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# Steering the adoption of battery storage through electricity tariff design

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## ABSTRACT

The economic viability of electricity storage using batteries, under different tariff structures and system configurations, is investigated. The economic outcomes of the different combinations of tariff design and system configuration are evaluated. Based on a discussion of the relevant literature, the following tariff designs are used in the study: (i) fixed energy prices, (ii) real-time energy pricing, (iii) fixed rate capacity tariffs, and (iv) capacity dependent capacity tariffs. Next, the different simulated system configurations are outlined: (i) no battery storage, (ii) battery storage only, and (iii) battery storage and decentralized renewable energy production with PV. Our study provides insights for policy makers, showing that capacity block pricing only incentivises storage as part of an (existing) PV installation, while the combination of real time energy pricing and capacity block pricing promotes a wider adoption of battery storage.

## KEYWORDS

Simulation, Policy, Tariff design, Capacity Payments, Storage, Optimization.

## 1. INTRODUCTION

Smart grids have been widely researched as a possible solution for the decarbonisation of society's electricity demand, by allowing a greater penetration of renewable energy sources [1,2,3]. One possibility to arrive at such a low carbon smart grid, is the adoption of so-called microgrids. A microgrid is widely understood to be a grouping of electrical as well as heat loads and sources, being able to operate either in self-contained, islanded mode, or as part of the distribution system, in which case a microgrid is to act as a single, controllable load [4,5,6,7]. This of course raises the question of how such loads should be controlled, a discussion of standardisation and control principles can be found in [8], specifically aimed at controlling the load that microgrids represent.

A good overview of the drivers behind and challenges facing microgrids is given in [9], [10] zooms in on the challenges and opportunities concerning smart grids and microgrids. In previous work [11], it has been shown that there is a dearth of research looking at the policy

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impacts of different tariff schemes on the economics of microgrids, as most tariff policy research focusses on the utilities.

One main recurring component which has been widely investigated in the context of microgrids, is storage, both of heat and electricity. Storage is a well-researched component, as it greatly facilitates balancing of generation and load. As shown in [12], locally available storage allows for efficient control of the grid through the use of well-designed price signals. However, a suitable and robust business case for storage remains elusive, as evidenced by various publications looking at different possibilities: using the battery capacity of electric vehicles in a vehicle-to-grid setup was investigated in [13], while [14] investigates the possibility of using arbitrage possibilities. Both papers report favourable outcomes in some, but not all, scenarios. Further evidence of the precarious business case underpinning the adoption of storage is provided in [15], showing that round trip efficiency and capital costs –both drivers for the overall cost of ownership- are still significant barriers to the wide scale adoption of energy storage technologies.

Against this backdrop of proven societal benefits from the adoption of storage on the one hand and uncertain profitability on the other hand, this paper investigates the impact of government policy on the adoption of energy storage. More specifically, we look at the impact of a capacity tariff for electricity on the household adoption of battery storage. In order to effectuate this analysis, we simulate different household microgrid configurations under varying electricity price and tariff schemes, minimizing the total operational cost over the period of one year for a modal residential Belgian consumer. The choice of nationality is driven by ease of access to the relevant data; as the authors are attached to a publicly funded Belgian university, the Belgian transmission and distribution system operators readily made the required data available. As systems costs and technical performance of intermittent generation and storage are not only the subject of significant technological change but also important drivers of the overall profitability of any given microgrid configuration [15], no a priori assumptions are made when it comes to installation costs or technical performance of intermittent generation or storage. The analysis made will instead indicate the tipping point, expressed as an annualized cost below which different systems configurations become economically viable.

The following section provides a more in depth literature review concerning the issues of interest directly linked to the research question at hand. Section three states the research goal as well as the central research hypothesis, thereby also clearly delineating the contribution of this work. The fourth section details the research methodology used, and discusses in order the research method, the research variables and the design of the simulation model. A presentation of results and a discussion of these results and policy implications closes this paper.

## **2. LITERATURE REVIEW**

Research into microgrids is a fertile field, as evidenced by the comprehensive literature review establishing a functional layer based classification [16]. This review provides a good starting point and provides a broad overview of microgrid concepts as well as existing microgrid test beds. As [16] provides a good basis of information, the remainder of this section will be explicitly focussed on the areas of interest of this paper, being policy measures used to influence system configuration on the one hand, and microgrid modelling and simulation on the other hand.

As mentioned in the introduction, little research has been done on the impact of policy on microgrid economics [11]. A popular investigated policy intervention is carbon taxation, as it

is present in a majority of earlier work [17,18,19,20,21,22]. The reported results of this policy intervention are mixed however: either they result in no noticeable impact on the microgrid, compared to the no intervention scenario [17,18,22] or they incentivise the installation of solar PV, but only when combined with a feed-in tariff for electricity generated by these panels. [19,20]. Only one case reports a somewhat favourable outcome of carbon taxation where renewable generation is concerned [21].

As already outlined above, economic incentives in the form of feed in tariffs can be effective [19,20], while sufficiently high tax credit, amounting to 50% of the installation cost in [22], will have a significant impact on the installed system configuration, heavily favouring the adoption of wind power. When the operation of the installed system is considered as well, the results are more mixed: conventionally fired CHP units still contribute the majority of the generated power in the system modelled in [22], while some of the considered feed-in tariffs are higher than the grid price of electricity, leading to the system buying all needed power from the grid, while selling all generated power from the solar panels at the same time.

Less work has been done on investigating the impact of different tariff systems, and the work available focusses exclusively on energy time of use pricing, however, once again, the impact is found to be negligible [18], or sometimes even negative, if emission costs are considered [23].

Time of use pricing is generally more studied as a measure to steer consumer loads [24], without taking the resulting economics into account [25]. Along a similar vein is the work presented in [12], capacity instead of energy price signals are used to steer a controllable load. The choice for using capacity pricing as a signal as opposed to energy pricing is made because this better reflects the economic realities distribution system operators are faced with, when serving the connected consumer loads. Furthermore, these measures are found to be effective in their stated goal of steering consumer loads.

There is a broad consensus in existing research where the simulation and modelling of microgrids is concerned: simulations are set-up and mathematical optimisation based on mixed integer programming is carried out [22,17]. The scope of different presented models in the literature differs however: some models are operational models, focussing exclusively on operational parameters [18], while others are investment models, taking both the investment and operational costs into account [17,19,20].

### **3. RESEARCH GOAL & HYPOTHESIS**

Based on the review outlined above in section 2 and the findings reported in [11] a clear research gap becomes evident: to the best of the author's knowledge there has been no research focussing on using capacity tariffs to encourage the uptake of storage technologies. The contribution of this paper is that it closes that research gap, by presenting the impacts of a capacity tariff scheme, both by itself as well as in conjunction with real time energy pricing and evaluating the impact of these pricing schemes on a residential microgrid. In doing so, this paper not only extends the breadth of scientific knowledge surrounding microgrids, but also expands the toolkit of policymakers, by providing evidence of the impact of capacity tariffs on the economics of different microgrid system configurations.

The above contribution translates itself to the following research hypothesis: capacity tariffs will be effective in differentiating between different system configurations, where the economics of these different systems are concerned, specifically favouring system configurations including storage. The reasoning behind this hypothesis is that system with

storage will be able to engage better in peak-shaving behaviour, allowing them to avoid the higher costs incurred for high peak usage of capacity. This hypothesis will be tested by simulating different system configurations -with and without storage as well as with and without intermittent generation-, under a no intervention scenario, a scenario with capacity tariffs, and a scenario with both capacity tariffs and real time energy pricing. This research aligns itself with those papers taking an operational approach, deliberately choosing not to take investment cost into account, but instead aiming to provide policy insights that are relevant regardless of the current installation costs of the investigated technologies.

**4. RESEARCH METHODOLOGY**

This section discusses in detail the methodology used to test the hypothesis outlined in section 3. A first subsection details the research method used, detailing both the simulation model as well as the optimisation problem being solved. The second subsection delves deeper into the policy interventions investigated, while the third and final subsection elaborates on the particulars of the simulations.

**4.1. Research method**

In order to investigate the impact of electricity tariff design on the adoption of battery storage, a simulation model is used. The model used is a refinement of the model presented in [26]: a residential consumer is modelled, consisting at a minimum of an exogenous load profile and a connection to the electricity grid, which serves as a limitless source or sink of electrical energy. Additionally, local distributed generation and/or storage can also be present. The model only incorporates electrical generation and load, heat is not included. As more fully elaborated upon in the authors’ previous work [13], the explicit focus of the model is the underlying economics, meaning abstraction is made of technical considerations such as line losses or most of the technical aspects of individual model components. Figures 1 and 2 present schematic overviews of the used model: figure 1 shows the modelled system without the presence of intermittent generation, while figure 2 shows the system layout for the case where intermittent generation is included in the modelled system. Additionally, both figures 1 and 2 also show the sign convention used: power and energy flows are considered positive when they are flowing towards the load. While this results in the seemingly counterintuitive situation where charging the storage component means a negative sign for the respective term,  $Q_s$ , this sign convention was chosen to ensure consistency across all of the terms used in the equation.

For the simulated system, the yearly operating cost, comprised of the payments made for the used energy and applicable tariffs, is minimized using Matlab.

