Improving the efficiency of renewable energy assets by optimizing the matching of supply and demand using a smart control algorithm

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Abstract

Given the fundamental profit gained by renewable energy assets in climate control, existing control algorithms are urged to be improved to match power supply and demand optimally. This paper explores various designed cases that lead toward an enhanced definition of a control algorithm with optimized behaviour. The core of improvement is exploiting future knowledge, which can be realized by current state-of-the-art forecasting techniques, to effectively store and trade energy. Based on several thousands of simulations of energy communities in the UK, the proposed smart control algorithm has demonstrated a robust performance and gained notable additional profit in theoretical and practical scenarios using probable data.

1 Introduction

Currently, the renewable energy market is growing at an incredible pace and its development is fundamental for climate control (BP, 2021; Bilgen et al., 2004). It is paramount to recognize that advancement is not solely made by persisting to expand the deployment of renewable energy assets but also by thoroughly understanding existing models in order to optimize the efficiency and ultimately gain both climate benefit and prosumer[1] benefit, which is also emerged by the European Commission (2015) and Gielen et al. (2019).

Considering a household or a community with either individual or shared renewable energy assets, e.g. solar panels or wind turbines, and potentially a battery storage of unknown size, a control algorithm should handle the matching of demand and supply of energy optimally, i.e. maximizing renewable energy usage and minimizing energy imports (and costs) from the central grid. Besides this control problem, there are many potential key factors in the setup of the renewable energy assets, e.g. battery type or size and individual versus shared assets, that play a role in the overall efficiency and profit gained by a control algorithm.

[1]Small-scale consumer with microgeneration and/or storage.

Based on the aforementioned urge to advance in the climate crisis using renewable energy assets and the wide solution space for optimizing control algorithms that play a fundamental role in climate control, this paper will research the following question:
How can the efficiency of renewable energy assets be improved by optimizing the matching of supply and demand using a smart control algorithm?

The discovered improvements will contribute to widening the theoretical foundation behind the efficiency of renewable energy assets and help advance toward the practical deployment of smarter control algorithms to ultimately directly impact the current climate crisis.

The outline of this paper is as follows. Section 2 documents the model and heuristic-based control algorithm which are used as a foundation for studying and optimizing. Section 3 precisely describes a potentially smarter control algorithm. Then, an assessment of the proposed smart control algorithm by conducting various experiments will be demonstrated in section 4 and discussed in section 6. In between, section 5 elaborates on why the performed research is deemed responsible. Finally, section 7 concludes and touches upon possible future work.

2 Methodology

To be able to adequately explore any possibilities within the solution space, it is trivial to first set a basis for the model and current state-of-the-art approaches regarding control algorithms for renewable energy assets. This section describes the model and the heuristic-based control algorithm based on related research efforts by Norbu et al. (2021) which poses as the basis of this research.

2.1 Model overview

The model of the energy management system used for this research primarily consists of or is linked to the following components:

Nomenclature

Abbreviations

BESS	Battery Energy Storage System
CES	Community Energy Storage
DoD	Depth of Discharge
HES	Household Energy Storage
RES	Renewable Energy System
RMSE	Root Mean Squared Error
RtC	Room to Charge
SoC	State of Charge

Parameters

η^c	Battery charging efficiency
η^d	Battery discharging efficiency
κ	Size of lookahead window [timestamps]
ω	Battery capacity [kWh]
$\tau^b(t)$	Import tariff at t [pence/kWh]
$\tau^s(t)$	Export tariff at t [pence/kWh]
p^{max}	Maximum power that battery can charge/discharge [kW]
SoC^{init}	Initial battery SoC [%]
SoC^{max}	Maximum battery SoC [%]
SoC^{min}	Minimum battery SoC [%]

Subscripts and Sets

N	Number of households in energy community
T	Number of time periods
t	Particular timestamp

Variables

Δt	Duration of time period t [h]
$\delta_c(t)$	p^{max} - $p_c^{bat}(t)$, charging boundary at t [kW]
$\delta_d(t)$	p^{max} - $p_d^{bat}(t)$, discharging boundary at t [kW]
$\Pi(T)$	Savings on annual bill, where $T = 1$ year [£]
$b(T)$	Annual bill, where $T = 1$ year [£]
$b^0(T)$	Baseline annual bill, where $T = 1$ year [£]
$d(t)$	Demand at t [kW]
$e^b(t)$	Imported energy at t [kWh]
$e^s(t)$	Exported energy at t [kWh]
$g(t)$	Generated power at t [kW]
$p_c^{bat}(t)$	Charging power of the battery at t [kW]
$p_d^{bat}(t)$	Discharging power of the battery at t [kW]
$RtC(t)$	Room to charge in battery at t [kWh]
$SoC(t)$	State of charge of battery at t [%]

- Solar photovoltaic(s) or wind turbine(s) encapsulated as generated power
- BESS (with attached HES or CES)
- Household or community represented as prosumer demand
- Central grid attachment via some energy plan

The flow of the power is modelled as follows:

- Prosumer demand can be covered by power coming from the grid, generator or battery.
- The battery can export energy to the grid and charge via generated power. Some battery setups can also charge via imported energy from the grid, however, this is not simulated within this research.
- Generated power can be sold directly to the grid.

To get an intuitive sense of the aforementioned model and flow, see Figure 1.

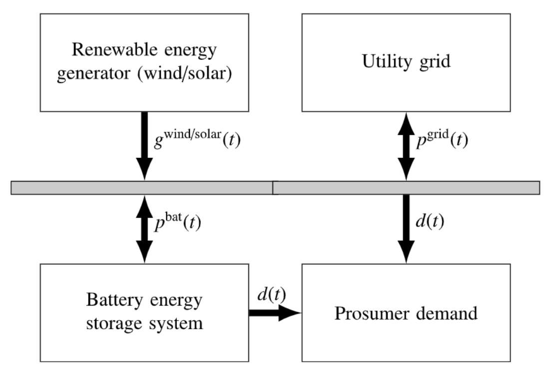

Figure 1: Power flow diagram by Norbu et al. (2021, p. 5) depicting the prosumer model.

2.2 Heuristic-based control algorithm

The heuristic-based battery control algorithm, proposed by Norbu et al. (2021), which will be used as the baseline for improvement in this paper, is a concise decision tree that determines whether to interact with the battery, i.e. charge or discharge, or interact with the central grid, i.e. sell or buy energy, based on the current residual power and battery state. Figure 2 depicts the aforementioned in the form of a flowchart.

3 Optimizing the control algorithm

The results during the process of optimizing the control algorithm have been summarized in this section. Logical actions and properties are defined and translated into the definition of an enhanced control algorithm that possesses the characteristics of the designed optimal behaviour.

3.1 Case Analysis

By manually designing and processing ostensibly intriguing scenarios, insights that are believed to lead to improvement have been summarized into cases with a description and analysis below.

Order of covering demand

The heuristic-based algorithm by Norbu et al. (2021) first subtracts demand from power (resulting in the residual power), then attempts to discharge the battery and ultimately decides to buy energy. Is this the optimal order of covering demand and why?

The first step essentially is directly covering demand with generated power, which is more efficient than discharging the battery given its stored energy dealt with loss due to $\eta^c \cdot \eta^d$ and other factors (e.g. self-discharging batteries). This loss factor is less than or equal to one (basic law of conservation of energy), however, realistically, this ratio is always lower than 1 thus less efficient (and certainly not more efficient) than directly covering with generated power.

