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Strategic and Operational Decision-Making in Delivery Fleet Electrification - A Case Study

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Executive Summary
This paper analyzes the decision-making process in electrifying delivery vehicle fleets, focusing on minimizing Total Cost of Ownership (TCO) through strategic and operational decisions. Based on a case study of a Swiss parcel logistics company, we utilize two quantitative models: A strategic model for optimizing infrastructure (e.g., PV systems, battery storage, grid connections) and an operational model for daily fleet management (e.g., charging schedules, state-of-charge management). The paper at hand examines the decisions taken at both levels and how they interact. It further explores how their integration can enhance performance and resilience. The findings highlight the importance of aligning strategic and operational decisions to create a cost-effective, scalable fleet electrification framework that enables partial grid independence and resilience through strategic infrastructure decisions and intelligent operations. This research provides logistics companies with strategies to lower electrification costs, boost efficiency, and improve resilience.

Keywords: Smart grid integration and grid management, Smart charging, Energy storage systems, Energy management

1 Introduction

Electrifying freight transport is a promising strategy to support net zero goals, yet it faces significant technical and economic challenges [1]. Critical considerations are the costs associated with infrastructure investments, such as grid connection expansion, compared with those of alternative electricity supply solutions like photovoltaic (PV) systems and battery storage [2]. Full grid connection reinforcement, while sometimes necessary, can be costly or even unfeasible, requiring innovative approaches to manage energy demands effectively [3].

Currently, it is unanswered which decision dimensions need to be considered on strategic and operational level to decide whether it makes sense to invest in infrastructure to gain higher levels of autonomy from the grid and what contribution a (partly) autonomous electricity system can make to resilience increase in delivering the orders to customers. To close this gap, the paper at hand develops a strategic and an operational decision support model and will show how these models can be used to derive decisions in PV and battery sizes in relation to fleet size and grid connection costs.

This research is based on a single case study within an ongoing project in Switzerland, where multiple stakeholders — including a site owner, a logistics operator, an energy provider, and a charging infrastructure partner — collaborate to develop scalable and cost-effective electrification strategies. The case study provides the practical foundation for building and applying the strategic and operational models proposed in this paper.

2 Literature Review

The electrification of vehicle fleets presents substantial opportunities and challenges, particularly in balancing operational costs, energy system integration, and resilience. Recent research increasingly emphasizes the importance of coupling fleet electrification with local energy systems and optimizing the use of electric vehicle (EV) batteries beyond mobility purposes.

Flexible charging strategies, such as controlled (V1G) and bidirectional (V2G) charging, have been identified as essential for enhancing grid flexibility and renewable energy integration. Andersen and Powell [4] highlight that well-designed electricity tariffs and policy tools are critical to incentivize small-scale V2G deployments, addressing profitability challenges for aggregators and enabling broader distributed flexibility services. The need for supportive tariff structures and reduction of double taxation on V2G energy flows is a recurring theme for realizing the full potential of distributed V2G systems.

Advancements in multi-use optimization strategies, where EVs simultaneously provide multiple services such as peak shaving, energy arbitrage, and frequency regulation, have shown significant potential to improve the economics of fleet electrification. Englberger et al. [5] developed a multi-use control framework combining behind-the-meter and front-of-the-meter applications for commercial EV fleets, demonstrating that stacking value streams can significantly boost annual revenues and enhance battery lifetime. Similarly, Biedenbach and Strunz [6] introduced an optimization model for heavy-duty electric trucks that jointly addresses self-consumption, peak shaving, tariff optimization, and arbitrage trading, underlining the large potential savings achievable with bidirectional depot charging.

The optimal integration of EVs into decentralized energy systems has also been explored through scalable frameworks, such as the REVOL-E-TION model by Rosner et al. [7], which enables flexible participation of EV fleets in local energy markets and grid services. This model emphasizes the importance of modular and scalable control architectures, particularly in settings with mixed charging and discharging objectives.

At the household scale, Kern et al. [8] investigated combined vehicle-to-home (V2H) and vehicle-to-grid (V2G) applications, showing that V2H revenues are highly seasonal and that coupling V2G with V2H strategies can maximize economic returns. Their findings underline the broader principle that multi-seasonal and multi-service approaches enhance the viability of bidirectional EV integration.

