Optimization of Battery Swapping Stations with Heterogeneity, Charging Degradation and PV-Option

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ABSTRACT

This dissertation focuses on the study of Battery Swapping Stations (BSS), which are structures where electric vehicle users swap their depleted batteries for fully or partially charged ones. The objective is to simulate the daily operations and battery charging schedule of a BSS using a novel Mixed Integer Linear Programming (MILP) model proposed. This model takes into account battery heterogeneity, the utilization of local photovoltaic (PV) production, and battery degradation. The proposed model addresses various operational issues that are relevant to BSS. For instance, it incorporates grid energy import limits incentives and battery degradation costs based solely on the charging profile. Additionally, the model facilitates the implementation of the battery charging schedule based on a continuous charging profile without interruptions. By introducing this model, several existing gaps in the technical literature concerning BSS are addressed, thus allowing a better understanding of BSS operations and further advancements in the field.

KEYWORDS. Battery Swapping Station. Electric Vehicles. Photovoltaic Power Production. Mixed-Integer Linear Programs. Distributed Energy Sources. Battery Heterogeneity.

OC – Otimização Combinatória, PM – Programação Matemática, EN&PG – PO na Área de Energia, Petróleo e Gás

RESUMO

Esta dissertação foca no estudo das Estações de Troca de Baterias (ETB), estruturas onde os utilizadores de veículos elétricos trocam as suas baterias descarregadas por outras totalmente ou parcialmente carregadas. O objetivo é simular as operações diárias e o cronograma de carregamento da bateria usando um novo modelo de Programação Linear Inteira Mista (PLIM) proposto. Este modelo leva em consideração a heterogeneidade da bateria, a utilização da produção fotovoltaica local e a degradação da bateria. O modelo proposto aborda várias questões operacionais relevantes para o ETB. Por exemplo, incorpora incentivos de limites de importação de energia da rede e custos de degradação da bateria com base apenas no perfil de carregamento. Além disso, o modelo facilita a implementação do cronograma de carregamento da bateria com base em um perfil contínuo sem interrupções. Com a introdução deste modelo, várias lacunas existentes na literatura técnica sobre ETB são preenchidas, permitindo assim uma melhor compreensão de suas operações e maiores avanços no campo.

PALAVRAS CHAVE. Battery Swapping Station. Electric Vehicles. Photovoltaic Power Production. Mixed-Integer Linear Programs. Distributed Energy Sources. Battery Heterogeneity.

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1. Introduction

During the past years, problems induced by significant emission levels of Greenhouse Gases (GHGs) have been widely discussed around the globe. Several countries have already committed to net zero carbon emissions by 2050 [IEA, 2021b], seeking for carbon-neutral economies. In this context, the electrification of transportation modals has gained momentum following these net-zero goals, leading to Electric Vehicles (EVs) to increase their market share all over the world. In fact, despite the pandemic-related worldwide downturn in car sales, with an estimated global overall drop of 16%, electric car registrations increased by 41% in 2020 [IEA, 2021a]. Although the increasing penetration of EVs and the respective net zero objectives, there are still critical aspects that current EV systems and related infrastructure are not capable of efficiently handle in comparison to Internal Combustion Engine Vehicles (ICEVs). One can refer to their driving range and the time spent in the battery charging process. Furthermore, the lack of public locals for charging and stations, electric network distribution congestion, battery degradation, and recycling process are also critical for the sustainable integration of EVs in modern cities. On one hand, charging stations, also named Battery Charging Station (BCS), are the most popular adaptation of the current gas stations for EVs. This type of structure requires hours of waiting until the EV replenishes its batteries, which induces a loss of time and higher costs for commercial applications. Although it is possible to make use of fast chargers to decrease the charging time, the process increases the battery degradation effect, reducing its lifetime as a consequence [Joos et al., 2010]. The installation of EV chargers at public or private parking lots, on the other hand, would expand the access to charging locals, where EV owners would take advantage of the parked car time, enabling even overnight recharging. However, it is not always a feasible solution due to network congestion and other aspects.

