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Optimal Sizing of Stationary Battery Storage Taking into Account Indirect Flexibility in Tertiary Buildings: Use case of an Electric Vehicle Community

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ABSTRACT

This article proposes a method for taking into account the indirect flexibility (charging of Electric Vehicles) available in buildings for the sizing of stationary battery storage systems (direct flexibility). A Linear Programming approach was applied to data sourced from the Predis-MHI platform (a living lab) such that the day-to-day charging of EVs, as well as the scheduling of the charging and discharging of the proposed battery, were optimized whilst simultaneously dimensioning the battery capacity. Our results indicate that based on the percentage increase in self-consumption with reference to the base case, it is possible to reduce the battery capacity required by up to 100% as compared to a methodology that doesn't account for the indirect flexibility. Whilst relevant, the sizing approach proposed in this article assumes optimal human behavior, which is usually difficult to achieve. Our proposed approach can be adapted and used for the dimensioning of direct flexibilities for both residential and commercial/public buildings.

INTRODUCTION

The topic of climate change is a cause for immediate action and in recent times has gained a justifiably large response from the press, researchers, and the general populace. The resulting consequence has been a global shift towards sustainable practices in all sectors of the economy. Transportation and electricity generation have been identified as major contributors of Green House Gases (GHGs). Statistical data indicates that transport accounted for 25.8%, energy industries (electricity generation, petroleum refinery, heat production, etc.) 24.1.0%, and the building sector 14.2% of the EU's GHG emissions in 2019[1]. Given these figures, these two sectors have seen an enormous shift and uptake of sustainable policies, innovations, and interventions (renewable energy and E-mobility).

Additionally, Energy Communities (a group of individuals with a common goal, who actively participate in the energy sector and organize collective and citizen-driven energy actions [2]) have emerged and are a key component in achieving the EU's energy transition goals. These energy communities bring to the table energy services, however, they play an ancillary role of increasing energy awareness and potentially streamlining the behavior of their members (in terms of energy use) in a desirable and much-needed direction [3].

As renewable energy and e-mobility (electric vehicles, electric bicycles, etc.) adoption increases, they pose a threat to the reliability and robustness of existing grid infrastructure. The Smart Grid concept has been proposed, as a means to mitigate if not alleviate these potential challenges [4], which will emerge. Tertiary sector buildings offer a perfect paradigm, in that they are normally used during the day (when solar energy is available), and its occupants who own personal transportation units would have them on or close to the site. Thus, it is possible to use e-mobility solutions (Electric Vehicles) as an effective means of indirect flexibility. In reality, this is difficult to achieve since in many energy systems (buildings included) humans are expected to interact with the said system as such [5], humans are thus an (often overlooked [6]) important parameter to consider for all phases of a building's life cycle (conception, design, and operation).

In this article, we propose a Linear Programming (LP) approach for sizing stationary battery storage systems (direct flexibilities) taking into account an optimal behavior from EV users (indirect flexibility) in a tertiary sector building set-up (the Predis-MHI platform of G2ELab).

DIRECT AND INDIRECT FLEXIBILITIES IN LITERATURE

Flexibility is a key concept for achieving energy transition goals. This has become particularly feasible and necessary owing to the increased adoption and integration of Distributed Energy Resources (DERs). The French Agency for Environment and Energy Management (Agence de l'Environnement et de la Maîtrise de l'Energie – ADEME) has proposed a plan for 100% Renewable Energy penetration in France by 2050 and estimates that buildings would be capable of offering flexibility services of approximately up to 18% of the peak demand (100 GW) [7]. At the scale of the building, and given the increasing growth of prosumers (DERs) in the energy sector, flexibility is key in maximizing Self-Consumption (SC).

In this paper, we propose to classify Flexibility into two distinct groups, direct and indirect flexibility. Direct flexibility can be defined as devices within the global energy system whose actions can be fully automated/controlled using software or a control signal and can significantly affect the overall performance of the global energy system (e.g. heat pumps, batteries, etc.).

Conversely, indirect flexibility is defined as actors or sub-systems in the global system that cannot be controlled directly with a control signal but whose actions directly influence the performance of the energy system, mainly referring to the human in the loop [8].

