Energy management strategy for a renewable-based public electric-bus microgrid: peak load demand reduction and PV generation use-optimization using a second-life battery system

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Energy management strategy for a renewable-based public electric-bus microgrid: peak load demand reduction and PV generation use-optimization using a second-life battery system

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Enclosed within my humble contribution to the field of smart grids and to the public transport system of the city of Pamplona.

ABSTRACT

This thesis proposes an energy management strategy for an electric public transport microgrid scenario comprising a fast-charging station (rated at 300 kW), a photovoltaic (PV) system (rated at 134 kWp-100kW inverter) and a second-life battery system (rated at 84kWh - 80kW maximum power discharge). This microgrid is used by the bus fleet of line 9 in the city of Pamplona, Spain. The microgrid is connected to the utility grid allowing for the control of the power exchange between them through the battery and its control program. The proposed strategy uses the battery state of charge (SOC), the charging station power demand and the PV power production as input parameters for the control strategy. The simulation of this system is performed on Matlab using a one-year dataset using four energy management strategies. The final strategy results in a reduction of the peak power demand of the charging station by 80 kW consistently throughout the year (35% of the total daily peaks). Roughly one third (32%) of the energy needs of this charging station are expected to be met by energy produced from the PV system. The average battery SOC is maintained at around 90% and the battery never discharges below 50% SOC.

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1.1. Overview of the microgrid and problem statement

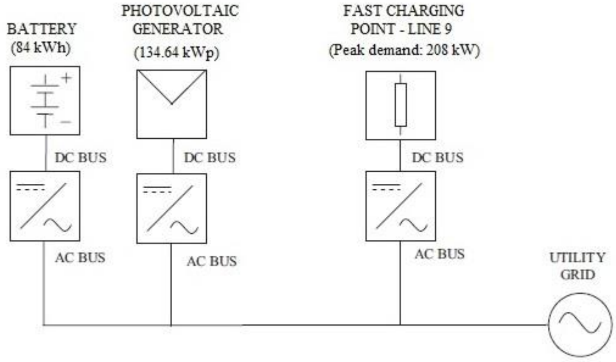

Figure 1: Block diagram of the bus fast-charging station microgrid

The microgrid under study is located in the campus of the *Universidad Publica de Navarra (UPNA)* in the city of Pamplona, Spain.

It is composed of the three following elements:

- **A fast-charging point** used for the charging of the public Pamplona buses accross line 9.
  - This charging point has a rated power capacity of 300 kW and currently feeds off the utility grid through a 340 kVA transformer.
  - This charging point is used by six public buses during work weeks (less on Saturdays, and none on Sundays during holidays). It is one of two charging station across the line, the other one is located at the RENFE train station of Pamplona and is not the subject of the present study.
  - Each bus travel for 6.5km between the two charging points (for a total route of 13km). It consumes an average of 10 kWh to 12 kWh per half trip, and charges between 3 to 5 minutes in average at the charging point.
- **A photovoltaic system** is installed on the roof of UPNA's « Aulario » building. This PV system is meant to supplement the fast-charging station energy needs.
  - Installed capacity is around 135 kWp.
  - The PV system inverter capacity is 100 kW.
- **A battery system** composed of two battery banks. Each of which contains 96 nissan leaf second-life batteries. The total energy capacity of the system is 84kWh.
  - This battery system is meant to manage the energy and power flow of the microgrid so as to reduce dependence on the utility grid and make the most of the photovoltaic system.

1.2. Power profile of the microgrid

1.2.1. Typical power profile of the fast-charging station

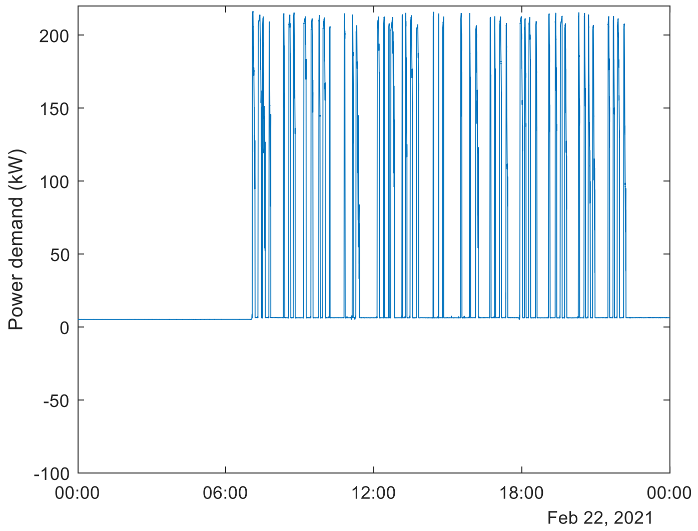

Figure 2: Power demand profile of the UPNA fast-charging station on February 22nd, 2021 (maximum power demand of 216.5kW)

The power demand profile shown in figure 2 is based on real data collected on **Monday, 22nd of February 2021**, at the level of the « charging point/electric grid » connection. Each power demand peak corresponds to one bus charging:

- The number of power peaks/charges: 50
- Maximum power peak demand : 216.5 kW
- Minimum power demand during the day: 3.5 kW (equivalent to the consumption of the charging station)
- Energy demand during the day: 772 kWh

It represents a typical daily power demand profile of the UPNA fast-charging point during workdays. Unlike power profiles in the residential or commercial sectors where one or two daily peak power demands are experienced, loads used for sustaining electric transport typically have multiple peaks a day.

At the level of this fast-charging station, based on the data collected between July 2020 and June 2021 :

- The maximum power peak demand was: 218 kW
- The total energy demand in the year was: 219 380 kWh

It is worth noting that based on the most recent data collected in January and February 2022, the maximum daily peaks observed are slightly higher and go up to 225 kW.

The data collected between these two periods (a total of 365 days) was used in this study for the development of the energy management strategy. Therefore, the maximum peak power used as a reference for improvement is 220 kW (slightly higher than the real peak). The peak shaving results will remain the same in both circumstances.

1.2.2. Power generation of the photovoltaic system

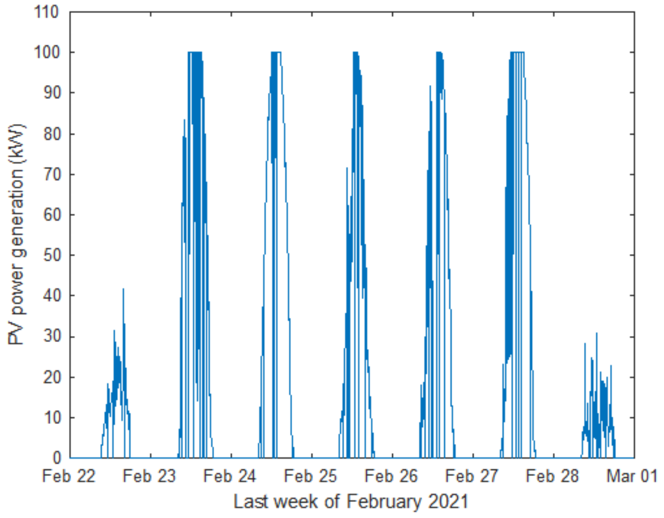

Figure 3: The simulated power generation of the photovoltaic system – last week of February 2021

The installed photovoltaic capacity is 135 kWp and the PV inverter is rated at 100kW.

During the current study, the PV power generation data for this system was not available for the time period between July 2020 and June 2021. Therefore, the PV power data was simulated based on the power generation of a smaller system installed in the « los pinos » building. The data was then extrapolated to simulate the larger system.

1.2.3. The Net Power exchange with the grid

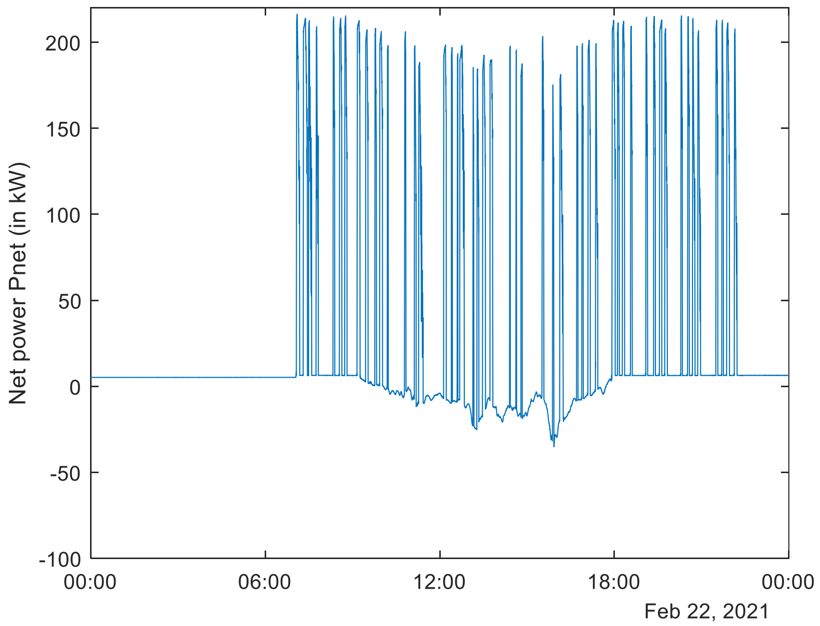

Figure 4: The expected net power exchange with the grid with no battery system or energy management strategy on February 22nd, 2021

The expected net power exchanged with the grid in this microgrid is illustrated in figure 4. The power *Pnet* illustrated is equal to the load power demand *Pload* minus the power generated by the photovoltaic system *Ppv*

$$Pnet(i) = Pload(i) - Ppv(i)$$

1.2.4. The battery system

Figure 5: EV second life battery – BEEPlanet [1]

The battery system is composed of two EV second life battery connected in parallel from local manufacturer battery company BEEPlanet. Each battery is composed of 96 Nissan leaf second life modules all connected in parallel.

The main characteristics of the battery that are relevant to the study are the following:

- Nominal energy capacity: 84 kWh (42 kWh x2)
- Nominal current capacity: 116 Ah (58 Ah x2).
- Maximum operating current: 100 A (50 A x2)
- Operating voltage 600V – 800V
- Inferred maximum charge and discharge power: 80 kW (40 kW x2)

For the simulation the battery is modeled as a « battery » block on matlab (refer to Chapter 3 for more details).

1.3. Problem statement

The scenario under study is that of a grid-tied microgrid consisting of an « EV buses » fast-charging station, a photovoltaic system, and a battery system. The latter is the point of intervention to manage power and energy flows within the microgrid.

The basic idea is to use the excess power energy production of the PV system and use it to meet the power and energy needs of the load, thereby reducing reliance on the utility grid.

The stated objective of the study will be to develop an energy management strategy whereby the battery system controls the power and energy flow of the microgrid in order to primarily:

- Shave the daily and yearly power demand of the load (the UPNA fast-charging station) as much as possible, consistently and without any seasonal or any other exceptions. The maximum power peak demand from the utility grid should move from its current maximum (220-250 kW) to a lower value consistently.
- The use of the power PV generation should increase and be monitored.

To simulate and evaluate the performance of the different strategies, data for the load was recorded second by second for a whole year between July 2020 and June 2021. The PV data is simulated for the same period base done PV data collected on a 6 kW PV inverted.

Chapter 3 and 4 include a detailed account of the models used for simulating the energy management strategies. It also includes the key performance indicators (quality criteria) used for the analysis.

2. Relevant past work on microgrid energy management at UPNA

The main task at hand in this study is to reduce the peak power demand from the grid by the fast-charging station. Therefore, the first step will be to look at different approaches to achieve this objective. The power profile demand of the charging station will have to be shared between the battery and the power grid.

Two relevant studies were undertaken in the past few years at UPNA that are worth reviewing before starting design of an energy management system for our microgrid [2][3]. This chapter reviews these two works, their results and what we can learn from them in the context of the current microgrid. Prior to that, a general introduction to three different approaches to dealing with electric signals that were used in these two studies is necessary.

2.1. Signal processing approaches

2.1.1. Real-time battery state of charge control (SOC)

This first approach is based on a simple and straight forward decision tree:

- If a bus is not charging: the battery will charge itself either from the photovoltaic system or from the utility grid.
- Else if a bus is charging at the EV station: the battery will discharge itself providing energy to the charging station at maximum possible power discharge capacity.

The initial power demand from the grid (220 kW for example) is therefore replace by a new value that depends on the battery's maximum possible discharge rate. If the latter is 220kW then the peak has been shaved completely. However, when the battery is charging itself from the grid: that will act as a load whose power peak is also to be managed. Therefore, the battery cannot recharge itself at say 220kW otherwise that would defy the whole purpose.

The practical considerations when basing an energy management strategy on this approach are the following:

- What is a good power rate at which the battery can recharge itself that will gives us satisfactory peak shaving? This can be done by trial and error or using optimization procedures like a swipe analysis.
- If the battery cannot discharge itself at the full peak power (for example 220 kW), the peak shaving capacity can change if *Pmax(discharge)* is smaller than *Pmax(recharge)*.
- What is a good energy capacity for the battery (in kWh) so that it has always enough reserve to operate at maximum power throughout the day, throughout the week and throughout the year? This energy capacity will be different if the battery is only allowed to recharge itself from the photovoltaic system.

2.1.2. The use of a low-pass filter modeled as a moving-average block

The second approach is based on energy conservation and spreading the energy demand using a battery (and hence the power demand) throughout the day, the week, the year or for couple of hours. The algorithm instructed to the battery will have to monitor the past, present and future power demand of our microgrid. Then make decisions on when and on how much to charge or discharge the battery based on this data.

- *The basic idea of a moving-average block*

The basic idea is to think of what the target is: how do we want the power profile exchanged with the grid *Pgrid* to look like while keeping the same energy demand. The answer is to calculate the area under the power profile curve and divide it by the time window.

For example, based on the data collected in figure 3, the energy demand of the charging station on the 22nd of February 2021 is 772 kWh. When this value is divided by 24h (the time period of the dataset), it gives us an equivalent power profile with constant energy demand throughout the day at a peak power of 32.16 kW.

Based on this finding, the energy management strategy would be to ask the battery inverter to operate during the day in such a way to always maintain a *Pgrid* to 32.16 kW. During the moments when a bus charges, the battery will need to provide energy to the charging-station with a rate between 188 kW and 190 kW. The battery will also need to always have enough energy reserves to operate at these power rates all day long without discharging completely and therefore losing control of the power absorbed from the utility grid.

Here are the practical issues so far with this approach:

- The battery might not be able to operate at the desired power discharge rates.
- The battery might not have the energy capacity necessary to always handle the demand.

The solution at this stage would be to play with the time used to calculate the average until a suitable maximum power is found. This assumes however that the battery is allowed to charge itself from the grid during the night. If not, the battery is only allowed to recharge when photovoltaic production is available.

In such a case, the simple moving average (SMA) or the central moving average (CMA) are practically more useful.

- *Simple moving average (SMA)*

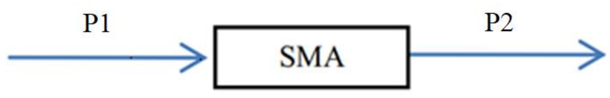

Figure 6: Simple moving average (SMA) block

The output signal (P2) relates to the input signal (P1) based on the following equation:

$$P2(i) = \frac{1}{n} \sum_{j=i}^{n} P1(j-n)$$

At any instant time (i), the output (i) is equal to the average of the input across the past n values. This parameter “n” is also called the moving average window [4].

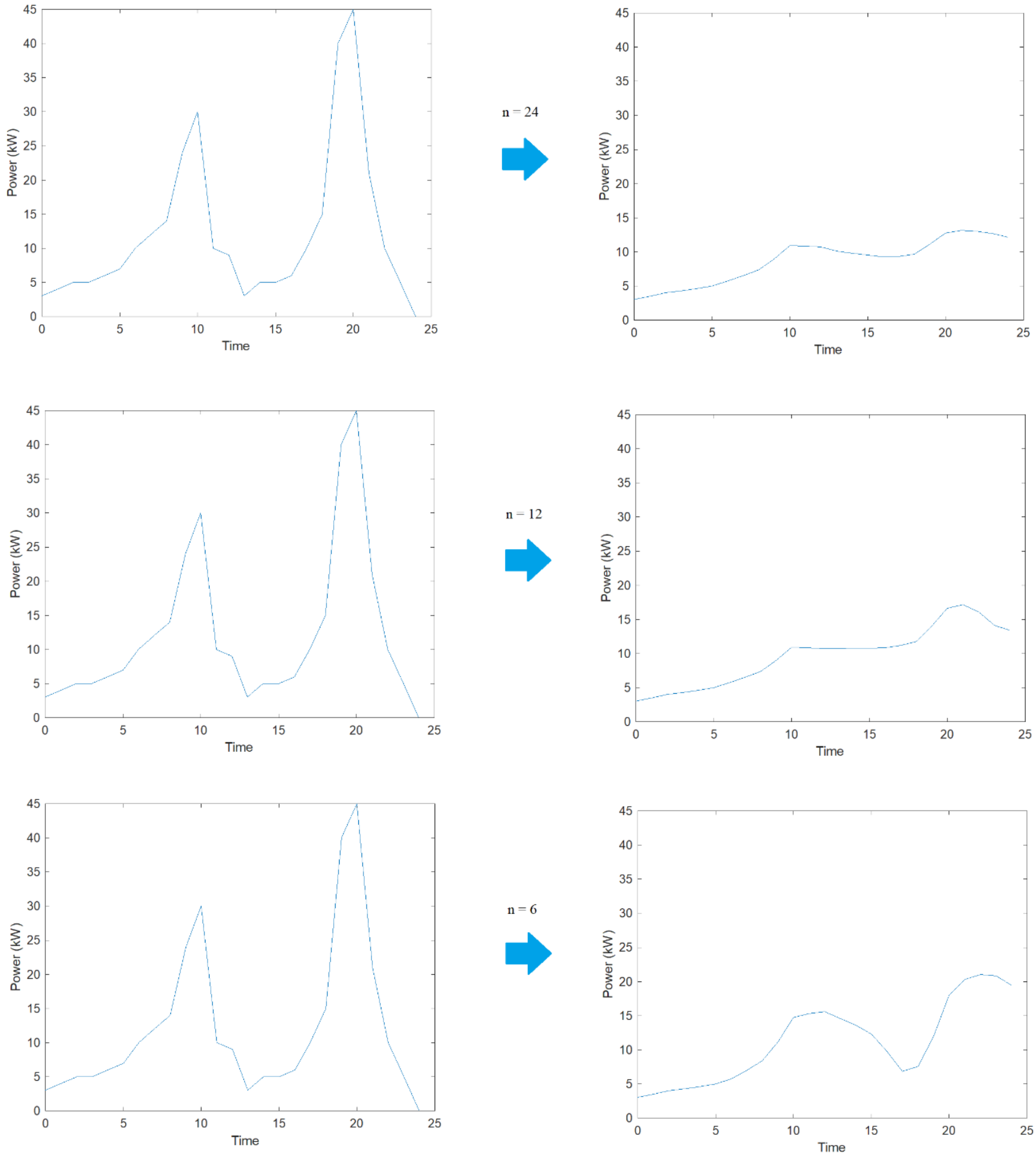

Figure 7: The SMA output signals using the same signal input and three different moving average windows "n"

In the three instances in figure 7, the area below the output curve is the same as the input curve. However, the power profile is different depending on the chosen moving average window.

In this example, the energy management strategy will consist of sending an instruction to the battery inverter every time period “i” such that:

$$Pbat(i) = P1(i) - P2(i)$$

- *Centered moving average (CMA)*

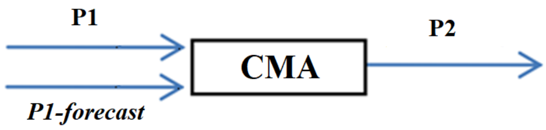

Figure 8: Centered moving average (CMA) block

The output signal (P2) relates to the input signal (P1) based on the following equation:

$$P2(i) = \frac{1}{2n}\sum_{j=i}^{n/2} P1(j-\frac{n}{2}) + \frac{1}{2n}\sum_{j=i}^{n/2} P1.forecast(j+\frac{n}{2})$$

The output signal (P2) at any time "i", is equal to the average of the input signal values across [-n/2,n/2]. The moving average window is "n"; however, it considers both past values and future values in calculating the average. This strategy requires therefore an additional input which is the forecasted values of signal P1 over at least the next n/2 values [5].

Naturally this strategy also requires managing the error in forecast. In the case of simulations done on data that is already available, the CMA is carried out on the real "future" values. This is called a centered moving average (CMA) assuming perfect forecasting [6]. This is used to define a baseline for evaluating SMA-based and CMA-based energy management strategies. Depending on the context and the power constraints of the microgrid, the CMA-based strategies might or might not be better than the SMA-based strategies.

2.2. Review 1: battery sizing for the UPNA fast-charging station

This work was carried out at UPNA in the year 2020/2021 [3]. The microgrid scenario analyzed consists of the same UPNA fast-charging station, a battery system, but no photovoltaic power source. The battery system regulates the power and energy demand of the microgrid by charging itself from the utility grid.

The objective of this work was to find a suitable size (battery capacity in kWh) for the battery system to achieve peak power shaving on the fast-charging station energy demand. The battery operation was modeled based on multiple energy management strategies: the SMA strategy, the CMA strategy (using forecasting and perfect forcasting) and the real-time battery state of charge (SOC) control. The power peak for each strategy was found using different values for the battery capacity (between 0 to 100 kWh) – refer to figure 9.

Results:

- The real-time battery state of charge (SOC) control yields to the lowest power demand by the microgrid compared to other strategies for any battery size (in kWh)
- A battery of 40 kWh is able to reduce the peak demand of the charging station from 220kW down to 75kW.

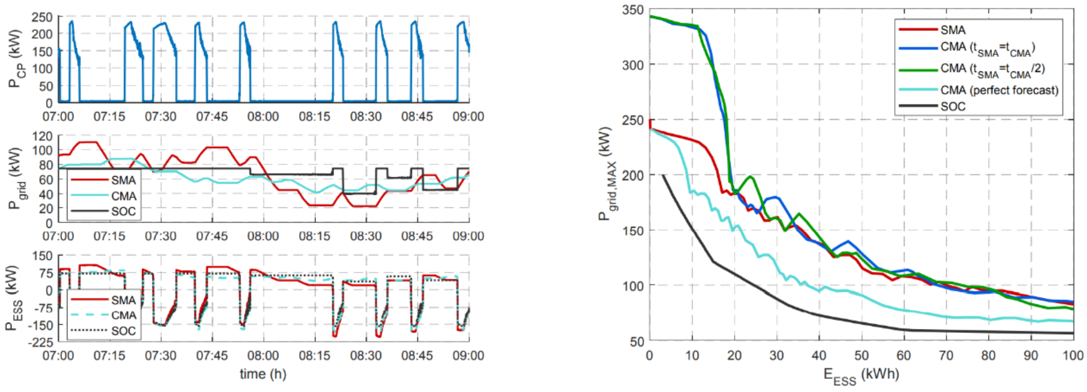

Figure 9 : (On the right) Pgrid before and after using a 40kWh battery for the SMA, CMA with perfect forecast and SOC control strategies (on the left) a comparison of the different strategies for the maximum grid power needed depending on battery size – adapted from [3]

The study however has made a couple of assumptions that do not fit in the context of the present study:

- It assumes that the battery system can provide discharge powers up to 150kW.
- For practical reasons, the SOC strategy necessitates to know exactly when the next bus charge will occur. The model assumed that this value is known with great accuracy.

