Development of a Hybrid Charging Field for Fleet Electrification: Addressing Power Grid Constraints with Solar, Storage, and Operational Strategies

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1 Introduction

When examining the current energy related challenges faced from both a global and national perspective two major crises can be identified as unfolding simultaneously. The first, widely recognized, is the ongoing threat of global warming driven by greenhouse gas emissions. This phenomenon manifests in rising sea levels and global temperatures, which triggered a significant increase in natural disasters such as wildfires, extreme weather events, and the accelerated extinction of entire species[1] The second crisis, emerging more recently, is the overloading of the Dutch power grid. This issue has led to severe congestion in the electricity distribution network, effectively stalling the integration of new renewable energy sources[2] While the rollout of renewable energy sources (RES) has been at the forefront of efforts to combat fossil fuel emissions, it has revealed itself to be a double-edged sword in the context of its impact on grid stability and capacity. As the deployment of decentralized solar and wind installations accelerates, the strain on local and regional distribution infrastructure has intensified, highlighting a critical bottleneck in the energy transition[3]

One of the sectors in which both of these problems coexist is the commercial transportation sector. Heavy-duty vehicles, particularly trucks used in freight operations, are simultaneously driving greenhouse gas emissions and putting increasing pressure on the Dutch power grid as they transition to electric drivetrains. The electrification of heavy-duty trucks, while critical for decarbonizing the sector, introduces new challenges to the grid. Large-scale en-route charging, often exceeding several hundred kilowatts per vehicle, can cause sudden demand spikes, transformer overloading, and stability issues, especially in rural areas where medium-voltage (MV) infrastructure is insufficiently represented.[4] These developments are essential, considering that diesel-powered trucks are responsible for the vast majority of tailpipe CO_2 emissions in this category. In 2015, heavy-duty diesel trucks emitted 280 million tonnes of CO_2 in the European fleet, and without intervention, this could increase to 386 million tonnes by 2050.[5] Encouragingly, battery-electric trucks are rapidly gaining traction: by 2030, they are projected to comprise over 75% of new registrations in Germany and about 60% across Europe, signifying a strong push towards electrification. [6]

This study investigates the possibilities and limitations of the construction, modularity and operation of a HDEV charging infrastructure in Heerenveen, where grid congestion limits additional power exchange. The research considers integrating photovoltaic (PV) systems and battery energy storage system (BESS) to optimize the charging infrastructure performance and mitigate the limitations imposed by low contracted peak power for grid exchange. By examining the technical and economic dimensions of these strategies, this work aims to contribute a comprehensive understanding of how charging infrastructure can be tailored to local energy constraints while supporting the electrification of transportation.

2 Literature Review

The electrification of heavy-duty freight transport poses both technical and economic challenges. High-powered depot charging systems must be integrated within constrained distribution grids, while also aligning with logistics schedules and the evolving nature of fleet electrification. This literature review addresses seven key themes critical to these challenges:

1. The total cost and operational feasibility of heavy-duty electric vehicles (HDEVs);
2. The joint use of battery energy storage systems (BESS) for EV charging and market participation;
3. PV-buffered battery systems for power spreading in grid-constrained depots;
4. The design of energy management systems (EMS) under grid limitations;
5. Phased electrification and the economic viability of EMS strategies;
6. Strategies for modular fleet electrification; and
7. The use of synthetic versus historically derived demand profiles in fleet models.

While each theme has been studied in isolation, this thesis contributes a novel synthesis by combining real-world, retroactively generated EV charging profiles with a multi-phase deployment strategy. This dual approach enables the scenario-based evaluation of charging control strategies (fast, smart, EMS) under both early-stage constraints and future deployment configurations—an integration not yet explored in existing literature.

2.1 Cost and Operational Feasibility of HDEVs

While early adoption of electric freight transport focused primarily on light- and medium-duty segments, technological progress in battery density, drivetrain efficiency, and high-powered charging systems has increased viability into the heavy-duty domain. A systematic review by Çelik [5] indicates that battery electric trucks with ranges between 200–300 km can already compete economically with diesel counterparts, particularly in urban or regional depot-based contexts. This competitiveness improves further when solar-integrated charging or off-peak energy tariffs are utilized, although actual viability remains highly sensitive to vehicle utilization and daily mileage. Furthermore, a recent study by Chowdhury [7] demonstrates that depot-based electrification for Class 8 trucks, the largest category of on-road freight vehicles used in long-haul and heavy-duty transport, can achieve 54–64% energy cost savings and 64–75% reductions in peak load through optimized charging schedules, provided route patterns and operational windows are well understood. Their machine-learning–enhanced optimization model shows that economic competitiveness hinges on structured operations and the alignment of charging windows with energy availability.

