Battery Swapping Stations for Long Haul Freight Charging Considering an Electrified Supply Chain

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***Abstract*—Electrification of heavy goods vehicles currently represents the most promising pathway to decarbonizing long-haul freight. The larger battery sizes compared to light-duty vehicles mean that charging times are likely to slow down freight operation significantly. Battery swapping stations, where the empty battery is swapped with another pre-charged battery, represent a promising alternative. In this paper we develop a model to determine the optimal logistics system, including the purchase of trucks, battery swapping stations, chargers, and warehouse space. By taking this integrated approach, we can understand the trade-offs of between battery swapping and other components of the supply chain. Using a case study involving seven cities, we show that battery swapping stations are installed when battery costs account for less than 40% of the truck cost. We show that the inclusion of swappable batteries results in a smaller truck fleet. The number of surplus batteries required depends strongly on the charging speed; with 500 MW (the current fastest chargers), around 1.2 batteries per truck were selected. We find that battery swapping increases utilization of renewable energy by less than 1%; the high utilization of trucks and batteries does not provide much energy flexibility in the considered case.**

I. Introduction

The global transportation sector accounts for approximately 23% of greenhouse gas emissions, with road transport alone contributing 72% of this share [1]. This staggering environmental footprint underscores the urgency of decarbonizing freight and logistics systems [2]. Decarbonizing transportation is a critical pillar of the global shift toward sustainable energy systems, driven by the urgent need to mitigate climate change. This transition emphasizes renewable energy adoption and energy efficiency improvements to decarbonize the power sector [3]. Electrifying transportation fleets offers a dual opportunity to reduce reliance on fossil fuels while improving the flexibility of the grid [4]. By decoupling charging from driving, battery swapping stations (BSSs) allow operators to align battery charging with renewable energy availability, acting as grid-scale buffers to mitigate intermittency.

Rapid adoption of electric vehicles (EVs) is essential for decarbonizing transportation, but faces challenges such as range anxiety, long charging times, grid instability persist, lack of charging infrastructure, and limited driving range [5]. Although fast charging stations have made significant progress in reducing waiting times, a caveat to their use is the rapid degradation of EV batteries. To address these drawbacks, battery swapping stations (BSSs) have emerged as a promising solution that offers rapid battery exchange and grid flexibility. In a BSS, EV owners can swap their discharged batteries with fully charged ones in under a minute. Unlike regular charging stations, which force immediate charging and strain the power grid, BSSs separate charging from swapping. This allows operators to charge batteries slowly over time, using smart charging schedules to reduce the impact on both transmission and distribution systems [6].

The integration of renewable energy generation into BSS operations is critical, but challenging. The variability of renewable energy threatens the reliability of the power grid, requiring additional flexibility, such as from battery storage. Battery systems compensate for fluctuations with fast-ramping capabilities, shift energy to off-peak periods, and store excess renewable output. Furthermore, they avoid no-load costs and minimum power constraints inherent in conventional generation. With a higher power density than pumped hydro or compressed air storage, they offer modularity for diverse grid needs [7]. Despite high costs, advancements have improved battery cost-effectiveness, making them essential for integrating renewables while reducing planning costs and curtailment.

Innovations like vehicle-to-grid (V2G) technology further enhance this flexibility. A critical innovation in this domain is vehicle-to-grid (V2G) technology, which enables electric vehicles (EVs) to function as mobile energy storage systems [8]. By integrating with the power grid by charging when energy is abundant and discharging during shortages, energy efficiency and renewable energy hosting capacity can be significantly enhanced, reducing curtailment of distributed energy resources (DERs) and stabilizing voltage deviations in systems with high DER penetration [9]. Furthermore, EVs can act as non-wire alternatives, deferring costly transmission infrastructure upgrades while supporting ancillary services like frequency regulation during idle periods. These advances position EVs as flexible grid assets that align with the broader goals of sustainable energy transitions [10].