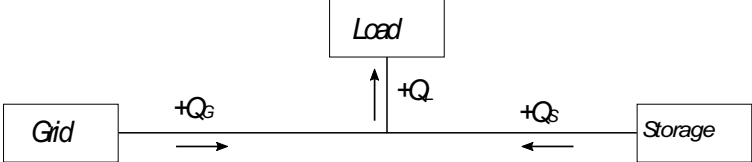


Figure 1. Model without intermittent generation

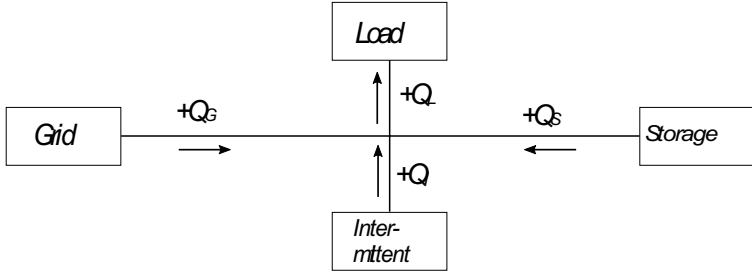


Figure 2. Model with intermittent generation

The formulation of the problem is as follows (please consult the nomenclature at the end of this paper for the meaning of the used symbols). We minimize the cost function

$$\min_{Qg} \left[ \sum_{t=1}^{24} Q_G(t) \cdot P_G(t) + |Q_G(t)| \cdot C_{p1} + \max(|Q_G(t)| - C_b, 0) \cdot (C_{p2} - C_{p1}) \right] \quad (1)$$

subject to the following constraints:

$$Q_L(t) = Q_G(t) + Q_S(t) + Q_I(t) \quad \forall t = 1, \dots, 24 \quad (2)$$

$$S_{in}(1) - \sum_{\tau=1}^t Q_S(\tau) \leq S_{max} \quad \forall t = 1, \dots, 24 \quad (3)$$

$$\sum_{\tau=1}^t Q_S(\tau) \leq S_{in}(1) \quad \forall t = 1, \dots, 24 \quad (4)$$

The decision variables used in the simulation model is the vector  $Q_G(t)$  with the index  $t$  running over a 24-hour period. At the start of each 24-hour period, we renumber the indexes of the hours considered, so that the first hour has index 1, and the last hour has index 24. A rolling 24-hour window is used: after the optimization is finished for the first 24 hours, the solution for the first hour is saved, after which the optimization is carried out for hours 2 through 25, yielding the solution for the second hour, and so on and so forth.

Before elaborating on the cost function and the constraints, it is important to discuss the sign convention used. All flows of power to the load are positive, while all flows of power away from the load are negative, by convention. This does not impact  $Q_I$  as the amount of power available from the distributed generation will always be non-negative. However, said sign convention has some repercussions where the interpretation of the signs of the decision variables,  $Q_G$  and  $Q_S$  are concerned. For  $Q_G$ , this simply means that power bought from the grid will have a positive sign, while power sold to the grid will have a negative sign. It is especially important to keep the sign convention in mind with regards to  $Q_S$ , as charging storage will be reflected by a negative value of  $Q_S$ , while discharging power from storage will result in a positive sign for  $Q_S$ .

Equation 1 details the cost function to be minimized and has two components. The first component contains the cost for electricity used from the grid –or, conversely, the benefit realised by selling electricity to the grid-, while the second component represents payments made to the grid operator for the grid capacity used. It should be noted that the actual payments are calculated using a block tariff scheme, where all capacity used above a certain level,  $C_b$ , has to be remunerated at a higher tariff.

For each timestep considered, i.e. for each value of index  $t$ , the sum of the amount withdrawn from the grid, the amount withdrawn from storage and the power available from the intermittent generation must be equal to the load that needs to be served; this is enforced by equation 2. Equations 3 and 4 are two sets of constraints on the battery: equations 3 enforces that the battery can never be charged past its fully charged state, while equations 4 states that the battery cannot be further discharged when it is already empty. These are two sets of twenty-four equations each, as they have to be met for each hour of the 24-hour modelling window.

The resolution used in the simulation set-up is one data point per hour. This means that all the variables considered are to be read as energy amounts. However, as one of the main aims of this paper is to investigate the impact of capacity tariffs, capacity used is also included: electricity bought or sold during each hour is assumed to be uniformly distributed over that hour, which means that the peak capacity during that hour also corresponds to the electricity bought or sold. For example, assume that during a certain hour, 1.5 kWh of electricity was bought from the grid, this corresponds to a capacity usage of 1.5 kW during the entirety of this one-hour window, resulting in a peak capacity usage of, again, 1.5 kW for the hour under consideration. Consecutive hours are linked through the storage component, as the amount of energy in storage at the end of timestep  $t$ , is also the amount of energy that will be in the storage component at the start of timestep  $t+1$ . With the addition of time-varying energy prices, as is the case for some simulations setups discussed below, this linkage through the energy stored in the storage component, causes the system to become a non-causal one, as the optimal decision at any given moment is dependent on future events. The modelling intricacies this entails are further discussed in [26].

## 4.2. Research variables

In this study, the household electricity bill is split into two parts, an energy component and a capacity component. The energy component provides remuneration for the energy provider and can either be a reflection of the fluctuating wholesale market price, or fixed rate per kWh consumed. In the studied Belgian setting, household electricity consumers are currently charged using a fixed rate scheme. Spot pricing was however included to open up the possibility of price arbitrage by storage owners.

Likewise, two options are investigated for the capacity part of the electricity bill. The first option is a fixed capacity tariff, where all capacity used, has to be remunerated at a fixed rate,  $C_{p,f}$ . The second option is capacity block pricing, where there are two capacity tariffs: a lower one,  $C_{p,1}$ , which is the tariff for all capacity falling in the lower block, limited by  $C_b$  and a higher tariff, for all capacity used above  $C_b$ .

In total, this leads to three investigated scenarios, as show in table 1. Scenario A serves as a base case, without any additional policy intervention, as it most closely resembles the actual situation in Belgium. Scenario B builds on scenario A by introducing block capacity pricing, while scenario C not only incorporates block pricing, but real time energy pricing as well. It is important to mention that these scenarios also have repercussions on the objective function used: the objective function as detailed by equation 1 is the most general form, and holds true for scenario C. The objective functions for the other two scenarios are derived from it, as shown in table 1.

Table 1. Pricing & tariff design scenarios

Scenario	Energy pricing	Capacity pricing	Objective function
A	Fixed price	Fixed rate	$\min_{Q_G(t)} \sum_{t=1}^{24} (Q_G(t) \cdot p_{G,fix} +  Q_G(t)  \cdot C_{p,f})$
B	Fixed price	Block pricing	$\min_{Q_G} \left[ \sum_{t=1}^{24} Q_G(t) \cdot P_{G,fix} +  Q_G(t)  \cdot C_{p1} + \max( Q_G(t)  - C_b, 0) \cdot (C_{p2} - C_{p1}) \right]$
C	Real time	Block pricing	$\min_{Q_G} \left[ \begin{array}{c} \sum_{t=1}^{24} Q_G(t) \cdot P_G(t) \\ +  Q_G(t)  \cdot C_{p1} \\ + \max( Q_G(t)  - C_b, 0) \cdot (C_{p2} - C_{p1}) \end{array} \right]$

The described optimization problem is solved for a simulated year using a 24-hour sliding window. After an optimal solution for the next 24-hour window is found, the results for the first hour are saved after which the optimization is run again, but now for hours two through twenty-five. This process is repeated until a solution for the entire year is obtained.

4.3. Design of the simulation model Following the elaboration on the used simulation framework in the previous section, this subsection provides greater detail on the design of the investigated policy interventions on the one hand, and the simulated system configurations on the other hand. Furthermore, the used data sources and instance generation are also discussed.

#### 4.3.1. Energy and capacity price points

As Schreiber et al. report favourable results with such capacity tariff design in [12], the same values for  $C_{p,f}$ ,  $C_{p,1}$  and  $C_{p,2}$  are used as starting points in this study. The numerical values of these parameters can be found in table 2.

Table 2. Capacity prices

$C_{p,f}$	0.0652 €/kW
$C_{p,1}$	0.0581 €/kW
$C_{p,2}$	0.1872 €/kW

Since the overall goal of the capacity block tariffs is to reduce the peak load on the system, the cut-off point for the lower capacity block is designed to encourage peak shaving by the individual consumer. As such, the threshold for the capacity block tariff scheme is set as function of the average consumer load, being 1.2 times the average hourly load.

Spot price data was obtained from Belpex [27], while the fixed energy price was set to the yearly average of the spot price data, in order to eliminate any bias towards either spot pricing or fixed pricing due to a difference in overall price level.

#### 4.3.2. System configurations

A variety of systems configurations is investigated for a modal Belgian household with a yearly electricity consumption of 3600 kWh. In the base case, only this load is present, without any



intermittent generation or storage components available. This base case serves as a dual baseline: it will allow for an estimation of the impact of the investigated policy measures on an average consumer when no actions are taken by the consumer, while it also serves as a common backdrop against which the other system configurations can be evaluated.

This base system configuration is then expanded with storage capacity in the form of batteries, intermittent generation provided by solar photovoltaic panels or a combination of both. Battery storage is available in 0.9 kWh increments, ranging from 0.9 kWh to 4.5 kWh of storage. Solar photovoltaic generation is available as a 2.1 kWp installation. It should however be noted that not all possible combinations have been simulated: without solar PV, small to medium battery storage has been included, while for systems with PV, only medium to large battery storage was included.

#### 4.3.3. Data sources and instance generation

All data exogenous to the model are based on existing datasets: the electricity price data were obtained from Belpex [27], the load data is based upon the synthetic load curve for a residential Belgian consumer made available by Synergrid, the Belgian Federation of grid operators [28] and the solar generation data was obtained from Elia, the Belgian Transmission system operator [29]. In order to evaluate the stability of the obtained results, the addition of weighted white noise was used in order to effectuate three simulation runs based upon different realizations for each combination of scenario and system configuration. Descriptive statistics for the exogenous datasets used are reported in table 3. The statistics in table 3 clearly show that each of the simulations ran can be considered as a different realisation of the same year, as the each of the three data sets used are shown to be similar, yet distinct. The very low median and high skewness of the solar generation data is due to the fact that there are many hours each year when it is dark, meaning solar PV panels produce no electricity. Finally, comparison of tables 2 and 3 clearly show that the capacity tariffs on the whole cover a similar range as the real time energy price, except for the price of the higher capacity block,  $C_{p,2}$ , leading to the expectation that the block capacity tariff will be effective at steering the consumer load, as the capacity price signal encountered when entering the more expensive capacity price block will outweigh the energy price signal.

Table 3. Descriptive statistics of the exogenous data sets

Descriptive statistics	Load data (kW)			Solar generation data (kW/kWp)			Real time price data (€/kWh)		
	Mean	0.41	0.41	0.41	0.22	0.23	0.23	0.08	0.08
Median	0.40	0.40	0.40	0.00	0.00	0.00	0.09	0.09	0.09
Skewness (unitless)	0.56	0.56	0.57	1.82	1.82	1.83	-0.77	-0.74	-0.96
Standard deviation	0.14	0.14	0.14	0.37	0.37	0.37	0.04	0.04	0.04
Minimum	0.14	0.13	0.15	0.00	0.00	0.00	-0.38	-0.41	-0.43
Maximum	1.02	0.94	0.94	1.98	1.97	1.84	0.32	0.31	0.32

An important assumption made is that the system has perfect knowledge about the future, meaning that the predicted load, price profile, and solar irradiance for the coming twenty-four-hour period will always completely match the corresponding realisations of that period. While this may be somewhat unrealistic, as in reality, some measure of forecast error will always be present, this assumption was made in order not to only simplify the modelling work, but more

importantly also to ensure that any forecast error would not skew or interfere with the research question at hand.

