Department of Mechanical Engineering

FACULTY OF ENGINEERING AND DESIGN

FINAL YEAR MEng PROJECT REPORT

Impact of battery optimisation on achieving cost-effective carbon net-zero for microgrids

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Abstract

To combat climate change, unprecedented levels of variable renewable energy growth must be facilitated by increased sustainable flexibility in the power grid. This project aimed to minimise the carbon footprint and cost of grid electricity usage by a community centre microgrid in Bristol, UK. A day-ahead half-hourly multiobjective linear programming optimiser was developed in Python to simulate and optimise the operation of a commercial-scale lithium-ion battery and smart hot water tanks, to aid in the microgrid's strive to operate at a fully net-zero carbon footprint. The optimisation model used historical data of real-time pricing, average regional emissions intensity, and energy flows, such as its rooftop PV and water heaters, within the microgrid. To improve the battery's lifetime cost and carbon effectiveness, its design and operational parameters were iteratively optimised for high savings and low degradation using a lifecycle approach to assessing its impacts. When optimised, the battery's estimated carbon payback and lifetime were found to be 4.7 and 16.5 years, respectively. By cycling approximately half of its capacity every day, the modelled 80kW/160kWh battery achieved a total annual cost and carbon footprint savings of 16.7% and 15.1%, respectively, for the microgrid. Pure cost-only optimisation was found to result in nearly 5% savings in annual greenhouse gas emissions of the system. Although it was estimated to be environmentally and economically feasible, a thorough analysis of its net present value would be required to find whether it would be a profitable investment for the community microgrid.

Contents

Nomenclature

Abbreviation/Acronym	Definition
API	Application Programming Interface
APX	Amsterdam Power Exchange - day-ahead price
BMS	Battery Management System
CCGT	Closed-Cycle Gas Turbine
CHP	Combined Heat and Power generator
CO2eq	Carbon Dioxide Equivalent of global warming potential
CSV	Comma-separated values file
DHW	Domestic Hot Water
DoD	Depth-of-Discharge
DSM	Demand Side Management
DSR	Demand Side Response
ECC	Easton Community Centre
FEC	Full Equivalent Cycle of a battery
EV	Electric Vehicle
FFR	Firm Frequency Response service to the grid
GA	Genetic Algorithm
GHG	Greenhouse Gas
GSHP	Ground Source Heat Pump
HH	Half-hourly
HWT	Hot Water Tank
LCA	Life-cycle Assessment
LFP	Lithium Iron Phosphate battery chemistry type
LP	Linear Programming
MEF	Marginal Emissions Factor
MILP	Mixed-Integer Linear Programming
MH	Meta-Heuristic optimisation
NCA	Lithium Nickel-Cobalt-Aluminium Oxide battery
NMC	Lithium Nickel-Manganese-Cobalt Oxide battery
OCGT	Open-Cycle Gas Turbine
OF	Objective Function
OSCE	Owen Square Community Energy
PSO	Particle Swarm Optimisation algorithm
PV	Solar Photovoltaic panels

RES	Renewable Energy Sources
SOC	State-of-Charge
SP	Supply Period
SSP	System Supply Price of electricity on the spot market
V1, V2, V3, V4	Versions of the Optimiser
WPD	Western Power Distribution

1 Introduction

1.1 Background

1.1.1 Energy

Climate change is a critical threat to humanity and the global civilisation must act immediately on its mitigation and adaptation. Otherwise, as the most recent IPCC report reminds, humans "will miss a brief and rapidly closing window of opportunity to secure a liveable and sustainable future for all" (Hans-O. Pörtner et al., 2022). As the global energy sector is responsible for 34% of all anthropogenic GHG emissions and together with transport and buildings, it accounts for over half of them, a major transformation of these, increasingly interconnected sectors, needs to be at the forefront of the global climate action to achieve the crucial target of net-zero GHG emissions by 2050 (Jim Skea et al., 2022).

At the same time, the recent attempted Russian invasion of Ukraine has put Europe's dependence on energy imports from undemocratic countries into the spotlight, strengthening the need to become self-reliant in energy needs (The Economist, 2022). Subsequent fossil gas price hikes have had landslide effects across energy markets in Europe, putting millions of people at risk of energy poverty (C40 Cities, 2022).

The core problem of these two crises, the excessive reliance on fossil fuels, therefore, needs to be stopped. With plummeting costs of technologies, decarbonisation now can be achieved swiftly by electrification, renewable generation, and energy efficiency. As Figure 1 shows, necessary renewable growth is already underway (Jim Skea et al., 2022).

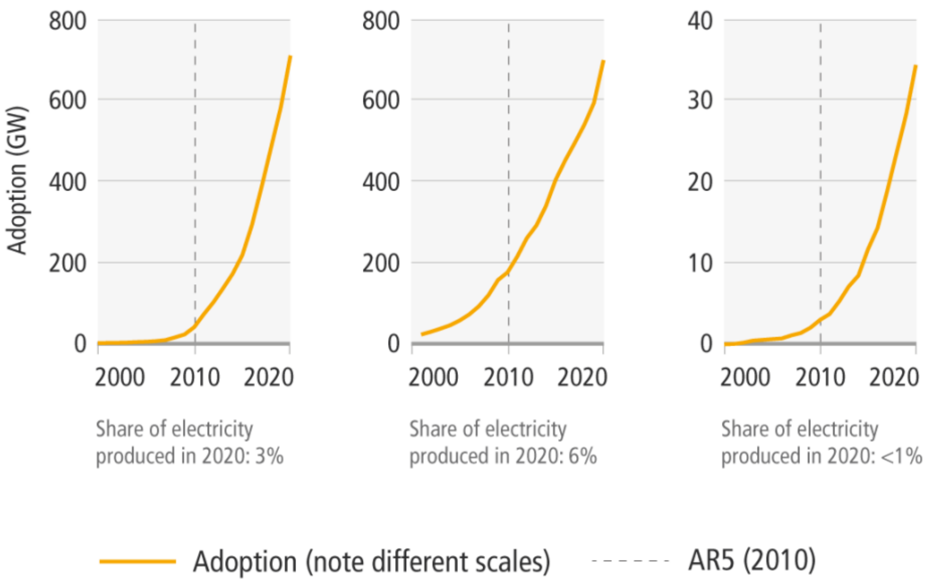


Figure 1: Recent unprecedently rapid global growth of variable renewable energy sources. Adapted from IPCC's report (Jim Skea et al., 2022)

1.1.2 Flexibility

A major issue with the combination of heat, transportation and industry electrification progressing during the same time as the fast growth of intermittent renewable electricity generators is the mismatch between available power supply and demand at any given time. Increased electricity demand in certain times could need multiple times the available low-carbon generation, while just a few hours later, a solar or wind power generation may need to be curtailed due to the lack of electricity usage, making these crucial technologies economically less feasible. An example of such a situation is shown in Figure 2 with excess solar followed by a gap between the load and generation.

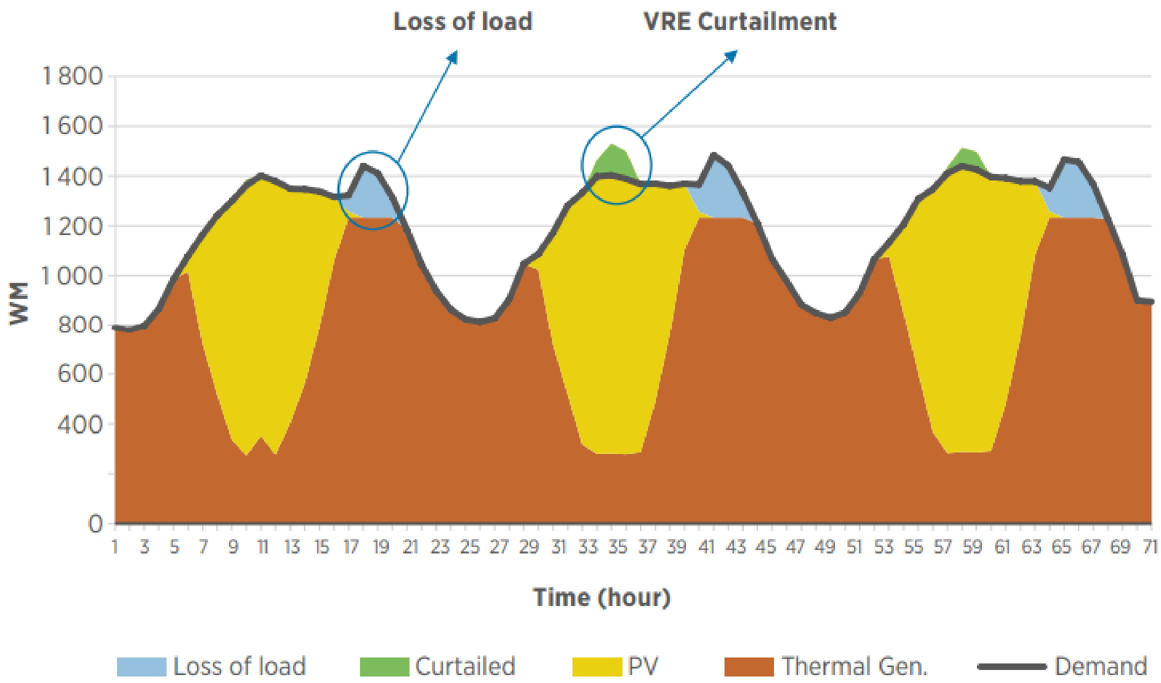


Figure 2: Renewable overgeneration leading to curtailment followed by a power supply shortage. From (IRENA, 2018)

Power grids in such situations need flexibility. In conventional networks, sufficient flexibility can be achieved by balancing and regulatory authorities. However, for national grids to accommodate as much variable renewable capacity as needed, more flexibility actors need to get engaged in different flexibility services. These can include dispatchable generation, such as reservoir hydro plants, demand-side management, or electricity storage (IRENA, 2018).

As dispatchable generation is typically provided by fossil gas peaking power plants and their low-carbon alternatives are often limited by geography, the main growth in grid flexibility should be firstly sought in smart solutions of energy storage systems and demand response (The CCC, 2020). They should be preferably installed close to distributed renewable generation and users of their power. This way, transport losses are limited, and less infrastructure is needed. Prosumers, connected to the grid, consuming, and producing power at different times, may play this role, often in the form of microgrids with multiple energy users and producers connected to a smartly managed local grid, which is connected to the distribution grid via one point of coupling (Lantero, 2014).

Microgrids may have different objectives and operational strategies. Some of them want to maximise self-consumption of their on-site generated renewable power, participate in ancillary services, or they may want to purchase power at a variable tariff and shift their consumption to lower-price times. With more and more countries and companies pledging to achieve net-zero carbon targets, a new optimisation goal emerged, carbon optimisation (Krishnan et al., 2022). By using electricity at lower-carbon times, microgrids can pay for fewer carbon offsets to achieve their targets. For example, Google shifts non-urgent tasks of its data centres to times and regions of high renewable generation, aiming to run them net-zero 24/7 by 2030 (Pinchai, 2020).

1.1.3 Grid emissions

The UK National grid has achieved an extraordinary reduction in its carbon intensity, mainly by nearly completed coal phase-out, rapid wind production growth, and implementation of an emissions trading scheme for large power plants. In 2010, the average carbon intensity was over 500 gCO2eq/kWh, whereas, in 2021, it fell under 150 (BEIS, 2021a). British Government has set a new ambitious target for a continuation of this trend, a fully carbon-free National grid by 2035 (HM Government, 2021). As shown in Figure 3, achieving this target together with the decarbonisation of other sectors will require greatly increased generation from variable RES and thus, grid flexibility.

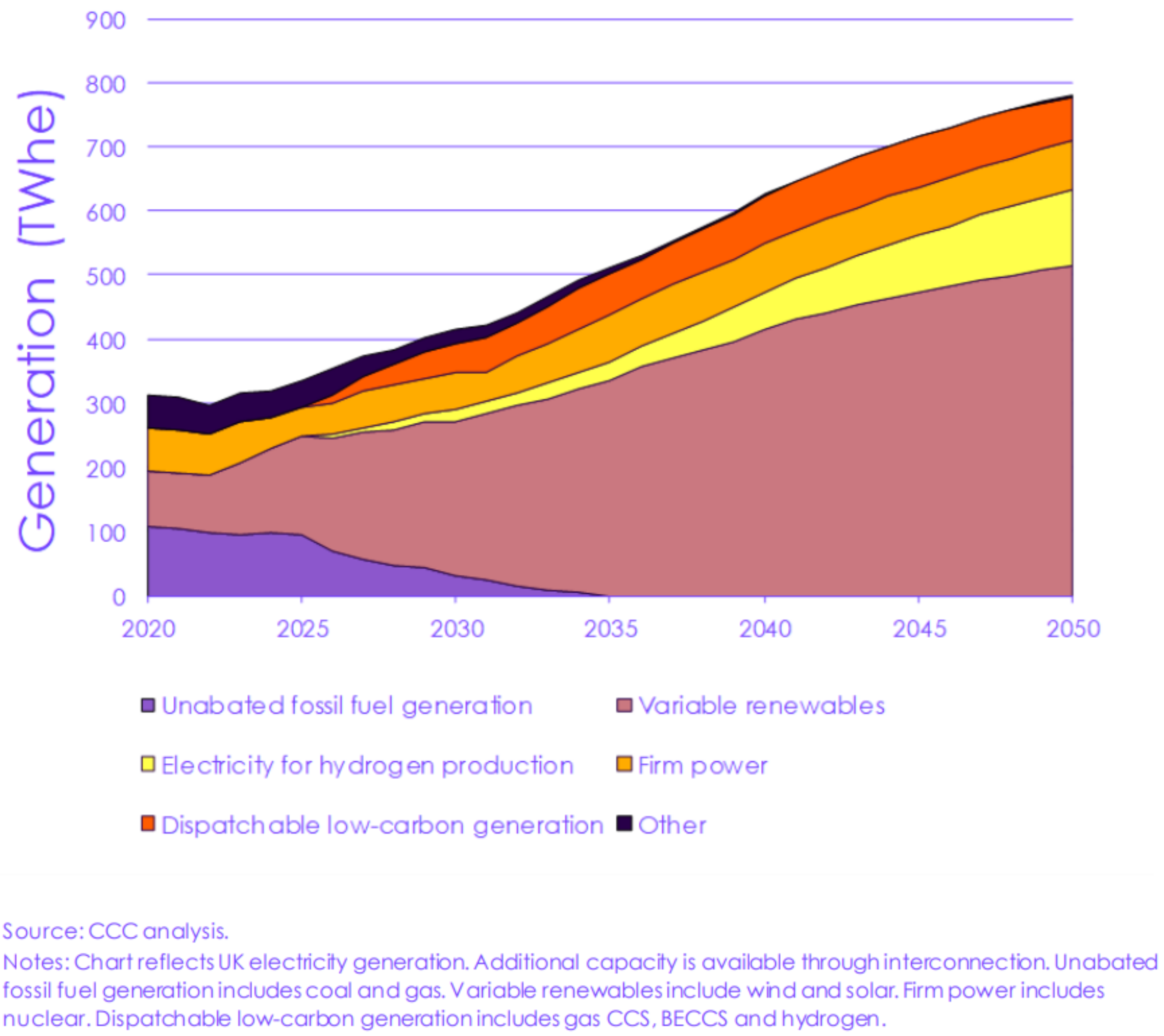


Figure 3: Example of a UK power generation forecast achieving all decarbonisation targets produced by the Parliamentary Committee on Climate Change (The CCC, 2020)

1.2 Owen Square Community Energy

The Owen Square Community Energy (OSCE) is an energy co-operative supplying electricity and heat to Easton Community Centre in Bristol and its annex, a Nursery, pictured in Figure 4. For over ten years, it has been striving to provide its customers energy sustainably and affordably. It has been awarded the Regen Green Energy Award in 2017 for its implementation of low-carbon heating source, a ground source heat pump (GSHP) (OSCE, 2017). OSCE operates a physical electrical microgrid with one smart metered connection to the Western Power Distribution grid and multiple innovative energy solutions.

Figure 4: The Easton Community Centre, (Google Maps, 2022)

The microgrid is being continuously upgraded with altogether 43 kWp of PV panels on the buildings' roofs, 140kW$_{th}$ GSHP with vertical boreholes in the park, which can be recharged in the summer, and in 2021, two 3kW smart Mixergy hot water tanks were installed to provide a controllable source of hot water to the complex. A diagram of the system is provided in Figure 5.

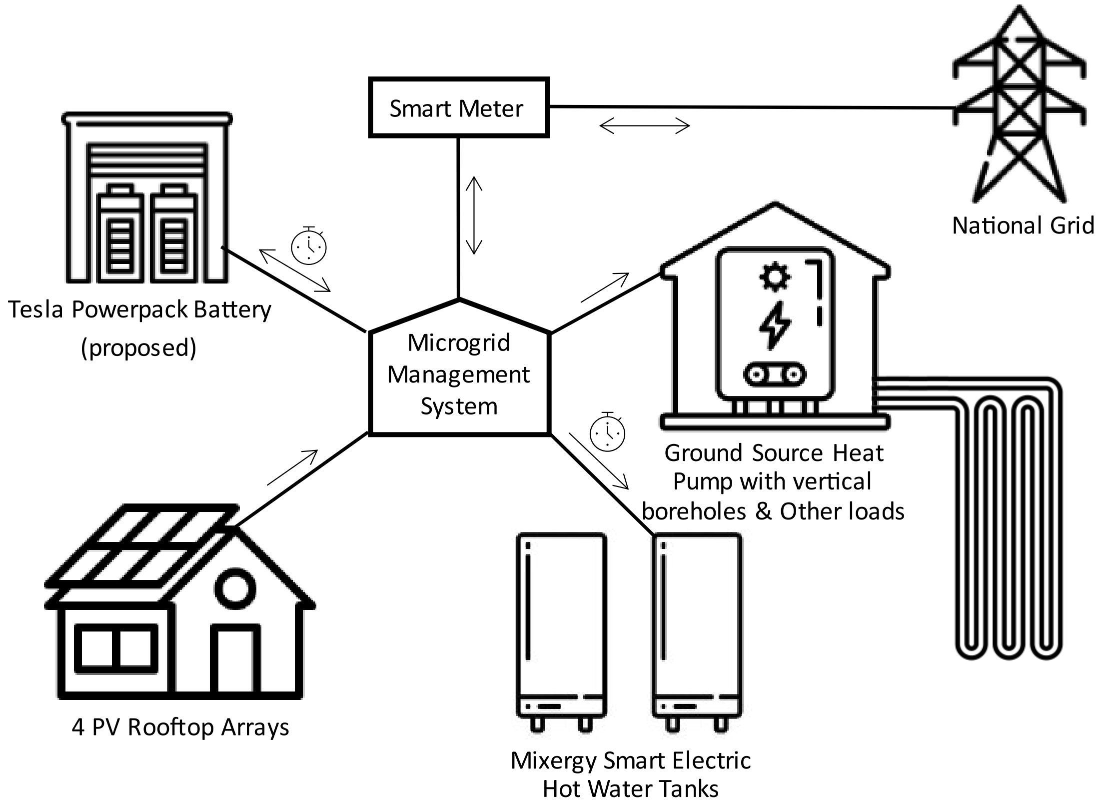


Figure 5: Diagram of technologies within the Owen Square Community Energy microgrid with power flows and time-based load shifting shown. Other power-consuming devices are not shown. Icons: (Freepik and Smashicons, 2022)

1.2.1 Previous projects

OSCE has collaborated with multiple University of Bath students on their Final Year Projects previously. For example, (Shah, 2019) researched the feasibility of extending the GSHP heat network to nearby housing, (Calvert, 2019) investigated the economic impacts of a thermal store in the space heating system, and (Porter, 2021) developed an artificial neural network model for energy use forecasting. Optimisation of the latest technology, the Mixergy tanks, was modelled by (Vetterlein, 2021a) using a linear programming (LP) model.

1.2.2 Current needs

OSCE newly aims to move its sustainability substantially by providing its customers affordable energy with zero carbon footprint. As the building complex now runs fully on electrical power, achieving this goal may take several forms, from purchasing carbon offsets for electricity consumed to buying a share in a wind turbine park and using its zero-carbon power in the following years (Ripple, 2022).

To have better control over the carbon savings while getting additional monetary value and aid the energy transition, the currently proposed solution is an implementation of the Tesla Powerpack 2023 model, a stationary lithium-ion battery, into the grid to provide flexibility. This 160+kWh battery should optimise OSCE's energy costs and carbon by buying electricity on a variable, real-time pricing, tariff during low-cost and low-carbon times, while earning further revenue by providing a firm frequency response to the grid (Rand, 2022). OSCE data sets were provided by the project initiator, Damon Rand, from Clean Energy Prospector (CEPro), which manages the OSCE microgrid. Estimates of the current power data, using fixed 2022 pricing and average annual national carbon intensity, are shown for context in Table 1

Table 1: Summary of OSCE annual energy consumption, generation, and costs. Data are initial estimates of the current state, using (BEIS, 2021b; Good Energy, 2022; Limejump, 2022)

	Total imports	PV generation	Total PV exports
Annual energy	81.5 MWh	31 MWh	10.5 MWh
Annual cost/revenue	33,900 GBP		1,600 GBP
Annual carbon	12 tCO2eq		- 1.5 tCO2eq

1.3 This report

To get a good understanding of the state-of-the-art approach to energy storage carbon optimisation, relevant literature is reviewed in Section 2, together with research on the carbon intensity of a power grid. Specific project aims and objectives are then set, followed by a detailed description of the model, its input data sourcing, and development. This includes validation of an optimisation model developed by (Vetterlein, 2021a), from which this project's tool was developed to optimise HWTs and a battery. Output data is then analysed in Section 5, including a simplified lifecycle assessment model, aiding in the battery's design and operation parameter settings. At last, the key results and their importance is discussed, ultimately leading to answering the question:

What maximal carbon savings are achievable by a financially feasible optimisation of an energy storage operation and design in the OSCE renewable microgrid?

2 Literature review

2.1 Microgrid Demand Response Optimisation

Microgrid optimisation has been a subject of increasing academic interest over the past decade, as the relevant technologies matured and become more accessible (Rangu et al., 2020).

Summary of reviewed literature developing day-ahead unit commitment multiobjective optimisation strategies of flexible devices within a grid-connected microgrid, aiming at cost and emissions reduction is shown in Table 2. A large variety of approaches towards such optimisation problems was found. Despite modelling grid-connected systems, 3 studies, (Fouladfar et al., 2019; Kanchev et al., 2014; Taha et al., 2018) did not account for grid carbon intensity and only optimised its own polluting power generator. Furthermore, only (Kopsakangas-Savolainen et al., 2017) used a variable average grid carbon intensity factor, which was accounted for by a fixed carbon price of 12 GBP/t CO2eq, while presenting comparable numerical results. This paper only considered load shifting by hot water storage, with no option to export power back to the grid. Thus, it was found to be mostly relevant to the Mixergy HWT cost and carbon optimisation part of this project.

Despite the differences between the studies, they all achieved both relative cost and carbon savings based on their own methodology. These varied a lot but were generally higher for the carbon reduction. The main target for carbon and cost savings by a battery for this project was calculated by taking the average of the literature values, i.e. 22% and 9.8%, respectively. A standalone target for Mixergy HWT-only multiobjective optimisation was based on the upper values of (Kopsakangas-Savolainen et al., 2017), at 8% carbon savings and 7% cost savings related to water heating.

Table 2: Summary of reviewed literature optimising microgrid flexibility towards lower emissions.