In this context, an alternative solution would be to use the so-called Battery Swapping Station (BSS), a structure where the EVs would only swap their depleted batteries for fully or partially charged ones. While the EVs would need hours to fully charge their batteries in a BCS, the BSS can provide a swapping service in a few minutes (e.g., less than 5 minutes) [Ahmad et al., 2020]. Recently, Tesla® presented a battery swapping simulation for its Model S, where the charging procedure was even faster than refilling a gas tank. In addition, a commercial use of BSS was made in China during the 2008 Summer Olympics for electric buses [Liang e Zhang, 2018]. Moreover, lining up with the desired net-zero emission target, BSS can be operated with Photovoltaic (PV) panels such as a recent application in Germany [ACM, 2021]. From an electrical-grid-wide perspective, several benefits in promoting the battery swapping process are pointed by Ban et al. [2019], with the main ones being the load peak shaving, by the grid operator perspective, and customers benefits with EV price reduction by the adoption of battery leasing business model, keeping the ownership for the BSS or some company.

Although the BSS adoption can provide multiple benefits, several operational challenges still needed to be addressed, such as the battery charging schedule, demand forecasting, and battery lifetime management. Moreover, a wide discussion over battery degradation, interchangeability, and feasibility is presented by Ahmad et al. [2020]. In this sense, the use of computational models can bring insights into the BSS daily operation and all trade-off decisions involved, especially in cases with hundreds of batteries and different battery models, subjected to hundreds of EV arrivals a day.

Given the BSS context challenges and based on the developed research of Shalaby et al. [2021], in this work, we propose a mathematical model that represents the daily operation of a BSS considering PV generation, taking into account critical feasibility and sustainability features for the business in the long-term, such as battery heterogeneity and battery degradation due to charging process. The model's main objective is to maximize the daily profit of the BSS considering the decision of the battery charging schedule and the acceptance/rejection of the EV swapping requests.

1.1. Contributions Regarding the Existing Literature

Several works can be found in technical literature where the BSS is discussed over different aspects. Aiming at contextualizing the contributions of this paper, some related works are discussed further on. A multi-objective optimal scheduling of a BSS considering the number of batteries taken from stock, charging damage, and charging cost has been shown by Battapothula et al. [2019]. In [Mahoor et al., 2019], a mathematical model was developed to minimize the BSS operation cost considering uncertain constraints, random customer demands of fully charged batteries, demand shifting and energy sell back. The battery degradation process was also modeled to ensure a practical solution. Taking into account studies where the BSS used distributed generation, Feng et al. [2020] studied an integrated PV-BSS model considering battery degradation, speed-variable charging, and weather/traffic forecast, with the Particle Swarm Optimization techniques used to handle the problem.

The main reference study of this work is Shalaby et al. [2021] one, which developed a mixed integer non-linear model to define PV-based BSS operations, where sensitivity analyses were made upon homogeneity of batteries. The study concluded that the PVs could increase the BSS profit by 67% and decreases costumer's non-attendance. The proposed model also enables the sale of partially charged batteries, as long as the battery level stays higher or equal to the customer's minimum desired level. Moreover, Shalaby et al. [2021] also cited the lack of studies in the technical literature considering a BSS operation with renewable generation, highlighting the existing gap.

Despite the relevance of the aforementioned technical literature, most works usually develop algorithms and solution methods to solve a BSS model, or even bring aspects such as battery degradation and uncertainty. However, there is a lack of studies that bring relevant aspects the BSS operation implementation. Moreover, a study that mixes the use of PV generation, battery heterogeneity (multiple battery types) and battery degradation in a BSS context was not found. In this sense, this dissertation presents a novel formulation based on the model developed by Shalaby et al. [2021], where two extensions are proposed and further evaluated based on the consideration of battery degradation and control over the battery charging profile. To summarize, the main technical contributions of this dissertation are twofold: (i) Development of a novel mathematical model to assess the daily schedule of a BSS considering multiple battery types, PV generation flexible use, and battery degradation, extending the model presented by Shalaby et al. [2021]; (ii) Development of a battery degradation cost model based exclusively on the batteries charging power, adapting the model developed by Gao et al. [2017].