Focusing on heavy-duty applications, Razi et al. [9] demonstrated through a case study of electric trucks in factory settings that predictive smart charging algorithms can significantly lower grid-related costs, particularly when leveraging local renewable generation and dynamic pricing. Their work reinforces the necessity of smart energy management for high-power vehicle fleets to ensure both cost-efficiency and grid stability.

Collectively, the literature establishes that optimal fleet electrification requires an integrated view of strategic infrastructure investments (e.g., PV, batteries, grid connection) and operational energy management (e.g., smart charging, V2G, tariff optimization). It also stresses that economic viability is highly sensitive to contextual factors such as tariff structures, station costs, and system design parameters. However, gaps remain regarding decision frameworks that jointly optimize strategic and operational dimensions for fleets, particularly under real-world boundary conditions—a gap that the present study aims to address.

3 Case Study in Switzerland

This research was initiated to explore cost-effective solutions for the electrification of delivery vehicle fleets. The project focuses on the single case study of a parcel logistics company, committed to fully electrifying its fleet by 2035. The company operates 12 parcel delivery hubs across Switzerland, each with different infrastructure situations and boundary conditions, presenting a unique opportunity to develop quantitative models to optimize TCO of the electric vehicle fleet and its corresponding infrastructure.

The case study is situated at a former freight yard, located in a city in Switzerland and owned by a railway company, that spans 16.7 hectares and currently accommodates a variety of rail-related and logistics facilities, including an intermodal terminal, general cargo handling areas and a parcel distribution center.

Thanks to its central location adjacent to the main railway station, the site offers substantial urban development potential. Plans are underway to relocate much of the international freight traffic from this location to a newly developed facility further outside the city. This transformation opens opportunities to reorganize current logistics utilizations within the site. As a result, large areas—especially in the western and southern sections—are expected to be repurposed for new developments, such as residential and commercial spaces. The northeastern section will remain in use as a container terminal.

The logistics company has been operating from this strategically positioned site since 2021. Given the site's ongoing transformation and the potential for pioneering urban development, the logistics company, the railway company and an energy provider have partnered to conduct a comprehensive case study at the site. The objective is to analyze the current operational setup, define future requirements for electrified fleets, and evaluate technical and economic measures to optimize operations.

Table 1 - Available data from the case study

Data	Description
Vehicle operation data	Distance, operating hours, idle times, delivery stops
Vehicle battery & consumption data	Battery limits, energy consumption, battery capacities
Cost data	Vehicle and e-truck costs, stationary battery costs per kWh
Second-life battery data	Storage capacity & charging power
Fleet electrification planning	Expansion plans, vehicle procurement timelines
Power grid data	Grid connection capacity, tariffs, flexibility levels
Site power demand	Base and peak loads
PV yield per kW	Daily PV yield curves
Public data sources	Incentive programs, road and infrastructure data, taxes

The parcel logistics company currently operates a fleet of 10 electric delivery vehicles at the site, each assigned to a dedicated charging station. On average, the vehicles travel 39 kilometers per day over 7 hours and 40 minutes and make 111 stops. The installation of a 60 kWp photovoltaic (PV) system and a 220 kWh stationary battery storage unit is currently in the planning phase to cater to the demand of the electric vehicles on site. Table 1 provides an overview of the available data for the study of this paper.

The power supply for the site is currently managed through a site-wide electrical network operated by a train operator, with its own transformer stations and medium-voltage (level 5) connection to the energy company grid. One of these transformer stations is located at the freight yard under investigation itself. The train operator distributes electricity internally to site tenants via a low-voltage (level 7, 400V) system. Based on an agreement between train operator and energy company, tenants are billed directly by the energy company for their electricity consumption.

Several tenants, including the parcel logistics company and another tenant company, are in the process of forming a local energy community (ZEV). The aim is to optimally integrate PV generation, stationary storage, mobile storage (vehicles), and consumers to minimize peak grid demand and limit PV surplus feed-in. With the site undergoing major redevelopment, the power infrastructure will also be completely redesigned. The existing transformer has reached the end of its technical life, and the future energy demand will significantly exceed current levels. As part of the new infrastructure planning, the power supply agreement between train operator and energy company will also be revised. It is likely that the site under investigation will be decoupled from the train operators medium-voltage grid and that the energy company will directly supply tenants or ZEVs going forward.