Hodencq et al. [9] proposed an approach for sizing PV systems that takes into account the Global Warming Potential (GWP) of the components and the operational carbon impact, positive feedback (reduced demand with time) and the degradation of the individual components of the PV system with self-sufficiency as a constraint (i.e. the energy system must achieve the defined SC). The results showed that small PV systems are effective at reducing the carbon intensity of a building's energy system whilst systems designed to achieve higher self-sufficiency tend to increase the carbon footprint of the said building. The optimal level of self-production to reap maximum benefit from the addition of a solar PV system is, however, dependent on many factors, which include the energy mix of the grid electricity, and the demand profile.

Current approaches for sizing storage systems both for residential and public buildings do not take into account indirect flexibility. Tostado-Veliz et al [10] proposed a MILP strategy for sizing solar PV systems taking into account grid failures and demand response (using direct flexibilities) with the objective function being to reduce the system cost. Previous works have focused on sizing taking into account financial costs [11], and environmental impacts [12],[9], however, similar to other building-related models the human in the loop has been ignored in these solutions. Taking into account the indirect flexibility is bound to yield a smaller system size and financial commitment reducing the building's carbon impact.

USE CASE: THE PREDIS-MHI PLATFORM

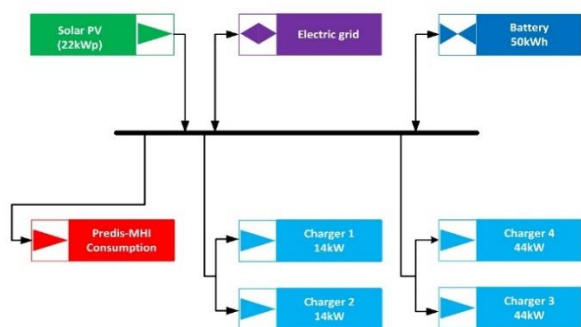


Figure 1 Predis-MHI electricity system (represented using OMEGAlpes graphical representation [13])

This article considers the Predis-MHI platform (a living lab), which is a platform of the Grenoble Electrical Engineering Laboratory (G2ELab) dedicated to the study of smart, highly energy-efficient buildings and occupant behavior. The platform is a 600m² multi-floor space composed of lecture rooms, a demonstration room, a

student's foyer, and offices housed in the Grenoble Energy-Education and Research (GrEn-ER) building [14]. The energy system of the platform is composed of a 22 kWp solar PV system, 50kWh lithium-ion battery, lighting, Heating, Ventilation and Air-Conditioning (HVAC), electrical outlets, and 4 EVs charging stations (2 -14 kW chargers and 2 – 44 kW added in August 2021). Figure 1 shows the energy system of the platform.

Data Management

To allow for further improvements of the proposed model, this article follows the Open and Reproducible Use Cases for Energy (ORUCE) principles [15]. Thus, the data, associated code and notebooks are available online and can be modified and applied to different use cases and scenarios.

Data Analysis

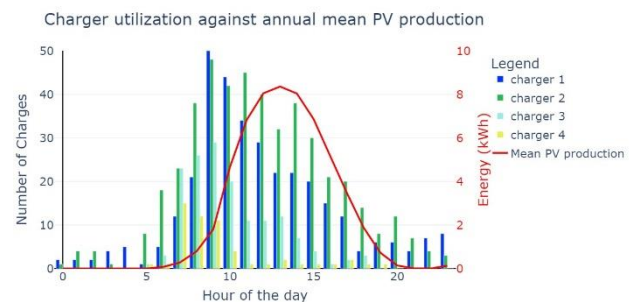


Figure 2 Annual hourly charger utilization vs PV production

Figure 2 shows the charging patterns of the occupants of the building compared to the average annual solar PV production. It can be deduced from Figure 2 that the behavior of EV owners concerning the charging of their EVs is less than ideal with 9 and 10 AM being the favored time (occupants are plugging and charging their vehicles when they arrive). Ultimately, Figure 2 shows that there exists some degree of indirect flexibility that can be used to improve the SC rate.