The other option is importing energy from the central grid. Looking only at any current timestamp, denoted by t, it follows from intuition that generated power is "free", thus, importing energy is the least optimal action for $\{t \in T \mid \tau^b(t) \geq 0\}$ and most optimal for $\{t \in T \mid \tau^b(t) < 0\}$. However, when looking ahead, covering demand using imported energy might be tactful to do at possibly non-trivial seeming timestamps compared to the heuristic-based algorithm, as explored below.

Matching demand with battery capacity

The heuristic-based algorithm by Norbu et al. (2021) charges at any opportunity it gets, however, while safe it is simply not optimal, as it can miss out on selling opportunities. For example, given some excess power α at t, i.e. $g(t) - d(t) > 0$, and some (forecasted) future excess demand β at $t+1$, i.e. $g(t+1) - d(t+1) < 0$, where $\alpha > \frac{|\beta|}{\eta^c \cdot \eta^d}$, $\alpha \leq \frac{\delta_c(t)}{\eta^c} \leq \omega$, $|\beta| \leq \delta_d(t+1) \cdot \eta^d$ and $T = 2$, the heuristic approach (charging α) misses out on exporting $(\alpha + \beta) \cdot \Delta t$. In essence, the battery should never be filled more than needed with the knowledge of perfect future data.

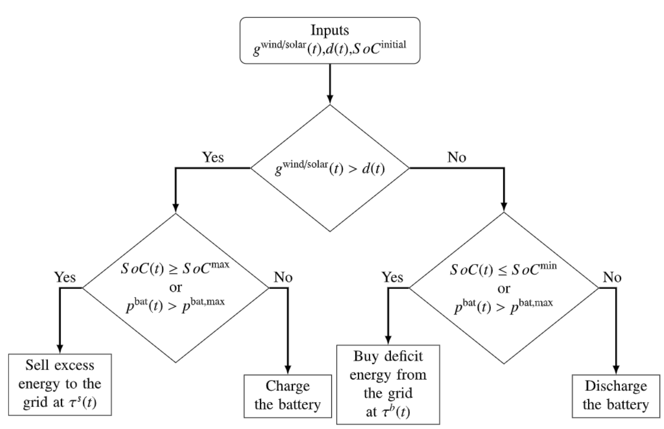

Figure 2: Flowchart of heuristic-based battery control algorithm strategy by Norbu et al. (2021, p. 7).

Expensive future excess demand

Given some usable capacity in a battery at some t, i.e. $SoC(t) > SoC_{min}$ and $\delta_d(t) > 0$, and consecutive negative residual power, i.e. excess demand, in the (forecasted) future that is more than the battery can cover, i.e. $g(x) - d(x) < 0$ for $x \in X$ where $X = \{t, t+1, ..., t+n\}$ and $min(SoC(t), \sum_{x \in X} \delta_d(x) \cdot \Delta t) - \sum_{x \in X} \frac{g(x)-d(x)}{\eta^d / \Delta t} < 0$, where future import tariffs are higher than the current import tariff, i.e. $\forall x \in Y$ where $Y = X \setminus \{t\}$ it holds that $\tau^b(t) < \tau^b(x)$, it is intuitively smarter to buy energy currently at t and discharge the battery at a later moment (when import tariffs are the highest) as this reduces the total cost for covering excess demand in X.

Maximizing profit exported energy

Given some (forecasted) future where we currently are in a timespan with excess power, i.e. $g(x) - d(x) \geq 0$ for $x \in X$ where $X = \{t, t+1, ..., t+m\}$, and as far as we can look in the future (denoted as timestamp n), excess demand timespans, i.e. $g(i) - d(i) < 0$ for $i \in Y$ where $Y = \{m+1, m+2, ..., n\}$, do not exist or are already known to be covered maximally by current excess power from X while still resulting in leftover energy to export, it is optimal to calculate the amount of energy that needs to be charged for possible future coverage of Y and then charge the battery at times when selling prices are as low as possible until the desired SoC is reached to ultimately export any leftover energy at the highest export prices.

Out of control costs

Given any $\alpha = g(t) - d(t)$, $\beta = \alpha - \delta_c(t)$ for $\alpha \geq 0$ and $\gamma = |\alpha| - \delta_d(t)$ for $\alpha < 0$, then, if $\beta > 0$ or $\gamma > 0$, the battery cannot handle charging or discharging this amount of residual power (α) and thus β needs to be exported or γ needs to be imported. No smart algorithm can go beyond these battery constraints, these profits or losses must occur.

Expensive charging exploit

In addition to figuring out the ratio of charging/exporting and discharging/importing based on generated power, charging the battery with imported energy should be considered at any t if this is possible from a technical standpoint. Intuitively, it is similar to using your phone while it charges. Besides this battery setup unlocking the world of energy trading (e.g. importing energy at tariffs that make exporting it later on profitable), which is out of scope for this paper as it does not focus on the efficiency of renewable energy assets in essence, it is needed to cover all demand truly as cheap as possible whenever the battery, given perfect knowledge, is not able to. Any excess demand that needs imported energy should have, if and only if there was room to charge up until the current t, charged previously at some timestamp t_{prev} with imported energy if $\tau^b(t_{prev}) \cdot \eta^c \cdot \eta^d > \tau^b(t)$, capped at the maximum throughput for the RtC in the period $[t_{prev}, t)$ and of course any other constraints within this process such as $\delta_d(t)$.

3.2 Improved Control Algorithm

This section defines the optimized control algorithm in its entirety while simultaneously elaborating on the implementation of the beneficial insights and derived properties from the case analysis in subsection 3.1. Additionally, the correctness of the algorithm is highlighted and an example scenario is processed expressively to possibly increase the intuitiveness behind the functioning of the algorithm.

Looking back while looking ahead

For each timestamp $t \in T$, actions will be decided by looking ahead at estimated forecasts (which should yield optimal results with high accuracy and otherwise still be relatively robust) and operate similarly to the ideas presented in the case analysis in subsection 3.1. However, if we merely look ahead within this lookahead window, e.g. calculate for the current timestamp how much residual power is present in the future to decide whether we can export energy now, we already need to know the optimal residual power for that future timestamp as well, which is essentially the problem we are trying to solve already. A possibly counter-intuitive way (and hence mentioned) of implementing the case analysis of subsection 3.1, which denotes optimal actions in a future-oriented manner, is by attempting to satisfy the same idea while approaching it by looking at previously processed timestamps when looking in the future (which may seem like the past but are still the future with respect to the actual timestamp that is being processed), as these timestamps are certain to already have taken optimal decisions in earlier iterations within the lookahead window. Thus, please be aware of this way of thinking when reading the upcoming paragraphs that describe the steps taken by the algorithm within the lookahead window.

Step 1: Skipping excess power

Any excess power within the lookahead window, i.e. $g(t) - d(t) \geq 0$, is skipped by the algorithm (meaning no decisions are made immediately), as then its leftover residual power can be used in future timestamps within the lookahead window which look back respectively. If no future timestamp needed or was able to use this residual power (completely), all leftover power will be exported to the central grid. This falls back on the idea of matching demand with battery capacity (in this case skipped excess power is potential battery capacity) optimally as presented in the case analysis in section 3.1.

Step 2: Using battery power

As analysed in section 3.1, unless $\tau^b(t) < 0$, using battery power is the first action in the optimal order of covering demand. Thus, any excess demand will be covered as much as possible or needed using the battery, i.e. $min(\delta_d(t) \cdot \Delta t, SoC(t) \cdot \omega, \frac{g(t)-d(t)}{\eta^d/\Delta t})$. Do note that such actions require changes to be made for RtC, SoC, p_d^{bat} and other variables the algorithm keeps track of. Also, it might seem like this step will yield suboptimal results given the possibility of expensive future excess demand as illustrated in section 3.1, however, step 4 in this section 3.2 will satisfy said case.