## 5. RESULTS AND DISCUSSION

First, the quantities of electricity bought from and sold to the grid are discussed. Next, the yearly costs are analysed.

Figure 3 shows the amount of electricity bought from or sold to the electricity grid, for the second week of January, under scenario A (no additional policy intervention). This figure mainly serves as a baseline for comparison with the policy intervention scenario B and C. It should also be noted that the results for the base case and the system with only 1.8 kWh of storage are identical for scenario A, meaning they are superimposed over one another in figure 3. Only one week's worth of simulated data is shown because such an interval allows for the data to be displayed in a clear and legible way, while still showing the general trend that is present in all the data points. Similarly, the choice was made to only depict 4 system configurations out of the 8 investigated. Similar figures for the four system configurations not shown here, can be found in appendix A. Similarly, the results are also presented group per system configuration, instead of per scenario for readers who might prefer such a visualisation in appendix B. At this point also bears repeating that the resolution of the simulation is one data point per hour, with the assumption that the energy quantities -so the load, charging or discharging storage and generation from solar PV- remain constant during this one-hour window. This also means that the energy quantities depicted in the figures discussed in this section, are also the power flows during that same hour: a load of 1 kW over the period of one hour corresponds to 1 kWh and vice-versa.

Figures 4 and 5 show the system configurations during the second week of January again, but now under policy scenario B and C respectively. As is immediately apparent, the outcomes for both the base case and the PV system without battery storage do not change. This is as expected, as neither of those systems have battery storage, they cannot adapt their behaviour based on the pricing scheme that is in effect. In contrast, the two systems depicted that incorporate battery storage show marked changes. When comparing figures 3 and 4, both depicted system configurations incorporating storage have flattened their respective peaks in figure 4. This is expected behaviour, as both simulated systems use their available storage components to avoid going over the capacity threshold. Under scenario C however, the resulting load profiles of the system configurations incorporating battery storage become more erratic, as shown in figure 5. Not only do the battery-enabled simulated systems show higher peaks, their net consumption of electricity is also less stable throughout a twenty-four hour period. Both of these behaviours are due to the arbitrage possibilities offered by the real time pricing of energy that the system seeks to exploit. Interestingly, figure 5 also shows a few instances where the consumption of electricity by the systems with installed battery storage capacity is higher than under scenario's A or B, indicating that sometimes the price signal from the energy component is high enough to override the penalty imposed by the capacity component for exceeding the capacity threshold.

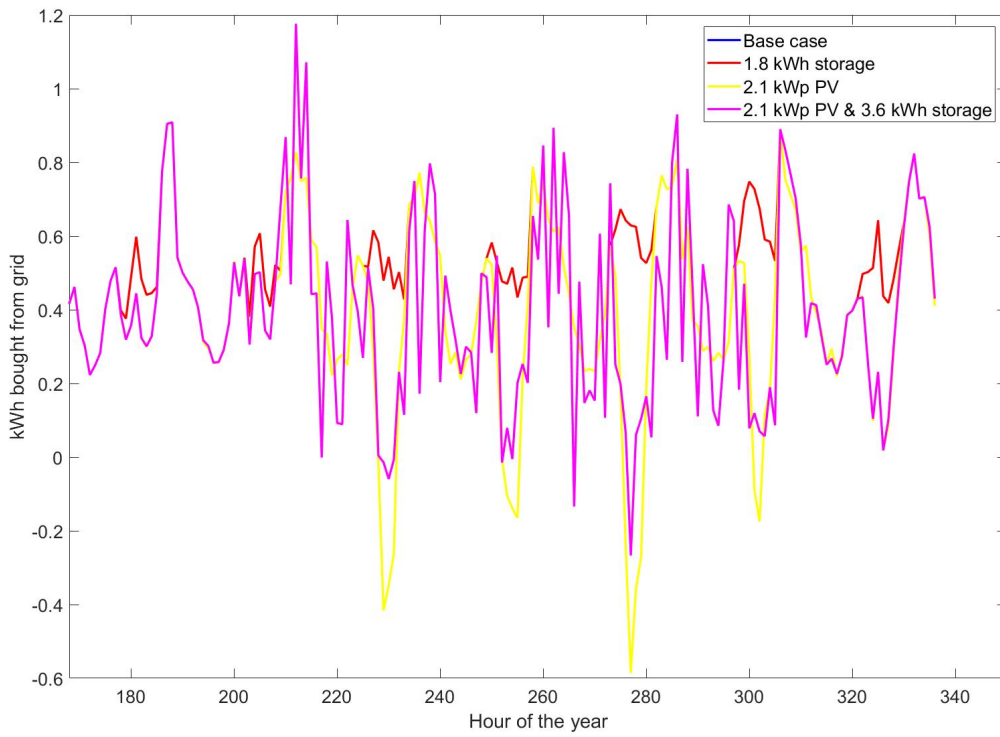


Figure 3. Second week of January for scenario A (Fixed energy & fixed capacity pricing)

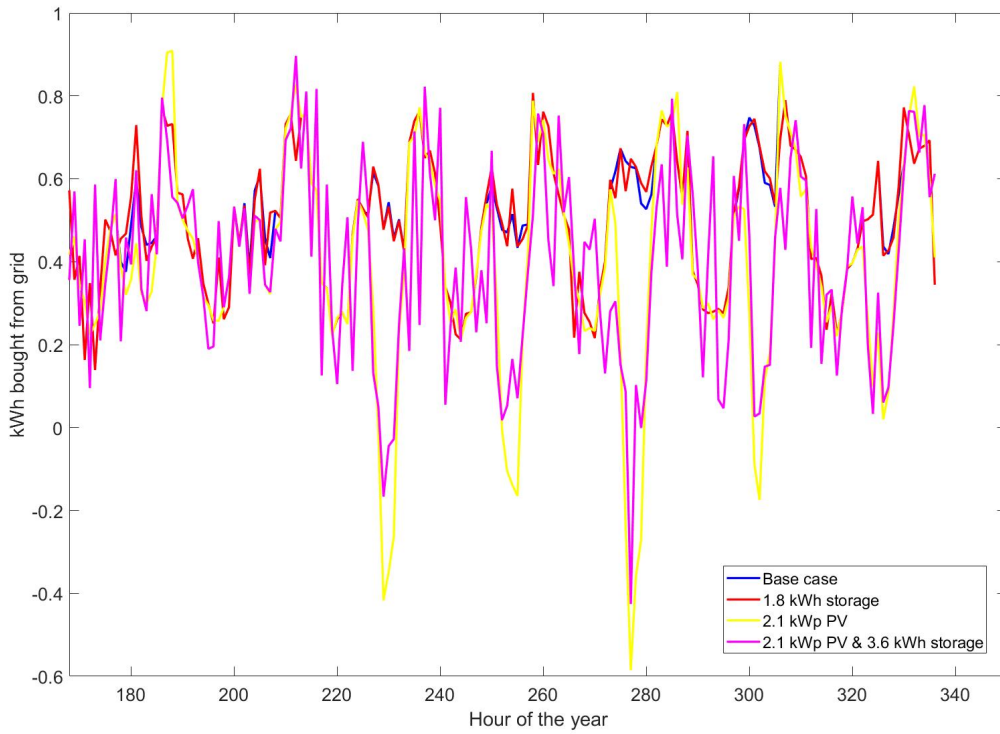


Figure 4. Second week of January for scenario B (Fixed energy & block capacity pricing)

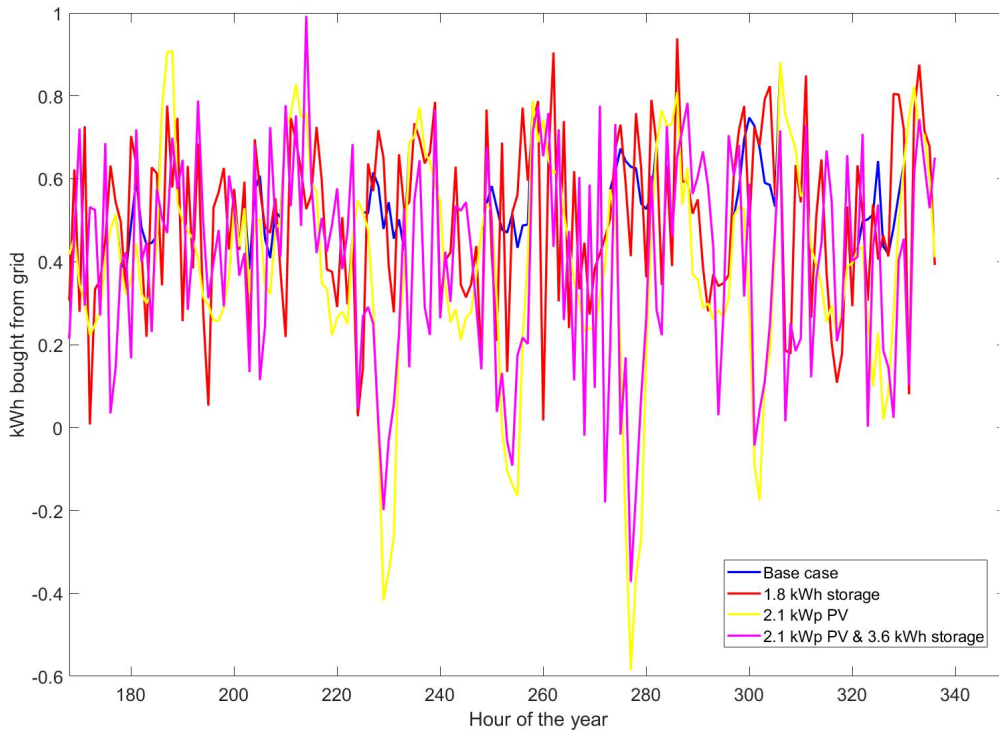


Figure 5. Second week of January for scenario C (Spot energy & block capacity pricing)

The behaviour of the battery component in the simulated results is also worth analysing. Figures 6 and 7 show the storage state throughout the year for a system with 1.8 kWh of storage capacity and without or with 2.1 kWp PV generation respectively. Figure 6 shows three distinct battery usage profiles, one corresponding to each scenario. As expected, in the no intervention scenario, the battery is not used. Under scenario B, the battery is only used during the winter months, in order avoid exceeding the capacity threshold. Lastly, the battery will be used throughout the year in scenario C, as the system tries to exploit any price arbitrage opportunities offered by the real time pricing of electricity. When looking at figure 7 however, these three different profiles are far less distinct: irrespective of the scenario, the battery will now be used throughout the year, as the storage capacity is needed in order to increase the self-consumption of generated electricity by the solar PV panels. Figures for the other system configurations exhibit the same behaviour as discussed here, and can be found in Appendix C.