Reference	Technologies Included	Algorithm	CO2 Savings	Cost Savings	Features
Aghajani et al., 2017	Fuel-cell, Diesel generator, PV, Turbine, Battery	PSO	14%	21%	Cost of RES operation
Fouladfar et al., 2019	CHP, Battery, EV, PV, boiler	PSO, other MHs	37%	10%	Multiple prosumers
Kanchev et al., 2014	CHP, Battery, Capacitor, PV	Dynamic programming	29%	4%	Fuel costs only
Kopsakangas-Savolainen et al., 2017	Smart Water Heater - DSR	Generalised Reduced Gradient	3-8%	7%	Variable Grid carbon factor
Shan et al., 2019	EV, Turbine, Fuel-cell, PV, Battery	GA	unspecified	unspecified	Variable Grid carbon factor
Taha et al., 2018	Battery, Diesel gen., Wind, PV	MILP		7%	Battery storage, rEff

Battery modelling differed between the 5 papers that were optimising it. (Kanchev et al., 2014), (Fouladfar et al., 2019) and (Shan et al., 2019) modelled a battery within a complex system as a simple energy store defined by its maximal capacity, power limits, and SOC at any time. Whereas (Taha et al., 2018) and (Aghajani et al., 2017) assigned the battery a roundtrip efficiency while also accounting for a cost of throughput, i.e. limiting how much energy is cycled through. This might be a more realistic approach, possibly influencing the battery operation results significantly. However, (Aghajani et al., 2017) also assigned a cost of generation to the microgrid's PV panels, which could be counterproductive when optimising for different, actually marginal, sources of costs. Additionally, the paper achieved equating all imports and exports by implementing an energy balance equation.

Although similar literature typically uses nature-inspired metaheuristic algorithms (MH), such as the Particle Swarm Optimisation (PSO) or Genetic Algorithm (GA) (Alam and Arefifar, 2019; Rangu et al., 2020), not all papers from Table 2 utilised them. The 3 studies that have used MH all included five or more different technologies, some with non-linear models, resulting in high complexity of the optimisation problem. Mathematical algorithms were used for the remaining, simpler, optimisation models.

Load shifting of HWT only was done in Excel using a non-linear Generalised Reduced Gradient algorithm, while (Kanchev et al., 2014) used more robust dynamic programming for 3 optimised devices with non-linear (day/night) behaviour and (Taha et al., 2018) used the deterministic Mixed Integer Linear Programming (MILP) to optimise 2 flexible loads under constraints from other loads. This required linearisation by a piecewise approximation of the diesel generator model. Thus, mathematical optimisation algorithms seem to be more effective for simpler systems. In fact, (Pickering et al., 2016) found piecewise linearised MILP to be 2 orders of magnitude faster than generic metaheuristic algorithm, while achieving slightly higher savings, for cost-only optimisation of a microgrid with multiple simplified flexible loads and energy storage systems.

While the rest of the papers from Table 2 achieved multiobjective optimisation by adding to monetary costs a product of a carbon price and the carbon content of a given energy flow, (Aghajani et al., 2017) utilised PSO algorithm for separate optimisation of two conflicting objectives, cost and emissions. This led to a series of pareto set solutions, out of which the non-dominated ones formed a pareto front as shown in Figure 6. From these, the optimal solution can be found by an additional algorithm, or manually.

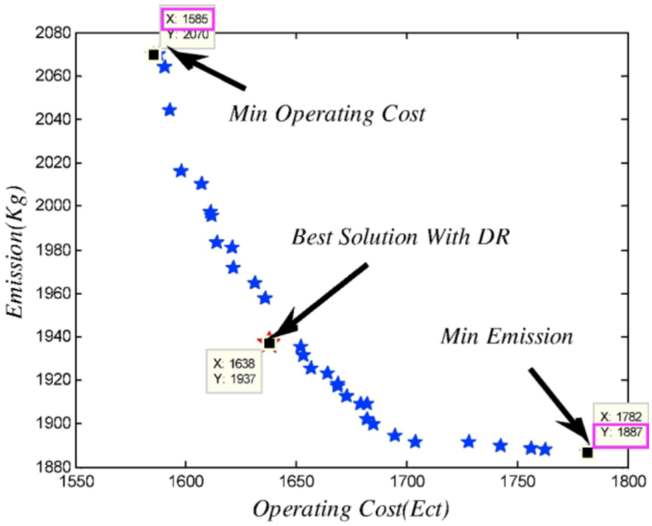


Figure 6: Pareto set solutions for the multiobjective metaheuristic PSO algorithm in (Aghajani et al., 2017), showing the trade-off between cost and emissions. DR = Demand Response

While the multiobjective optimisation studies modelled a battery only considering the short-term perspective of a single optimisation, unimpacted by its operation, another approach is possible. (Bordin et al., 2017) optimised a lead-acid battery in an off-grid system by linear programming while accounting for capacity degradation caused by the depth of its cycles (DoD). It found that an economical operation of energy storage is crucial to a microgrid's lifetime profitability.

2.2 Grid Carbon Intensity

Estimation of GHG emissions attributable to a timed use of power from the national grid is still an active area of research with no clear industry standard (Allen, 2022). Dozens of different emission factor estimation techniques exist and they can vary, for a given place and time, by up to 68% (Ryan et al., 2016).

2.2.1 Marginal and average emissions factor

An annual average emissions factor is the currently typical approach to calculating Scope 2 GHG emissions of organisations, taking their share of the total electricity produced within a year, diving by the total power-related GHG emissions. A preferable alternative is a supplier-specific accounting for the generators from which the power consumed was purchased (Sotos, 2015).

However, the specific generators are not always known and taking the annual average value does not create incentives to use power during lower-carbon times and lacks the ability to account for such consumption behaviour. To estimate carbon intensity with higher granularity, an average hourly or half-hourly factors can be used (Alasdair et al., 2020) and calculated as:

$$C_t = L * \frac{\sum_{g=1}^{G} P_{g,t} * c_g}{D_t}$$

Where:

- C_t = Grid average intensity at time *t*
- L = Factor accounting for transmission and distribution losses
- $P_{g,t}$ = Power generation of fuel type *g* at time *t*
- c_g= Carbon intensity factor of fuel *g*
- D_t = Total Electricity demand at time $_t$

This approach, however, fails to account for the grid-level impact of additional changes to power consumption. As the electricity spot price and generation mix is mostly driven by merit order of power sources, shown in Figure 7, all sources with a lower marginal cost of generation than the one needed for current demand, the marginal plant, already run at full power. Thus, if an additional load is connected to the grid, the marginal power plant will need to cover its demand, therefore, assigning this additional load the short-run marginal emissions factor (SR-MEF), i.e. the carbon intensity of the marginal plant (Hawkes, 2010).

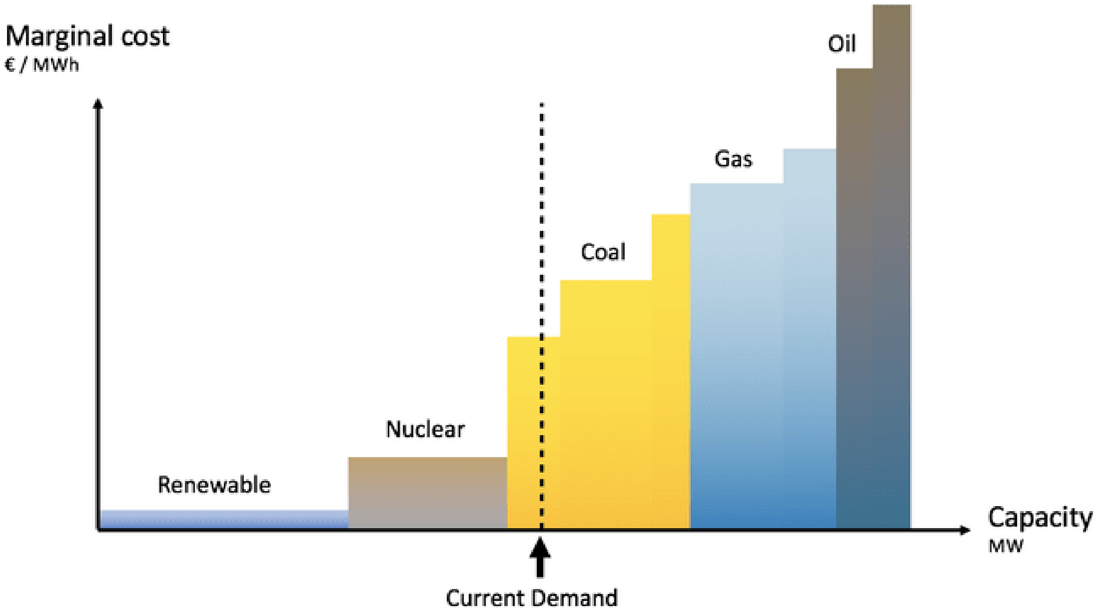


Figure 7: An example of power generation sources in merit order, ranked based on their marginal costs. From (Corradi, 2019)

The SR-MEF, thus, should be used for calculating the emissions *avoided* or *caused* by a change in load, while the grid average should be used for accounting of an organisation's real-time Scope 2 emissions footprint, including their *reduction.* Values of *avoided* and *reduced* emissions by a given action can have very different values (Corradi, 2019). Although SR-MEF correctly estimates the impact of flexible load change, it may not create the right signal for when the flexible load should run as in the UK grid, 70% of the annual marginal power was found to be provided by gas turbines (Corradi, 2018). Most of the time, therefore, SR-MEF may stay nearly flat, no matter what the total power demand and RES supply are.

Moreover, the SR-MEF is computationally complex (Corradi, 2018) and it cannot account for changes to the grid if such an additional load change would be sustained (Hawkes, 2014). For example, if a new industrial load is connected to the grid, it would result in an immediate rise in a gas plant's power output. However, if this load is kept reasonably constant over the course of multiple years, it may enable more wind power to be connected to the grid. This describes the long-run marginal emissions factor (LR-MEF), which is typically used for policy appraisals and is estimated as a flat value for a given year, as shown in Figure 8 (BEIS, 2021b).

Although the LR-MEF has been decreasing in the UK power grid in the past years, the average emissions follow a much steeper trend, overtaking it in 2015. Even greater divergence was found for the US grid, where the LR-MEF has been steadily increasing over the past decade (Holland, 2022), which is mostly attributable to gas replacing coal as the firm power source, while coal plants are kept in reserve.

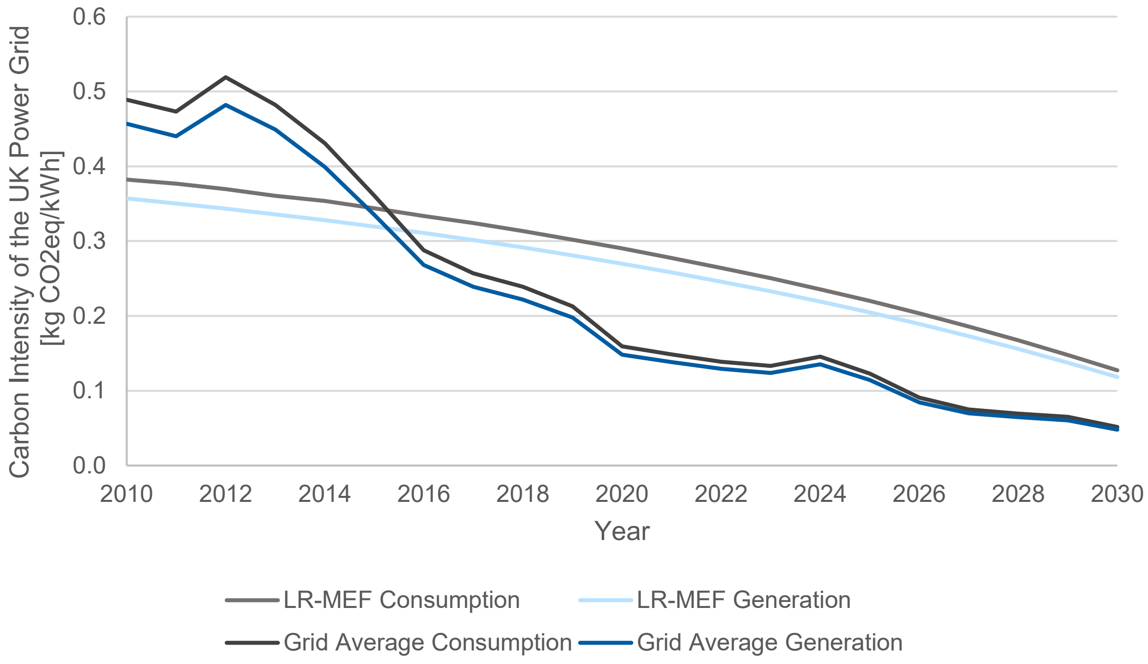


Figure 8: UK National average annual grid carbon intensity and Long-run Marginal Emissions Factor (BEIS, 2021a)

Different emissions factors can be used for flexible load optimisation. (Braeuer et al., 2020) found that for the German national grid, marginal emissions factors resulted, due to their high volatility, in much higher use of an energy storage system than the average factor. This corresponds with the findings of (Corradi, 2018), as German SR-MEF was mostly driven by hydro plants and coal plants with widely different emissions intensities. As part of an ongoing research at the University of Bath, multiple carbon battery optimisation approaches are being tested, including taking the average half-hourly grid intensity for battery's power imports, and the annual LR-MEF for its exports, as it displaces the need for additional power plant's capacity (Roberts, 2022).

2.2.2 Average factor assumptions and scope

Estimation of average grid emissions factor is subject to multiple assumptions and methodological decisions, which may impact its final values. These include time granularity, regionality, calculation of interconnectors' carbon intensities, and accounting for system losses. Moreover, each generation source needs to have a carbon intensity attributed, which can vary based on whether it includes only direct impacts, such as CO2 resulting from burning fuels, or also indirect ones, looking at the source's impacts from a more LCA perspective. This would include, for example, the footprint of building a hydro plant dam. A comparison of four approaches to average emissions factor estimation is presented in Table 3.

Table 3: Summary of consumption-based average grid carbon intensity accounting approaches of 3 UK data sets and 1 Finnish study. "g"=gCO2eq

	electricityMap, 2022	Kopsakangas-Savolainen et al., 2017 - paper	Rogers and Parson, 2022 – Grid Carbon app	NG-ESO, 2022 – carbonintensity .org.uk
Time granularity	Hourly	Hourly	HH	HH
Regionality	Not open access	-	No	Available
Interconnectors	Hourly data	-	9 - 513 g/kWh	Daily average
Grid losses	Included	Not included	Included	Included
Gas Plants	Generic	Generic	OCGT vs CCGT	OCGT vs CCGT
Wind, PV, Nuclear	11-45 g/kWh	0 g/kWh	0 g/kWh	0 g/kWh
Biomass	240 g/kWh	0 g/kWh	120 g/kWh	120 g/kWh
Forecast	Not open access	-	No	Yes, 96h ahead

2.3 Carbon pricing

To work with carbon emissions cost-effectively, a common approach is to assign a monetary value to a given amount of carbon dioxide equivalent GHG emissions. This enables a direct comparison between money and carbon in equal units. Carbon pricing has been implemented in some regions on the policy level as either a carbon tax or an emissions trading scheme, such as the UK ETS and EU ETS (World Bank, 2021). Currently, EU ETS has a price of around 70 GBP/t CO2eq, significantly higher than in the past years (Ember, 2022).

For organisations and individuals, internal carbon pricing is a method of accounting their environmental impacts. The internal value of carbon can be used to trade within the company and make business decisions, or it can only work as a shadow costing, assessing the organisation's footprint. Internal carbon price ranges widely, from near 0 to approximately 80 GBP/t across industries (McKinsey, 2021). When used to cut its impacts and achieve net-zero, businesses can set the carbon price to the cost of a carbon offset, an alternative to cutting emissions. Cost of carbon offsets has been rising recently, and it is, as of 2022, at approximately 11.5 GBP/t (Hodgson and Noonan, 2022), while different schemes may have very different costs. The cost of offsets is expected to rise substantially in the upcoming decades (Henze, 2022).

Estimating the value of climate impacts on people in the future addressable to current GHG emissions, the social cost of carbon (SCC), is an active area of research. Models with different assumptions and perspectives can find SCC to be multiple orders of magnitude higher or lower than other models, as presented in Table 4. Omitting the highest SCC found by (Archer et al., 2020), the other estimates found in (BEIS, 2021b; Nordhaus, 2017) were approximated to be around the level of 100 GBP/t CO2eq. When this value is added to a typical consumer electricity price in the UK, it can increase approximately by up to 15% (Good Energy, 2022; NG-ESO, 2022).

Table 4: Value of Carbon emissions as SCC from various sources, such as the DICE model, compared

Source:	BEIS	DICE	DICE	Various	Archer et al.
CO_2 value / price: [2022 GBP/t CO_2eq]	248	20	113	47	36000
Range:	124-373	16-24	78-147	14 – 70	3600-270000
Year of publication:	2021	2017	2017	<2017	2020
Use case:	Policy impacts	Research, policy	Research, policy	Research, policy	Research
Features	Increasing annually	High (5%) discount rate	Low (2.5%) discount rate	Different models	Beyond 2100 impacts
Ref:	(BEIS, 2021)	(Nordhaus, 2017)	(Nordhaus, 2017)	(Nordhaus, 2017)	(Archer et al., 2020)

3 Methodology

3.1 Aims and Objectives

From OSCE's needs and the reviewed literature, a set of key aims was produced for this project's optimisation problem from the perspective of the microgrid, while considering impacts on the wider world. The main measurable objectives of this project are listed below. To illustrate the optimisation idea, Figure 9 shows the type of demand-response this project aims.

Key Aims

- To develop, on real-life past OSCE data, an optimisation tool that would shift electricity demand of OSCE microgrid based on power grid's forecasted information using hot water tanks and battery day-ahead load management.
- To advise OSCE on carbon-optimal battery's design selection and operation from a lifecycle perspective as this was found to be important by (Bordin et al., 2017).
- To compare battery costs and impacts with other carbon reduction strategies.
- Validate the battery model by using different optimisation problem data.
- To investigate the impacts of optimised battery implementation on the national grid and the environment if replicated on a greater scale.

Objectives

I. To reduce OSCE's annual water heating emissions by 8% through load shifting while cutting its operation costs by at least 7%.
II. To reduce OSCE's annual grid-related emissions by 22% through economically feasible implementation of a battery to the microgrid.
III. To achieve a practical trade-off between carbon emissions reduction and increased cost of electricity for carbon-effective battery's operation, compared to cost-only optimised operation, lower than 11.5GBP/CO2eq.

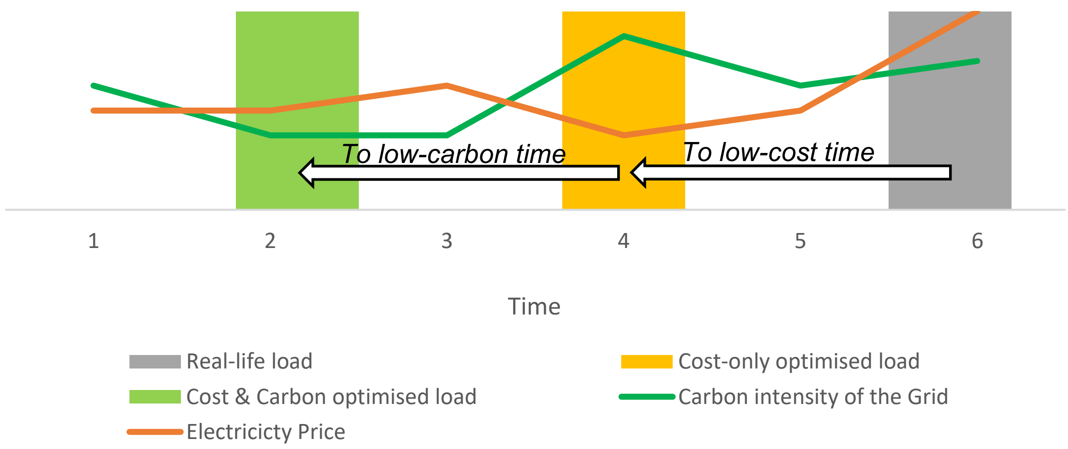


Figure 9: Visualisation of the aimed load optimisation towards low-cost and low-carbon time. On top of that, a battery should also sell electricity when profitable. Not real data.

3.2 Data

As the optimisation model was set to run on historical data, theoretically, it could optimise for any length of time. However, to be practically useful, the optimisation was set to be always for 24 hours ahead, corresponding to the day-ahead prices introduced here. Still, real historical power usage is to be used here, which in reality would need to be replaced by a forecasting model, such as the ANN tool developed by (Porter, 2021), and it is out of the scope of this project. All data is sourced in half-hourly (HH) supply periods as those are used by the smart meters and power exchanges to settle trading balances. All datasets were decided to be run with matching dates and supply periods, unless specified otherwise, to improve the accuracy of the model's estimates. Thus, sources of long high-quality data had to be used. Their final availability is shown in Figure 10.

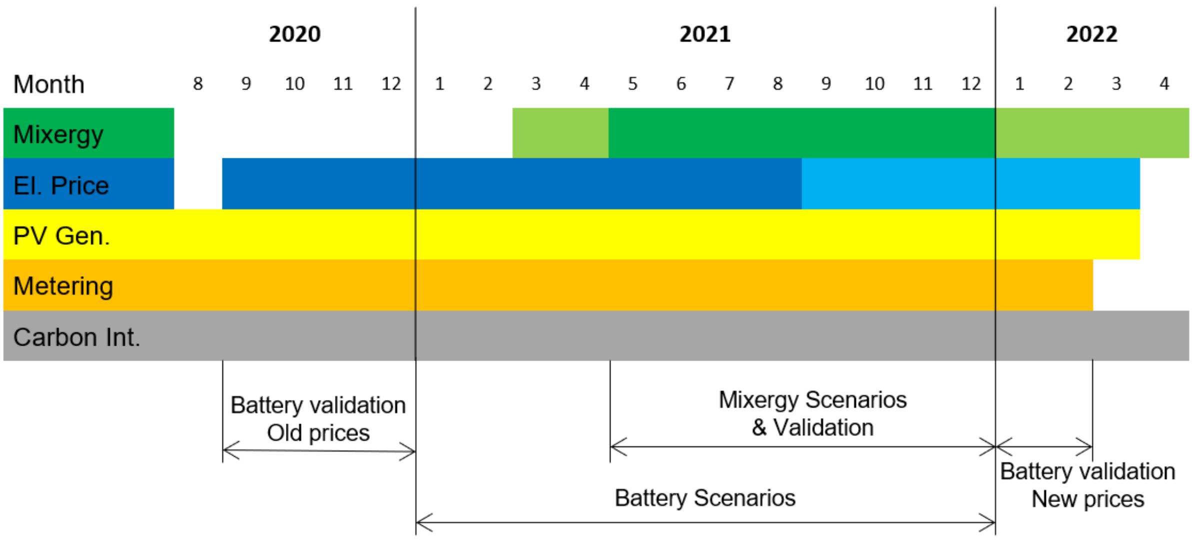


Figure 10: Data availability for the project. For Mixergy, light green indicates incomplete data. Light blue indicates much higher and more volatile "New" spot prices, as explained below.

3.2.1 Electricity price

OSCE is considering switching to a fully flexible tariff from its current day-night import (Good Energy, 2022) and flat export PPA (Limejump, 2022) tariffs**.** To enable the highest potential benefits of flexibility, the fully flexible tariff is assumed here, albeit the current tariffs are tested in Section 0. An overview of flexible price components is given in Table 5.