Step 3: Using past excess power

If excess demand is still not fully covered by the previous step (2) and $\delta_d(t) > 0$, the algorithm continues to look for available excess power that can be used to charge the battery between the starting timestamp of the lookahead window and the current future timestamp that is being looked at. To maximize the profit of exported energy as discussed in section 3.1, the algorithm will sort any previous timestamps with $g(t) - d(t) > 0$ and $\delta_c(t) > 0$ based on ascending export tariffs, such that the revenue remains as large as possible. Before that, the algorithm also should know how much energy at such timestamps can be discharged and should not consider any timestamps before other timestamps that have no room to charge, as the energy cannot reach the current timestamp due to said bottleneck. Thus, iterating back until, for some timestamp x, $RtC(x) = 0$ or the starting timestamp of the lookahead window is reached, a list to keep track of throughput values is generated by calculating $min(RtC(t), min_{global})$ where min_{global} is a variable, initially set to ∞, to keep track of the minimal global throughput and t the respective timestamp. Then, based on the aforementioned pricing strategy and (dis)charging boundaries at the respective timestamps, excess power will be charged into the battery as much as possible and needed at the available timestamps.

Step 4: Using previously discharged energy

If excess demand is still not fully covered by the previous steps (2 and 3), it can only be covered by importing energy. However, instead of directly importing, the first thing to consider is the case in section 3.1 that depicts a scenario with expensive future demand, which could be the case for the current timestamp (i.e. import tariff is currently higher than previous timestamps). If any previous timestamp, let us refer to such a timestamp by x, had a lower import tariff and discharged energy from the battery, it is possible to swap the discharged energy at x for imported energy and use the newly available energy in the battery, if $\delta_d(t) > 0$, at the timestamp t which is currently being looked at. Additionally, it needs to be checked whether enough room to store energy is available during the period of $[x, t)$. Then, sorted on ascending import tariffs, discharged energy is swapped as much as possible and needed to cover the demand at t.

Step 5: Using previously imported energy

Besides the previous step (4), there is another possibility for additional benefit regarding the need to import energy, if the RES is set up accordingly, by preventively charging using substantially cheaper imported energy as discussed in section 3.1. The algorithm should compare the benefit compared to the previous step and also, similarly to step 3, calculate how much room to charge is available and needed.

Step 6: Directly importing energy

If excess demand is still not fully covered by the previous steps, which would be the case if it is out of control as illustrated in section 3.1 or simply since buying energy at the current timestamp is the best option (left), energy needs to be imported from the grid. Similar to the first step of skipping excess power, the excess demand can be skipped and any leftover excess demand will be imported from the grid by the algorithm.

Output of the algorithm

After processing the steps taken by the algorithm as described above, the algorithm should return the actions for the current timestamp t ($= 0$ within the lookahead window, referred to as 0_{la}) which are as follows:

- $g(0_{la}) \cdot \Delta t$, denoting the leftover energy that will be exported (values in g have been altered to reflect actions taken within the lookahead window), referred to as $opt_{export}(t)$
- $d(0_{la}) \cdot \Delta t$, denoting the leftover energy that will be imported (values in d have been altered to reflect actions taken within the lookahead window), referred to as $opt_{import}(t)$
- $p_c^{bat}(0_{la}) \cdot \Delta t$, denoting the optimal amount to charge at t, referred to as $opt_{charge}(t)$ (which is the energy change in the battery, not the actual input)
- $p_d^{bat}(0_{la}) \cdot \Delta t$, denoting the optimal amount to discharge at t, referred to as $opt_{discharge}(t)$ (which is the energy change in the battery, not the actual output)

It can then be deduced that:

- $SoC(t+1) = SoC(t) + opt_{charge}(t) - opt_{discharge}(t)$
- Cost at $t = opt_{import}(t) \cdot \tau^b(t) - opt_{export}(t) \cdot \tau^s(t)$

Correctness of the algorithm

When running the algorithm, at each $t \in T$, the following asserts are made to check if the algorithm satisfies properties that classify the algorithm as working properly:

- $0 \leq SoC(t) \cdot \omega \leq \omega$ (capacity boundaries)
- $p_c^{bat}(t) \leq p_c^{max} \wedge p_d^{bat}(t) \leq p_d^{max}$ (power boundaries)
- $(g(t) - d(t)) \cdot \Delta t = e^s(t) - e^b(t) + \frac{opt_{charge}(t)}{\eta^c} - opt_{discharge}(t) \cdot \eta^d$, checks that not more or less output is created from some input, i.e. the residual energy at t equals the leftover energy (which will be exported or needs to be covered using imports) combined with the energy going into the battery to charge (part of the original residual energy) minus the energy coming out the battery by discharging (not part of original residual energy) based on a supposedly optimal decision at t

4 Assessment of proposed algorithm

In order to assess the newly introduced smart control algorithm, several experiments have been conducted and are described in this section in addition to the environment in which they operated.

4.1 Experimental Setup

Norbu et al. (2021) carefully studied energy projects and the resulting work provides a definition of a heuristic-based control algorithm that can be used as a baseline algorithm for comparison. Access has been granted to repositories containing an assemblage of code produced by Sho Cremers, Sonam Norbu and Peter Zhang for computing the cost of an energy community given demand and generation profiles of several consumers, as specified in the work of Norbu et al. (2021). This code, after meticulous examination, is used to run the baseline control algorithm and as a starting point for implementing the algorithm described in subsection 3.2. When computing the cost of a community, this paper considers $b(T)$ to be the bill of the total operational costs for the whole community, which is the sum of $e_i^b(t) \cdot \tau^b(t) - e_i^s(t) \cdot \tau^s(t)$ for all $t \in T$ for all prosumers $i \in N$.

Regarding data available for simulation, a collection of recorded energy demands of households connected to a smart grid during two trials, i.e. Thames Valley Vision and Low Carbon London, and dynamic tariffs from an Octopus Agile energy plan are utilisable. The Thames dataset by Scottish Southern Electricity Networks (2018) contains 200 households over a timespan of a year (from January 2017 to December 2017) with intervals of 30 minutes. The London dataset by UK Power Networks (2015) contains 5567 households over a timespan of 2.5 years (from November 2011 to February 2014) with intervals of 30 minutes. Historical data of the Octopus API has been recorded by EnergyStatsUK (2022) and provide Octopus Agile import and export tariffs for London from roughly 2018 to 2022 with intervals of 30 minutes ($\Delta t = 0.5$). Given the similarity in interval frequency, all data can adequately be matched on a month-day basis. As for matching the years, unfortunately, no proper overlap is achievable in the data, thus the best remaining option for simulation is using complete years. Tariff data used is from 2020 to 2021, whereas the London and Thames data is the first complete year available, i.e. 2012 and 2017, ultimately resulting in $T = 365 \cdot 24 \cdot 2 = 17520$ time periods. To be able to put any output of experiments into perspective, the following annual energy bills for the average prosumer have been calculated for the datasets:

- No generated power and no battery:
  - Thames dataset: $b(T)/N = £15.51$
  - London dataset: $b(T)/N = £349.93$
- Generated power but no battery:
  - Thames dataset: $b(T)/N = -£4.10$
  - London dataset: $b(T)/N = -£44.02$

As for simulating the battery, based on the research of May et al. (2018), a lead-acid battery is a remarkably well-established option for energy storage and is the only BESS that is nearly entirely recycled (99% in Europe and the USA) which supports the ultimate goals of improving renewable energy assets: climate control and sustainability. Lithium-ion batteries have a troubling low rate of recyclability (less than 1%), yet as a result of rapidly developing technologies are deemed as the future of batteries due to a longer life cycle and higher energy density (Yanamandra et al., 2022). Additionally, based on the research of Kebede et al. (2021), lithium-ion batteries are also considered to be more techno-economically viable than lead-acid batteries. Given the mentioned advantages of lithium-ion batteries and the future potential of proper recycling as comes with battery maturity according to Yanamandra et al. (2022), lithium-ion batteries have been selected to be simulated. The technological downsides that need to be accounted for when simulating a BESS using a lithium-ion battery are a depth of discharge of 80% and practical efficiencies of around 85% for (dis)charging the battery, according to performance tests carried out by Bila et al. (2016). The aforementioned translates into the following attributes: $\eta^c = \eta^d = 85\%$, $SoC^{min} = 20\%$.