2. BSS Operational Scheduling Formulation

This section presents the proposed mathematical model for BSS daily operational scheduling, where its daily decisions depend mainly on aspects such as the batteries charging status, i.e., which moments the batteries will be kept in charge at a certain power rate, as well as the acceptance of EV customers' swapping requests at each period, for each type of battery. These decisions are represented by the model variables $P^{T}_{t,m,b}$, $K_{t,m,b}$, and $S_{t,m,b}$, respectively, and they are present in most of the model constraints. Moreover, different aspects such as the electricity price π_t, PV generation forecast E^{PV}_t, and the remaining energy level for each arriving $E^{EV}_{t,m}$ are considered by the model and have direct influence at the optimal battery schedule. The proposed model is formulated as the following mixed-integer non-linear programming (MINLP) problem.

$$\text{Max} \quad \sum_{t\in\mathcal{T}}\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}_m} \lambda\Delta E_{t,m,b} \tag{1}$$

$$+\sum_{t\in\mathcal{T}} \pi_t E_t^{PVS} \tag{2}$$

$$-\sum_{t\in\mathcal{T}}\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}_m} D\Big(\pi_t Pb_{t,m,b} + \big(1+\delta^+\big)\pi_t Pa_{t,m,b}\Big) \tag{3}$$

$$-\,\phi(K) \tag{4}$$

Subject to:

$$E_{t,m,b} = E_{t-1,m,b} + (D\cdot P^T_{t,m,b}) - \Delta E_{t,m,b} \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{5}$$

$$\Delta E_{t,m,b} = (E_{t-1,m,b} - E^{EV}_{t,m})S_{t,m,b} \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{6}$$

$$K_{t,m,b} + S_{t,m,b} \leq 1 \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{7}$$

$$E_{t,m,b} \leq \overline{E}_m \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{8}$$

$$SOC_{t,m,b} = \frac{E_{t,m,b}}{\overline{E}_m}\cdot 100 \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{9}$$

$$SOC_{t_f,m,b} \geq SOC^{(t_f)} \qquad \forall\, m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{10}$$

$$E_{t-1,m,b} \geq \tilde{E}_{t,m}S_{t,m,b} \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{11}$$

$$\sum_{b\in\mathcal{B}m} S_{t,m,b} = A_{t,m} \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M} \tag{12}$$

$$\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}m} K_{t,m,b} \leq N \qquad \forall\, t\in\mathcal{T} \tag{13}$$

$$\underline{R}_m K_{t,m,b} \leq P^G_{t,m,b} \leq \overline{R}_m K_{t,m,b} \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{14}$$

$$P^T_{t,m,b} = P^{PV}_{t,m,b} + P^G_{t,m,b} \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{15}$$

$$E^{PV}_t = \sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}m} E^{PV}_{t,m,b} + E^{PVS}_t \qquad \forall\, t\in\mathcal{T} \tag{16}$$

$$P^{PV}_{t,m,b} = \frac{E^{PV}_{t,m,b}}{D} \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{17}$$

$$P^G_{t,m,b} = Pb_{t,m,b} + Pa_{t,m,b} \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{18}$$

$$\sum_{m\in\mathcal{M}}\sum_{b\in\mathcal{B}m} Pb_{t,m,b} \leq \overline{P}^G \qquad \forall\, t\in\mathcal{T} \tag{19}$$

$$E_{t,m,b}, \Delta E_{t,m,b}, P^{PV}_{t,m,b} \geq 0 \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{20}$$

$$P^G_{t,m,b}, Pb_{t,m,b}, Pa_{t,m,b} \geq 0 \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{21}$$

$$P^T_{t,m,b}, SOC_{t,m,b}, E^{PVS}_t \geq 0 \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{22}$$

$$S_{t,m,b}, K_{t,m,b} \in \{0,1\} \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{23}$$

$$\Big(K_{t,m,b}, K_{t-1,m,b}, S_{t,m,b}\Big) \in \Omega \qquad \forall\, t\in\mathcal{T},\ m\in\mathcal{M},\ b\in\mathcal{B}_m \tag{24}$$