Although planning is still in the early stages, the logistics company is expected to remain a part of the future ZEV and continue to operate within the restructured energy landscape of the current site.

4 Methodology

Building on insights from the case study, which incorporates real-world data such as operational schedules and energy consumption patterns, two quantitative models are developed to support strategic and operational decision-making in fleet electrification.

4.1 Strategic Model

The strategic model developed in this study addresses long-term investment decisions necessary for the electrification of delivery vehicle fleets. It focuses on optimizing the sizing of key infrastructure components, including the photovoltaic (PV) system, stationary battery storage, vehicle batteries, and the grid connection, while also incorporating considerations for fast and bidirectional charging capabilities. The overarching objective is to minimize the Total Cost of Ownership (TCO) by balancing capital investments, operational costs, and potential revenues from surplus PV electricity.

At the core of this approach is a mathematical optimization model designed to capture the complex interactions between the electric vehicle fleet, on-site PV generation, stationary energy storage, and the grid connection. The model is implemented in Python using the Gurobi solver and formulated as a Mixed-Integer Linear Programming (MILP) problem. It optimizes not only the infrastructure dimensions but also the charging and discharging schedules of the vehicles, while adhering to physical constraints such as vehicle state-of-charge requirements, station capacities, and grid limitations.

The model operates within a scenario-based framework, where different fleet compositions, PV system sizes, battery capacities, and other infrastructure parameters are systematically varied. Each scenario represents an independent optimization run, enabling comprehensive evaluation of different configurations. The results are saved in a centralized database to allow comparative analysis. The modeling pipeline structure is illustrated in Figure 1.

Real-world operational data form the foundation of the model. Inputs include vehicle energy consumption profiles, detailed driving and rest schedules, PV production profiles based on hourly data over the past three years, battery specifications, and local electricity tariffs under dynamic pricing structures. This high temporal resolution allows for simulation across annual cycles or full three-year periods, ensuring that seasonal fluctuations in PV generation and energy demand are accurately represented.

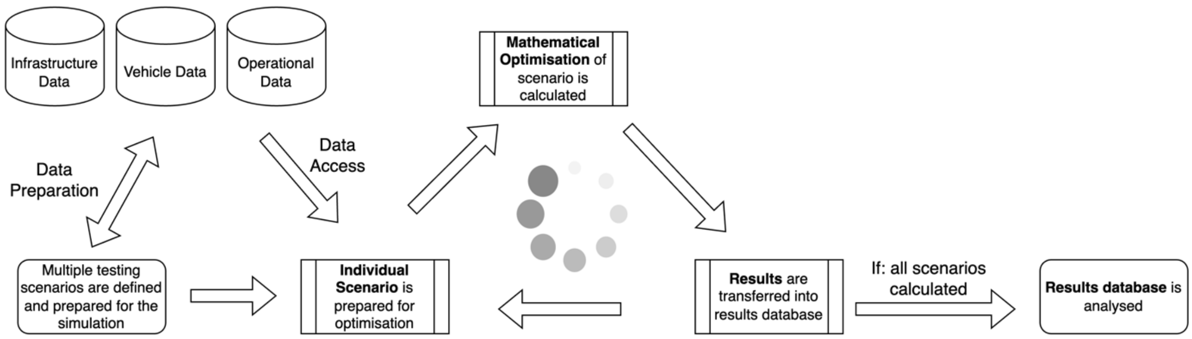

Figure 1 - Model pipeline of strategic model

The model incorporates a detailed cost structure, accounting for investment and maintenance costs associated with PV installations, stationary batteries, and grid upgrades. Operational costs, including dynamic grid electricity charges and potential revenues from PV surplus feed-in, are also modeled. Depreciation of infrastructure investments is calculated within each scenario, and energy losses due to charging and discharging inefficiencies of vehicles and batteries are explicitly considered.

The optimization results provide key outputs, including the economically optimal sizing of the PV system and stationary battery storage, optimal charging and discharging strategies for the fleet, and system performance indicators such as grid dependency, self-sufficiency rates, and cost savings potential. Visualizations of charging patterns, battery usage profiles, and energy sourcing breakdowns are produced to support interpretation and strategic decision-making for infrastructure planning.

