

Research papers

How battery energy storage impacts grid congestion – An evaluation of the trade-offs between different battery control strategies

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ABSTRACT

To reduce greenhouse gas emissions, countries around the world are pursuing electrification policies. In residential areas, electrification will increase electricity supply and demand, which is expected to increase grid congestion at a faster rate than grids can be reinforced. Battery energy storage (BES) has the potential to reduce grid congestion and defer grid reinforcement, thus supporting the energy transition. But, BES could equally exacerbate grid congestion. This leads to the question: What are the trade-offs between different battery control strategies, considering battery performance and battery grid impacts? This paper addresses this question using the battery energy storage evaluation method (BESEM), which interlinks a BES model with an electricity grid model to simulate the interactions between these two systems. In this paper, the BESEM is applied to a case study, wherein the relative effects of different BES control strategies are compared. The results from this case study indicate that batteries can reduce grid congestion if they are passively controlled (i.e., constraining battery power) or actively controlled (i.e., overriding normal battery operations). Using batteries to reduce congestion was found to reduce the primary benefits provided by the batteries to the battery owners, but could increase secondary benefits. Further, passive battery controls were found to be nearly as effective as active battery controls at reducing grid congestion in certain situations. These findings indicate that the trade-offs between different battery control strategies are not always obvious, and should be evaluated using a method like the BESEM.

1. Introduction

To reduce greenhouse gas emissions, countries around the world are pursuing policies of electrification [1]. Electrification is the process of replacing technologies powered by fossil fuels with electric alternatives which are “typically more efficient, reducing energy demand, and have a growing impact on emissions [reductions] as electricity generation is decarbonised” [2].

In the residential sector, electrification is expected to lead to three main areas of development: 1) Increasing distributed generation (e.g., from rooftop photovoltaic (PV) panels); 2) Electrification of residential heating/cooling and cooking; 3) Transport electrification (e.g., electric vehicle (EV) charging) [1,3–5]. These developments are expected to increase both the quantity of electricity being transported on the electricity grid and the simultaneity (or coincidence factor) of power flows on the grid [4,6,7]. As a result, grid congestion is expected to become more common, forcing distribution system operators (DSOs) to limit

new grid connections [3,5,8,9]. Grid congestion occurs when there is insufficient grid capacity to transmit available power from one location to another [3]. Grid congestion can be quantified in terms of peak power flows on the grid and the number of hours per year when power flows exceed a certain percentage of grid capacity. Historically, DSOs have resolved grid congestion issues by reinforcing the grid, but rates of electrification are expected to outpace rates of grid reinforcement in the coming years, leading to delays in electrification projects [3,10]. Therefore, it is of interest to investigate solutions which can defer grid reinforcement so that electrification projects can proceed.

There are numerous proposals for deferring grid reinforcement, such as implementing flexible distributed generation, demand side management, power curtailment, local balancing market mechanisms and/or energy storage [11,12]. Battery energy storage (BES) is particularly well suited for grid reinforcement deferral due to its ability to reduce grid congestion by managing power flows locally on the grid. However, whether or not batteries will help reduce grid congestion in practice is

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largely dependent on the strategy used to control the battery [13–17].

1.1. Battery control strategies

BES can involve several stakeholders [18], but this paper focuses on two principle parties: The battery owner and the DSO. At the time of writing, European DSOs were not allowed to own or operate batteries directly [19,20]. Therefore, ‘battery owners’ were assumed to be individual households in this paper. From these stakeholders, battery owners are generally concerned with the performance of the battery (e.g., how much profit the battery can earn), while DSOs are generally concerned with the grid impacts of the battery (e.g., the battery causing increases or decreases in grid congestion) [18,21]. Currently, the battery owner chooses how their battery is controlled, with little to no input from the DSO.

Battery control strategies determine at which time and at which rate a battery will be charged and discharged [22]. While batteries are technically able to provide a variety grid services for the DSO [22–24], batteries tend to be controlled such that they provide the most benefit for the battery owner [25]. ‘Benefits’ can be measured in purely technical-economic terms, but there are also less tangible benefits associated with battery ownership, such as becoming more ‘energy independent’ (i.e., becoming less reliant on commercial companies and DSOs for electricity supply) and resolving environmental concerns (e.g., behaving in a way which is perceived as being pro-environmental in an effort to reduce the moral guilt experienced over climate change) [26–29]. In general, a battery owner will be more satisfied with their battery if they derive more benefit from it, however they themselves define these ‘benefits’ [26]. Therefore, it is not necessarily predictable how a battery owner will operate their battery.

This lack of predictability can be a particular concern for DSOs, who want to ensure that batteries do not exacerbate grid congestion or cause other problems on the grid. Such concerns are not unrealistic: studies have shown how certain battery control strategies might worsen local grid congestion, due to their relatively high operating power and potentially high (dis)charge simultaneity [14–16]. These concerns are evidenced by a 2023 regulation proposed in Germany which would allow DSOs to throttle battery (dis)charge power at critical moments [30]. Similarly, Dutch DSOs have stated the need to allow DSO control of household and community batteries to prevent batteries from exacerbating grid congestion [31].

There have been other proposals to address these potential issues by time-limiting consumer connection capacities or charging consumers in proportion to their peak electricity import/export to incentivise peak reductions [32]. For example, regulations in Flanders, Belgium intend to passively reduce electricity peaks by charging consumers based on their peak electricity consumption each month (i.e., capacity pricing) [33]. Similarly, some countries allow the DSO to actively control consumer assets as the need arises (e.g., French DSOs being allowed to turn off household water heaters for up to two hours per day) [34,35]. Allowing active control of batteries creates its own set of challenges, such as developing secure and reliable communications infrastructure, though research targeted towards remote control and cyber-resilience of EV charging (e.g., [36,37]) could likely be applied to BES systems.

While batteries may increase grid congestion, there is also the potential for batteries to reduce congestion, if controlled appropriately [13]. Such battery control strategies may come with a (opportunity) cost for the battery owner [13]. A study by Kalkbrenner [38] found that while consumers preferred owning and operating batteries for their own benefit, they were also willing to temporarily give up control of their batteries to benefit the electricity grid. Similarly, it has been proposed that battery owner participation in grid congestion management could be increased using financial incentives [39], though it is unclear how effective such methods would be in practice.

In other instances, it may be possible to restrict battery (dis)charge power such that batteries both reduce grid congestion and maintain

benefits for the battery owner. Restrictions could, e.g., be applied by imposing a hard limit on maximum battery (dis)charge power through regulation (i.e., passive control) or by overriding battery operations with an external control signal (i.e., active control). E.g., a study by Sheng Zhou et al. [15] found that limiting battery power to 27 % of rated capacity (i.e., reducing (dis)charge power from 3.2 kW to 0.86 kW) was an effective means of passively reducing peak power flows on the grid while having minimal impact on the battery owner's derived benefits. However, it is unclear if such findings hold true under different operating conditions.

In summary, much of the literature surrounding battery control strategies tends to focus on methods to address a specific problem, and does not consider the viability or wider implications of such a control scheme [15,40]. For example, Stecca et al. [40] note in a review of battery control papers that the majority assumed that the DSO would have some measure of control over battery systems. However, as noted above, there are many communication, security and regulatory challenges which must be overcome to implement DSO control of batteries in practice. Similarly, there is a societal question regarding how much control a DSO *should* have over household batteries (e.g., should DSOs be allowed to override normal battery operation at any time or only during emergencies?). To add to this, it remains unclear what the trade-offs are for the DSO and the battery owner if the DSO is allowed to override normal battery operations. Therefore, to inform public policy and BES regulations, it is of interest to estimate the impact batteries could have on the grid generally and on the performance of the battery itself (with respect to the battery owner's expectations), considering different battery control techniques.

This leads to the main research question of this paper: What are the trade-offs between different battery control strategies, considering battery performance and battery grid impacts? This paper answers this question by evaluating the relative costs and benefits resulting from different battery control strategies, considering different passive and active battery control mechanisms. In this paper, passive battery control refers to constraining the maximum rate of battery (dis)charge; Active battery control refers to the DSO overriding normal battery operations to use the battery for grid congestion management. Costs and benefits were evaluated in terms of key performance indicators (KPIs) relating to battery performance and battery grid impacts.

2. Methodology

The battery energy storage evaluation method (BESEM) was developed to analyse the relative grid impacts and performance of BES considering different scenarios. The BESEM is an elaboration of a method first proposed by van Someren et al. [41] and further elaborated upon by van Someren [42]; the referenced works demonstrate the generalisability and explainability of the BESEM. Fig. 1 shows the general structure of the BESEM.

At its core, the BESEM consists of two models: An electricity grid modelling tool and a BES model. The electricity grid modelling tool simulates power flows on the electricity grid based on electricity grid topology, load and generation profiles, BES location and BES (dis)charge profiles. The BES model simulates battery (dis)charge profiles based on the BES control strategy, BES characteristics, electricity market conditions and electricity grid conditions.

The two models are integrated to create a feedback loop between the two systems. This approach allows the two models to be run iteratively to minimize or maximize a given goal, e.g., minimizing grid congestion. Both models calculate various KPIs which are used to evaluate and compare the relative impacts of different scenarios.

The following sub-sections describe the various components of the BESEM. All data and models used in this paper are available at the 4TU research data repository [43].

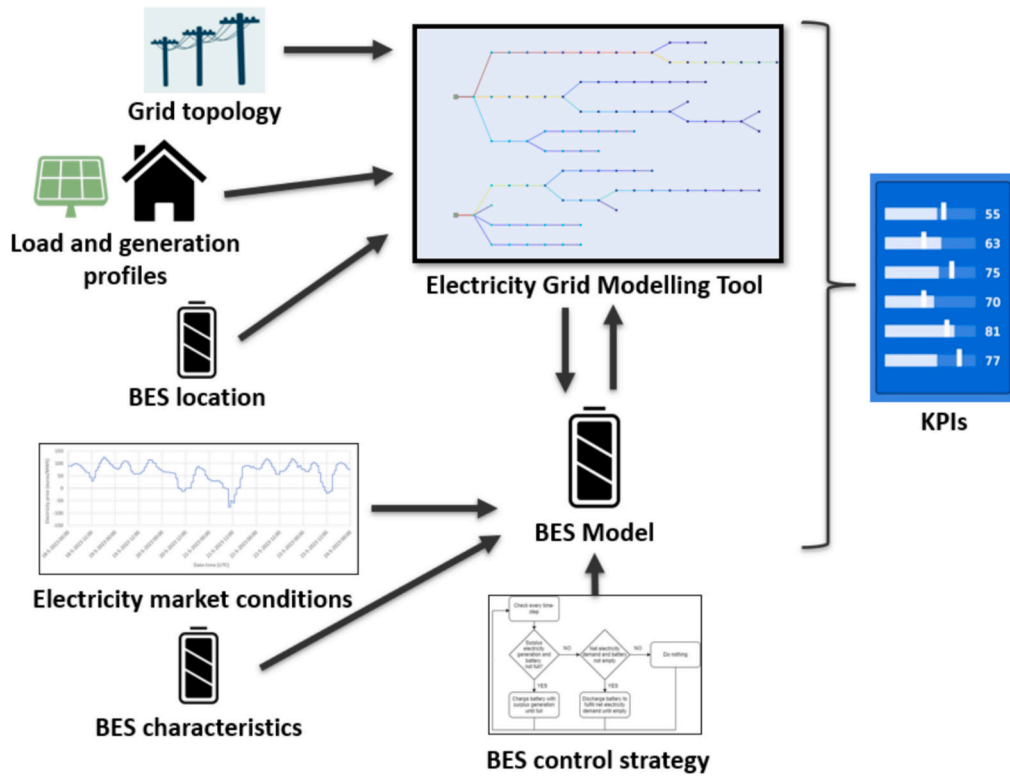


Fig. 1. Battery energy storage evaluation method (BESEM) concept, consisting of two interlinked models (Electricity Grid Modelling Tool and BES Model). Arrows indicate model inputs, with the link between the Electricity Grid Modelling Tool and the BES Model indicating iterative data flows between the two models; KPIs are calculated when the iteration is complete.