The objective function of the proposed model is illustrated by (1) – (4). The Expression (1) represents the swapping revenue, which is based on the energy sale $\Delta E_{t,m,b}$ of an accepted swapping request, evaluated at a fixed price λ per kWh to the customer. Therefore, customers only pay for the energy they receive in the swapped battery, discounting the energy of the depleted battery. The Expression (2) represents the revenue provided by the sale of PV generation to the grid E_t^{PVS} at spot price π_t. The Expression (3) represents the energy purchase costs from the grid, where $Pb_{t,m,b}$ is the amount below the established limit, with energy price π_t, and $Pa_{t,m,b}$ is the power that exceeds it, with a price increase of δ^+ $(\%)$. All the related power is used during the chosen time step D given in hours. Finally, (4) considers the use of $\phi(K)$ function, which describes the degradation cost and will be further discussed in Section 2.1. Constraints (5) define the energy level balance of the batteries, where the previous energy level ($E_{t-1,m,b}$) is added with the charged energy ($D{\cdot}P_{t,m,b}^{T}$) and balanced with the sold energy ($\Delta E_{t,m,b}$), in case of swapping assignment. In (6), the energy sold to a customer is defined based on swapping acceptance and on the energy level of the income EV customer depleted battery ($E_{t,m,b}^{EV}$). Constraints (7) indicate a relation of mutual exclusion between the charging status ($K_{t,m,b}$) and the swapping acceptation ($S_{t,m,b}$), establishing that a battery can be either swapped or charged or neither swapped nor charged. On the other hand, Constraints (8) bound the battery energy level. Equations (9) define the batteries' State of Charge (SoC), while (10) establish the batteries' minimum SoC in the final time slot, that way all batteries will start the next day at the desired level ($SOC^{(t_f)}$). Constraints (11) establish that a swap request can only be accepted if the battery satisfies the minimum desired energy level ($\tilde{E}_{t,m}$). Constraints (12) establish the swapping service based on the binary matrix A, which is equal to one if there is an EV arrival of model m at time t and zero otherwise. Constraints (13) limit the total batteries in charging by the total number of available chargers N, while (14) establish the batteries charging power rate bounds. Equations (15) show the composition of the BSS charging power, which may come both from the PV generation ($P_{t,m,b}^{PV}$) or from the grid ($P_{t,m,b}^{G}$). The PV generation distribution is defined with (16), where a part could be directed for the batteries charging or sold to the grid. These equations are given in energy measure (KWh), therefore, Equations (17) convert $E_{t,m,b}^{PV}$ values from energy to power rate unit (KW), creating variables $P_{t,m,b}^{PV}$. Equations (18) show the composition of the grid power used by the BSS, with $Pb_{t,m,b}$ being the portion below the recommended limit by the grid operator (L), where Constraints (19) represent this limitation, while $Pa_{t,m,b}$ is the above limit portion. The variables domain are shown in (20)-(23) and, at last, a set of constraints that establish a charging control behavior is defined in (24), which will be further detailed in Section 2.2. Regarding the non-linearity of the model, Equations (6) contain a bilinear product comprising binary variables ($E_{t-1,m,b} \cdot S_{t,m,b}$), which was chosen to be rewritten using McCormick envelopes [McCormick, 1976], since, for this case, it is an exact linear reformulation. Therefore, an auxiliary variable $Y_{t,m,b}$ is created to substitute the bilinear product, introducing Constraints (25) – (28) in the mathematical model, thus recasting the MINLP problem as a MILP one.