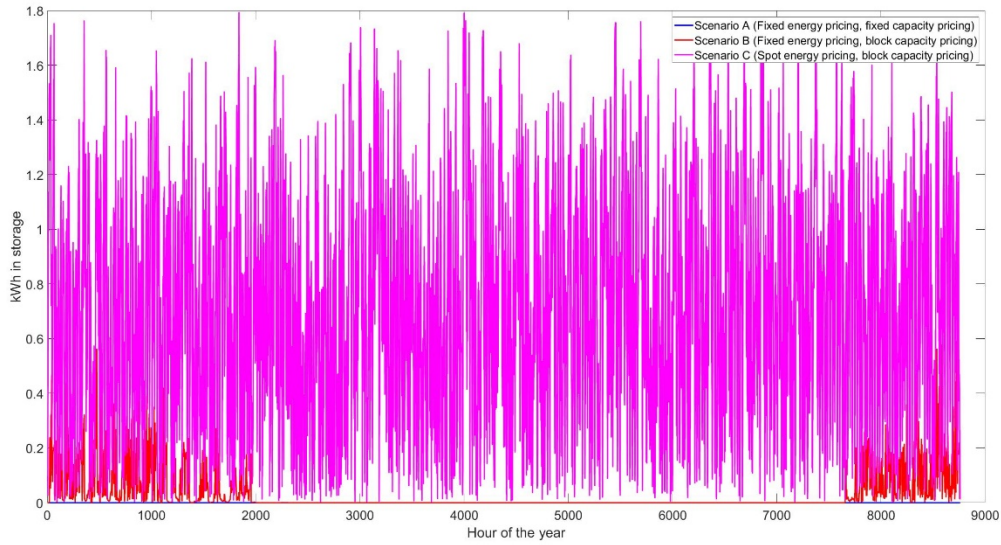


Figure 6. Storage state for a system with 1.8 kWh of storage capacity

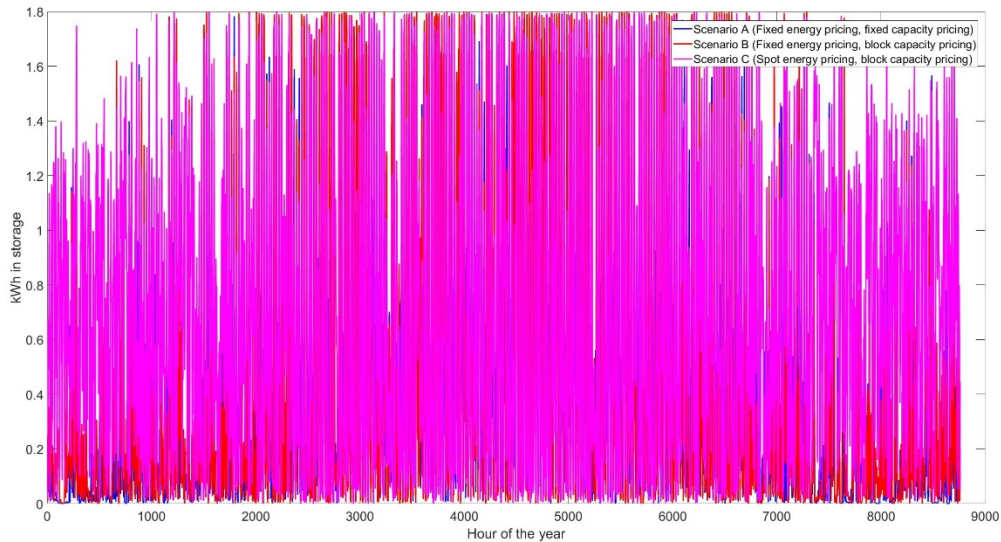


Figure 7. Storage state for a system with 1.8 kWh of storage capacity and 2.1 kWp PV capacity

The findings outlined above are in accordance with the results discussed in [9], as they both show that capacity tariffs can function as control signals for controlling distributed storage, if such storage is present in the system. Nevertheless, this by itself does not indicate if such capacity tariff design provides incentive for the adoption of electricity storage by consumers. To address this question table 4 lists for each of the system configurations the yearly operating cost under the different policy scenarios as derived from the simulations.

Before discussing the economic outcomes, an important point needs to be reiterated: as stated in the introduction, it was a conscious choice of the authors to not include capital or maintenance costs for any of the simulated components. This has a significant impact on how the results presented below should be interpreted: if there is a difference in reported costs between various rows in table 4, this does not immediately mean that the configuration with the

lower reported cost is more economical and should be adopted, but rather provides a guideline by providing insight in the height of the annualised capital and installation cost which will allow the considered technology to be economically viable. The benefit of this approach is that it does not pin the obtained results down to any specific level of technological advancement and technical performance but provides valuable insights valid regardless of the technical performance of the considered components.

Comparing columns A and B in table 4, it is clear that the block pricing capacity tariff scheme does not have a large impact on the base case system configuration. While this might seem counterintuitive, as this system configuration has no battery storage, meaning that it is impossible to shift any part of the load to avoid exceeding  $C_b$ , for the majority of the observations, the used capacity remains below the capacity threshold. As denoted in table 2, the capacity tariff for the lower block,  $C_{p,1}$  is lower than  $C_{p,f}$ , so the majority of the capacity used will be charged at a lower tariff under scenario B as compared to scenario A, explaining the lower cost reported in table 4. When the combination of real time energy pricing and capacity block pricing is considered in scenario C, the results show that the outcome for the base case scenario is a reduction of the yearly energy procurement cost.

Note that under scenario A, the resulting outcomes for the base case as well as all the systems incorporating only battery storage are identical: the battery will simply not be used, as there is no reason to use it: there are neither time-dependent energy prices, which would open the possibility to engage in price arbitrage, nor is there a block capacity tariff, which would encourage keeping the load profile below the capacity threshold. Seeing as the solution algorithm is clearly able to find the solution which does not use the battery if that is the lowest cost one, the fact that the operational costs for systems with battery storage are higher than the base case under scenario B and C might seem surprising. This is explained, however, by the shorter decision horizon used in the simulation: only the upcoming 24 hours are taken into account when deciding on the solution for the next hour, as opposed to the entirety of the upcoming year.

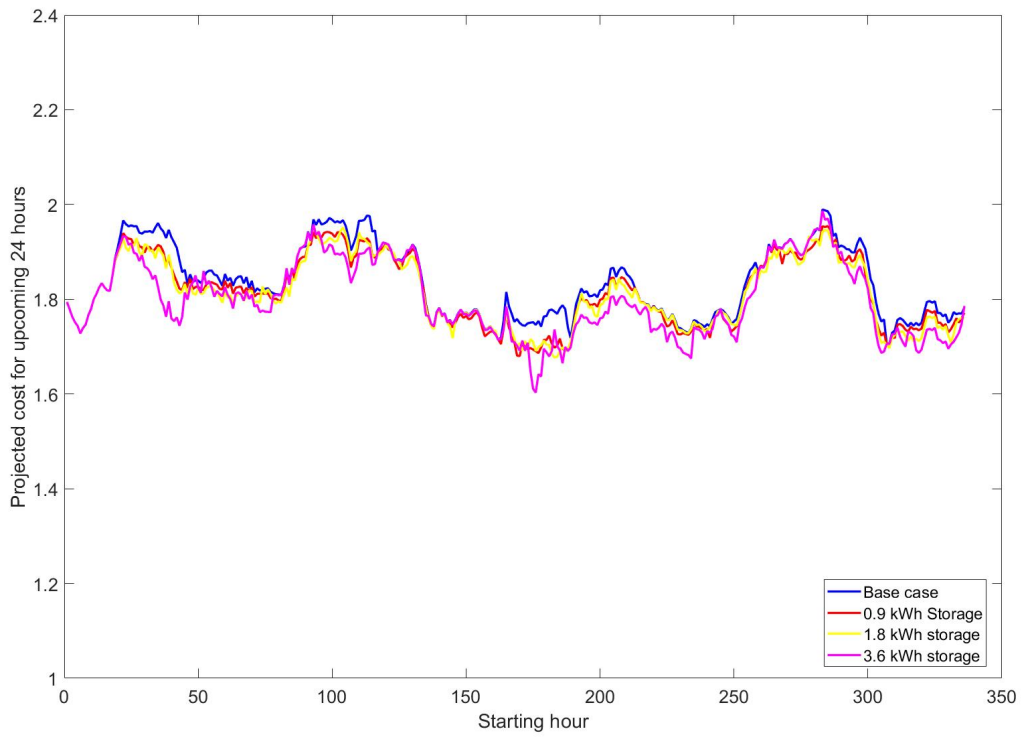


Figure 8. Projected costs per 24 hours in € for Scenario B (Fixed energy & block capacity pricing)

