without batteries (Power price old).

The battery located in Great Britain is operated less actively than the battery added in Germany and has a lower number of charging/discharging cycles over the 58 simulating years, as seen from Table 5. The battery is connected to the middle of Great Britain. The price impact in this region is smaller than for in the German area. The power price in the middle of Great Britain is reduced from 39.60 EUR/MWh in the simulation without batteries to 39.46 EUR/MWh in the simulation with batteries. The median of the power price over all time steps over 58 simulation years is 41.55 EUR/MWh and is equal in the two simulations. The price impact off the battery in this region is smaller since the battery is much smaller, only 1/10 of the size of the battery in Germany. Furthermore, the price characteristics in the two regions are different and the average price in the area in Great Britain is lower than the median price, implying that there are fewer high price peaks in this region. Figure 7 shows the operational pattern of the battery in Great Britain for the same week as in the previous plots. We see that this battery has fewer cycles for in this week than the battery in Germany had. Figure 8 plots the operational pattern (charging and discharging) for the same week and weather scenario and the simulated power price with (Power price) and without (Power price old) batteries. As in Figure 6, we see that the battery is discharged when the price is higher and charges when the price is low. Comparing the price simulations, we see that the price is slightly higher in simulation with batteries in the first period the battery discharge compared to the price in the simulation without batteries. This is an unexpected behaviour as we expect the price in an area to be reduced when the battery discharge energy to that area.

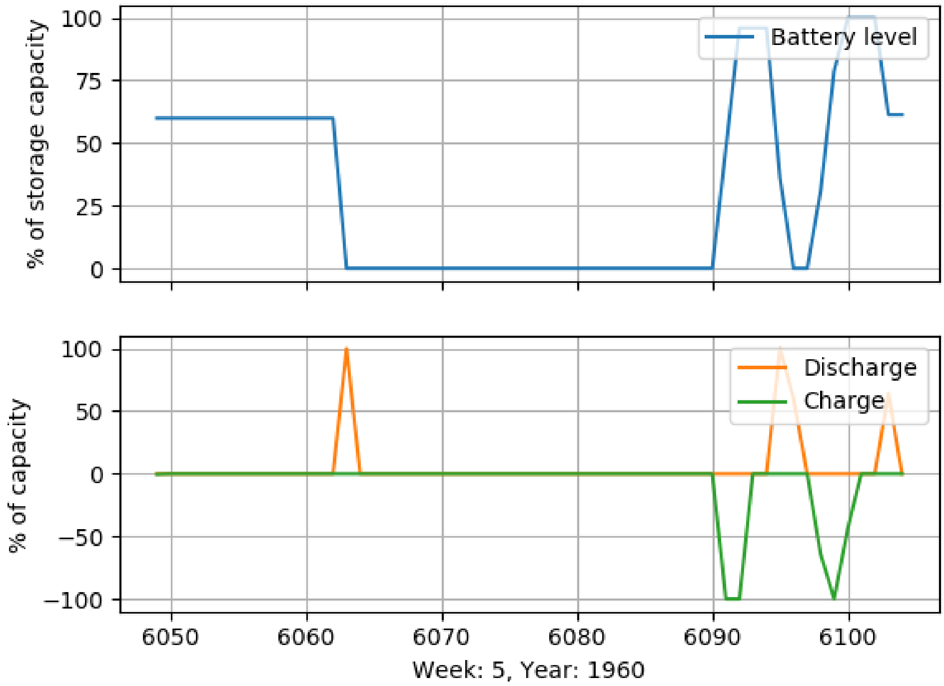

Figure 7. The battery charge level of the battery added in Great Britain over time (top) and the operational charging/discharging pattern (bottom) for week 5, weather year 1960.