$$Y_{t,m,b} \leq \overline{E}_m S_{t,m,b} \qquad \forall t \in \mathcal{T}, m \in \mathcal{M}, b \in \mathcal{B}_m \tag{25}$$

$$Y_{t,m,b} \leq E_{t-1,m,b} \qquad \forall t \in \mathcal{T}, m \in \mathcal{M}, b \in \mathcal{B}_m \tag{26}$$

$$Y_{t,m,b} \geq E_{t-1,m,b} - \overline{E}_m(1 - S_{t,m,b}) \qquad \forall t \in \mathcal{T}, m \in \mathcal{M}, b \in \mathcal{B}_m \tag{27}$$

$$Y_{t,m,b} \geq 0 \qquad \forall t \in \mathcal{T}, m \in \mathcal{M}, b \in \mathcal{B}_m \tag{28}$$

2.1. Battery Degradation Model

Batteries are the main resource of a BSS and there are inherent associated costs to their use that must be considered as operational costs. Besides their acquisition capital, there exist operating costs associated with the battery degradation process, since in the long term, they induce the need for battery replacement.

Overall, the battery degradation rate depends on several factors such as charging and discharging cycles, aging, discharge depth, temperature, and also on its current State of Health (SoH), composing a non-linear and complex process. Designing a feasible mathematical model that accurately represents the battery degradation cost is a critical challenge in the existing literature, although fundamental for more realistic model applications. In this sense, this research leverages the ideas and results presented in Gao et al. [2017] to develop a battery capacity degradation rate model based on the charging current profile. Overall, based on several experiments, the authors developed a general curve for battery degradation based on the used charging rate and the battery's actual capacity loss, i.e, their State of Health (SoH). In order to incorporate these capacity degradation values in the proposed BSS model, a normalization together with a piecewise-linear function are applied, which can be seen in Fig. 1, following the same charging rate bounds of the original study. Moreover, it is assumed that all batteries have the same capacity loss state, equal to 10%. The following set of Constraints (30) – (35) is used to describe the degradation cost, therefore defining the function $\phi(K)$ to describe the battery degradation as an operational cost.

$$\phi(K) = \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} \sum_{b \in \mathcal{B}_m} \frac{C_m \theta_{t,m,b}}{2} \tag{29}$$

Subject to:

$$P^{T}_{t,m,b} = V^{DC}_{m} I_{t,m,b} \qquad \forall\, t \in \mathcal{T},\ m \in \mathcal{M},\ b \in \mathcal{B}_m \tag{30}$$

$$I_{t,m,b} = I^{Nom}_{t,m,b} I^{C}_{t,m,b} \qquad \forall\, t \in \mathcal{T},\ m \in \mathcal{M},\ b \in \mathcal{B}_m \tag{31}$$

$$\underline{I}^{C} K_{t,m,b} \leq I^{C}_{t,m,b} \leq \overline{I}^{C} K_{t,m,b} \qquad \forall\, t \in \mathcal{T},\ m \in \mathcal{M},\ b \in \mathcal{B}_m \tag{32}$$

$$\theta_{t,m,b} \geq \alpha_\gamma I^{C}_{t,m,b} + \beta_\gamma K_{t,m,b} \qquad \forall\, t \in \mathcal{T},\ m \in \mathcal{M},\ b \in \mathcal{B}_m,\ \gamma \in \Gamma \tag{33}$$

$$\theta_{t,m,b} \leq \overline{\theta} K_{t,m,b} \qquad \forall\, t \in \mathcal{T},\ m \in \mathcal{M},\ b \in \mathcal{B}_m \tag{34}$$

$$I_{t,m,b}, I^{C}_{t,m,b}, \theta_{t,m,b} \geq 0 \qquad \forall\, t \in \mathcal{T},\ m \in \mathcal{M},\ b \in \mathcal{B}_m \tag{35}$$