In the present study, the battery system used can only provide a maximum 80 kW of power to the microgrid. Therefore, the results found in figure 9 should be different when battery power constraints are applied to the models. Also ideally, we would also like a strategy that does not rely on forecasting of bus arrival time, as is the case for the SOC control strategy used in this reviewed work.

The conclusion therefore is that: in the context of power peak management, optimizing for battery energy size is secondary to optimizing for its maximum power discharge capacity. This work also does not include renewable generation in the study of the microgrid.

2.3. Review 2: Energy management strategy for a residential microgrid

This work was carried at UPNA as doctorate research between 2011 and 2015 [7] and then the results of which were published in the journal of Applied Energy in 2015 [2].

This work proposed an energy management strategy for a residential microgrid comprised of the usual electric load of a single-family home (maximum power peaks of 5.75 kW), a photovoltaic panel and a small wind turbine (both rated at 6 kW), and a 34-kWh battery (and 6 kW inverter). A simulation based on a one-year data of residential consumption and renewable production was carried out [2].

The final energy management strategy was designed following the following steps:

- The net power (which is the power demand minus the renewable power generation) is the starting point. It represents the net power exchanged with the grid in the absence of a battery system and an energy management strategy (Strategy 0).

- First a simple moving average filter is used with a moving average window of 24h (Strategy 1).
- A state of charge (SOC) controls was introduced to keep the battery operating at an average SOC of 50% and to avoid the battery from ever emptying or fully charging (Strategy 2)
- Then the simple moving average filter was replaced by a centered moving average filter with the same window period used of 24h.
    - The load consumption was forecasted using persistence forecasting (Strategy 3 and 4)
    - The renewable energy production used persistence forecasting first (Strategy 3) then it was based on numerical weather prediction (NWP) models (Strategy 4).
- Finally, Strategy 4 was validated experimentally in the lab.

The primary objective of the study is to smooth the profile of the power exchanged with the utility grid by minimizing its peaks and its fluctuations.

To evaluate the five strategies and compare them, five key performance indicators were used:

- P+: the maximum power absorbed from the grid.
- P-: the maximum power injected into the grid.
- MPD: the maximum power derivative or the maximum ramp-up rate of the power exchanged with the grid
- APD: the average power derivative or the average ramp-up rate of the power exchanged with the grid.
- PPV: the power variability of the power exchanged with the electric grid.

The results are summarized in Table I.

Table I: the key performance indicators evaluated for all the strategies (0-4)

Strategy	P+ (kW)	P- (kW)	MPD (W/h)	APD (W/h)	PPV
0 (Net power)	5.75	-6.45	18468	1122	13.28
1 (SMA)	4.71	-2.40	12839	44.42	2.51
2 (SMA + SOC control)	2.83	-3.45	1241	104.46	4.88
3 (CMA + forecasting 1)	2.19	-3.43	1554	71.39	4.33
4 (CMA + forecasting 2)	1.90	-1.56	619	52.65	2.98

In the context of a residential microgrid and based on the simulation results, the use of a CMA filter with numerical weather forecasting yields to a satisfactory decrease in the power peak and power variability. The maximum and average fluctuations are also minimized throughout the year. The approach used in this work will be a template for the present analysis of the fast-charging station microgrid. The SMA strategy does not depend on forecasting which is good. At this stage, once again it is expected that the results between the different strategies applied to our microgrid wouldn't be that different as it is the case here. In residential microgrids, the maximum peak experienced are of the order of 6 kW usually once a day. In the bus charging station microgrids, the power grid experiences peak demands of the order of 220-225kW between 50 to 60 times a day.

3. Design of the energy management strategy: methodology and the proposed approach

3.1. The objective of the energy management strategy

The objectives of the energy management strategy for the fast-charging station are as follow:

- *Reducing the peak power demand from the utility grid:* this objective is more concerned with grid stability by reducing the peak and the rate of fluctuations when exchanged power with the grid. A contrast would be an economic objective of cost reduction on the utility bill, in which case the battery operations would be based on the electricity prices and on price arbitrage (which is not the focus in the present study)
- *Optimization the use of photovoltaic production:* this can be achieved by allowing the battery to recharge only when PV generation is available. No battery charging from the utility grid is allowed. This adds an additional constraint on energy management of the microgrid, however it assures that the PV production is used as much as possible.

3.2. The quality criteria or key performance indicators (KPIs)

The energy management strategies will be assessed and compared using a set of key performance indicators divided into primary and secondary ones:

The primary quality criteria are:

- ***P+:*** the maximum power absorbed by the fast-charging station from the grid (*in kW*).
- ***ratioPV*:** the percentage of the load energy demand met by the photovoltaic system (*in %)*. Given that the battery only uses energy produced by the PV system, this ratio is calculated using the following equation.

$$ratioPV = \frac{E(load) - E(after\ EMS)}{E(load)}$$

  - E(load) is the energy demand from the load during normal operations.
  - E(after EMS) is the energy use of the charging station after applying the energy management strategy.
- ***batteryEOL***: the expected battery end-of-life (in years). This is calculated based on the state-of-charge profile of the battery under the energy management strategy. The equations used are explained in the section 3.4 about battery modeling.

The secondary quality criteria are:

- ***avgSOC***: the average state-of-charge of the battery – the higher this value, the higher the performance of the battery in terms of power discharge capacity and expected end of life.
- ***minSOC***: the minimum state-of-charge of the battery – this gives us an idea on the operating range of the battery and the maximum depth of discharge.
- ***maxSOC***: the maximum state-of-charge of the battery.

- ***PPV***: the power variability of the power exchanged with the utility grid. Please refer to [2] for the way of calculating this parameter.

3.3. The proposed approach

The performance of different energy management strategies will be simulated on data recorded at a 1-second interval during one year from the power consumption of the fast-charging station and the power generation of a 3.6 kWp photovoltaic system over the same period. The PV data is extrapolated to simulate the larger 134 kWp system that was installed only a year later (no real data is available for the same period as the load).

The analysis of the microgrid and the design of the energy management strategy will be as follows:

- ***Strategy 0:*** The input signal considered in the analysis is the net power (Pnet) exchange between the microgrid and the utility grid.
    - This is found using: Pnet = Pload – Ppv.
- ***Strategy 1:*** A low-pass filter modeled as a simple-moving average block is applied to Pnet.
    - The main task is to choose a suitable moving average window.
- ***Strategy 2***: A control of the average state of charge of the battery is added to Strategy 1 to maintain the average SOC at around 90%
    - The power regulator is Pp=Kc*(90 – avgSOC(i)) where the avgSOC(i) is the moving average of the battery SOC over a window like that found in strategy 1.
    - The simulation is also to be optimized for the coefficient factor Kc
- ***Strategy 3:*** we make sure that the battery never discharges to 0% or charges to 100%. An additional SOC controls is added to either directly set values for maxSOC and minSOC or to do it indirectly by means of a factor to slow down the charge or discharge of the battery when it approaches 100% and 0%.
- ***Strategy 4:*** we replace the SMA filter in strategy 1 and strategy 3 by a CMA filter assuming perfect forecasting. If the quality criteria (P+ and ratioPV) are significantly better than the SMA-based strategies. The forecasting of the load and PV generation is introduced to the energy management strategy, otherwise this line of work is to be discarded. Strategy 3 would become the final strategy to implement in the real-life system.

3.4. The battery modeling

To simulate the microgrid, the battery system must be modeled to:

- Estimate the state-of-charge SOC of the battery.
- Estimate the maximum power charge and discharge based.
- Estimate the battery expected end-of-life.

3.4.1. Battery state-of-charge (SOC) estimate

The battery SOC is a parameter given by the battery inverter, therefore when implementing the energy management strategies experimentally, there is no need for an SOC estimate. However, for simulation it is needed. The following equation is used [8]:

```
SOC(i)=SOC(i-1)-93*PbatSOC(i)/Cbat*Ts;
```

- *SOC(i)* is the battery state-of-charge to be estimated at time "i" (in %).
- *SOC(i-1)* is the previous state of charge of the battery (in %).
- *PbatSOC(i)* is the last power discharge or recharge of the battery (in kW).
- *Cbat* is the energy capacity of the battery (in kWh).
- *Ts* is the time sampling period (1-second in this case).

3.4.2. Battery power operation constraints estimate

The battery system is composed of two batteries connected in parallel each with an operating voltage between 600V and 800V. The battery system operates at a maximum current output of 100 A (50A each). The voltage at which the battery operates depends on its state-of-charge. Each battery is composed of 96 nissan-leaf second life modules.

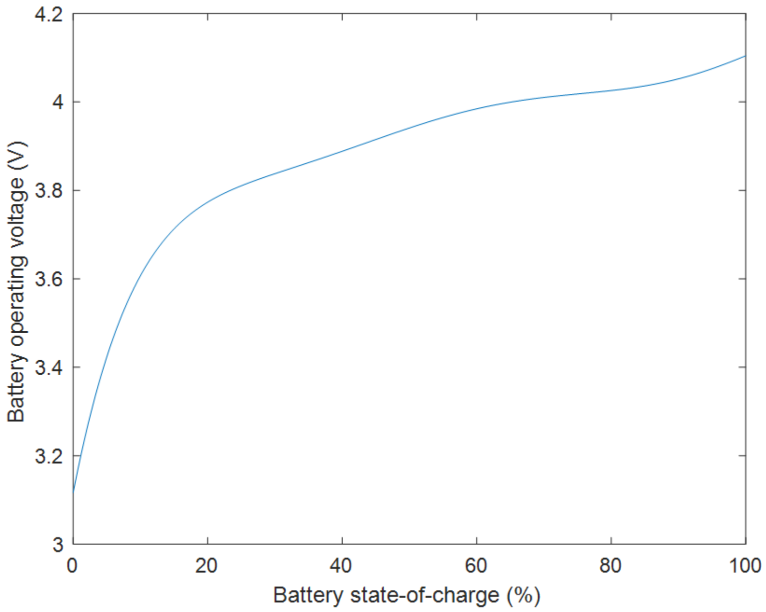

Figure 10: Operating voltage as a function of the battery SOC for nissan leaf battery (nominal voltage 3.5V)

The function in figure 10 is extrapolated to our battery system with nominal voltage of 720 V (figure 11). The resulting function is used to find the maximum power charge or discharge of the battery depending on the current SOC value.

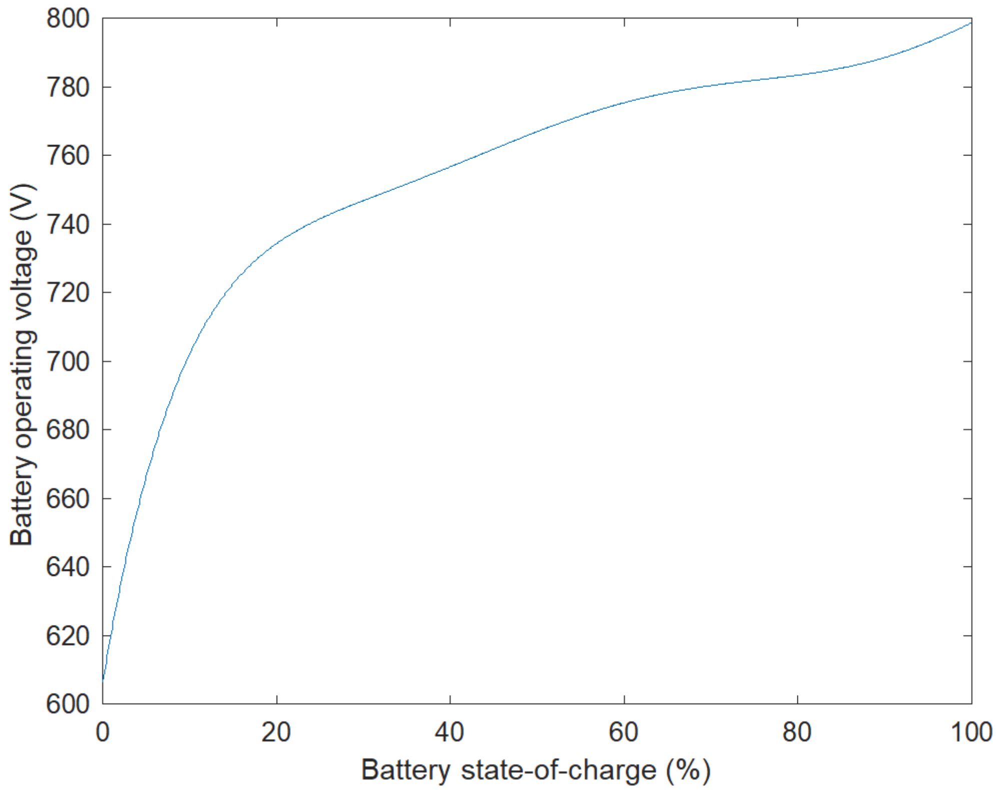

Figure 11: Battery operating voltage as a function of its state-of-charge for a battery system of nominal voltage 720 V

The maximum operating power of the battery is found using the following equation:

$$maxPbat(i) = f(SOC(i)) * Imax$$

- *maxPbat(i):* The maximum battery discharge or charge rate at time t.
- *f(SOC(i)):* Operating voltage of the battery at time t from figure 11.
- *Imax:* maximum current output of the battery system evaluated at 10 A.

As we run the simulation, when the battery power instruction exceeds maxPbat(i) (when the battery discharges) or is below -maxPbat(i) (when the battery charges), the Pbat instruction is then replaced by either of which.

3.4.3. Battery expected end-of-life estimate

The expected end-of-life of the battery is estimated in the following way:

$$batteryEOL = \frac{1842}{EFC} = \frac{1842}{\frac{CT}{2 * Cbat}} = \frac{1842}{\frac{\int i \, dt}{2 * Cbat}} = \frac{1842}{\frac{\int i \, dt}{2 * Cbat}} = \frac{1842}{\frac{\int Pbat(t) * 1/f(SOC(t))dt}{2 * Cbat}}$$

- *batteryEOL:* the expected battery end of life in years.
- *1842:* is the number of equivalent full cycles at which a second life battery is considered to arrive at its end of life [9].

- *Cbat:* the battery capacity in amp-hour (Ah)
- *Pbat(t):* the operating power profile of the battery over one year.
- *f(SOC(t)):* the operating voltage of the battery over the year calculated from the SOC-voltage function in figure 11.

4. The microgrid NET power exchange with the grid (simulation)

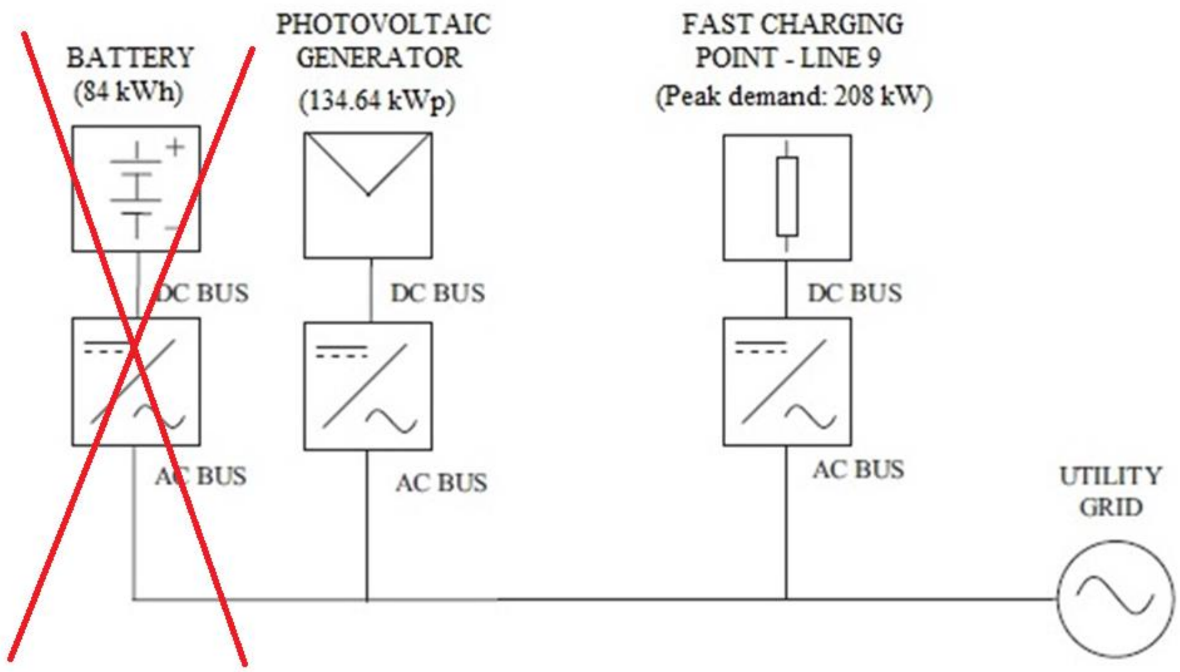

Figure 12: The fast-charging station microgrid without a battery system (Strategy 0)

The baseline scenario is represented in figure 12. This scenario illustrates the microgrid without any capacity for energy or power flow control. The power exchanged with the grid is called the net power (*Pnet*) and corresponds to the power demand from the charging station minus the PV power generation.

The *Pnet* simulated for the period July 2020 and June 2021 is shown in figure 13. The power demand of the battery station is based on real data collected over the same period.

The PV generation was based on data collected for a year during that period from a smaller PV installation located at the UPNA pinos lab building (installed capacity with degradation of 3.6 kWp). This data has been extrapolated using simple linear extrapolation from 3.6 kWp to 134.64 kWp (with PV inverter rated at 100 kW). This extrapolation is not entirely accurate but close enough. A proper model for this kind of extrapolation is explained in [10], it was not used here because the cell and ambient temperatures data (Tc) and the irradiation on an inclined surface ($G(\beta, \alpha)$) were not available for that time period. The key performance indicators of the signal *Pnet* (1-year) are summarized in Table II.

Table II: Quality criteria of the net power exchanged with the grid (Strategy 0)

	P+	ratioPV	P-	Peak shaving	avgSOC	maxSOC	minSOC
Pnet (Strategy 0)	218.00 kW	18.63 %	-100.00 kW	-	-	-	-

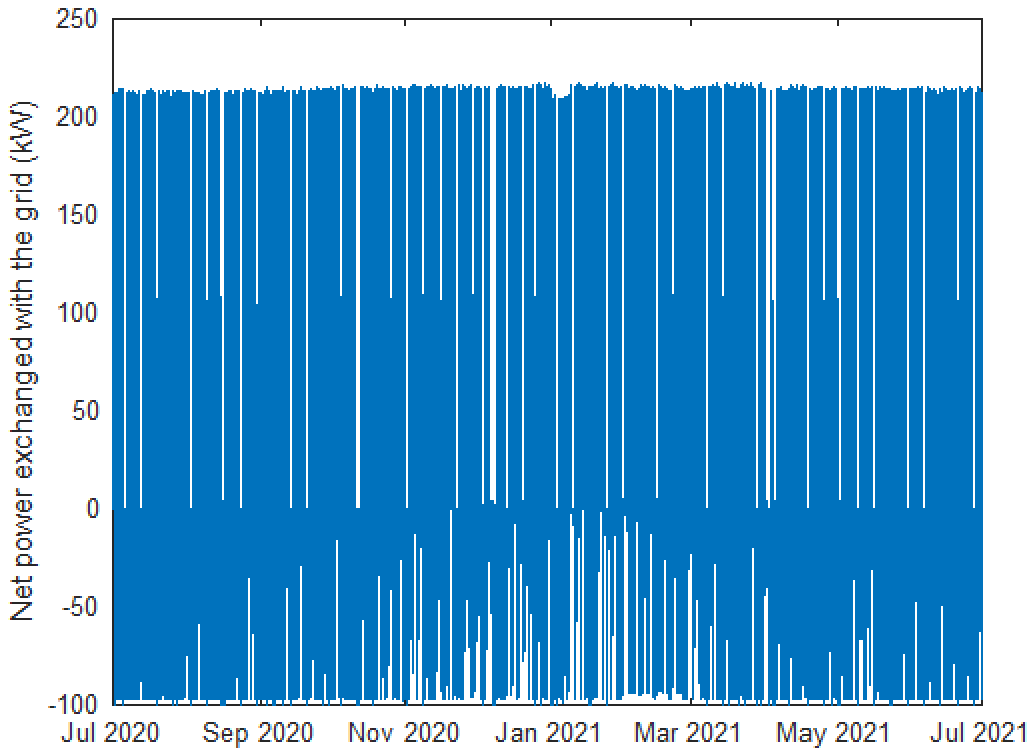

Figure 13: Simuated net power (Pnet) exchanged with the grid (Strategy 0) between July 2020 and June 2021

5. The design of the energy management strategy: a simulation using MATLAB

The goal of this work is to shave the power peak absorbed from the electric grid by the load (public electric bus fast-charging station) all the while optimizing the use of the solar photovoltaic production. This is done using a simulation on MATLAB where the net power demand Pnet signal (refer to chapter 4) is processed using first a low-pass filter followed by a control of the state of charge of the battery where its rate of charge and discharge are slowed down depending on need.

The proposed approach and the models used for the second life battery, solar panel and the fast-charging station are explained in detail in chapter 3.

The analysis in all the strategies below is performed based on a 1-day, 7-day and 1-year datasets of Pnet (net power demand) respectively depending on computing power. All datasets include data about power second by second, making optimization algorithms of $O(n^2)$ time complexity on 1-year dataset (roughly 32 million seconds) very long. When an optimization for a variable is performed (such as the moving average window for example), it makes sense to make an optimization swipe for a 1-day or 7-day dataset, find the optimum value as a starting point, then find what values best works for the larger 1-year dataset heuristically.

5.1. Strategy 1: Simple moving average (SMA) filter

The modeling of a low-pass filter using a simple moving average (SMA) block on MATLAB with a simple moving average window (Mavg) is explained in chapter 2**.**

5.1.1. Block diagram and description of the strategy

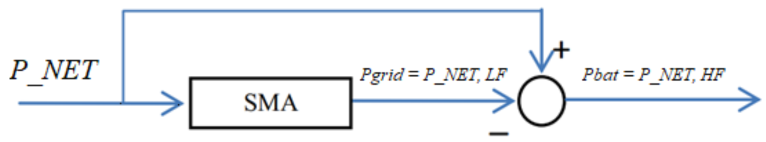

Figure 14: Block diagram of the simple moving average energy management strategy (Strategy 1) – adapted from [2]

In Strategy 1, a low-pass filter based on a simple moving average is applied to Pnet, the resulting low frequency component is defined as the power to absorb from the grid (Pgrid) while the high frequency component is assigned to the second life battery (Pbat). In the case when the battery is not able to charge or discharge at the required power, the difference in power will be absorbed from the grid instead. Figure 14 illustrates the block diagram for this strategy.

$$Pbat = P_{NET} - Pgrid$$

The trailing moving average of *Pnet* can be calculated using a range of moving average windows (Mavg): values can range from a couple of minutes to a whole year. Figure 15 shows *Pgrid* as the average of *P_NET* for a whole year, while figure 16 and figure 17 shows the resulting *Pgrid* for a moving average window of “7 days” and “24 hours” respectively. It is assumed in these last three figures that the battery can always meet its power requirements (an ideal battery with no capacity limits or power limits). This is shown at this level for illustration only.