However, these advantages only materialize under strict operational conditions: route patterns must be predictable, idle times sufficient for recharging, and electricity prices consistently favourable relative to diesel. Simulation results by Klein and Schiffer [8] further reveal that without synchronized schedule and charging optimization, depot infrastructure becomes a limiting factor. Their branch-and-price model, tested on a medium-sized commercial fleet, reduced total charging infrastructure requirements by 57% and energy costs by over 5%, while maintaining delivery performance. These findings emphasize the importance of co-optimizing logistics and energy systems to avoid localized overloads or partial charge failures.

Design–operation coupling is increasingly central in planning for scalable electrification. Bertucci [9] show that jointly optimizing schedule, charger locations, and transformer constraints reduces total cost of ownership by over 3.5% in Dutch logistics scenarios. Similar patterns are echoed in typological analyses of depot layouts and clustering behaviour, which indicate that certain depot types are more amenable to electrification than others. These structural constraints underscore the need to integrate real-world operational data—beyond technical specs and cost projections—into electrification feasibility assessments.

Recent modelling efforts reflect this shift by embedding logistical parameters directly into optimization logic. Qiu . [10] develop a hybrid framework that includes vehicle duty cycles, charger capacities and time-of-use tariffs, yielding peak avoidance rates over 90% and significantly lowering cost relative to unmanaged charging. Meanwhile, van Huffelen [11] implement a grid-constrained scheduling heuristic that combines arrival–departure constraints with solar forecast inputs. Their model shows substantial improvements in both charger utilization and delay minimization, particularly under transformer capacity limits. Collectively, these studies demonstrate that robust electrification strategies must jointly optimize for cost, grid constraints, and operational feasibility. This thesis builds on such approaches by explicitly integrating phase-dependent grid limits, vehicle availability, and delivery windows into its comparative evaluation of charging strategies.

2.2 Joint Operation of BESS for Market and EV Support

Battery energy storage systems (BESS) play a dual role in depot-scale electrification. Functionally, they buffer the mismatch between existing peak demands, PV generation and vehicle demand, reducing peak grid import and increasing self-consumption. Economically, they open access to electricity markets—participating in arbitrage, frequency containment reserve (FCR), or capacity trading—thereby generating revenue that improves battery investment viability. However, these two functions often conflict: market-driven dispatch may undermine vehicle readiness, while charging support can constrain profitability.

To explore this tension, Paudel [12] introduces a co-optimization framework that jointly schedules stand-alone BESS and fast-charging operations. Their model balances revenue maximization with vehicle support obligations, but it assumes full fleet electrification and static vehicle behaviour—factors that limit its flexibility during phased deployment. In a related study, Khan [13] demonstrates that BESS assets can recover up to 25% of annual system costs through wholesale market participation. Yet, this framework relies on highly elastic demand profiles, which diverge from the fixed routing patterns characteristic of logistics fleets.

Some EMS approaches shift the focus from market participation to system-level coordination. For example, Sossan [14] proposes a forecast-based EMS that dynamically reallocates battery usage between grid services and EV support. While this improves cost performance and energy autonomy, it does not account for route fulfilment or guarantee charging success under operational constraints. These assumptions—particularly the use of flexible, price-responsive demand—limit applicability to logistics environments where charging windows are non-negotiable and delivery schedules must be upheld.

Across the literature BESS are often framed as either economic assets or physical buffers, rarely as hybrid systems with evolving roles. In early electrification phases, batteries may focus on market revenue or PV smoothing. While in later phases ensuring reliable charging becomes critical. Additionally, This order can reverse in heavily constrained situations. Few EMS architectures explicitly reallocate battery priorities as fleet size increases or as the system transitions from low to high electrification.

This thesis addresses this oversight by simulating BESS operations under both cost-driven and feasibility-driven EMS strategies. By varying fleet size and grid import capacity, the model reveals when BESS must shift from economic optimizer to operational enabler. This dynamic allocation not only enhances realism in system modelling but also informs investment planning by identifying the conditions under which BESS offer the highest system value.