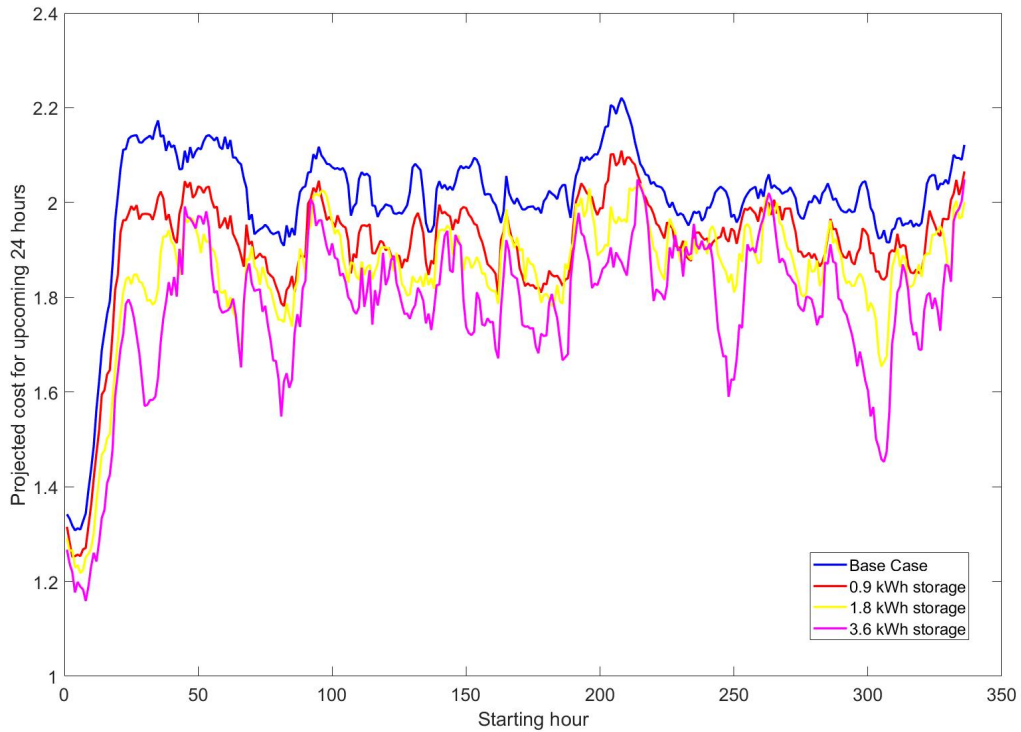


Figure 9. Projected costs per 24 hours in € for Scenario C (Spot energy & block capacity pricing)

Figures 8 and 9 show data supporting this conclusion: they show, for the first two weeks of the year or 336 hours, the projected cost that will be incurred over the upcoming twenty-four-hour period, for scenario's B and C respectively. As can be seen in figures 8 and 9, if the actual horizon of the problem were to be limited to the same twenty-four hours that the optimisation problem is limited to, the system configurations including battery storage would outperform the base case, with performance increasing with battery size. While scenario C does allow the system configurations with battery storage to engage in price arbitrage, resulting in lower costs than under scenario B, the price paid in optimization outcome due to the limited horizon is still the dominating factor, as even the largest of the simulated storage capacities is still outperformed by the base case system configuration.

Table 4. Simulation results: average yearly operating cost in €

System Configuration	Scenario		
	A	B	C
Base Case	539.26 (0.37)	515.82 (1.31)	534.85 (1.20)
0.9 kWh storage	539.26 (0.37)	539.59 (0.47)	547.00 (0.41)
1.8 kWh storage	539.26 (0.37)	539.76 (0.55)	538.35 (1.33)
3.6 kWh storage	539.26 (0.37)	540.38 (0.70)	534.93 (2.35)
2.1 kWp PV	272.90 (0.30)	401.75 (8.45)	419.17(9.07)
1.8 kWh storage, 2.1 kWp PV	230.24 (0.72)	332.27 (6.15)	342.65(7.16)
3.6 kWh storage, 2.1 kWp PV	213.26 (0.24)	272.45 (4.88)	281.77(5.19)
4.5 kWh storage, 2.1 kWp PV	211.10 (1.06)	253.13 (4.50)	263.32 (5.28)

**Format:** Average operating cost in €/year (standard deviation in €/year)

Probably the most interesting result, however, concerns the case of the solar installation without any storage capability. If there is no policy intervention, opting for the installation of solar PV without battery storage is by far the most cost-effective investment the simulated homeowner could make: yearly energy procurements are halved in this case, and no battery storage needs to be installed. However, as soon as block capacity pricing is introduced, the cost savings realized by the solar PV only system configuration drop dramatically: the surplus of electricity produced by the solar PV systems has to be sold to the grid, incurring hefty capacity charges. Where the base case system configuration saw a decrease in costs under real time pricing combined with block capacity prices, a similar reduction in yearly costs does not hold true for the pure PV system, as for this system configuration, the yearly energy procurement costs are highest when both policy interventions are combined, as the peak production of solar PV does not coincide with the moments of peak electricity pricing.

The combination of PV generation and battery storage becomes much more attractive when the battery storage is considered as an upgrade to an existing PV system, as both under scenarios B and C, significant savings are made by transitioning from a pure PV system to a PV system with battery storage. Specifically, in the case of the 3.6 kWh & PV and the 4.5 kWh & PV system configurations, adding that amount of battery storage allows the simulated home owner to return to a pre-policy intervention yearly operating cost, albeit with higher total system costs.

Seeing as this research is the first, to the best of the authors knowledge to investigate the impact of capacity tariffs on the economics of microgrids, no direct comparisons with earlier published research can be made. However, some parallels can still be drawn: firstly, it is worth reiterating



that, following published findings in [9], capacity tariffs are able to steer consumer loads. Secondly, when comparing the proposed capacity tariff put forward in this research with the time of use-schemes [18,23], our results are in line with the published findings, in that the capacity tariff put forward does not encourage the uptake of renewables. Furthermore, as table 4 shows, the proposed capacity tariff actually disincentives the installation of solar PV: the yearly operating costs for a system with PV generation rises with nearly € 130 if block capacity tariffs are implemented. However, this is not a problem when the stated goal of implementing the block capacity tariff is kept in mind, as it is aimed at promoting the uptake of storage systems, not necessarily renewables. Finally, our results are also in line with the findings published in [30], as the implementation of block capacity pricing, both separate from as well as in conjunction with real time energy pricing does not negatively impact consumers who do not have any microgrid technologies.

In summary, the results presented in this section show that the hypothesis put forward in section 3 holds: figures 3,4 & 5 as well as figures 6 & 7 show the response, respectively of the system as a whole or of the battery component, to the implementation of a block capacity tariff, and table 4 clearly shows that the proposed block capacity tariff has virtually no impact on some system configurations, like the base case configuration, or the battery only configuration, while at the same time severely impacting a system configuration that only has solar PV installed.

Based on the above discussion, the policy implications are clear: if the policy goal is only to incentivise the adoption of storage in conjunction with, or as an upgrade to existing solar PV installations, implementing block capacity pricing should suffice. In contrast, should it be the aim of policy makers to arrive at the widest possible adoption of storage, both capacity block pricing and real time electricity pricing will be useful, but will not suffice by themselves to provide a profitable business case for grid-connected battery storage.

## 6. CONCLUSION

The impact of electricity tariff design on the adoption of battery storage is investigated. Using an optimization simulation model, the effect of two policy interventions is studied: (i) block capacity pricing and (ii) the combination of block capacity pricing and real time energy pricing on a variety of system configurations, consisting of battery storage, solar PV generation or a combination of both. Due to the uncertainty and volatility of present and future prices for both battery storage and solar PV panels, the impact of the considered policy alternatives were investigated by comparing the simulated average yearly operating costs of the different system configurations to a base case system configuration without storage or solar PV. Notwithstanding that capacity tariffs have been shown to be effective at controlling the use of distributed storage, our results show that these capacity tariffs by themselves only weakly incentivize the installation of battery storage, except as an upgrade to existing solar PV installations. We also show that the combination of block capacity pricing and real time energy pricing might promote a wider adoption of battery storage but will not suffice by itself.

## ACKNOWLEDGEMENTS

We thank Prof dr. Johan Springael for assistance with the specification of the objective function.

## NOMENCLATURE

$Q_G(i)$	kWh bought from grid at time step $i$
$Q_S(i)$	kWh discharged from storage at time step $i$
$Q_L(i)$	Load, in kWh, at time step $i$

$Q_I(i)$	Intermittent power production, in kWh, at time step $i$
$p_G(i)$	Grid price for electricity at time step $i$
$p_{G,fix}$	Fixed electricity price
$C_b$	Capacity limit of the lower capacity block, in kW
$C_{p,f}$	Fixed capacity tariff, in €/kW
$C_{p,1}$	Capacity tariff for the lower capacity block, in €/kW
$C_{p,2}$	Capacity tariff for the higher capacity block, in €/kW
$C_{cap}(i)$	Capacity payments due to exceeding the lower capacity block incurred during timestep $i$
$S_{max}$	Maximum storage capacity, in kWh
$S_{in}(t)$	State of charge of storage, in kWh, at the beginning of time step $i$

## REFERENCES

1. Allan G, Eromenko I, Gilmartin M, Kockar I, McGregor P., The economics of distributed energy generation: A literature review, *Renew and Sustain Energy Rev*, 2014 December; 40;269-86
2. Ringler P, Keles D, Fichtner W., Agent-based modelling and simulation of smart electricity grids and markets – A literature review, *Renew and Sustain Energy Rev*, 2016 May;57;205-15
3. Connor PM, Baker PE, Xenias D, Balta-Ozkan N, Axon CJ, Cipcigan L. Policy and regulation for smart grids in the United Kingdom, *Renew and Sustain Energy Rev*, 2014 December;40;269-86
4. Lasseter R, Akhil A, Marnay C, Stevens J, Dagle J, Guttromson R, et al., Integration of Distributed Energy Resources: The CERTS Microgrid Concept. White paper. Prepared for the U.S. Department of Energy;2002.
5. Lidula NW, Rajapakse AD, Microgrids research: A review of experimental microgrids and test systems. *Renew and Sustain Energy Rev*, 2014 August;36;428-39
6. IEEE Smartgrid [Internet] IEEE joint task force on quadrennial energy review, Utility and Other Energy Company Business Case Issues Related to Microgrids and Distributed Generation (DG), Especially Rooftop Photovoltaics, Presentation to the U.S. Department of Energy 2014, [cited 7 April 2017], available from [http://smartgrid.ieee.org/images/files/pdf/IEEE\\_QER\\_Microgrids\\_October\\_3\\_2014.pdf](http://smartgrid.ieee.org/images/files/pdf/IEEE_QER_Microgrids_October_3_2014.pdf)
7. Lo Prete C, Hobbs BF, Norman CS, Cano-Andrade S, Fuentes A, von Spakovsky MR, et al., Sustainability and reliability assessment of microgrids in a regional electricity market, *Energy* 2010 May;41;192-202.
8. Palizban O, Kauhaniemi K, Guerrero JM. Microgrids in active network management-Part I: Hierarchical control, energy storage, virtual power plants, and market participation, *Renew and Sustain Energy Rev*, 2014 August;36;428-39.
9. Hirsh A., Parag Y., Guerrero J. Microgrids: A review of technologies, key drivers, and outstanding issues, *Renew and Sustain Energy Rev*, 2018 July;90;402-11.
10. Yoldaş Y., Önen A., Muyeen S.M., Vasilakos A.V., Alan İ. Enhancing smart grid with microgrids: Challenges and opportunities, *Renew and Sustain Energy Rev*, May 2017;72;205-14.
11. Milis K., Peremans H., Van Passel S. The impact of policy on microgrid economics: A review, *Renew and Sustain Energy Rev*, January 2018;81-2;3111-119.
12. Schreiber, M, Wainstein, ME, Hochloff, P, Dargaville, R, Flexible electricity tariffs: Power and energy price signals designed for a smarter grid, *Energy* 2015 December;93;2568-2581
13. Gouch, R, Dickerson, C, Rowley, P, Walsh, C, Vehicle-to-grid feasibility: A techno-economic analysis of EV-based energy storage, *Applied Energy* 2017 April;192;12-23