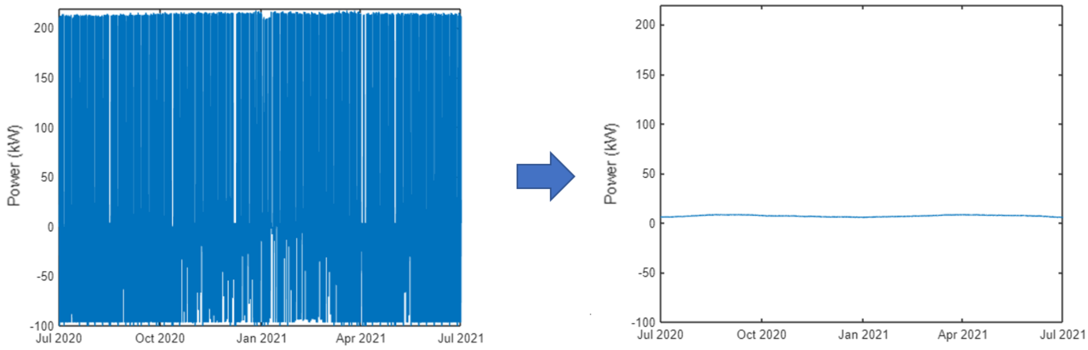

Figure 15: Net power demand for a year (left) and the resulting Pgrid with strategy 1 on a "1-year moving average window" using an ideal battery (right)

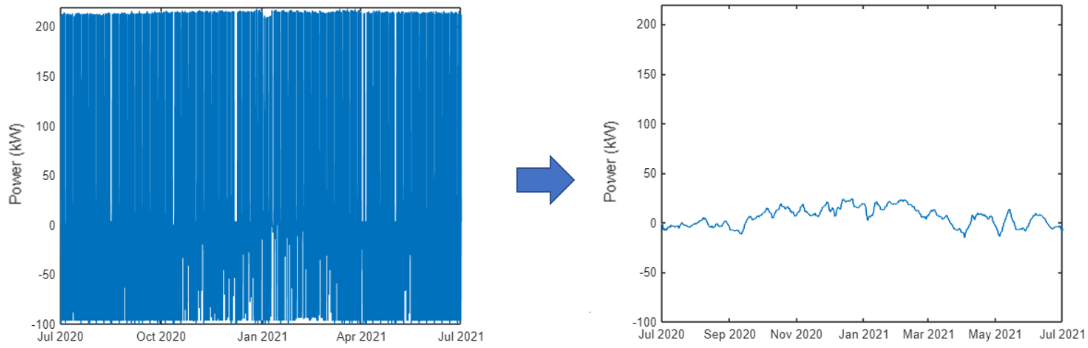

Figure 16: Net power demand for a year (left) and the resulting Pgrid with strategy 1 on a "7-day moving average window" using an ideal battery (right)

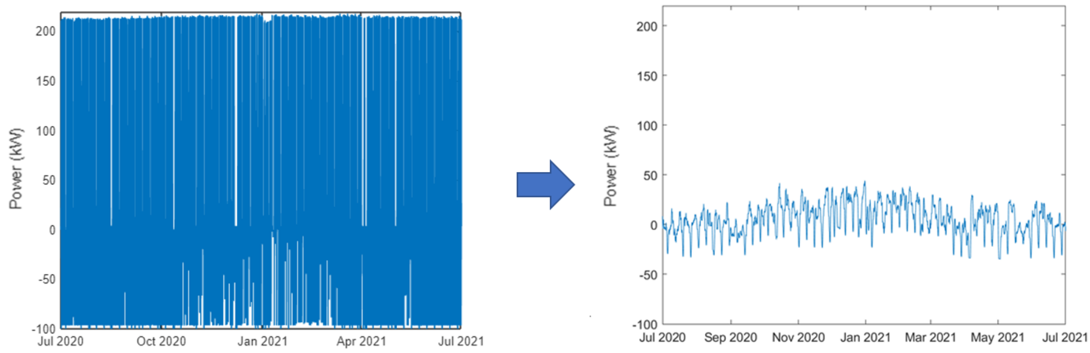

Figure 17: Net power demand for a year (left) and the resulting Pgrid with strategy 1 on a "24-hour moving average window" using an ideal battery (right)

It is observed that using different moving average windows yield to different power profile absorbed from the grid (*Pgrid*). Each power profile has a different maximum power peak (*P+*), different photovoltaic use (*inferred from the area under the power P- injected back into the grid*) and as a result different number of battery cycles expressed in terms of end-of-life (batteryEOL).

In the following section, we investigate in Matlab what the optimum value for the moving average could be based on a 7-day dataset for Pnet. This is performed for both an ideal battery and one that models the constraints of the current system (refer to chapter 1).

5.1.2. Method 1: Moving average windows swipe analysis for a one-week dataset

A low-pass SMA filter is applied to a 7-day dataset of Pnet (based on data from the last week of February 2021). Different values of the moving average window are used: starting with a “3-min” window all day to a “7-day” (168 hours) with small increments of three minutes.

- ***Using a 84 kWh battery with no power charge or discharge limits***

A swipe is run on Matlab for a battery model with capacity of 84 kWh and with no power charge or discharge limits. Figure 18 shows the maximum power demand observed in Pgrid as a function of the SMA moving average window (Mavg). It is observed that beyond a certain value of the Mavg that is smaller than 24h, no peak shaving occurs. The lowest value for $P+$ of 60 kW is found at Mavg=1h03.

In Figure 19, the percentage of energy met by the photovoltaic system reaches its maximum of 67% around Mavg=24h. However, it is worth noticing that a local maximum of ratioPV=55% exists around Mavg=1h before reducing significantly and then increasing beyond this local maxima when Mavg is greater than 5h.

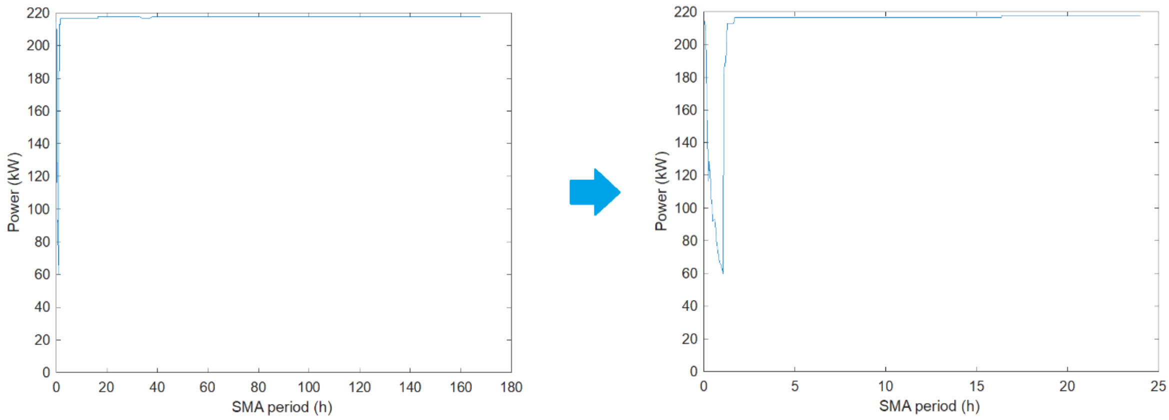

Figure 18: The maximum power of Pgrid under Strategy 1 as a function of the SMA period - Mavg=[0,168h] (right) and MVG=[0,24h] (left)

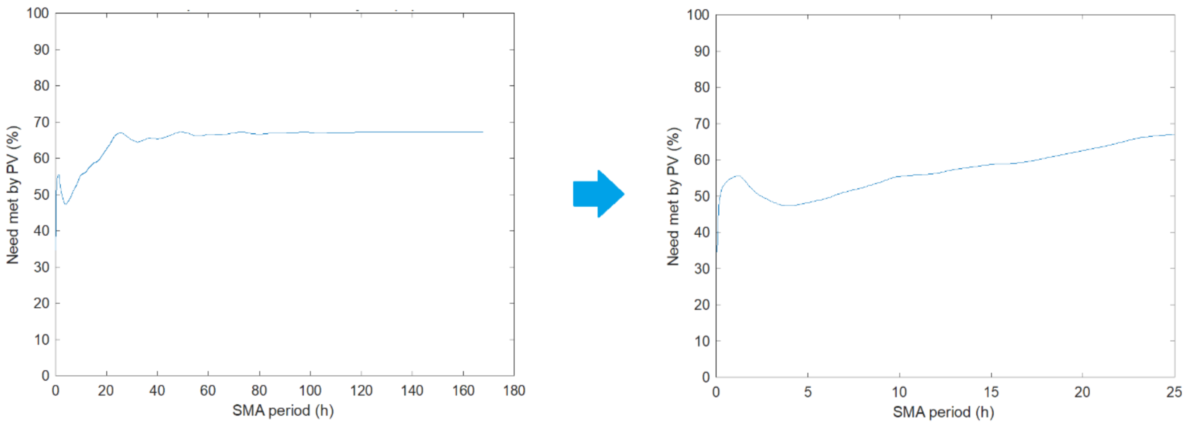

Figure 19: The portion of energy demand met by the photovoltaic system with Strategy 1 and an battery of 84 kWh with no power charge or discharge limits

Table III: Suitable simple moving average window with a 84kWh battery with no power charge or discharge limits

Mavg = 1h03 (“Simple moving average window period”)	
P+ (maximum power absorbed by the grid)	60 kW
ratioPV (% of need met by the PV system)	55%
Maximum power	=220 kW – (P+) = 160 kW

Results: Table III summarizes the values of two quality criteria (P+ and ratioPV) using a simple moving average window period of 1h03. This analysis also defines the maximum power that can be shaved by a 84 kWh battery with no power limits in the week of February 2021. This value is equal to 160 kW of power peak demand reduction. This value is expected to be less for a realistic battery of 84 kWh.

- ***Using a 84 kWh battery with a power constraints modeled after the UPNA-Aulario battery system***

A similar swipe is run on Matlab but this time by using a battery of similar capacity (84 kW) and with maximum power, voltage, and current constraints modeled after the second-life battery system found at UPNA-aulario. Please refer to chapter 3 for more details on the model. A typical “State-of-charge vs voltage” graph for a Nissan leaf second-life battery is used as the basis to the modeling of our battery system.

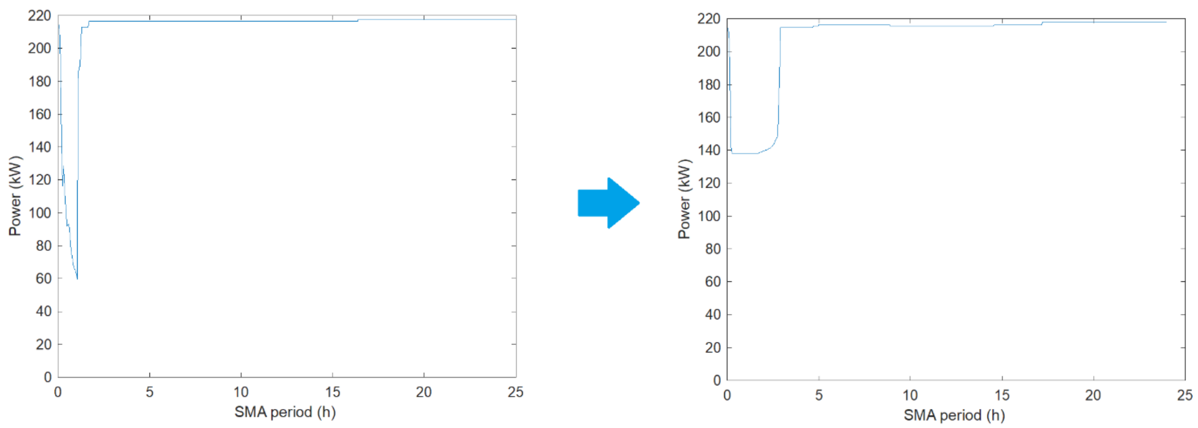

Figure 20: The maximum power demand for Pgrid in Strategy 1 using a realistic 84kWh battery (right) and an ideal 84kWh battery (left)

In Figure 20, the swipe results for the realistic battery are shown next to that of an ideal 84kWh battery. The *Mavg* swipe range is 24 hours only, as values beyond 24h do not yield any reduction in the peak power absorbed from the grid. From this swipe analysis of the last week of February 2021, the maximum power demand for *Pgrid* reaches its lowest value (140 kW) when Mavg is between 20 minutes and 1h42.

Figure 21 shows the percentage of the load needs met by the photovoltaic generation (ratioPV) under different values of the SMA period. Similarly, to the ideal battery scenario, the load need is met by the PV system mostly (at around 60%) when Mavg=24h. However, under such scenario, no peak shaving is achieved under Strategy 1. A local maximum is found around a value of Mavg=30 min that fortunately coincides with an optimum value for peak shaving.

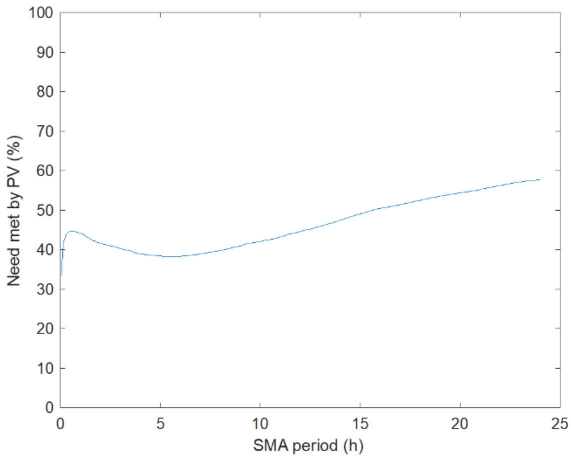

Figure 21: Portion of the laod need met by the PV system as a function of the simple moving average window period

Results: A suitable simple moving average window with a 84 kWh battery with power charge and discharge limits is found to be Mavg = 30min for the energy management strategy 1. Based on a dataset of one week, the minimum peak power demand is reduced by 78 kW (as opposed to a theoretical maximum of 160 kW for an ideal battery) and 45% of the weekly needs of our fast-charging station is expected to be met by the PV (compared to a 57% maximum possible when Mavg=24h for a realistic battery)

Table IV: Suitable simple moving average window with a 84kWh battery with power charge or discharge limits

Mavg = 30 min ("Simple moving average window period")	
P+ (maximum power absorbed by the grid)	140 kW
ratioPV (% of need met by the PV system)	45%
Peak Power shaved	=218 kW – (P+) = 78 kW

5.1.3. Applying the optimum Mavg to the 7-day dataset and calculating the key performance indicators (quality criteria)

Energy management "Strategy 1" with a SMA window of Mavg=30 min is simulated in Matlab and applied to a 7-day net power demand *(Pnet)* dataset (last week of February 2021).

The figures 22, 23 and 24 show respectively *Pnet* without using any strategy, *Pgrid* the power exchange profile with the grid after applying Strategy 1, *Pbat* the power fluctuations inside of the battery and SOC the state-of-charge of the battery over the simulated week. Finally, Table V is a summary of the key performance indicators (or quality criteria) for Strategy 1.

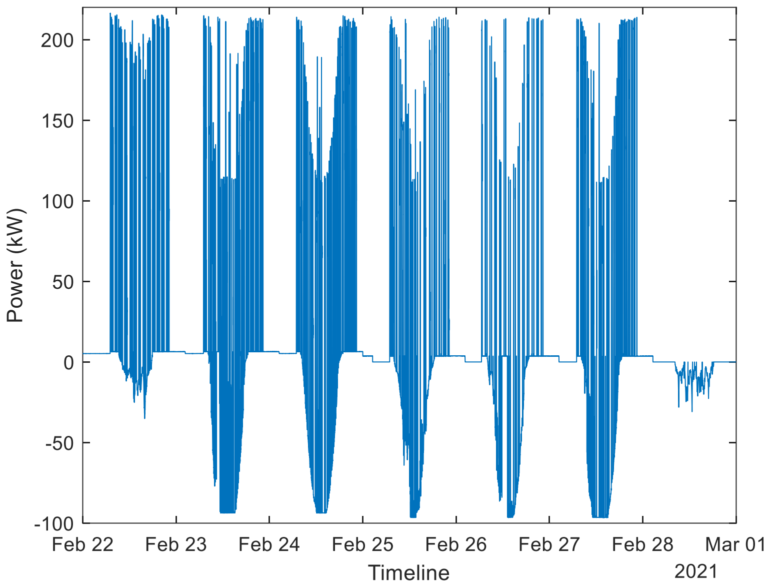

Figure 22: The simulated net power exchange with the grid (P_NET) during the last week of February 2021 without applying any energy management strategy

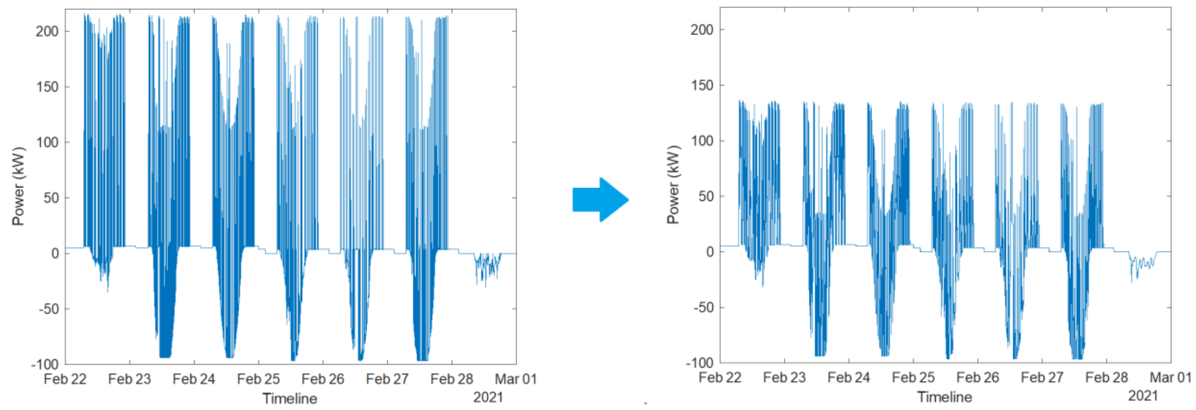

Figure 23: Net power exchange with the grid before (left) and after (right) applying Strategy 1

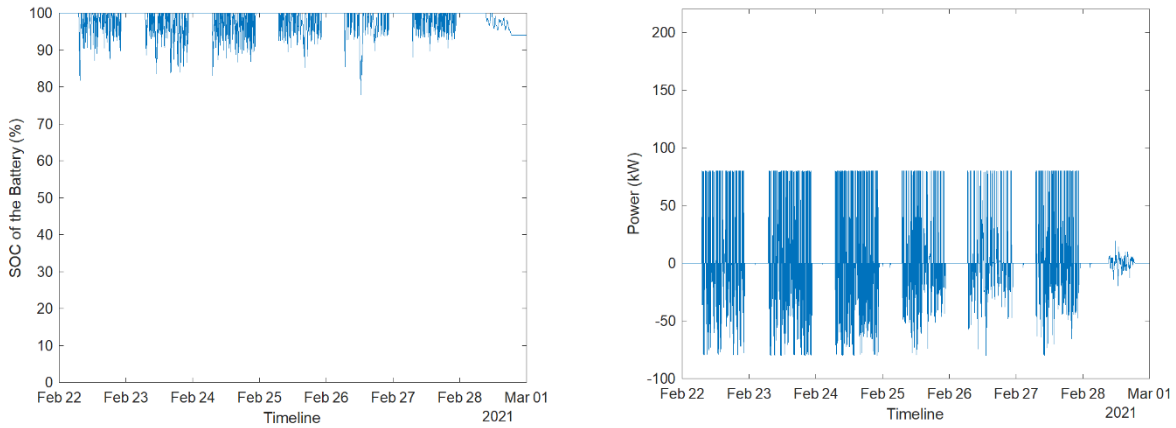

Figure 24: State-of-charge (SOC) of the battery (left) and the operating power profile of the battery (right) under Strategy 1

Table V: Key performance indicators for the energy management strategy - Strategy 1

Strategy 1: SMA filter with SMA window Mavg = 30 min					
	Quality criteria	Description	No strategy	Strategy 1	Reference
Primary quality criteria (related to **Pgrid and the battery**)	**P+**	Max power load demand	216.37 kW	**136.8 kW**	**60 kW**
	ratioPV	% load need met by PV	15 %	**32.2 %**	**70%**
	lifetime	End of life (battery)	-	**2 year 8 months**	**10 years**
	PPV	Power profile variability	15.04	7.44	2.40
Quality criteria related to the **State-of-charge (SOC)** of the battery	maxSOC	Maximum state-of-charge	-	100 %	-
	minSOC	Minimum state-of-charge	-	77.8 %	-
	avgSOC	Average state-of-charge	-	98 %	95%
	maxDOD	Maximum depth of discharge	-	22.2 %	-
	DOD median	Median DOD	-	0.2-0.5 % (microfluctuations)	5%
Operating power profile (battery)	maxPbat	Maximum battery power (discharge)	-	79.86 kW	216.37 kW
	minPbat	Maximum battery power (charge)	-	-79.86 kW	-100 kW

5.1.4. Applying the optimum Mavg to the 1-year dataset and calculating the key performance indicators (quality criteria)

Energy management "Strategy 1" with a SMA window of Mavg=30 min is simulated in Matlab and applied to a 1-year net power profile *(Pnet)* dataset (from 1st of July 2020 to 30th June 2021).

The figures 25, 26 and 27 show respectively *Pnet* without using any strategy, *Pgrid* the new power exchange profile with the grid after applying Strategy 1, *Pbat* the power fluctuations inside of the battery and SOC the state-of-charge of the battery over the simulated week.

Finally, Table VI is a summary of the key performance indicators (or quality criteria) for Strategy 1 applied and simulated for a whole year.