2.3 PV-Buffered Battery Systems for Power Spreading in Grid-Constrained Depots

In logistics depots with constrained grid connections the charging heavy-duty electric vehicles (HDEVs) presents a significant operational challenge. Peak charging demands frequently exceed contracted import capacity, particularly during busy hours. On-site photovoltaic (PV) systems can generate substantial energy—especially around midday—but temporal misalignment with vehicle arrival and departure schedules limits their direct use. A promising solution is to buffer solar energy in a local battery energy storage system (BESS), then deploy it strategically to EVs at different times, effectively "spreading" available power throughout the day.

Riaz [15] analyse the combined PV–EV hosting capacity of a depot, finding that storage redirects otherwise curtailed solar energy to EVs and increases service rates under fixed grid limits. Similarly, Le Corguillé and Nocquet [16] simulate time-series charging profiles to demonstrate how buffering shifts peak demand and enables higher average charging capacity without exceeding import constraints.

Expanding the systems perspective, Tushar [17] develops a multi-objective EMS framework that integrates vehicle scheduling, power flow, and battery dispatch, highlighting the operational gains from daytime solar integration. Moghaddam [18] incorporate PV forecasts into BESS control logic but focus primarily on cost trade-off's and not on the ability to meet fixed departure schedules. Meanwhile, Saleem [19] propose a congestion-aware EMS that directs surplus PV to storage, yet they do not analyse how this buffering affects individual session feasibility.

To build on these foundations, Biedenbach and Strunz [20] present a depot-scale multi-objective control model combining PV self-consumption, tariff arbitrage, peak shaving, and bidirectional charging. They show that when PV is buffered, dispatch becomes more flexible—enhancing both grid resilience and vehicle readiness. Sayarshad [21] takes this further by integrating routing and charging coordination in urban fleets subject to price signals and capacity limits, demonstrating that buffered solar energy can adaptively support varying departure times—a concept directly applicable to logistics depots facing strict deadlines.

Although the potential of PV–BESS to enable dynamic power spreading is widely acknowledged, most studies evaluate high-level energy or cost metrics rather than charging success. Few quantify how stored solar energy can be allocated across individual vehicle sessions to meet departure time requirements. This gap is especially relevant for depots with large PV systems—such as the 800 kWp setup in this thesis—where fast grid charging alone is infeasible. By combining detailed PV data with strategic battery dispatch, this work aims to quantify how an "artificial solar boost" can improve scheduling flexibility and ensure operational feasibility under real-world constraints.

2.4 Energy Management Systems for Grid-Constrained Depots

In the absence of grid expansion, depot operators must increasingly rely on smart energy management systems (EMS) to coordinate local generation, battery storage, and electric vehicle (EV) charging. This is particularly relevant in regions facing structural congestion and delayed connection upgrades—challenges common across large parts of the Netherlands. Unlike residential EMS applications, which can leverage flexible loads and demand response, HDEV depots are governed by strict logistics: trucks must depart fully charged within tight and often non-negotiable time windows.

Coordinated EMS frameworks have shown promise in improving system autonomy. For example, Saleem [19] and Engelhardt [22] explore PV–battery scheduling schemes that reduce grid dependency and increase self-consumption. Yet these studies typically assume flexible EV charging behaviour—using time-window availability models or probabilistic forecasts that do not reflect the deterministic nature of depot operations. Moreover, performance evaluation tends to focus on energy metrics such as import reduction, peak shaving, or self-sufficiency, while operational indicators like route fulfilment or charging reliability remain under-examined.

Some progress has been made toward operational integration. For instance, Moghaddam [18] couples EMS scheduling with predictive arrival models, optimizing for both electricity costs and battery degradation across dynamic fleet profiles. Their results show that forecast-based EMS designs can outperform baseline methods in small-scale depots. However, the model does not scale to larger fleets, omits distinctions between fast and smart charging strategies, and lacks adaptive control logic for different deployment stages.