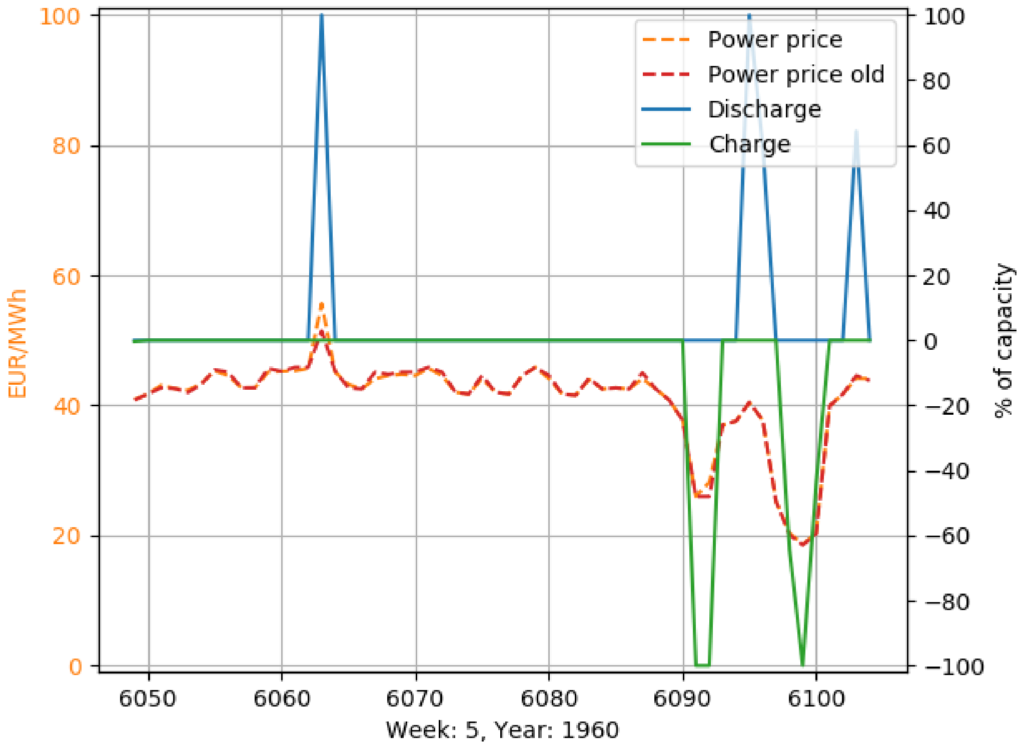

Figure 8. The operational pattern (charging and discharging) of the battery added in Great Britain, plotted for week 5 of weather year 1960, and the resulting power price in the simulation with batteries (Power price) and in the simulation without batteries (Power price old).

The duration curve of the resulting power price in the simulation with batteries and without batteries are plotted for the German and the Great Britain areas in Figure 9 and Figure 10 respectively. We can see some smaller differences in the plotted duration curve when including batteries, but the price level is mostly the same. We notice that the power prices are reduced in some periods with prices below the median and increased in some periods with prices higher than the median when including batteries. This can seem strange but can be a result of the battery being charged at relatively high price to be discharged at an even higher price and vice versa in periods with low prices. An example of this can be seen in Figure 6, where the battery at the end of the week is discharging at a price that is lower than the price when it charged earlier the same week. This is because the price has fallen during the week, and even though the price is relatively low, the battery can now be charged at an even lower price, and it is therefore still profitable to discharge at this price. Figure 11 and Figure 12 show the same duration curves but is zoomed in on the tails of the curves, i.e. the lowest and highest prices. From these plots we see that the battery increases prices in the periods with the lowest prices and reduce prices in the periods with the highest prices. This implies that the battery discharge in the periods with the highest prices and charge in the periods with the lowest prices. Overall, the average power price is also lower when batteries are included, which indicated that the system is more efficient.