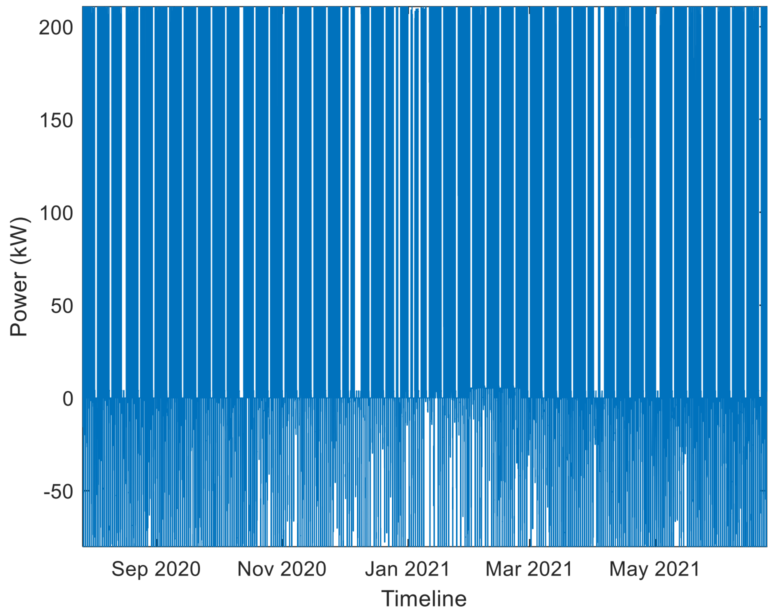

Figure 25 : The simulated net power exchange with the grid (P_NET) between July 2020 and June 2021 without applying any energy management strategy

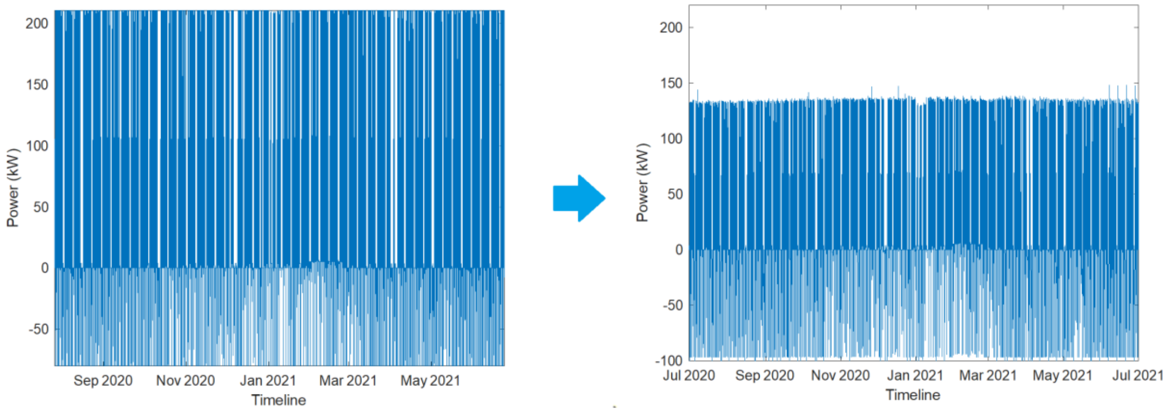

Figure 26: Net power exchange with the grid before (left) and after (right) applying Strategy 1 (1-year dataset)

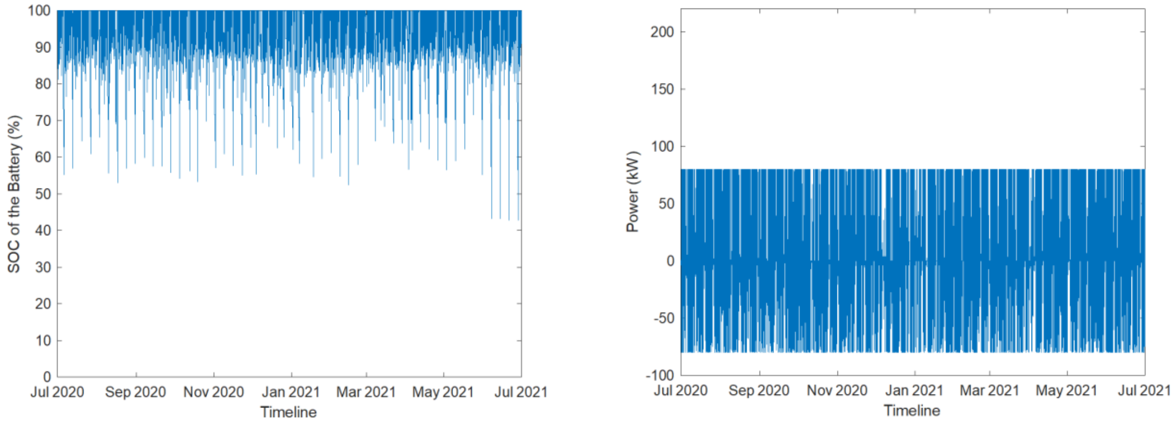

Figure 27 : State-of-charge (SOC) of the battery (left) and the operating power profile of the battery (right) under Strategy 1

Table VI: Key performance indicators for the energy management strategy - Strategy 1 (1-year dataset)

Strategy 1: SMA filter with SMA window Mavg = 30 min					
	Quality criteria	Description	No strategy	Strategy 1	Reference
Primary quality criteria (related to **Pgrid and the battery**)	**P+**	Max power load demand	216.37 kW	**148 kW**	**60 kW**
	ratioPV	% load need met by PV	15 %	**31.35 %**	**70%**
	lifetime	End of life (battery)	-	**2 year 3 months**	**10 years**
	PPV	Power profile variability	15.32	10.93	2.40
Quality criteria related to the **State-of-charge (SOC)** of the battery	maxSOC	Maximum state-of-charge	-	100	-
	minSOC	Minimum state-of-charge	-	42.78%	-
	avgSOC	Average state-of-charge	-	95.5%	95%
	maxDOD	Maximum depth of discharge	-	57.21%	-
	DOD median	Median DOD	-	0.2%-0.5%	5%
Operating power profile (battery)	maxPbat	Maximum battery power (discharge)	-	79.86 kW	216.37 kW
	minPbat	Maximum battery power (charge)	-	-79.86 kWs	100 kW

5.1.5. Method 2: Choosing a moving average window heuristically

- *Frequency spectrum analysis of Pnet*

Using the swipe analysis to identify suitable candidates for Mavg of our SMA filter requires great computing power if an $O(n^2)$ optimization is performed on the one-year dataset. Method 1 resulted in choosing a Mavg=30 min by performing a swipe analysis of our main quality criteria of interest (P+ and ratioPV) based on a range of Mavg values.

One other way to decide on a suitable moving average window for Strategy 1 SMA filter, is to perform a frequency spectrum analysis of Pnet using the fourier transform. This enables us to identify the most recurrent cycles in our electric signal. These outliers are suitable candidates to use directly on the one-year *Pnet* dataset.

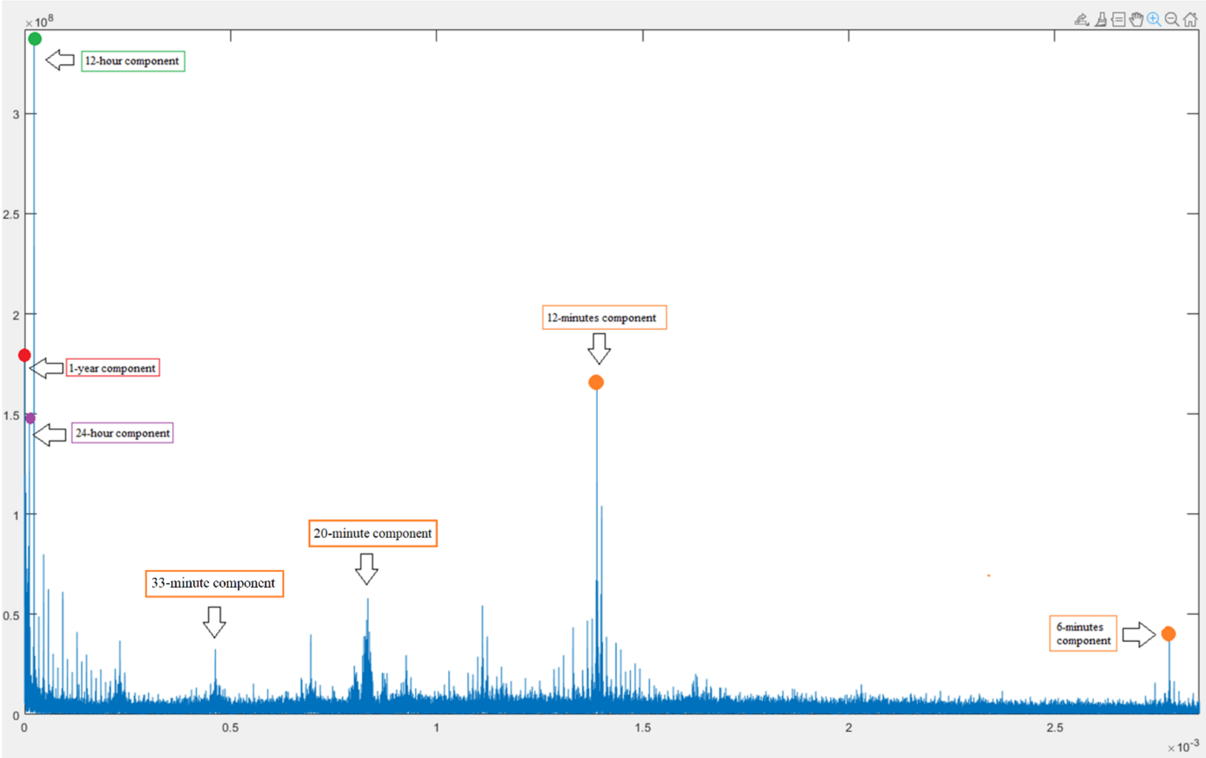

Figure 28: Frequency spectrum analysis of Pnet

In figure 28, the frequency spectrum analysis of *Pnet* is shown. It can be observed that a few recurrent components stand out from the graph, some of these components can be easily identified as follows:

- 12-hour component: average duration of bus service
- 1-year component: seasonal fluctuation of the PV generation
- 12 minutes component: average waiting time between two buses
- 24-hour component: availability of solar power
- 6 minutes component: average duration for charging a bus
- 7-days component: weekly trend where workdays and weekends have different.

In figure 29 and 30, we run Strategy 1 on the 1-year dataset of *Pnet* using six different moving average window periods (Mavg = 24h, 12h, 1h30, 33min, 30min, 12min and 6min). We notice an improvement in terms of the peak power load absorbed from the grid as we decrease Mavg from 24h to 30 minutes. The battery also seems to empty less often, hence it is able to peak shave most of the year.

On the other hand, as we decrease the value of Mavg below 30 minutes, we can see a resurgence of peak events despite of the improved SOC profile, this is probably explained by the fact that as Mavg diminishes below 30 minutes, the average of Pnet within that window gets higher and higher hence making the Strategy of little value for us.

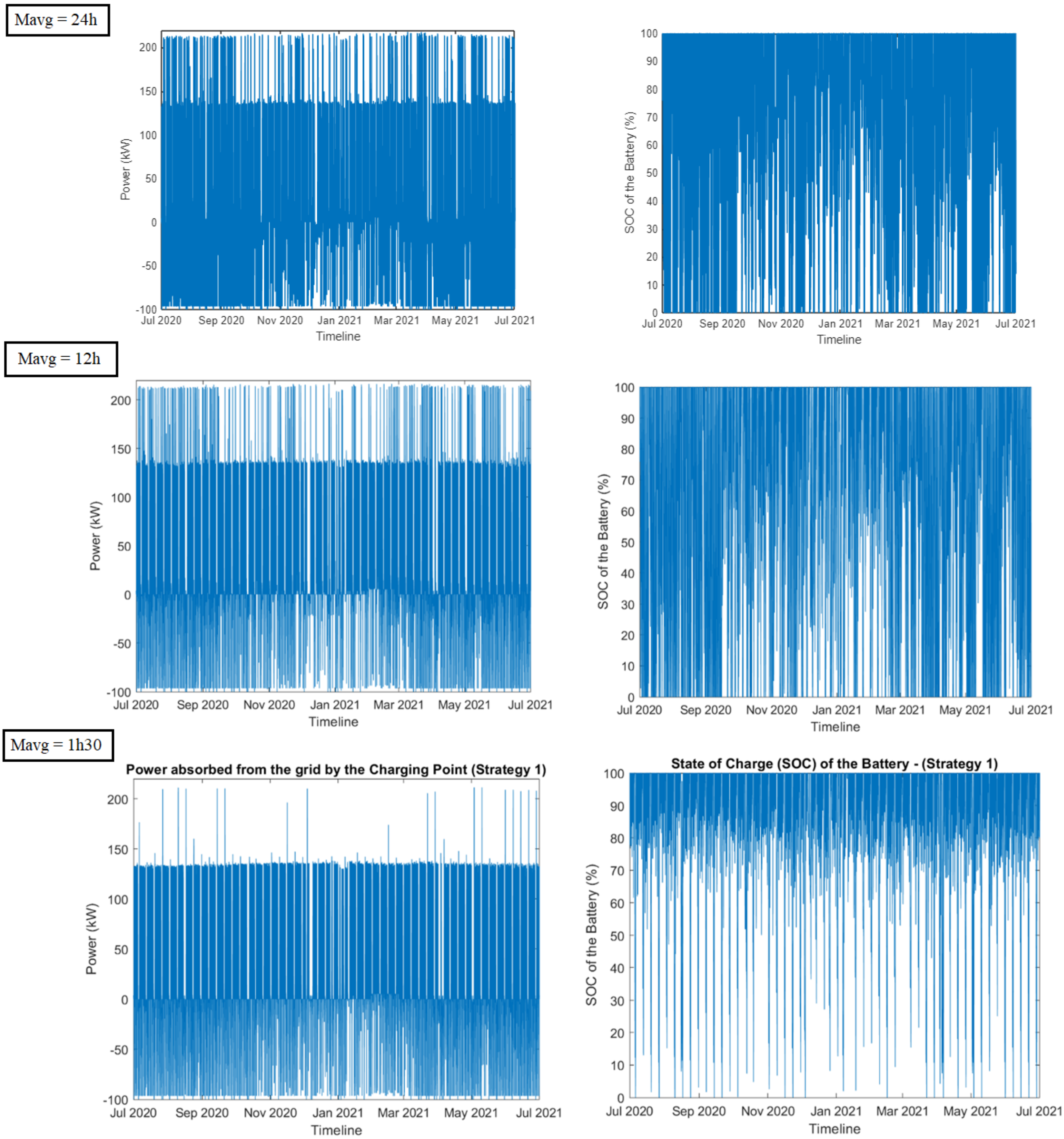

Figure 29: Simulation of Pgrid and SOC profiles for a whole year with three different moving average window periods (24h, 12h and 1h30)

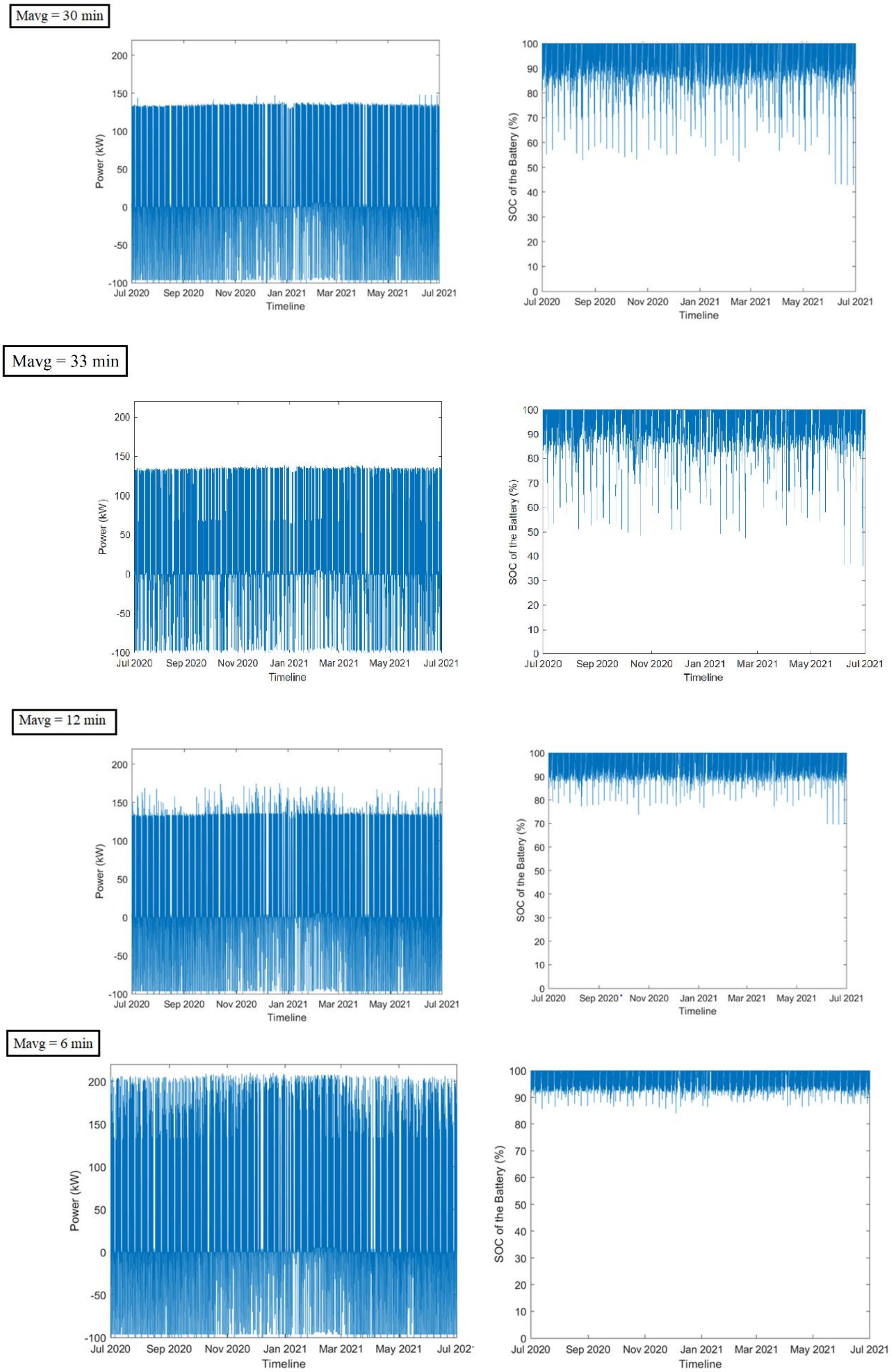

Figure 30: Simulation of Pgrid and SOC profiles for a whole year with three different moving average window periods (30 min, 33min, 12 min and 6 min)

- *Quality criteria (comparison using different Mavg)*

In this sub-section, we compare the main quality criteria (or key performance indicators) in the 1-year simulation of the fast-charging station microgrid for the seven different values of Mavg used in figure 29 and figure 30. The results are shown in Table VII.

Table VII: Comparison of the quality criteria (P+, ratioPV, lifetime and PPV) for different SMA average windows (Mavg)

	P+	ratioPV	Lifetime (battery)	PPV
Mavg = 24 h	217.81 kW	**37.00%**	2year 5months	**10.80**
Mavg = 12 h	216.56 kW	33.50%	2year 4months	10.92
Mavg = 1h30	211.40 kW	30.85%	2year 4months	**10.80**
Mavg = 30 min	148.00 kW	31.35%	2year 3months	10.93
Mavg = 33 min	**138.68 kW**	31.43%	2year3months	10.89
Mavg = 12 min	175.00 kW	30.00%	2year 6months	11.33
Mavg = 6 min	210.00 kW	27.00%	**2year 8months**	12.27
Strategy 0	218.00 kW	15%	-	15.32
Possible Improv.	138.00 kW	40%	-	7.5

5.1.6. Summary of results and conclusions – Strategy 1

As mentioned in chapter 3, the main priority in implementing an energy management strategy for our fast-charging station microgrid is to reduce the grid peak power demand (P+) , all the while optimizing for ratioPV and the life expectancy of our second-life battery.

This can be done in one of the following way:

- **Option 1:** Run a multivariable optimization algorithm on the 1-year dataset to find the best values for out control variables (refer to chapter 3) – this will require high computing power.
- **Option 2:** Settle with a Mavg = 33min for our SMA filter then investigate SOC control to find avenues where ratioPV and battery life expectancy can be improved if possible.
- **Option 3:** Choose Mavg = 24h for the SMA filter to have the highest possible ratioPV then use SOC control in the following strategies to shave the peak.

Option 1 is to be discarded for now given the high computing power required.

Option 3 is also to be discarded for practical reasons: to ensure rapid performance when implementing the strategy in the real-life system, it is good practice to keep only the smallest possible windows (be it for the SMA filter or for the upcoming SOC controls)

Therefore, we settle for Mavg = 33min as simple moving average window for our SMA filter (Strategy 1), sacrificing 5.65% of PV use for a more reliable operation of the real-life system.

Table VIII: Summary of Strategy 1 (quality criteria)

	P+ (kW)	ratioPV	Battery EOL	PPV	Peak Shaved (kW)	Average SOC
Strategy 1 (SMA filter without SOC control)	138.68	31.43%	2year3months	10.89	79.13	95.11%
Strategy 0 (Pnet)	218.00	15%	-	15.32		-
Possible Improv.	137.00	37%	-	7.5	80.00	-

Strategy 2 and 3 in the following sections will aim to introduce controls to the state of charge of the battery.

5.2. Strategy 2: Simple moving average (SMA) with average state-of-charge control

The quality criteria results obtained in Strategy 1 are relatively satisfactory as:

- Strategy 1 can consistently peak shave at a value (79.13 kW) close to the maximum power discharge capacity of the battery (80.00 kW).
- Strategy 1 is also able to improve the load's reliance on solar PV as a source of energy by doubling its use from 15% without any strategy implemented to 31.43% using Strategy 1. This number is particularly good given that a CMA filter (refer to section 5.4) with perfect forecasting (practically impossible) would yield to only to 37% of PV usage.

We can in theory stop here our design, however, it is advised to introduce some control mechanism to the battery program to maintain its operations around a desired average state-of-charge as a way of:

- Slowing down the discharge of the battery to avoid loss of control and emergence of power peaks due to a fast emptying of the battery.
- Having in the battery program a way to change average state-of-charge at will for research or for any practical issue encountered in the implementation.
- Diminish the time when the battery is operating under predefined SOC limits: a common good practice is to avoid operating under 20%

In Strategy 1, It is observed that the simulated SOC of the battery has the following characteristics:

- An average SOC of 95.11%
- An average Depth of Discharge of 5% (using the matlab rainflow algorithm)
- A minimum SOC of 36.13%
- A maximum SOC of 100%

Given all the above, there are considerations to be considered as the SOC controls are introduced in the simulation:

- An average SOC as high as possible is a good thing for power peak shaving as the Nissan leaf second life battery operate at a higher voltage (and therefore delivers more power). However, we would like to be able to reduce that average SOC to 90% as the present data, at UPNA, on the aging models of Nissan leaf second life battery is performed at an average SOC of 90% a at a Depth of Discharge of 5%.

- It is important to make sure that it is possible to control the set average SOC of the battery at a desired value (90%) without compromising our quality criteria especially the P+ and ratioPV (refer to Table VIII).

- It is important also that the model's input and subsequently the output response are coherent: meaning if a value for the average SOC is set at 90%, the battery needs to show in simulation that it is indeed operating at 90%.

5.2.1. Block diagram of the strategy and description (average SOC control)

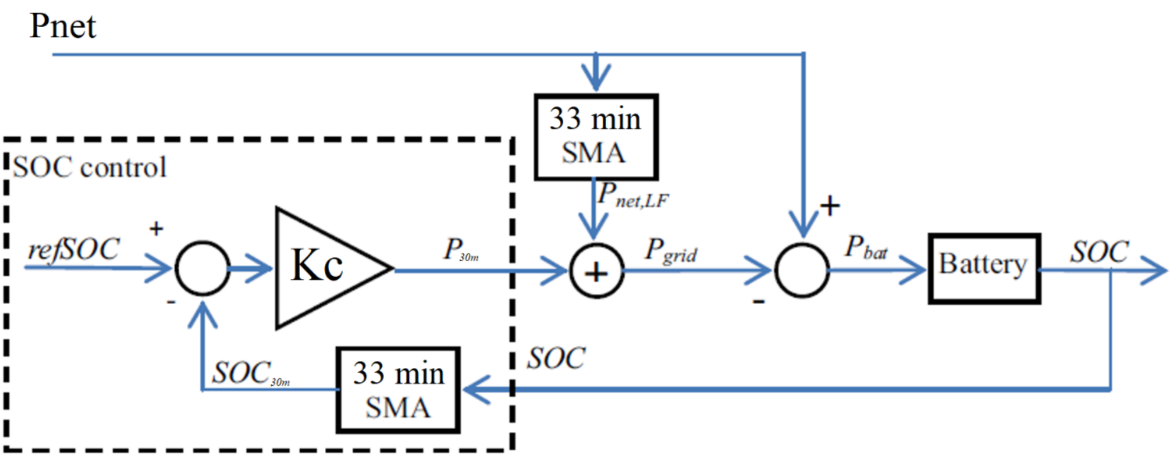

Figure 31: Block diagram of Strategy 2 using the simple moving average low pass filter with average SOC control -diagram adapted from [2]

The signal *Pnet (=Pload-Ppv)* is first processed through the low-pass filter designed in Strategy-1 then a feedback loop taking as input the SOC of the battery and the desired control value (in our case we take our average SOC as refSOC = 90%).