Expanding on these themes, Klein & Schiffer [8] demonstrate how a branch-and-price framework can jointly optimize EV routing and charging under transformer capacity limits. Their model achieves a 57% reduction in infrastructure requirements and 5% energy cost savings, all while maintaining rigid delivery schedules—highlighting the importance of logistics-aware EMS design in grid-constrained settings. Similarly, Sayarshad [21] introduces an integrated routing-and-charging optimization for bus fleets that adapts to both time-of-use tariffs and grid constraints. This approach illustrates how real-time EMS logic can flexibly shift charging priorities based on evolving system conditions, suggesting a pathway for scalable EMS architectures in heavy-duty contexts.

In real-world deployments, EMS architectures must reconcile energy efficiency with logistical determinism. This includes ensuring route-compliant charging even under grid constraints, solar variability, or partial system failure. To this end, the present thesis develops and compares multiple EMS coordination schemes under realistic depot conditions—explicitly modelling fixed route schedules, fleet growth stages, battery sizing, and PV integration. Performance is assessed not only in terms of energy cost and import reduction but also in terms of operational reliability, enabling a more comprehensive evaluation of EMS feasibility under real-world constraints.

2.5 Phased Electrification and the Economic Viability of EMS Strategies

Several recent studies explore the intersection of smart charging, battery storage and energy management systems (EMS) within EV fleet electrification. Increasingly, researchers recognize that electrification is not an all-or-nothing process: deployment is staged, and system behaviour evolves with fleet size. However, while phased rollout is gaining attention, it remains underexplored in terms of how EMS value, control strategy, and charging feasibility change across stages.

Sharma and colleagues [23] examine depot charging infrastructure build-out under phased deployment, showing that EMS solutions optimized for full fleet operations underperform when only a fraction of the fleet is electrified. Feeley and Kim [24] validate this finding through pilot-scale studies of time-varying charging in mid-size fleets noting a 25% reduction in ROI period for EMS systems when flexibility is limited early on. Similarly, Patel [25] identify a tipping point—roughly 40% electrification—beyond which EMS logic becomes increasingly valuable compared to simpler strategies.

Recent industry publications such as FleetOwner [26] and Powell [27] further emphasize the benefits of incremental deployment from an infrastructure and cost-risk perspective. They argue that full fleet electrification may lead to overbuilt systems, underutilized chargers, and higher upfront investment. Modular deployment, coupled with staged EMS logic, offers a more flexible and economically efficient path.

Yet despite this progress, the literature still lacks systematic benchmarking of charging strategies—such as fast charging, fixed-rate smart charging with time-of-use (TOU) awareness, and coordinated EMS control—across fleet electrification phases. Moreover, many models assume that charging can be shifted purely based on price signals, overlooking the strict timing constraints imposed by logistics operations. In depot environments, where truck departures are governed by preassigned routes and delivery slots, price-responsive flexibility is largely infeasible.

Crucially, no studies integrate phased electrification with retroactively derived demand profiles based on actual vehicle routing and idle times. As a result, key questions remain unanswered: How does the value of EMS coordination scale with available flexibility? At what stage do route-based constraints begin to dominate? And which control strategies are justifiable under real depot operations?

This thesis addresses these gaps by modelling phased deployment stages using real logistics data as the foundation for EV charging demand. By comparing multiple control strategies across fleet sizes and infrastructure conditions, it identifies the conditions under which EMS logic shifts from optional to essential. In doing so, it delivers scenario-based, deployment-aware insights that support more targeted and adaptable infrastructure planning.

2.6 Strategies for Modular Fleet Electrification

A fully electrified fleet introduces non-linear infrastructure demands: peak charging power rises disproportionately with the number of vehicles, while grid constraints and delayed network upgrades hinder expansion. In this context, modular deployment—where infrastructure investment scales with incremental fleet adoption—offers a pragmatic and capital-efficient pathway to electrification.

Powell [27] analyses rapid EV adoption impact on distribution grids in the western U.S., revealing up to a 50% increase in peak net demand under full fleet electrification. Their simulations show that uncontrolled charging can drive disproportionate grid upgrades, while managed deployment with adaptive control strategies reduces incremental grid investments by approximately 30%. Similarly, Haffner and colleagues [28] investigate modular infrastructure design for large-scale bus depots in Hamburg. Their case study demonstrates how depots can phase infrastructure—starting with capacity for 40 vehicles and expanding to 240—without triggering grid overload, provided expansion is aligned incrementally with fleet growth.