Existing research on BSS optimization focuses on three key areas: cost efficiency, grid integration, and battery longevity. Various algorithms have been proposed for BSS research that focus on optimizing charging and swapping schedules to balance operational costs, grid demands, and user needs. In [11], a Gaussian Mixture Model is proposed to optimize the delivery path of mobile battery swapping trucks, minimizing travel distance when servicing EV users. Many models are often structured as formal optimization problems, categorized by their objectives and constraints. Key objectives include: minimizing operational costs [12], reducing the cost of purchased energy [13] and maximizing revenue [14]. Most algorithms enforce battery inventory constraints to meet swapping demand [15]. Some incorporate additional constraints, such as renewable energy prioritization [13], inventory balancing [14], grid peak-load avoidance [16], customer choice probabilities on dynamic routing acceptance [14], or battery degradation limits [17]

Recent studies also explore BSS-grid synergies, which focus on integrating BSS with power systems and renewable energy sources. [18] aligned solar-powered charging cycles for electric buses with metaheuristic optimization, reducing grid stress through improved peak-to-average ratios. [19] tackled grid-centric efficiency by formulating a charging schedule that minimizes distribution network energy losses while preserving voltage stability, ensuring BSS operations align with smart grid security constraints. Meanwhile, [16] addressed the dual challenges of grid support and battery longevity, proposing a V2G scheduling strategy that modulates charge-discharge cycles to mitigate degradation, enabling BSS participation in peak regulation without compromising battery lifespan. [20] presented an innovative approach to leverage supply chain flexibility to increase renewable energy use, demonstrating that supply chain scheduling could effectively increase renewable generation utilization with incentives as low as $0.01 per MWh.

Based on that, our battery-swapping model treats batteries as modular, transportable assets that enable centralized charging and optimized distribution across supply chains. Unlike studies focusing on isolated BSS components, we explicitly model the interdependency between truck fleet energy consumption, warehouse storage, renewable generation, and battery swapping dynamics. By coupling supply chain logistics, manufacturing processes, and energy systems into a unified framework, our approach ensures efficient renewable integration while minimizing system-wide costs. Through a case study with a comprehensive sensitivity analysis, we quantify how critical parameters such as battery costs and charging speeds govern BSS effectiveness.

II. Problem Formulation

To model the coupling of the supply chain, power system, and battery swapping stations, we develop a formulation that finds the lowest overall system cost. Our problem objective is to minimize the total capital and operation cost of the coupled system, which can be described as:

$$\begin{aligned} \min \quad & \Delta_t N_t \Bigg(\sum_i k_i^{\text{store}} W_i + k^{\text{truck}} Y + \sum_i k^{\text{batt}} B_i \\ & + \sum_i k^{\text{chg}} N_i^{\text{charger}} \Bigg) + k^{\text{power}} \sum_t z_t \\ & + \sum_t \sum_i 10^{-3} (p_i^{\text{charge}(t)} + p_i^{\text{production}(t)}) \Delta_t \end{aligned} \tag{1}$$

To calculate the total cost of the system across time and all locations, the following variables are needed: Δ_t, the size of each time step in hours; N_t, the number of time steps; k_i^{store}, the levelized cost of warehouse storage at a given location i in $\$/\text{kg-hour}$, which varies by location; k^{truck}, the levelized cost of each truck in $\$/\text{hour}$; W_i, the maximum capacity of the storage facility at location i in kg; and Y, the total number of trucks in the fleet.

Additionally, for the battery swapping infrastructure, we include: k^{batt}, the cost per additional swappable battery unit; B_i, the number of additional batteries deployed at location i; k^{chg}, the cost per charger unit; and N_i^{charger}, the number of chargers installed at location i. To determine the use of non-renewables and incentivize efficient energy usage, we include a power penalty, k^{power}, in $/KWh, and the amount of non-renewables used at each time, z_t, in kWh. In the objective, we also include the total electricity charging efficiency for charging batteries $p_i^{\text{charge}(t)}$ and production processes $p_i^{\text{production}(t)}$ in kW. The factor 10^{-3} is a weighting factor to create a secondary objective that disincentivizes solutions that waste renewable power.