4.2 Performance Perfect Forecasts

To get an initial grasp on the performance of the newly introduced control algorithm, the baseline algorithm and the smart control algorithm are both simulated within the environment as described in subsection 4.1 in combination with perfect future knowledge (i.e. original data). Battery size and how far we look into the future are not specific, thus, various values have been considered to gather a complete overview:

- $\omega/N \in \{0.25, 0.5, 0.75, 1, 1.5, 2, 2.5, 3, 4, 5, 7.5, 10, 15, 30, 50\}$
- $\kappa \in \{2, 4, 8, 16, 24, 32, 40, 48, 56, 64, 72, 80, 88, 96\}$

The results of the 450 simulations are carefully summarized in Figure 3 by showing for the average prosumer the operational profit gained by the smart control algorithm as a boxplot (based on outcomes for the various κ) per battery size. Operational profit per prosumer is defined as $-b(T)/N$ (note: a negative bill is counter-intuitive for profit thus the sign is flipped), not considering the cost of assets. For the baseline control algorithm, the operational profit per prosumer, i.e. $-b^0(T)/N$, has been plotted per battery size as well to compare the algorithms easily. All the details per κ per battery size can be seen in Appendix B and Appendix C for the London and Thames dataset respectively. These details reveal that a lookahead window of 8-12 hours is outperforming the baseline control algorithm nearly always and looking ahead 24 hours was always more profitable compared to the baseline control algorithm. Additionally, based on the annual bills when having generated power yet no battery, the smart control algorithm is able to achieve between 10% to 70% more operational profit at times compared to the heuristic-based control algorithm.

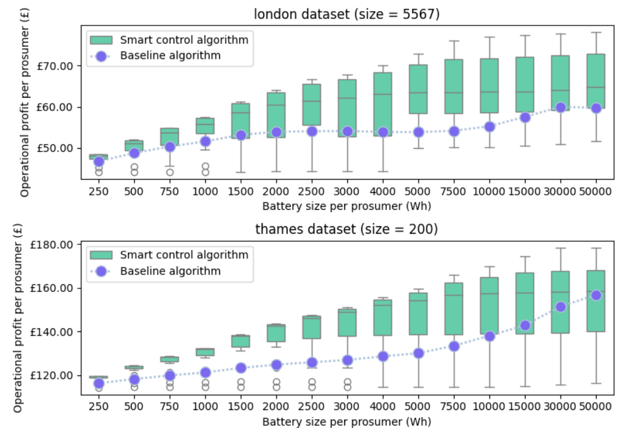

Figure 3: High-level comparison between operational profits of the baseline algorithm and smart algorithm for the average prosumer using various battery sizes and lookahead amounts represented in boxplots, following the experiment described in subsection 4.2.

4.3 Robustness of smart control algorithm

In order to be more certain that the smart control algorithm works adequately, the robustness is tested by experimenting with erroneous future forecasts for power and demand predictions in addition to tariff predictions. All experiments performed in this subsection consider $\kappa \in \{6, 8, 16, 24, 32, 40, 48, 64, 72, 96\}$. As there are various techniques used to estimate the future - some more accurate or costly than others - which all deserve to be considered, a broad range of functions that alter the data uniquely have been experimented with and are clarified below.

Constant functions

The simplest function to quickly assess the robustness of the algorithm is a constant margin of the form $y \pm c \cdot \sigma_{data}$ in which uniformly a random value is picked for $x \in (0, \kappa]$. Note that the standard deviation is not within the lookahead window but the complete data. As for c, values ranging from 0.5 up to a hundred thousand have been considered and the results of 3080 experiments have been summarized in Figure 4. The operational profit per prosumer is averaged over various lookahead window sizes of $\kappa \in \{6, 8, 16, 24, 32, 40, 48, 64, 72, 96\}$.
Based on these experiments, the smart algorithm outperforms the baseline algorithm each time with complete future tariff knowledge, however, when tariff uncertainty is introduced next to power and demand uncertainty, the smart control algorithm only always beats the baseline control algorithm for a margin of less than or equal to one standard deviation.

Linear functions

Future estimations often become more inaccurate as time passes, as patterns are often not that clear for longer pe-

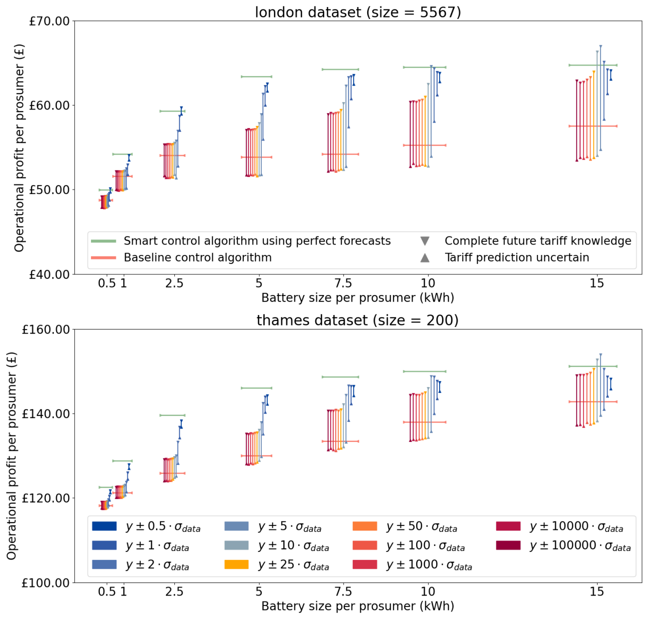

Figure 4: High-level comparison between operational profits of the baseline algorithm and smart algorithm for the average prosumer using various battery sizes and lookahead amounts with uncertain forecasts based on constant margins.

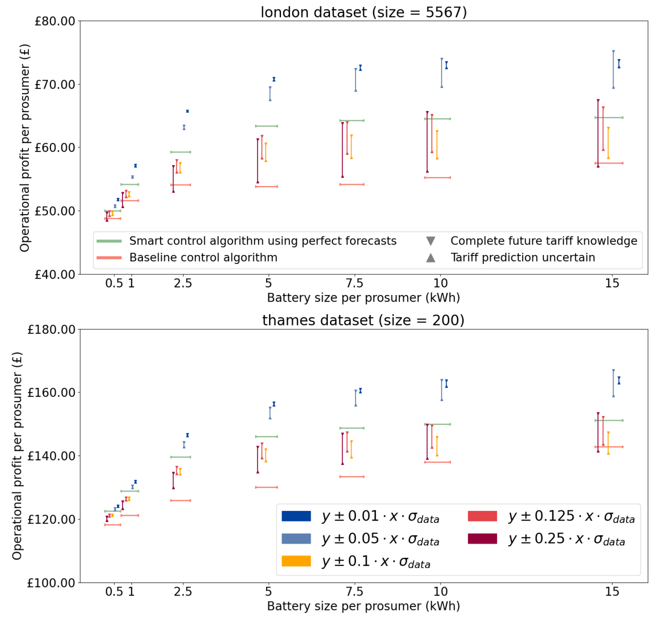

Figure 5: High-level comparison between operational profits of the baseline algorithm and smart algorithm for the average prosumer using various battery sizes and lookahead amounts with uncertain forecasts based on linear margins.

riods. To illustrate the robustness of the smart control algorithm with uncertainty following said characteristics, a linear function of the form $y \pm c \cdot x \cdot \sigma_{data}$ where $x \in (0, \kappa]$ is considered as margins to uniformly pick a random value. Figure 5 summarizes 1400 experiments using various linear margin functions in combination with various sizes for the lookahead window (κ) and various sizes for the battery per prosumer (ω/N). Interestingly, $c \leq 0.05$ outperforms even the smart control algorithm using perfect forecasts, also with tariff uncertainty. Moreover, all functions outperform the baseline control algorithm with only power and demand uncertainty.