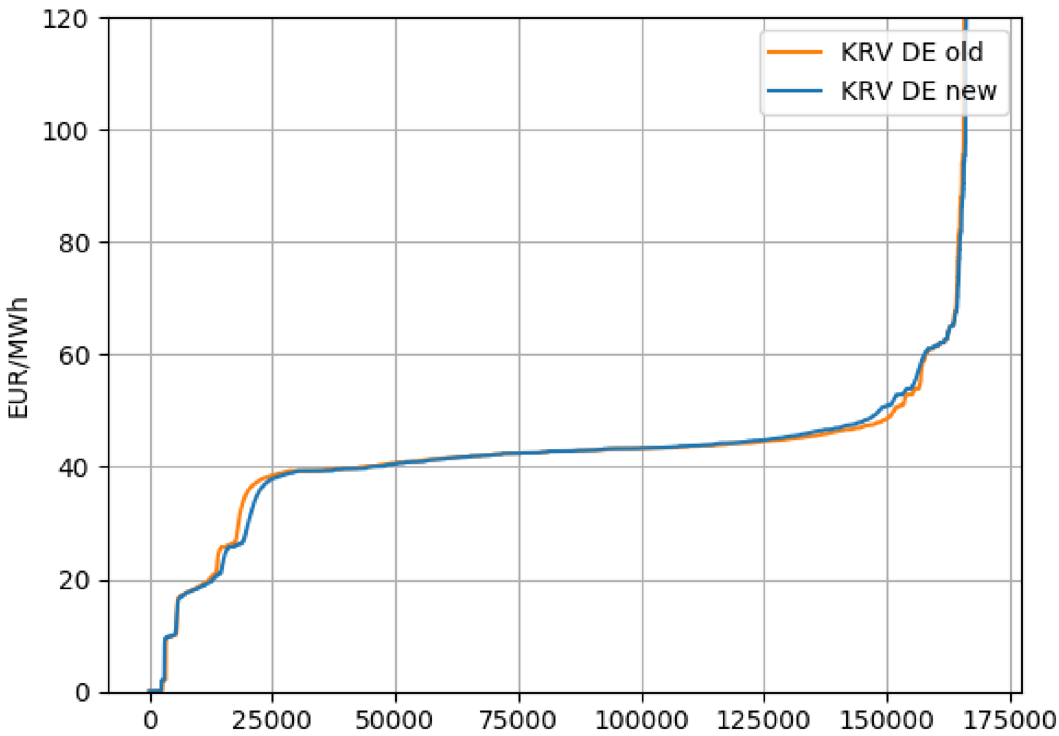

Figure 9. Duration curve of the power price in Germany from the simulation without batteries (KRV DE old) and with batteries (KRV DE new).

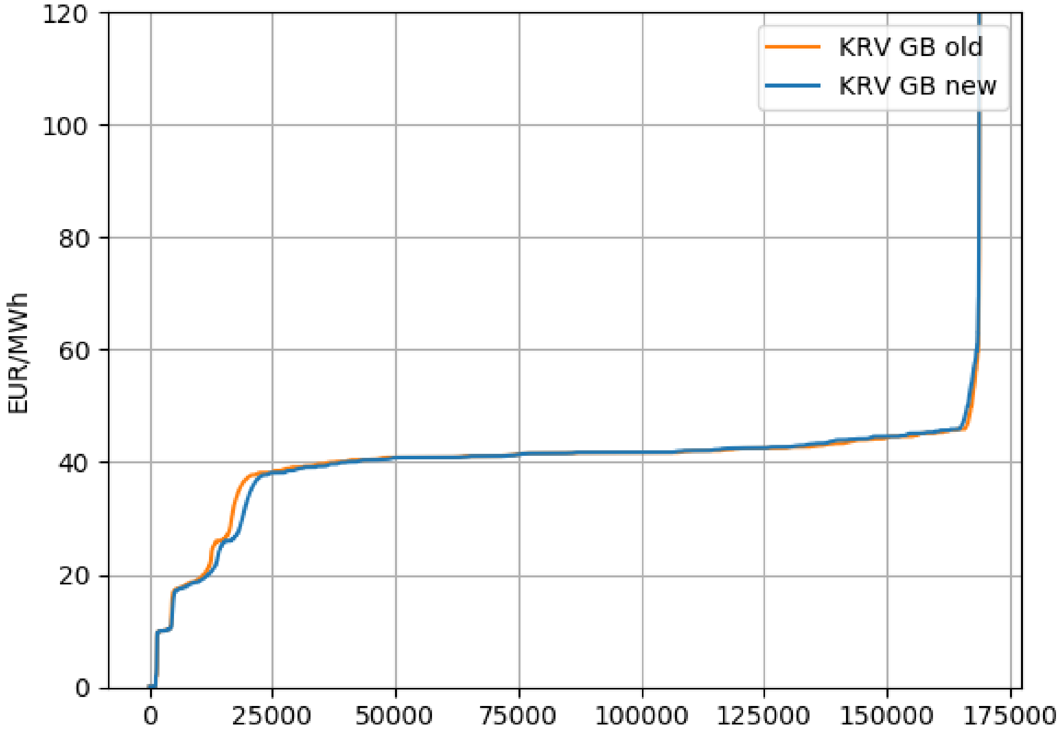

Figure 10. Duration curve of the power price in Great Britain from the simulation without batteries (KRV GB old) and with batteries (KRV GB new).