The constraints of the coupled optimization problem with battery swapping can be expressed as:

$$\begin{aligned} C_i^{(t)} - C_i^{(t-1)} = \Delta_t \left(\beta \cdot p_i^{\text{charge}(t)} - \frac{1}{\beta} \cdot p_i^{\text{discharge}(t)} \right) \\ - \sum_j \left(E_{ij} y_{ij}^{(t)} + \alpha E_{ij} \hat{y}_{ij}^{(t)} \right) \end{aligned} \tag{2a}$$

$$\Delta_t (p_i^{\text{production}(t)} + p_i^{\text{discharge}(t)}) \geq \sum_{\tau=0}^{\tau} \alpha m_i^{(t-\tau)} \tag{2b}$$

$$C_i^{(t)} \leq \left(Y_i^{(t)} + B_i \right) \cdot \eta \tag{2c}$$

$$\Delta_t p_i^{\text{charge}(t)} \leq \left(Y_i^{(t)} + B_i \right) \cdot \gamma \tag{2d}$$

$$\Delta_t p_i^{\text{discharge}(t)} \leq \left(Y_i^{(t)} + B_i \right) \cdot \gamma \tag{2e}$$

$$p_i^{\text{charge}(t)} \leq N_i^{\text{charger}} \cdot \gamma \tag{2f}$$

$$\Delta_t \sum_i (p_i^{\text{charge}(t)} + p_i^{\text{production}(t)}) \leq \sum_i r_i^{(t)} + z_t \tag{2g}$$

$$C_i^{(T)} = C_i^{(0)} \tag{2h}$$

All constraints are for all locations i and time steps t where appropriate.

Our formulation incorporates the novel battery swapping constraints while maintaining the core transportation and inventory constraints from the previous model [20]. Constraint

(2a) tracks the accumulated charge in batteries at each location. The accumulated charge level $C_i^{(t)}$ at location i and time t depends on the previous energy level, energy gained through charging and discharging with efficiency factor β, and energy consumed by departing trucks. The terms E_{ij} and αE_{ij} represent the energy required for loaded and empty trucks, respectively, where α is a factor accounting for the reduced energy consumption of empty trucks.

The constraint (2b) ensures that sufficient energy is available for production processes, requiring that the combined energy of the production charging energy and battery discharge meet the energy needs of all manufacturing activities. The parameter α represents the energy intensity of the production process, and $m_i^{(t-\tau)}$ indicates the production quantity.

Constraints (2c), (2d), and (2e) establish limits on energy storage and charging/discharging rates. The parameter η represents the energy capacity per battery, and γ represents the maximum charging/discharging speed per battery unit. These constraints ensure that the model respects the physical limitations of battery charging capacity in both stationary locations and idle trucks.

Constraint (2f) restricts total charging power based on available charging infrastructure capacity, where γ is the charging speed per charger. Constraint (2g) establishes the overall energy balance, ensuring that total energy consumption does not exceed available energy from renewable and non-renewable sources.

Finally, constraint (2h) ensures energy sustainability by requiring that the final energy level at each location is equal to the initial level.

In addition to these battery swapping-specific constraints, our model incorporates the truck balance constraints [20, eq. (2a)], inventory balance constraints [20, eq. (2b) (2g)], and fleet size constraints [20, eq. (2d)] from previous model. These include tracking the number of stationary trucks at each location, monitoring product inventory, ensuring warehouse capacity constraints are met, and maintaining the overall fleet size limit.

All decision variables must be non-negative:

$$\begin{aligned} &y_{ij}^{(t)}, \hat{y}_{ij}^{(t)}, z_t, X_i^{(t)}, Y_i^{(t)}, C_i^{(t)}, p_i^{\text{charge}(t)}, \\ &p_i^{\text{discharge}(t)}, p_i^{\text{production}(t)}, B_i, N_i^{\text{charger}} \geq 0 \end{aligned} \tag{3}$$

We relax the integer variables for the number of trucks and batteries to be continuous to keep the computational burden manageable, though this necessitates implementing a rounding policy when applying the solution in practice.

III. Results

To determine the optimal use of battery swapping stations, we conduct a case study as described in [20], which included 7 cities in the network, with each city having a deterministic time-varying demand for product in kilograms. Products are manufactured in Savannah and and must be distributed to the other cities. The case study extended across a 2-month planning horizon and contained hourly time steps. We implemented the proposed model in Python using Gurobi on an ROG Zephyrus G16 laptop.