2.1. Electricity grid modelling tool

As described by van Someren et al. [41], electricity grid modelling can give important insights into the interactions between BES and the grid. Therefore, it is important to model the grid in a way which is representative of real-world behaviour. In this paper, Pandapower (version 2.14.1) was selected to model the electricity grid. Pandapower is an open-source software package developed by the Fraunhofer Society for the Advancement of Applied Research and has been validated using industry-standard software tools and a variety of case studies [44]. Pandapower uses the Newton-Raphson iterative method to solve power flow equations using first principles (i.e., Ohm's law, Kirchhoff's Laws and Joule's Law), and treating the grid as a steady-state system (i.e., grid transients and harmonics are not simulated) [45,46]. To improve model run-times and prevent non-convergence results, it is common to simulate grids in Pandapower as a single-phase system and to omit thermal effects [44]. These abstractions were applied in the BESEM.

The BESEM is able to operate at any time interval, but for the purposes of this paper, a 15-min time interval was chosen. Fifteen minutes is the common program unit in European electricity markets (i.e., the time in which supply-demand mismatch must be resolved) [47]. Further, 15 min is generally considered a sufficient time resolution to capture regular grid congestion issues, since grid infrastructure is generally able to withstand higher power flows over shorter time periods without suffering additional degradation or outages [48].

As a final output, Pandapower calculates voltage levels, current flows and power losses throughout the grid for each time step. These results can then be analysed to identify congestion issues and bottlenecks within the grid. These data can be used to inform battery control strategies (as described in section 2.2.2) and calculate grid impact KPIs, such as peak loads and hours of grid congestion. The primary electricity grid model inputs are described in the following sub-sections.

2.1.1. Grid topology

To create an electricity grid model, it is necessary to define the characteristics and interconnections of relevant grid components. Important input parameters include cable lengths and impedance values, transformer capacities and efficiencies, and the location of loads and generators. Pandapower treats the grid as a nodal network, where each node is an infinite bus which acts as a junction between cables, transformers and/or loads and generators.

2.1.2. Load and generation profiles

Each grid connection in the grid model requires a load and/or generation profile. Load and generation profiles may be representative of an existing situation, or may be designed to simulate future scenarios, as demonstrated by van Someren et al. [49]. E.g., to simulate the (future) impacts of EV charging on a section of electricity grid, EV charging load profiles can be added to various household connections on a grid model.

2.1.3. BES location

BES acts as a combined load/generator which can be charged or discharged (or remain inactive) at each time step. As described in van Someren et al. [41], the physical location of a BES system can affect the performance and grid impacts of the BES. Therefore, it can be of interest to compare different battery siting configurations to determine which configuration produces a preferable result (e.g., it may be possible to reduce installed battery capacity and/or reduce grid congestion by siting batteries closer to loads). The location of each BES system being simulated must be defined within the grid model, but may be changed between scenarios. The (dis)charge profile of each BES system is defined by the BES model, described below.

2.2. Battery energy storage model

The BES model creates a (dis)charge profile for each battery. The

battery's operation is determined by the battery control strategy, the battery's characteristics and (potentially) electricity market conditions and electricity grid conditions. This battery (dis)charge profile is fed into the electricity grid model to evaluate the impacts of BES on the electricity grid.

The BES model also calculates battery performance KPIs, such as electricity self-consumption rates, net electricity costs, and the number of cycles the battery undergoes. The BES model inputs are described in the following sub-sections.

2.2.1. Battery characteristics

A battery's characteristics determine the physical constraints under which the battery must operate. The primary characteristics affecting the battery's performance are the battery's available storage capacity, maximum (dis)charge power, roundtrip efficiency, and location on the grid [50–53]. The BESEM allows for additional details (such as battery degradation) to be modelled if desired, though these were not implemented in this paper.

2.2.2. BES control strategy

The BES control strategy determines at which times and which power the battery will charge and discharge. In the BESEM, different BES control strategies can be implemented to compare their relative effects on battery performance and battery grid impacts. In this paper, three BES control strategies were considered:

- Self-consumption maximisation (SCM), which had the primary goal of minimizing electricity imports and exports at the household level;
- Electricity cost minimization (ECM), which had the primary goal of minimizing net electricity costs at a household level by trading on the day-ahead electricity market; and
- DSO override (DO), which had the primary goal of reducing grid congestion by allowing the DSO to override normal battery operations.

In this paper, a SCM strategy was implemented by having the battery charge whenever the battery owner had net PV generation, and to discharge whenever the battery owner had net consumption. In either case, the battery would (dis)charge at the highest rate possible without causing additional electricity imports/exports. Electricity market prices were not taken into consideration for this strategy.

An ECM strategy was implemented by creating a daily battery (dis)charge schedule based on electricity day-ahead market prices. For each day, the lowest and highest hourly market prices were compared. If the difference between these prices was great enough to earn profits (e.g., to overcome the costs associated with battery inefficiencies and degradation), the battery was set to charge and discharge at these times, respectively, and the corresponding amount of battery capacity was reserved. If the battery had capacity remaining, this process was repeated for the second-lowest and second-highest hourly market prices, etc. If the price differential was insufficient to earn profits, the battery did not run. In this paper, the price differential required to cycle the battery was set at 0.025 €/kWh, which would be considered a relatively low minimum required yield [54], but this value was chosen to evaluate the largest potential grid impacts of an ECM-controlled battery. Further, the battery was limited to one full cycle per day. This constraint may lead to sub-optimal results [54], but it was implemented here to simplify battery control strategy implementation, and because it has been shown that additional daily cycling does not significantly increase battery profitability when considering the hourly, day-ahead electricity market [54]. This control strategy assumed an hourly flexible energy contract and an electricity net metering policy, wherein households only pay tariffs on their annual net electricity imports (as exists in The Netherlands at the time of writing).

DSO override (DO) is a proposed battery control strategy which allows a DSO to temporarily override normal battery operation to reduce

grid congestion. The DO strategy used (simulated) forecasts of grid power flows based on the results from the electricity grid modelling tool. These power flows were analysed to identify periods of grid congestion (i.e., times when power flows exceeded the congestion threshold). The battery was then scheduled to (dis)charge as needed to reduce grid power flows below the congestion threshold value. The battery was also scheduled to pre-(dis)charge as needed to ensure that sufficient battery capacity was available during the congestion periods. If the battery had insufficient capacity to prevent congestion, it would instead (dis)charge to reduce peak power flows on the grid as much as possible. This was done because the degree of grid congestion has traditionally been defined in terms of peak power flows on the grid – reducing peaks increases available grid capacity, from a DSO perspective.

Fig. 2 provides an illustrative example of how the different battery control strategies were expected to behave on a day in June with high generation peaks, resulting in negative electricity pricing in the midday (dashed purple line). All times are given in local time.

The SCM strategy (orange line) charged the battery as soon as there was net production (around 7:00, soon after sunrise). It then gradually discharged the battery when there was net consumption (from around 18:00 to 7:00 the following day). Note that the orange line shows relatively small battery charge and discharge powers. This occurred because household loads were small relative to PV generation in the summer months.

The ECM strategy (light blue line) charged the battery at 12:00 (when the lowest electricity prices occurred this day) and discharged the battery at 20:00 (when the highest electricity prices occurred this day).

The DO strategy (dark blue line) charged the battery to reduce the solar generation peak on the grid (flattening the dotted green line to the solid green line from 11:00 to 14:00). It also pre-discharged the battery (from 6:00 to 10:00) to ensure that sufficient battery capacity was available to reduce the generation peak.

Appendix A provides flowcharts describing the algorithms used to implement these battery control strategies.

2.2.3. Electricity market conditions

Electricity market conditions drive the behaviour of price-driven battery control strategies, such as the ECM strategy described above. To gain insight into how electricity market prices in particular can influence battery operations, annual price profiles for different years can be used as inputs in the BESEM.

Other electricity market conditions can include the magnitude of electricity feed-in tariffs, taxes, and electricity contract types (e.g., fixed pricing vs. hourly pricing), among others.

2.3. Key performance indicators

The BESEM presents results in terms of KPIs calculated by the electricity grid and BES models. KPIs can give insight into the relative costs and benefits of different scenarios. The KPIs used in this paper are described in Table 1, and are divided into two categories: 1) Battery performance KPIs (relevant for the battery owner); and 2) Grid impact KPIs (relevant for the DSO). The formulas used to calculate these KPIs are given in Appendix B.

3. Case study – NO GIZMOS project

In this paper, a case study was analysed to evaluate the trade-offs between different battery control strategies in a practical setting. NO GIZMOS¹ is a research project which aimed to establish a mechanism for DSOs to control household batteries [55].

¹ NetOptimalisatie voor Grootchalige Inpassing Zon- en windstroom Middels Opslag en Software, or Grid Optimization for Large-Scale Implementation of Solar and Wind Power Using Storage and Software



Fig. 2. Battery (dis)charge schedules for a day with high PV generation, resulting from the SCM (orange), ECM (light blue) and DO (dark blue) battery control strategies. Positive values represent battery charging and negative values represent battery discharging. For context, hourly electricity rates (purple) and MV grid power flows with (solid green line) and without (dotted green line) DO-controlled batteries are also shown. For the MV grid profile, positive values represent net consumption and negative values represent net production. Electricity market prices were multiplied by ten for clarity. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Summary of KPIs used in this paper.

KPI name	Unit	Definition
KPIs for battery performance		
Self-consumption energy	kWh	The difference between household PV generation and electricity exports
Net electricity profits	€	The net profits earned by during a given period, considering hourly pricing on day-ahead hourly electricity markets. It was possible for net electricity profits to be negative, which was interpreted as net costs.
Battery cycles	n/a	The number of full battery (dis)charge cycles incurred during a given period.
DO override cycles	cycles	The number of full battery cycles incurred by DSO override control (DO) during a given period.
KPIs for battery grid impacts		
Peak grid load	kW	The maximum net electricity load on a given section of the grid.
Peak grid generation	kW	The maximum net electricity generation on a given section of the grid.
Hours of load congestion	hr	The number of hours when power flows from net electricity loads exceeded a given threshold during a given period.
Hours of generation congestion	hr	The number of hours when power flows from net electricity generation exceeded a given threshold during a given period.