Due to the interdependencies between system components, the optimization problem is inherently complex. For example, increasing PV capacity may reduce reliance on stationary batteries if vehicles return to the depot during periods of peak solar generation, allowing direct charging without intermediate storage. However, realizing this potential benefit depends on having sufficient vehicle charging power and appropriately sized charging infrastructure. An overview of the model's most important input parameters is provided in Table 2.

Table 2 - Data inputs for the TCO Optimization Model

Data	Description
PV-Performance Factor	Time-dependent PV output.
Grid Connection Limit (Current)	Maximum charging power that can be drawn from the existing grid connection. Represents the upper limit for simultaneous vehicle charging.
Grid Connection Limit (Upgrade Options)	Potential upgrade levels of the grid connection and associated costs (site-specific data for the case study).
Vehicle Charging Limit	Maximum charging power for vehicle *v* (where *v* = vehicle 1 to 10).
Vehicle Energy Consumption	Electricity consumption of vehicle *v* in period *t* due to driving.
Vehicle Battery Capacity	Battery capacity of vehicle *v.*
Grid Electricity Cost	Cost per kWh drawn from the grid, including energy and power tariffs.
PV Installation Cost	Cost per installed kilowatt-peak (kWp) of solar capacity (fixed and variable).
Battery Storage Cost	Cost per installed kilowatt-hour (kWh) of stationary battery capacity (fixed and variable).
Vehicle Costs	Fixed and variable costs for the procurement and operation of the electric vehicle fleet, including charging infrastructure.
Vehicle Charging Efficiency	Efficiency for charging and bidirectional charging of vehicle batteries.
Stationary Battery Charging Efficiency	Efficiency for charging the stationary battery storage system.

4.2 Operational Model

The operational model focuses on optimizing daily fleet operations, based on infrastructure parameters defined by the strategic model. It responds flexibly to energy prices, load management, and operational requirements, and accounts for dynamic electricity tariffs, variable energy availability from local PV systems, and vehicle state-of-charge (SoC) requirements. To implement to operational model, sun2wheels energy management system has been advanced and extended for this project.

Many energy management systems are built according to the "rule-based" principle. In this approach, an exact rule is defined for every situation that may occur in a building, specifying how loads — such as the load of a wall box — must behave. This type of control is particularly widespread among energy management systems for prosumers: as soon as surplus electricity is produced, flexible consumers like charging stations, storage systems, etc. are activated to avoid or reduce energy exports.

For e-mobility, and especially for fleet applications, such "rule-based" approaches are only of limited use, as it is unclear in such modes at what point a vehicle has been sufficiently charged to drive the next route. The situation becomes even more complex when the tariff for energy procurement from the utility/DSO is variable or dynamically structured.

The solution to this problem is therefore a predictive approach: for each vehicle, a Pick-Up State of Charge (SoC) is defined, which must always be met. Consequently, it is the task of the predictive algorithm to reach the Pick-Up SoC at minimal cost.

sun2wheel has therefore developed such a predictive algorithm under the name "V2X Oracle". The main input parameters for the V2X Oracle are defined in the following section.

The most important output of the model is the required charging/discharging power for each vehicle at every 15-minute interval. However, these values must be converted into discrete charging modes or "rule-based" commands that can be processed by a load management system.
The load management system essentially acts as the instance that can perform exact load distribution. This ensures that, despite predictive control, the load management system can react to rapidly changing and poorly predictable residual loads (such as a sudden power drop from a PV system or the unexpected/unplanned activation of a large machine).

Table 3 - Input parameters for operational model

Input Name	Description
Grid Connection Size	Maximum possible connection capacity to the public grid in kW
Vehicle Battery Size(s)	Size of the vehicle battery in kWh (can also be interpreted as stationary storage)
Arrival and Departure Time	Time period during which the vehicle is plugged in
Pick-Up SoC	State of charge in percent that must be reached by departure time
Energy and Grid Tariff	Time-varying grid and energy tariff
Residual Load	Time series of non-controllable loads (machines, lighting, etc.)
Efficiency Curve	Round-trip efficiency for charging/discharging the vehicle battery
Multi-Vehicle Setup	Definition of multiple vehicles
Solar Forecast	Forecast of solar production for at least the next 24 hours
Integration into sun2wheel Backend	Integration into existing load management system
Algorithmic Parameters	Various algorithmic parameters, such as learning rates and termination criteria