These studies highlight the importance of rollout timing and strategy yet often focus on infrastructure layout and transformer sizing, rather than operational logic. Few models dynamically benchmark control strategies—such as fast charging, fixed-rate smart charging, or EMS-coordinated charging—across fleet deployment stages.

Moreover, no existing studies couple phased deployment scenarios with empirically grounded charging demand. Without using real logistics data, previous analyses cannot account for how actual route-based constraints interact with modular infrastructure availability. This limits their ability to assess when more advanced charging control becomes necessary to maintain system feasibility.

This thesis addresses that shortcoming by simulating phased infrastructure and fleet deployment alongside control strategy benchmarking using retroactively generated EV demand. It explicitly models infrastructure availability, vehicle constraints, and scheduling feasibility across a spectrum of fleet sizes and grid capacities. In doing so, it provides actionable insights into how—and when—charging control strategies must evolve to maintain reliability and cost-efficiency throughout the electrification trajectory.

2.7 Use of Historically-based Synthetic Demand Profiles in Fleet Electrification Models

A common methodological feature in fleet electrification studies is the use of synthetic electric vehicle (EV) demand profiles. These are artificially constructed—often in the absence of detailed operational data—and serve as default inputs for scheduling algorithms, EMS control schemes, and infrastructure planning models. While such profiles support tractability and enable high-level scenario analysis, they frequently sacrifice operational realism, particularly in logistics depots where vehicle duty cycles are tightly coupled to deterministic schedules.

Synthetic EV demand is typically derived from archetype-based models, travel surveys, or national mobility statistics. For instance, Mueller [29] constructs depot arrival and charging demand profiles based on assumed delivery patterns, without reference to historical fleet behaviour. Similarly, Folckson and Nykvist [30] use stylized vehicle archetypes to assess electrification feasibility based on technical characteristics such as payload and range, omitting actual routing and idle patterns.

Agent-based approaches, such as that of Zeyringer et al. [31], simulate synthetic demand at regional scale using geospatial mobility data. While this enhances geographic realism, these methods still lack validation against real-world logistics data and often disregard the fine-grained operational constraints that dominate fleet scheduling at the depot level.

The use of synthetic profiles introduces several methodological limitations:

1. **Assumed flexibility** — Synthetic models typically assume vehicles can defer or shift charging to respond to price signals. In logistics operations, however, charging windows are rigidly defined by delivery schedules, making such flexibility unrealistic.

2. **Lack of heterogeneity** — Archetypal profiles smooth over route-specific differences in idle time and energy demand, potentially underestimating peak power requirements and masking infeasibility risks.

3. **Feasibility blind spots** — Without actual arrival and departure data, it is impossible to evaluate whether proposed schedules are operationally viable under real-time grid and infrastructure constraints.

In summary, synthetic demand models are useful for broad planning exercises but lack the fidelity required for evaluating control strategies, EMS logic, or phased deployment feasibility in constrained logistics environments.

This thesis addresses this shortcoming by retroactively transforming historical diesel fleet telemetry into EV-compatible charging demand. By extracting actual arrival times, idle durations, and distance-based energy needs, it generates high-resolution power demand profiles with route-level granularity. This enables the evaluation of electrification potential under current system limitations and allows for direct comparison of charging strategies across real operational windows. To my knowledge, this is the first study to combine retroactive diesel-based demand generation with phased infrastructure and EMS benchmarking—providing a more realistic and operationally grounded framework for fleet electrification planning.

2.8 Research Gaps

Building on the reviewed literature six key research gaps emerge that directly motivate the modelling choices in this thesis. These gaps are grouped into two thematic clusters: those related to system realism and deployment (G1–G3), and those related to EMS architecture and control logic (G4–G6).

Group A: System Realism, Strategy Benchmarking, and Deployment Planning

G1. Lack of EMS benchmarking across phased deployment scenarios
Most EMS studies assume full-fleet electrification or static system conditions. Few evaluate how EMS performance, feasibility, and economic justification vary across different deployment stages. As electrification scales the relative importance of BESS buffering, route-aware charging, and coordination logic changes. This dynamic is poorly captured in current literature, limiting the ability to guide rollout strategies over time.