This feedback loop corrects the initial power to be assigned to the battery, such as when the average SOC observed within the past 33 minutes:

- Is below 90%: the battery should charge more or discharge less.
- Is above 90%: the battery should charge less or discharge more.

The following equation illustrates this corrective action of the feedback loop:

$$Pbat(i) = Pnet(i) - Pnet.LF(i) - Kc * (refSOC - SOC30m(i-1))$$

Pnet: the signal processed which is equal to Pload minus Ppv

Pnet.LF: the power to be initially defined as Pgrid which is represents a moving average of Pnet across 33 minutes.

refSOC: is the reference value of the desired average SOC for the operation of the battery.

SOC33m: is the moving average of the battery state-of-charge across the last 33 minutes, the moving window is chosen to be the same as that of the low-pass filter for Pnet.

Kc: is the control coefficient of our feedback loop. It is used to make sure the input control (refSOC) and the output (the SOC of the battery) are consistent.

Pnet, Pnet.LF, refSOC and SOC33m are all known quantities.

In the following subsections, we calculate an appropriate control coefficient Kc and introduce rectification to the equation if any lag between refSOC and the average SOC output is observed. Analysis is first performed on a 7-day dataset then the results are applied to the larger 1-year dataset, amendments are then made in the later in case the results are not satisfactory

5.2.2. Calculating the control coefficient Kc via a swipe analysis

This control coefficient can be calculated using control systems theory as explained in [7][11][12]. Or it can be determined via a swipe analysis, and then rectify the equation if any lag between input and output is found. For that effect, we use a randomly selected 7-day dataset (last week of February 2021) and simulate strategy 2 across a range of values for Kc ranging from 0 to 0.5 kW/%. An increment of 0.001 is used. The results are illustrated in figure 32.

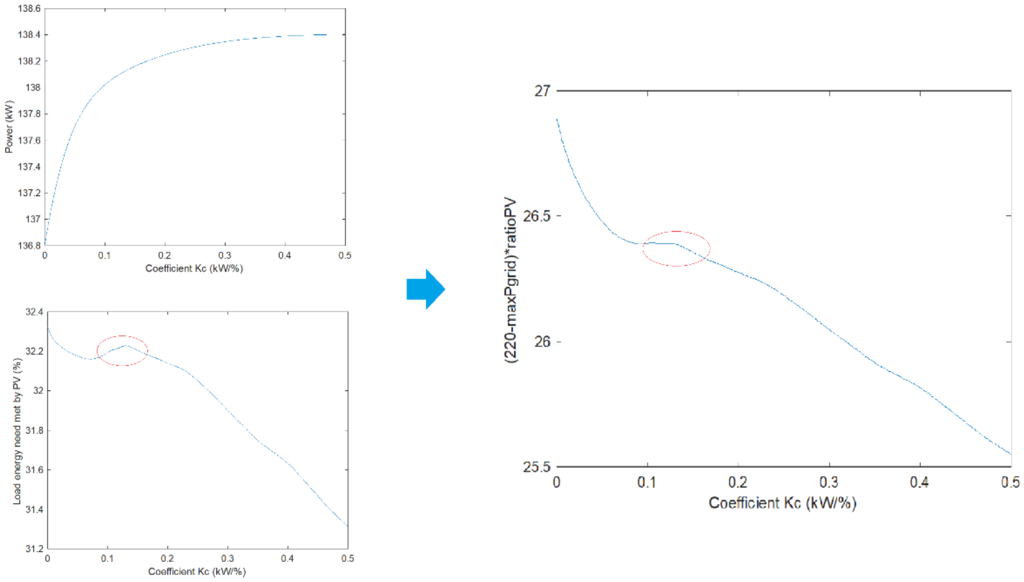

Figure 32: Graphs of P+ (top right), ratioPV (bottom right) and normalized multiplication of the two KPIs (left) as a function of coefficient Kc

The quality criteria P+ and ratioPV do not change significantly. However, based on the swipe analysis shown in figure 32 we decide to pick a value for Kc that corresponds to the local maxima in both the ratioPV function and that of the normalized multiplication.

We settle therefore for ***Kc = 0.113 kW/%***

5.2.3. Correcting the lag between refSOC and the average SOC of the battery

To verify that the control feedback loop works properly, a swipe of the average SOC of the battery is performed using refSOC as a variable between 0% to 100% with an increment of 1%.

The resulting function f(refSOC)=avgSOC should be a linear function equivalent to y=x, if not a modification of the gain equation needs to be performed accordingly. Figure 33 illustrate this swipe analysis.

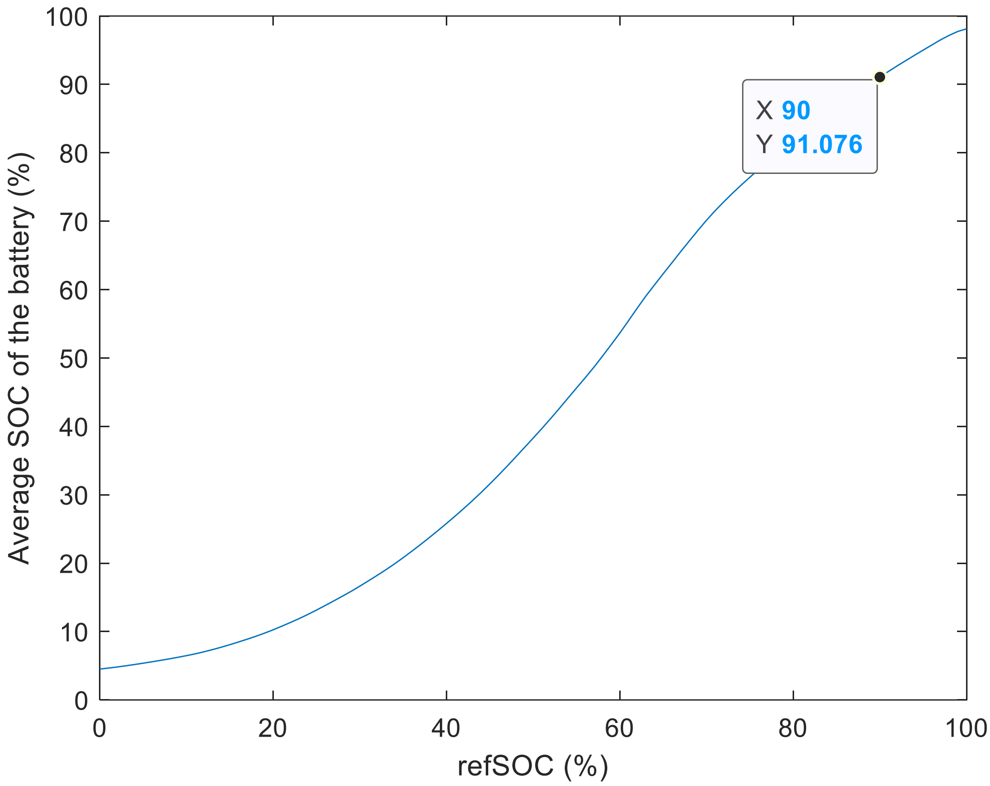

Figure 33: The average SOC of the battery as a function of the input refSOC

For the values of refSOC greater than 60, the f(refSOC) behaves as a linear function where y=x. This is sufficient for our design as when refSOC is lower than 60 as an input: the undesirable high-power peaks show up again in the power absorbed from the grid (Figure 34). Therefore, no adjustment to the model is necessary at this point.

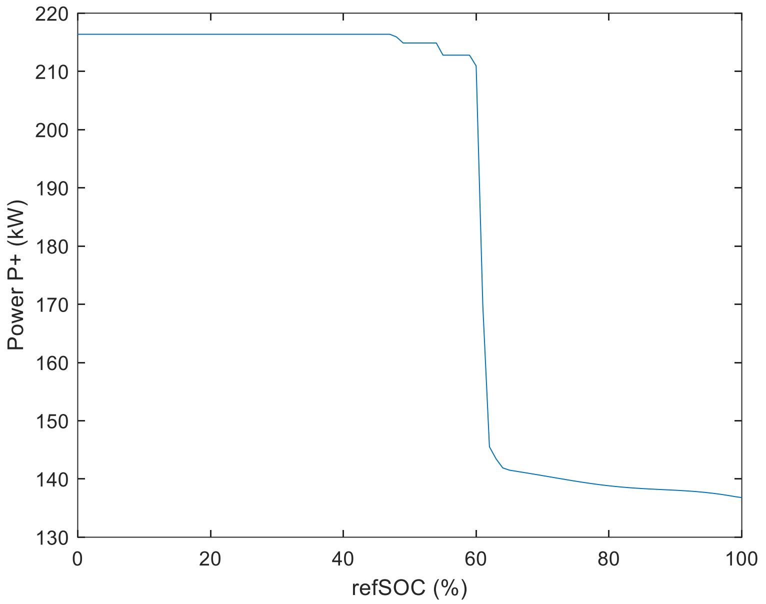

Figure 34: The evolution of quality criteria P+ as a function of the input refSOC (%)

5.2.4. Applying the strategy to the 7-day dataset

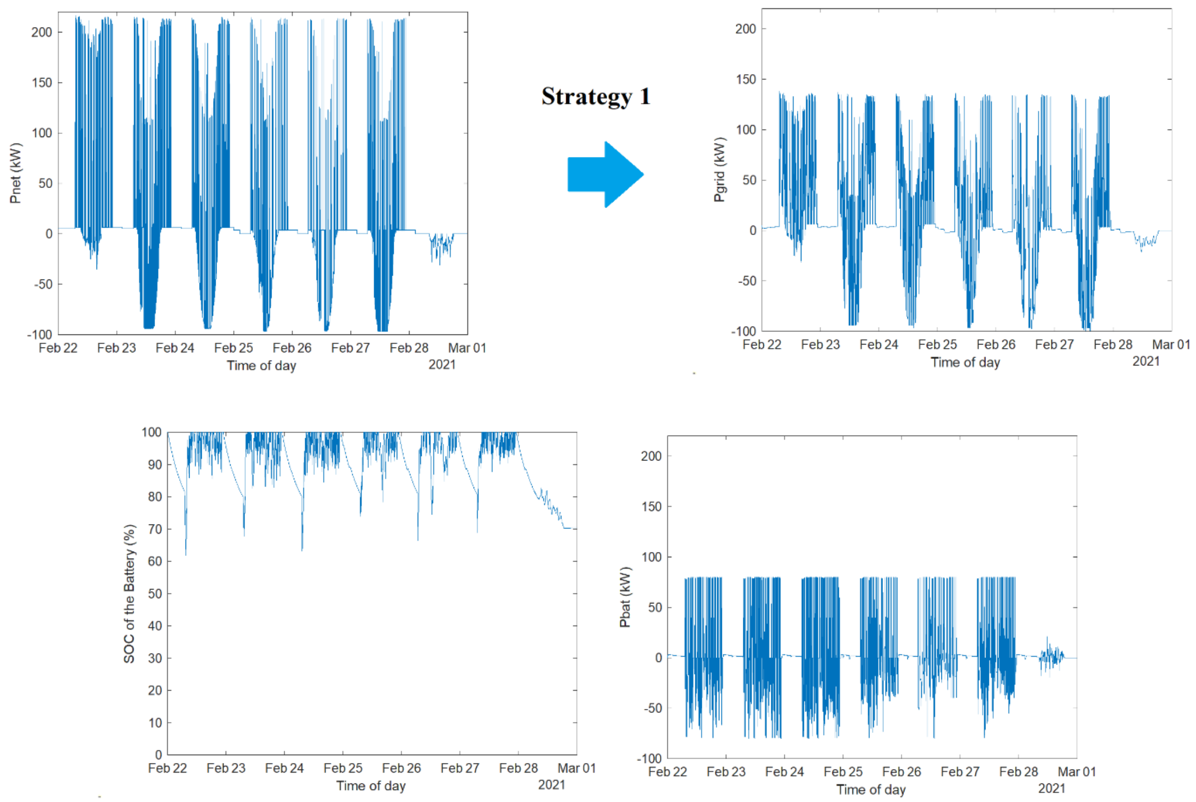

Figure 35: Pnet (top left), Pgrid (top right), battery state-of-charge (bottom left) and Pbat (bottom right) with energy management Strategy 2 (7-day DATASET)

Table IX: quality criteria results of Strategy 2 applied to a 1-week dataset

7-day DATASET	P+ (kW)	ratioPV	Battery EOL	PPV	Peak Shaved (kW)	Average SOC
Strategy 2 (SMA filter with avgSOC control)	138.06	38.17%	2year4months	7.323	78.31	91.07%
Strategy 0 (Pnet)	218.00	15%	-	15.32		-
Possible Improv.	137.00	37%	-	7.5	80.00	-

5.2.5. Applying the strategy to the 1-year dataset

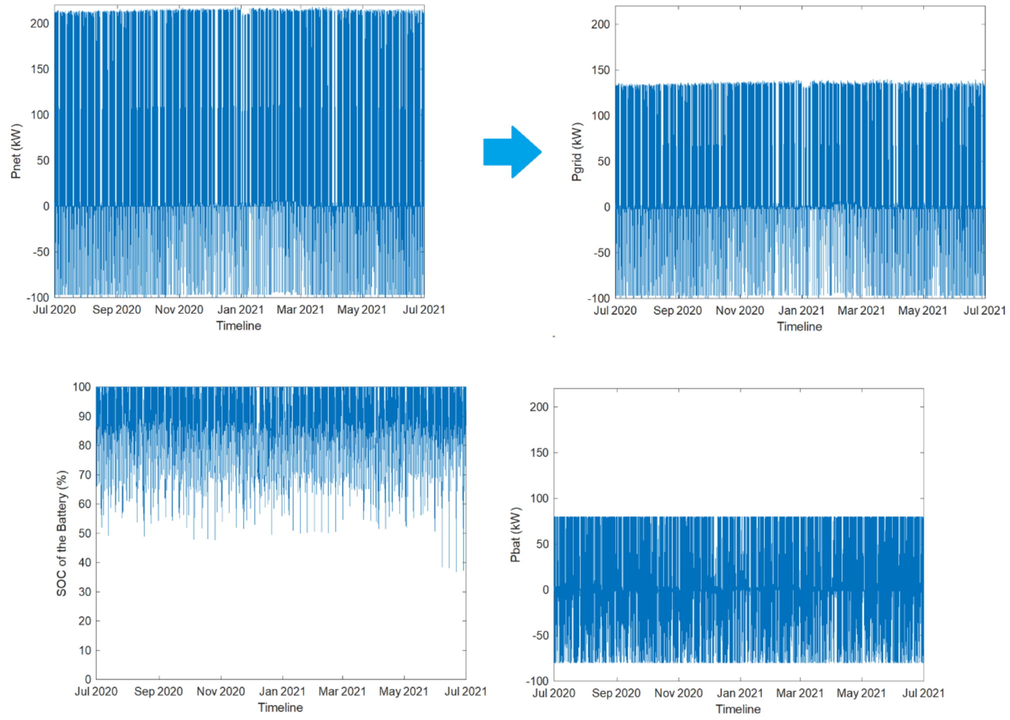

Figure 36: Pnet (top left), Pgrid (top right), battery state-of-charge (bottom left) and Pbat (bottom right) with energy management Strategy 2 (1-year DATASET)

5.2.6. Results and conclusion – Strategy 2

Table X: Quality criteria results of Strategy 2 and comparison with Strategy 0 and Strategy 1

Simulation using the 1-year DATASET	P+ (kW)	ratioPV	Battery EOL	PPV	Peak Shaved (kW)	Average SOC
Strategy 0 (Pnet)	218.00	15%	-	15.32		-
Strategy 1 (SMA filter without SOC control)	138.68	31.43%	2year3months	10.89	79.13	95.11%
Strategy 2 (SMA filter with avg SOC control)	139.52	31.06%	2year2months	10.89	78.28	89.60%
Possible Improv.	137.00	37%	-	7.5	80.00	-

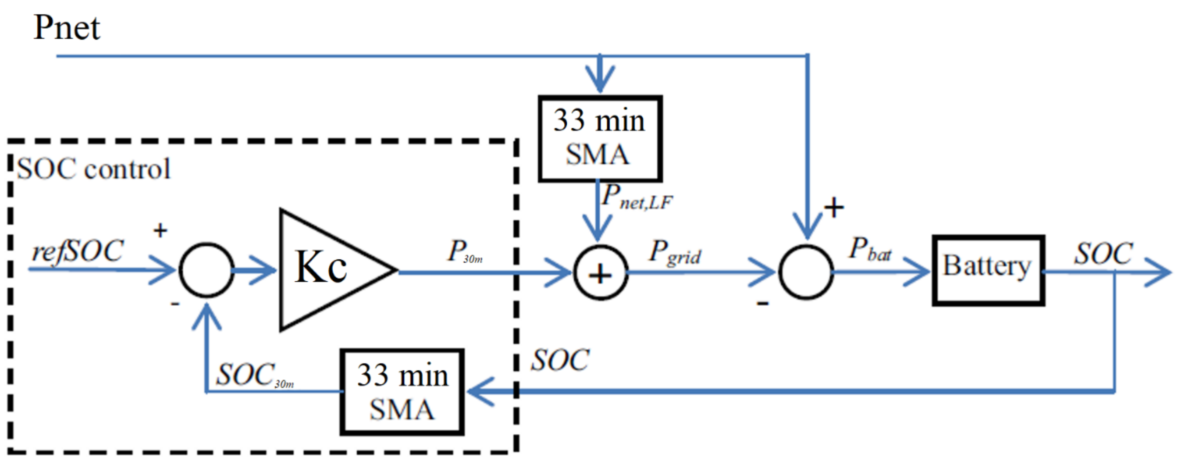

Figure 37:Final block diagram of Strategy 2

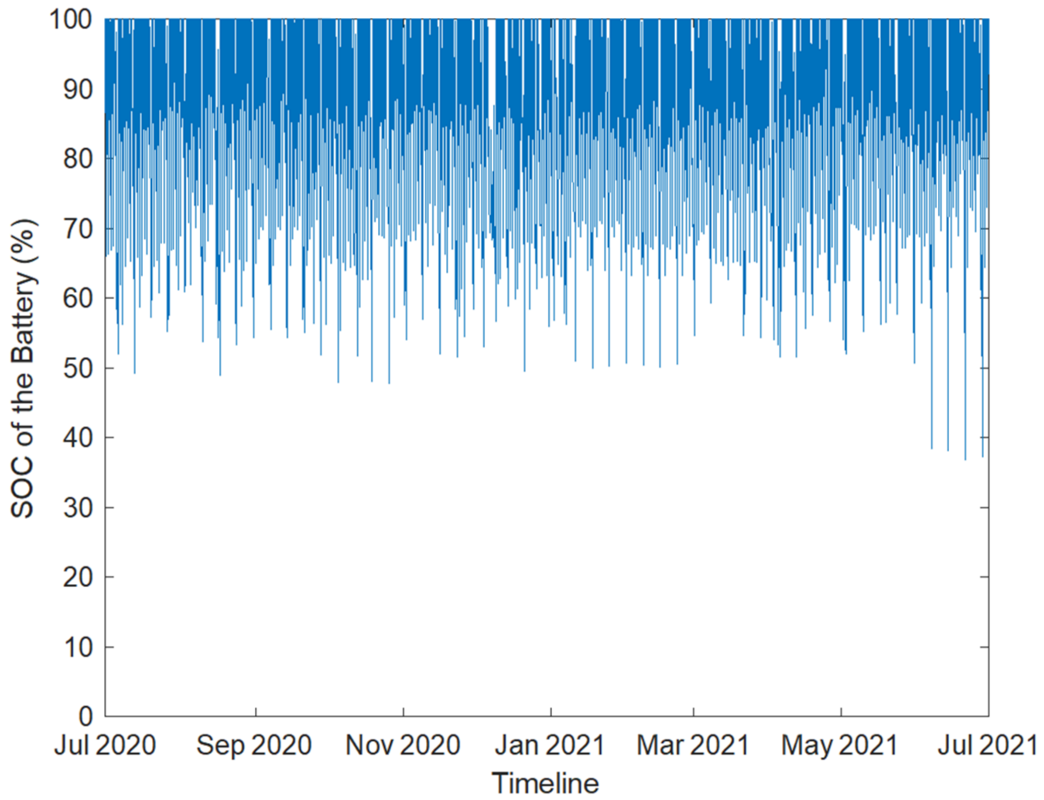

Figure 38: Simulated State-of-charge (SOC) profile of the battery using Strategy 2

The following model is being used by Strategy 2:

$$Pbat(i) = Pnet(i) - Pnet.LF(i) - 0.1130 * (90\% - SOCavg(i-1))$$

In this simulation, we can center the average SOC of the battery around 90% successfully without compromising on the gains (from Strategy 1) in power peak shaving and PV energy use in a significant way.

The **next step** now in the design of the strategy is to define a SOC maximum limit for the battery and handle any loss of control in instances where the battery would empty completely.

5.3. Strategy 3: SMA filter with average SOC and SOC limits controls

After applying a low-pass filter to our *Pnet* signal considering the battery energy and power limits (Strategy 1), we made sure that the battery operates at a defined average state-of-charge throughout the year (Strategy 2). Now, what is left to do is to limit the SOC fluctuations to a maximum value (lower than 100%) and to a minimum value (higher than 20%). This should be done without having power peaks emerge again or loosing too much on the ratioPV quality criteria and the expected battery end-of-life.

In this section we perform the following:

- Firstly, a Strategy 3 (v1) is designed where a SOCmax value is introduced to give a maximum value to the operating SOC of the battery in the one-year simulation.
- A suitable value for SOCmax is chosen by doing a swipe of potential values between 90% and 99% to see how it affects P+, ratioPV and the batteryEOL.
- Secondly a Strategy 3 (v2) is designed on top of (v1) where we slow down the battery's discharge when the SOC gets closer to 20%.
- Unlike with SOCmax, it is best not to define a "set value" for the minimum SOC of the battery because if the SOC reaches this minimum value, the battery will cease to give power to the charging station, and we will be getting peaks again in our *Pgrid* profile.
- It is better to add a SOC control to our strategy so that the battery slows down discharging as it approaches the said SOCmin value.

This latter approach is not used for SOCmax simply because it is not practically possible to control the SOC below 100% as it approaches it, and at the same time keep having consistent peak shaving throughout the year. The average battery SOC will need to be very small (around 10%) which presents several issues: low average SOC lead to low power charge and discharge and, the battery tends to age faster as the average SOC lowers.