The NO GIZMOS case study was set in a rural village in the Netherlands which had a relatively high penetration of solar PV systems: approximately 230 kW of installed PV capacity divided among 155 houses, with an additional 600 kW of PV capacity in neighbouring sections of the MV grid. The regional MV grid had a relatively low rated capacity of 1 MW. For context, a local energy cooperative wished to install an additional solar park, but this was not possible due to grid congestion resulting from existing PV generation. Further, this section of the grid had a relatively low priority for reinforcement, so it was unlikely that the grid's capacity would be expanded in the near future. It was therefore of interest to study how household batteries might be used to reduce grid congestion and thereby allow a new solar park to be connected to the grid. However, it was not clear how different battery control strategies would affect grid congestion.

In the case study, nine household batteries were installed in the case study area. Using the BESEM, different battery control strategy scenarios were tested to evaluate their relative effects on battery performance and battery grid impacts (i.e., the KPIs defined in Table 1).

The scenarios studied in this paper were broken down into different categories, as depicted in Table 2. First, a reference case was simulated with no batteries. All other scenarios were compared to this reference case to determine their relative impacts. Then, batteries were run to maximize household self-consumption (SCM) or minimize household electricity costs (ECM). Within these, passive controls were applied by limiting (i.e., output bounding) battery (dis)charge power to 15 kW, 12

Table 2
Summary of case study scenarios.

	Reference case: No batteries			
	Self-consumption maximisation (SCM)		Electricity cost minimisation (ECM)	
Passive control	0.5–15 kW		0.5–15 kW	
Active DSO override (DO) control	Yes	No	Yes	No

kW, 8 kW, 4 kW, 2 kW, 1 kW or 0.5 kW. A range of battery powers was chosen to establish any trends associated with different KPIs, and to ensure that minima/maxima were not overlooked. Additionally, active DO control was either enabled or disabled for each scenario. With DO enabled, the normal SCM or ECM battery control strategies were overridden during instances of grid congestion (defined as grid power flows exceeding 700 kW in this case study). All these scenarios were simulated for a one-year period (01-04-2022 through 31-03-2023) to gain insight into the relative impacts of different battery control strategies under the same operating conditions.

The following naming convention was used to reference the different battery control strategies described in Table 1: primaryControlStrategy_DO. The ‘primary control strategy’ was either self-consumption maximisation (SCM) or electricity cost minimisation (ECM); If the primary control strategy name was followed by ‘DO’, then distribution override was enabled, otherwise it was not. The following sub-sections define the BESEM inputs and outputs which were used for the case study.

3.1. Electricity grid model and load/generation profiles

The electricity grid modelled in the case study was based on existing electricity grid infrastructure, and is illustrated in Fig. 3 below. As shown, the area being modelled consisted of the LV grid behind two MV-LV transformers (referred to as transformers A and B, indicated by grey squares), which acted as interconnections with an external MV grid. Both transformers had a rated capacity of 160 kW, which together could account for up to one third of the power flows on the regional MV grid. In this case, the LV grid was operated at 230 V and the MV grid was operated at 10 kV.

The LV cables extended from the transformers in a radial pattern. In Fig. 3, green dots indicate the locations of household connections/junctures, and battery symbols indicate the locations of household batteries. In total, there were 102 consumers connected to the two transformers, 70 on transformer A and 32 on transformer B. Each LV cable is labelled using the following format: Transformer.Cable#.Branch#. For the branches in particular, the 0th branch was considered the main cable, which was defined as the longest continuous cable segment. Other branches were numbered numerically based on their relative position from the transformers. Appendix C provides additional details of the individual cable sections, including their type, impedance, maximum rated current, length and number of consumer connections.

For the purposes of this case study, consumer load and generation profiles were also created. Generation profiles were estimated based on a survey of the number of PV panels and their orientations within the case study area. Using local solar irradiation data [56], the method proposed by Masters [57] was used to simulate household PV generation profiles.

Load profiles were estimated based on one year of power flow measurement data taken at the transformer level at a 15-min interval. The simulated PV generation profiles were subtracted from these measurement data to determine an average household load profile for each transformer. Due to a lack of details, all consumer connections behind each transformer used the same average load profile.

Fig. 4 illustrates the average consumer load profile (blue line) and generation profile (yellow line) for one year at a 15-min time interval. In these profiles, generation peaks tended to be relatively high but short

lasting, while load peaks tended to be relatively low but longer lasting. Further, average household consumption was estimated to be 3500 kWh/annum and average household generation was estimated to be 4000 kWh/annum.

3.2. Battery energy storage model

The batteries used in this case study had a nominal capacity of 10 kWh, of which 8 kWh was considered useable (to minimize battery degradation, the top 5 % and bottom 15 % of battery capacity was not used). The batteries had a maximum (dis)charge power of 15 kW and a roundtrip efficiency of 95 %.

In the case study, electricity price data were used from the Dutch day-ahead electricity market from 01/04/2023 to 31/03/2024 [58]. Notably, this period experienced negative pricing during the spring and summer months due to surplus PV generation. This was the same period during which transformer measurements were made to derive average household load profiles. These historical data were used to maintain any correlations between electricity market prices and electricity supply and demand, as described by Tanaka, et al. [59]. Regarding other market conditions, this paper assumed that households only paid tariffs on annual net electricity imports (i.e., net metering, as exists in the Netherlands at the time of writing) and that all consumers had hourly flexible energy contracts.

For the case study, the battery control strategies described in Table 2 (i.e., SCM, ECM, DO and the variations therein) were simulated using the BESEM.

3.3. Key performance indicators

The KPIs described in Table 1 were calculated as outputs from the BESEM for all scenarios. These KPIs were selected because they give a range of insights into battery performance and battery grid impacts, with the relevance of each KPI varying per scenario. The KPI values are presented in the Results section, and their implications are described in the Discussion section.

3.3.1. Sensitivity analysis

A sensitivity analysis was also performed to gain additional insight into how the KPIs addressed in this case study were impacted by changes to various model input parameters. In this paper, a summary of the most relevant sensitivity results are presented; a more thorough sensitivity analysis has been published by van Someren [42]. In this sensitivity analysis, the following model input parameters were varied, and their range of tested values are summarised in Table 3:

- 1) Battery capacity: The amount of electric energy which can be functionally stored in each battery.
- 2) Capacity pricing: With capacity pricing enabled, households were fined €0.20 for each quarter hour their net household import/export exceed 8 kW.
- 3) ECM cost threshold: The minimum profitability required for the ECM battery control strategy to cycle the battery. This parameter is representative of how degradation costs affect battery cycling frequency, although it is only pertinent to the ECM and ECM_DO scenarios.
- 4) Electricity price standard deviation (SD): Two different electricity price profiles were tested. These profiles were compared with one another based on the relative SD in prices over a year. The price profiles were: a) a typical annual price profile in the Netherlands from 01/04/2023 to 31/03/2024; and b) a volatile price profile in the Netherlands, from 01/04/2022 to 31/03/2023.
- 5) Electricity tariffs: Electricity tariffs were applied as a fixed percentage of the quarter hourly electricity costs/profits of individual households. E.g., with a 20 % tariff rate, all electricity imports cost 20 % more and all electricity exports earned 20 % less.

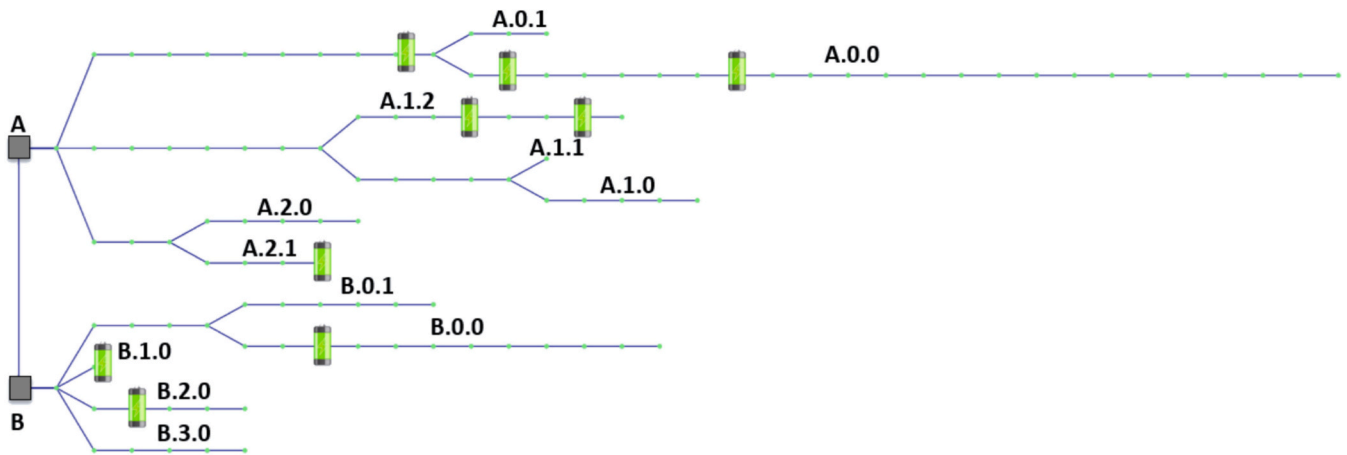


Fig. 3. Schematic overview of the modelled grid area, including household connections/junctures (green dots), battery locations (battery symbols) and transformer locations (A and B, represented by grey boxes). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

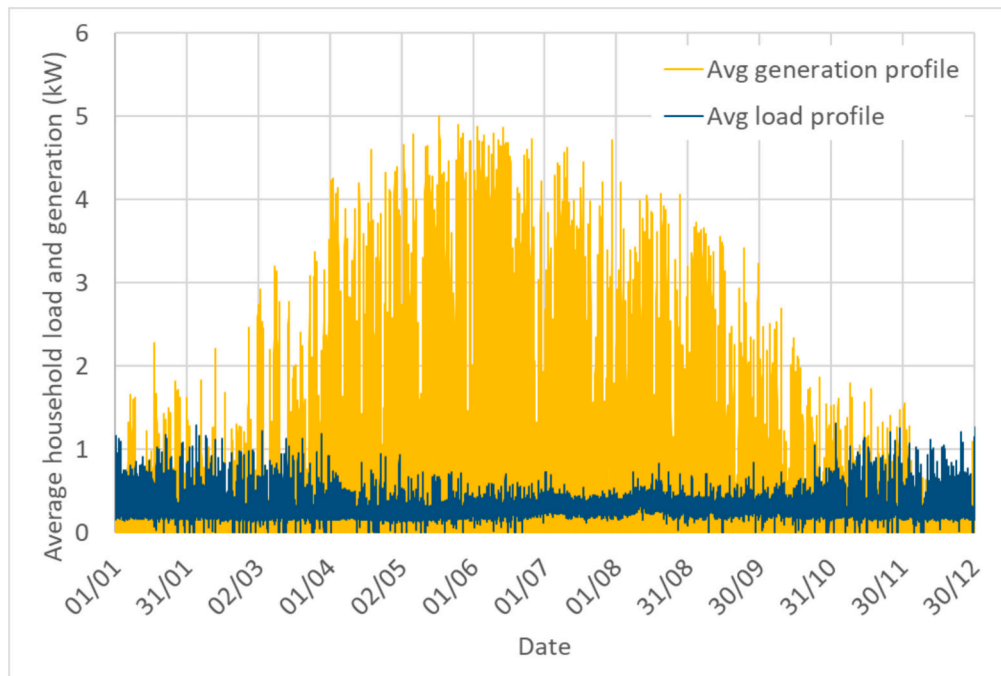


Fig. 4. Simulated average consumer load profile (blue line) and generation profile (orange line) for one year. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3

Summary of input parameters and the range of values tested. The reference case is indicated by the underlined values.