Table 5: Components of the total per kWh electricity price with their min and max values from available data. Standing charges and similar costs are not included in the model. Edited from (Vetterlein, 2021a)

Component	Description	Data Sourcing	Value [p/kWh]	Applies to
APX	Day-ahead electricity market price on the EPEX Power Exchange	Limejump API	-4 - 186	Forecasted Import, Export
SSP	System Sell Price - settlement market spot price, paid retrospectively to a supplier for energy used	Limejump API	-9 - 400	Paid Import, Export
BSUoS	Balancing Services Use of System. Recovery of ESO costs in providing balancing services.	National Grid	-0.06- 4	Import, Export
AAHEDC	Assistance for Areas of High Electricity Distribution Costs	GoodEnergy	0.028	Import, Export
DUoS	Distribution Use of System charge – time-variable, highest for weekday late afternoon	WPD – LV Site Specific Tariff	0.036-8.41	Import
GDUoS	Generator Distribution Use of System - Subsidy for local generation; flat without an installed battery	WPD – LV Site Specific Tariff	0.041 – 8.56	Export
FCL	Final Consumption Levy to pay for green energy and other gov schemes	(Vetterlein, 2021a)	4.51	Import

The market price components were sourced from REST API api.limejump.com using a loader developed by (Vetterlein, 2021a). They were then combined with CSV files of other charges (National Grid ESO, 2022; WPD, 2022) into one main CSV pricing file that could be used by the optimiser. The optimiser should use the forecasted, APX, price with all other components.

The key component of the total price per kWh is the market spot price, which has seen major developments in 2021, reaching unprecedented levels of variability and peak prices, mostly driven by increased natural gas prices and high post-covid demand (Alvarez and Molnar, 2021). This change was identified to potentially impact the optimisation considerably and thus, the lower, more stable prices are referred to here as the “Old” prices, while the “New” normal prices were set to start on 01/09/2021. To illustrate the difference, a plot of APX-SSP market prices before and after this date is shown in Figure 11.

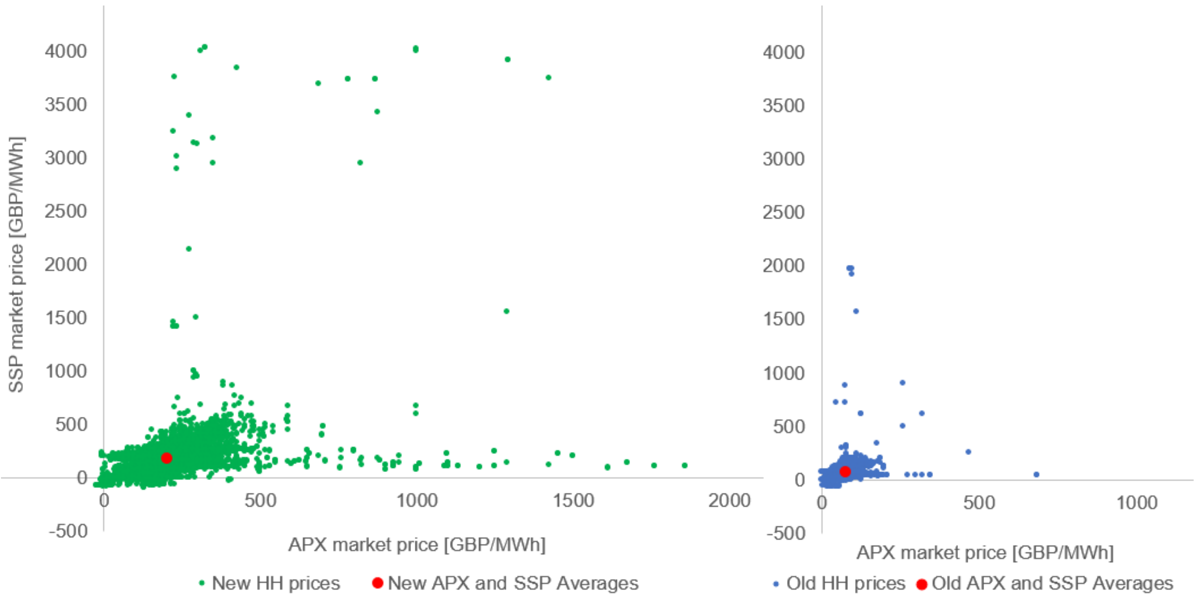


Figure 11: Plot of half-hourly sets of APX and SSP market spot prices for 200 days after (left) and 200 days before (right) 01/09/2021 with their respective averages in red. Part of the variation is due to seasonality. (Limejump, 2022)

3.2.2 Grid emissions

To optimise power loads for carbon emissions and then calculate the solution's total impact, a source of grid emissions factor with desired, HH, granularity was needed. As the power is purchased on the spot market, it is not always clear upfront by whom is the electricity generated and so a supplier-specific approach was ruled out. Another transparent approach is using general power grid data. It was decided that the average carbon intensity, rather than a marginal factor, should be used due to better data availability and the need for the total system's impact minimisation while hypothesising that it is a good measure of what type of flexibility the national grid needs at a given time.

A good computer-readable source of live and forecasted UK grid carbon intensity was found to be the well-documented api.carbonintensity.org.uk REST API developed by National Grid ESO (NG-ESO, 2022). A data loader function was developed to access its data, retrieving it in a JSON format. Despite being near its border (Figure 12), regional carbon intensity for South-West England was selected to be used for higher accuracy of the local grid conditions. This dataset is provided only in the form of a forecast, not retrospectively as the actual data, however, it was deemed to be a good representation of the actual emissions based on a comparison of these datasets on the national level.

The carbon intensity value directly from the API, including transmission and distribution losses, (Alasdair et al., 2020) was decided to be used for both imported and exported electricity. Losses were kept for exports as OSCE is in an urban area, so its exported power is typically consumed nearby. Thus, the same value has been used for the optimisation problem and subsequent accounting of both import and export carbon intensities. This is very different to cost accounting, which differs between forecast and actual cost, as well as between import and export.

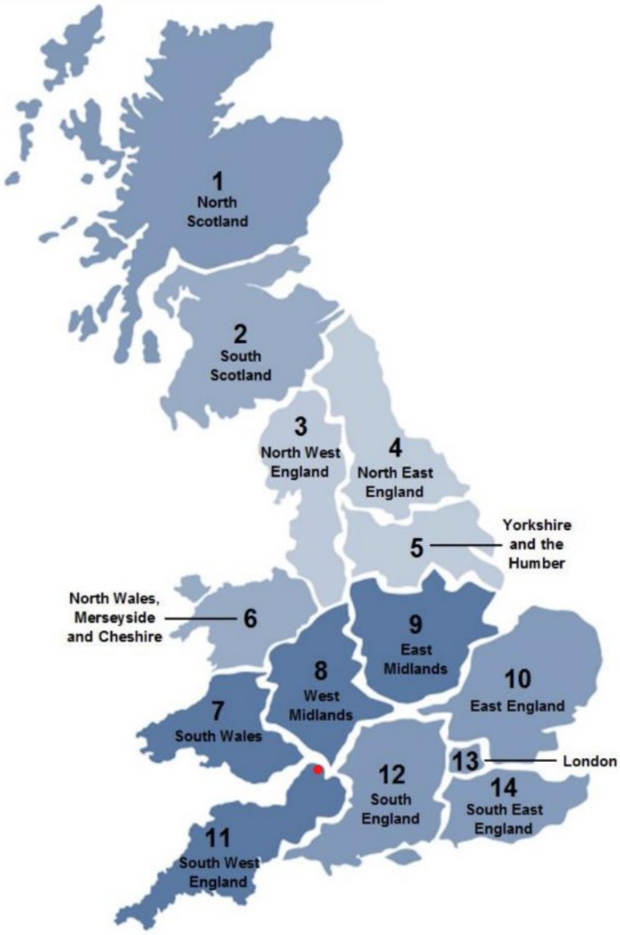


Figure 12: Division of the UK national power grid into regions for the purposes of more accurate carbon intensity data. Red dot shows OSCE's location. From (Alasdair et al., 2020)

The methodology of carbonintensity.org.uk accounts only for the direct emissions from a marginal electricity unit generated, not from the lifecycle impacts of the power sources, as noted in Table 3. Different methodological assumptions tend to lower its values compared to another data source, ElectricityMap. For example, on the 2nd of May 2022 at noon, the UK carbon intensity was 329 gCO2eq/kWh according to ElectricityMap (electricityMap, 2022) versus 252 and 251 gCO2eq/kWh based on the carbonintensity.org.uk forecasted and actual values, respectively (NG-ESO, 2022). This difference was mostly the result of lower carbon value for CCGT, rather than the generic natural gas plant value used by ElectricityMap. Carbonintensity.org.uk data were found to be sufficiently methodologically accurate to be used in the project as its gas-power data is appropriate and the lack of lifecycle impacts of RES does not have a major effect on the results.

South-West England carbon intensity was found to be more seasonally variable than the national one. It follows a similar pattern as OSCE's net power exchanges with the grid, both shown in Figure 13. Higher electricity imports, mostly driven by the GSHP, occur during the winter weeks with the highest carbon intensity. This suggests that OSCE's net annual carbon emissions may be higher than the national and regional averages.

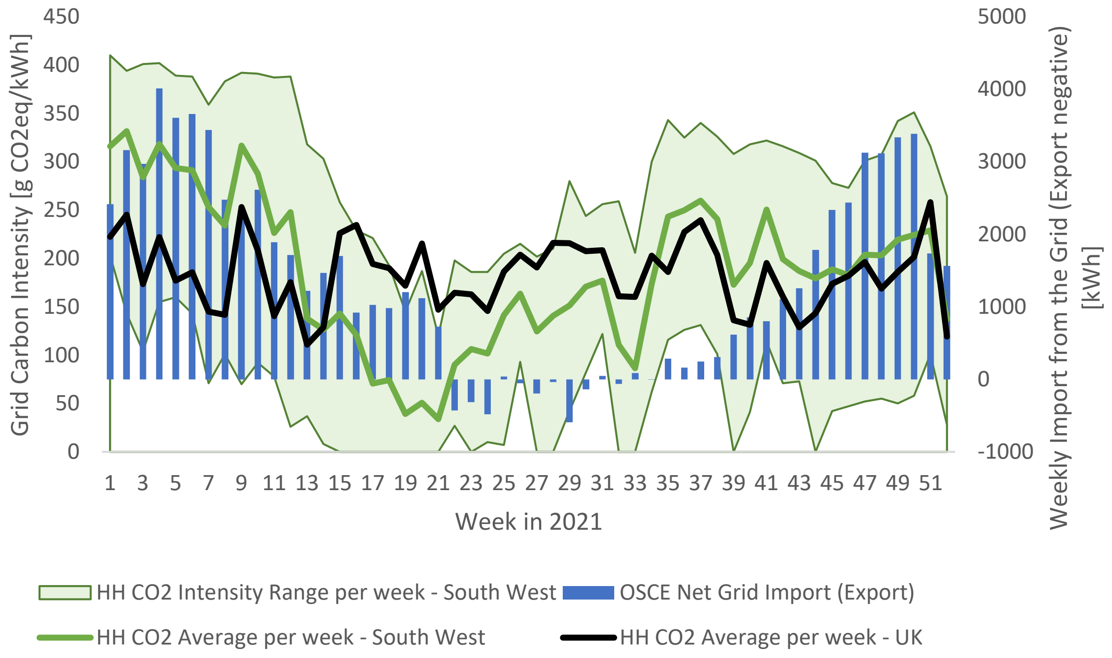


Figure 13: Carbon Intensity of the grid for SW England (with HH Min-Max range) and England as a whole, together with OSCE electricity weekly consumption (right axis).

3.2.3 OSCE Data

Necessary data from historical power flows within OSCE were sourced using existing loader functions developed by (Vetterlein, 2021a) for PV generation from CSV files and hot water demand from Mixergy API. Additionally, as the battery should optimise the total power imported from and exported to the national grid by OSCE, the actual HH historical import and export data, shown as weekly sums in Figure 13, were sourced from a Smart metering CSV file provided by CEPro. As the most recent PV generation data was only available for a different array than previously, the data points were scaled to achieve the smallest possible difference in annual production between them. Afterwards, they were scaled up to account for the full 43 kWp of PV capacity. As the arrays are from different manufacturers, have a different orientation, and were installed within a period of four years, the scaling factors do not match their respective peak power ratios exactly. PV data was provided in a series of daily CSV files, therefore, a Python script to combine them is included in Appendix A.

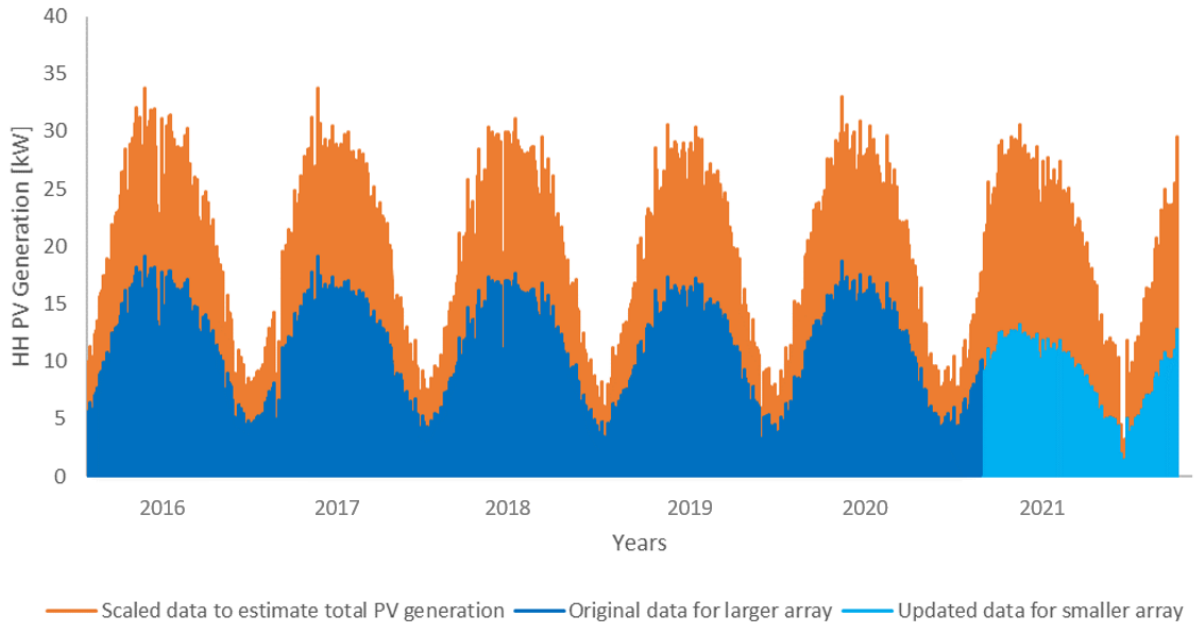


Figure 14: Half-hourly (peak) PV generation since the beginning of the dataset with their scaled-up version estimating the full 4-array PV generation

3.3 Battery

3.3.1 Optimisation

To achieve Objectives II. and III., a battery operation model was needed to be developed and optimised towards lower cost and carbon cycling schedules. This model should include day-ahead information about the national grid, power flows within the microgrid, and a flexible operation of a battery. For optimisation itself, Linear Programming was proposed as it was found powerful enough to optimise battery operation in the literature (Pickering et al., 2016; Taha et al., 2018) and it was used successfully in the development of a HWT optimiser for OSCE by (Vetterlein, 2021a).

As long as the battery's BMS properly controls its power flows and correctly estimates its SOC, which then changes linearly with the amount of input and output energy, its operation should be describable by a series of linear equations. These include, for example, limiting the SOC to certain levels, converting exchanged energy to equivalent delta SOC, or updating the SOC for every supply period. It can also include a roundtrip efficiency factor, sometimes ignored in the literature (Fouladfar et al., 2019), which limits the battery's potential to run on very small price margins. A possible source of error could be the use of a flat maximum power flow, while in reality, this may change with SOC level based on the system's technical limitations. For Li-ion batteries, charging power is often very limited for upper SOC levels (Buchmann, 2010). At the same time, the planned day-ahead half-hourly optimisation would create sets of only 48 decision variables, which should not be a problem for LP to handle.

3.3.2 Lifecycle

As the key aim of the battery installation and optimisation is a reduction of environmental impacts, it should not be modelled as a stable, impactless, entity. It is crucial to estimate capital costs and embodied carbon emissions of the battery, as they typically account for the largest share of its impacts. Accounting for the production impacts needs to be combined with the battery's lifetime to be comparable with its positive operational impacts. A lifetime of a battery is mostly limited by its capacity degradation, which is influenced by multiple operational factors (Lander et al., 2021).

To account for the battery's impacts over its lifetime, a simplified lifecycle assessment (LCA) was added to this project and its scoping overview is shown in Table 6.

Table 6: Summary of the lifecycle impacts in and out of the scope (OoS) of this report's simplified lifecycle assessment with some aspects assessed only partially.

	Costs	**Emissions**
Production	In scope – battery price	In scope – LCA inventory
Transport, Installation	Partly in scope – battery price	Out of scope
Operation & Maintenance	Out of scope	Out of scope
Service	In scope – Cost savings, FFR	In scope – Carbon savings
Time-changing aspects	Discounting, el. prices – OoS	Future carbon value - OoS
End of Life	Partly – Lifetime estimate	Partly – Lifetime estimate

An estimate of the battery's lifetime will be found by using a previously developed, as of 05/2022 unpublished, capacity degradation tool (Samal, 2021), which is based on two works of (Keil et al., 2016; Olmos et al., 2021). This tool combines cycling degradation with calendar ageing to estimate total capacity loss based on operational parameters of a battery, which are to be found from the optimisation model and are further introduced in section 5.3.1. Relevant to this work are mainly the depth-of-discharge (DoD), the number of annual full equivalent cycles (FECs), and the mean State of Charge (mSOC). This tool estimates the degradation of two Li-ion chemistry types, LFP and NMC, which are not identical to the typical Tesla NCA. However, NMC shows similar degradation patterns for relevant operational parameters (Keil et al., 2016), thus it was used to estimate the Powerpack's degradation. An example of a degradation curve from the tool is shown in Figure 15.

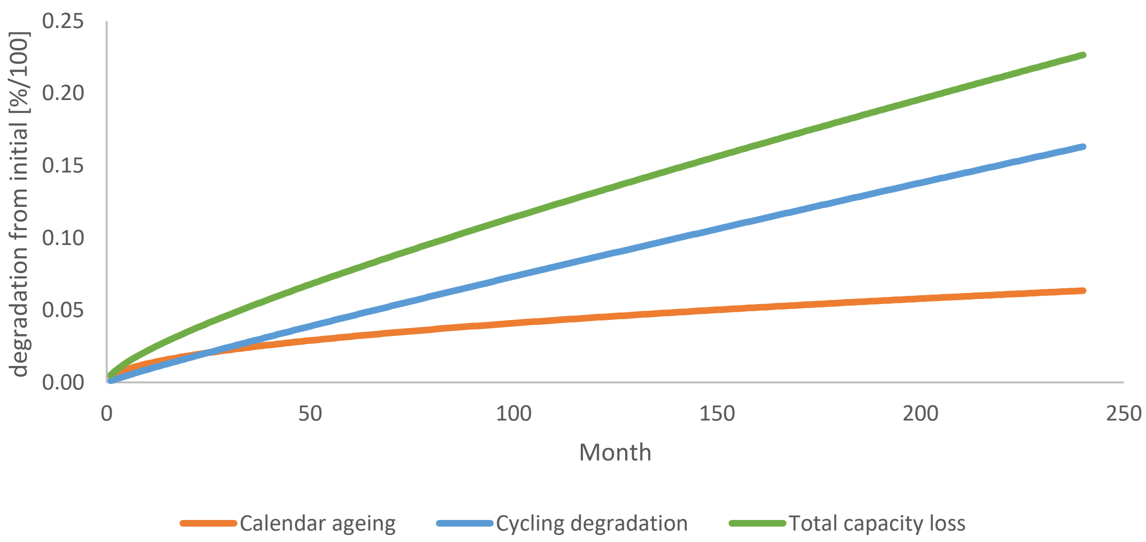


Figure 15: Graph of an example of the NMC battery capacity loss modelled by the battery degradation tool for a low-use scenario (Samal, 2021b).

To estimate the battery's installation price, a simple parametric costing estimate based on the total installation price of 2-hour residential and commercial-scale Tesla battery packs is shown in Figure 16. 4 data points of Tesla Powerwall in the UK ("Tesla," 2022), older US Powerpack quote (Lambert, 2020) and OSCE's 2020 UK Powerpack quote (Rand, 2022) were included. A 160kWh Powerpack's price was thus estimated to cost 527 GBP/kWh. As there have been many battery price-pressuring effects in the past years, such as high inflation rate, increased production efficiencies, or increased demand (Lambert, 2022a), this estimate may not be very accurate. A 4-hour, half the power, version was estimated to cost 428 GBP/kWh, using the difference between such versions of the grid-scale Megapack (Tesla US, 2022).

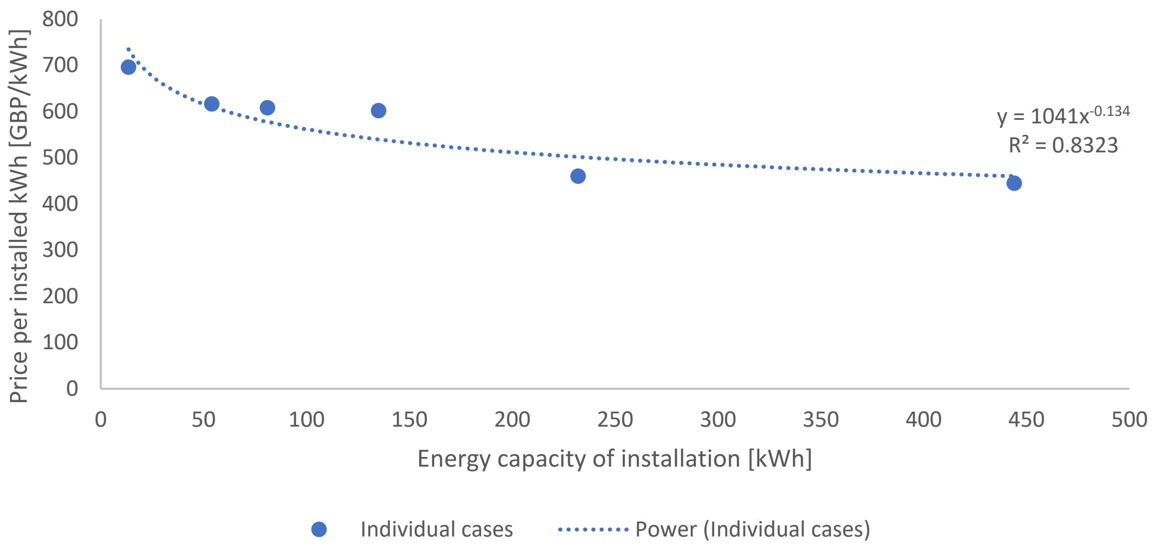


Figure 16: Cost estimate of the Tesla Powerpack based on the total capacity of the battery. 4 Tesla Powerwall and 2 Tesla Powerpack data points shown with a power trendline, all prices in 2022 GBP.

The battery can limit its power used for optimised electricity trading by using the rest of it on a Firm Frequency Response (FFR), which helps with grid stabilisation. The revenue from FFR was estimated to be proportional to the power available at 84,000 GBP/MW/year based on real installation's data (Rand, 2022).

As embodied carbon emission estimates of batteries vary heavily (Raza, 2021) and Tesla does not disclose this value despite claiming to be a leader in battery sustainability (Tesla, 2021), a generic estimate was used. It was found to be 76 kgCO2eq/kWh, using the EverBatt model with GREET LCA inventory data for US-produced NCA batteries (ANL, 2018).