5.3.1. Block diagram of strategy 3 (v1) – average SOC and maximum SOC controls:

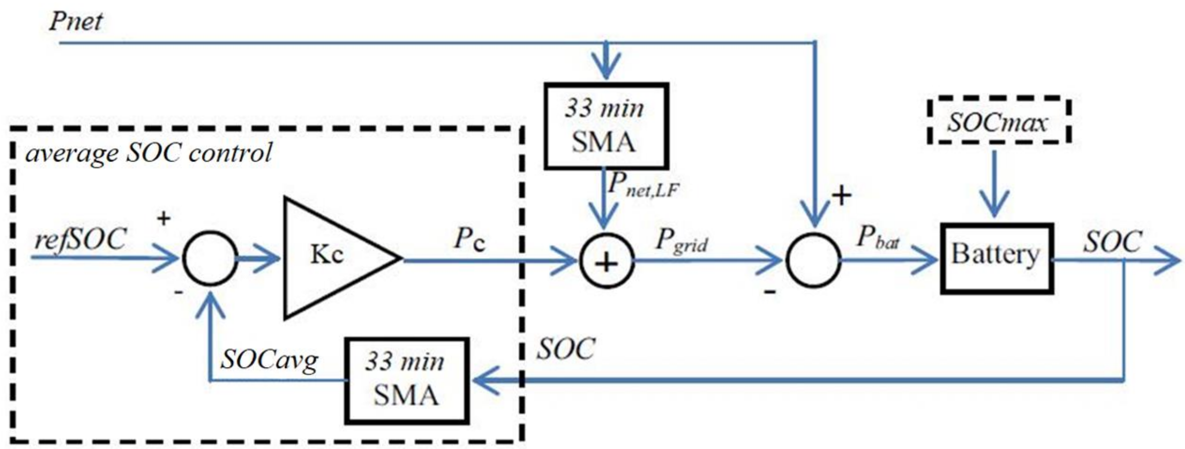

Figure 39: Block diagram of Strategy 3 (v1) including the control of the average SOC and the maximum SOC

In the block diagram shown in figure 39, the model used in the Matlab simulation for the battery (battery block) includes a constraint on the maximum possible value for the SOC.

In the real-life system, there is no need for a battery block in our model as the SOCmax is a parameter that is also defined directly on the inverter. For more details on the battery block modeling, please refer to chapter 3.

5.3.2. Choosing a suitable SOCmax (swipe analysis)

Given that the battery is operating at a 90% average SOC, we choose a value of SOCmax between 90% and 99%.

We also try to choose a value in such a way that it does not affect the quality criteria P+ (max power absorbed from the grid), ratioPV (how much of the energy need of the load is met by the PV panels) and the average SOC of the battery.

For this, we perform a swipe of values of SOCmax on the entire 1-year dataset and see how it affects the above-mentioned quality criteria (figure 40).

Result: we find that SOCmax between 90% and 99% do not affect P+, ratioPV and batteryEOL that much. We choose finally to settle for SOCmax=95% as it keeps the averageSOC of the battery close to our desired value (averageSOC=90%)

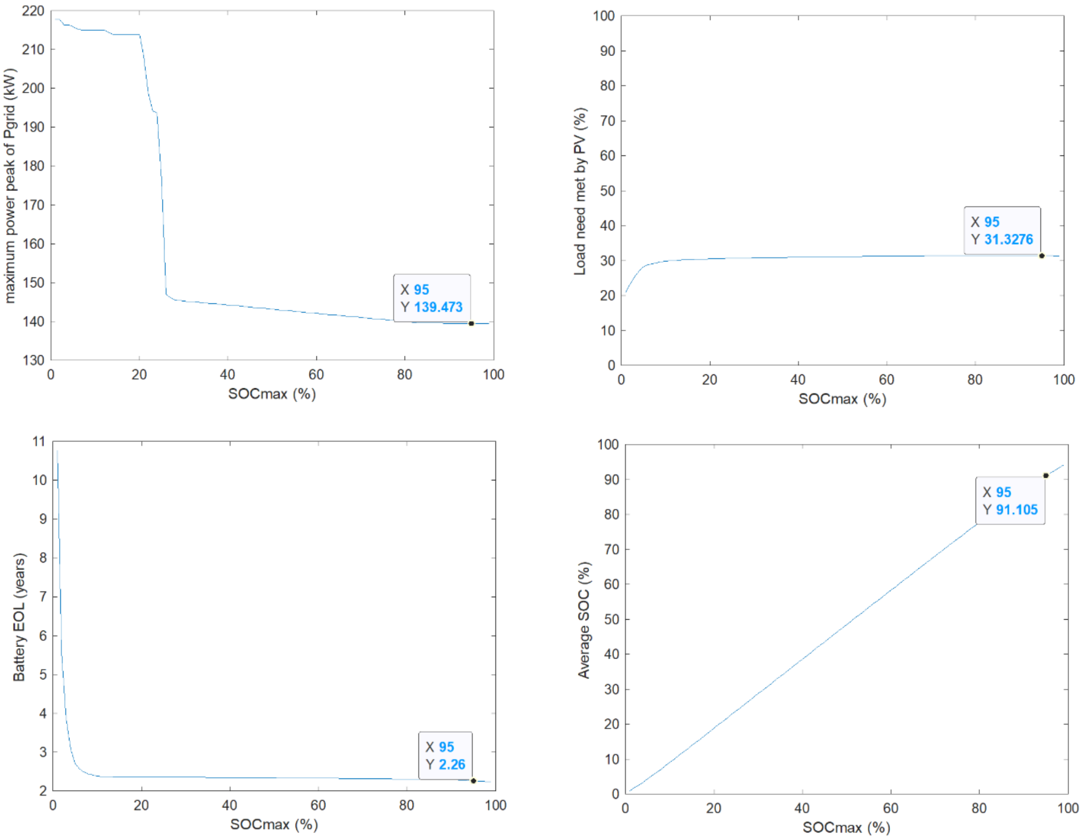

Figure 40: How the maximum power peak of Pgrid (top left), ratioPV (top right), battery end-of-life (bottom left) and the average SOC (bottom right) change as a function of SOCmax for values between 1% to 99%

Table XI: Quality criteria results for Strategy 3 (v1) and comparison with Strategy 0, 1 and 2

Simulation using the 1-year DATASET	P+ (kW)	ratioPV	Battery EOL	PPV	Peak Shaved (kW)	Average SOC
Strategy 0 (Pnet)	218.00	15%	-	15.32	00.00	-
Strategy 1 (SMA filter without SOC control)	138.68	31.43%	2year3months	10.89	79.13	95.11%
Strategy 2 (SMA filter + avg SOC control)	139.52	31.06%	2year2months	10.89	78.28	89.60%
Strategy 3.v1 (SMA + avg SOC and max SOC controls)	139.47	31.33%	2year3months	10.93	78.53	91.11%
Possible Improv.	137.00	37%	-	7.5	80.00	90.00%

5.3.3. Block diagram of strategy 3 (v2) – average, maximum and minimum SOC controls

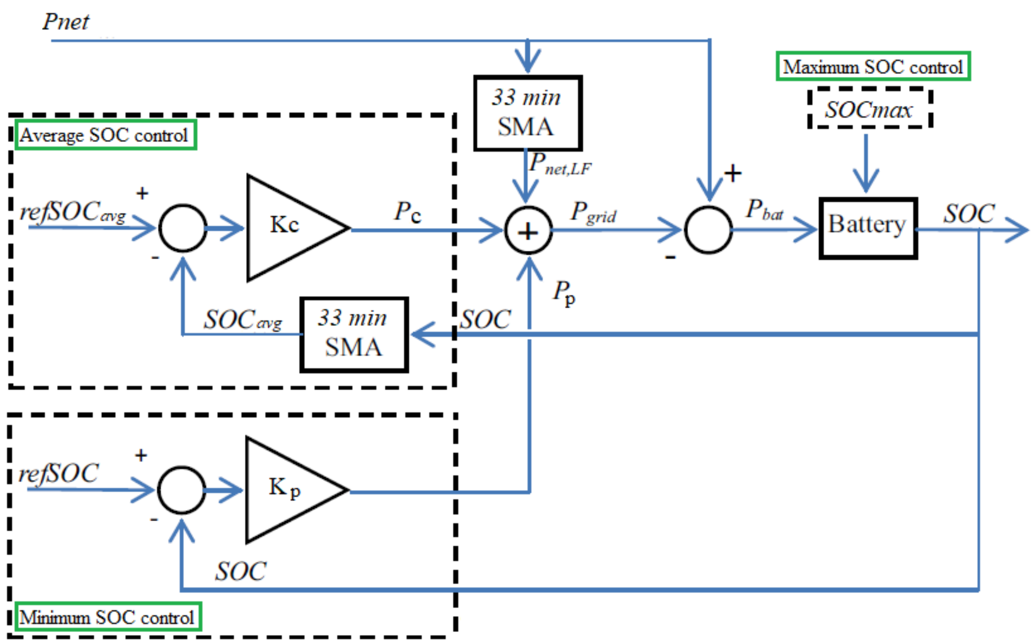

Figure 41: Block diagram of Strategy 3 (v2) including the control of the average, minimum and maximum SOC

In the block diagram shown in figure 41, we control the minimum SOC of the battery using the following equation:

$$Pp = Kp(i) * (refSOC - SOC(i))$$

- Kp(i): is a control coefficient expressed in kW/% and changes depending on SOC(i)
- refSOC: is the SOC value below which the control is activated to slow the discharge of the battery.
- SOC(i): is the SOC of the battery second by second in %

And the power instruction to the battery inverter is given by the following equation:

$$Pbat = Pnet - Pnet.LF - Kc * \left(refSOCavg - SOCavg(i)\right) - Kp(i) * (refSOC - SOC(i))$$

The coefficient Kp(i) is defined as follows:

- If SOC(i) > refSOC:

$$Kp(i) = 0$$

- Else if SOC(i) <= refSOC

$$Kp(i) = KpMAX * \frac{|\,(100 - refSOC) - SOC(i)\,|}{100 - refSOC}$$

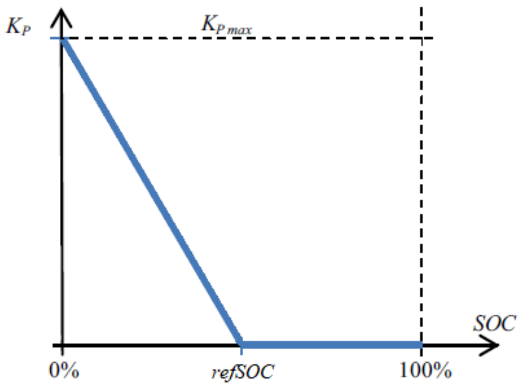

Figure 42: Proportional factor Kp as a function of SOC

To illustrate how this works, let's imagine that refSOC=50%. This means that whenever the SOC performs below 50%, we want to slow down the discharging of the battery in such a way that we limit its depth of discharge and eventually never reach values below 20%. It is an indirect way to set a minimum value for SOC.

There are two instances:

- When the SOC is greater than refSOC (in our example 50%) nothing happens, and this strategy operates the same as Strategy 3 (v1).
- When the SOC takes values smaller than refSOC (in our example 50%):
  - In the control equation $Pp = Kp(i) * (refSOC - SOC(i))$ the quantity *(refSOC – SOC(i))* is always positive and Kp(i) is greater than 0: therefore, Pp becomes positif.
  - We substract Pp from Pbat, asking the battery to discharge slower than it is. (Pbat is positive when the battery gives power to the system, and it is negative when is recharges)
  - The rate of slowing the discharge is controled by the coefficient Kp(i). The closest this quantity is to real-time SOC(i)=0%, Kp(i) approaches to a maximum value KpMAX, making the slowing down of discharge most aggressive. The different values that Kp(i) takes depending on SOC(i) is illustrated in figure 42.

5.3.4. Choosing suitable KpMAX using swipe analysis

The next step is to choose a suitable value for KpMAX. For this purpose, we fix refSOC to a high value say 90% and perform a swipe analysis to see how the minimum SOC evolve by taking different values of KpMAX between 0.01 kW/% and 0.5 kW/% with an increment of 0.005%. We also would like to see that once refSOC is fixed, whether the value KpMAX has an impact on P+, ratioPV and batteryEOL.

This swipe of values of KpMAX is performed on the entire 1-year dataset and the results are shown in figure 43.

Result: Once refSOC is fixed, the value of KpMAX is not a significant variable therefore we opt for KpMAX=Kc= 0.113 kW/% then perform a swipe analysis with refSOC in the next section. It is worth observing that the minimum SOC when refSOC=90% is above 50% and the other quality criterias (P+, ratioPV and battery EOL) remain at values close to what was found in previous strategies. This is positive because it is expected that the quality criteria worsen as we add to the model more constraints; it is not the case however when refSOC=90%;

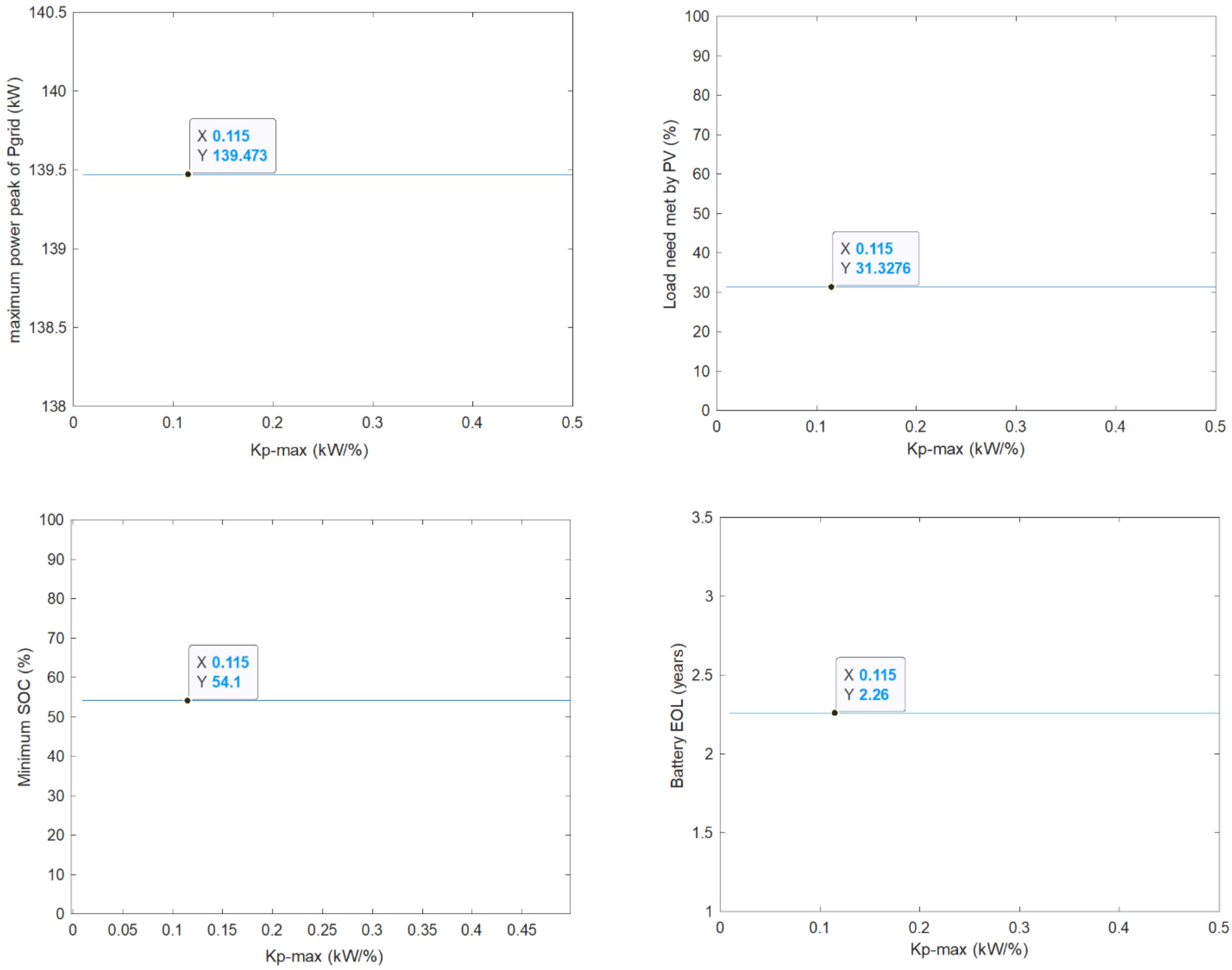

Figure 43: How the maximum power peak of Pgrid (top left), ratioPV (top right), battery end-of-life (bottom left) and the minimum SOC (bottom right) change as a function of KpMAX for values between 0.01 kW/% to 0.5 kW/%

5.3.5. Choosing a suitable refSOC using swipe analysis

To choose a suitable refSOC value below which the battery is instructed to slow down its discharge (to avoid a battery operating too much under a SOC of 20%), we simulate Strategy 3 (v2) on a 1-year dataset of Pnet and see how the minimum SOC, P+, ratioPV, batteryEOL and the average SOC evolve as refSOC changes.

We choose the following constants:

- Moving average period of 33 minutes for the two SMA filters.
- The average SOC reference = 90%
- The coefficient Kc = 0.1130 kW/%
- The maximum SOC = 95%
- The coefficient KpMAX = 0.1130 kW/%

The variable refSOC changes between the following values:

- Minimum value: 0%
- Maximum value: 100%
- Increment value: 1%

Criteria of selection:

- We want a value of refSOC that keeps the minimum SOC above 20% in the simulation.
- We want a value of refSOC that keeps the average SOC at the desired 90%.

The results of the numerical swipe are shown in figure 44.

It is observed that the change in our quality criteria occur only with values of refSOC beyond 95%. However, any values lower than this, yield to good values for our criteria:

- The minimum SOC is about 54% well above the 20% limit.
- The average SOC also remains close to the desired 90%.
- All other quality criteria remain at very good values.

We decide therefore to choose refSOC to be 50% meaning that the “minimum SOC control” will operate only in the rare event when the battery is pushed to operate below 50% of its state-of-charge. Something that do not happen at all in this simulation based on 1-year of data.

This SOC control is kept however as a measure in case of rare events when the battery must charge three to four electric buses back-to-back with a full charge without any time for recharging itself. An event that is very unlikely to occur, but it should be kept as a safety measure regardless.

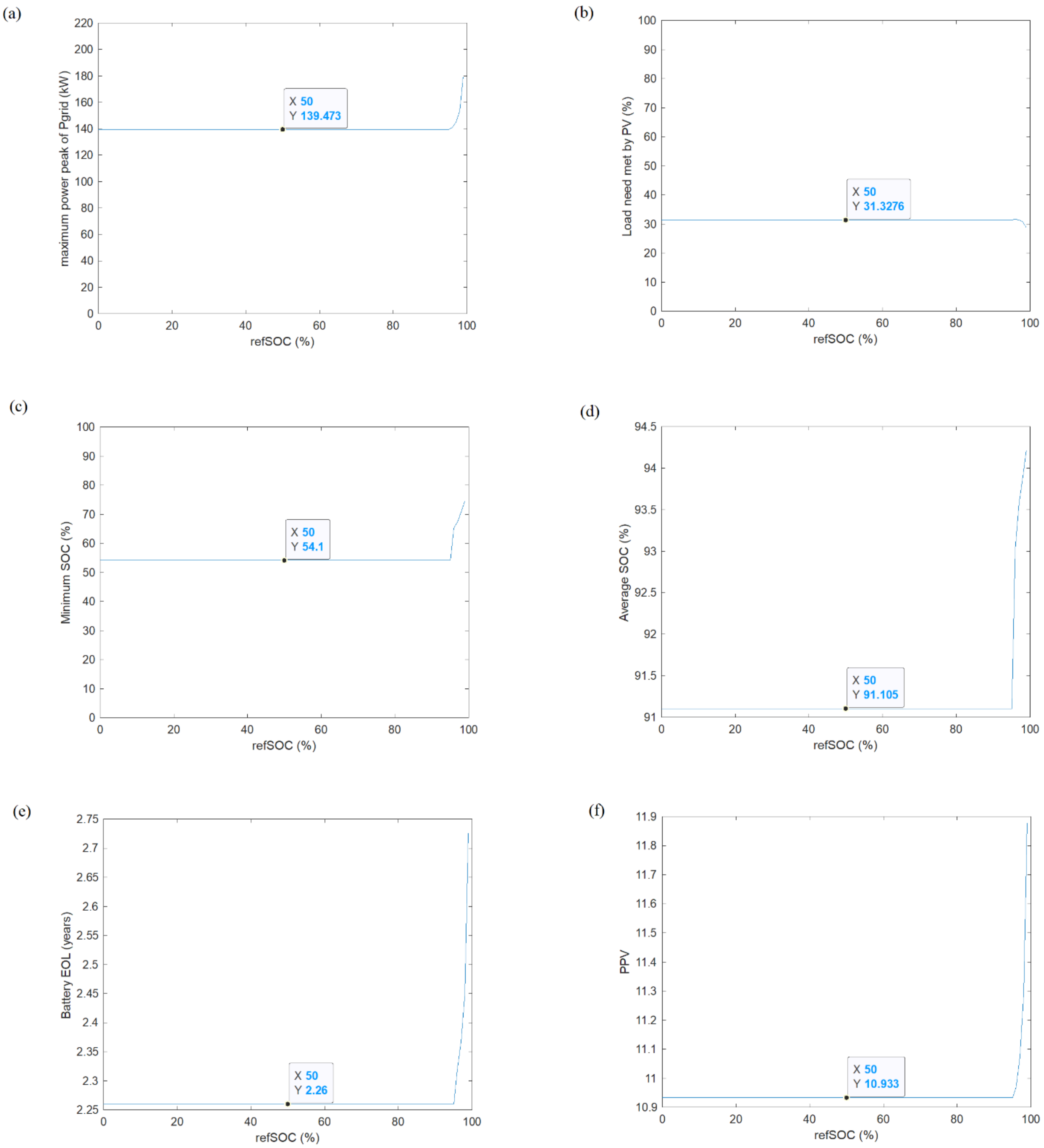

Figure 44: The variation of P+ (a), ratioPV (b), minimum SOC (c), average SOC (d), battery expected end-of-life (e) and PPV (f) as a function of refSOC using energy management strategy 3 (v2)

5.3.6. Summary and results of final SMA-based energy management strategy 3 (v2)

Energy management strategy (3-v2) consists of taking first the signal Pnet of our fast-charging station microgrid into a low-pass filter modeled as a moving average block of 33 minutes moving average window. The resulting SOC of the battery is then adjusted to operate around an average SOC of 90%, a maximum SOC of 95% and a minimum SOC of 54% as per the MATLAB modeling and simulation.

The results of simulating this strategy on the 1-year dataset are shown in Table XII, figure 45, 46 and 47.

Conclusion: Using this strategy we can keep the battery operating between 95% SOC and 54% SOC, while keeping the average SOC around 90% and the quality P+, ratioPV, battery end-of-life close to their best values.