G2. Minimal research using retroactively generated EV demand based on real diesel operations
The majority of studies rely on synthetic EV demand profiles generated from archetypal assumptions or national travel statistics. These approaches fail to capture intra-depot variability, route constraints, or fixed idle windows common in logistics. No prior work integrates retroactively derived EV demand from historical diesel fleet telemetry—an approach that enables route-specific feasibility analysis and strategy evaluation grounded in real operations.

G3. Absence of comparative analysis between fast, smart, spread and EMS-based charging strategies across deployment phases
While some studies compare fast and smart charging in isolation, none benchmark these strategies under phased electrification. There is no analysis of how charging feasibility, system costs or EMS value evolve as more vehicles are electrified and infrastructure scales. This gap obscures when the shift to more complex EMS coordination becomes both operationally necessary and economically justifiable.

Group B: EMS Architecture and Control Logic Design

G4. Lack of EMS frameworks that jointly optimize cost and feasibility under route-based EV constraints
Most EMS designs treat EV charging as a flexible or exogenous load ignoring strict availability and departure schedules in logistics operations. Few systems model charging feasibility explicitly under transformer limits or BESS constraints. The trade-off between charging success and system cost remains poorly quantified.

G5. Lack of adaptive EMS architectures that evolve with system constraints and electrification levels
EMS models often assume fixed grid limits or static demand. In practice, depots transition through multiple operational phases—from pilot deployments under severe constraints to larger-scale operations with greater flexibility. EMS logic must adapt across this spectrum, yet current literature rarely explores dynamic reconfiguration of control priorities based on system maturity.

G6. Limited monetization of EMS features and integration layers
Most evaluations focus on aggregate cost savings or energy import reductions. Few studies disaggregate the value contributed by specific EMS features, such as route-aware charging, BESS integration, or curtailment logic. Without this, investment planning and system design trade-offs remain speculative.

This thesis addresses these six gaps by developing a modular EMS framework that: (1) benchmarks charging strategies across phased deployment; (2) integrates real diesel-based operational data into EV demand profiles; and (3) quantifies both feasibility and cost across multiple EMS configurations. In doing so, it bridges the disconnect between abstract models and real-world logistics environments.

2.9 Research Questions

2.9.1 Sub-questions

- **SQ1:** How can energy infrastructure and site-level EMS architectures be designed to support modular, phased deployment of HDEV charging while adapting to changing fleet sizes and grid constraints?
- **SQ2:** How does the operational role and value of battery energy storage systems (BESS) evolve across different electrification phases, and how can they be operated to optimize the balance between charging support, market participation, and grid limitation management?

  SQ3: How can retroactively generated EV demand profiles based on real diesel telemetry be used to evaluate charging feasibility, EMS coordination, and investment decisions under realistic operational constraints?

2.9.2 Main Research Question

How can modular and grid-aware EV charging strategies and energy systems guide the phased construction and management of charging infrastructure to enable reliable and cost-effective electrification of heavy-duty vehicle fleets under logistical and grid constraints?

3 System Description and Baseline Analysis

This chapter provides an overview of the current system layout and operational characteristics of the system taken under consideration in this thesis. The company operates within the transport and logistics sector and currently maintains a fleet of approximately 35–40 trucks, which are scheduled to transition progressively from diesel to electric propulsion in the coming years.

3.1 Site Layout and Electrical Infrastructure

The current electrical infrastructure designated for the electrification of Bakker Warehousing is located at Komeet 7, 8448 CG Heerenveen. The facility is connected to the public grid via a medium-voltage/low-voltage (MV/LV) interface and operates under the following grid configuration:

- Location: Komeet 7, 8448 CG Heerenveen
- Technical connection class: AC5, >1 MVA up to 2 MVA
- Contracted import capacity (GTV): 105 kW
- Contracted export capacity: 1350 kW

The site is connected to a 2 MVA transformer, which supports a maximum active power output of approximately 1700 kW. Attached to this transformer are several critical components of the site's energy infrastructure: existing warehousing facilities, a new warehouse operational since November 2024, office spaces, and a photovoltaic (PV) system with a maximum inverter capacity of 800 kW.

In the second quarter of 2024, a stationary battery energy storage system (BESS) was installed with the primary objective of peak shaving. However, this system was decommissioned in Q2 2025. A detailed single-line diagram of the current configuration is shown in Figure 1.