14. Zafirakis, D, Chalvatzis, KJ, Baiocchi, G, Daskalakis, G, The value of arbitrage for energy storage: Evidence from European electricity markets, *Applied Energy* 2016 December;184;971-986
15. Aneke M, Wang M, Energy storage technologies and real life applications – A state of the art review, *Applied Energy* 2016 October;197;350-377
16. Martin-Martines F, Sánchez-Miralles A., Rivier M. A literature review of microgrids: a functional layer based classification, *Renew Sustain Energy Rev*, 2016 September;62;1133-53
17. Siddiqui A, Marnay C, Edwards JL, Firestone R, Ghosh S, Stadler M. Effects of a Carbon Tax on Microgrid Combined Heat and Power Adoption. *J of Energy Eng.* 2005 April;131;2-25.
18. Rocha P, Siddiqui A, Stadler M. Improving energy efficiency via smart building energy management systems: a comparison with policy measures. *Energy and Build* 2105 February;88;203-13.
19. Anastasiadis AG, Vokas G, Papageorgas P, Kondylis G, Kasmis S. Effects of carbon Taxation, Distributed Generation and Electricity Storage Technologies on a Microgrid. *Energy Procedia* 2014;50; 824-31.
20. Mehleri ED, Sarimveis H, Markatos NC, Papageorgiou LG. Optimal design and operation of distributed energy systems: Application to greek residential sector. *Renew Energy* 2013 March;51;331-42.
21. Yu N, Kang J-S, Chang C-C, Lee T-L, Lee D-Y. Robust economic optimization and environmental policy analysis for microgrid planning: An application to Taichung Industrial Park, Taiwan. *Energy* 2016 October;113;671-682.
22. Zachar, M, Trifkovic M, Daoutidis P. Policy effects on microgrid economics, technology selection, and environmental impact. *Comput and Chem Eng* 2015 October;81;364-75.
23. Aghaei J, Alizadeh MI, Multi-objective self-scheduling of CHP (combined heat and power)-based microgrids considering demand response programs and ESSs (energy storage systems). *Energy* 2013 June;55;1044-54.
24. Wang H, Fang H, Yu X, Liang S. How real time pricing modifies Chinese households' electricity consumption, *J of Clean Prod* 2018 March;178;776-90.
25. Kühnlenz F, Nardelli P, Karhinen S, Svento R. Implementing flexible demand: Real-time price vs. market integration. *Energy* 2018 April;149;550-65.
26. Milis K, Peremans H. Economical Optimization of Microgrids: A Non-Causal Model. *ASME 2016. Energy Sustainability, Volume 2: Photovoltaics; Renewable-Non-Renewable Hybrid Power System; Smart Grid, Micro-Grid Concepts; Energy Storage; Solar Chemistry; Solar Heating and Cooling; Sustainable Cities and Communities, Transportation; Symposium on Integrated/Sustainable Building Equipment and Systems; Thermofluid Analysis of Energy Systems Including Exergy and Thermoeconomics; Wind Energy Systems and Technologies.*
27. Historical market data [Internet] Epexspot Belgium, [cited 16 October 2016], available from <https://www.belpex.be/market-results/historical-data/>
28. Synthetic load profiles [Internet] Synergrid [cited 16 October 2016], available from [http://www.synergrid.be/index.cfm?PageID=16896&language\\_code=NED](http://www.synergrid.be/index.cfm?PageID=16896&language_code=NED)
29. Solar generation data [Internet] Elia [cited 12 September 2014], obtained from <http://www.elia.be/en/grid-data/power-generation/Solar-power-generation-data>
30. Rahman M, Hettiwatte S, Shafiullah G, Arefi A. An analysis of the time of use electricity price in the residential sector of Bangladesh, *Energy Strategy Rev* 2017 December;18;183-98.

## Appendix A

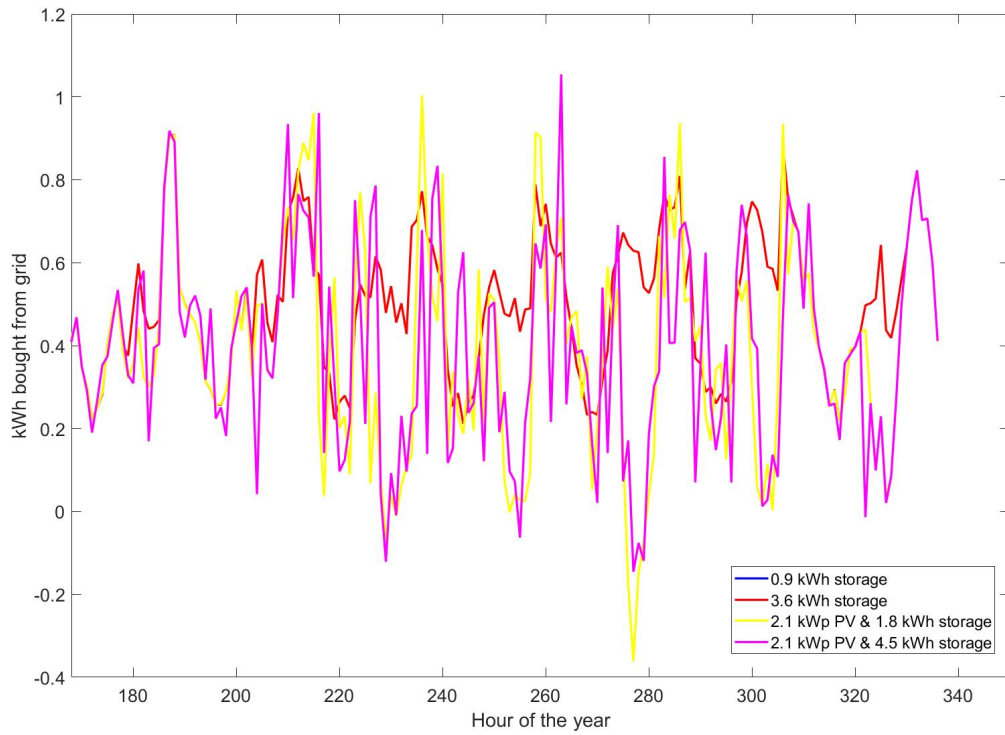


Figure A.1 Second week of January for scenario A (Fixed energy & fixed capacity pricing)

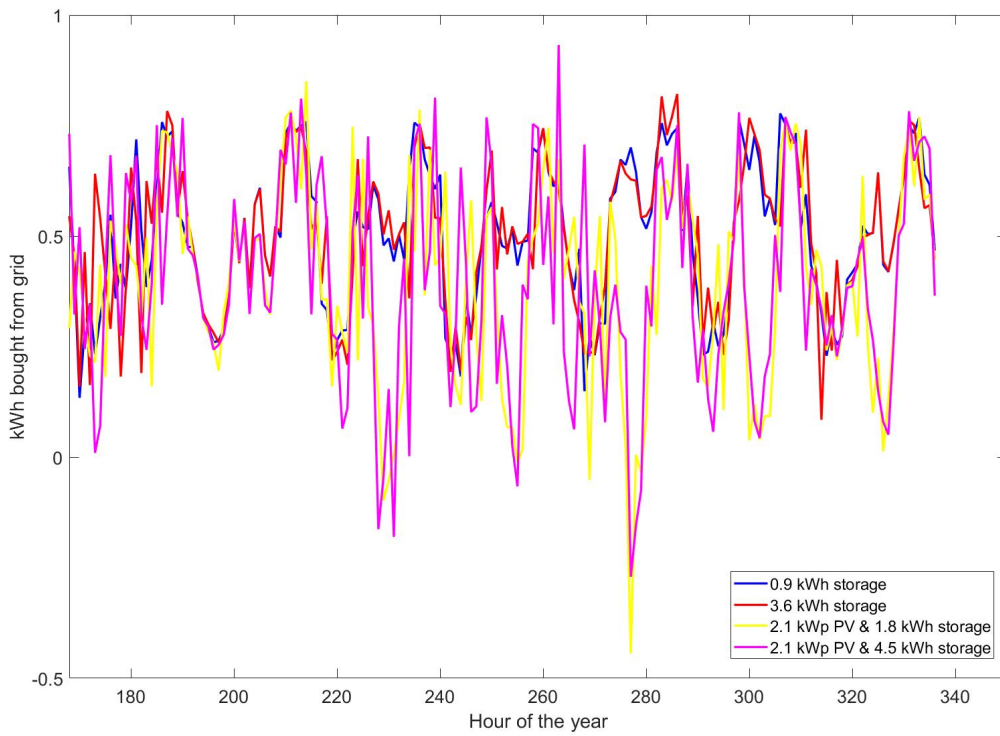


Figure A.2 Second week of January for scenario B (Fixed energy & block capacity pricing)