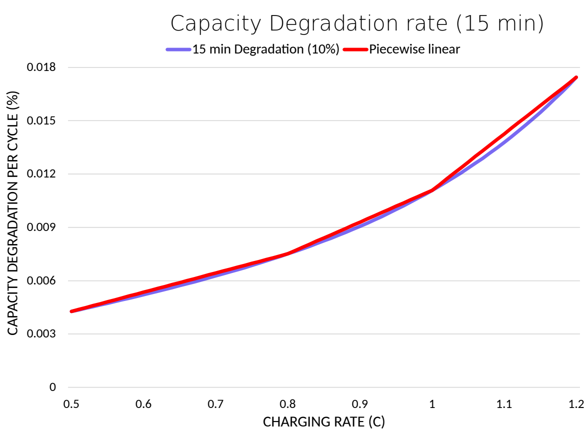


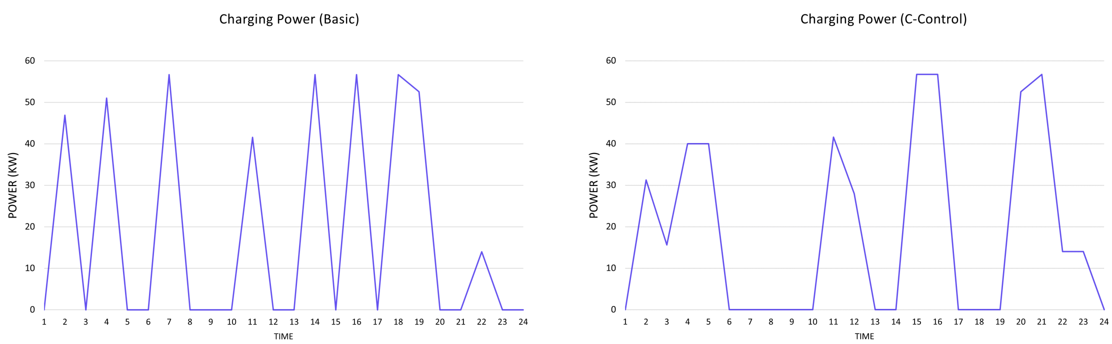
Fig. 1: Battery degradation curve linearized for 15min time slots

Expression (29) accounts for the battery degradation cost $C_m \theta_{t,m,b}$, which is directly related to battery type m capital cost C_m, since expensive batteries have proportionally higher degradation costs. Equations (30) relate the charging power with the charging current based on the volts of direct current of the respective battery model (V_m^{DC}). Constraints (31) relate the charging current with the respective C-rate ($I_{t,m,b}^{C}$) based on the nominal current ($I_{t,m,b}^{Nom}$) of 1C, while (32) bound the C-rate limits. Constraints (33) establish the degradation percentage $\theta_{t,m,b}$ based on the C-rate value $I_{t,m,b}^{C}$ through a piecewise-linear function with α_γ and β_γ coefficients, while Constraints (34) bound the $\theta_{t,m,b}$ values up to $\overline{\theta}$, took as the maximum value of the respective degradation curve. The variables' domain is shown in (35).

2.2. Charging Control Constraints

The basic formulation aims at deciding the batteries' optimal charging schedule such that the BSS daily profit is maximized. As the operation of the station proceeds, multiple swapping services are performed while stored batteries are being charged for future EV customers, also enabling multiple feasible solutions of charging schedule. In this context, it would be common to see multiple feasible solutions of charging schedule that leads to the same customer service. However, these multiple solutions can enable undesirable behaviors in the charging schedule, which can include repeatedly turning on and off movements on the chargers. Fig. 2a exemplifies the cited situation, which pictures a possible result of the basic model formulation.

In this context, a model extension is proposed by including the constraints (36) – (38) along with the insertion of variables $U_{t,m,b}$ and $V_{t,m,b}$, therefore creating the set Ω in (24). The new constraints propose a sequence of logical relationships to disable the charging profile observed in Fig. 2a, mainly establishing that only one charging process must occur between two battery swapping for the same battery index b. The expected behavior can be seen in Fig. 2b, where the charging profile is smoother and there are fewer chargers shutdowns.