Converging and diverging functions

Usually, uncertainty boundaries are not constant or linear, thus, a more complicated type of experiment is also contemplated where up until a point in the lookahead window the uncertainty converges and then starts diverging. This led to creating the following function for setting the margins to uniformly pick a random value:

$$y \pm \begin{cases} s_1 \cdot \sqrt{x}, & \text{for } x < \lfloor r \cdot \kappa \rfloor = d \\ s_1 \cdot \sqrt{d} + (s_2/w) \cdot (x - d)^n, & \text{else} \end{cases}$$

Here, s denotes a scalar, where s_1 scales the converging function and s_2 scales the diverging function with exponent n. Another scalar is w, which can be seen as a control for the width. In the performed experiments w is commonly defined as $\kappa - d$ $(= \lceil (1 - r) \cdot \kappa \rceil)$. The d is the timestamp within the lookahead window where the converging function is continued by the diverging function, which can also be defined as a ratio r of the lookahead window multiplied by its size κ.

This function aims to be a more naturalistic margin for the picked random values where the beginning can be fairly accurate and then shift into larger misconceptions. An example of such a function can be seen in Figure 6 and on actual power data in Figure 7.

Figure 8 summarizes 1400 experiments using various converging and diverging margin functions in combination with various sizes for the lookahead window (κ) and various sizes for the battery per prosumer (ω/N). The results show similar (profitable) results compared to the smart control algorithm using perfect forecasts and remarkably tolerable tariff uncertainty compared to previous experiment types.

5 Responsible Research

To be able to faithfully consider the output of the research in this paper, this section will elaborate on the reproducibility and feasibility of the findings in the paper and elaborate on any other aspects that were considered to ultimately contribute to responsible research.

Reproducing research is a challenge that many researchers fail to tackle, even as much as 70% according to Baker (2016), which should and could easily be prevented. To preclude said issue, the conceptual description of the proposed control algorithm in section 3 contains all details needed to develop the smart control algorithm, which is also available on request, and additionally, the design choices and correctness of the proposed control algorithm have been carefully denoted in subsection 3.1 and section 3.2 respectively.

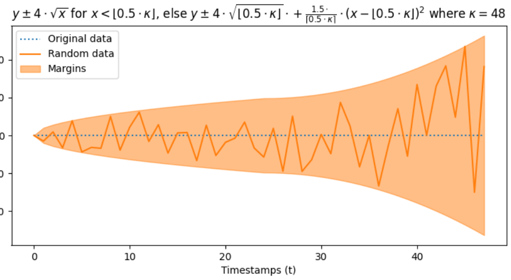

Figure 6: Example of the shape of a converging and diverging margin function on flat original data.

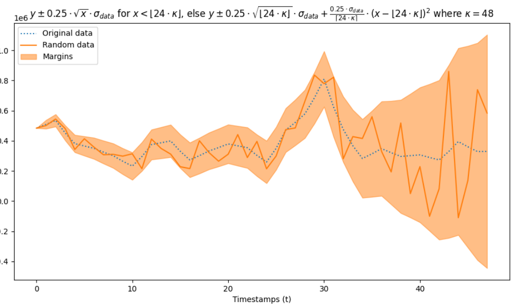

Figure 7: Example of the shape of a converging and diverging margin function on actual community power data of a day in the London dataset.

Then, section 4 attempts to provide a comprehensive understanding of how to recreate the experiments by illustrating and denoting the exact methods that were pursued in the conducted simulations, which are plotted using a color palette that is colorblind-safe.

There is no guaranteed stability, as endeavoured in section 4, without feasibility. Therefore, it is critical to justify the feasibility of various uncertainties and κ used in the experiments by denoting the ability of several techniques (with different complexities) used to forecast certain types of data, such as wind predictions. Values that are not yet justifiable aim to be indicative of what future progress could achieve.
Related research efforts regarding wind predictions are as follows. O'Brien and Ralph (2015) found an error of 25-30% in true wind speeds for forecasts of 30 hours by evaluating the performance of a wind-forecasting system that utilised a Numerical Weather Prediction (NWP) model and is operating in a similar environment as the data used in this paper. Forbes and Zampelli (2020) describe the accuracy of wind energy forecasts in the UK and found an energy weighted RMSE of 31.98% for forecasting a day ahead. The energy trading market is leading (also in complexity) and can accurately forecast 36 hours ahead at high frequencies using ensemble learning as described by Suárez-Cetrulo et al. (2022), which shows several techniques obtaining a scaled RMSE and scaled mean absolute error of less than 1e-3. Another promising long-term prediction model is

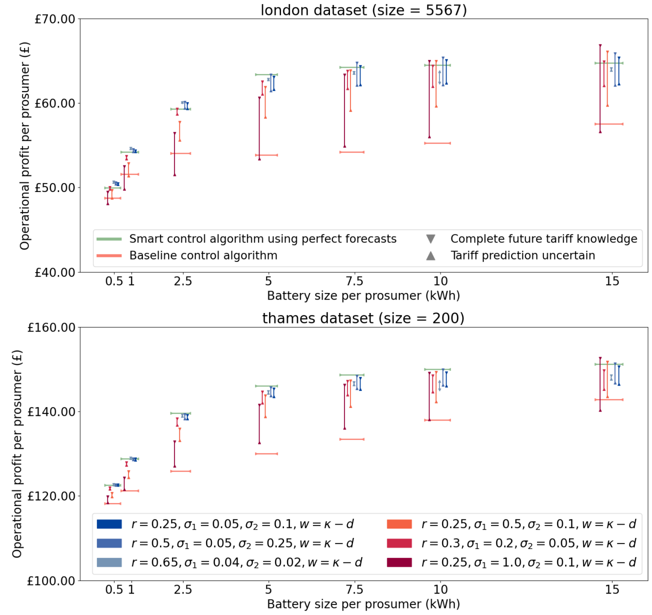

Figure 8: High-level comparison between operational profits of the baseline algorithm and smart algorithm for the average prosumer using various battery sizes and lookahead amounts with uncertain forecasts based on converging and diverging margins.

demonstrated by Torabi et al. (2018), a cascade neural network is able to improve one day ahead forecasts by 84% and one week ahead predictions by 73% based on the RMSE of other already progressive prediction models.
Forecasting energy consumption based on electricity consumption provides promising forecasts, presumably due to the nature of repetitive and alike human behaviour causing stable patterns in the data, of 62.5 hours ahead with a prediction error of around 10% using the TBATS model (which forecasts timeseries based on multiple seasonalities) according to Gellert et al. (2022).
While tariffs can and are often known for various types of contracts, some agile contracts or energy markets call for predicting electricity prices. The energy trading sector has led to the proper development of forecasting tools in this area, even though a decade review by Lu et al. (2021) shows the serious challenge of predicting electricity prices due to many variables: economic factors, trade factors such as cross-border energy flow, policy factors, environmental factors, calendar factors such as holidays and lastly general consumption, production, supply, storage, and capacity play a role in energy prices. Using artificial neural networks, day-ahead predictions with a mean absolute percentage error of 7.8 have been achieved (Pavićević and Popović, 2022).
All in all, the various values for κ and the range of uncertainties in the experiments in section 4 should be reasonably elucidative for the stability of the performance of the proposed smart control algorithm when taking into account the current state-of-the-art technologies of fore-

casting supply, demand and tariffs.