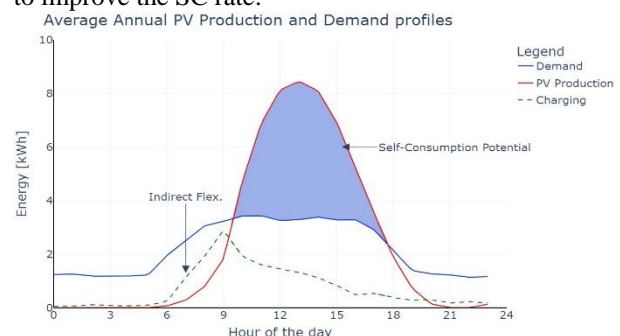


Figure 3 Annual hourly demand and PV production

Additionally, comparing the annual average demand of the Predis-MHI platform (without EV charging) to the average annual PV production, see Figure 3, we show that there exists a significant potential to increase the SC of the platform using the indirect flexibility (EV charging). The natural SC (SC of a building without any technical

interventions such as batteries or load shifting [16]) of the entire platform was estimated to be 46.69% for the period of study used in this article (01/01/2021 – 31/12/2021).

LP FORMULATION

The optimal sizing of direct flexibilities implies that both the long-term and short-term constraints of the system need to be accounted for. The addition of indirect flexibilities further implies that mid-term constraints have to be introduced into the optimization. In the case of the proposed optimization, the mid-term constraint was to ensure that the energy consumed within a defined period (1 day for the study) is exactly met by the charging schedule proposed by the optimizer whilst respecting the operating hours of the building (8:00 – 20:00). For this LP optimization, the objective function was defined as:

$$\text{objective} = \min[\text{Capacity}_{\text{battery}}] \quad 1$$

To ensure that the battery state of charge (SOC) stays within defined operational bounds (20% - 100% considered for the study):

$$\text{SOC}_{\text{Min}} \times \text{Cap}_{\text{bat}} \leq E_{\text{bat}}(pd, t) \leq \text{SOC}_{\text{Max}} \times \text{Cap}_{\text{bat}} \quad 2$$

Where $\text{SOC}_{\text{Min}} \times \text{Cap}_{\text{bat}}$ and $\text{SOC}_{\text{Max}} \times \text{Cap}_{\text{bat}}$ refers to the minimum and maximum allowed battery energy respectively and $E_{\text{bat}}(pd, t)$ is the electric charge in the battery for the period pd (day) at time step t , expressed as:

$$E_{\text{bat}}(pd, t) = E_{\text{bat}}(pd, t-1) \times [1 - \Delta_{\text{sd}}] + [P_{\text{bat}}(pd, t) \times \eta_{\text{bat}} \times ts] \quad 3$$

Where $P_{\text{bat}}(pd, t)$ is the charge/discharge power of the battery for period p at time t , Δ_{sd} is the self-discharge rate of the battery and η_{bat} is the battery efficiency. Additionally, to ensure continuity between the various periods, the battery's SOC at the end of each period was defined as:

$$E_{\text{bat}}(p, T+1) = E_{\text{bat}}(p, T) \times [1 - \Delta_{\text{sd}}] + [P_{\text{bat}}(p, T) \times \eta_{\text{bat}} \times ts] \quad 4$$

Where T is the last time step in the set $\{0, 1, 2 \dots T\}$, and the final battery energy is constrained as defined in equation (2). Thus, the starting battery energy for the various periods was defined as:

$$E_{\text{bat}}(pd, t) = \begin{cases} E_{\text{bat}}(pd, T), & \text{if } pd = 0 \text{ and } t = 0 \\ E_{\text{bat}}(pd-1, T+1), & \text{if } pd > 0 \text{ and } t = 0 \end{cases} \quad 5$$

Where $E_{\text{bat}}(pd, t)$ is the final energy at the end of the simulation, i.e. the optimizer determines the ideal SOC to initialize the battery. This condition is especially important as the SC increases and the required battery capacity increases in response (at higher SC, the initial battery SOC impacts the dimensioning of the battery). Further, to ensure that the battery charging and discharging power

stayed within defined safe operating bounds:

$$R_{\text{discharge}} \times \frac{\text{Cap}_{\text{bat}}}{ts} \leq P_{\text{bat}}(pd, t) \leq R_{\text{charge}} \times \frac{\text{Cap}_{\text{bat}}}{ts} \quad 6$$

Where $R_{\text{discharge}}$ and R_{charge} are factors that represent the proportion of the nominal capacity that can be charged or discharged from the battery at any given time step. The charging of EVs was defined mathematically as

$$E_{\text{charger}_X \text{ original}}(pd) = \sum_t^T P_{\text{charger}_X}(pd, t) \times ts \quad 7$$