4 Development

4.1 Version 1

The battery optimiser was developed by extending and building up on the work of Sebastian Vetterlein for the University of Bath Final Year Project (Vetterlein, 2021a) and later for CEPro (Vetterlein, 2021b). The original FYP model, referred to as Version 1 (V1) here, is optimising OSCE water heating costs by shifting the smart Mixergy hot water tank heating schedules to periods of low forecasted import price and to times of available local PV generation. To do this, it models the building's hot water needs from Mixergy API past data and then creates a new heating schedule, satisfying all hot water demands.

The V1 model is developed in Anaconda Python 3.8 and utilises a Linear Programming library PuLP (Mitchell et al., 2022) for solving the optimisation problem. Its objective function, OF, minimises the total cost of electricity usage of all HWTs in the system for all supply periods (SP). It accounts the cost of electricity use within each SP microgrid's PV generation at the export rate, assuming that to be the opportunity cost of this electricity not being sold to the grid. It does not account for other loads within the microgrid. Version 1's decision variables and OF1 are presented below.

LP Decision Variables

- i(SP) = Imported HWT electricity during Supply period [kWh/SP]
- s(SP) = Self-consumed HWT electricity during Supply period [kWh/SP]

Objective function

$$OF1 = min\,(\sum_{SP=1}^{OD}\sum_{m=1}^{M}(\,i(SP)(m) * I(SP) + s(SP)(m) * X(SP)))$$

Where:

- OF = Objective Function
- SP = Supply Period [in this project, its length is 0.5h]
- OD = Optimisation Duration in number of Supply Periods [in this project set to 48]
- I(SP) = Day-ahead (APX) import price of electricity including all charges [p/kWh]
- X(SP) = Day-ahead (APX) export price of electricity including all benefits [p/kWh]
- M = Total number of Mixergy HWTs [here set to 2 different ones]

In total, 7 equations constraining the HWTs are part of the original model and they can be found in (Vetterlein, 2021a) or in the source code in Appendix 1. The HWT model was found to be reliably saving water heating costs on a small sample of available daily data. As more than 8 months of continuous data were available during validation of the V1 model for its use in this project, its optimisation was run for each day during this period to compare the results with findings from the original paper. As shown in Figure 17, the results of the longer data optimisation follow a very similar savings pattern as the original paper's for APX cost. The average daily APX savings were higher by only 1.6 percentage points. A much higher variation of daily SSP cost savings, observable on the graph, also agreed with the findings of the original data. However, (Vetterlein, 2021a) found the SSP savings to be 25.2% on average, while the new optimisation found it to be only 15.6%. This is an interesting observation to investigate further, however, the optimisation model was still found to provide reliable savings.

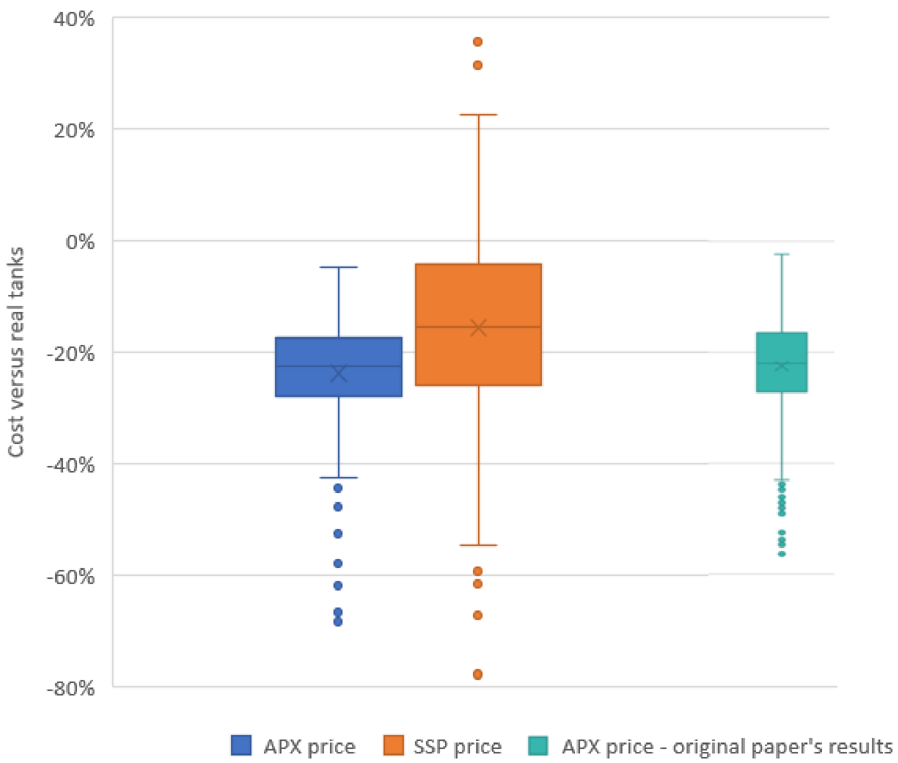


Figure 17: APX and SSP savings for 8 months in 2021 on the left, excluding 1 SSP price outlier at +191%. For comparison shown original APX savings from synth-days, adapted from (Vetterlein, 2021a). 24-hour optimisation periods used.

Based on the validation run, it was decided that 3 subsequent versions of this tool introduced in the next sections should be developed instead of building a new model. This was to streamline the development process and enable more space for additional features and analysis. An overview of the model's structure is shown in Figure 18 with colour-coded parts that stayed unchanged from Version 1.

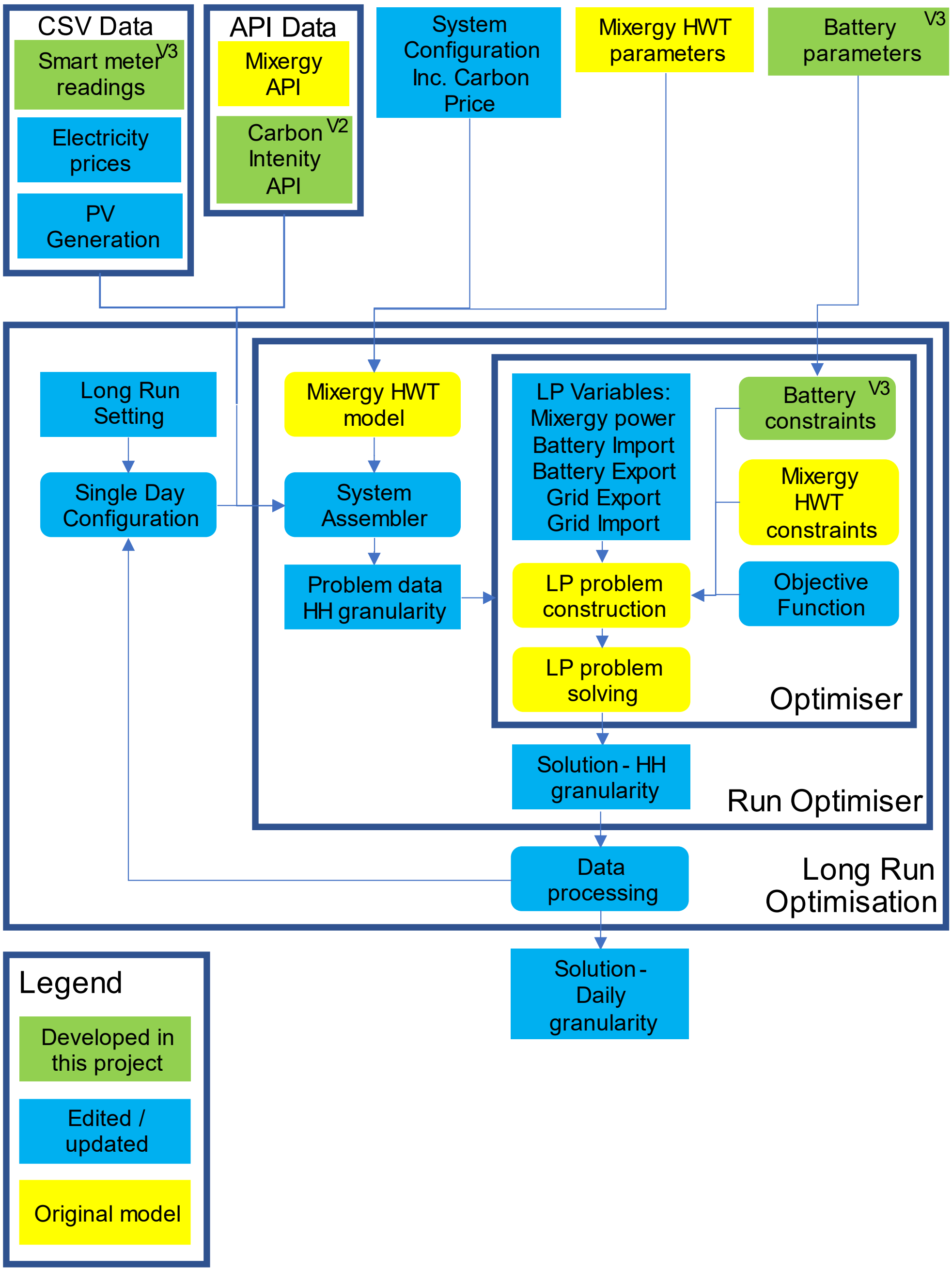


Figure 18: Diagram of the Optimiser's operation in its Version 4. Processes and data entities are divided into 3 categories based on their evolution since the Original, Version 1, model (Vetterlein, 2021a). Version at which the feature was introduced = V2 & V3 in the top-right corner

4.2 Version 2

In version 2, to create a multiobjective optimiser, the carbon intensity of the grid and a new variable, Carbon price, were introduced. Aside from loading these data and exporting them with the solution dataset, the only difference from V1 was their inclusion in the Objective Function, combining the carbon cost with the monetary cost, as shown below:

$$OF2 = min(\sum_{SP=1}^{OD} \sum_{m=1}^{M} (i(SP)(m) * \left(I(SP) + CP * C(SP)\right) + s(SP)(m) * (X(SP) + CP * C(SP))))$$

Where:

- C(SP) = Carbon Intensity [g CO2eq/kWh]
- CP = Carbon Price [p/g CO2eq/kWh]

In this version again, only hot water tanks were optimised for lowering their forecasted self-consumption opportunity cost and electricity import cost. The available self-consumption potential was based on total PV generation. This would not always be the case due to other loads in the microgrid. As carbon intensity of import and export, used for self-consumption, was taken the same, carbon optimisation should not increase self-consumption. This could, however, happen, if the grid intensity would fall during high regional PV generation. To assess the impacts of the daily optimisations over a long timeframe, a new function, Long Run Optimisation, was built from the V1's Bulk Run configuration. This function runs the 24h optimisation for each day within a specified period, outputting summarised data of daily granularity.

4.3 Version 3

Version 3 has kept the overall structure of the model, including some of the data loading functions and the Long Run function. However, its objective was modified. To properly account for a newly introduced battery in the microgrid, all real electricity flows needed to be taken into account. Thus, the V3 Objective function minimises the sum of the total import costs and the negative value of total export costs, later comparing it with the “Real” values, using past OSCE data. This means that total daily electricity costs or emissions can be negative, or near zero, despite high power use. Analysing the optimiser’s performance should, therefore, be based on absolute values rather than on relative ones, especially for higher granularity data. PV generation data was not used in this version as metered export and import power flows include it. This version uses energy in kWh/SP for all appropriate variables, unlike V1 and V2, which used power in kW for some of them, later converting it to kWh.

Linear programming’s limitations, mostly the inability of decision variables usage in other than linear forms of equations and in looping functions, influenced the development of this version. Ensuring that the simulated import and export have the right values, accounting for original power use, battery and mixergy loads, could not be done by simply assigning them all the power flows. In such a case, both of them would be non-zero at any point, and both would contribute to the final OF value. Instead, a power balance equation was used to ensure that all exports to the microgrid equal all the imports for each SP. The simulated import and export variables were bounded to be only positive and negative, respectively. Similarly, the battery’s power flow was modelled by two distinct decision variables, instead of one “net” variable, to enable the implementation of the roundtrip efficiency.

The balance equation, however, ensures that for export price < import price during SP, the power exchange with the grid stays one-directional, otherwise, the imported energy would cost more than the profit from the same energy exported. This is not the case in reality as even during high PV generation, some electricity is imported within the supply period. The optimiser automatically cancels this import with the same amount of export, saving money which would not be saved in reality. Although the impact on cost is only approximately 0.6%, the appropriate value was subtracted from the simulated savings for all runs in the Results section. Similarly, if it would ever occur that the export price would be higher than the import price, the optimiser would simply maximise imports and exports, making virtual money that could not be really earned. A solution to this problem was not found, however, due to FCL applying only to imports, it stays always higher than the export price in the data used.

Aside from the optimisation problem datasets, a battery in the model has a series of design and operational parameters, which are summarised in Table 7

Table 7: List of Optimiser's battery input parameters.

Input parameter	**Unit**	**Description**
bCapacity	kWh	The total max. capacity of the battery when new
bPower	kW	Maximum available power for trading, additional power may be reserved for FFR
rEff	%	The roundtrip efficiency of the battery, experimentally found by CEPro to be 85%
SOCmin	%	The level of SOC below which the battery should not get
SOCmax	%	The level of SOC above which the battery should not get
mSOC	%	The SOC at which the battery should be every midnight
CP	GBP/t CO2eq	Carbon Price getting carbon emissions the same units as the electricity prices
CoT	p/kWh	The virtual cost of energy throughput through the battery, introduced in Version 4

LP Variables, all in [kWh/SP]

- $HWT_i(SP)$ = Mixergy electricity use for water heating during the SP, simulated
- i(SP) = Simulated total electricity imports during SP (positive; <bPower)
- x(SP) = Simulated total exports electricity during SP (negative; <bPower)
- $b_i(SP)$= Simulated electricity imported to the battery during the SP (positive)
- $b_e(SP)$ = Simulated electricity exported from the battery during the SP (negative)

Objective Function

$$OF3 = min\ (\sum_{SP=1}^{OD}(i(SP) * (I(SP) + CP * C(SP)) + x(SP) * (X(SP) + CP * C(SP))))$$

Constraints

1) Battery updating its SOC each SP:

$$b_{SOC}(SP) = \ b_{SOC}(SP-1) + b_i(SP) * \sqrt{rEff} * SOC_d + b_e(SP) * \frac{1}{\sqrt{rEff}} * SOC_d$$

Where:

- $b_{SOC}(SP)$ = Battery State of Charge at the end of Supply period [%]
- rEff = Battery roundtrip efficiency [%]
- SOC_d = Rise in b_{SOC} per kWh of energy input, calculated from its parameters [%/kWh]

2) Power balance equation:

$$0 = \ i(SP) + x(SP) - Other(SP) - b_e(SP) - b_i(SP) - \sum_{m=1}^{M} HWT_{i,m}(SP)$$

Where *Other(SP)* = All non-optimised “Real” loads during the SP, found as:

$$Other(SP) = SM_i(SP) - SM_e(SP) - \sum_{m=1}^{M} HWT_{R,m}(SP)$$

Where:

- $SM_i(SP)$ = Actual Import Smart metering for the SP (positive) [kWh/SP]
- $SM_e(SP)$ = Actual Export Smart metering for the SP (positive) [kWh/SP]
- $HWT_R(SP)$ = Real power usage of Mixergy HWTs [kWh/SP]

3) Limiting battery’s SOC within its specified bounds:

$$SOCmin \leq b_{SOC} \leq SOCmax$$

4) Mixergy HWT constraint from V1.

4.4 Version 4

Version 4 of the optimiser had only the OF upgraded to place a price on battery usage as was done, for example, in (Aghajani et al., 2017). Each kWh cycled through the battery has an internal cost, which makes the battery cycle only on higher margins. This is hypothesised to prolong the battery's lifetime while keeping its savings nearly as high as without the cost of throughput.

$$OF4 = min\,(\sum_{SP=1}^{OD}(i(SP) * (I(SP) + CP * C(SP)) + x(SP) * (X(SP) + CP * C(SP)) + b_e * CoT))$$

Where:

- CoT = Cost of Throughput [p/kWh]

The value of the Cost of Throughput can be linked to the battery's impacts, but it can also be used simply to limit its usage. This is further discussed in Section 5.3.3.

5 Results and Analysis

The approach to processing data from the model follows the versioning from its development process and implementation of additional features, while it introduces decisions behind the various Scenarios' input values. In the first part, validated results from the Version 1 original hot water optimiser, shown in Section 4.1, are compared with the multi-objective Version 2 optimiser, which aims to minimise both electricity cost and carbon emissions. Total savings over multiple months are discussed, together with a detailed analysis of a single day's multi-tank optimisation results.

Version 3 of the optimiser utilising the new objective function, combining optimisation of Mixergy tanks and battery operations is introduced in Section 5.2. The impacts of battery and hot water optimisation are compared using multiple input parameter scenarios of the optimiser to estimate the potential carbon and cost reductions from each technology.

The impact of the battery alone is assessed in Section 5.3 using the Version 4 optimiser and a battery degradation model to estimate the useful lifetime of the battery. Different input parameters' effects are investigated to find an optimal battery operation scenario, which then feeds into the Carbon Pricing section, where the overall emissions savings potential is investigated. A whole-life approach is used to estimate the benefits of a battery implementation to the microgrid, aiming to help with answering the question of whether it should be implemented and in which configuration. Impacts of changes to some of the main initial assumptions are then investigated in a Model Validation section.

5.1 Grid Emissions

The addition of the product of a carbon price input and the half-hourly regional carbon intensity to the Version 2 of the model has effectively created new import and export electricity prices, which should influence the Mixergy heating schedule, shifting its load to lower carbon times. This optimisation minimises the total imported cost and the total opportunity cost from self-consumed PV generation.

The multi-day optimisation was run for the available 245 days in 2021, from 01/05 to 31/12, during which both Mixergy tanks, ECC and Nursery, had been operating. 21 of these days did not have full Mixergy usage data and thus, consumption for the same weekday during a different week within one month before the modelled date was used instead in combination with the actual PV generation, grid carbon intensity and electricity prices.

Three Scenarios were run, one (0CP) using only the Version 1 optimiser without carbon optimisation, and two other Scenarios with different Carbon Prices, 100 GBP/t CO2eq and 500 GBP/t CO2eq, denoted as 100CP and 500CP respectively. The main optimisation metric for all three is the forecasted APX price, while for the multi-objective optimisation Scenarios, carbon intensity has, although typically lower, influence as well. To get an overview of the comparison, Figure 19 shows weekly total savings of the APX electricity cost, SSP electricity cost and the CO2eq emissions in kilograms. The graph clearly shows a difference between results for the first 17 weeks and the rest of the run, when the real savings start to diverge a lot more. This large variance corresponds to the “New” electricity prices as defined earlier.

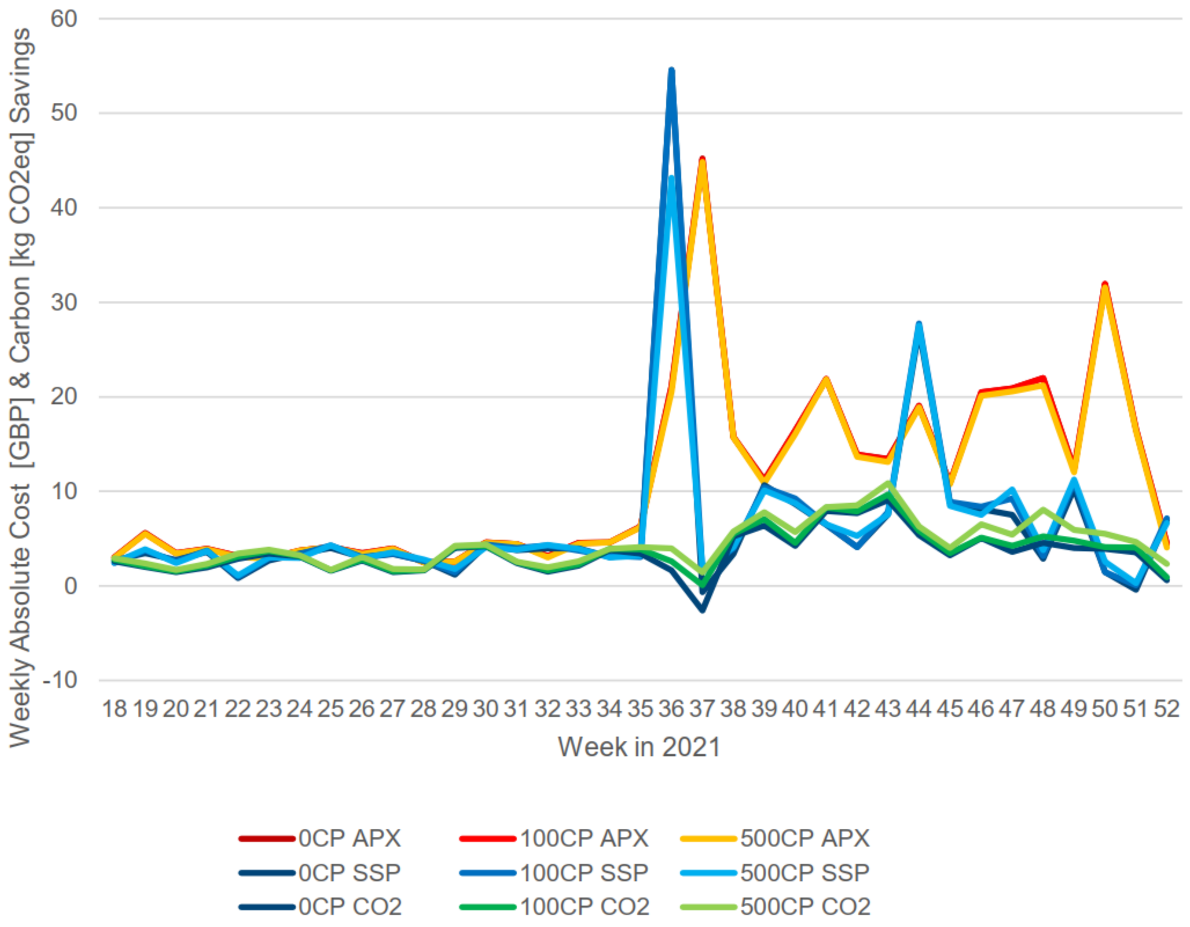


Figure 19: 3 Scenarios of Mixergy double-tank 24h optimisation savings results for 35 weeks in 2021. Version 1 Scenario with no Carbon Price (0CP) is often covered by the 100 GBP/t Scenario (100CP). 500 GBP/t Scenario is in lighter colours.

It can be observed that all three metrics follow a very similar path for all scenarios. APX savings are very close to each other for all three scenarios, ranging from 2.5 to 45 GBP/week with the 0CP Scenario slightly outperforming the two multi-objective ones. SSP savings saw greater variability between the scenarios, especially during times of higher volatility. From week 36, they do not seem to, on a weekly basis, follow the APX predicted savings very well. SSP weekly savings range from -0.7 to 55 GBP, which occurred just a week apart. Both of these extreme values were observed in the 0CP Scenario. The CO2 savings have stayed more stable within the year but have also increased after week 38. Their values between the three scenarios varied relatively more than the cost savings for many weeks. The 500CP Scenario even achieved more than double the 0CP Scenario's carbon savings in 3 weeks.

The overall statistics of savings are shown in Table 8. It can be observed that all types of savings are within single percentage points for the 3 different scenarios. An important result is that the 0CP Scenario, although not optimising for carbon, has achieved a 10% CO2 emissions reduction in total, increasing the carbon emitted for only 20 days during the optimisation. This suggests that the carbon intensity of the grid is lower during low price periods. As expected, APX savings decrease with the increasing value of another optimisation metric, while the carbon reductions follow an opposite trend. This was found to be true for every day in the range of dates, as linear programming should achieve the highest APX savings possible, the ideal scenario, when it is its only optimisation metric.