6 Discussion

After introducing a smart control algorithm defined in section 3 and putting it to the test in section 4 by simulating a manifold of scenarios, this section will reflect on particularities present in the conducted experiments.

Firstly, a conceivably anomalous sight of more profitable simulations with respect to the simulations using perfect forecasts can be seen in the outcomes of some experiments testing the robustness of the algorithm in subsection 4.3. A probable justification for this occurrence could be that the lack of knowledge after the lookahead window causes a suboptimal decision no matter the accuracy of the forecast, as the lookahead window does not span the range of timestamps that would influence the perfect decision in retrospective. From all the detailed results of simulations for various sizes of κ with perfect forecasts, presented in Appendix B and Appendix C, the total operational cost, i.e. $b(T)$, with respect to κ follows the shape of a positive-indexed reciprocal function, i.e. $y = 1/x$ for $x > 0$, and $\Pi(T)$ does not decrease, which confirms that more (accurate) knowledge guides the smart algorithm to make more profitable decisions. Based on said beliefs and findings, it seems that some of the imperfect forecasts accidentally directed the decision unknowingly towards a decision that matched the supply and demand of energy more or most optimally.

Secondly, it is essential to denote limitations regarding the experiments to critically assess the proposed smart control algorithm appropriately. Computationally speaking, the available equipment used to run simulations had an inferior level of performance to calculate the 'most optimal' profit possible where $\kappa = |T|$, which would provide even finer insight into the level of performance of the simulations carried out in subsection 4.3 where randomness was introduced to sample the robustness of the smart control algorithm. Moreover, due to a lack of available data, the simulations were run on real data yet originating from different years, thus, it merely provided a sound environment to evaluate the behaviour of the proposed algorithm, whereas true-to-life data could have supplied more relatable insights into actual cost and profit differences, especially for the energy communities that were considered in this paper. From weather to demand, all variables in the setup have a sensitive correlation, as confirmed by Hernández et al. (2012), thus, any output cannot be truly considered genuine or useful for any recommendations besides performance testing. For this reason, it is decided to not provide practical recommendations for the size of a battery storage unit for a particular prosumer as well.

7 Conclusions and Future Work

In this paper, reputable modifications for a heuristic-based control algorithm are discovered to ultimately improve the efficiency of renewable energy assets by matching the energy supply and demand more optimally. A heuristic-based control algorithm determines whether to interact with the battery, i.e. charge or discharge, or interact with the central grid, i.e. sell or buy energy, based on the current residual power and battery state. For a theoretically optimal decision, the future should be taken into account, which realistically can be forecasted with the current state of technology. Based on the idea of having perfect knowledge in the complete range of time, the following broad principles should be taken into account:

- A battery should never be filled more than needed as otherwise the surplus of energy could have been sold.
- If battery power is considered to be utilised while in the future excess demand requires to be covered by buying energy for a higher price than the current price, it would be beneficial to buy energy now and use battery power in the future.
- If energy can be sold to the central grid on multiple occasions, it should be sold at times when the selling price is as high as possible.
- If the battery is able to charge using imported energy from the grid, charging the battery with bought energy should have been considered if it were more profitable than having to buy energy later at a substantially higher price.
- If the available generated power and battery power cannot cover the demand, there is no other option than to buy energy. Similarly, if the battery cannot be charged more or at a higher rate, energy needs to be sold to the central grid.

Based on several thousands of simulations on areas in the UK with various probable ranges of forecasts and battery sizes, the smart control algorithm has demonstrated to gain additional profit for both theoretically perfect forecasts and plenty more realistic forecasts by exploiting the aforementioned characteristics. Therefore, the proposed smart control algorithm can be considered as a theoretical and presumably a practical improvement for the efficiency of renewable energy assets.

For future work, it would be worth investigating uncommon actions or trends in lookahead windows of unusual computationally large size in order to assess whether using these actions based on the estimation of some machine learning technique in small lookahead window sizes would benefit the overall efficiency of the smart control algorithm. In addition, various types of tariffs could be considered to gain a perspective of the usefulness of adapting to the proposed smart control algorithm for a particular prosumer. Additionally, actual forecasting models and more real data should be explored using the proposed control algorithm in order to advance towards practical deployment and directly improve the efficiency of renewable energy assets.

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A Processing an example scenario for the proposed smart control algorithm

To possibly increase the intuitiveness behind the functioning of the algorithm beyond the power of words, this appendix will provide a figurative systematic walkthrough of the improved control algorithm for an example scenario with expensive future demand which has been presented in Figure 9. In this scenario, as can also be deduced from looking at Figure 9 carefully, initially $T = 3$ and $SoC_{init} = 0$ ($\omega = 1$). To simplify, $\eta^c = \eta^d = 1$, $\Delta t = 1$ and forecasts remain constant. The algorithm will look ahead maximally for each $t \in T$ (note that with $T = 3$ there is a decreasing lookahead window size, as opposed to a real-time functioning system). Each iteration in Figure 9 for some t starts with showing the current state of variables and other details (for example, see subfigure $t = 0$), to then continue with processing each future timestamp in the lookahead window denoted by iteration i, e.g. subfigure $t = 0$ and $i = 1$, and showing the output of the iteration. The bottleneck of this scenario is the substantially higher import tariff at $t = 2$, i.e. 5, and the lack of generated power to cover future demand, thus, it would be optimal to import energy at $t = 1$, which a heuristic-based algorithm does not consider as it discharges immediately. For example, in the figures of $t = 0$ where $i = 1$ and $i = 2$ the algorithm already decides that importing energy earlier is the more optimal, as here the tariff is only 1. This action is realized in $t = 1$ at iteration $i = 1$.

Figure 9: Systematic walkthrough of improved control algorithm for an example scenario with expensive future demand.

B Detailed results of perfect forecasts on London dataset

This appendix shows the details of the experiments carried out in subsection 4.2 using the London dataset to give more insight regarding how far the smart control algorithm needed to look ahead (κ) in order to be more profitable than the baseline control algorithm for a broad range of battery sizes. The results can be seen in Figure 10 and Figure 11. The operational profit per prosumer is defined as $-b(T)/N$, which has a flipped sign to make the plot intuitively look like profit given a negative bill actually means getting money back (= profit). Thus, the increasing trendlines indicate more profit for larger values of κ. It is also worth mentioning that $-b_0(T)$ in the legend represents the operational profit of the baseline control algorithm per prosumer, so actually divided by N, similarly to the y-axis. Furthermore, BA stands for 'baseline control algorithm' and SA stands for 'smart control algorithm' in the legend.