Where $E_{\text{charger}_X \text{ original}}(pd)$ is the energy originally consumed by charger X (X a set of charger IDs [1, 2, 3, 4]) during period pd for the optimization horizon and $P_{\text{charger}_X}(pd, t)$ is the power of charger X for period pd at time t . Additionally, to respect the time constraints imposed by the operating hours of the building:

$$\sum_x^X P_{\text{charger}_x}(p, t) \times ts = 0, \text{ if } t < T_{\text{open}} \text{ or } t > T_{\text{close}} \quad 8$$

Where T_{open} and T_{close} refer to the opening and closing times of the GreEN-ER building respectively. Equation 9 below prevents mitigates the use of the grid for charging the battery.

$$P_{\text{import}}(pd, t) \leq P_{\text{load}}(pd, t) + \sum_x^X P_{\text{charger}_x}(pd, t) \quad 9$$

Where $P_{\text{import}}(p, t)$ and $P_{\text{load}}(pd, t)$ are the grid import power and demand power of the platform for period pd at time t respectively. The grid import and export are further constrained by ensuring that the SC for the evaluation period is equal to the defined rate, and is expressed as [17]:

$$\frac{\sum_{pd}^{PD} \sum_t^T P_{\text{load}}(pd, t) - P_{\text{import}}(pd, t)}{\sum_{pd}^{PD} \sum_t^T P_{\text{pv}}(p, t)} = R_{\text{sc}} \quad 10$$

Where R_{sc} , is an input to the optimization, and acts as a constraint for the LP problem (i.e. it is the desired SC rate for which the direct flexibility should be dimensioned). In addition, the power balance is ensured by:

$$P_{\text{pv}}(pd, t) - P_{\text{bat}}(pd, t) + P_{\text{grid}}(pd, t) + P_{\text{tot}}(pd, t) = 0 \quad 11$$

Given:

$$P_{\text{tot}}(pd, t) = [P_{\text{load}}(pd, t) + \sum_x^X P_{\text{charger}_x}(pd, t)] \quad 12$$

$$P_{\text{grid}} = P_{\text{import}}(pd, t) + P_{\text{export}}(pd, t) \quad 13$$

RESULTS

Using the optimization problem as defined above (solved using Gurobi [18]), a parametric study was conducted to determine the effect of indirect flexibility (the human actors, EV users in this case that do plug-in their vehicles

at the right moment) on the sizing of battery storage. Figure 4 shows the optimal battery size for a defined annual SC rate with and without the indirect flexibility and the percentage reduction in the required storage capacity with the direct flexibility only approach as reference.

From figure 4, it can be observed that an SC rate of 54% can be attained with no need for battery storage, however, in the case of the direct flexibility only scenario, a 6.00kWh battery is required to achieve the same 54% SC rate. Thus, it can be deduced that there exists a potential of increasing the SC rate by approximately 8% (with reference to the natural SC) using only the indirect flexibility.

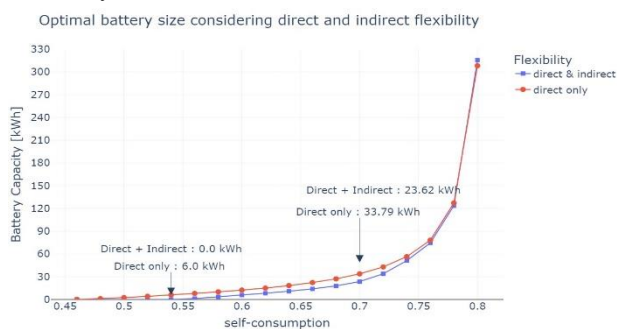


Figure 4 Comparison of battery sizing considering only direct flexibility and both direct and indirect flexibility

Figure 4 also shows the potential savings in terms of both financial and environmental impact (relative to the direct only approach), with the reduction in required battery capacity to achieve an SC rate of 70% being approximately 30.20%.