Scenario 500CP achieved 27% higher CO_2 savings when compared to the 0CP Scenario, while its APX Savings decreased by 1.7%. SSP savings were, interestingly, found to be higher for the lower carbon price scenario than for the one with no carbon optimisation. However, the 500CP Scenario's performance does not follow the same trend, achieving the lowest SSP savings. The carbon trade-off metric is calculated by simply dividing the difference between zero-carbon and the appropriate carbon-optimisation Scenario's total APX savings by the difference in their carbon savings. It should be, for this simple optimisation, lower than the Scenario's carbon price but higher than the lower CP scenario's one, which was found to be true. It effectively indicates how much more would OSCE need to pay for its electricity to achieve a ton of CO_2 savings, relative to pure cost optimisation (if APX would be used as the final electricity price).

Table 8: Summary of total cost and carbon savings achieved by a series of two-tank 24h optimisations for 245 days. Carbon trade-off calculated from 0CP scenario.

Optimiser Version:	**Version 1**	**Version 2**	**Version 2**
Scenario	**0CP**	**100CP**	**500CP**
Carbon price [GBP/t CO2eq]	0	100	500
APX Savings [%]	25.62%	25.58%	25.19%
SSP Savings [%]	15.65%	16.28%	15.59%
CO2 Savings [%]	10.20%	11.26%	13.01%
CO2 Trade-off [GBP/t CO2eq]	-	48.3	194.1

While the total amount of electricity needed was the same for all three scenarios, the share of it self-consumed, i.e., coming from PV arrays, increased slightly for higher carbon prices from 73.26% (0CP) to 73.67% (500CP). This suggests that the pure cost optimisation has utilised near maximum of the usable PV generation. As observable in Figure 20, the daily SSP savings show greater variance than the APX savings, which also never go to positive values. The chart also shows a slow progression towards lower CO_2 emissions with increasing carbon prices.

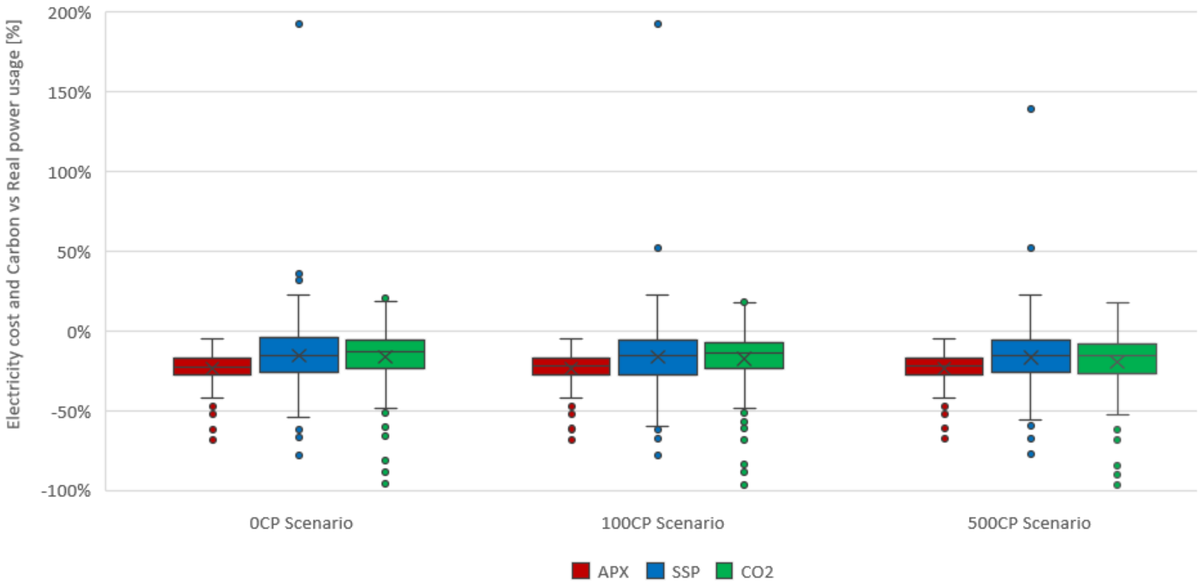


Figure 20: Daily Cost and Carbon savings when compared to the actual HWT power usage for the 3 scenarios of different input carbon prices.

To show the optimisation in detail, half-hourly data for one day with high results differences are presented below for the 0CP and 500CP scenarios, together with the grid carbon intensity and pricing data. For the 16th of September 2021, both scenarios' optimisations resulted in approximately 68% APX forecasted savings. However, the real cost, SSP, would have been higher than for the real power usage by 23% and 6% for the 0CP and 500CP scenarios respectively. The daily carbon emissions would have risen for the 0CP scenario, while for the 500CP, it would decrease, but by only about 1%.

As shown in Figure 21, with a higher carbon price, the power usage shifted more towards the middle of the day, when PV generation in the grid lowered its carbon intensity, further increasing the on-site self-generation. As the actual SSP price did not follow the APX forecast towards the 200 p/kWh levels, the optimised solutions would actually increase the real cost paid by shifting the consumption away from around 10 AM into the lower-carbon late evening. There, the difference between 0CP and 500CP is clearly visible as the 0CP scenario uses the power already from SP 43, when the carbon intensity of the grid is still near its daily peak of 314 g CO2eq/kWh.

Although the carbon savings from optimiser Version 2 are not achieving similar values as the APX cost savings, they have shown to be effective in further lowering the emissions when compared to the cost-only optimisation. At the same time, it did not raise the HWT power costs extensively as it shifted the consumption to lower-cost, lower-carbon times.

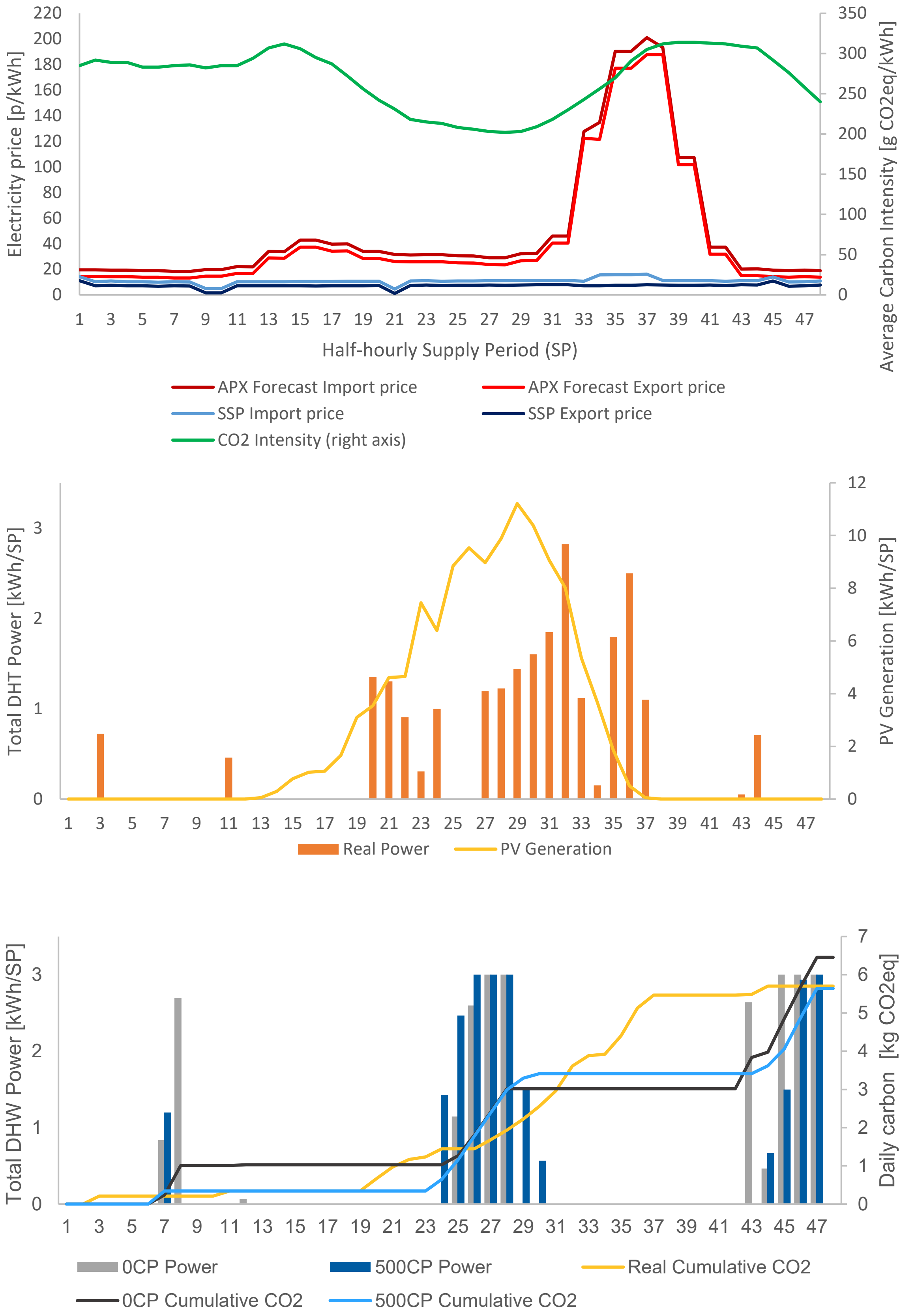


Figure 21: 0CP and 500CP Scenarios power schedules for 16/09/2021 and their cumulative emissions. Top and Middle: power grid data and the real power flows within OSCE for the day.

5.2 Battery

Version 3 of the optimiser utilises the newer objective function, which aims to reduce costs and emissions resulting from the total imports after subtracting the total exports from the microgrid. This is different to Version 1 and 2, where only Mixergy tanks and the full PV array were considered without any other power loads included. To compare the results from the two different approaches together with the impact of the battery on the overall savings, Version 3 was run for the same period of time as in the previous section, optimising a 160kWh battery with and without the 2 hot water tanks for APX price and grid emissions with 100 GBP/t carbon price. These Scenarios are denoted respectively as V3-Battery and V3-Battery+HWT in this section. To enable better comparison, the same pricing was used, although installing a battery on site can unlock more variable export payments, further increasing possible savings.

The total savings over the 8 months from the 1st of May 2021 are shown in Figure 22. As expected, the two runs that include a battery show much greater savings than the 0CP and 100CP scenarios optimising the Mixergy tanks only. As the costs are accounted differently in Versions 1 & 2 and Version 3, they should not be directly compared. In the earlier versions, self-consumed electricity from PV array is always assumed to cost the opportunity cost of its export. However, in a more realistic Version 3, this would be the case only if the microgrid is exporting this electricity. During PV generation when this electricity is consumed by other loads in the microgrid, HWT consumption would cost the import price. Thus, the cost savings are overestimated for the 0CP and 100CP scenarios, as shown on the chart.

The carbon accounting should, however, be compatible. The total CO2 savings from the 100CP HWT-only scenario is 132 kg. Version 3 Battery optimisation achieves with and without HWT 882 and 799 kg CO2 savings, respectively. Their difference should be attributable to the Hot water optimisation and is lower than the one achieved by the V2 optimiser. The difference between their performance comes mostly from altered consumption times when PV arrays generate power. Results from the Version 3 scenarios show that the battery has approximately 6 times greater impact on CO2 savings than the 2 Mixergy hot water tanks.

The Cost savings of V3 scenarios show a great difference between the predicted APX and realisable SSP values, despite the real total SSP cost over the 8 months being only 2% lower than the APX. This difference is mostly driven by the unreliability of the day-ahead APX price as a prediction of the actual, very variable, spot price in recent months.

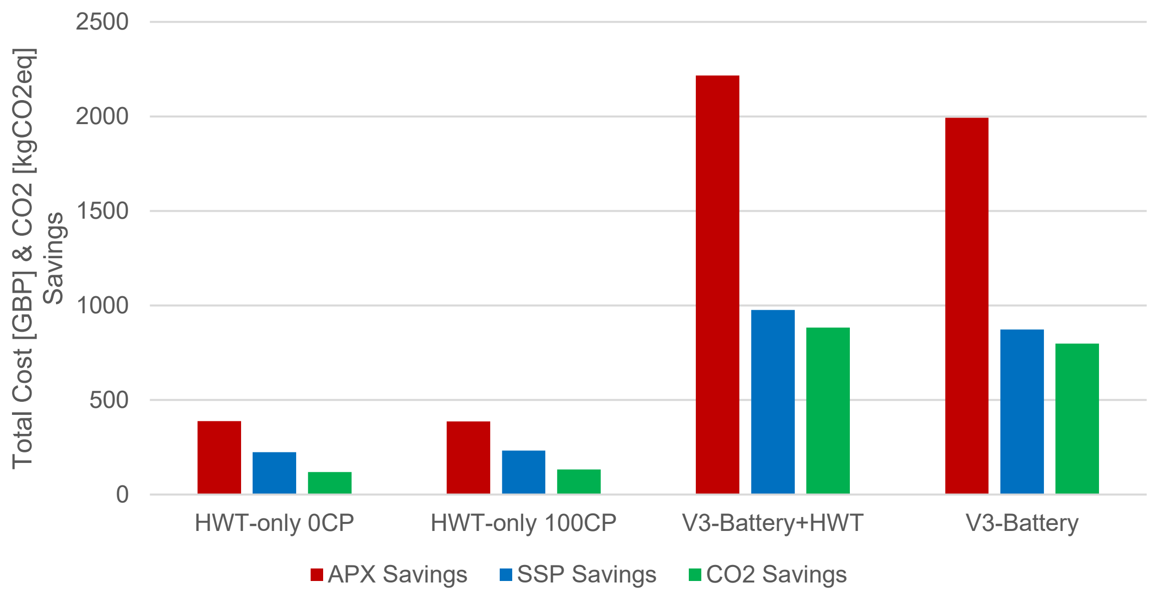
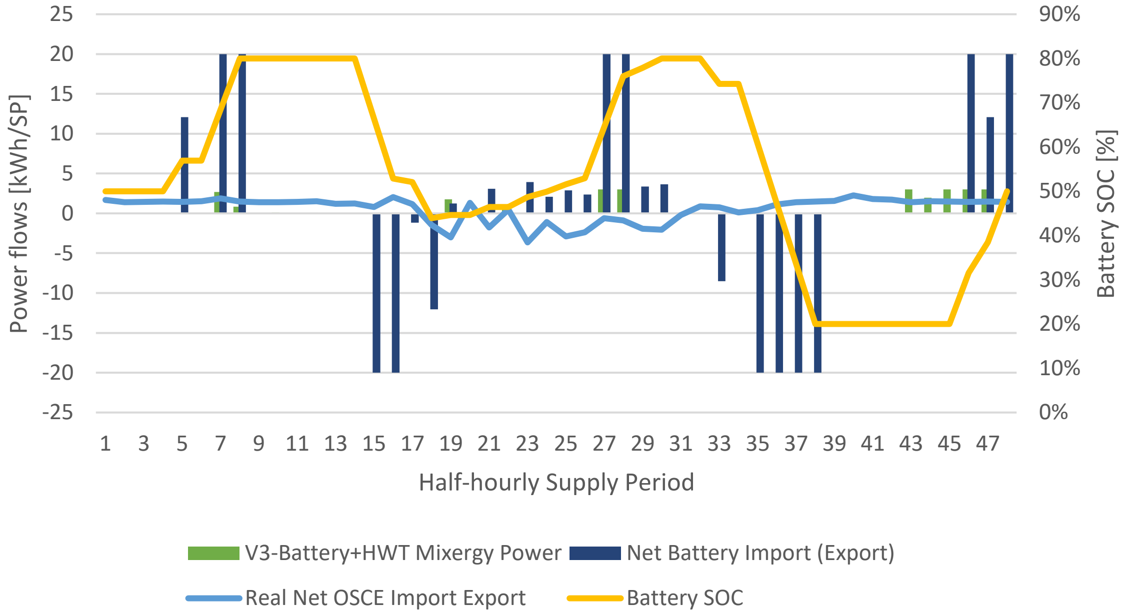


Figure 22: Total savings for Version 1 (0CP), 2 (100CP) and 3 (V3) of the optimiser for 245 days in 2021. Cost accounting differs between the versions.

To present the operation of the battery in detail, Figure 23 shows the optimisation results for the same day as Figure 21. As observable on the top chart, the V3-Battery+HWT scenario charges the battery to its set maximal SOC, 80%, during the expected morning low prices, then discharges during a local peak in the predicted price. During the day, it matches the PV real exports to the grid (blue line) so that the energy is not exported at a lower price than could later be. Before the forecasted extraordinary evening price peak, it charges to max SOC again to then discharge its full capacity for the highest APX export prices.

The HWT power consumption is much smaller than that of the Battery and roughly follows the same heating profile as the 0CP and 500CP scenarios were. Heating around the SP27 would have been accounted for as self-consumption at an export price in the previous versions of the optimiser, however, here it can be seen that the exports to the grid are lower than the HWT demands. Thus, it actually charges at the import price. The bottom chart shows the V3-Battery scenario's results, which are nearly identical to the scenario with HWT included. One of the optimisation's features observable from the graph is that the battery very often runs at its full power, 40 kW (or 20kWh/SP), whenever the price and carbon data signal it to be profitable.



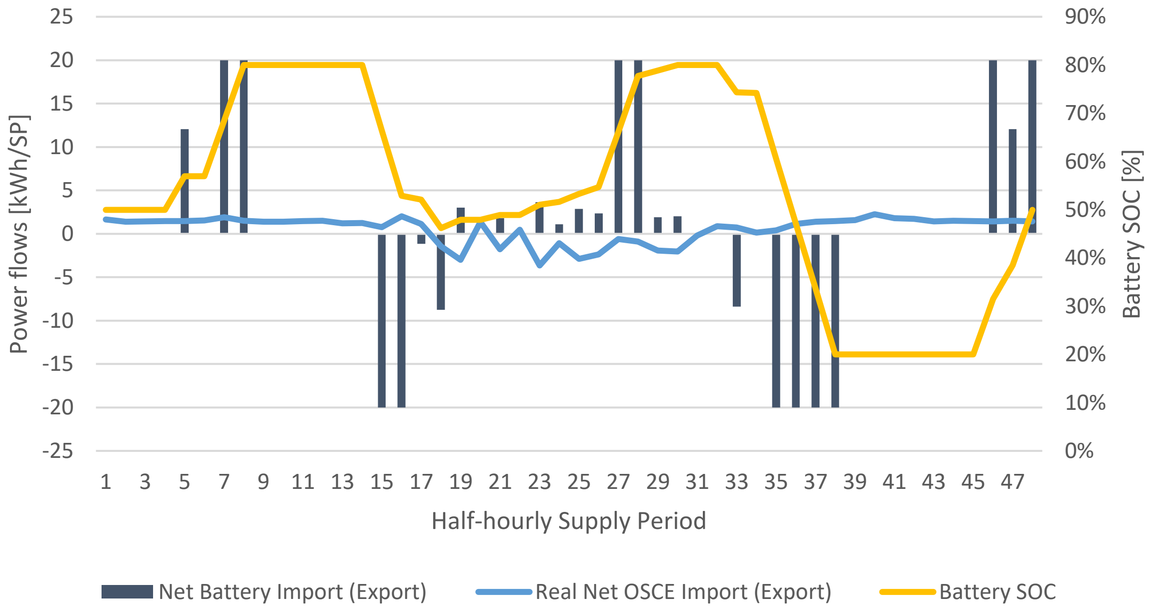


Figure 23: Power flows for the Battery + HWT (Top) and Battery only (Bottom) Scenarios one-day optimisation for 16.09.2021 with the Battery State of Charge through the day on the right axis (limited to 20-80%) Grid data in Figure 21.

The reasons behind the battery's operation shown above and its results can be further explained using Figure 24, which shows the cumulative predicted and realisable costs and carbon emissions for the Battery-only scenario. The real scenario's cumulative performance is much smoother as it uses less energy than with the battery and its APX cost rises significantly in the evening as energy was used during a predicted price peak. Its cumulative emissions rise slightly in the morning, then fall to near 0 as PV generated power is exported to the grid during the day.

Using a battery produces a much greater variability in the cumulative performance. As the battery charges in the early morning, both costs and carbon rise, then fall sharply during the 8 AM predicted peak prices. Despite its SOC staying around the initial 50%, its operation achieves profit already by 9 AM. To make the most profit from the evening peak, the battery was charged during the day, however, the cumulative APX cost did not get as high as in the morning. During the evening peak, the battery aimed at making over 100 GBP profit on the full day's electricity consumption and production of the microgrid. However, as the spot price line stayed flat, the SSP cumulative cost (light blue) actually overtook the Real scenario before midnight.

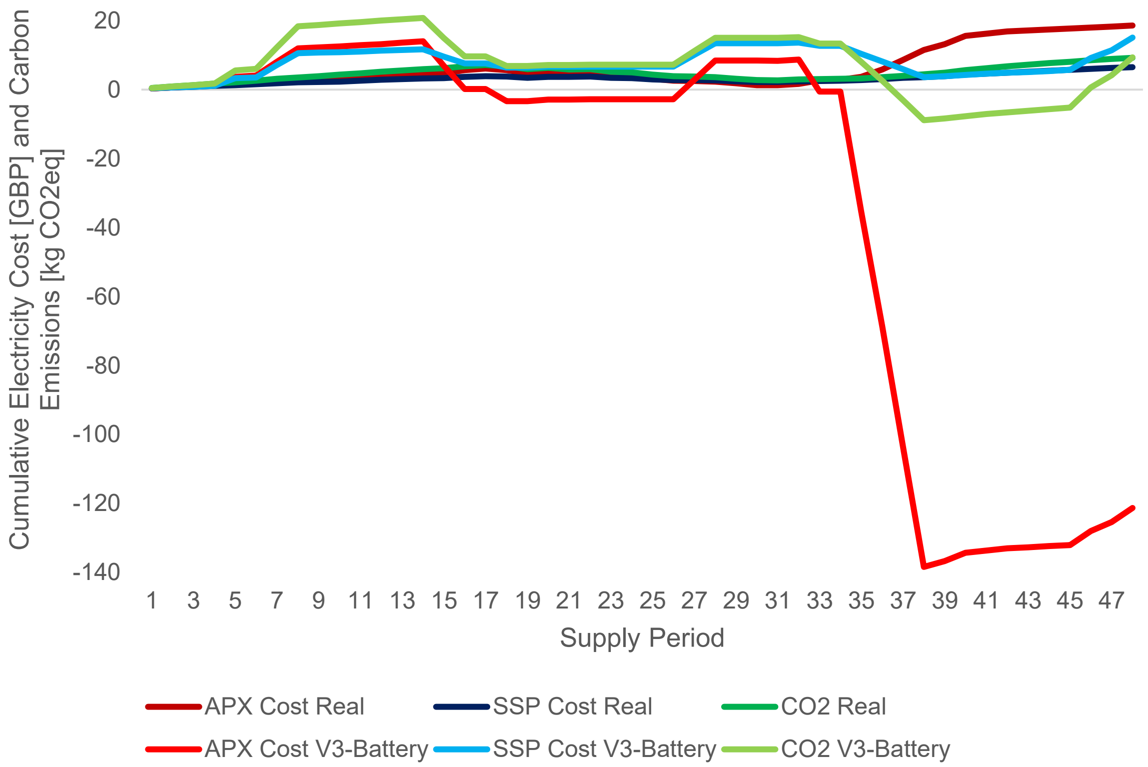


Figure 24: Cumulative APX, SSP costs and CO2 emissions during the 16th of September optimisation for the Battery-only scenario, together with the same data for the microgrid without a battery. Negative costs are profits.