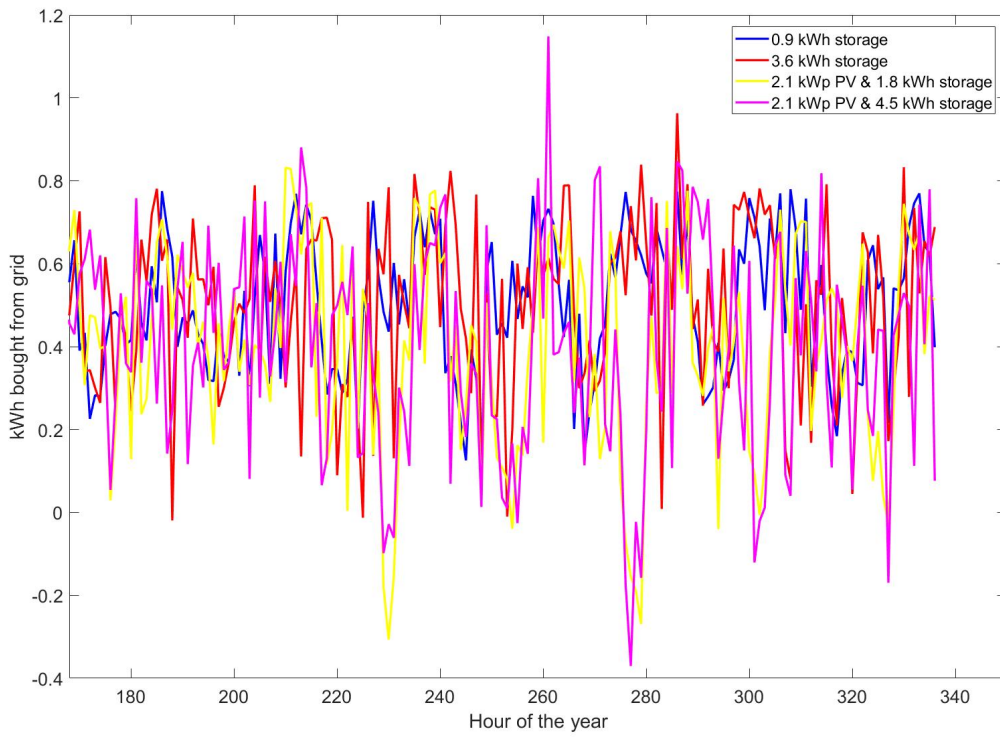


Figure A.3 Second week of January for scenario C (Spot energy & block capacity pricing)

Appendix B

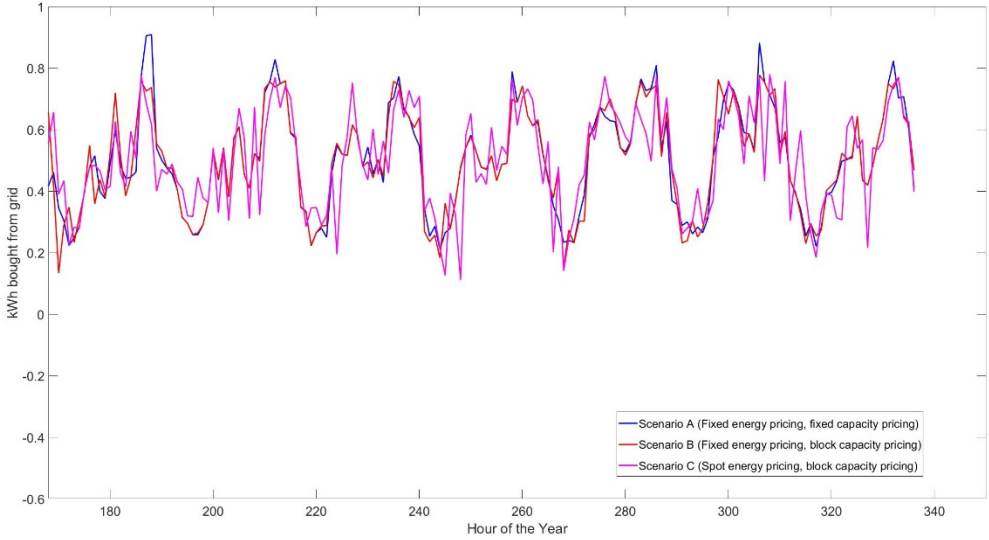


Figure B.1 Second week of January for a system with 0.9 kWh storage capacity

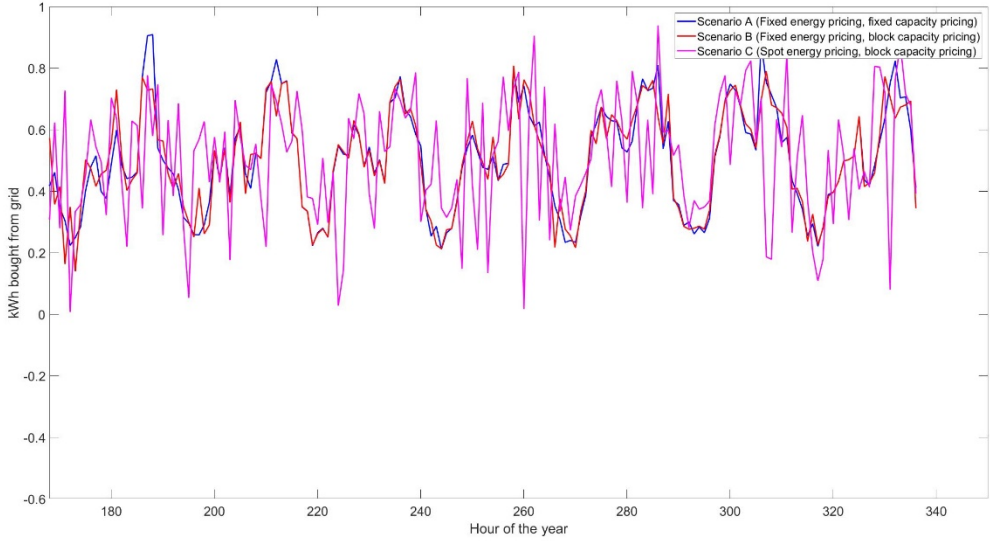


Figure B.2 Second week of January for a system with 1.8 kWh storage capacity

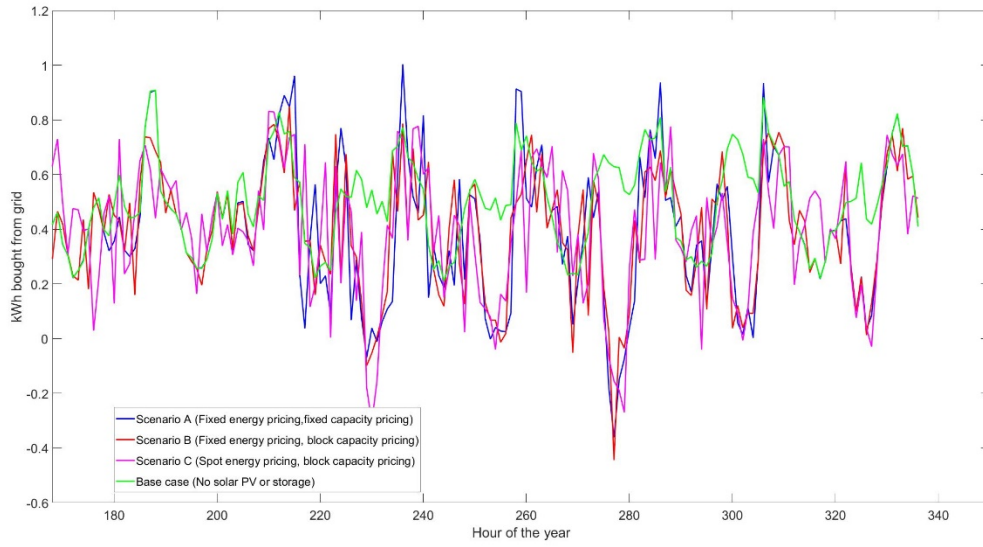


Figure B.3 Second week of January for a system with 1.8 kWh storage capacity & 2.1 kWp PV

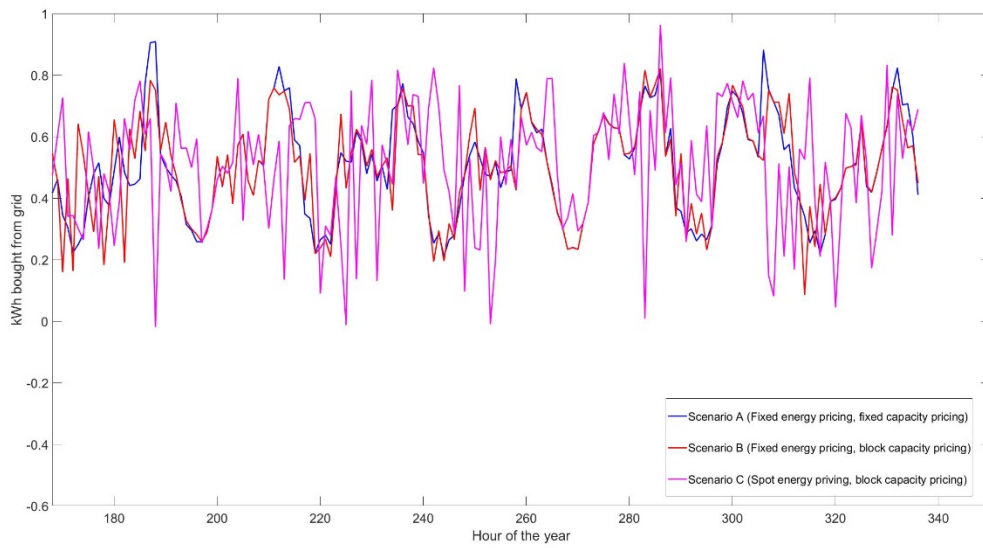


Figure B.4 Second week of January for a system with 3.6 kWh storage capacity

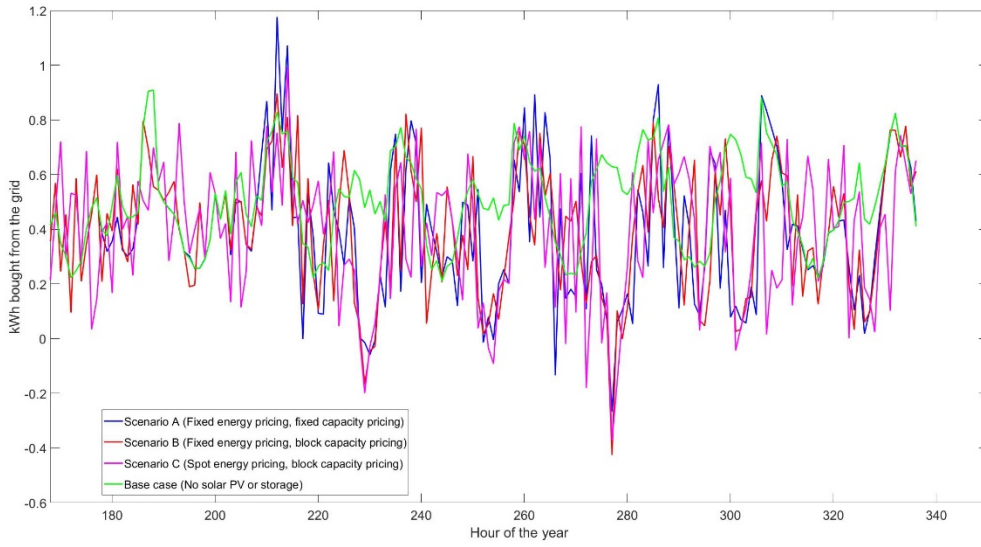


Figure B.5 Second week of January for a system with 3.6 kWh storage capacity & 2.1 kWp PV