The calculation of an optimal charging schedule while adhering to the grid connection capacity and considering variable and/or static tariffs as well as any excess PV power is the defined main task of the algorithm. The typical implementation of such algorithms is often done using "linear programming". In fact, the mathematical form of the problem is very well suited for optimizing the charging schedule, as it allows modeling the price times the average energy consumption per 15 minutes using linear relationships. Additionally, approaches from "Model Predictive Control" are very popular in the relevant literature. A major disadvantage of these methods is often long computation times, especially when the projection horizon is extended (e.g., weeks, months, or even years), as is necessary due to the annual variation in PV system electricity production. Although numerous libraries in various programming languages exist, implementing the solver with different levels of efficiency, they are often very cumbersome to integrate into existing backend systems, such as that of sun2wheel.

Since the charging/discharging efficiency depends on the charging/discharging power, this represents a non-linearity, which is difficult to handle using a linear programming approach. Therefore, sun2wheel decided to integrate the problem into such "classical" frameworks but to pursue a new approach that can be implemented independently of a numerical framework and even the programming language. This also allows for processing non-linear relationships, particularly to prefer high discharge powers over small discharge powers.

As an additional method, sun2wheel developed its own algorithm, where the gradients of the mathematical problem are calculated to iteratively optimize the charging schedule until a stopping criterion is reached. This methodology is not new and is already applied in fields like machine learning to train neural networks and similar constructs but not really applied yet in practice for smart-charging. During implementation, the speed of the algorithm was consistently optimized, primarily to ensure that the optimized charging schedule for an entire calendar year can be calculated as quickly as possible. The first version required well over 30 seconds for a horizon of 96 x 15-minute slots (=24 hours). The best-optimized version now takes about 300 milliseconds.

5 Findings

The preliminary results of the case study highlight the importance of the interaction between the strategic and operational models in achieving a cost-optimized electrification solution for delivery vehicle fleets. The key insight is that both models complement each other by addressing different levels of decision-making. Below, we outline how decisions are allocated between the two models and how their outputs interconnect, as well as some preliminary results of the respective models.

5.1 Decisions at the strategic level

The strategic model addresses long-term decisions that shape the overall infrastructure setup required for the electrification of the delivery vehicle fleet. Key decisions include:

- PV system and battery storage size: Optimizing PV and battery sizes to minimize grid dependency, enabling charging during low PV output. It considers seasonal PV variations, potentially selling excess power to reduce TCO.
- Grid connection: Balancing grid connection upgrade costs with investments in PV or battery storage.

- Configuration of vehicles and charging infrastructure: Considering the possibility of multi-day battery range, reducing daily charging demands. One charging station per vehicle is assumed, with options for fast charging or bidirectional functionality.

The outputs of the strategic model constitute the system configuration for the operational model.

The results presented in the following section are based on a single representative test scenario drawn from the broader set of scenarios evaluated in the strategic model. While the complete model configuration involves the simulation and comparison of multiple scenarios to support robust decision-making, this example illustrates the model's functionality and key outcomes under defined conditions.

In the specific test case, which is represented in the subsequent paragraphs, a photovoltaic (PV) system with an installed capacity of 98.4 kWp and a stationary battery storage system with a capacity of 220 kWh were assumed. The PV generation data used for the simulation corresponds to real hourly production profiles for the year 2024, thereby reflecting realistic seasonal and temporal variations. The vehicle fleet modeled consists of 10 delivery vans, each operating on typical delivery routes based on operational schedules (9.00 - 15.00), alongside a supply truck responsible for replenishing the distribution center during the night (22.00 - 4.00). Energy consumption patterns and travel schedules for both the vans and the truck are incorporated based on real-world data. All vehicles are equipped with Vehicle-to-Vehicle (V2V) charging capabilities, enabling enhanced flexibility in energy management within the fleet. The grid charging limit and price is set to typical values at the case study location. In this scenario, no money is earned by selling energy to the grid.

The optimization model determines the ideal charging and discharging strategies under these assumptions, aiming to minimize the total charging costs. It dynamically allocates available energy from the PV system, stationary battery, and grid connection, while considering operational constraints such as vehicle availability, battery state-of-charge requirements, and charging infrastructure limits. This scenario serves to demonstrate the capabilities of the strategic model to derive cost-effective and operationally feasible charging solutions under realistic boundary conditions.