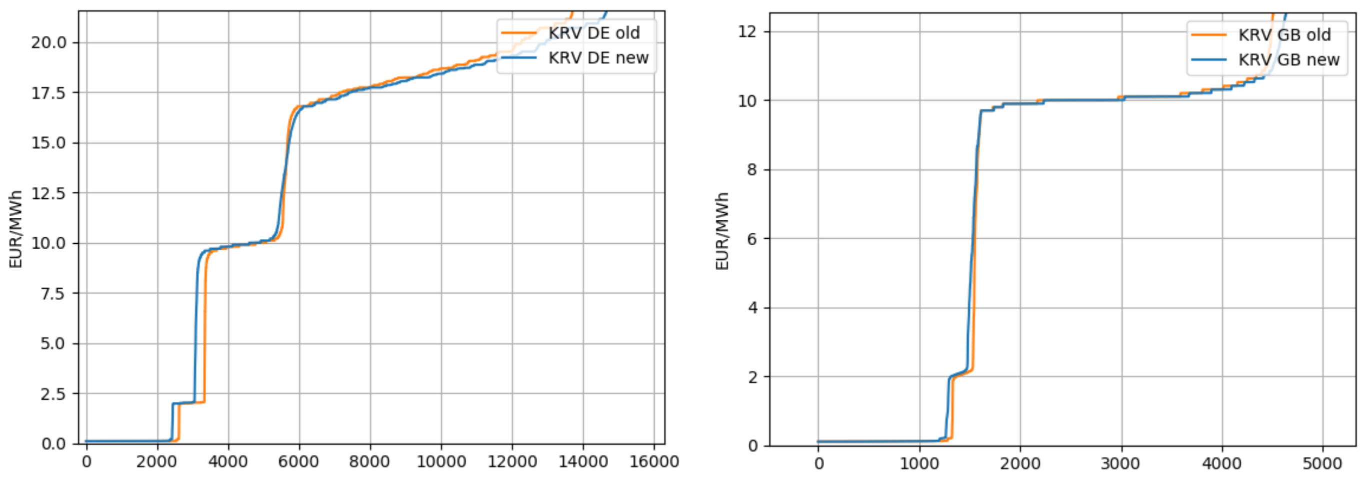

Figure 11. Duration curve of the power prices from the simulations without batteries (old) and with batteries (new). The figure is zoomed in on the tail with the lowest prices. The power prices in Germany to the left and in Great Britain to the right.

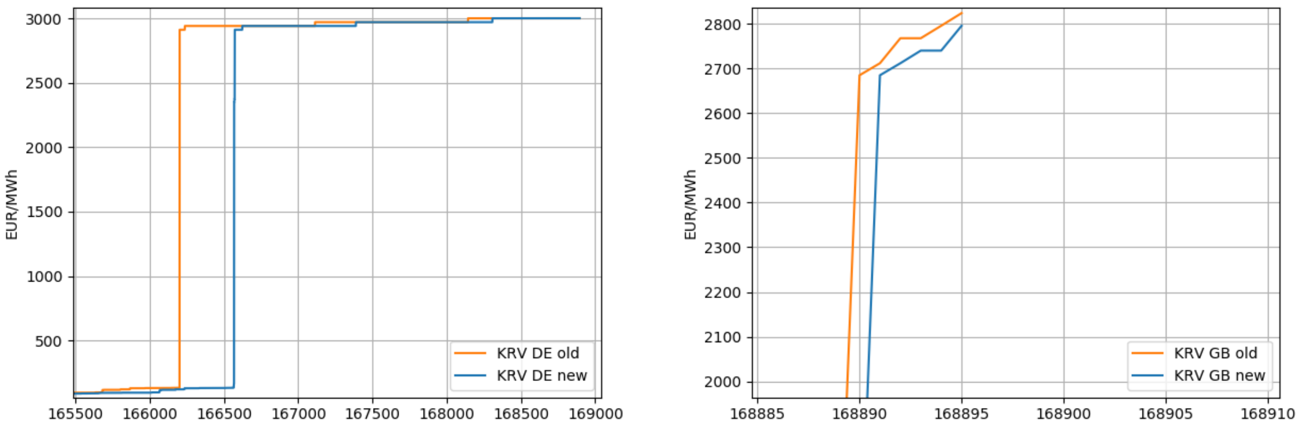

Figure 12. Duration curve of the power prices from the simulations without batteries (old) and with batteries (new). The figure is zoomed in on the tail with the highest prices. The power prices in Germany to the left and in Great Britain to the right.

5 Final remarks and discussion

Weekly deterministic
Both models that have been tested assume that all uncertainties are revealed by the beginning of the week and known for the whole week. The models will therefore operate the batteries more perfectly than what can be achieved real operation. An exception to this comes from the end of week charge state valuation method that is discussed below. The too perfect operation caused by the weekly deterministic assumption is also present for the other flexible resources (e.g. hydropower) but the relative importance is probably larger for flexible resources that is only used for short-balancing (a few hours).