As the results above show, the model is able to optimise a battery in the OSCE microgrid and thus, its performance and operation are investigated further below. Due to the lack of reliable Mixergy data for a full year and the aim to estimate the impact of the battery itself, hot water optimisation is not considered in the following Results subsections. To set a benchmark for battery performance, a full 2021 year's optimisation was run, using 100 GBP/t carbon price and the actual, slightly more variable, pricing available to the site after installation of the battery.

A summary of the results of this run is shown in Figure 25. More than 75% of days have achieved APX, SSP or CO2 savings, with APX savings on average being higher and less variable than the SSP, as observed before. Daily cost savings have seen multiple times more outliers than the carbon savings, which might be a result of spot price spikes, equivalent of which does not occur in the carbon intensity data. Especially for the cost savings, the mean value was found to be much higher than the median, in the case of APX even dragged by outliers above the upper quartile. Interestingly, one day, the 28th of February, has seen a loss in the APX price, which is possible only due to the multi-objectivity of the optimisation. In fact, this day saw the second-highest carbon savings, which overweighted the APX costs that typically dominate the objective function's value.

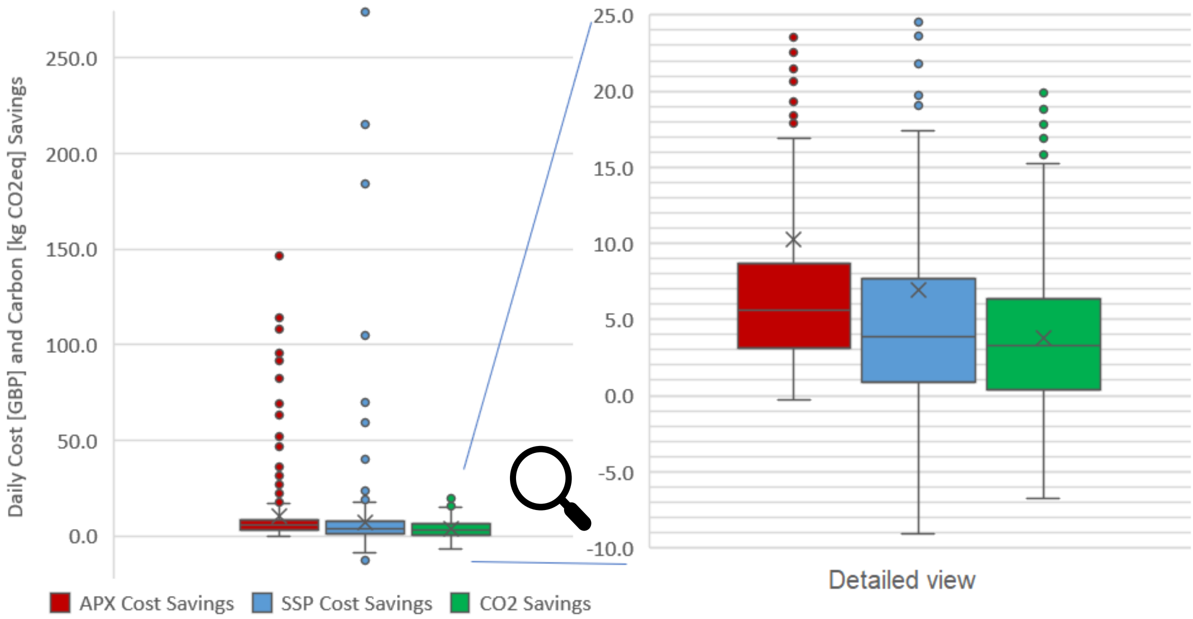


Figure 25: Statistics of daily savings, profits, or avoided emissions in absolute values for a full year run of the V3 battery optimisation for initial (Base) input parameters.

The overall relative annual savings to OSCE's power usage achieved by the implementation of the battery were found to be 26.4% and 17.7% for APX and SSP costs, respectively, and 8.1% for the carbon emissions. In absolute terms, 2,456 GBP in realisable, SSP, savings was achieved by the 160-kWh battery, which typically costs higher tens of thousands. This raises the question of whether the battery will pay for itself by the end of its life. As the total number of full equivalent cycles the battery performed in this annual scenario was 244 and a typical lifetime of an NCA battery is, based on a generic and possibly outdated estimate, approximately 500 cycles (Buchmann, 2010), this issue is investigated further to improve the lifetime performance of the battery and aid in its selection and operational decisions.

To illustrate the problem of battery over-utilisation, Figure 26 shows the battery operation during one day in January. The battery exports some energy in the evening peak, but otherwise, it only buys it for use by other loads in the microgrid when the import price increases, avoiding higher costs. This happened in the morning, at around 5 AM, the battery purchased power for approximately 13p/kWh, selling it at 10 AM, effectively avoiding the import price at the time, 17p/kWh. Thus, the savings would be their difference if the battery was modelled with 100% roundtrip efficiency. Accounting for the used 85% roundtrip efficiency, the savings in this case are roughly 1.5p/kWh, less than 10% of the import price at the time. It is highly possible that such trade is not profitable from a lifecycle perspective.

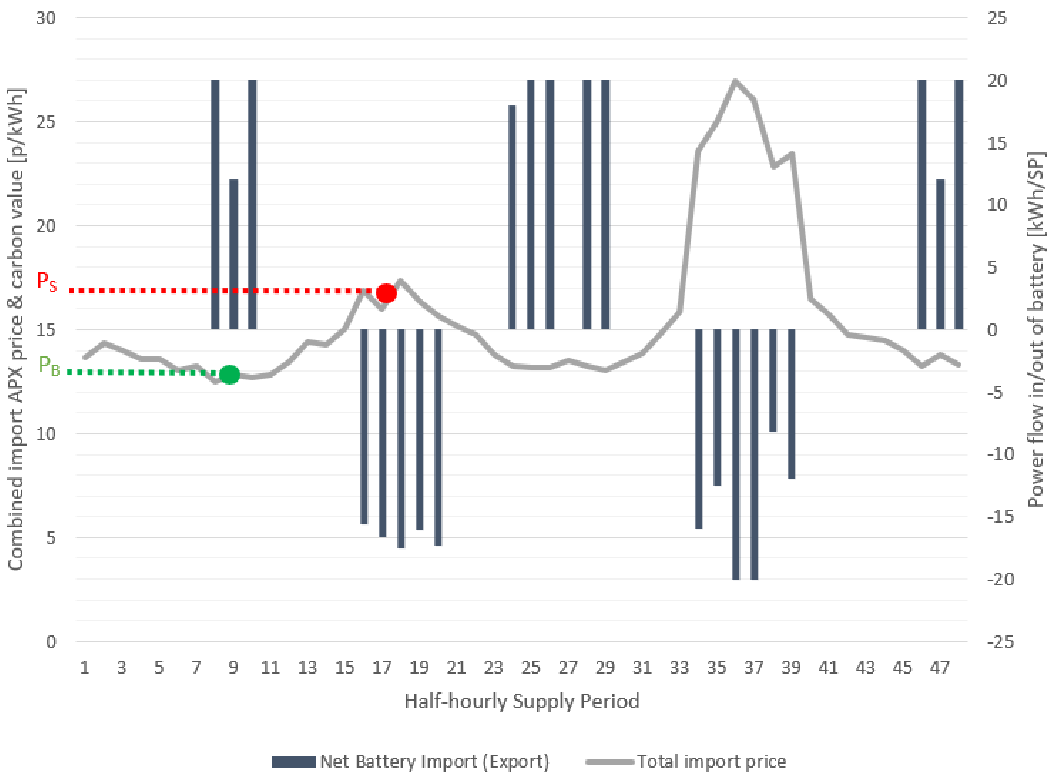


Figure 26: A case day, 25th of January, of simple battery cost & carbon optimisation showing the morning purchase price (green) and sell price (red) a few hours afterwards.

5.3 Design and Operation

To assess the battery's impact over its full lifecycle, this section focuses on the battery's operational parameters' influence on its functional lifetime and thus, achievable benefits of its introduction to the microgrid. Version 4 of the optimiser, which includes minimisation of the battery's usage in its objective function, is used here. The approach to finding an effective combination of battery operation and design input parameters (Optimised Scenario) starts with setting an initial (Base) scenario as summarised in Table 9.

By varying one parameter at a time, its impacts are assessed and a more effective value may be then selected for the final Optimised scenario. Where appropriate, interaction effects between two variables are also investigated. Additional changes to optimisation scenarios may be done, such as using different pricing or carbon intensity data, including HWT optimisation, or running the optimisation for different dates. These effects are investigated in Section 5.5, but in this section, all scenarios run from 01/01/2021 to 31/12/2021 and use the variable import and export pricing as outlined in the Methodology section, as well as the average regional half-hourly carbon emissions.

Table 9: List of the input parameters of the optimisation model with their baseline values.

Input parameter	Base Scenario	Justification
bCapacity	160 kWh	The smallest Tesla Powerpack model 2023
bPower	40 kW	2-hour version of the powerpack, additional 40kW of power is reserved for FFR
rEff	85%	Experimentally obtained by CEPro
SOCmin	20%	Saving battery's life by ensuring it doesn't discharge to very low levels of SOC
SOCmax	80%	Saving battery's life by ensuring it doesn't charge to very high levels of SOC
mSOC	50%	Middle of the SOC limits
CP	100 GBP/t CO2eq	Carbon Price approximating the typical SCC
CoT	-	Not used in V3. For V4 it needs to be found. Later set at 3p/kWh

5.3.1 Capacity degradation

Figure 27 shows the iterative process to finding more effective scenarios, which utilises the previously developed Battery capacity degradation model, as outlined in the Methodology section. Due to its limitations, the maximum possible timeline it can estimate is approximately 25-30 years, although it outputs higher lifetimes for batteries under very little usage.

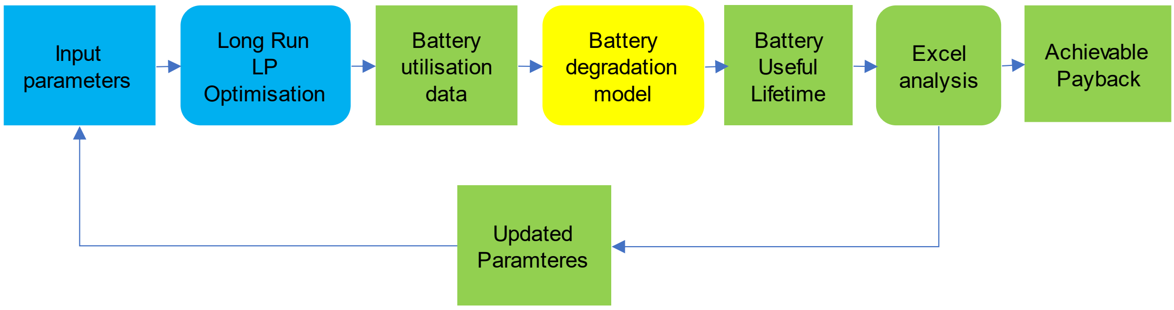


Figure 27: Diagram of the approach to finding improved operational and design parameters of the battery in the context of its useful lifetime.

Version 3 of the optimiser has achieved savings in all three metrics as shown in Figure 25. Its usage parameters are summarised in Table 10 together with the general assumptions used for the following scenarios as well. The inputs chosen did not account for the FFR cycling, which is a potential source of degradation underestimation.

Table 10: Battery degradation model's input parameters with typical values used through this section and the values obtainable from optimisation's data.

Input parameter	Value	Description
mSOC	50%	Middle State of Charge, here assumed to be the Scenario's midnight State of Charge
DoD	60%	Typical Depth of Discharge during a cycle; lower of the two values: (maxSOC – minSOC) or (average FEC/day)
Cycle Temp.	35°C	The battery temperature during charging or discharging, using an estimate for a well-cooled battery
Storage Temp.	15°C	The battery temperature during its idle time, here using an estimate for outdoor temperature in Bristol
C-rate	0.25C	The dis/charging C-rate during cycling, calculated as the bPower/bCapacity of the battery. Here 40kW/160kWh
Annual usage	244 FEC/y	The number of Full Equivalent Cycles that the battery undergoes during one year

The key output from the degradation model is the number of FECs that the battery will be able to cycle through before reaching 80% of its initial capacity, here assumed to be its end-of-life state. For the scenario above, it estimates the lifecycle at 2700 FECs, or 11 years of operational lifetime, which is much higher than the generic estimate of 500 FECs, however, it still puts its profitability into question. The degradation tool also estimated that in this case, 79% of the battery's end-of-life degradation was attributable to its cycling, while the rest to its simple ageing over the 11 years.

5.3.2 Capital impacts

To find the battery's lifetime revenue, the realisable, SSP, savings were combined with the CP value of carbon savings and the estimated revenue from the remaining battery's power capacity, 40 kW in the Base scenario, for FFR. The capital cost of the battery with the value of its embodied carbon was then simply divided by the total annual revenue to get an estimate of its "Payback" time. This is, however, not a proper payback period based on accounting standards as it does not include, among other aspects, discounting or electricity prices, carbon intensity and carbon value outlook. It is simply a way of comparison between the annual revenue and the estimated degradation. The equation to find the payback is:

$$Payback = \frac{SOC_{cap} * (b_{Price} + CP * b_{Carbon})}{SSP_{Savings} + CP * CO2_{Savings} + FFR\ Revenue}$$

Where b_{Price} is the per kWh purchase price of the battery, and b_{Carbon} its embodied carbon emissions per kWh. For the Base scenario, the Payback period is then:

$$Payback_{Base} = \frac{160 * (527 + 100 * 0.076)}{2456 + 100 * 1.39 + 3360} = 14.4\ years$$

As the simplified Payback time is found to be higher than the Lifetime estimate, limiting the degradation is necessary for the battery to become profitable.

5.3.3 Cost of Throughput

To account for the capital costs and embodied carbon of the battery during its operation, a new parameter, Cost of Throughput, has been introduced to the Version 4 optimiser. Its value was at first calculated by taking the degradation attributable to a single kWh cycled through the battery and multiplying it by the capital monetary cost with the carbon cost combined. The Cost of Throughput calculation equation, regardless of the total pack capacity, is shown below.

$$CoT = \frac{(b_{Price} + CP * b_{Carbon}) * d_{Cycling}}{LTC}$$

For the scenario above, b_{Price} and b_{Carbon} were estimated in the Methodology section, while the share of lifetime degradation from cycling, $d_{Cycling}$, and the number of FECs during the battery's lifetime, LTC, were found in the previous section. The CoT is, therefore:

$$CoT_{Base} = \frac{(527 + 100 * 0.076) * 0.79}{2700} = 0.156\ GBP/kWh$$

This factor was added to the scenario and the optimiser was run again. It resulted in annual savings in all three measured indicators, albeit the CO2 savings were only 0.8%. The battery cycled fully only 25 times during the annual run, nearly one-tenth of the Base scenario's value, while it achieved 15% APX savings, as opposed to the 26% in the Base scenario. The CoT greatly reduced the battery's cycling on low margins and for example, on the 25th of January, when the battery would cycle through 200kWh as shown in Figure 26, it did not run at all. In total, the Payback period was prolonged to 19 years, while its modelled Lifetime was found to be higher at 74 years. This is, however, unrealistic as the degradation model cannot estimate ageing over such a long period of time. Although the achieved ratio of Lifetime vs Payback is much better than in the Base scenario, it would be more effective for the battery to cycle more, getting to lower Payback times. For this purpose, a new performance indicator, Achievable Payback, was developed. It is the lowest Payback time for which it is lower than the Lifetime. To find it, multiple scenarios with varying CoT, already separated from the capital costs, were run producing the graph in Figure 28.

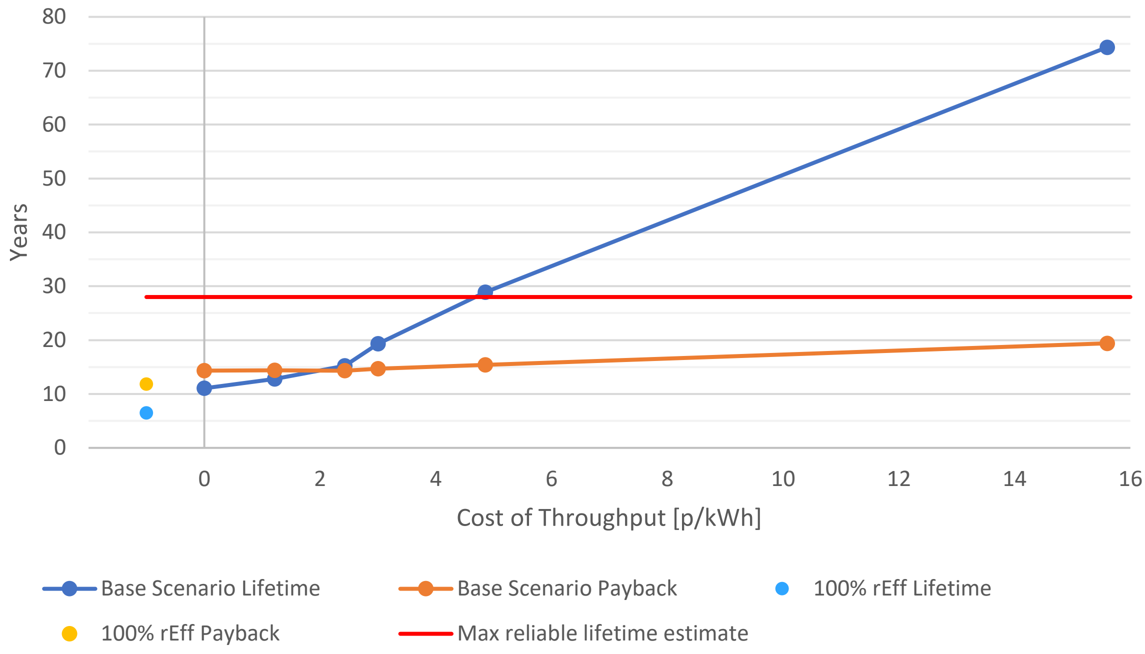


Figure 28: Lifetime and Payback time for the Base scenario with varied CoT parameter. For comparison only, results from the same scenario with 0 CoT & 100% Roundtrip Efficiency are added on the left, showing greatly reduced lifetime and somewhat reduced Payback time.

Figure 28 shows that the Lifetime of a battery increases much more steeply with the increasing cost of throughput than the Payback period. They both follow an approximate positive linear relationship with CoT and they cross at 2 p/kWh, where the Achievable Payback is 14.5 years. This method is being used further to find more effective battery operational parameters. The effect of the roundtrip efficiency is similar to the CoT, as a scenario with 100% rEff would achieve a payback of 11.8 years, while the battery would only last for 7. This is, however, unrealistic as all battery energy flows incur losses, despite some literature modelling batteries with such highly influential assumption (Kanchev et al., 2014; Shan et al., 2019).

5.3.4 Operation

This section investigates the effect of changing parameters on the battery's operation and its performance indicators, such as annual revenue or achievable payback. Scenarios use variable CoT, but for most of them, it is set to 3 p/kWh.

Available Power

The battery in question is the 80kW/160kWh Tesla Powerpack, which can dedicate part of its maximal power to providing FFR for payments from the grid operators. This was estimated to be proportional to the power available in the Methodology section. The rest of the power is then used for imports and exports from and to the grid and the OSCE microgrid. The lower the power, the less it can utilise short price surges.

Figure 29 shows the impact of the share of power available for each of the revenue sources. As expected, the revenue from trading increases with higher power, however, with decreasing returns per additional kW, following a diminishing returns trend. For CP of 100 GBP/t CO2eq, the value of carbon savings is much lower than the SSP. All but the 80kW trading scenario, whose Lifetime never reached its Payback time, had a rather low Achievable Payback. The total revenue peaks around 10:70 trading versus the FFR power division. However, to have greater potential for optimisation by the model, 40kW power was kept in the next sections.

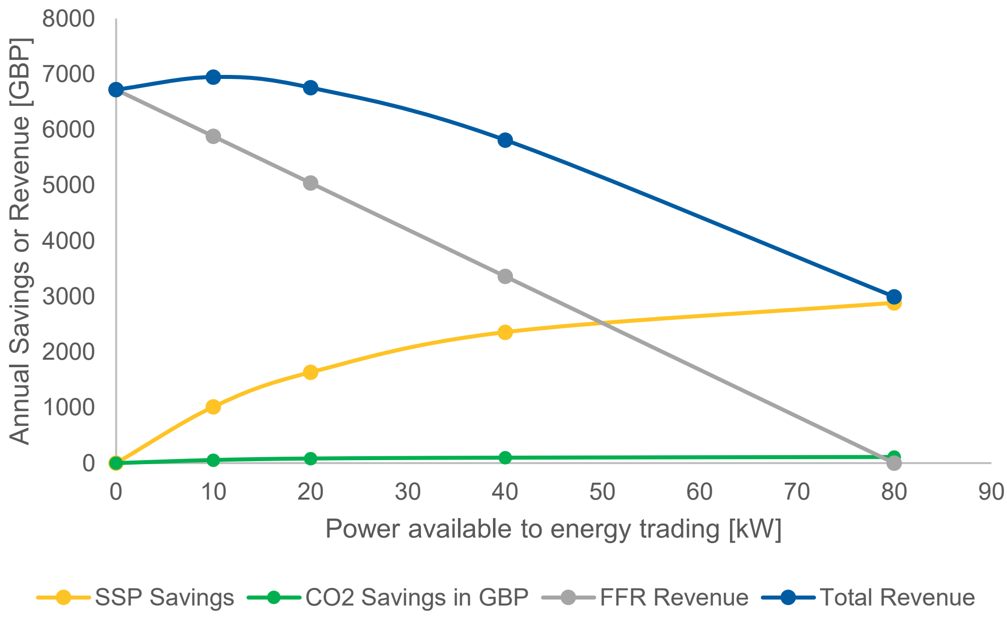


Figure 29: Annual battery revenue per source and total for 2021 based on the power available for trading. The rest of the 80kW was available for FFR.

State of Charge limits

Possible interaction effects of the two main day-to-day operational parameters were investigated by following the same procedure as in Section 5.3.3 to find the lowest achievable payback time. Due to a long computational time, not all possible combinations were run. All scenarios achieved a payback within 2 years from each other, between 13.8 and 15.5 years, as shown in Figure 30. From the graph, it seems that higher DoD limits are more effective until around 80%, when the payback stalls, while for higher DoD scenarios, the selection of lower mSOC was slightly beneficial.

As NCA Tesla batteries should not be charged above 90% (Merano, 2021), settings with DoD over 80% should not be used. Similarly, batteries should not be kept at low SOC, thus mSOC should be at least 40%. Despite enabling faster degradation, increased charging limits generally improved the performance, mostly by enabling more charging during low-price early morning hours and accumulating excess PV generation during the day for later use during peak prices. This is shown in Figure 31 and Figure 32, where the 30% mSOC scenario can charge all excess exports to sell them to the grid during the peak period (SP34-37), saving overall more than 3x on APX costs than the very limited scenario. Due to an error in the original data, the 80% DoD & 40% mSOC scenario was initially found the most effective, as opposed to the 70%-40%. However, the annual savings are off only by 0.1 percentage points, so its impact is nearly negligible.