(a) Charging Power (Basic)

(b) Charging Power (C-Control)

Fig. 2: Charging Power behavior change with C-Control constraints use

$$\Omega = \left\{ \left(K_{t,m,b}, K_{t-1,m,b}, S_{t-1,m,b}\right) \in \{0,1\}^3 \;\middle|\; \exists \left(V_{t,m,b}, U_{t,m,b}\right) \in \{0,1\}^2; \right.$$

$$K_{t,m,b} \leq K_{t-1,m,b} + V_{t,m,b} \tag{36}$$

$$U_{t,m,b} \geq K_{t-1,m,b} - K_{t,m,b} \tag{37}$$

$$\left. V_{t,m,b} \geq V_{t-1,m,b} - U_{t,m,b} + S_{t-1,m,b} \right\} \tag{38}$$

Constraints (36) establish that a charging battery can only charge if it was charging at the previous stage ($K_{t-1,m,b} = 1$) or if it has the allowance ($V_{t,m,b} = 1$) to start charging. On the other hand, Constraints (37) establish that when a battery stops being charged ($K_{t-1,m,b} = 1$, $K_{t,m,b} = 0$), it forces $U_{t,m,b} = 1$. Finally, Constraints (38) states that a battery acquires a charging allowance ($V_{t,m,b} = 1$) if it already obtained it before ($V_{t-1,m,b} = 1$) or if it already stopped being charged previously ($U_{t,m,b} = 1$) and a swapping request for it has been accepted ($S_{t,m,b} = 1$). Overall, these constraints establish that only one charging cycle occurs between two accepted swapping requests for the same battery index b, disabling multiple turn-on/off movements during the process while maintaining flexibility in the charging power.

References

ACM (2021). Battery swapping system. URL `https://acm.city/battery-swapping-system/`. Last accessed 24 May 2022.

Ahmad, F., Alam, M. S., Alsaidan, I. S., e Shariff, S. M. (2020). Battery Swapping Station for Electric Vehicles: Opportunities and Challenges. *IET Smart Grid*, 3(3):280–286.

Ban, M., Yu, J., Li, Z., Guo, D., e Ge, J. (2019). Battery swapping: An aggressive approach to transportation electrification. *IEEE Electrification Magazine*, 7(3):44–54.

Battapothula, G., Yammani, C., e Maheswarapu, S. (2019). Multi-objective optimal scheduling of electric vehicle batteries in battery swapping station. In *2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, p. 1–5.

Feng, J., Hou, S., Yu, L., Dimov, N., Zheng, P., e Wang, C. (2020). Optimization of photovoltaic battery swapping station based on weather/traffic forecasts and speed variable charging. *Applied Energy*, 264:114708. ISSN 0306-2619.

Gao, Y., Jiang, J., Zhang, C., Zhang, W., Ma, Z., e Jiang, Y. (2017). Lithium-ion battery aging mechanisms and life model under different charging stresses. *Journal of Power Sources*, 356: 103–114. ISSN 0378-7753.

IEA (2021a). Global EV Outlook 2021 – Accelerating Ambitions Despite the Pandemic. Technical report, International Energy Agency.

IEA (2021b). Net Zero by 2050 – A Roadmap for the Global Energy Sector. Technical report, International Energy Agency.

Joos, G., de Freige, M., e Dubois, M. (2010). Design and Simulation of a Fast Charging Station for PHEV/EV Batteries. In *2010 IEEE Electrical Power & Energy Conference*, p. 1–5.

Liang, Y. e Zhang, X. (2018). Battery Swap Pricing and Charging Strategy for Electric Taxis in China. *Energy*, 147:561–577. ISSN 0360-5442.

Mahoor, M., Hosseini, Z. S., e Khodaei, A. (2019). Least-cost operation of a battery swapping station with random customer requests. *Energy*, 172:913–921. ISSN 0360-5442.

McCormick, G. P. (1976). Computability of Global Solutions to Factorable Nonconvex Programs: Part I – Convex Underestimating Problems. *Mathematical Programming*, 10(1):147–175.

Shalaby, A. A., Shaaban, M., Mokhtar, M., Zeineldin, H. H., e El-Saadany, E. (2021). Optimal day-ahead operation for a pv-based battery swapping station for electric vehicles. In *2021 6th International Symposium on Environment-Friendly Energies and Applications (EFEA)*, p. 1–8.