Given the substantial decline in battery cell costs and the ongoing uncertainty surrounding the overall cost implications of truck battery packs, we specifically examine how the cost of batteries and charging speeds change the optimal solution. This sensitivity analysis reveals fundamental thresholds where the infrastructure strategy abruptly changes, providing crucial insights for real-world deployment decisions.

A. Changes in the cost of a single truck battery

Figure 1 shows the changes of both additional swappable battery storage and truck fleet size under different costs of a single truck battery.

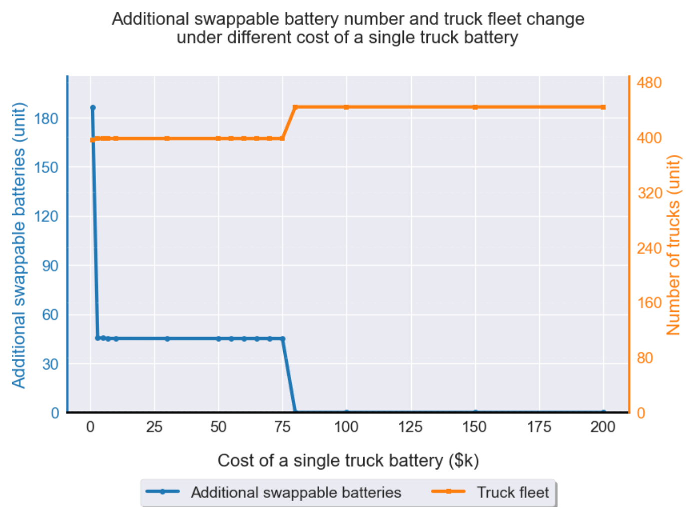

Fig. 1. Number of surplus batteries and truck fleet size change under different costs of a single truck battery.

The results show a clear turning point at around \$75,000 per 900 kWh battery (\$83/kWh) that completely changes how the system should be designed. The critical threshold occurs when battery cost reaches approximately 40% of the truck cost. Below this 40% ratio, the system strongly favors the deployment of battery swapping stations with substantial stationary storage and a smaller truck fleet. This allocation allows the system to capitalize on the relatively low cost of stationary energy storage compared to mobile transportation capacity, enabling efficient energy management through centralized charging and battery circulation.

While above the 40% cost ratio threshold, the economics shift toward a transportation-intensive approach where additional battery storage becomes negligible and the truck fleet expands from 398 to 443 vehicles. This transition reflects the fundamental trade-off between stationary battery storage and mobile distribution capacity in supply chain optimization.

The nature of this sharp transition indicates that the system either commits to battery swapping infrastructure when the cost ratio is favorable, or abandons additional stationary storage entirely when batteries become too expensive relative to trucks. This ratio-based threshold provides crucial guidance for BSS deployment decisions, suggesting that battery swapping stations only become economically justified when battery costs fall below approximately 40% of truck costs. We believe that the cost ratio is more significant than the $/kWh threshold, given there is also uncertainty around future truck prices.

If batteries become extremely cheap relative to trucks ($approx$ 0.5% of truck cost), then a large number of surplus batteries are purchased. In these cases, we see that the batteries are used for on-site energy storage at the manufacturing facility, as well as for use in the trucks. However, we believe that it is not likely that the battery will ever represent such a small fraction of the vehicle cost.

B. Changes in Charging Speed

Figure 2 shows how additional swapping battery storage and truck fleet size change under different charging speeds at a fixed battery cost of $10,000 (which is within the stable period where BSS is cost competitive).

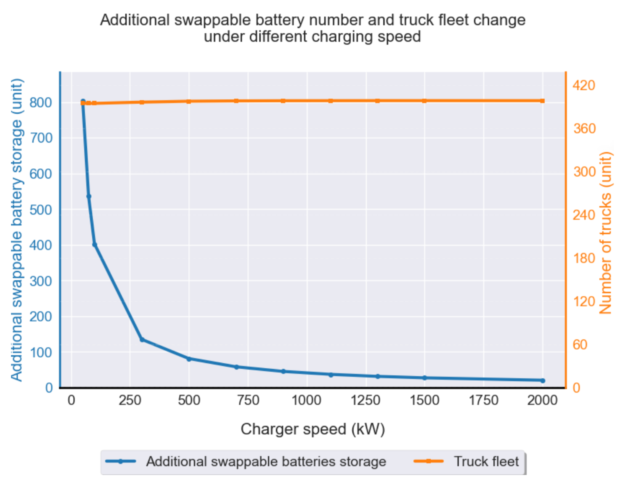

Fig. 2. Additional swappable battery number and truck fleet change under different charging speed