Figure 2 illustrates the timeline of the power flows across the entire simulation period. Although the figure provides an overall view rather than detailed resolution, general trends are clearly observable. The photovoltaic (PV) power generation curve, represented by green bars, is evident throughout the year, with peak production occurring during the summer months and significantly lower output during the winter. This seasonal variation directly influences the grid power draw (blue bar): during the summer, a greater share of the site's energy demand is covered by PV production, resulting in a noticeable reduction in grid dependency. Consequently, the cumulative cost of grid electricity (red line) remains relatively flat over the summer period, as most of the fleet's energy consumption can be supplied by the PV system. In addition to the grid and PV contributions, the figure also displays the bidirectional power flows (yellow bars). It is important to note that it only is given as directional inflow equivalent into the respective batteries and that charging from the stationary battery to any other vehicle is also counted as bidirectional charging.

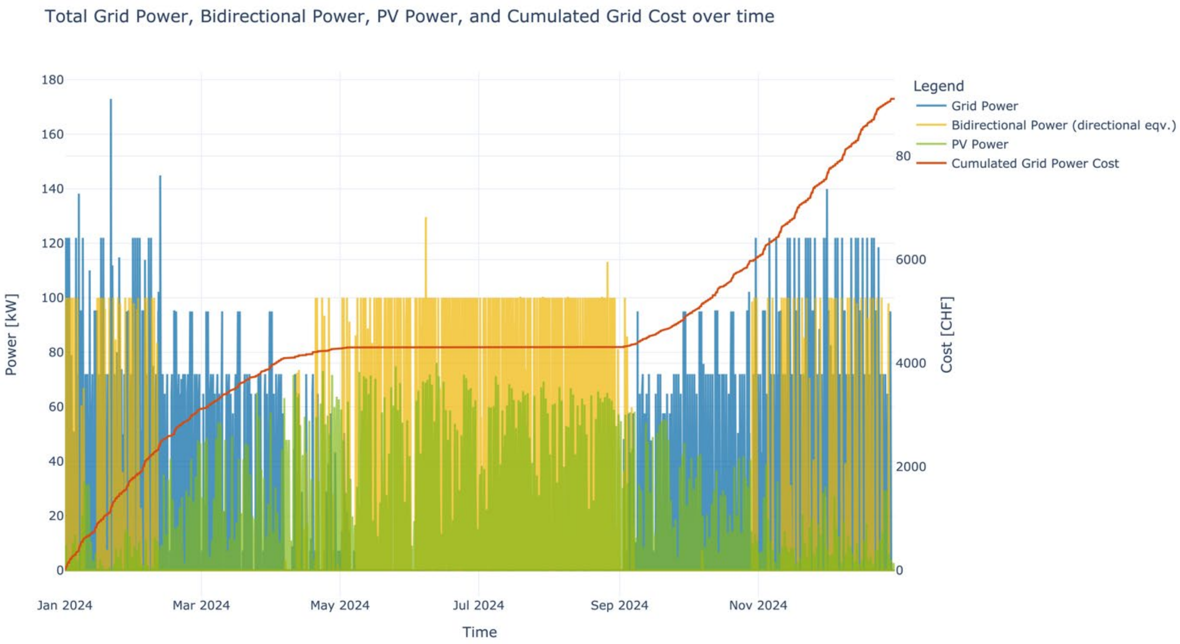

Figure 2 – Power flows of exemplary scenario calculation over the full optimization time period

Figure 3 presents an exemplary result showing the energy states of both the stationary battery system and the internal batteries of the vehicles over the course of the optimization period. As the supply truck remains parked at the depot during daytime hours, it is predominantly charged using photovoltaic (PV) energy. In contrast, the delivery vans are typically away from the depot during the peak sunlight hours, limiting their ability to directly utilize PV generation for charging. However, during the summer months, when the PV production curve extends over a broader portion of the day, the vans can capture more solar energy for charging upon their return to the depot. Notably, the stationary battery (blue line) is primarily charged during the summer months, as the photovoltaic (PV) system generates surplus energy beyond the immediate charging needs. In contrast, during the winter months, PV production is only sufficient to partially cover the direct vehicle charging demand, leaving no excess energy available for storage in the battery.