Input parameter name	Unit	Range of values tested
Battery capacity	kWh	<u>10</u> , 30
Capacity pricing	n/a	True, <u>False</u>
ECM cost threshold	€/kWh	<u>0.05</u> , 0.20
Electricity price standard deviation	n/a	<u>45.3</u> , 132.3
Electricity tariffs	%	<u>10</u> , 40
Grid congestion threshold	kW	<u>700</u> , 1000
Generation scaling	%	<u>100</u> , 200
Load scaling	%	<u>100</u> , 200

- 6) Grid congestion threshold: The level of MV grid net power flows (i.e., grid loading) above which the DO battery control strategy is enabled.
- 7) Generation scaling: PV generation scaling was applied to all household generation profiles in the case study area. This was meant to represent growth in household electricity generation.
- 8) Load scaling: Load scaling was applied to all household load profiles in the case study area. This was meant to be roughly representative of growth in household electricity consumption.

Sensitivity results were calculated in terms of the relative change in a KPI's value compared to a reference scenario. In this case, the reference scenario used the SCM_DO battery control strategy with the underlined values in Table 3 as model input values. The SCM_DO control strategy was chosen as a common reference to allow comparisons between different battery control strategies, and to prevent divide-by-zero issues. Input values were varied independently to determine their individual

impacts on the various KPIs.

For each KPI and for each varied input value, eq. 1 was used to calculate KPI sensitivity, where KPI_{new} is the KPI value resulting from the new model input value (i.e., the non-underlined value in Table 3), KPI_{ref} is the KPI value resulting from the original model input value (i.e., the underlined value in Table 3), KPI_{SCM_DO} is the KPI value resulting from the original model input value using the SCM_DO battery control strategy, $Input_{new}$ is the non-underlined input value in Table 3, and $Input_{ref}$ is the underlined input value in Table 3.

$$Sensitivity_{KPI} = ABS \left(\frac{\left(\frac{[KPI_{new} - KPI_{SCM_DO}]}{KPI_{SCM_DO}} \right) - \left(\frac{[KPI_{ref} - KPI_{SCM_DO}]}{KPI_{SCM_DO}} \right)}{\left(\frac{Input_{new} - Input_{ref}}{Input_{ref}} \right)} \right) \quad (1)$$

Relative KPI sensitivity assessment.

4. Results

The results from the case study are described below, where the relative impacts of the different battery control strategies on the various

KPIs are highlighted. The KPIs are broadly separated into two categories: those relating to battery performance and those relating to the grid impacts of batteries. Further, a sensitivity analysis of the results is provided to illustrate how model results can fluctuate when certain input parameters are varied.

4.1. Battery performance

Fig. 5 shows the results for the four KPIs relating to individual battery performance (y-axis), for different battery control strategies and variable maximum battery (dis)charge power (x-axis). In the figures, '0' battery power indicates the reference case, where no batteries were present. The four graphs in Fig. 5 are described in the following subsections.

4.1.1. (a) Self-consumption energy

Self-consumption is defined as the difference between household PV generation and electricity exports. An increase in self-consumption indicates that a household consumed more of their own PV generated electricity. A decrease in self-consumption indicates that a household

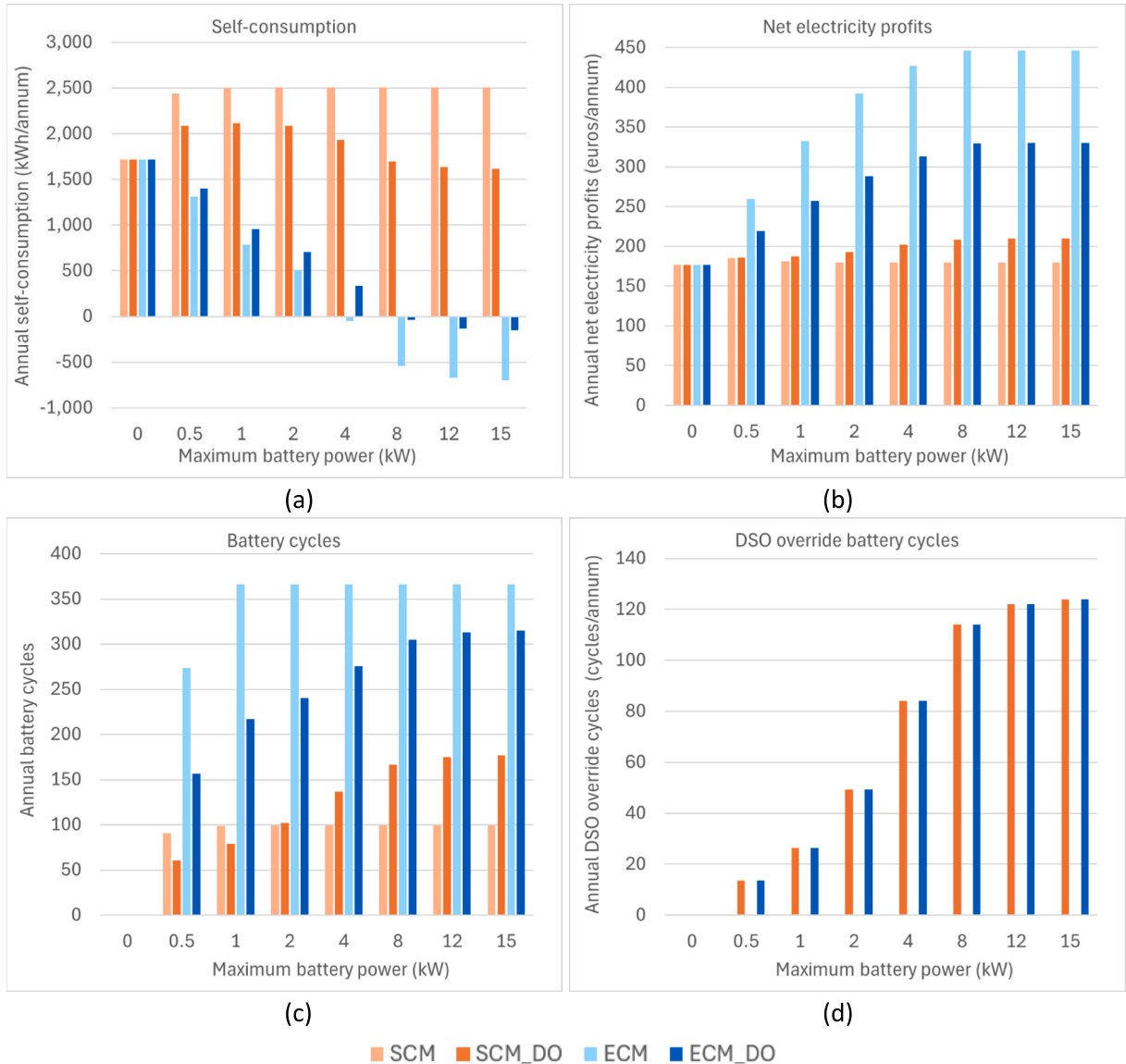


Fig. 5. Battery performance KPIs for different battery control strategies and maximum battery (dis)charge powers, including: (a) annual self-consumption energy (MWh); (b) annual net electricity profits (euros); (c) annual battery cycles; and (d) annual battery cycles used for DO.

exported additional electricity to the grid, with negative values indicating that electricity exports (in part, from batteries) exceeded PV generation.

Fig. 5(a) shows the variations in self-consumption achieved by the batteries for the different battery control strategy scenarios. Of the four control strategies, the SCM control strategy (light orange) achieved the highest amount of self-consumption. The amount of self-consumption energy was consistent for all maximum battery (dis)charge powers except 0.5–1 kW, which was slightly reduced due to the inability, at times, for the battery to fully charge from surplus generation.

Employing the SCM_DO control strategy (dark orange) resulted in decreasing self-consumption as maximum (dis)charge power increased. The reason for this was that, in this case study, surplus generation was the primary driver of grid congestion. As a result, the normal SCM control algorithm was overridden to charge the battery from the grid during moments of peak generation (i.e., importing surplus generation from neighbouring houses), and pre-discharge the battery in preparation for these moments (i.e., increasing grid exports). This had the net effect of reducing household self-consumption. At lower maximum battery (dis)charge powers, the impacts of DO on self-consumption were more limited because there were often household-level loads and generations of a similar power magnitude to offset (i.e., self-consume).

The ECM control strategy (light blue) tended to reduce self-consumption as maximum battery (dis)charge power increased. This was expected because this battery control strategy prioritised trading electricity, which increased electricity imports and exports, thereby reducing household self-consumption.

With the ECM_DO control strategy (dark blue), self-consumption decreased continuously as maximum battery (dis)charge power increased. However, unlike the ECM strategy, DO responded to local grid congestion, and thereby offset local supply and demand to a larger extent. This had the net effect of increasing self-consumption energy relative to the ECM control strategy.

4.1.2. (b) Net electricity profits

Net electricity profits are defined as the amount of profits a household could earn by buying and selling electricity on the hourly day-ahead market, assuming net metering.

Fig. 5(b) shows how battery profitability varied across the scenarios. For the SCM strategy, battery profitability was relatively consistent at different maximum battery (dis)charge powers, with a slight improvement at lower powers. This was the result of the battery (dis)charging too early at higher battery powers, thus missing the times with optimal pricing. At lower battery powers, the battery (dis)charge period was spread over more time, thus allowing the battery to (partially) (dis)charge during periods with a higher net profitability.

Interestingly, the SCM_DO strategy earned more profits than the SCM strategy in some scenarios. This was due to the SCM_DO control strategy increasing the number of battery cycles per year by up to 1.8 times compared to SCM control, as shown in Fig. 5(c). The increase in battery profits for the SCM_DO strategy therefore reflected this increase in additional energy trading at (generally) profitable market price differentials. However, the profits earned per battery cycle were on average lower for the SCM_DO strategy than for the SCM strategy.

The ECM strategy showed increasing battery profitability at higher (dis)charge powers, because the battery was better able to exploit the optimal times for electricity trading. Notably, because the electricity market operated on an hourly basis, and the batteries had a useable capacity of 8 kWh, the potential profits the battery could earn were the same if the maximum battery (dis)charge power was 8 kW, 12 kW or 15 kW (i.e., the battery could fully cycle during the optimal electricity price hour in all cases).

The ECM_DO strategy led to a decrease in annual profits of 15 % to 27 % relative to the ECM strategy, depending on maximum battery (dis)charge power. This can be explained by the fact that local congestion did not always coincide with electricity market rates (see 4.2.1). In practice,

this meant that the ECM_DO control strategy was often charging and discharging the batteries at non-optimal times, from a profitability perspective.