The sensitivity analysis of the charger speed reveals a critical relationship between the capacity of the charging infrastructure and the battery inventory requirements, demonstrating that slower charging significantly increases the need for surplus battery storage. When charging speeds increase from 50 kW to 100 kW, the required batteries per truck plummets sharply from 3 to 2, whereas increasing the charging speed to 2 MW reduces this ratio to just 1.1 batteries per truck. This dramatic decline in battery requirement reflects the fundamental constraint that slow charging creates bottlenecks in battery turnover, forcing the system to compensate with larger inventory buffers to ensure the continuous availability of charged batteries for swapping operations.

The analysis reveals a critical threshold at 700 kW, which equates to about 1 hour to charge from 0 to 70% state of charge. Below 700 kW charging speed, the system requires substantial additional battery storage. Beyond 700 kW, the relationship between charging speed and surplus battery requirements transitions into a relatively stabilized regime. As illustrated in Fig. 2, increasing the charging capacity to 1 MW requires only approximately 10% surplus inventory, a stark contrast to the significantly higher battery reserves required at lower charging speeds, such as 50 kW. This nonlinear reduction demonstrates that charging infrastructure investment above 700 kW provides diminishing returns in terms of battery inventory reduction, with the threshold marking the turning point where operational efficiency approaches near-optimality.

C. The Combined Influence of Battery Cost and Speed

To comprehensively evaluate the interaction between battery cost and charging speed in the system configuration, we present heat maps that illustrate the relative importance of these critical parameters across the entire operational space. Figures 3, 4, and 5 show the additional swapping battery storage, charger deployment, and truck fleet size variations among different combinations of battery costs and charging speeds.

Figure 3 reveals two distinct operational cases separated by a sharp transition zone around $75,000 battery cost. In the low-cost case, the system exhibits high sensitivity to charging speed, with battery storage requirements ranging from 1600+ units at 25 kW to 20 kW at higher charging speeds. This dramatic variation demonstrates that when batteries are economically attractive, charging infrastructure capacity becomes the primary bottleneck determining inventory requirements. In contrast, in the high-cost case, battery storage remains consistently minimal regardless of charging speed, indicating that economic constraints override operational considerations.

While most charging speed scenarios show a sharp transition to zero additional battery units at a single battery cost of $75,000, the highest charging speed (2000 kW) maintains non-zero additional battery deployment until the cost reaches $80,000. This subtle shift in the cost threshold suggests that the cost threshold is slightly dependent on the charging speed. Faster charging capabilities may marginally extend the economic viability of battery storage deployment, even at higher battery cost levels.

Figure 4 reveals that charger quantities are insensitive to battery cost variations, but highly responsive to charging speed requirements. Across all battery cost levels, the charger deployment remains consistent within each charging speed level, demonstrating that charging infrastructure needs are determined solely by power capacity requirements rather than battery economics. The charger deployment changes dramatically from approximately 1600 units at 25 kW charging speed to around 20 units at 2000 kW, reflecting the inverse relationship between individual charger capacity and the total number of chargers needed to meet system charging demands.

Figure 5 demonstrates an inverse relationship to battery storage, with fleet sizes remaining stable at approximately 395 trucks in the low battery cost regime and increasing substantially to 465-2000 trucks when battery costs exceed the economic threshold. Interestingly, the truck fleet exhibits dual sensitivity patterns: in the low battery cost case, fleet size remains relatively insensitive to charging speed variations,