Prototype
This report demonstrates how hydropower modules can be used to simulate batteries in power system modelling and provides some example results from using hydropower modules to simulate batteries in ProdRisk and EMPSW. Still, the use of hydropower functionality to simulate batteries needs to be tested further. Especially, the modelling of batteries in the EMPSW, as this model is recently developed prototype model and has not been used extensively to analyse future power systems previously. From the results we also identify some price changes that could be investigated further, e.g. that the power price in an area sometimes increase in periods when the battery is discharging. As the simulations are done on a large dataset, which includes many areas and power plants, the price changes could be a result of complex coherences in the system. Furthermore, the functionality in the model, and the possibilities within this functionality, could be explored more to see how batteries with different characteristics can be modelled.

End value setting
A challenge when using hydropower modules to model batteries is the weekly end-value setting of water (stored energy). The planning horizon for the batteries will typically be much shorter than for typical Norwegian hydro storages. Checking the end-week battery charge level for the batteries for a random selection of weeks we recognize some clear trends. For the battery in Germany, the trend is that the battery is emptied or very close to emptied at the end of the week. For the battery located in Great Britain the tendency is that the battery is charged between half full and full at the end of the week in the drawdown season (during late fall and winter). In the filling season (late spring and summer) on the other hand, the battery is emptied or close to emptied at the end of the week. The end value setting in EMPSW depends on the characteristics of the hydropower plant and the end value setting at the end of the week from the aggregated model in EMPS. The aggregated end value setting is disaggregated in EMPSW using the "siktemagasin" procedure. If there only is one hydropower module in an area, the end-value setting will equal the aggregated model, but if there are several hydropower plants the end-value setting is disaggregated across the reservoirs. In the drawdown season the end value settings are distributed equally across the individual hydropower plants, while they in the filling season are adjusted depending on the degree of regulation of the plants. The degree of regulation is a measure of how likely a reservoir is to spill water given the reservoir size (storage volume) and inflow to that reservoir. If a reservoir has a high degree of regulation, there is a low probability of spilling and the reservoir is given a high end-value setting.

Based on this we can try to reason towards what happens with our batteries in the model. In the German area, there are no other hydropower modules modelled other than our battery. The end-value setting should therefore be equal the end value in the aggregated system. The question then becomes what the end value setting from the aggregated model in EMPS is. Since there are no other hydropower plants in that area, the aggregated model is calculated only based on the battery. This can give some strange results as there is no inflow and no long-term storage of water. Furthermore, the EMPS model does not optimize pumping as part of the water value calculation and it is therefore not likely that the model sees any particular value of the small hydropower unit representing our battery. Based on the behaviour of the battery, which often is emptied or have a low filling at the end of the week, it seems likely that the end-value setting is very low. In the Great Britain area, there is another hydropower module modelled and the end value here will therefore be disaggregated from the aggregated model. In our modelling of batteries, the inflow is set to zero as we don't want any "free energy" into our system. Because of this one would expect the degree of regulation to become very high, and the battery to receive a high end-value setting in the filling season. This does not fit well with our results, where the battery seems to be emptied towards the end of the week in the filling season. It is therefore necessary to review how the degree of regulation is calculated in the procedure in EMPSW and how it handles zero inflow. In the drawdown season, the battery in Great Britain often has a partly charged battery at the end of the week, indicating that the end value setting is higher in this period. This could be a result of the end-value being set equal to the end-value of the other hydropower module in this period.

In general, the end value setting from the models should give the correct value of storing energy at the end of the week for the batteries. This should reflect the value of storing energy from one week to another and prevent the same behaviour at the end of every week. The challenge is related to how to calculate this value for batteries in the models that are based on an aggregate hydro model and use seasonal based hydro discharge heuristics to individualize water values from the aggregate system. For hydropower dominated areas, the aggregated water value calculation gives values that are better than no end value also for batteries. Since the batteries are small, they only have a small impact on the water value calculation and in the drawdown season the end values will be given by the hydro. In such areas, a "reasonable" end-value setting based on the aggregated water value calculation could also be realised for the filling season by adjusting the characteristics of the batteries to achieve a realistic degree of regulation in EMPSW.

For areas without hydropower the situation is different. It can be challenging to achieve a reasonable water value calculation on an aggregated level in EMPS for areas with batteries and without "normal" hydropower, among others because there is not inflow. A solution here could be to feed in an end value setting for these areas as input to EMPSW or set the end value for each week based on the power price of the according week. There also exist several other methods, but these often have longer computation time.

The FanSi model [4] that has many similarities with EMPSW model would also solve the weekly end value problem.

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ISSN:2535-5392
ISBN: 978-82-93602-16-3

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