4.1.3. (c) Battery cycles

Battery cycles are defined as the number of full battery charge/discharge cycles incurred over one year. Fig. 5(c) shows the number of annual battery cycles for each scenario. Notably, the SCM control strategy was relatively consistent for all maximum battery (dis)charge powers and relatively low compared to other control strategies. As noted in section 4.1.1, the SCM control strategy was primarily constrained by household electricity demand and did not discharge enough electricity to fully cycle the battery each day.

In contrast, the ECM control strategy achieved the highest number of battery cycles, and quickly plateaued at one cycle per day from a maximum battery (dis)charge power of 1 kW onwards. This was possible because the profit threshold required to cycle the battery was relatively low in this case study, at €0.025/kWh. Daily fluctuations on the day-ahead electricity market consistently exceeded this threshold, thus allowing the battery to be fully cycled on a near-daily basis to earn profits.

The SCM_DO and ECM_DO control strategies cycled the battery more frequently as maximum battery (dis)charge power increased. This can be explained by the grid impacts of the batteries, described in the following sub-section, but in brief: As maximum battery (dis)charge power was increased, the DO strategy used the increasingly available battery power to reduce congestion to a larger extent, and thereby cycled the battery more frequently. Notably, ECM_DO reduced battery cycles relative to the ECM strategy because when the algorithm overrode normal battery operations, it did not necessarily need the full battery capacity to reduce grid congestion.² In contrast, the SCM_DO strategy increased battery cycling relative to the SCM strategy because the DO strategy required relatively more battery capacity to reduce grid congestion, and therefore cycled the battery more frequently.

4.1.4. (d) DO override cycles

DSO override battery cycles are defined as the number of full battery cycles incurred by the DSO to manage grid congestion. This KPI provides insight into how much electric energy the DSO required to reduce grid congestion.

Fig. 5(d) shows how an increasing number of battery cycles (i.e., increasing battery capacity) was used for DO control at higher battery (dis)charge powers. This was caused by the relatively high peak power flows on the grid (reaching 831 kW for net load and 1102 kW for net generation compared to the 700 kW congestion threshold). As a result, the DO control strategies often needed to use as much battery capacity as possible to reduce peak power flows on the grid as much as possible.

4.2. Battery grid impacts

While battery performance KPIs are an important metric for the battery owner, it is also of interest to the DSO to evaluate the grid impacts of batteries. Fig. 6 shows the four KPIs related to the grid impacts of batteries (y-axis) for different battery control strategies and maximum battery (dis)charge powers (x-axis). As with Fig. 5, '0' battery power indicates the reference case, with no batteries present. The four graphs in Fig. 6 are described in the following sub-sections.

4.2.1. (a) – (b) peak grid load and peak grid generation

Peak grid load and peak grid generation are defined as the maximum power flow on the grid resulting from net loads and net (distributed)

² In this case study, battery capacity was fully allocated to either ECM or DO control on a daily basis; capacity was not shared between different battery control strategies on a single day.

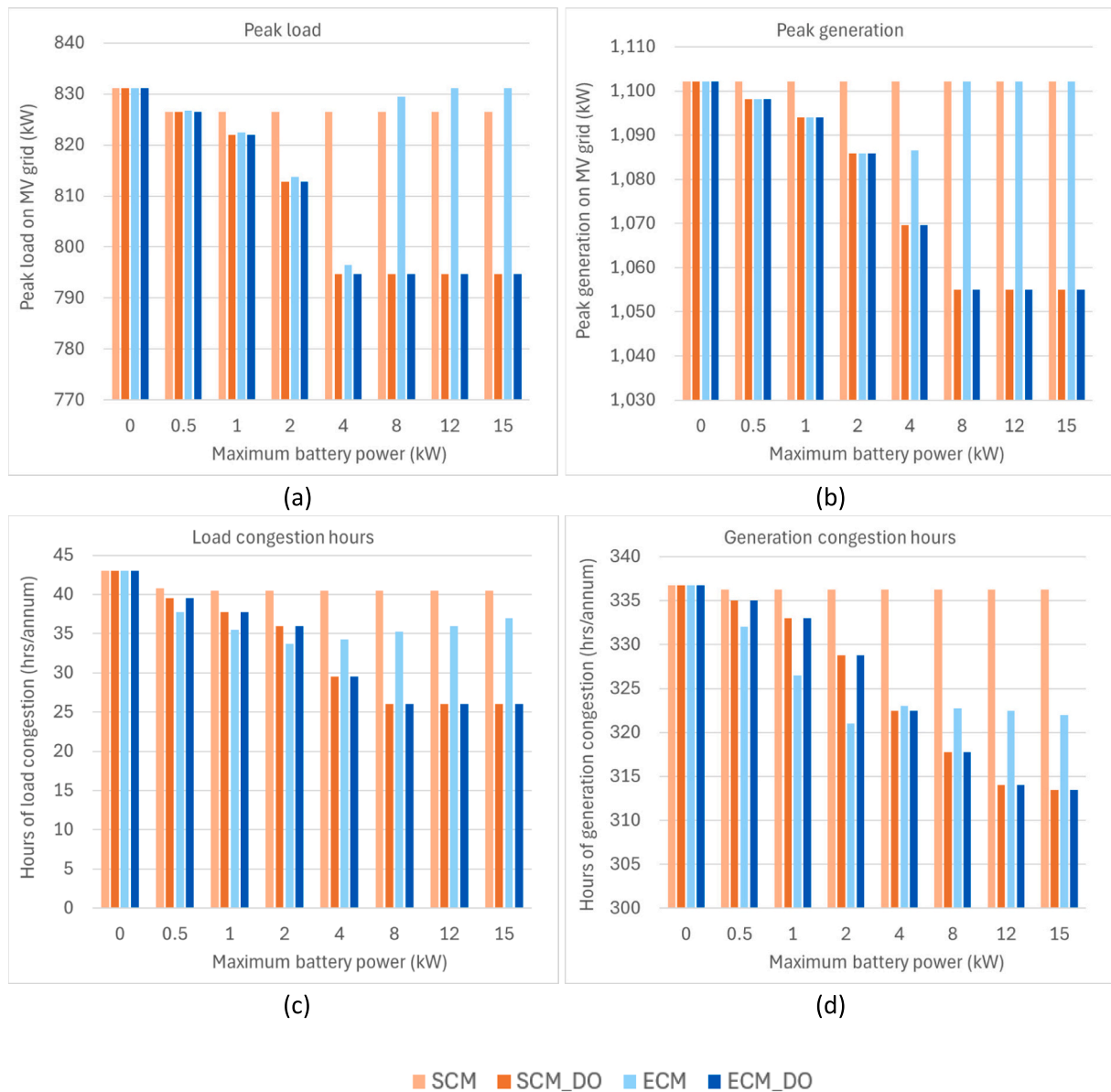


Fig. 6. Grid impact KPIs for different battery control strategies and maximum battery (dis)charge powers, including: (a) peak grid load on the MV grid (MW); (b) peak grid generation on the MV grid (MW); (c) hours of load congestion per year; and (d) hours of generation congestion per year.

generation, respectively. This KPI is indicative of grid congestion magnitude. Figs. 6(a) and 6(b) show the peak power flows on the MV grid resulting from net loads and net generations, respectively.

Notably, the SCM strategy (light orange) had a limited impact on peak loads and no impact on peak generations. Although increasing self-consumption can help reduce peak power flows in theory, in this case study the SCM-controlled batteries had no incentive to (dis)charge during times with peak load/generation due to net metering. As a result, the batteries were often fully (dis)charged before peaks occurred, and therefore could not reduce peaks on the grid.

For the ECM control strategy (light blue), a mismatch between local supply and demand with national electricity market prices frequently led to battery capacity being unavailable during (local) peak load/generation periods. This mismatch occurred because, in the project area, the majority of rooftop PV panels (including the nearby solar farms, which were installed on barn roofs) had a south-west orientation, whereas nationally PV panels tended to have a more southerly orientation on average. As a result, local peak generation from PV tended to be delayed relative to national peak PV generation and the

corresponding market dips. However, when maximum battery (dis)charge power was constrained to 0.5–2 kW, the batteries were forced to (dis)charge over a longer period of time. As a result, the ECM strategy was more likely to (dis)charge during times with peak power flows on the grid, which incidentally led to reductions in peak grid loads and peak grid generations by up to 4.2 % and 1.5 %, respectively.

In contrast, the SCM_DO (dark orange) and ECM_DO (dark blue) control strategies were able to reduce the peak grid load by up to 4.4 % and the peak grid generation by up to 4.3 %. The higher the available battery (dis)charge power, the more effectively the DO strategies were at reducing peak power flows on the grid, until a plateau was reached. This plateau was the result of the limited battery capacity available, which made it impossible for the batteries to reduce peak power flows on the grid beyond a certain point.

The fact that the DO-controlled batteries could more effectively reduce peak generations than peak loads had to do with the characteristics of these power flow profiles in this case study. In general, peak generations in this case study tended to be relatively high but short lasting, whereas peak loads tended to be relatively low but long lasting

(as noted in section 3.1). The effect of this was that less energy was required to offset peak generations than peak loads. As a result, the batteries, with their limited available capacity, were better able to reduce peak generations than peak loads in this case study.

4.2.2. (c) – (d) hours of load congestion and hours of generation congestion

Congestion hours are defined as the number of hours per year when grid power flows exceeded 700 kW, with power flows being attributed to either net loads or net (distributed) generation. This KPI is indicative grid congestion frequency. The hours of annual congestion from net loads and net generations are shown in Figs. 6(c) and 6(d), respectively. As with the peak power flows, the SCM strategy had a limited impact on grid congestion hours. Interestingly, the ECM strategy was able to reduce the hours of load congestion when maximum battery (dis)charge power was constrained. This resulted from the fact that constraining battery (dis)charge power prolonged the duration of battery (dis)charging, making it more likely that the battery would operate during periods of grid congestion, thereby reducing grid congestion incidentally.

Notably, the ECM_DO and SCM_DO strategies showed less reductions in grid congestion hours than the ECM strategy in some scenarios. This occurred because the DO strategies prioritised reductions of peak power flows over reductions of grid congestion hours. Because peak power flows could be relatively large compared to the available battery capacity, minimizing these peaks did not necessarily reduce these power flows below the grid congestion threshold.

It should be noted that none of the battery control strategies led to an increase in grid peak power flows or grid congestion hours in this case study.

4.3. Sensitivity analysis

Tables 4 through 7 illustrate the relative change in KPI values compared to a reference scenario for the different battery control strategies. It should be noted that in the following tables it is not possible to directly compare sensitivities between KPIs, so each column should be interpreted separately. However, since all results were calculated using a common reference case, it is possible to compare sensitivity results between different battery control strategies (i.e., between the same columns on different tables).

5. Discussion

In this paper, the BESEM was used to evaluate the effects of different battery control strategies (considering both active and passive controls) on battery performance and battery grid impacts. The following subsections discuss the implications of the of the case study results.

5.1. Results analysis – Battery performance

The results from the case study indicated that actively controlling

household batteries for grid congestion management tended to come at a (opportunity) cost for the battery owner. The more that DO was used, the greater the reduction in the primary battery performance KPIs (i.e., self-consumption energy for SCM and net electricity profits for ECM). However, active DO control could also be seen increase secondary battery performance KPIs (i.e., net electricity profits for SCM and self-consumption energy for ECM). Therefore, while DO did lead to an opportunity cost for the battery owner's primary goal (e.g., maximising battery profitability), it could also be seen to benefit the battery owner in other ways (e.g., reducing electricity imports/exports).