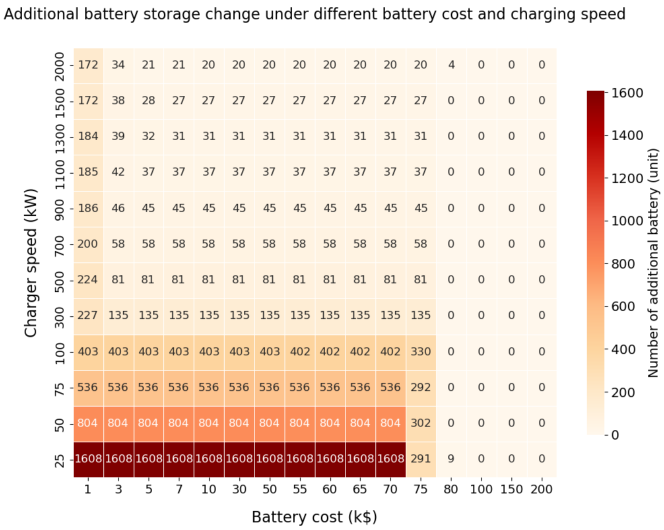

Fig. 3. Heat map of additional swapping battery storage changes under different costs of a single truck battery and different charging speeds.

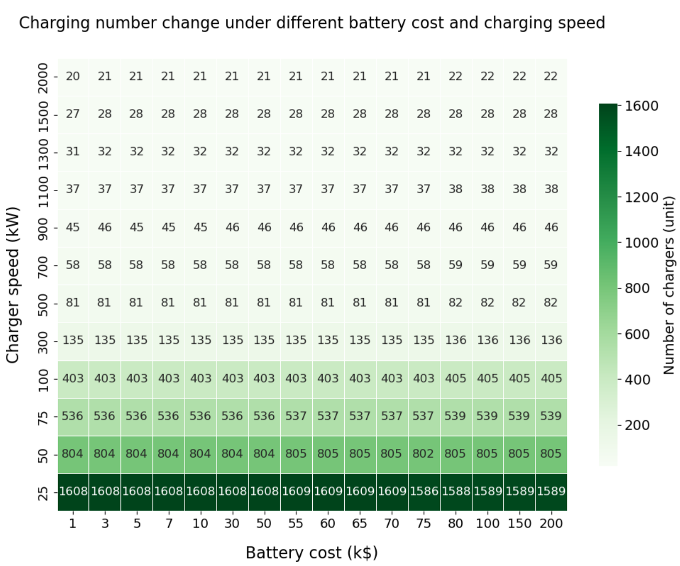

Fig. 4. Heat map of charger storage changes under different costs of a single truck battery and different charging speeds.

maintaining consistent levels around 395-398 trucks. However, in the high battery cost case, the truck fleet becomes highly sensitive to charging speed, with fleet sizes ranging from approximately 414 trucks at 2000 kW to 1952 trucks at 25 kW charging speed. This behavior indicates that when battery swapping becomes economically unattractive, the system compensates by expanding transportation capacity, and slower charging speeds exacerbate this need by creating operational bottlenecks that require even larger truck fleets to maintain service levels.

D. Renewable Energy Utilization

Finally, we consider the extent to which BSS increases the utilization of renewable energy. Applying a price penalty

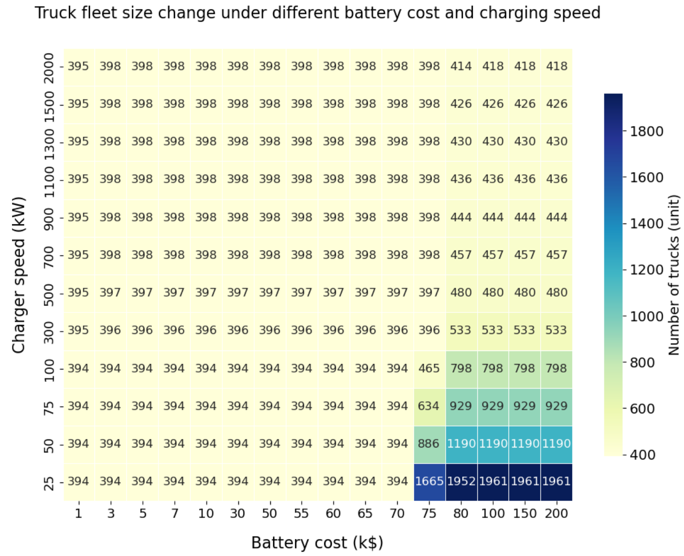

Fig. 5. Heat map of truck fleet size changes under different costs of a single truck battery and different charging speeds.