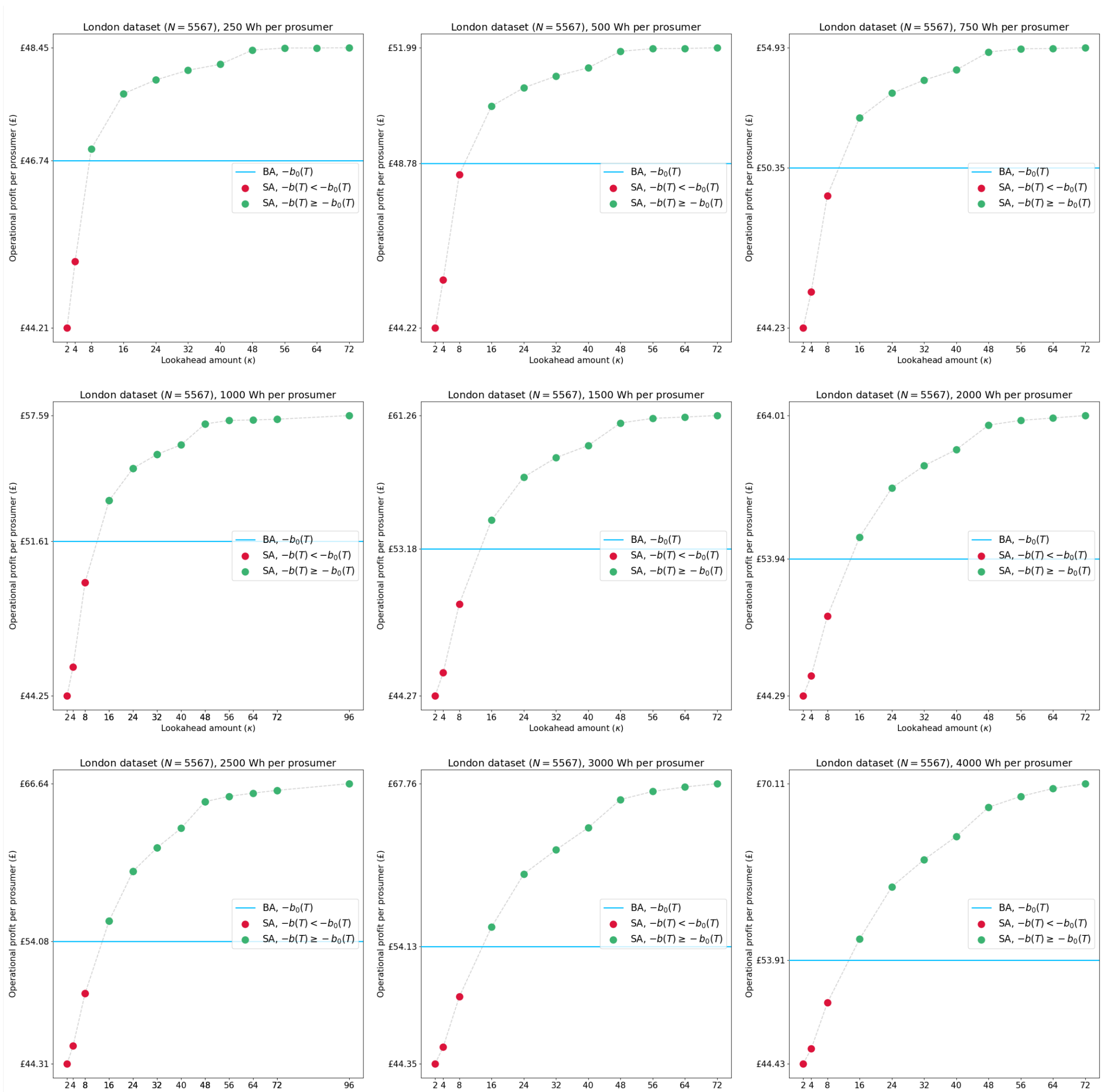

Figure 10: Overview of operational profits per prosumer for the baseline- and smart control algorithm using various sizes for the lookahead window (κ) and various sizes for the battery per prosumer (ω/N) on original historical data of London (part 1).

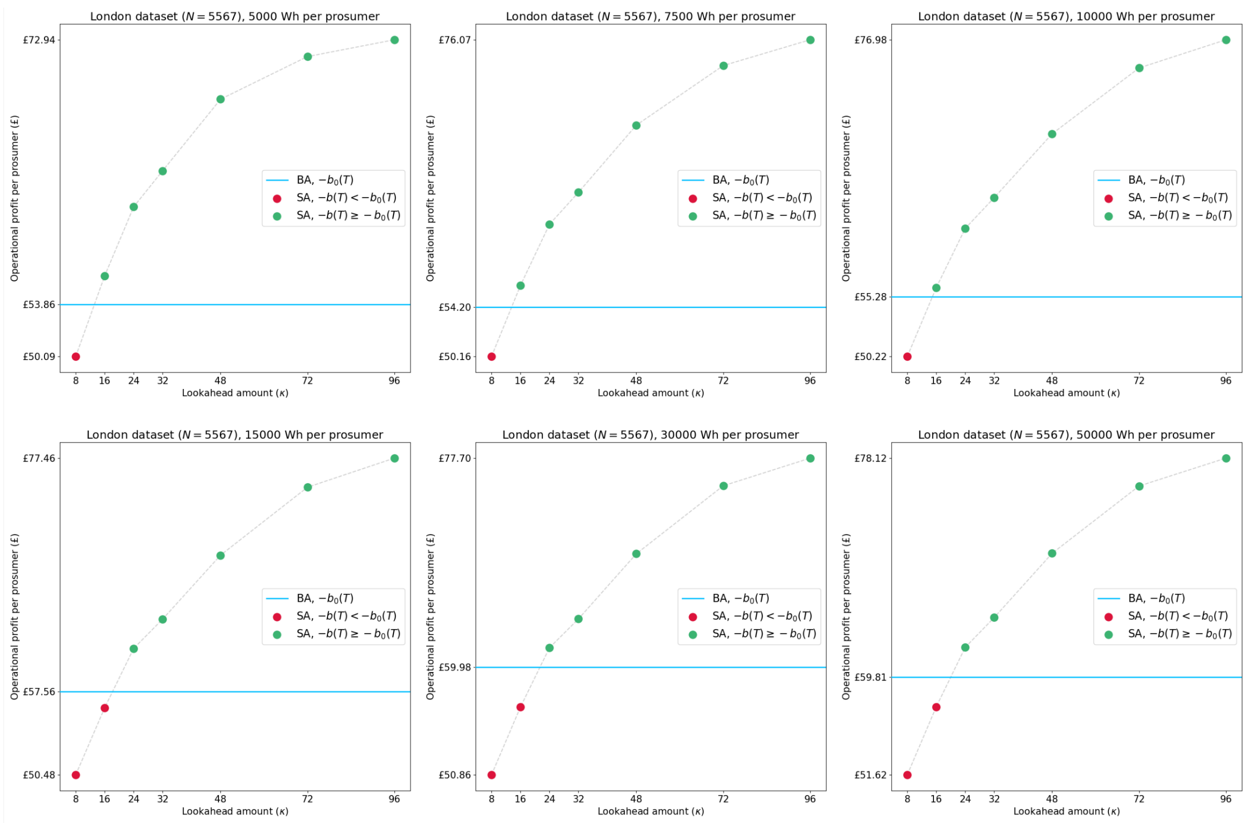

Figure 11: Overview of operational profits per prosumer for the baseline- and smart control algorithm using various sizes for the lookahead window (κ) and various sizes for the battery per prosumer (ω/N) on original historical data of London (part 2).

C Detailed results of perfect forecasts on Thames dataset

This appendix shows the details of the experiments carried out in subsection 4.2 using the Thames dataset to give more insight regarding how far the smart control algorithm needed to look ahead (κ) in order to be more profitable than the baseline control algorithm for a broad range of battery sizes. The results can be seen in Figure 12 and Figure 13. The operational profit per prosumer is defined as $-b(T)/N$, which has a flipped sign to make the plot intuitively look like profit given a negative bill actually means getting money back (= profit). Thus, the increasing trendlines indicate more profit for larger values of κ. It is also worth mentioning that $-b_0(T)$ in the legend represents the operational profit of the baseline control algorithm per prosumer, so actually divided by N, similarly to the y-axis. Furthermore, BA stands for 'baseline control algorithm' and SA stands for 'smart control algorithm' in the legend.