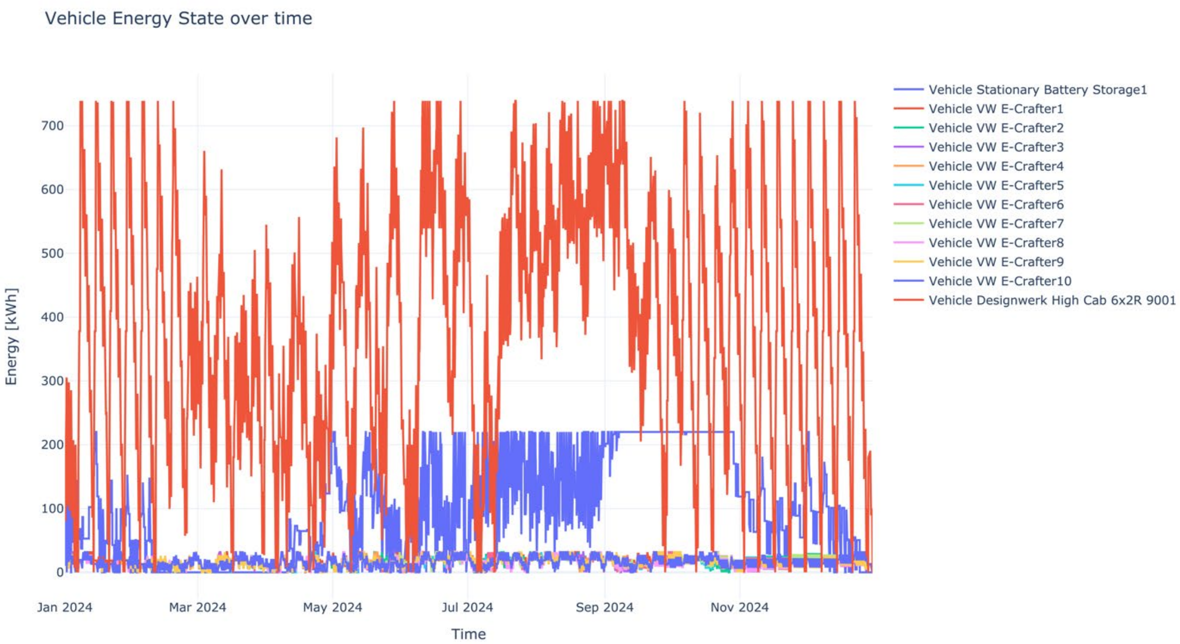

Figure 3 - Preliminary result of optimization tool. Energy graph of all the vehicles and stationary battery over the yearly time span

As the strategic model is still under development, no further analysis can be provided at this stage. In future work, additional scenario iterations will be calculated and systematically compared to enhance the robustness of the results. In particular, variations in PV system sizing, battery capacities, grid connection upgrades, and dynamic energy pricing structures, as well as different fleet compositions, will be systematically analysed to identify optimal investment strategies under different boundary conditions.

Validation of the model outputs against real-world operational data from the case study site is also planned, to assess the predictive quality and reliability of the optimization framework. This comparison will help ensure that the model results are not only theoretically sound but also practically applicable to the logistics company's future electrification plans.

5.2 Decisions at the operational level

To better test the algorithm and later offer the possibility of providing a simple user interface for one-off simulations, a simple user interface was created. It was designed so that any change in the input variables triggers a recalculation. This is possible thanks to the fast computation time.

The excerpt in Figure 4 shows a situation in which a vehicle must reach 80% SoC shortly before midnight. The black dashed line represents the local residual load ("Net Power excl. Vehicle"). The vehicle's charging/discharging power (blue line) is added to the residual load, forming the "Net Power incl. Vehicle". It can be seen that the connection capacity (10 kW in this example) is not exceeded, and that charging is shifted to periods with low dynamic tariffs (green upper curve, source: Groupe E, Switzerland). Between approximately 5:00 AM and 10:00 AM, the battery is discharged (see yellow lower curve) to avoid expensive imports from the grid. The same happens, with lower power, from around 6:00 PM until midnight. The green dot marks the desired pick-up time with the targeted SoC.