of $12/MWh to non-renewable energy we consider how the total energy consumption changes with and without BSS. As Figure 6 shows, at the turning point with $75,000 battery cost and 700 kW charging speed, the system achieves a 40.6 MWh increase in renewable consumption alongside an 11.7 MWh decrease in non-renewable consumption compared to the non-swapping baseline. The introduction of battery swapping creates a dual benefit in the energy ecosystem. The increase in renewable energy adoption suggests that battery swapping infrastructure enables better integration and utilization of clean energy sources. This occurs because battery swapping stations can be strategically charged during peak renewable generation periods, such as high solar or wind output hours, effectively serving as distributed energy storage systems. However, the increase is modest compared to the total energy consumption of the supply chain (which includes manufacturing), and it should be noted that the total energy consumption also increases slightly with battery swapping. In this case study, due to high capital costs, the trucks and batteries had high utilization (and thus not so much energy flexibility). It is likely that more substantive renewables increases would have been possible in freight systems with more redundancy.

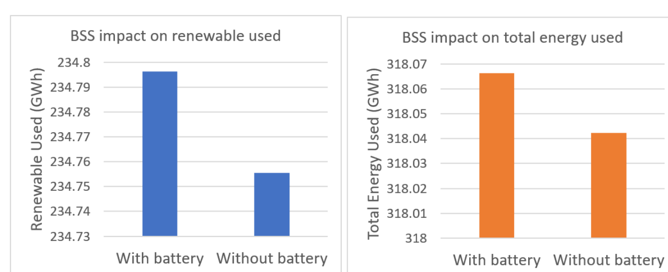

Fig. 6. Comparison of energy usage using battery swap and not using battery swap.

IV. Conclusion

This study investigates a system-level optimization framework that integrates supply chain logistics, power systems, manufacturing processes, and battery swapping stations to optimize cost efficiency and the use of renewable energy in freight transportation networks. An optimization framework was developed to model the interdependency between truck fleet energy consumption, warehouse storage dynamics, battery charging or discharge cycles, and renewable generation profiles. The formulation explicitly balances operational costs, grid flexibility, and sustainability, offering a unified approach to decarbonize freight logistics.

The case study across seven cities revealed critical insights into system design trade-offs. The results highlight the critical role of the relative cost ratio between batteries and trucks in determining optimal system architecture. When battery costs fall below \$75,000, which is 40% of truck costs (with 83 \$/kWh), the model favors deploying large-scale stationary battery storage with smaller truck fleets, leveraging centralized charging and battery circulation to minimize operational expenses. Above this threshold, the system shifts toward transportation-intensive configurations, where expanded truck fleets dominate and stationary storage becomes economically marginal. Furthermore, the speed of the charging infrastructure significantly impacts inventory requirements: below 700 kW, slow charging requires up to 800 surplus batteries to address turnover bottlenecks, while speeds exceeding 700 kW reduce redundancy to 10% by allowing rapid battery replenishment.

Comprehensive heat map analysis confirms that battery cost around \$75,000 defines distinct operational cases: below this threshold, charging speed primarily governs battery storage requirements, while above it, economic constraints necessitate truck fleet expansion that becomes highly sensitive to charging speed variations. However, the charger deployment depends solely on the charging speed requirements, remaining insensitive to battery cost in all scenarios. The case study demonstrates that the battery swapping system can increase the utilization of renewables and decrease the nonrenewables. Therefore, the unified system coupling transportation logistics with energy constraints optimizes system costs while ensuring the utilization of renewable energy.

Future work should prioritize integer-based formulations to address discrete fleet and inventory constraints, ensuring solutions align with real-world operational granularity. Expanding the case study to a larger-scale network with stochastic demands could further enhance system resilience. These advancements would provide actionable strategies for policymakers and operators to accelerate the transition to sustainable, grid-responsive freight systems.

References

[1] I. P. on Climate Change, "Transport," p. 599–670, 2015.

[2] A. Harrouz, D. Belatrache, K. Boulal, I. Colak, and K. Kayisli, "Social acceptance of renewable energy dedicated to electric production," in *2020 9th International Conference on Renewable Energy Research and Application (ICRERA)*, 2020, pp. 283–288.