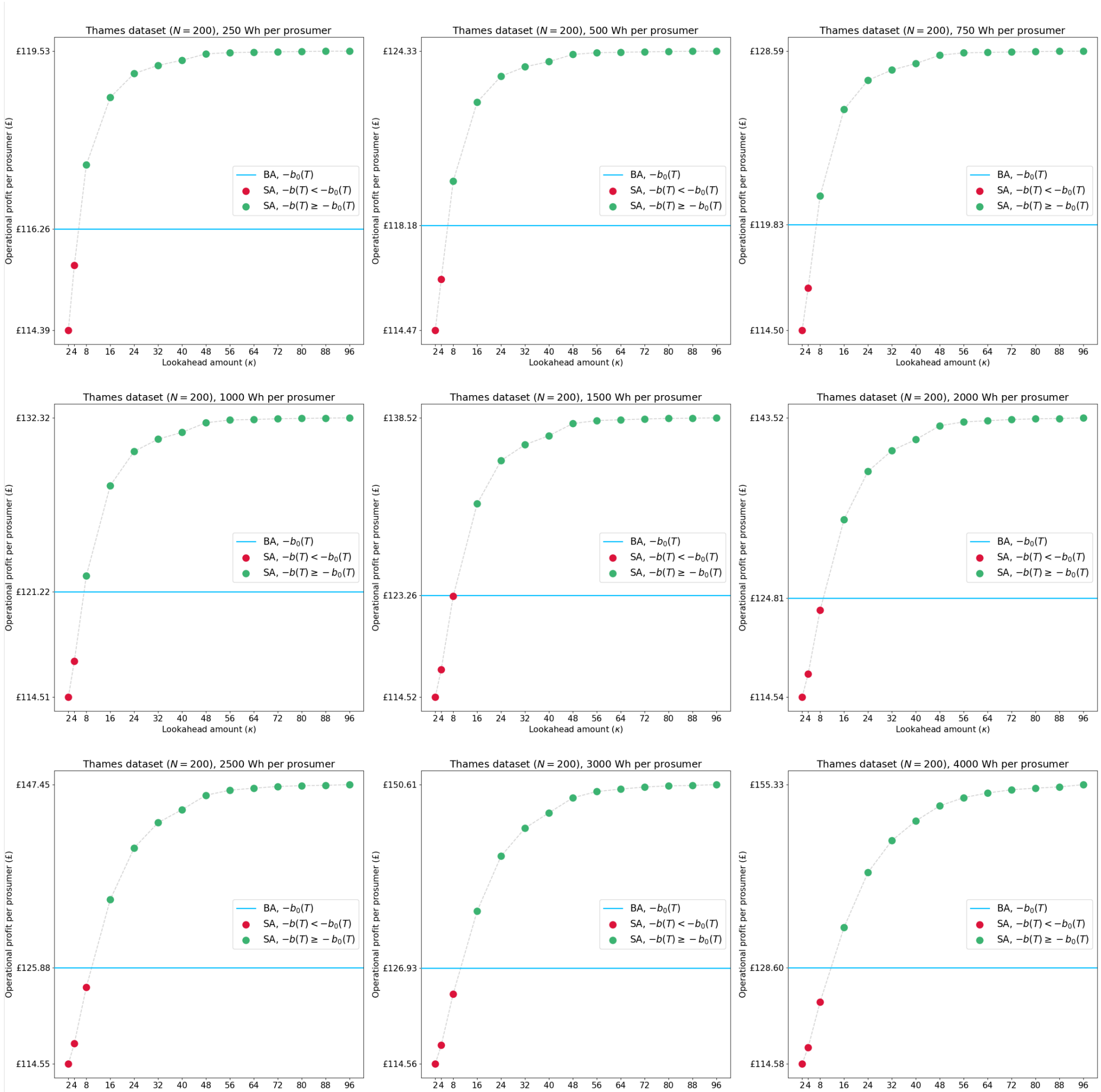

Figure 12: Overview of operational profits per prosumer for the baseline- and smart control algorithm using various sizes for the lookahead window (κ) and various sizes for the battery per prosumer (ω/N) on original historical data of Thames (part 1).

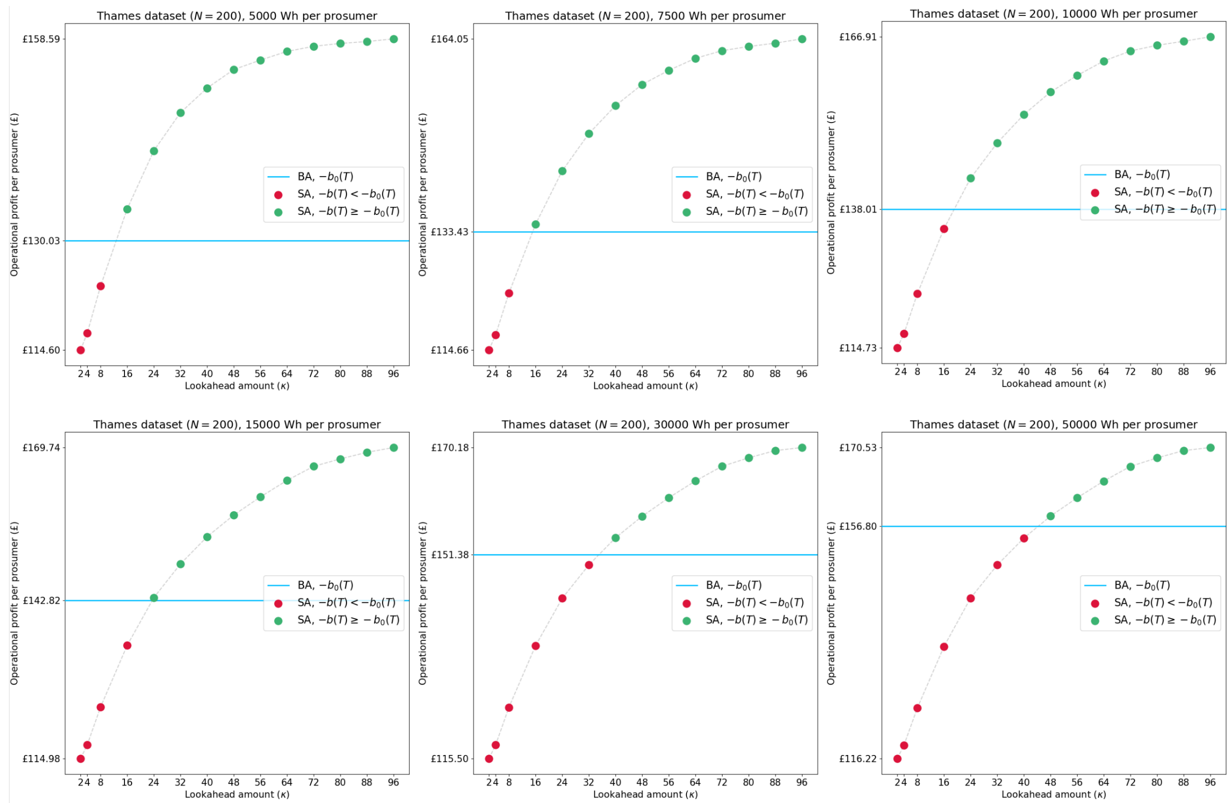

Figure 13: Overview of operational profits per prosumer for the baseline- and smart control algorithm using various sizes for the lookahead window (κ) and various sizes for the battery per prosumer (ω/N) on original historical data of Thames (part 2).