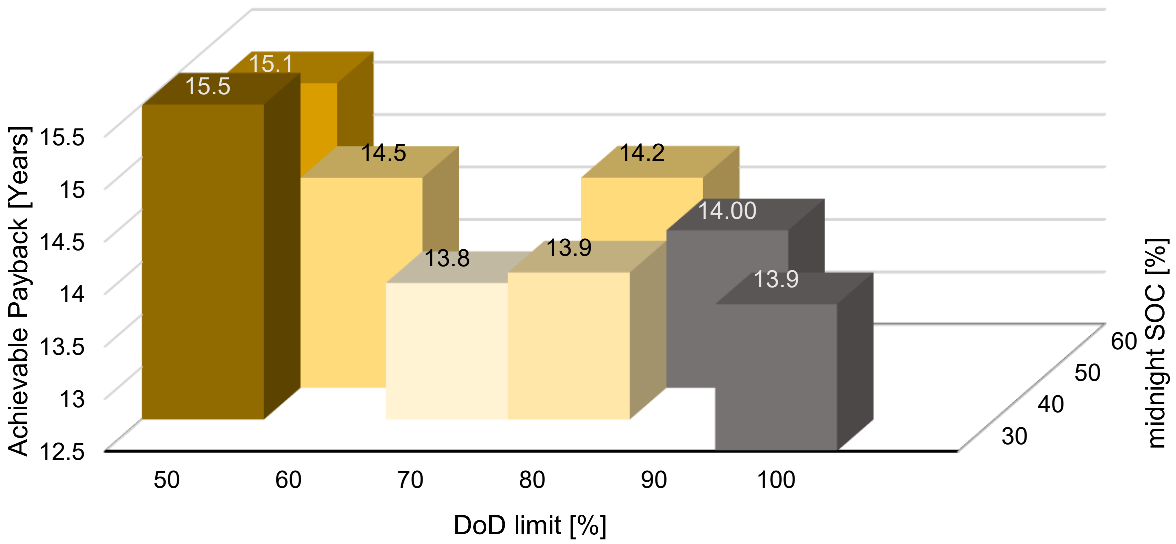


Figure 30: Achievable payback found by varying the CoT for combinations of midnight SOC and DoD. Remaining parameters as in the Base. DoD is calculated as SOCmax - SOCmin. Grey values are outside of typically recommended operational parameters; lighter color=better

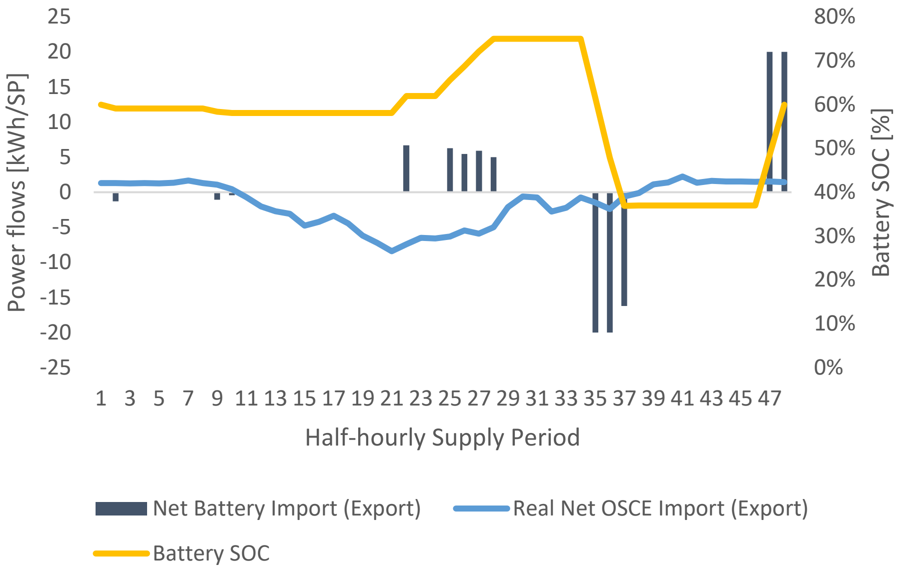


Figure 31: Case day of 16/06/2021 for a scenario with a very limited DoD and a high mSOC (60%). SOCmin=25%; SOCmax=75%. Price peak occurred between SP 34 and 37.

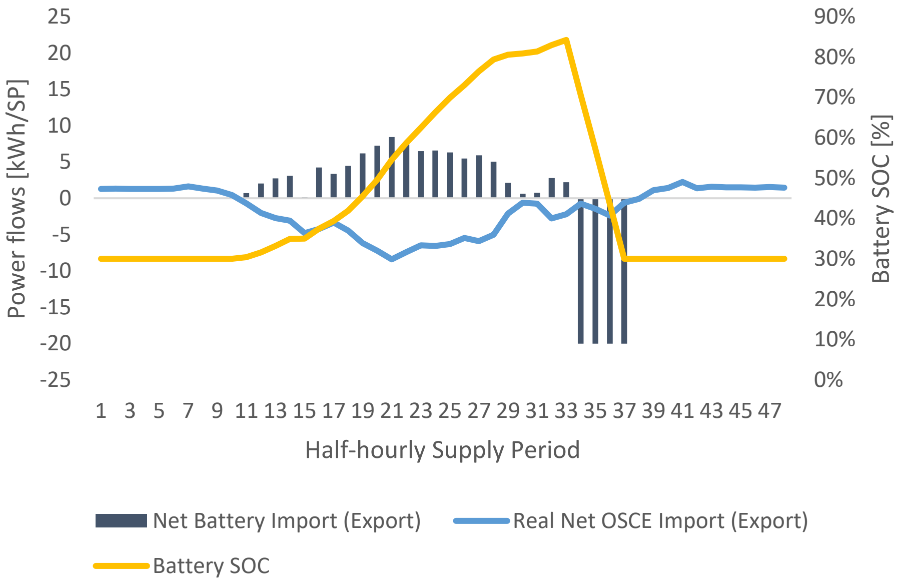


Figure 32: Case day of 16/06/2021 for the scenario with unlimited DoD and a very low mSOC (30%). SOCmin=0%; SOCmax=100%. Price peak occurred between SP 34 and 37.

Energy Capacity

Two different battery sizes were compared with the Base scenario: a half its size battery, and a battery of double the capacity. Both were run with two maximal power rating values. Although different purchase prices per kWh play a role in their payback times, the 80kW/320kWh battery would achieve it after approximately 14 years, just slightly lower than the Base 160kWh one. Thanks to high FFR revenue, the 40/320 scenario would achieve the lowest payback time. The smaller battery would achieve longer payback than the bigger ones if half of its power would be used for FFR, but when run at 40kW, due to the lack of FFR revenue, it would not pay for itself within its shorter lifetime. However, with half the capacity, it achieved more than half of the Base scenario's savings. Doubling the pack size and capacity would lead to over 80% increased savings in all three metrics, while the pack would have a longer lifetime.

Table 11: Annual carbon, APX cost and SSP cost savings achieved by batteries of different pack sizes and their maximum power available, using Version 4 optimiser.

Scenario	Configuration	APX	SSP	CO2	Lifetime
Low bCapacity, FFR	20kW/80kWh	13.8%	9.7%	3.3%	16.7 years
Low bCapacity, no FFR	40kW/80kWh	16.4%	11.8%	3.6%	12.5 years
Base Scenario: CoT=3p/kWh	40kW/160kWh	25.2%	17%	5.7%	19.3 years
High bCapacity, high FFR	40kW/320kWh	31.7%	20.6%	8.7%	29.2 years
High bCapacity, 50% FFR	80kW/320kWh	47.0%	30.6%	10.5%	23.7 years

Battery Chemistry

The new alternative type of Tesla battery is using LFP chemistry, which tends to degrade much slower and is not heavily affected by large depths of charging (Beard, 2019). This means that the battery can achieve a longer lifetime than the original NCA battery while operating at slightly lower payback times by not setting any CoT. However, this would not have a large effect on the savings, assuming all other parameters stay as in the Base scenario, while its lifetime would be only 2 years longer than the Base NCA, according to the degradation model.

Optimal Settings

To investigate the carbon savings achievable in the next section, a new scenario to be used was selected. From the findings in this section, 40% mSOC, 10% SOCmin, and 90% SOCmax were chosen, together with their most appropriate CoT at 3 p/kWh. Other settings are kept as are in Table 9.

5.4 Carbon price

Effects of varying input carbon price on the total CO2 and cost savings were investigated and are described below. 11 scenarios were modelled with carbon prices ranging from 20 to 5000 GBP/t, together with two scenarios with carbon-only and cost-only optimisation. Figure 33 shows the relative APX and CO2 savings of these scenarios. As found above, even cost-only optimisation resulted in carbon savings. However, carbon-only optimisation produced a higher APX annual cost than without a battery.

The trade-off between the cost and carbon changes significantly over the CP range. Interestingly, the highest APX saving was not achieved by the cost-only optimisation, but by the 100 GBP/t one, surpassing it by 0.05%. This is due to the existence of CoT in the objective function. For some small margins, cycling is not profitable when optimised only for cost, but when the additional value of carbon comes to the optimisation, it makes the battery run, saving APX cost in the process. The highest relative combined savings of forecasted cost and carbon was found for the scenario with 900 GBP/t CP, which saved 18.6% of carbon emissions and 26.4% of APX cost. However, for such high carbon prices, the battery was cycling over 250 FECs per year, increasingly shortening its lifespan.

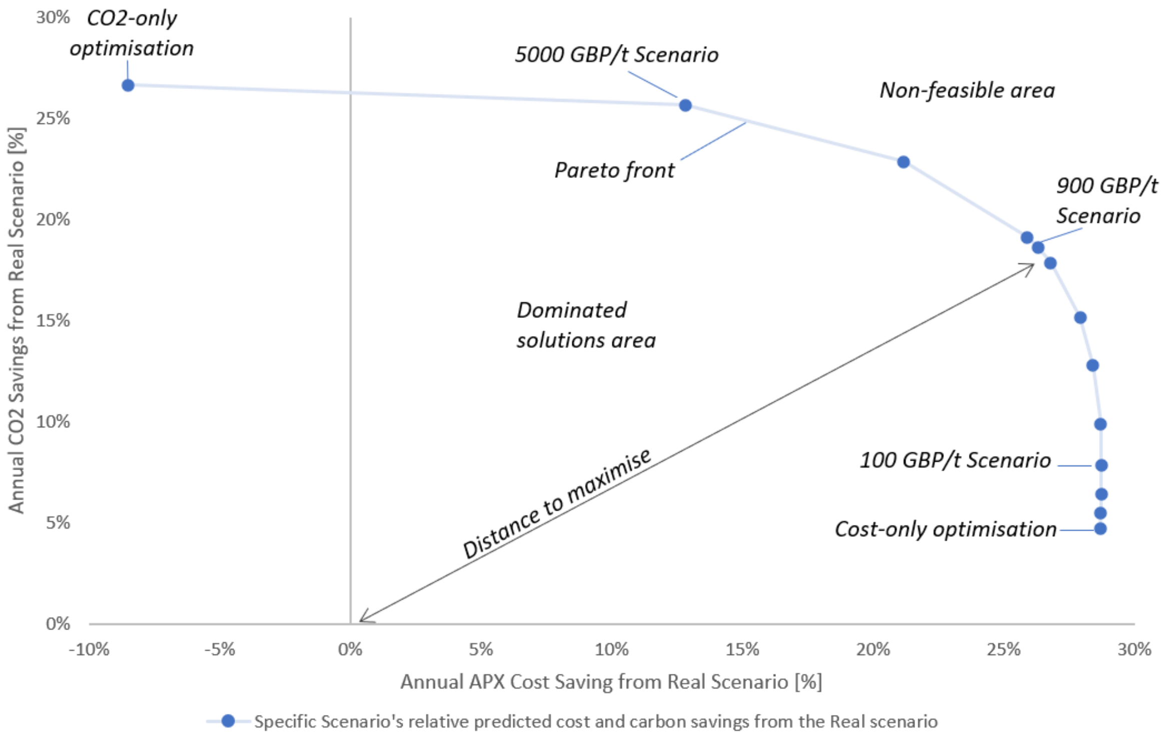


Figure 33: Pareto criterion graph for relative annual day-ahead (APX) cost and CO2 savings for 13 scenarios with varying input carbon price in the Version 4 optimiser. Non-optimal solutions would fall within the "Dominated" area.

Due to the complexity of the optimisation model, the final cost to OSCE for saving a tonne of carbon emissions does not have to equal the internal model's input carbon price, as shown in Figure 34. For CP < 500 GBP/t, OSCE would annually save more SSP costs than with a cost-only optimisation.

For higher input carbon price, the trade-off is positive, which means that OSCE would need to pay more money to its supplier than if it would have used a cost-only optimisation. In such cases, the carbon saved in all scenarios results in a much lower cost increase than the input carbon price would suggest. However, these savings always result in a shorter battery lifespan. For example, to save 2 tonnes annually, the input CP should be set to 800 GBP/t, resulting in an annual SSP cost rise by 70 GBP, effectively producing a 35 GBP/t trade-off. In this scenario, the battery would keep operating for only 8 years.

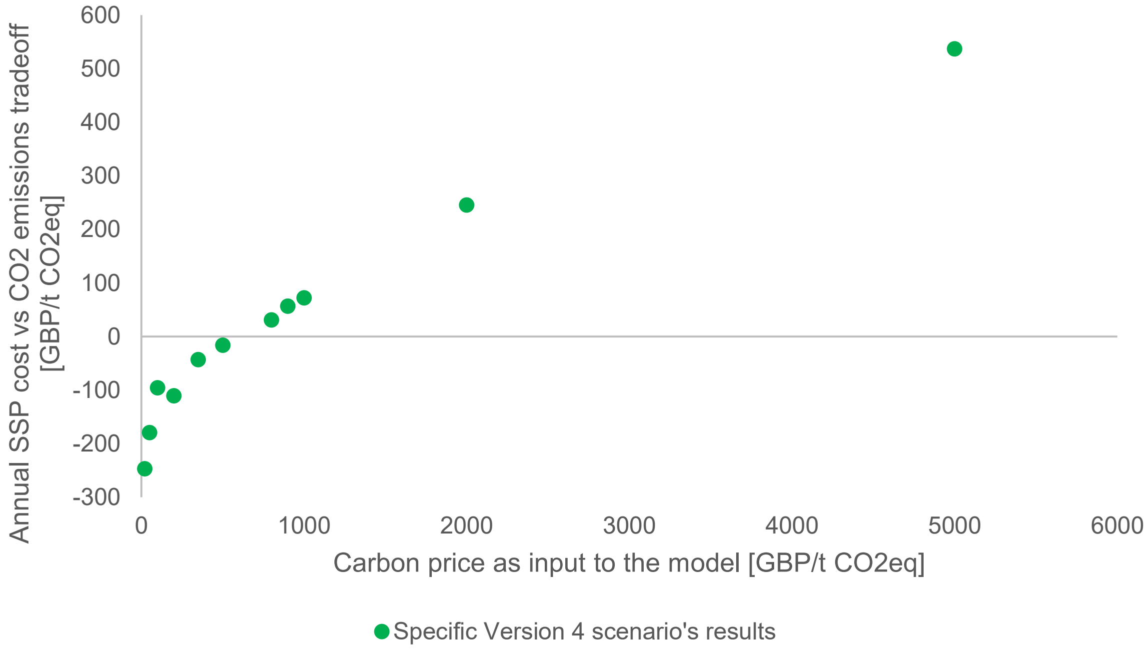


Figure 34: Trade-off between carbon savings and SSP savings for otherwise identical Version 4 scenarios compared with the cost-only optimisation. Data from the Figure 33 scenarios, but SSP, not APX cost is used here.

Based on the knowledge obtained in the hitherto sections, a new, Optimised, scenario's parameters were selected and are shown in Table 12. As not all possible combinations of parameters could have been run, it is not granted that no better settings exist. However, this scenario has outperformed the previous scenarios in multi-objective optimisation while staying financially viable.

Table 12: Optimiser V4 input parameters for the Optimised scenario optimising for cost and carbon.

Input par.	Optimised	Justification
bCapacity	160 kWh	The smallest Powerpack option. Kept to save the most per kWh installed (Table 11) and to be comparable with previous results.
bPower	40 kW	Although higher share of FFR power increases revenue (Figure 29), 40 kW can achieve greater CO2 savings
rEff	85%	Real value
SOCmin	10%	As per Figure 30
SOCmax	90%	As per Figure 30
mSOC	40%	As per Figure 30
CP	900 GBP/t	Maximisation of combined savings in Figure 33
CoT	7 p/kWh	Optimum for achieving economical operation, given all other parameters. Found by Figure 28 process

5.5 Optimised Usage

The Optimised Scenario's daily savings performance is shown in Figure 35, which can be compared with the results from the Base scenario (Figure 25). Due to the higher influence of carbon value in this scenario, the APX saw more daily losses, while the CO2 savings have generally shifted upwards and spread more widely. They now range from -6 to 23 kg CO2eq per day with an average of 7.1 kg, higher than the Base scenario's upper quartile was. This was achieved together with prolonging the operational lifetime of the battery by 50%.

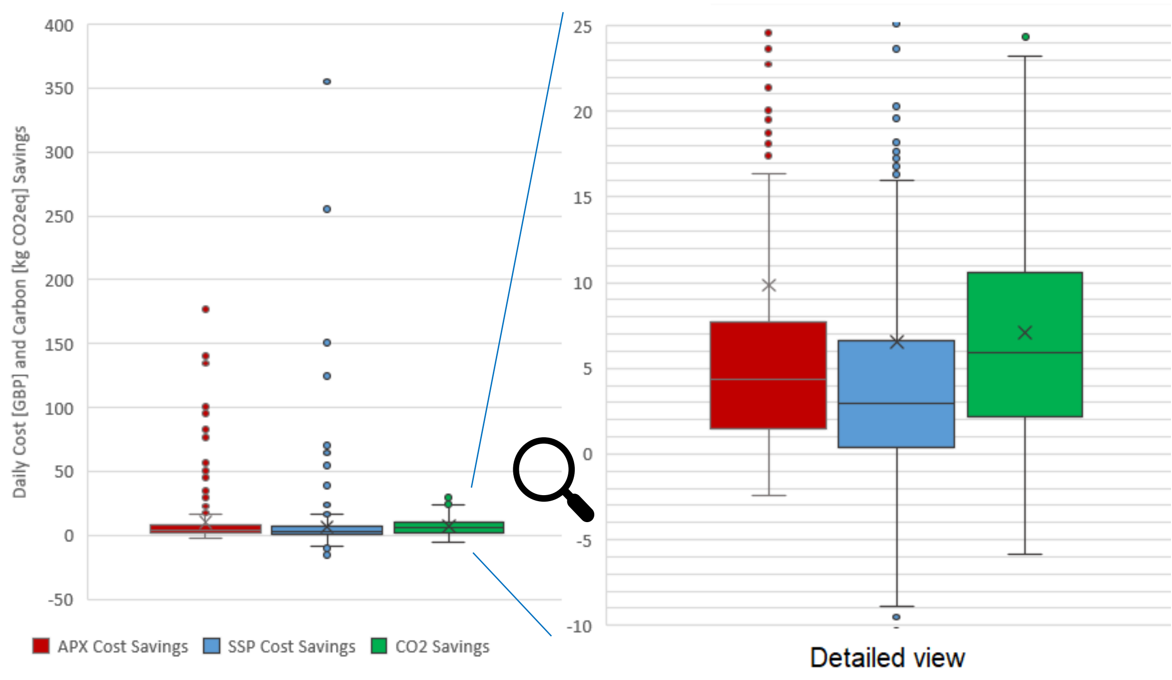


Figure 35: Statistics of daily savings, profits, or avoided emissions in absolute values for a full year run of the battery optimisation - Optimised scenario using Version 4 Optimiser. Variation of the graph in Figure 25 for the updated scenario.

Optimised Scenario's final annual, daily, and monthly savings statistics are shown in Table 13 with their standard distribution confidence intervals. Although annual Carbon savings achieved were lower than the cost savings at only 15.1%, they showed a lower variation with their full monthly savings' 95% confidence interval, 25 – 401 kg CO2eq, being in positive values, suggesting reliable carbon savings on a monthly basis. Variability of cost savings was greater with higher granularity. As the distribution of daily savings is skewed by positive outliers as observable in Figure 35, they increase both the mean and variability of overall statistics. With outliers excluded, the daily APX cost and SSP cost savings fall to 4.3 ±7.9 and 3.2 ±8.8 GBP, respectively. When compared with the Cost-only scenario, the Optimised Scenario achieves 3 times higher carbon savings at an effective cost-carbon trade-off of 130GBP/t.

Table 13: Overall annual, monthly, and daily savings on total electricity usage of the microgrid for the Optimised scenario of Version 4 optimiser over full 2021 year of 24h optimisations.

	APX Cost	SSP Cost	CO2eq
Annual savings from real scenario	25.3%	16.7%	15.1%
Daily average savings:	9.8 GBP	6.6 GBP	7.1 kg
95% Confidence Interval	± 41.3 GBP	± 51.6 GBP	± 12.7 kg
Monthly average savings:	294 GBP	196 GBP	213 kg
95% Confidence Interval	± 501 GBP	± 328 GBP	± 188 kg

From a lifecycle perspective, the battery was found to pay for itself within 14.9 years, which is lower than its estimated lifetime, as shown in Table 14. Carbon payback is significantly lower at 4.7 years. 59% of battery revenue was estimated to come from the Frequency response.

Table 14: Simplified lifecycle impacts and benefits of a 160kWh battery based on the Optimised scenario, assuming repeated 2021 performance. EoL at 80% of original capacity.

Operational Lifetime Estimate (Samal, 2021)	16.5 years	
Capital Costs		84,320 GBP
Annual total SSP Savings		2,310 GBP
Annual FFR Revenue		3,360 GBP
Total Annual Financial Revenue		5,670 GBP
Simplified Financial Payback period	14.9 years	
Embodied CO2		12.16 t CO2eq
Annual CO2 Savings		2.59 t CO2eq
Simplified Carbon Payback period	4.7 years	

5.6 Model Validation

To see the optimiser's effectiveness outside of the original problem data set, it was run with methodologically or practically different carbon intensity and price data. All scenarios in this section use Version 4 optimiser with parameters from the Optimised scenario, but with CoT and CP changed back to 3 p/kWh and 100 GBP/t, respectively. This makes the optimisation viable but less carbon–effective. Comparison with original dataset results, referred to as "Original", is based on the same model input parameters.

5.6.1 Price Data

Fixed Tariff

The optimiser was run on realistic contracts for the OSCE electricity import and export. These were, however, established in 2022, during higher market prices than in 2021, thus, absolute savings between Fixed Tariff and Original are not directly comparable. Fixed PV export PPA price was 153.7 GBP/MWh (Limejump, 2022), while the import price was not completely flat, it ranged between night charge of 302 and daily peak of 451 GBP/MWh (Good Energy, 2022).

The battery saved money mostly by enabling higher PV self-consumption and importing during the night. Annual exports were cut by nearly 70% in this scenario compared to the Real values with no battery. Overall emissions and cost savings were 4.1% and 6.8%, respectively, much lower than for the Original datasets.

Price Levels and Seasonality

As the original data for optimisation was the year 2021, which has seen major changes in the power markets, two scenarios were run to see the impact of the model on either purely "New" normal or "Old" normal (i.e., before 9/2021) prices as discussed in the Methodology section. Their results are compared with results from the same period in 2021 in Table 15.

Table 15: Summary of optimiser's runs for two periods of time in different years.