[3] H. Song, Y. Lee, G.-S. Seo, and D. Won, "Electric vehicle charging management in smart energy communities to increase renewable energy hosting capacity," in *2023 11th International Conference on Power Electronics and ECCE Asia (ICPE 2023 - ECCE Asia)*, 2023, pp. 453–458.

[4] H. Yang, C. Guo, J. Ren, and J. Sheng, "A coordinated charging strategy on battery swapping station in microgrid considering battery to grid," in *2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia)*, 2019, pp. 3322–3326.

[5] R. Sushmitha, K. Asha, J. Tejaswini, V. Hemanthakumari, K. Harshitha, and N. K. Suryanarayana, "Implementation of electric vehicles charging station and battery management system," in *2023 2nd International Conference for Innovation in Technology (INOCON)*, 2023, pp. 1–5.

[6] C. Crozier, T. Morstyn, and M. McCulloch, "The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems," *Applied Energy*, vol. 268, p. 114973, 2020.

[7] N. Li, C. Uçkun, E. M. Constantinescu, J. R. Birge, K. W. Hedman, and A. Botterud, "Flexible operation of batteries in power system scheduling with renewable energy," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 2, pp. 685–696, 2016.

[8] C. Crozier, T. Morstyn, M. Deakin, and M. McCulloch, "The case for bi-directional charging of electric vehicles in low voltage distribution networks," *Applied Energy*, vol. 259, p. 114214, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261919319014

[9] L. Shuguang and Y. Zhenxing, "Progress and prospect of electric vehicle's v2g technology," in *2019 6th International Conference on Information Science and Control Engineering (ICISCE)*, 2019, pp. 412–416.

[10] S. Cai and R. Matsuhashi, "Model predictive control for ev aggregators participating in system frequency regulation market," *IEEE Access*, vol. 9, pp. 80 763–80 771, 2021.

[11] N. Promsuk, "Gmm-p: Intelligent method based a mobile battery swapping service for electric vehicles," in *2021 25th International Computer Science and Engineering Conference (ICSEC)*, 2021, pp. 346–350.

[12] Q. Lou, X. Zhang, and J. Xu, "Optimal scheduling and sharing model for electric vehicle battery swapping," in *2023 IEEE 7th Conference on Energy Internet and Energy System Integration (EI2)*, 2023, pp. 3330–3335.

[13] X. Yu, F. Wang, and H. Wang, "Optimal battery swapping and charging strategy considering on-site solar generation," in *2023 IEEE/IAS Industrial and Commercial Power System Asia (ICPS Asia)*, 2023, pp. 1082–1087.

[14] L. Ni, B. Sun, X. Tan, and D. H. K. Tsang, "Inventory planning and real-time routing for network of electric vehicle battery-swapping stations," *IEEE Transactions on Transportation Electrification*, vol. 7, no. 2, pp. 542–553, 2021.

[15] M. C. Kocer, O. Yurdakul, and S. Albayrak, "Optimal scheduling of battery swapping stations for electric public transportation," in *2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*, 2021, pp. 1–5.

[16] J. Zhang, W. Wang, R. Wang, T. Li, X. Zhao, J. Li, and X. Yu, "An electric vehicle scheduling strategy for the power grid peak regulation based on v2g," in *2023 3rd International Conference on New Energy and Power Engineering (ICNEPE)*, 2023, pp. 1181–1187.

[17] A. Siddiqua, V. Cherala, and P. K. Yemula, "Optimal sizing and adaptive charging strategy for the battery swapping station," in *2023 IEEE PES 15th Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, 2023, pp. 1–6.

[18] T. Boonraksa, P. Boonraksa, W. Pinthurat, and B. Marungsri, "Optimal battery charging schedule for a battery swapping station of an electric bus with a pv integration considering energy costs and peak-to-average ratio," *IEEE Access*, vol. 12, pp. 36 280–36 295, 2024.

[19] S. S. Amiri and S. Jadid, "Optimal charging schedule of electric vehicles at battery swapping stations in a smart distribution network," in *2017 Smart Grid Conference (SGC)*, 2017, pp. 1–8.

[20] R. Davila Severiano and C. Crozier, "Scheduling electrified freight transportation to increase renewable generation utilization," in *2024 56th North American Power Symposium (NAPS)*, 2024, pp. 1–6.