Table XII: Quality criteria results for energy management strategy (3.v2) and a comparison with other strategies

Simulation using the 1-year DATASET	P+ (kW)	ratioPV	Battery EOL	PPV	Peak shaving (kW)	Average SOC	Min SOC
Strategy 0 (Pnet)	218.00	15%	-	15.32	00.00	-	-
Strategy 1 (SMA filter without SOC control)	138.68	31.43%	2year3months	10.89	79.13	95.11%	42.78%
Strategy 2 (SMA filter + avg SOC control)	139.52	31.06%	2year2months	10.89	78.28	89.60%	36.40%
Strategy 3.v1 (SMA + avg SOC and max SOC controls)	139.47	31.33%	2year3months	10.93	78.53	91.11%	31.40%
Strategy 3.v2 (SMA+ avg, min and max SOC controls)	139.47	31.33%	2year3months	10.93	78.53	91.10%	54.10%
Possible Improv.	137.00	37%	-	7.5	80.00	90.00%	

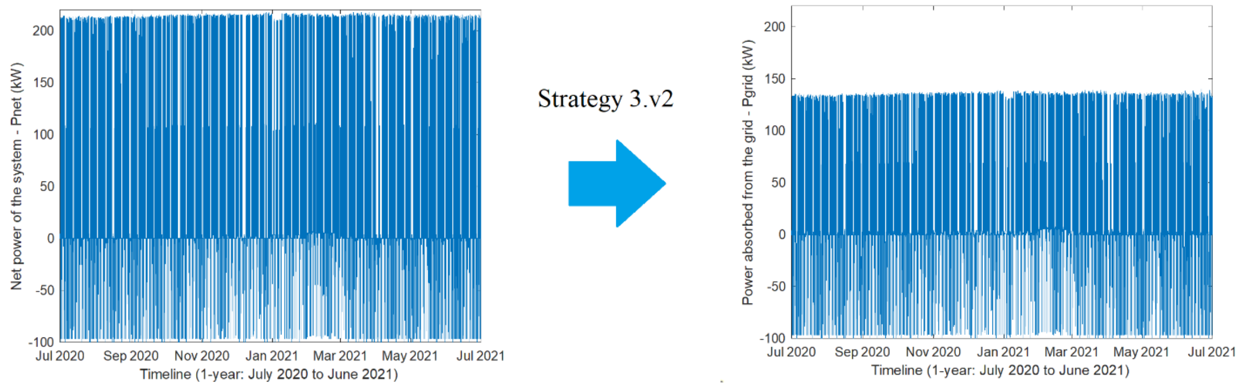

Figure 45: Power absorbed from the grid (Pgrid) by the fast-charging station over a year using energy management strategy 3.v2 for a whole year (simulation using Matlab) – power peak shaving of 78.53 kW

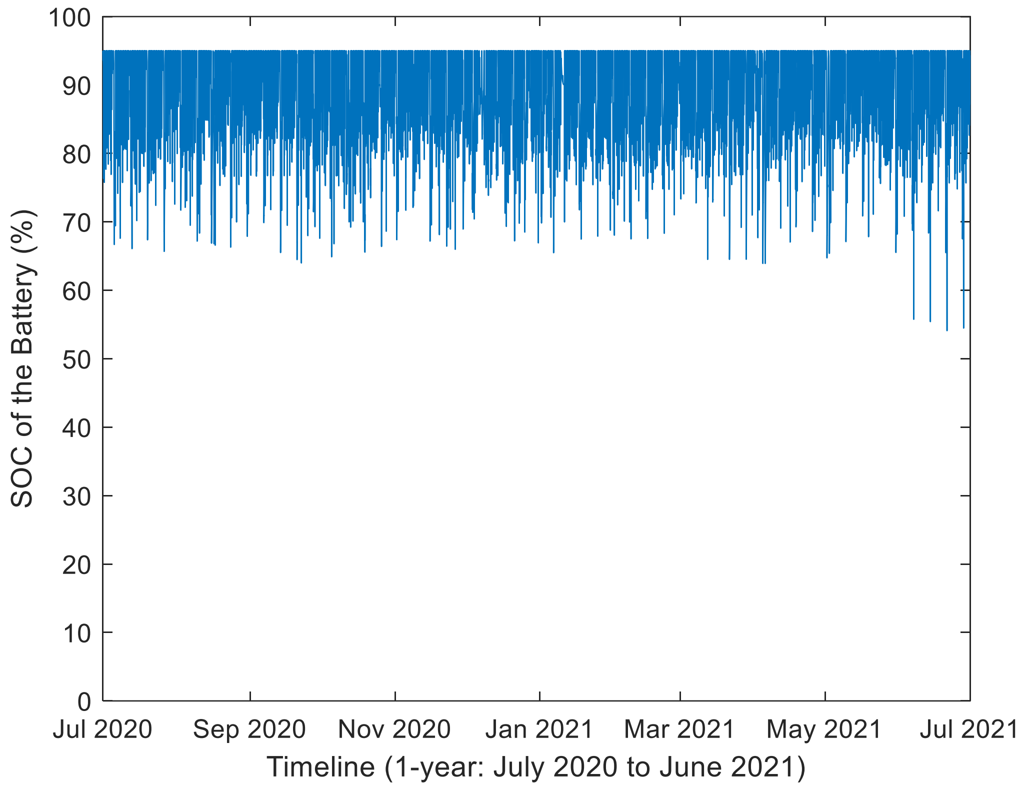

Figure 46: State-of-charge SOC of the battery using energy management strategy 3.v2 for a whole year (simulation in Matlab)

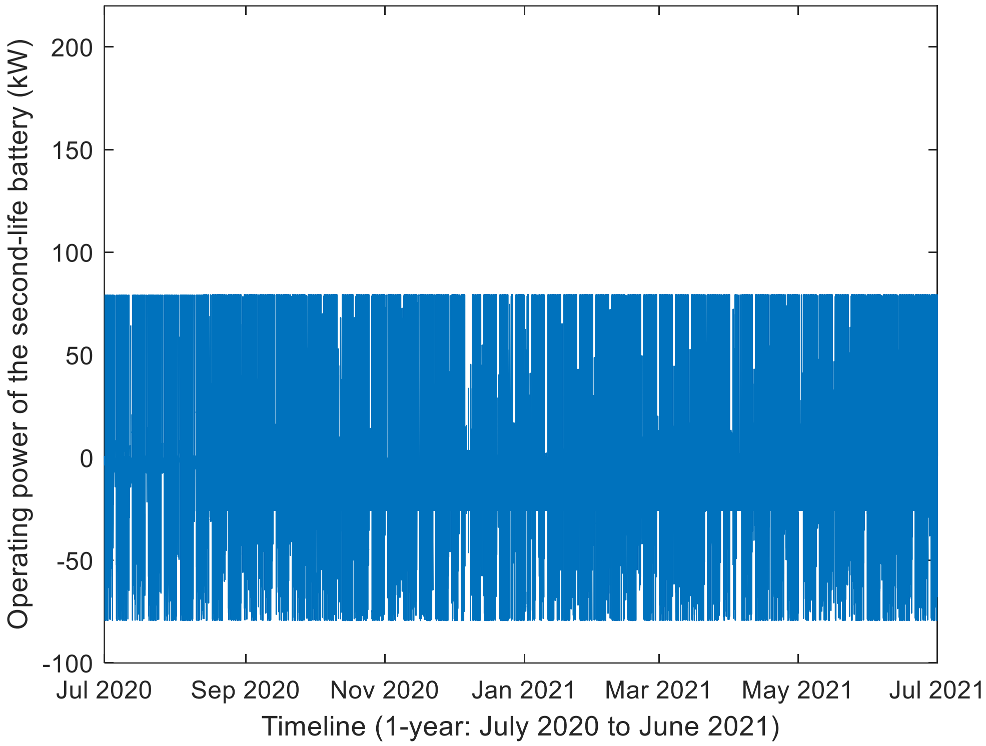

Figure 47: Operating power of the battery using energy management strategy 3.v2 for a whole year (simulation in Matlab)

5.4. Conclusion

5.4.1. Comparison of SMA-based and CMA-based strategies

In order to assess if at this point, using a central moving average low pass filter is worth it or not, we run two more simulations using two strategies:

- **Strategy 4:** CMA low-pass filter with perfect forecasting.

This strategy is similar to strategy 1. However, it uses the central moving average (CMA) function instead of the simple moving average (SMA). The moving average window remains the same as previously (33 minutes). We assume that the forward half of this moving average window is based on perfect forecast. Practically speaking, we just run the CMA-filter on the 1-year dataset using real data instead of a trailing moving average. Figure 48 is the block diagram of this strategy.

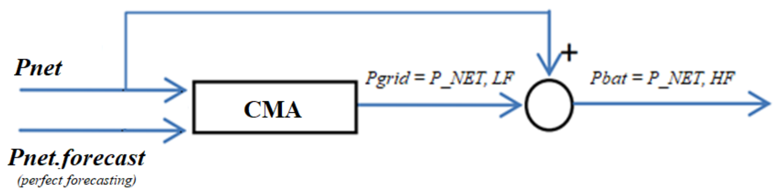

Figure 48: Block diagram of an energy management strategy based on the central moving average with perfect forecasting – Strategy 4

- **Strategy 5:** CMA low-pass filter with perfect forecasting and SOC controls

This strategy is similar to strategy 3.v2. However, instead of processing *Pnet* through a SMA low-pass filter, we use a CMA low-pass filter assuming perfect forecasting as above. Figure 49 is the block diagram of this strategy.

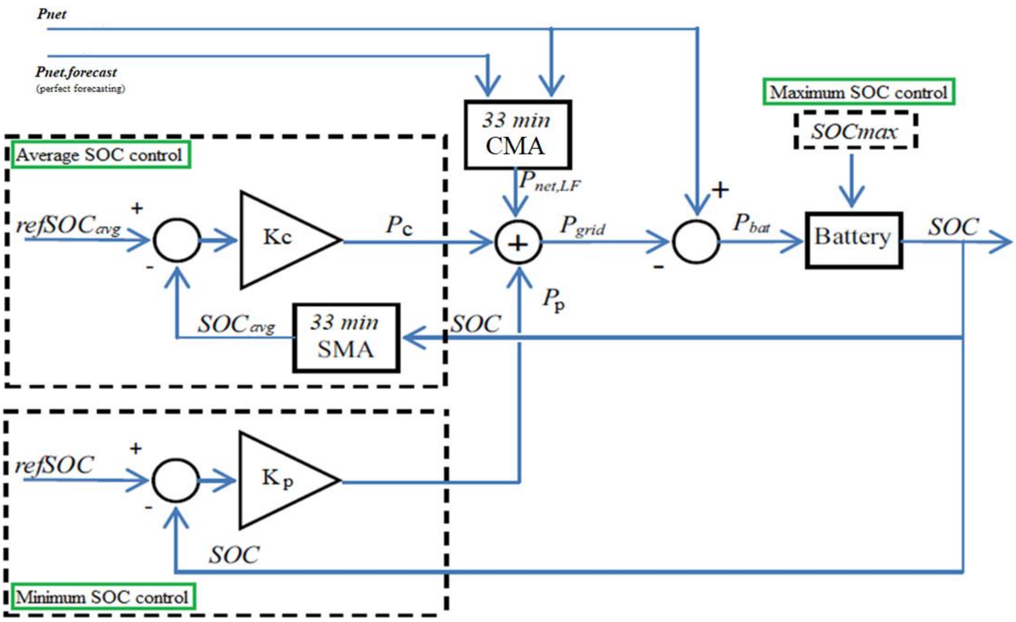

Figure 49: Block diagram of an energy management strategy with CMA low-pass filter and SOC controls – Strategy 5

We run a simulation for the two strategies and the characteristics of the resulting Pgrid and SOC are show in Table XIII.

<u>Comment:</u> both strategies bring slight improvements to quality criteria P+ (power absorbed from the grid by the fast-charging station) at about less than 1kW, and to ratioPV (the portion of the energy need of the fast-charging station met by the PV system) at about slightly more than 1%. The battery expected end-of-life remain the same, however.

These improvements **are not significant enough** to pursue the CMA-based strategies further, therefore at this stage: we settle for strategy 3.v2 (SMA + avg,min and max SOC controls) as model to implement our fast-charging microgrid.

Table XIII: Comparison of the SMA-based and the CMA-based energy management strategies using the quality criteria

Simulation using the 1-year DATASET	P+ (kW)	ratioPV	Battery EOL	PPV	Peak shaving (kW)	Average SOC	Min SOC
Strategy 0 (Pnet)	218.00	15%	-	15.32	00.00	-	-
Strategy 1 (SMA filter without SOC control)	138.68	31.43%	2year3months	10.89	79.13	95.11%	42.78%

Strategy 2 (SMA filter + avg SOC control)	139.52	31.06%	2year2months	10.89	78.28	89.60%	36.40%
Strategy 3.v1 (SMA + avg SOC and max SOC controls)	139.47	31.33%	2year3months	10.93	78.53	91.11%	31.40%
Strategy 3.v2 (SMA+ avg, min and max SOC controls)	139.47	31.33%	2year3months	10.93	78.53	91.10%	54.10%
Strategy 4 (CMA with perfect forecasting)	138.22	32.65%	2year3months	10.68	79.78	98.11%	77.73%
Strategy 5 (CMA with perfect forecasting + avg, min and max SOC controls)	138.74	32.54%	2year3months	10.73	79.26	92.22%	72.16%
Best values	138.22	32.65%	2year3months	10.73	79.78	91.10%	77.73%

5.4.2. Choosing Strategy 3.v2 for implementation in the real-life system

Strategy 3.v2 presents several advantages:

- The peak shaving simulated using this strategy (78.53 kW) is very close from the possible maximum discharge power of the battery (80.00 kW).
- The system is expected to meet its power needs by "31.33%" from the photovoltaic system. This is very close to the theoretical limit defined by the CMA strategies of (32.65%)
- It enables the control of the average, minimum and maximum state-of-charge of the battery without compromising too much on the peak shaving gains (by less than 1 kW) and the ratio of energy need met by the PV system (by less than 1%) compared to strategy 1 (the simplest SMA-based strategy)
- The strategy also does not depend on any forecasting of the load or PV production. At the same time, it performs peak-shaving and pv self-consumption services close to methods with perfect forecasting (strategy 4 and 5).
- Based on the simulation, the strategy is expected to provide comfortable battery reserve as its minimum SOC is expected to be higher than 50%. In fact, besides a couple of times going to 54%, the battery operates mostly between 60 and 70% SOC with an average of 91%.
- The minimum SOC control is designed for a worst-case scenario that is very unlikely to ever occur making it very robust for unpredictable charging times.

Refer to Table XIII for a comparison of all strategies based on key performance indicators (quality criteria)

The expected power exchange with the electric grid of our fast-charging station microgrid is shown in figure 45 along with the simulated SOC of the battery (figure 46) and the operating power profile of the battery (figure 47).

The block diagram of the Matlab simulation using strategy 3.v2 is show in figure 50.

5.4.3. Input-output model of energy management strategy 3.v2

The model used for the simulation takes in 12 inputs for one output.

The simulation model inputs are:

- ***Pload:*** the power absorbed by the fast-charging station from the electric grid.
- ***Ppv:*** the power generation of the solar pv system.
- ***SOC(1h):*** the state-of-charge of the battery for the last hour.
- ***Pload(1h):*** Pload for the last hour.
- ***Ppv(1h):*** Ppv for the last hour.
- ***SMAperiod(Pnet):*** the moving average window period for the low pass filter applied to Pnet – the optimum found value in our analysis for this input is 0.56h.
- ***SMAperiod(SOC):*** the moving average window period for the low pass filter applied to SOC – the optimum value found in our analysis for this input is 0.56h.
- ***refSOCavg:*** the desired average SOC value for the operation of the battery system.
- ***Kc:*** the coefficient used to adjust the battery SOC to our desired refSOCavg – the optimum value found in our analysis for this input is 0.1130 kW/%.
- ***SOCmax:*** the maximum SOC allowed for the operation of the battery system.
- ***refSOC:*** the SOC value below which the strategy instructs the battery to slow down its discharge rate. This is an indirect way to avoid instances where the battery operates below 20% - we choose an optimum value for this input of 50%.
- ***Kp:*** the coefficient (or in this case the proportional factor) used to instruct the battery to slow down below refSOC value – we choose a value for this input of 0.1130 kW/%.

The model outputs are:

- ***Pbat***: the instructed power at which the battery should operate given to the battery system inverter.
- ***Pgrid***: the power absorbed by the charging station from the electric grid
- ***SOC:*** the state-of-charge of the battery

Important: It is worth noting that the Matlab simulation and the real-life model to be implemented in the system have differences (refer to Figure 38 and 39):

1. The simulation runs a battery model to produce and simulate the SOC of the battery. This won't be necessary with the real-life model as the SOC is an input that can be taken from the battery.

2. To set limits to the battery, we use a votlage-SOC model in the simulation, this won't be necessary for the real-life system as we can simply take the battery voltage and battery current as inputs.
3. The maximum state of charge (SOCmax) can also be programmed on the battery inverter and be taken as an input
4. In the real-life system Pgrid is not an output but a consequence of applying the strategy. It can be measured by gathering wattmeter data at the fast-charging station.

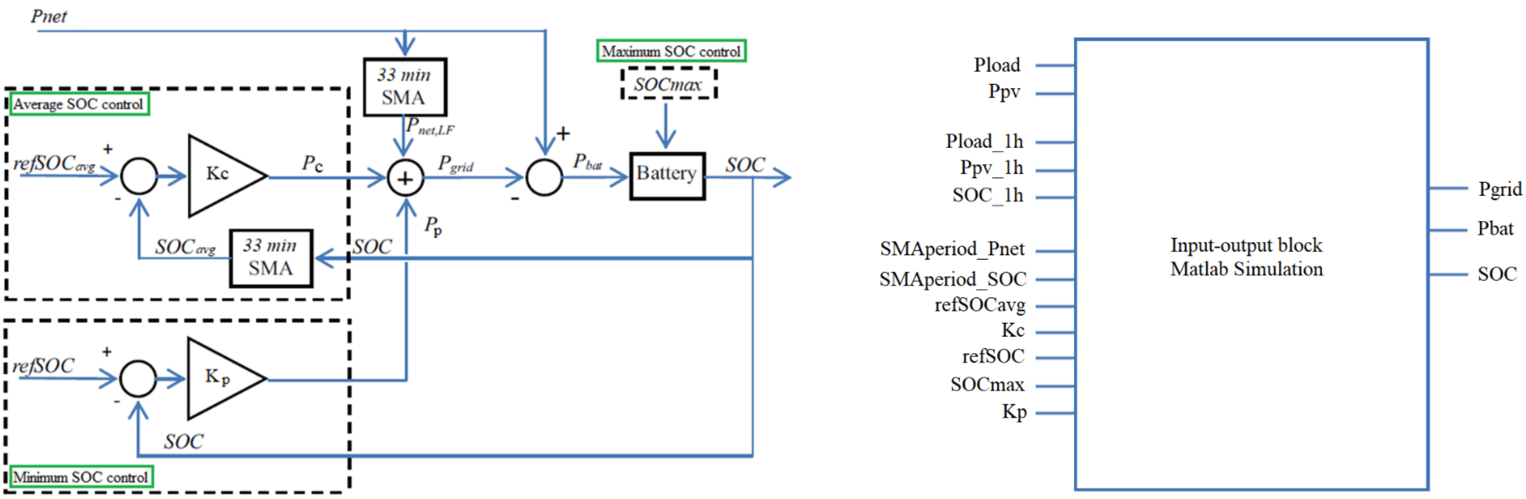

Figure 50: Block diagram and input-output model of the energy management strategy 4.v2 using the matlab simulation

5.4.4. Visual results of the simulation using strategy 3.v2 on 1-day dataset

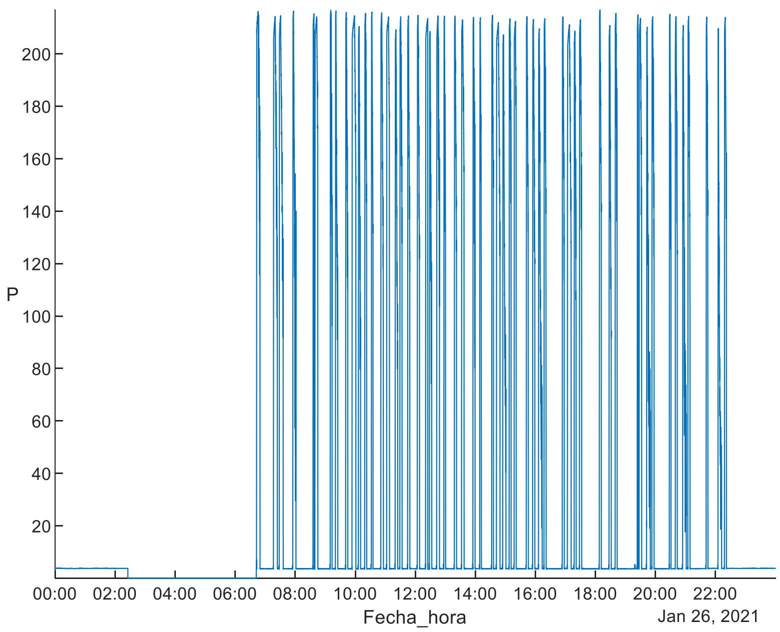

Figure 51: Power absorbed from the grid (Pload – real data) by the charging station on Jan-26, 2021

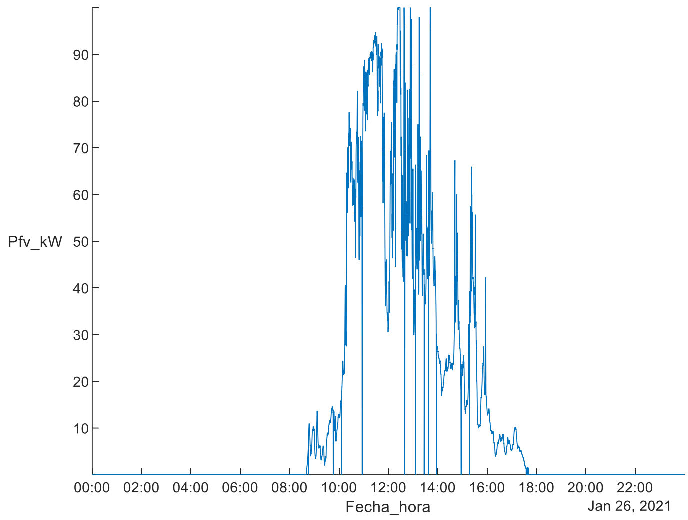

Figure 52: Simulated power generation of the photovoltaic system (UPNA Aulario building) on Jan-26 2021