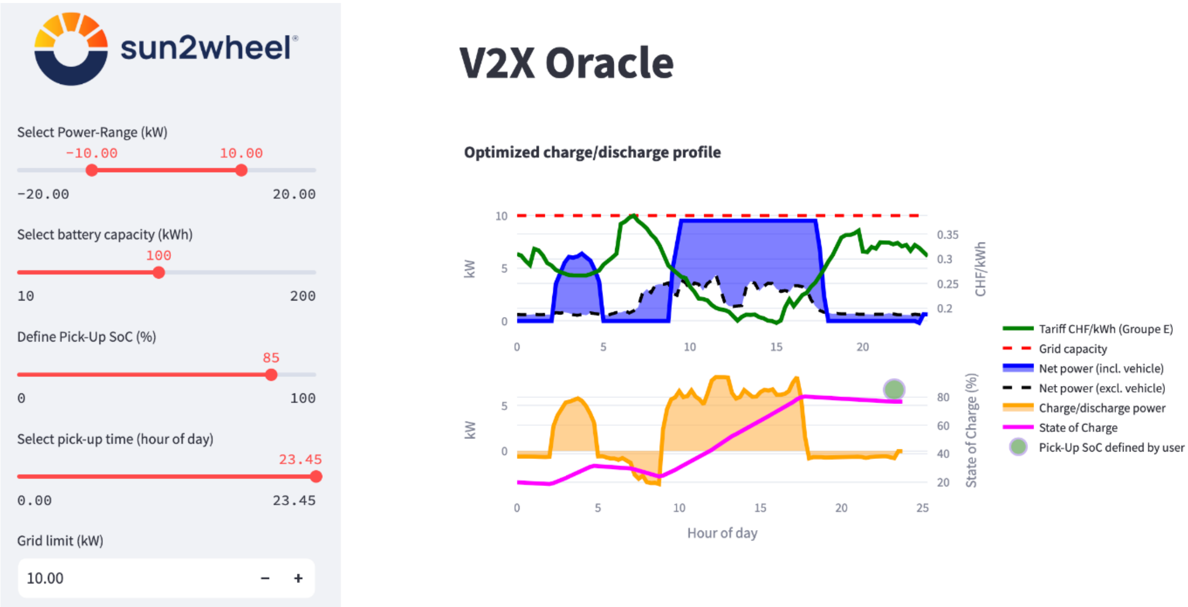

Figure 4 – Experimental user interface for algorithm testing

5.3 Interactions between the decision levels

Currently, the two models are not connected by a feedback loop but operate as a two-stage optimization process. However, it is planned to provide a quantitative analysis to demonstrate how the interaction between both models could enhance overall performance:

- Input from strategic to operational model: The strategic model defines the boundary conditions for the operational model, such as number and capacity of charging stations, available energy from the PV system, size of the battery storage, size of vehicle batteries.
- Potential feedback loop from operational to strategic model: Operational insights can refine strategic model assumptions, adjusting PV system sizing or grid connection requirements, leading to more accurate and cost-effective long-term planning.

Together, the models form a closed-loop system for continuous TCO reduction. For instance, operational data may reveal that initial assumptions about battery size are excessive, prompting strategic revisions for more accurate planning.

6 Conclusion

Preliminary findings highlight the value of integrating strategic and operational models to optimize infrastructure investment, daily fleet operations, cost minimization, and resilience. By clearly defining the roles of each model and ensuring integration of outputs and feedback loops, the decision-making process could become more holistic and aligned with the goal of minimizing TCO. The interaction between the models ensures that electrification decisions are not only theoretically sound but also practically viable, creating a robust framework for other logistics companies aiming to electrify their fleets. Further examples of companies requiring large-scale energy supplies could provide valuable insights for refining this framework. Continued discussions on the battery system integration remain essential for addressing grid stability challenges, ensuring that future electrification strategies are both efficient and scalable.

Acknowledgments

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Presenter Biography

Joel Weingart is a researcher at the Institute of Sustainable Development at the Zurich University of Applied Sciences (ZHAW), with expertise in logistics and supply chain management. He holds a bachelor’s and master’s degree in engineering, specializing in Vehicle Systems Engineering. His current work focuses on urban logistics modeling and optimization, circular economy research, and energy management for electric vehicles and fleets.

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Maike Scherrer is head of the research area Sustainable Supply Chain Management and Mobility at the Institute of Sustainable Development at the Zurich University of Applied Sciences (ZHAW). In her research, she emphasized questions of how technological and digital changes influence the possibility to redesign supply and logistics chains for higher levels of sustainability, circularity, and resilience.