Dates	Year	Prices	Real APX cost	APX Saving	SSP Saving	CO2 Saving
1.9.-31.1.	2020	"Old"	2,780 GBP	16.4%	16.0%	7.2%
1.9.-31.1.	2021	"New"	8,140 GBP	31.5%	17.1%	11%
1.1.-1.3.	2021	"Old"	3,400 GBP	18.8%	13.3%	2.4%
1.1.-1.3.	2022	"New"	6,370 GBP	11.2%	10.8%	9.3%

Despite total real electricity imports being within a 20% difference for the two scenarios in each period of time, the APX cost was nearly doubled (winter) and tripled (autumn) for New prices from the Old ones during the same period year before. Interestingly, the CO2 savings were higher for the time under New prices. This may be the result of higher battery usage during more variable spot prices. APX cost savings have seen greater variability between years than SSP, suggesting a potential for robust, albeit lower, savings by the battery even under very different pricing conditions. For both time periods, the cost savings were higher for 2021. To investigate the cost savings variability, weekly APX savings over 1.5 years are shown in Figure 36. Not only did the New prices seem to enhance profitability (weeks 35-52), but also seasonality, with higher savings during the winter period (weeks 1-9).

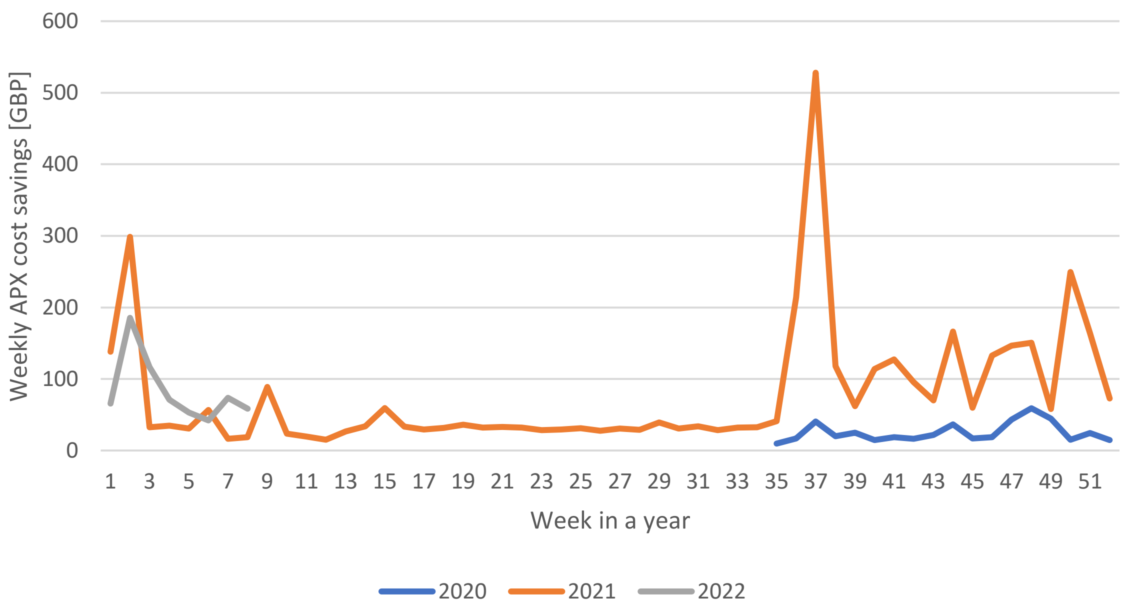


Figure 36: Weekly APX (forecasted) cost savings by battery over the full period of available OSCE metering data.

5.6.2 Carbon Intensity Data

National average Carbon Intensity

As regional carbon intensity was used in the previous scenarios together with national spot prices, there could have been a more significant interaction between them if national carbon intensity would be used. Thus, forecasted, and actual national emissions were used instead of the forecasted regional ones in Optimiser Version 4. Between these 3 scenarios, the cost savings have differed only very little, under 1%. Relative carbon savings roughly halved from 7.8% for regional to 3.8% and 4.4% for national forecasted and actual intensity, respectively. The total emissions, real and simulated, were found to be lower by about 18%. While the annual average of HH intensity is higher for the National emissions than for SW England, the opposite trend is mostly the result of ECC's annual consumption patterns in combination with the seasonally variable regional carbon intensity and higher battery utilisation, as shown in Figure 13 and Figure 36.

Long-Run Marginal Emissions

Another carbon accounting methodology discussed in Methodology was assigning grid average carbon to the imports and flat LR-MEF for 2021, 258 g/kWh (BEIS, 2021b), to the exports. In this case, the battery achieved similar cost savings as the effect of carbon is smaller compared with APX price, however, the total annual emissions increased by 2.5%, probably as a result of the lack of winter price and carbon peak exports, which have cut the overall carbon down for variable intensity data.

5.6.3 Outcomes

The optimiser Version 4 has achieved cost and carbon savings relative to a situation with no battery in place for different pricing and carbon intensity data. The only scenario for which battery optimisation did not result in carbon savings was the last, marginal emissions, one.

6 Discussion

6.1 Objectives

A comparison between targets for this project set out in Section 3.1 and the results achieved by the developed optimiser is presented in Table 16. Objective I., created from the results of the (Kopsakangas-Savolainen et al., 2017) paper, was met by the hot water optimiser in Version 2 by a large margin. In fact, even Version 1 of the original optimiser optimising HWTs for cost only, would satisfy these targets, as presented in Table 8. Interestingly, the cost savings were much higher than the carbon savings, an opposite trend than the benchmark paper found. One potential source of this finding could be the greater variation in carbon intensity in the model of the Finnish power grid caused by its higher usage of coal.

Objective II. and III. Have not been satisfied, however, that does not directly result in a failure of the developed tool. As most of the reviewed literature, setting the rough target of Objective II., optimised more complex microgrids towards their own fossil fuel consumption reduction without taking the lifecycle of the technologies into account, this report's results should, in fact, be lower. As shown in Figure 33, the battery can cut OSCE's annual carbon emissions by over 25% for scenarios with a very high carbon price. They were ruled out, however, due to their lifetime financial infeasibility.

Similarly, Objective III. could be met for a different combination of CP and CoT parameters, which would result in lower, but cheaper, annual carbon savings, outperforming the cost estimate of carbon offsets. As the battery was found to be able to repay its purchase cost within its lifetime, the additional carbon savings coming from its installation can be assumed to not increase energy costs to OSCE. The optimal value of carbon price as an input parameter of the model was found to be 900 GBP/t CO2eq. This is significantly higher than most of the SCC estimates, however, it does not actually result in such high carbon trade-off for OSCE, when compared with other battery scenarios, due to the cost of throughput parameter.

Table 16: Summary of results in the metrics set in the 3 main Objectives in Section 3.1

	Objective I.	**Objective II.**	**Objective III.**
Metric	Annual HW savings	Total CO2 savings	Carbon-trade-off
Target value	8% CO2, 7% cost	22%	11.5 GBP/t
Achieved value	11.3% CO2, 25.6% cost	15.1%	130 GBP/t
Optimiser version	V2	V4	V4
Scenario	100 GBP/tCO2eq	Optimised	Optimised
Target met?	Yes	No	No

6.2 The Model

All versions of the optimiser were found to provide cost and carbon savings on annual basis. This agrees with other works utilising mathematical optimisation techniques (Kanchev et al., 2014; Muqeet and Ahmad, 2020; Pickering et al., 2016). However, the results were found to be very variable, and their means were largely skewed by a few daily optimisation outliers achieving exceptionally good results. This approximately follows the findings of the Version 1 optimiser paper (Vetterlein, 2021a). HWT optimisation's realisable, SSP, savings were found to be lower than in the original paper. As discussed in Validation Section, this is mostly the result of very variable and unpredictable electricity market prices during the latter half of 2021, when many promising day-ahead optimisations did not achieve the expected savings on the SSP price.

Because this model utilised a deterministic optimisation method on a simple problem, the Pareto criterion graph in Figure 33 shows a much smoother non-dominated solutions front than Figure 6 from (Aghajani et al., 2017), which used a metaheuristic PSO algorithm.

A single 24-hour battery-only optimisation took on average, using a 2.50GHz Intel Core i5 device, 6 seconds, while the LP optimisation itself took only 0.077 ±0.0603 seconds. Such short execution ensures the microgrid management system's ability to run the process every day.

6.3 Key Outcomes

As the results of the V4's Optimised scenario show (Table 14), a 160kWh Tesla battery was found to be able to pay for its purchase costs while achieving significant annual carbon savings to OSCE, achieving a carbon payback time of approximately 5 years. Thus, OSCE should consider purchasing such a battery and operating it with the developed optimiser. However, due to long estimated payback times, further research and validation would be required to find the actual net present value of the battery, as well as the impact of using forecasted energy demand and generation, as opposed to the actual historical data used by this model.

Batteries with larger energy capacity were found to achieve lower per kWh savings but higher overall savings, showing that there is greater flexibility potential than the advised smallest Powerpack achieves. Thus, the optimal solution to OSCE's needs was found to be a 160 kWh Tesla battery pack in its 2-hour, 80kW, configuration as that unlocks significant FFR revenue compared to the 4-hour version. If the new generation of Powerpack will be equipped with LFP cells (Lambert, 2022b), slightly better savings and battery lifetime can be achieved by lowering the CoT parameter, which lets the battery cycle more. For either chemistry, lower midnight SOC and wider DoD limits were found to be profitable even from a lifecycle perspective. However, when paired with low cost of throughput, high daily DoD was found to lead to greater battery degradation, making it economically infeasible. This roughly agrees with the results of (Bordin et al., 2017).

Using the optimiser could have additional benefits. For example, participation in emerging high-granularity carbon markets, such as the Energy Tag (EnergyTag, 2021), could be potentially included in the optimisation model to enable additional revenue from carbon trading. However, battery impacts should also be compared to alternative approaches to cost and carbon saving. The aforementioned Ripple Energy Scheme offers annual cost and carbon savings for lower capital investment than the battery, as summarised in Table 17. While its monetary payback period is comparable to the one of the battery, Ripple claims multiple times higher carbon savings. They are, however, calculated by a simple multiplication of the annual average emissions factor of the UK grid and OSCE's consumption. Thus, the values use different carbon accounting principles. Additionally, a flexibly operated battery can help with greater penetration of RES in the power grid, while the wind power plant would increase variable renewable generation. Selection of a carbon-minimisation strategy, thus, should be based on OSCE's priorities as both solutions were found to be financially viable while aiding the energy transition in different ways.

Table 17: Summary of performance comparison between battery installation and purchase of a share in a wind power project for OSCE. Data: (Ripple, 2022)

	Ripple Wind Energy Share	**Optimised Tesla Powerpack**
Capital cost	47,700 GBP	84,320 GBP
Annual savings / revenue	3,500 GBP	5,700 GBP
Annual CO_2 savings	17.3 tCO_2eq	2.6 tCO_2eq
Lifetime	25 years	16.5 years

6.4 Observations

As expectable, a 160kWh battery provided greater annual savings than the hot water tanks with approximately 24 kWh of combined capacity. The inclusion of hot water tanks in battery optimisation, however, increased total cost and carbon savings by 12% and 10%, respectively. As hypothesised in Section 3.2.2, even the optimised results show an average annual emissions factor of net grid imported electricity, 193 gCO2eq/kWh, to be higher than the annual UK grid average factor for 2021, 149 gCO2eq/kWh (BEIS, 2021b). This is mostly due to the seasonality of GSHP heating demand and the SW regional emissions factor.

Alternative scenarios with different input data sets were presented in Section 0. When using the national grid average emissions factor, the total annual emissions would be approximately 18% lower than for the regional factor.

An interesting phenomenon was observed for cost-only optimisation scenarios as they achieved annual carbon savings despite not considering it. Although this was found to be a trend, the CO2 savings were mostly driven by a few very successful days in terms of both cost and carbon. As shown in Figure 37, very high peak prices in November 2021 occurred during periods of high average carbon intensity. A simple linear trendline fit suggests a positive, albeit very weak, relationship between day-ahead price and carbon. Further analysis is in Figure 38**Error! Reference source not found.** and Figure 39 for a case study of a daily cost-optimisation with large cost and carbon profits.

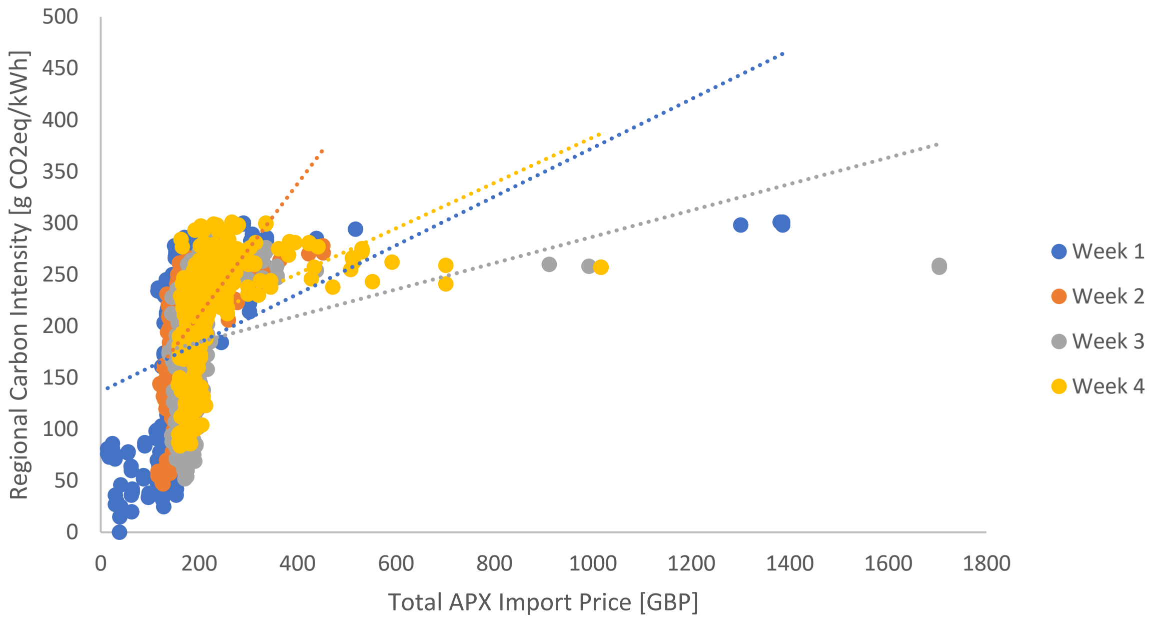


Figure 37: Half-hourly SW England carbon intensity versus the APX Import price (including all components, besides flat levies) for 4 weeks in November 2021. Trendlines are linear and show only a weak correlation.

For the case date shown below, the battery would purchase electricity during the period of nearly carbon-free electricity, then sell it during peak demand, which falling wind and PV generation could not meet. This way, the cost-optimised battery would help facilitate greater adoption of wind power in the UK grid, while cutting required fossil gas consumption.

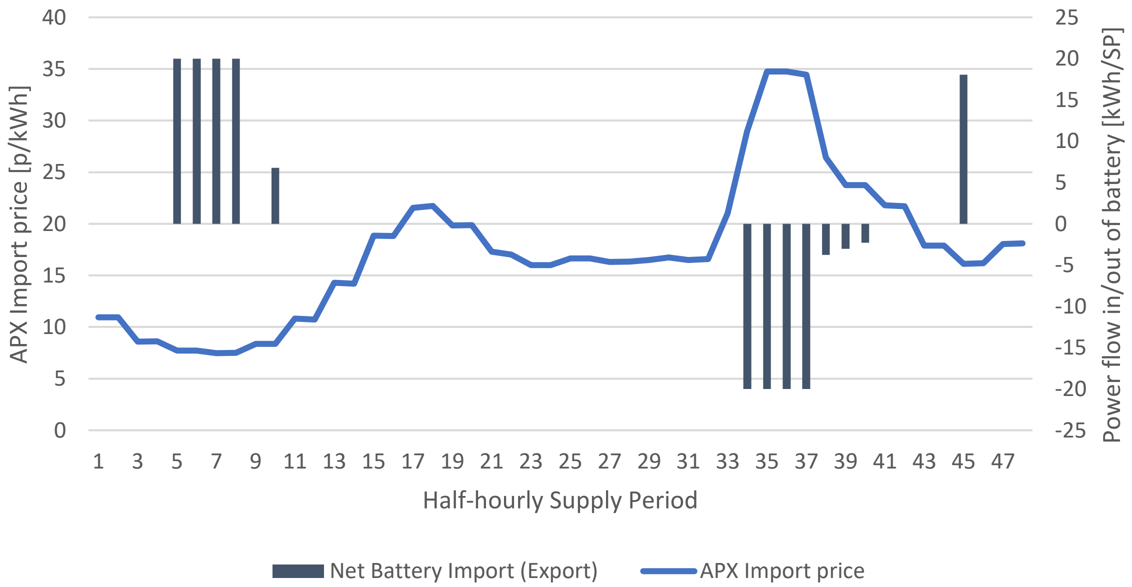


Figure 38: Cost-only battery optimisation on the 01/11/2021 with day-ahead import price

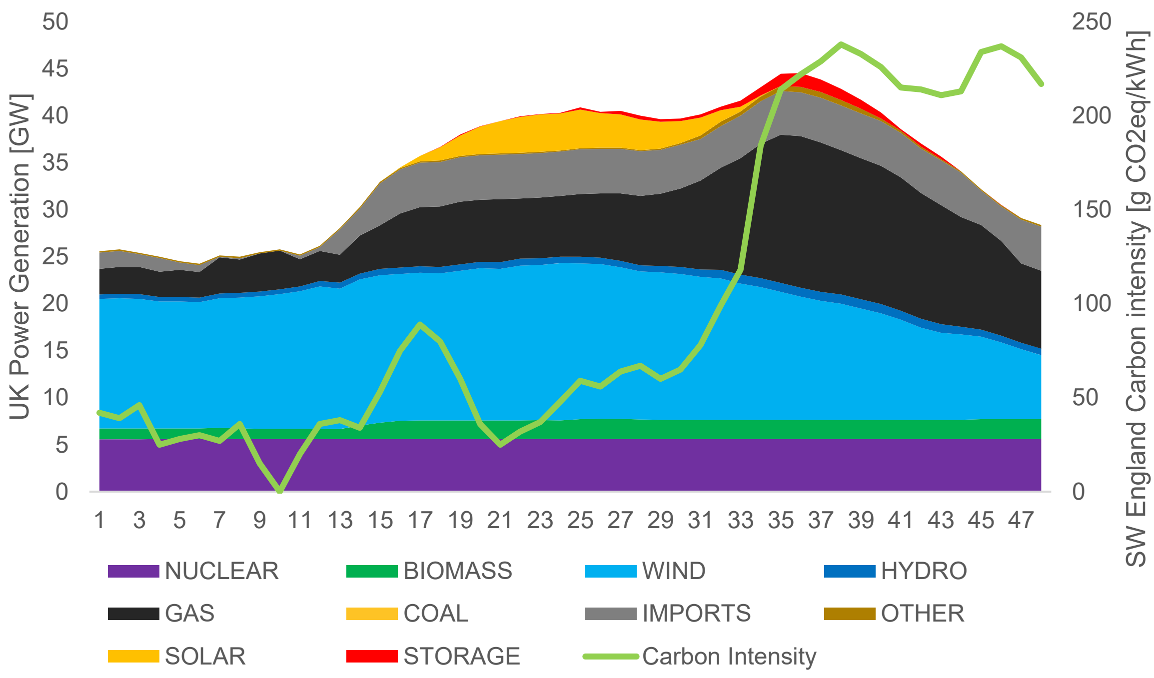


Figure 39: Power generation by source in the UK for 01/11/2021 with regional SW England Average Grid Carbon intensity. (National Grid Data portal, 2022)

6.5 Limitations

The optimisation, as well as the degradation model and subsequent analysis, use assumptions that could, if incorrect, change the outcomes of this project.

The optimiser was using real historical energy flows within OSCE. If implemented into the OSCE microgrid management system, this would not be possible and an additional error from day-ahead energy flow forecasting would be introduced to the results of the model. This, however, may not have such a significant impact as the battery is mostly driven by the power costs and carbon, i.e., it operates to a degree independently from the OSCE power flows. Still, for example, storage of rooftop PV generation is always more profitable than importing the same electricity from the grid and thus, a good forecasting model is required. The model also does not account for any self-discharge over time. Additionally, simplification of its SOC limits together with the roundtrip efficiency lead to the model using not the exactly same SOC min and max parameters as were inputted. This should have only a limited impact. Similarly, although linearisation of the battery's operation is common in the literature, the maximal power available to a battery can change with changing SOC. Including this would require a non-linear optimisation algorithm.

Due to the high complexity of battery capacity fade, the degradation model is largely based on multiple simplifying assumptions that could significantly limit its ability to predict degradation accurately. The inputs to the model, such as the operation temperature, incur potentially significant inaccuracies as well. Moreover, the model was based on the NMC battery type, not NCA used by Tesla, which may further worsen the estimate. The utilisation of the battery for frequency response was not included in the degradation model and it could have a large impact on the battery lifetime.

Analysis of the battery's performance could be influenced by using the actual regional, currently unavailable, grid carbon intensity, for accounting, rather than the forecasted one. Additionally, the concept of battery's lifetime and payback times was very simplified and to become a proper lifecycle impact assessment with economic feasibility analysis, it would need to include future value of carbon, changing carbon intensity of the grid and market prices, together with their variabilities, or operation and management costs.

7 Conclusions

A day-ahead half-hourly multiobjective battery and hot water tank optimiser was developed for use in a community centre microgrid management system. It was built upon a previously developed hot water optimiser and it used linear programming optimisation Python package PuLP to solve daily cost and carbon minimisation problem using real-life historical data. The battery entity was implemented in the tool with roundtrip efficiency, cost of energy throughput, and other operational parameters.

A simplified lifecycle assessment was used to find effective combinations of battery design and operational specifications, utilising a previously developed battery degradation model. In agreement with reviewed literature, the impact of battery cycling parameters was found to be profound in its ability to achieve profitability over its lifetime. When using a half-hourly average regional emissions intensity of the power grid, the carbon payback of a 160kWh Tesla Powerpack was found to be 4.7 years, while its lifetime was estimated at 16.5 years. Allowing a share of the total battery power capacity to firm frequency response was found crucial to its financial sustainability.

An optimised set of parameters was found to include wide DoD limits, high input carbon price, together with a high cost of throughput. The Powerpack in this carbon-and-cost minimising scenario achieved robust, statistically significant, monthly carbon savings resulting from power grid electricity use. The annual realisable cost based on the electricity spot price and greenhouse gas savings were maximised at 16.7% and 15.1% of the microgrid's total annual values, respectively. In this scenario, the battery used daily, on average, 53% of its full cycle and altogether, the equivalent of 32% of the total microgrid's electricity usage cycled through the battery.

The inclusion of two smart electric hot water tanks in the optimisation increased the total modelled savings by 10% annually without affecting the buildings' occupants. Interestingly, pure cost optimisation of the energy stores in the microgrid resulted in total annual carbon emissions falling by approximately 4.5%, which was mostly the result of battery exports utilising price hikes during high-demand low-renewable periods.

7.1 Future work

As discussed, microgrid electricity flow day-ahead forecasting should be included in the model to achieve more realistic cost and carbon savings. Additionally, marginal emissions impacts should be included in the optimisation to find the real carbon emissions avoided by the battery. Potential flexibility from the on-site heat pump, if linearised, as well as other nearby houses and their power consuming devices, could be added to the model to increase the potential savings. Furthermore, the model could be improved by including a near real-time optimisation during the given day based on actual spot prices, which could decrease the difference between forecasted and realisable cost savings. Similarly, optimising the battery daily for more than 24 hours ahead could enable multi-day energy storage, which was not developed in this model. A variable carbon price could also be included in the model to optimise for carbon even during days with very different electricity price levels. Finally, a better battery design and operation scenario could be developed if more combinations were run and a proper long-term analysis was conducted, both of which could be at least partially automated.

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Appendix

Appendix A

The full source code of the Optimiser's versions can be found on https://github.com/Skeletonik/FYP-Optimiser-V1234 as FYP-x repository.