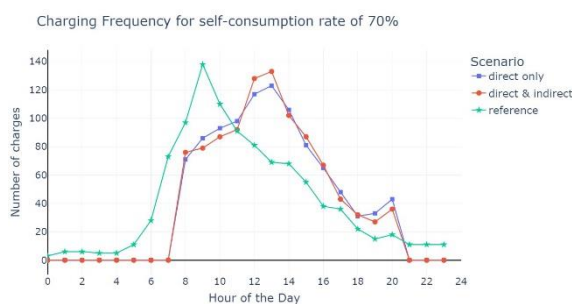


Figure 5 Comparison of charging frequency for direct only and direct & indirect strategies (SC=70%)

For the platform, it was found that the optimal SC with respect to the results in figure 4 (i.e. the SC for which the gain of using indirect flexibility is maximized) was approximately 70%. Considering this SC rate, figure 5 shows a comparison of the hourly charging frequency for the reference case, the direct only, and direct and indirect flexibilities using the battery capacities determined for an SC rate of 70%. From figure 5, by using the indirect flexibility, we were able not only to achieve a lower rate of SC but also to maximize the use of the indirect flexibility (i.e. more charging occurring at peak sun hours). To assess the potential effort required to move from the

sub-optimal (reference case) to the optimal case (direct only and direct and indirect approaches), an evaluation indicator is proposed such that:

$$effort = \frac{\sum_t |freq_{optimal}(t) - freq_{reference}(t)|}{\sum_t freq_{reference}(t)} \quad 14$$

Where $freq_{optimal}(t)$ and $freq_{reference}(t)$ are the hourly charging frequency (i.e. number of times a vehicle was charging for said hour during the evaluation period) of charging in the optimal and reference cases respectively. Where a value of zero implies zero to minimal effort would be required, whilst a value of one would imply the greatest level of effort would be required to reach the optimal case. Thus, the effort required to reach the direct only and direct and indirect optimals were calculated to be 0.51 and 0.52 respectively, indicating that a lower level of effort is required from EV users to reach the direct only scenario optimal relative to the effort level required to attain the direct & indirect scenario optimals.

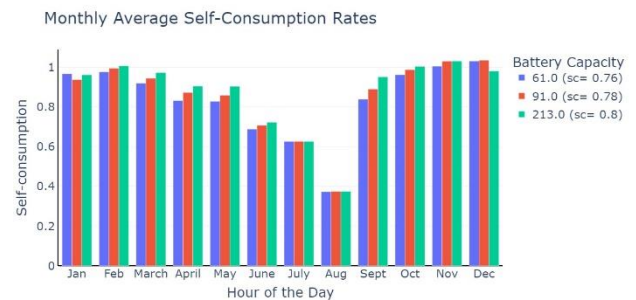


Figure 6 Comparison of monthly SC rates for different battery capacities

Additionally, the growth of the battery capacity with increasing SC was observed to be linear in both cases until approximately 76%, beyond which the battery capacity required grows exponentially and consequently diminishes the gain of using the indirect flexibility. We evaluate the impact of the battery on the monthly SC rate of the platform. From Figure 6, which shows the monthly SC rates for different battery capacities (using both the direct and indirect flexibilities), it can be seen that the impact of the significantly larger battery is greatest during the spring and autumn seasons when PV production is relatively high (more than in winter but lower than in summer). For the summer periods, however, the significantly larger battery capacity has little to no impact on the SC rates, indicating that, the production is in excess of the load and the batteries are underutilized for these months.

CONCLUSION

The indirect flexibility potential of a building (and in extension its occupants' behaviors) is an important parameter that should be taken into account for the dimensioning of energy storage systems (both for tertiary sector and residential buildings). Whilst it is difficult to ensure optimal behavior from occupants, methods and tools exist and are constantly under development to

influence occupant behaviors towards an optimal point. The results of this study indicate that indirect flexibility alone can improve a building's SC, however, by taking into account the indirect flexibility available, it is possible to achieve the same SC rates as a sizing, which only takes into account the direct flexibility using a significantly smaller battery capacity. Indirect flexibilities are a key aspect of the energy system of a building and are indispensable for achieving the energy transition and climate mitigation goals.

Our work did not take into consideration the long-term effects of behavioral change of occupants (i.e. reduced demand due to increased energy awareness) or the growing adoption of EVs for private transportation needs. Additionally, we assumed optimal behavior from the EV users in this sizing approach, which in reality might be difficult to achieve. Further work is required on mechanisms and tools to influence human actors towards a globally optimum behavior. Energy communities, nudging and the use of feedback indicators present a suitable use case for such a study.

SUPPLEMENTARY MATERIALS

A Gitlab repository including the code and data sources is available: https://gricad-gitlab.univ-grenoble-alpes.fr/NanaKofi/battery_sizing

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