In addition, passively controlling household batteries by constraining maximum battery (dis)charge power was found to be more situational on its impact the battery owner's primary goal (i.e., increasing self-consumption energy for SCM or net electricity profits for ECM). For the SCM control strategy, limiting maximum battery (dis)charge power had almost no impact on the rates of self-consumption, and in fact increased battery profitability to a limited extent. In contrast, the profitability of the ECM strategy was reduced by up to 30 % when limiting maximum battery (dis)charge power.

These results indicate that it is important to consider several battery performance KPIs when using household batteries for grid congestion management, and to design incentives/compensations for battery owners accordingly.

5.2. Results analysis – Battery grid impacts

This case study found that the SCM and (unconstrained) ECM control strategies had limited impact on peak power flows on the grid, reducing them by less than 1 %. In contrast, using passive battery control to constrain the (dis)charge power of ECM-controlled batteries led to peak power flow reductions of up to 4.2 %. Using active DO battery control reduced peak power flows by up to 4.4 %.

These results indicate that passive and active battery controls can have comparable effectiveness, depending on the battery control strategy used and the wider circumstances where the battery is implemented. Since passive battery controls are easier to implement in practice (e.g., no communication infrastructure is needed to affect battery control), these results support an argument to passively control household batteries through regulation. However, the case study results also indicate that passively controlling batteries may have limited to no beneficial grid impacts if the batteries are controlled in a different way (e.g., as with the SCM-controlled batteries). It is therefore important to consider how incentives/regulations will drive battery behaviour before determining how passive battery controls might help reduce grid congestion.

Relatedly, while the battery control strategies studied in this paper had no adverse grid impacts, other battery control strategies (e.g., aggregating household batteries to act on grid balancing markets) may lead to increases in local grid congestion. Such impacts could theoretically be limited through passive battery controls. However, active DO controls may be harmful in such circumstances as batteries are controlled for cross purposes. Such alternate battery control strategies

Table 4

SCM battery control strategy - Relative impact of input parameters (left column) on KPIs (top row). White shaded cells represent little to no impact; Yellow cells represent middling impact; Green cells represent large impact.

KPI / Input Parameter	Self- consumption	Electricity profits	Battery cycles	Override cycles	Peak load	Peak generation	Load congestion hours	Generation congestion hours
Battery capacity	1 %	0 %	18 %	0 %	0 %	0 %	0 %	0 %
Capacity pricing	0 %	0 %	0 %	0 %	0 %	0 %	0 %	1 %
ECM cost threshold	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
Electricity price SD	0 %	125 %	0 %	0 %	0 %	0 %	0 %	0 %
Electricity tariffs	0 %	11 %	0 %	0 %	0 %	0 %	0 %	0 %
Grid congestion threshold	0 %	0 %	0 %	0 %	0 %	0 %	363 %	244 %
Generation scaling	17 %	194 %	13 %	0 %	0 %	39 %	15 %	119 %
Load scaling	109 %	153 %	25 %	0 %	7 %	5 %	226 %	18 %

Table 5

ECM battery control strategy - Relative impact of input parameters (left column) on KPIs (top row). White shaded cells represent little to no impact; Yellow cells represent middling impact; Green cells represent large impact.

KPI / Input Parameter	Self-consumption	Electricity profits	Battery cycles	Override cycles	Peak load	Peak generation	Load congestion hours	Generation congestion hours
Battery capacity	156 %	118 %	0 %	0 %	2 %	1 %	15 %	5 %
Capacity pricing	125 %	622 %	0 %	0 %	0 %	0 %	1 %	1 %
ECM cost threshold	52 %	53 %	130 %	0 %	0 %	0 %	16 %	2 %
Electricity price SD	73 %	72 %	0 %	0 %	0 %	0 %	0 %	0 %
Electricity tariffs	0 %	32 %	0 %	0 %	0 %	0 %	0 %	0 %
Grid congestion threshold	0 %	0 %	0 %	0 %	0 %	0 %	332 %	235 %
Generation scaling	136 %	105 %	0 %	0 %	0 %	39 %	13 %	119 %
Load scaling	208 %	335 %	0 %	0 %	6 %	5 %	218 %	19 %

Table 6

SCM DO battery control strategy - Relative impact of input parameters (left column) on KPIs (top row). White shaded cells represent little to no impact; Yellow cells represent middling impact; Green cells represent large impact.

KPI / Input Parameter	Self-consumption	Electricity profits	Battery cycles	Override cycles	Peak load	Peak generation	Load congestion hours	Generation congestion hours
Battery capacity	31 %	16 %	18 %	11 %	4 %	2 %	15 %	4 %
Capacity pricing	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
ECM cost threshold	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
Electricity price SD	0 %	126 %	0 %	0 %	1 %	0 %	0 %	0 %
Electricity tariffs	0 %	15 %	0 %	0 %	0 %	0 %	0 %	0 %
Grid congestion threshold	121 %	29 %	94 %	212 %	5 %	0 %	233 %	232 %
Generation scaling	14 %	205 %	34 %	41 %	0 %	39 %	13 %	126 %
Load scaling	86 %	213 %	10 %	5 %	2 %	5 %	224 %	18 %

Table 7

ECM DO battery control strategy - Relative impact of input parameters (left column) on KPIs (top row). White shaded cells represent little to no impact; Yellow cells represent middling impact; Green cells represent large impact.

KPI / Input Parameter	Self-consumption	Electricity profits	Battery cycles	Override cycles	Peak load	Peak generation	Load congestion hours	Generation congestion hours
Battery capacity	117 %	70 %	8 %	11 %	4 %	2 %	15 %	4 %
Capacity pricing	73 %	1221 %	94 %	0 %	0 %	0 %	0 %	0 %
ECM cost threshold	30 %	31 %	76 %	0 %	0 %	0 %	2 %	0 %
Electricity price SD	41 %	98 %	53 %	0 %	1 %	0 %	0 %	0 %
Electricity tariffs	0 %	26 %	0 %	0 %	0 %	0 %	0 %	0 %
Grid congestion threshold	62 %	108 %	51 %	212 %	7 %	0 %	233 %	232 %
Generation scaling	85 %	156 %	70 %	41 %	0 %	39 %	13 %	122 %
Load scaling	153 %	296 %	91 %	5 %	2 %	5 %	224 %	18 %

The above tables illustrate how certain KPIs are particularly sensitive to changes in certain model input parameters. Notably, the battery control strategy itself is the main determinant of how sensitive a given KPI is to changes in a given parameter. These results are elaborated upon in the discussion.

require additional investigation to gain insight into how they might affect battery-grid interactions.

5.3. Sensitivity analysis

Considering the SCM control strategy (Table 4), it can be seen that the most impactful input parameters are load and generation scaling. This can be explained by the fact that self-consumption is highly dependent on the ratio of electricity consumption and production at a household level. Changing this ratio will affect how the battery performs, which consequently affects other KPIs (e.g., if electricity generation is higher, the battery will cycle more frequently). The impacts of the grid congestion threshold, in this case, are merely incidental, since raising the threshold by definition reduces the amount of grid congestion which occurs. It is notable that increasing the volatility of electricity prices also provided increased profitability for this control strategy. Again, this is largely incidental (volatile electricity prices still largely follow household supply and demand profiles), but it is notable how a SCM-controlled battery can still benefit from increasing price volatility. Finally, it is notable that increasing battery capacity did not significantly

impact any KPIs, particularly self-consumption. This can be explained by the fact that battery capacities were already well calibrated to matching household supply and demand, and that insufficient demand (in the summer months) and supply (in the winter months) are the main limiting factors on improving household self-consumption.

Regarding the ECM control strategy, it is again observed that load and generation scaling have a large impact on most of the KPIs. This can be attributed to more surplus electricity to trade (for increased generation) and more household demand to offset, thus reducing electricity imports and exports (for increased load, particularly in summer months). Notably, battery profitability was shown to be relatively sensitive to changes in remuneration schemes: Adding capacity pricing, increasing the ECM cost threshold (i.e., increasing degradation costs), increasing electricity tariffs and increasing electricity market volatility all affected electricity profits to a relatively high degree. This is notable, since it illustrates how susceptible the business case for ECM-controlled batteries is to changes in public policy and regulations, as well as changes in technological factors such as battery lifetime. These results indicate the need for clear and consistent policy needed to promote battery ownership.

Looking at the SCM_DO and ECM_DO control strategies, the grid congestion threshold was observed to have a relatively large impact on most of the KPIs. This is logical, since this parameter determines how frequently DO is enabled. As above, load and generation scaling also have a relatively large impact on several KPIs, in part because they directly result in higher peaks on the grid, and in part because they affect the SCM and ECM portions of the control strategies, respectively, as described above. Finally, the profitability of ECM_DO in particular was found to be sensitive to changes in nearly all input parameters. As with the ECM control strategy, this is indicative of how unpredictable the business case can be for an ECM-controlled battery.

6. Conclusion

This paper analysed the trade-offs of different battery control strategies considering their effects on battery performance and battery grid impacts. This analysis was carried out by applying the BESEM to a case study of a rural village in The Netherlands. The BESEM combines an electricity grid model with a BES model to simulate the interactions between these two systems. In the case study, KPIs relating to battery performance (relevant for the battery owner) and battery grid impacts (relevant for the DSO) were compared for a number of different battery control scenarios.

In general, the results from this case study indicated that household batteries can help reduce grid congestion if active DO control and (situationally) passive controls constraining battery (dis)charge power are applied to BES. Using batteries to help reduce grid congestion tended to provide fewer primary benefits to the battery owners (e.g., reducing self-consumption energy for a SCM-controlled battery), but could increase secondary benefits (e.g., increasing net electricity profits for a SCM-controlled battery). Further, in certain situations, passive battery controls were found to be nearly as effective as active battery controls at reducing grid congestion.

In summary, BES has the technical potential to help reduce grid congestion and defer grid reinforcement if the BES is appropriately controlled. The costs and benefits for different stakeholders resulting from different battery control strategies are not immediately obvious, and changes in certain input parameters (e.g., introducing capacity pricing) can significantly impact battery performance and battery grid impacts, as indicated in the sensitivity analysis in this paper. Therefore, different battery use cases should be evaluated on a case-by-case basis using a methodology such as the BESEM. Using such a methodology to evaluate practical battery applications can help inform policy and regulations surrounding BES and its integration in the public electricity grid. For follow-up research, the authors suggest that the BESEM could be used to test the impacts of more sophisticated battery control strategies (e.g., deploying household batteries on electricity balancing markets) and/or different financial incentives (e.g. capacity based contracts or time-of-use tariffs). Further, the scope of the BESEM could be expanded to include other congestion management strategies, such as PV curtailment or EV charge control. Finally, societal aspects, such as battery owner

acceptance of external active or passive battery controls should be investigated.