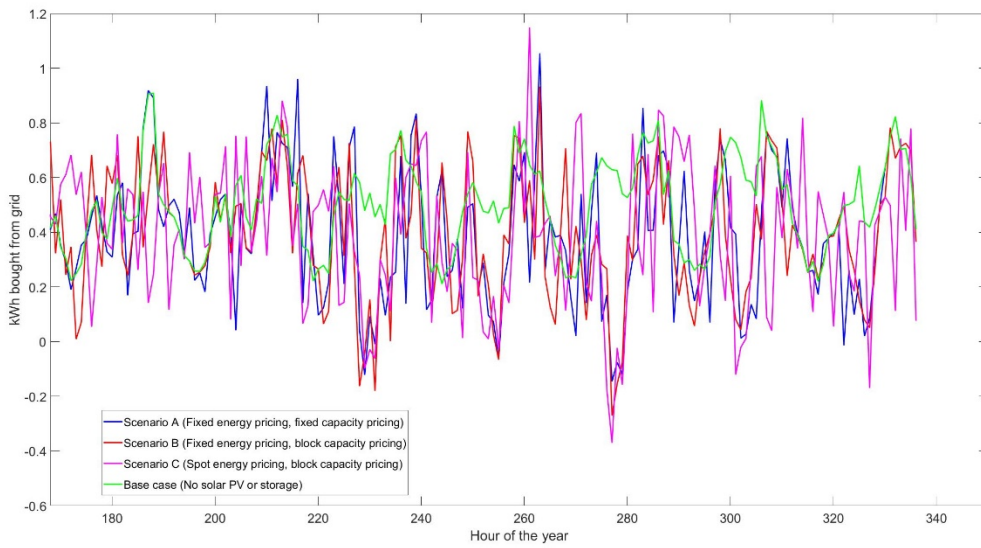


Figure B.6 Second week of January for a system with 3.6 kWh storage capacity & 2.1 kWp PV



## Appendix C

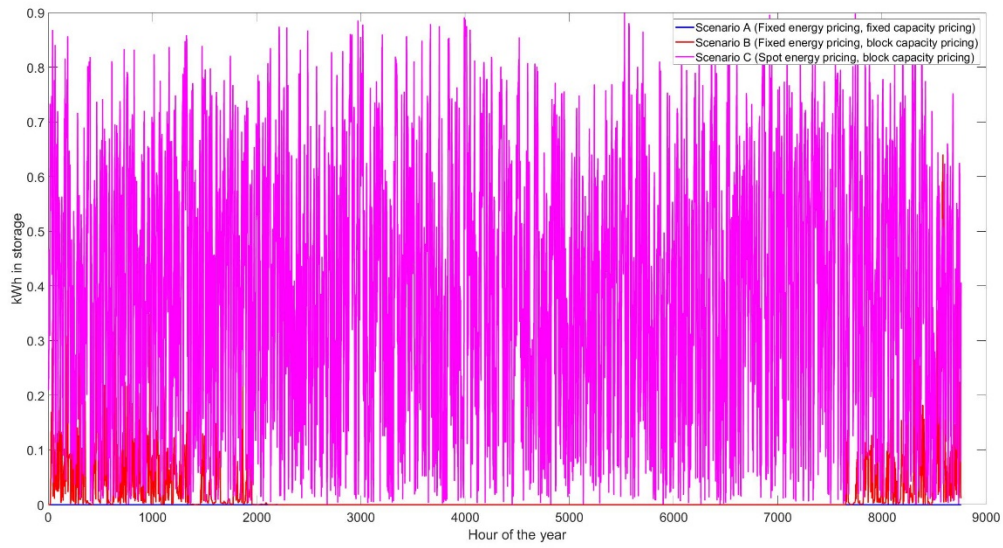


Figure C.1 Storage state for a system with 0.9 kWh of storage capacity

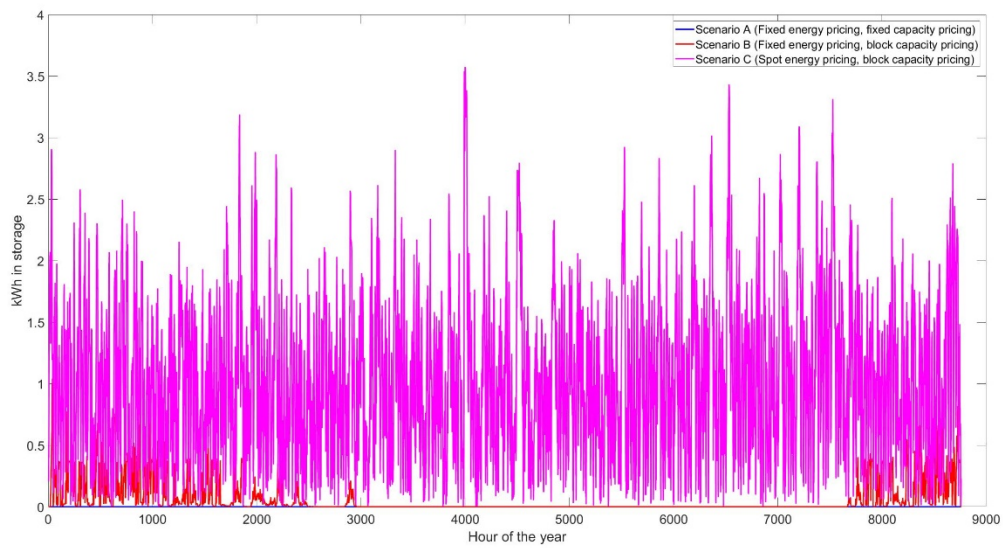


Figure C.3 Storage state for a system with 3.6 kWh of storage capacity

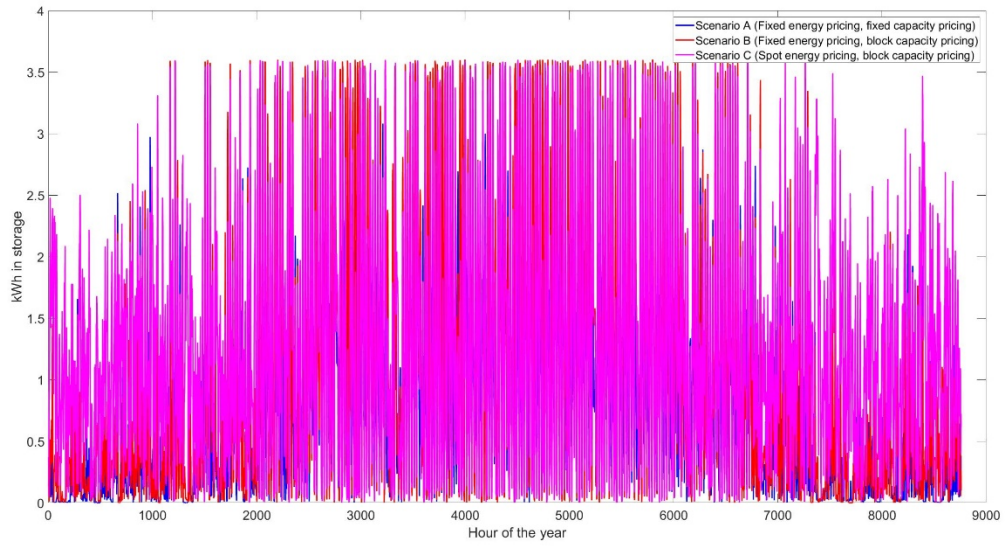


Figure C.3. Storage state for a system with 3.6 kWh of storage capacity and 2.1 kWp PV capacity

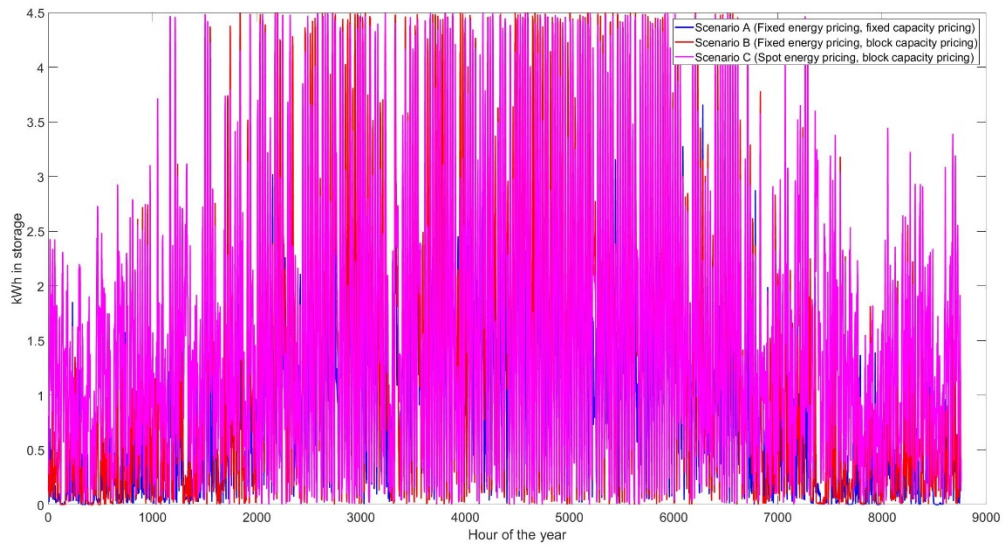


Figure C.4. Storage state for a system with 3.6 kWh of storage capacity and 2.1 kWp PV capacity