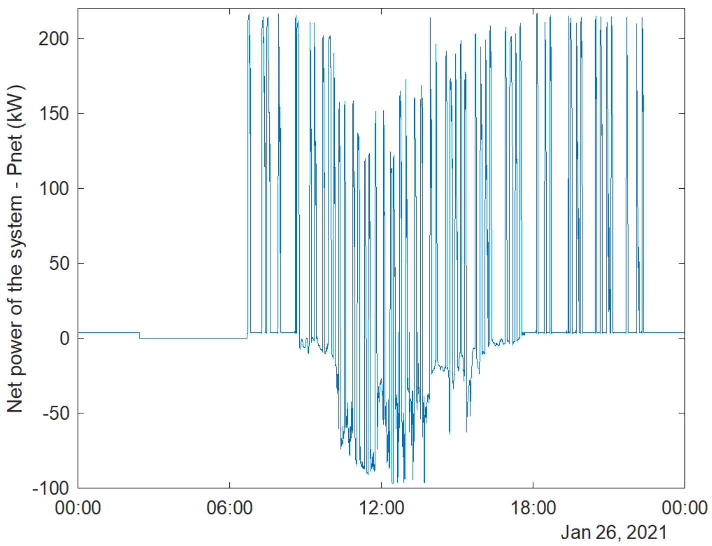

Figure 54: Net power exchange with the grid (Pnet=Pload-Ppv) on Jan-26 2021

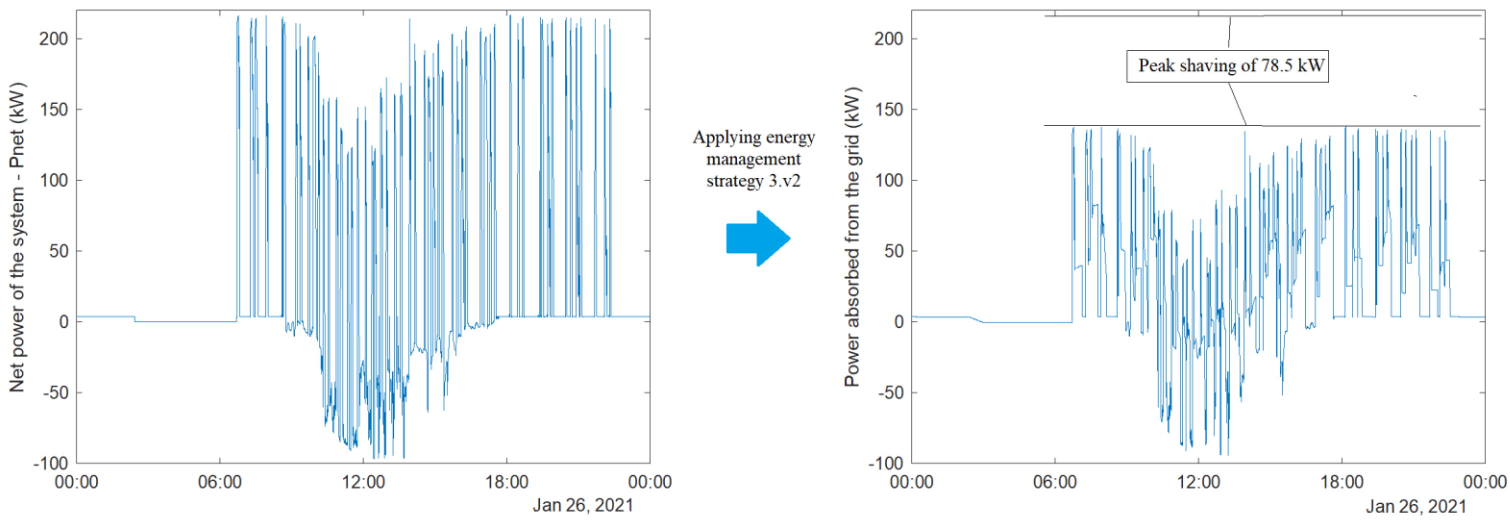

Figure 53: Power absorbed from the grid (Pgrid - left picture) after simulating strategy 3.v2

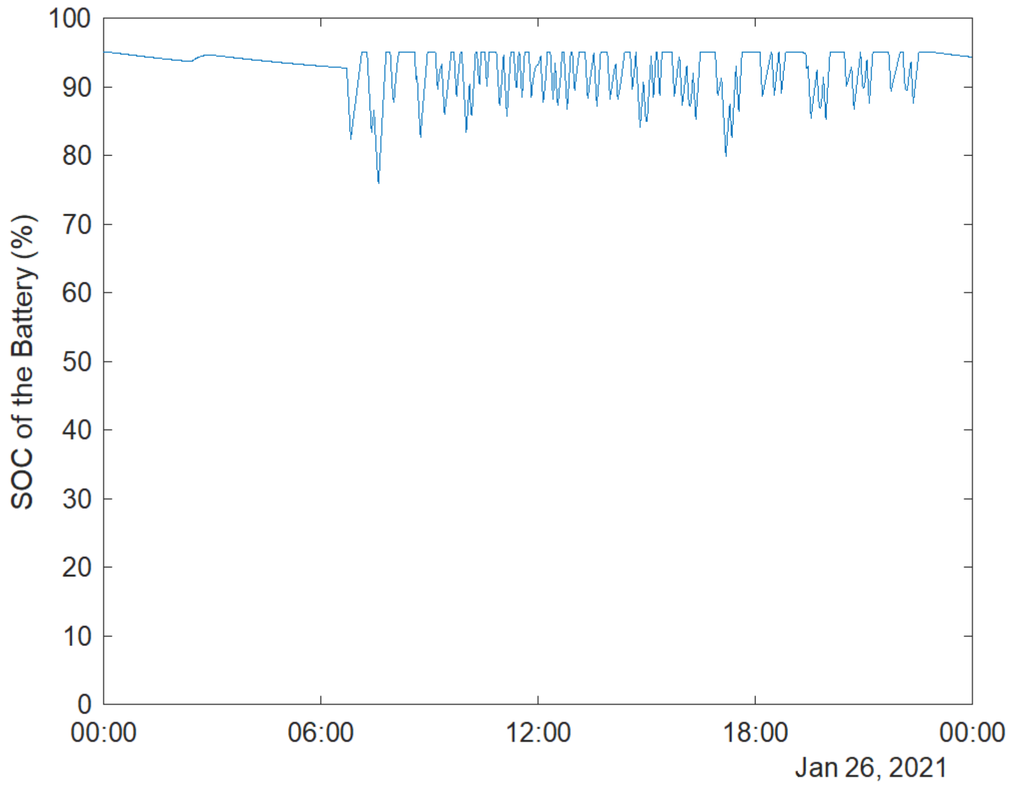

Figure 55: State-of-charge of the battery with Strategy 3.v2 on January 26th, 2021

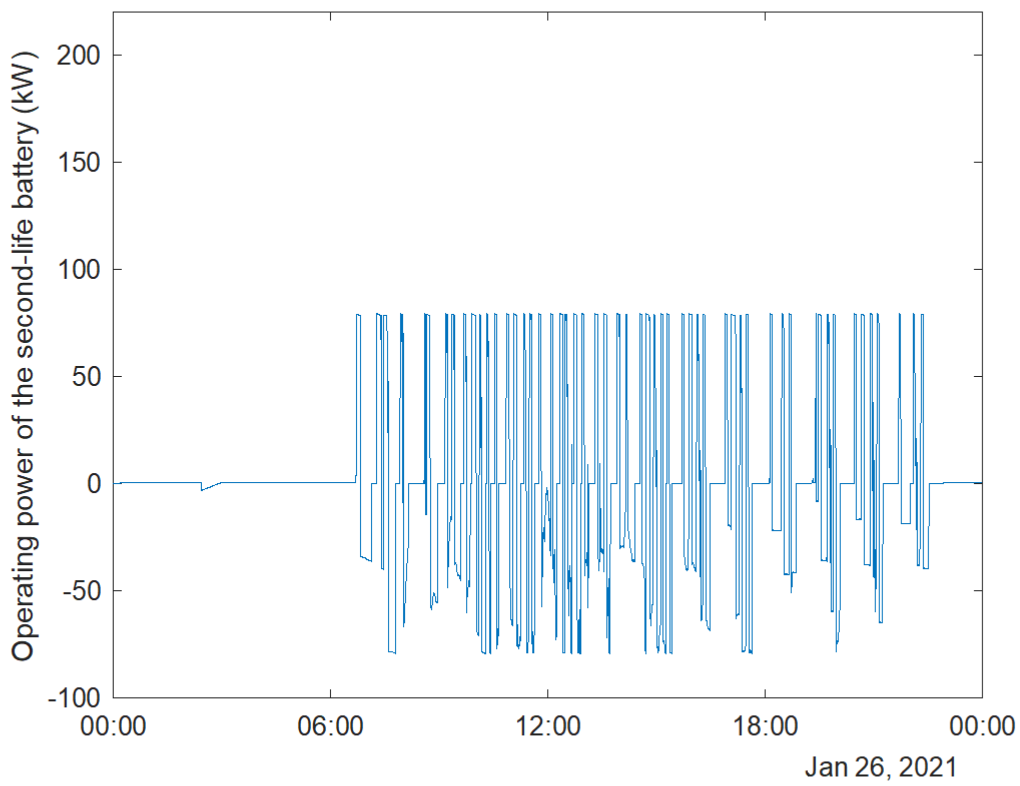

Figure 56: Power profile of the battery with Strategy 3.v2 on January 26th, 2021

6. Implementation and experimental results

6.1. Designing the energy management strategy for the PLC control system

6.1.1. Simulink modal diagram

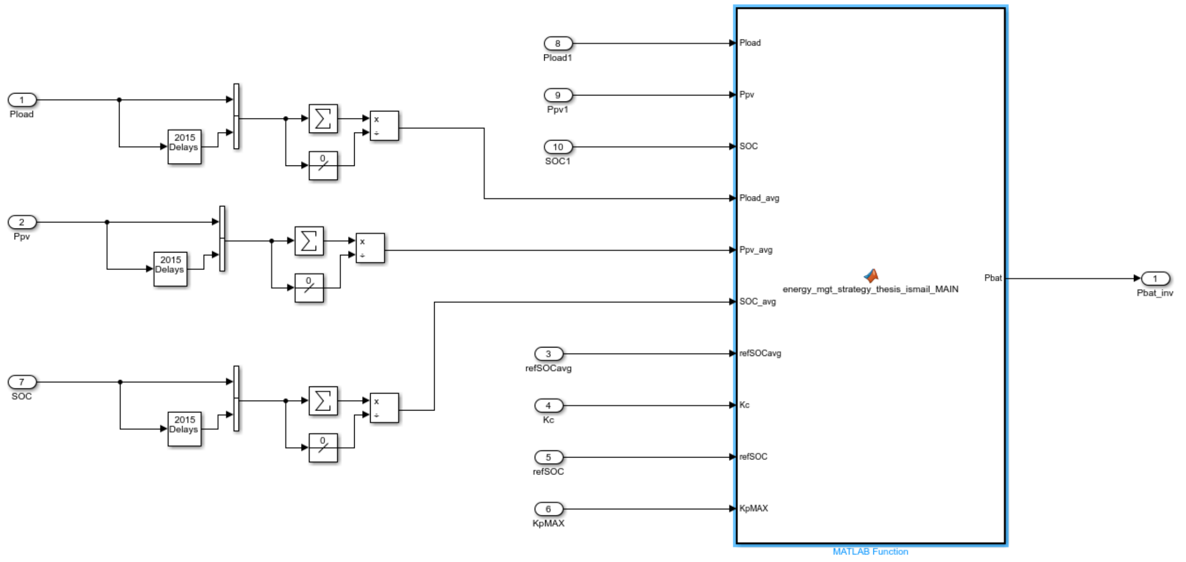

Figure 57: Simulink model of the energy management strategy 3.v2

The input and output parameters shown in figure 57 are as follow:

- Pload: the power demand of the fast-charging station - in watt
- Ppv: the power generation of the photovoltaic system - in watt
- SOC: the state-of-charge of the battery system - in %
- Pload_avg: the power demand average of the fast-charging station over the last 2016 seconds (the moving average window) – in watt
- Ppv_avg: the power generation of the photovoltaic system over the last 2016 seconds (the moving average window) - in watt
- SOC_avg: the average state-of-charge of the battery system over the last 2016 seconds (the moving average window) – in %
- refSOCavg: the requested average state-of-charge of the battery – value=90%
- refSOC: the value of state-of-charge under which the battery discharge is slowed down by – value=50%
- Kc: the control coefficient to maintain the battery system SOC around refSOCavg – in kW/%
- KpMAX: the control coefficient that control the speed of discharge of the battery when the SOC goes below refSOC – in kW/%
- Pbat: is the instruction given for the battery inverter second by second – in watt

6.1.2. The mathematical model

The output and inputs of the energy management strategy 3.v2 relate using the following mathematical model:

$$\boldsymbol{Pbat}(i) = Pnet(i) - Pnet.LF(i) - \boldsymbol{Kc}\,.\left(\boldsymbol{refSOCavg} - SOC.LF(i)\right) - Kp(i).\left(\boldsymbol{refSOC} - \boldsymbol{SOC}(i)\right)$$

- $Pnet(i) = \boldsymbol{Pload}(i) - \boldsymbol{Ppv}(i)$
- $Pnet.LF(i) = \boldsymbol{Pload\_avg}(i) - \boldsymbol{Ppv\_avg}(i)$
- $\boldsymbol{Kc} = 0.0113\ kW/\%$
- $\boldsymbol{refSOCavg} = 90\%$
- $SOC.LF(i) = \boldsymbol{SOC\_avg}(i)$
- $Kp(i) = 0;\ if\ \boldsymbol{SOC}(i) > \boldsymbol{refSOC}$

  $Kp(i) = \boldsymbol{KpMAX} * \dfrac{100 - \boldsymbol{refSOC} - \boldsymbol{SOC}(i)}{100 - \boldsymbol{refSOC}};\ if\ \boldsymbol{SOC}(i)\ \leq \boldsymbol{refSOC}$
- $\boldsymbol{refSOC} = 50\%$
- $\boldsymbol{KpMAX} = 0.0113\ kW/\%$

6.1.3. Model for the PLC control system

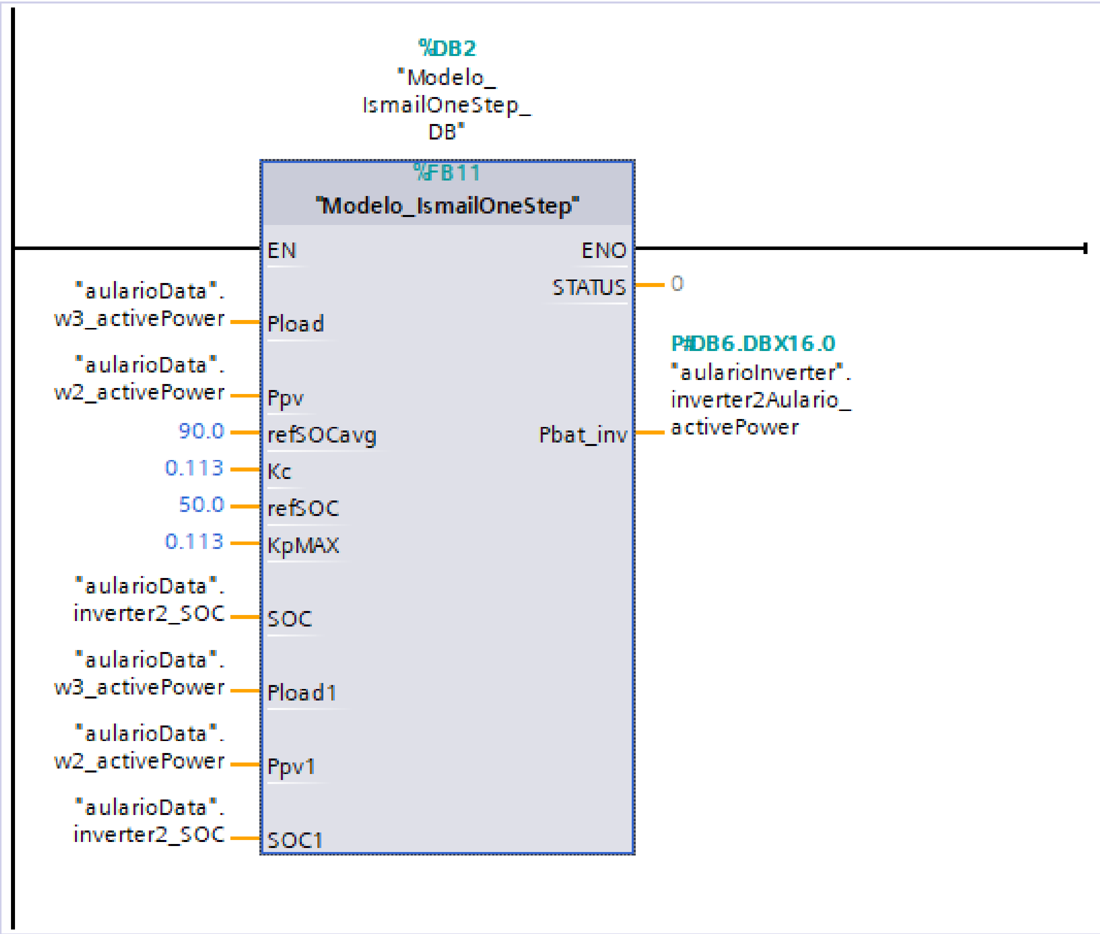

Figure 58: Energy management strategy 3.v2 model on the PLC control software with the input and output entries (real system)

Please refer to [13][14][15] for a detailed description of the plc control system and how to use upload Simulink modals

6.2. Validation of the Matlab simulation (real-life microgrid)

6.2.1. Difficulties with the implementation of the modal

The energy management strategy 3.v2 has been validated in Matlab (refer to chapter 5) Unfortunately, due to multiple time constraints and technical difficulties, the real-life implementation of the strategy will only be shared in a future scientific publication and not in the present master thesis report.

The main difficulties include:

- Delays in the delivery of the system on time to perform necessary implementation (3 months delays).
- As of February 17th, 2022, the battery system encounters hardware-based issues and does not respond properly to the PLC control instructions. The implementation of the strategy is currently not possible until this issue is resolved.

6.2.2. Guidelines and good practices for future implementation of the energy management strategy 3.v2

These are important guidelines related to the proper implementation of the strategy on the PLC control system:

- The energy management strategy is designed to input real-time data of the microgrid second-by-second. For that effect, the “cyclic-interrupt” block is used on the PLC control software. The input cycle is to be set to 1,000,000 µs.
- As of February 17th, 2022, the photovoltaic and the battery systems are not connected directly to the fast-charging issues due to legal issues: the actual electric set-up is shown in figure 59.
    - Therefore, the resulting power exchange with the utlity grid is not directly measured but inferred from the battery operating power data found on the online EMPRO monitoring system [16]
    - The equation used:

$$Pgrid = (Plaod - Ppv) - Pbat$$

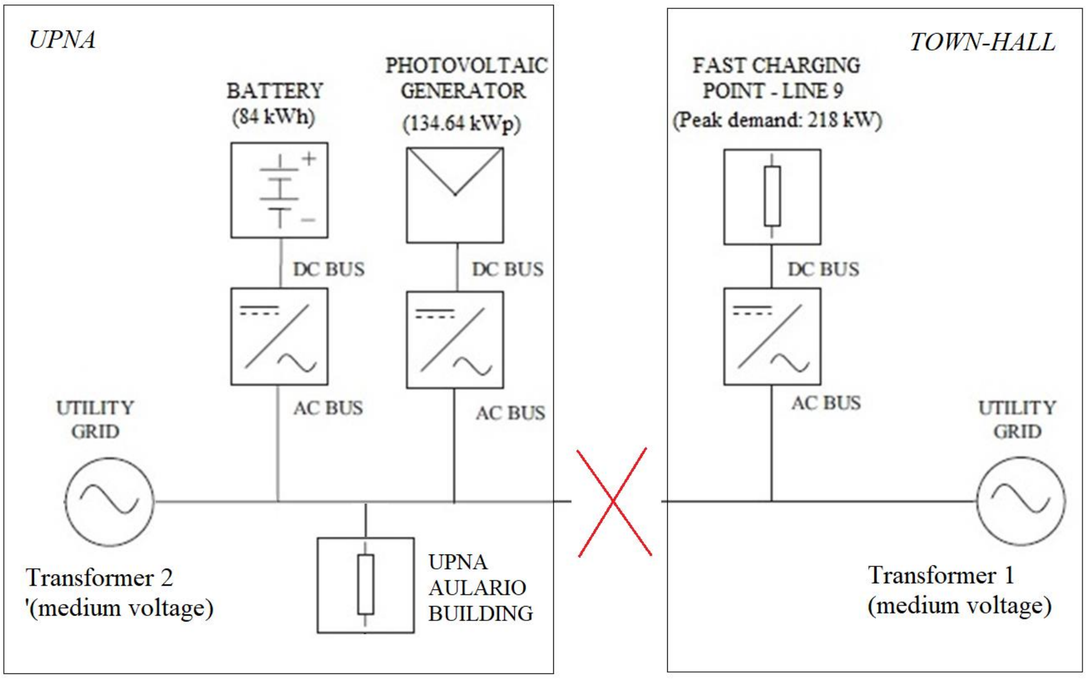

Figure 59: the current legal demaration of the fast-charging station microgrid

7. Main conclusions of the present work

7.1. The battery power capacity first, energy capacity second

The simulation was done based on a battery system with maximum operating voltage of 800V and maximum current of 100A (50A x2). The maximum discharge and recharge capacity is 80 kW: the minimum peak shaved was around 78 kW on the final energy management strategy. With peak demands of 218-220 kW, the battery system is only able to reduce the peak demand by about 35% consistently. With such a scenario, the optimization beyond a simple SMA low-pass filter is marginal and negligeable. The differences between strategies 1,2,3(v1),3(v2) and 4 are very small. The use of CMA los-pass filter and forecasting modals wouldn't yield to significant improvements in peak shaved and PV use. The priority with working with fast-charging station microgrids should be to design the battery system is such a way that at the maximum power capacity is at least equivalent to 60-70% of the peak demand. It is only after designing the battery system based on its voltage and current ratings, that optimizing for the battery energy capacity becomes important. The simulation work should be performed prior to acquisition of the battery.

7.2. Second-life batteries not suitable for the energy management of fast-charging station microgrids

The simulation shows that under energy management strategy 3(v2), the battery system is expected to perform at about 822 EFC/year (equivalent full cycles per year). According to the datasheet, the battery should be able to perform at the very least 5000 EFCs in its lifetime. In other words: 6 years of battery operation. According to battery aging experiments performed at UPNA, second-life batteries should be at best (depth of discharge 5% and average SOC of 90%) able to perform around a bit less than 1900 EFCs in their lifetimes [17]. At 822 EFC/year rate of operation, the battery would only last for about 2 years and 3 months. Only an economic study would determine whether it is economically profitable to change the battery system ever 2 or even 6 years. However, operationally, and logistically, it is more interesting to have reliable batteries with 8000 EFCs and more.

7.3. For a higher photovoltaic use, the battery should only charge when PV is available

The microgrid without any battery system, would meet 18.63% of its yearly energy need from the PV system in place (134 kWp – 100 kW inverter). The PV system can in theory meet up to 77.14% of the total. In the present work, PV system is expected to meet about 32.5% of the total energy needs of the charging station in a year, using the *"energy management strategy 3(v2)"*. This is made possible, by allowing the battery to only recharge itself when PV generation is available. The use of the utility grid for recharge would keep the battery at its maximum SOC most of the time making it less likely to use the excess generation in PV.

8. Recommended future work

This is a list of recommended future work to expand on the current study:

- Implementation of energy management strategy 3.v2 (SMA + average, minimum and maximum SOC controls) in the real-life system. Compare results to the Matlab simulation.

- Design and implementation of an energy management strategy based on real-time state of charge control of the battery (based on the work referenced in chapter 2 and [3]) with the following parameters:

    - Battery is only allowed to recharge when photovoltaic production is available.
    - The model used should not require an accurate forecast of the next bus arrival time.
    - The battery should operate within the known constraints of system: (600-800V operating voltage range and a maximum operating current of 100 A)

- Cost benefit analysis and comparison of the two strategies mentioned above.

- Sizing and market research of a more suitable battery solution for the fast-charging station microgrid. The new battery system should be able to operate at 150kW to 200kW maximum power discharge with enough battery energy reserves to maintain an average SOC at around 80-90%.

    - This will enable to perform advanced grid stability analysis by significantly reducing the power variability of the power exchanged with the grid.
    - The CMA-based strategies and load/PV forecasting can yield to significantly better power peak-shaving and PV generation use.

- Developing a city-level microgrid and energy management strategy assuming a scenario with full electrification of the public bus transport in Pamplona.
    - Design and sizing of a suitable cost-effective energy storage system.
    - Design and sizing of a suitable renewable production fleet for the microgrid.
    - Matlab-Simulink simulation designed for city-level grid stability.

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