Abbreviations

BES	Battery energy storage
BESEM	Battery energy storage evaluation method
DO	DSO override
DSO	Distribution system operator
ECM	Electricity cost minimisation
EV	Electric vehicle
KPI	Key performance indicator
LV	Low voltage
MV	Medium voltage
PV	Photovoltaic
SCM	Self-consumption maximisation
SOC	State of charge

CRediT authorship contribution statement

Christian Van Someren: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Martien Visser:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Han Slootweg:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: C. van Someren reports financial support was provided by Netherlands Enterprise Agency. H. Slootweg reports a relationship with Enexis BV that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. – Battery control strategy flowcharts

This appendix provides flowcharts describing the Self-consumption maximisation (Fig. 7), Electricity cost minimization (Fig. 8) and DSO override (Fig. 9) battery control strategies. Table 8 lists the variables used in the flowcharts. Variable names are denoted in italics.

Table 8

List of variables used in flowcharts.

Variable name	Unit	Definition
<i>i</i>	n/a	The current timestep.
<i>n</i>	n/a	The total number of timesteps being simulated.
<i>day</i>	n/a	The current day.

(continued on next page)

Table 8 (continued)

Variable name	Unit	Definition
<i>m</i>	n/a	The total number of days being simulated.
<i>availableCapacity</i>	kWh	The amount of battery storage capacity not currently reserved for battery (dis)charge.
<i>batteryCapacity</i>	kWh	The maximum amount of useable battery storage capacity.
<i>capacityRequirements</i>	kWh	The amount of battery capacity required to prevent <i>MV_powerFlows</i> from exceeding <i>congestionThreshold</i> .
<i>congestionThreshold</i>	kW	The power flow on the MV grid above which the grid is considered congested.
<i>costThreshold</i>	€/kWh	The minimum price differential required to charge and discharge the battery.
<i>kWh_overload</i>	kWh	The amount of energy transport which surpasses the <i>congestionThreshold</i> . This value counts only the greater of energy transport resulting from net loads or net generations.
<i>MV_powerFlows</i>	kW	An array with the (forecasted) power flows on the MV grid for the upcoming day. Positive values represent net loads and negative values represent net generations.
<i>P_battery</i>	kW	An array showing the planned battery (dis)charge power at a given time.
<i>P_battery_max</i>	kW	The maximum rate of (dis)charge for the battery.
<i>prices</i>	€/kWh	An array of day-ahead electricity market price for the current day.
<i>t_high</i>	n/a	The unreserved timeslot with the highest electricity price.
<i>t_low</i>	n/a	The unreserved timeslot with the lowest electricity price.
<i>t_overload</i>	hours	The amount of time during which energy transport which surpasses the <i>congestionThreshold</i> . This value counts only the greater of energy transport resulting from net loads or net generations.
<i>timeStep</i>	Hours	The length of a timestep.

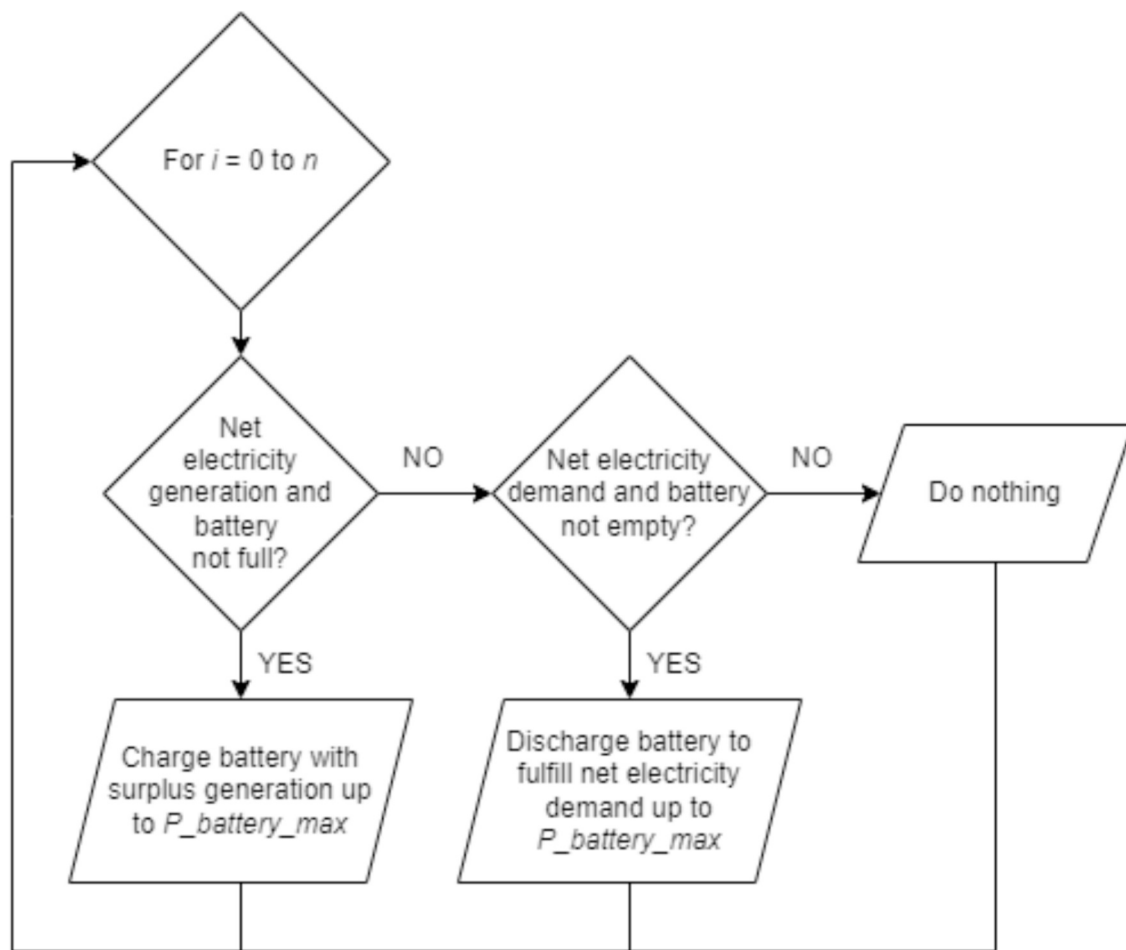


Fig. 7. Self-consumption maximisation (SCM) battery control algorithm.

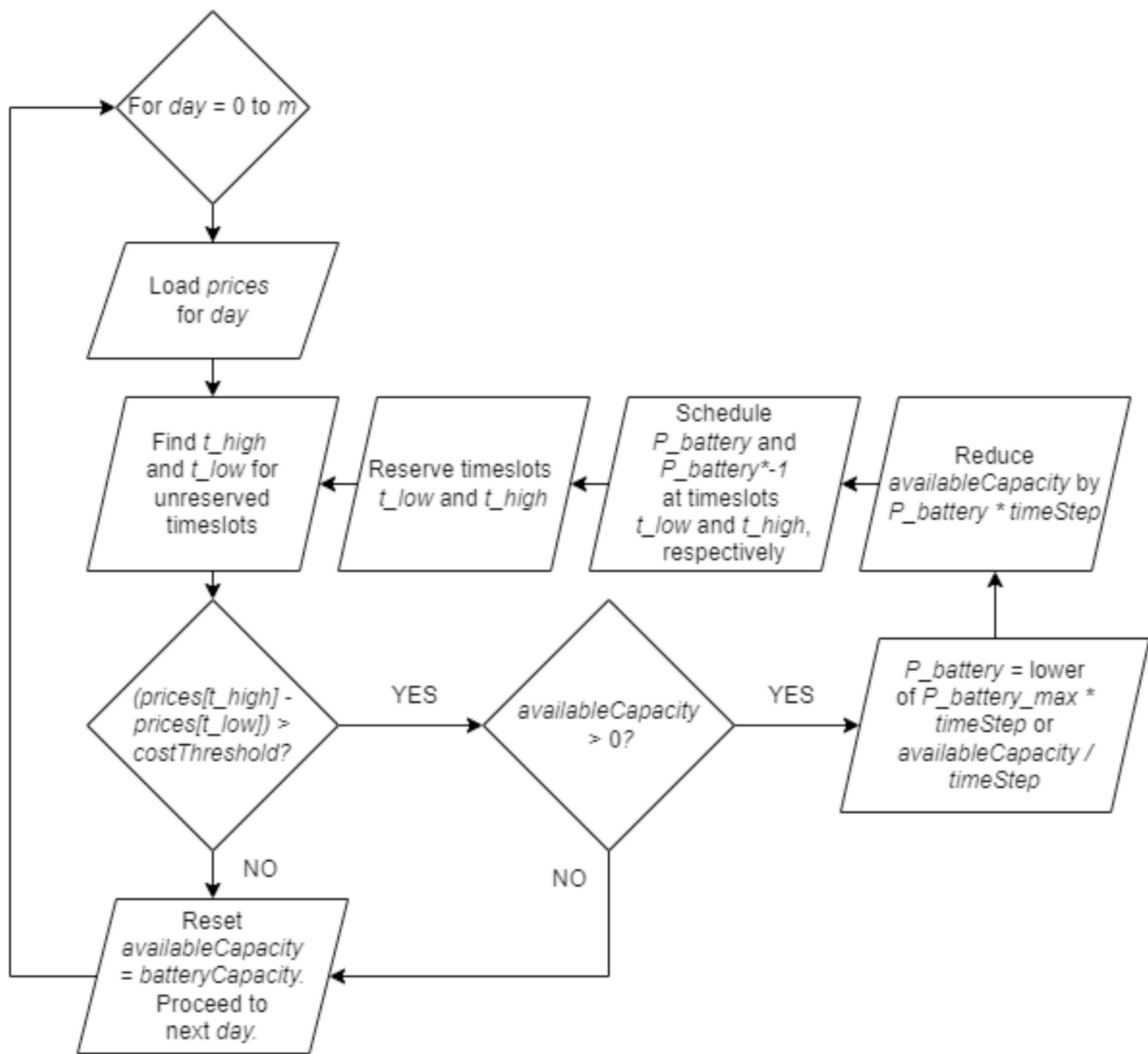


Fig. 8. Electricity cost minimisation (ECM) battery control algorithm.

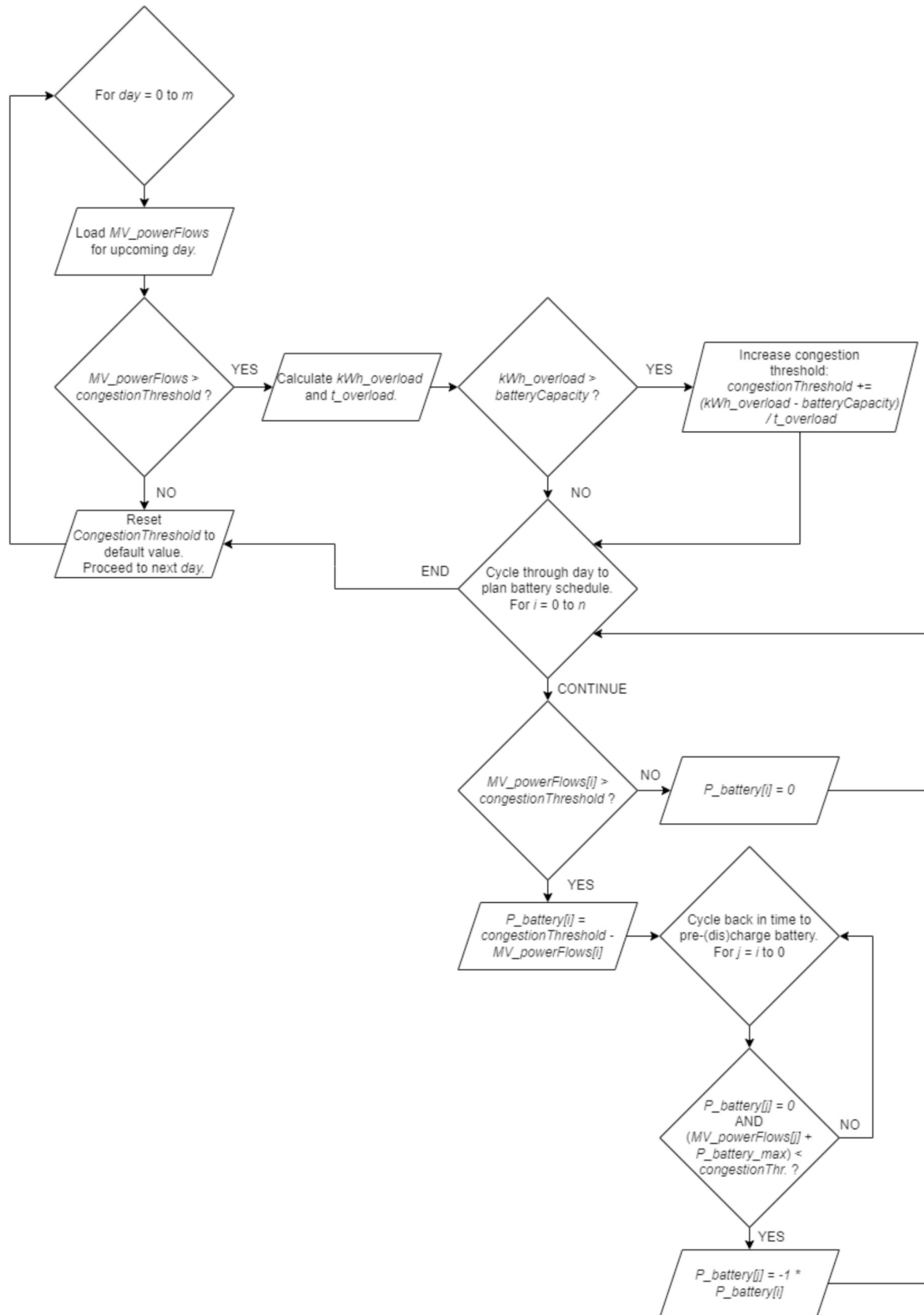


Fig. 9. DSO override (DO) battery control algorithm.

Appendix B. – Key performance indicator equations

The following appendix lists the equations used to calculate the various KPIs defined in this paper. Table 9 defines all the variables used in the following equations.

Table 9

List of KPI equation variables.

Variable name	Unit	Definition
i	n/a	The current timestep.
n	n/a	The total number of timesteps.
x	n/a	The grid location identifier for a given consumer/generator/battery.
$batteryCapacity_x$	kWh	The (usable) storage capacity of the battery at location x .
$batteryCycles_x$	n/a	The number of full (dis)charge cycles incurred on the battery at location x .
$batteryLosses_x$	kWh	The total energy loss incurred from (dis)charging the battery at location x .
$chargeEfficiency$	%	The efficiency losses when the battery is charged.
$costsOverrides_x$	€	The costs of importing/exporting electricity from the battery at location x resulting from Distribution Override battery control.
$dischargeEfficiency$	%	The efficiency losses when the battery is discharged.
$DO_schedule_{x,i}$	kW	The battery (dis)charge power resulting from Distribution Override battery control for the battery at location x and timestep i . Positive values represent charging and negative values represent discharging.
$energyOverrides_x$	kWh	The amount of electric energy cycled through the battery at location x resulting from Distribution Override battery control.
$generationCongestion$	Hours	The number of hours where the MV grid exceeds the congestion threshold due to net generations.
$generationThreshold$	kW	The net power flow on the MV grid below which the grid is considered congested.
$loadCongestion$	Hours	The number of hours where the MV grid exceeds the congestion threshold due to net loads.
$loadThreshold$	kW	The net power flow on the MV grid above which the grid is considered congested.
$MV_netPowerFlow_i$	kW	The net power flow on the MV grid at timestep i .
$MV_peakGeneration$	kW	The peak generation on the MV grid.
$MV_peakLoad$	kW	The peak load on the MV grid.
$netProfits_x$	€	The amount of money earned (or lost) buying and selling on the day-ahead electricity market at location x .
$nOverrides_x$	hours	The number of hours which DO actively controlled the battery at location x .
$P_battery_{x,i}$	kW	The battery (dis)charge power at location x , timestep i . Positive values represent battery charging and negative values represent battery discharging.
$P_generation_{x,i}$	kW	The generation at location x , timestep i .
$P_load_{x,i}$	kW	The load at location x , timestep i .
$P_netPowerFlow_{x,i}$	kW	The net power flow resulting from loads, generations and/or battery (dis)charge at grid location x , timestep i . Positive values were used to represent loads and battery charging; negative values were used to represent generations and battery discharging.
$prices_i$	€/kWh	The day-ahead electricity market price for timestep i .
$selfConsumption_x$	kWh	The amount of electricity generated at location x which is also consumed at location x .
$timeStep$	Hours	The length of a timestep.

Equation B.1 - Net grid load

$$P_{netPowerFlow_{x,i}} = P_{load_{x,i}} - P_{generation_{x,i}} + P_{battery_{x,i}} \quad (B.1)$$

Equation B.2 - Self-consumption

Note that only values of $P_netPowerFlow$ which are less than zero (i.e., net exports) are summed.

$$selfConsumption_x = \sum_{i=0}^n \begin{cases} (P_{generation_{x,i}} + P_{netPowerFlow_{x,i}}) \times timeStep, & P_{netPowerFlow_{x,i}} < 0 \\ P_{generation_{x,i}}, & otherwise \end{cases} \quad (B.2)$$

Equation B.3 - Net electricity profits

$$netProfits_x = \sum_{i=0}^n -1 \times P_{netPowerFlow_{x,i}} \times prices_i \times timeStep \quad (B.3)$$

Equation B.4 - Battery capacity requirements

Note: The batteryCapacity value was continually summed for each subsequent timeStep until the over-/underloading condition is no longer true. In this way, the battery capacity required to offset a prolonged period of grid overloading/congestion could be calculated.

if $MV_netPowerFlow_i > loadThreshold$:

while $\frac{MV_peakLoad_i}{loadThreshold} < 0.0001$:

$$batteryCapacity_x^1 = batteryCapacity_x^0 \times \frac{MV_{peakLoad_i}}{loadThreshold} \quad (B.4a)$$

if $MV_{netPowerFlow_i} < generationThreshold$:

while $\frac{MV_{peakGeneration_i}}{generationThreshold} < 0.0001$:

$$batteryCapacity_x^1 = batteryCapacity_x^0 \times \frac{MV_{peakGeneration_i}}{generationThreshold} \quad (B.4b)$$

Equation B.5 - Battery cycles

Note: Battery cycles were calculated based on the total amount of energy discharged from the battery (i.e., $P_{battery_{x,i}} < 0$), thus excluding (dis) charge losses.

$$batteryCycles_x = \sum_{i=0}^n \begin{cases} \frac{P_{battery_{x,i}} \times timeStep}{batteryCapacity_x}, & P_{battery_{x,i}} < 0 \\ 0, & otherwise \end{cases} \quad (B.5)$$

Equation B.6 - Battery losses

Note: Charge and discharge losses are only summed when battery power is greater than or less than zero, respectively.

$$batteryLosses_x = \sum_{i=0}^n \begin{cases} P_{battery_{x,i}} \times chargeEfficiency \times timeStep, & P_{battery_{x,i}} > 0 \\ -P_{battery_{x,i}} \times dischargeEfficiency \times timeStep, & P_{battery_{x,i}} < 0 \end{cases} \quad (B.6)$$

Equation B.7 - DSO overrides

$$nOverrides_x = \sum_{i=0}^n \begin{cases} timeStep, & DO_schedule_{x,i} \neq 0 \\ 0, & otherwise \end{cases} \quad (B.7a)$$

$$energyOverrides_x = \sum_{i=0}^n \begin{cases} abs(DO_schedule_{x,i}) \times timeStep, & DO_schedule_{x,i} < 0 \\ 0, & otherwise \end{cases} \quad (B.7b)$$

$$costsOverrides_x = \sum_{i=0}^n \begin{cases} DO_schedule_{x,i} \times prices_i \times timeStep, & DO_schedule_{x,i} \neq 0 \\ 0, & otherwise \end{cases} \quad (B.7c)$$

Equation B.8 - Peak power flows

$$MV_{peakLoad} = \text{Max}(MV_{netPowerFlow_i} \in MV_{netPowerFlow}) \quad (B.8a)$$

$$MV_{peakGeneration} = \text{Min}(MV_{netPowerFlow_i} \in MV_{netPowerFlow}) \quad (B.8b)$$

Equation B.9 - Hours of congestion

$$loadCongestion = \sum_{i=0}^n \begin{cases} timeStep, & MV_{netPowerFlow_i} > loadThreshold \\ 0, & otherwise \end{cases} \quad (B.9a)$$

$$generationCongestion = \sum_{i=0}^n \begin{cases} timeStep, & MV_{netPowerFlow_i} < generationThreshold \\ 0, & otherwise \end{cases} \quad (B.9b)$$

Appendix C. – Cable properties for the case study

Table 10

Cable properties for the case study.

Cable Section	Cable Type	Cable impedance (Ω/km)	Maximum current (A)	Cable length (m)	Number of households
A.0.0	NAYY 4x120mm2 SE Aluminum	0.225 + j0.080	242	458	33
A.0.1	NAYY 4x50mm2 SE Aluminum	0.642 + j0.083	142	147	3
A.1.0	NAYY 4x95mm2 SE Aluminum	0.642 + j0.083	230	924	14
A.1.1	NAYY 4x95mm2 SE Aluminum	0.208 + j0.080	230	187	1
A.1.2	NAYY 4x95mm2 SE Aluminum	0.478 + j0.080	230	104	8
A.2.0	NAYY 4x95mm2 SE Aluminum	0.478 + j0.080	230	294	7
A.2.1	NAYY 4x95mm2 SE Aluminum	0.478 + j0.080	230	117	4
B.0.0	NAYY 4x95mm2 SE Aluminum	0.208 + j0.080	230	408	15
B.0.1	NAYY 4x95mm2 SE Aluminum	0.642 + j0.083	230	130	6
B.1.0	NAYY 4x150mm2 SE Aluminum	0.208 + j0.080	270	151	1*
B.2.0	NAYY 4x95mm2 SE Aluminum	0.478 + j0.080	230	332	5
B.3.0	NAYY 4x95mm2 SE Aluminum	0.642 + j0.083	230	440	5

* Note: Connection B.1.0 was connected to an active dairy farm, hence the relatively large cable capacity for a single connection.

Data availability

My data is freely available at a research databank and is referenced in the article.

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