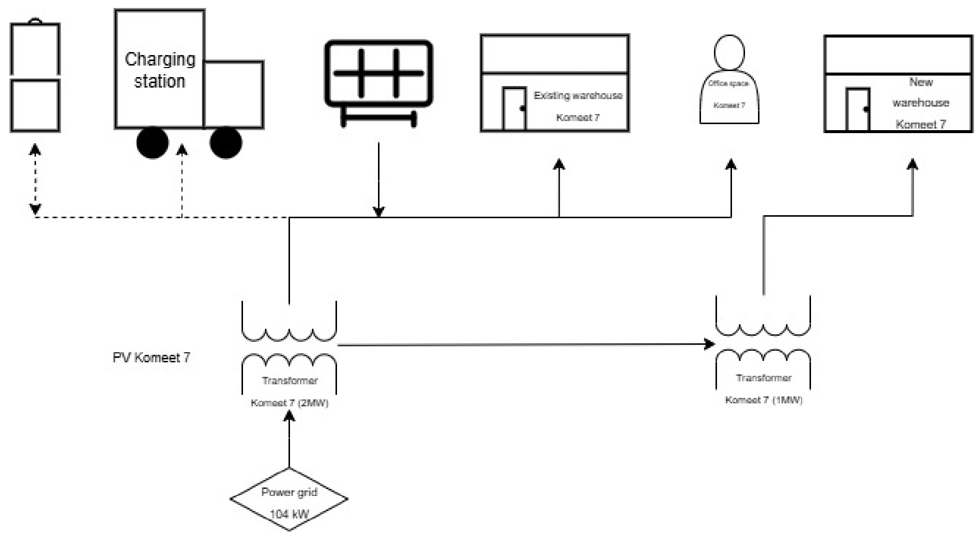

Figure 1: Single-line diagram of the current situation

3.2 Bakker Warehousing PV Generation Profile

Bakker Warehousing currently operates approximately 1.2 MW of installed peak photovoltaic (PV) capacity, supported by a total converter capacity of 800 kW. Due to daily fluctuations in electricity market prices, the PV array is deliberately oriented to maximize generation during the early morning and late afternoon hours. This design trade-off results in reduced output during midday hours—when energy prices are typically lower—but enhances production during high-value periods at the beginning and end of the day. The aim is to align on-site generation with market signals to improve the economic performance of self-consumed and grid-exported energy. The production profile on a 15-minute interval basis for the year 2024 is shown in Figure 2.

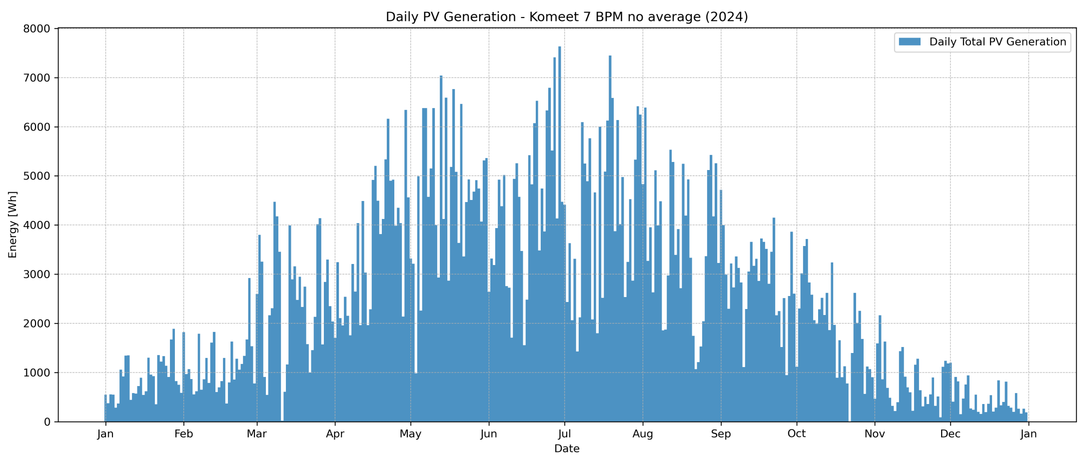

Figure 2: 15-minute interval PV generation of 2024

3.3 Permanent Load

Base load refers to the demand side of all non-EV charging systems. These demands can be categorized in the following way:

- semi-controllable Loads: warehouse cooling
- uncontrollable loads: Office energy use, lighting

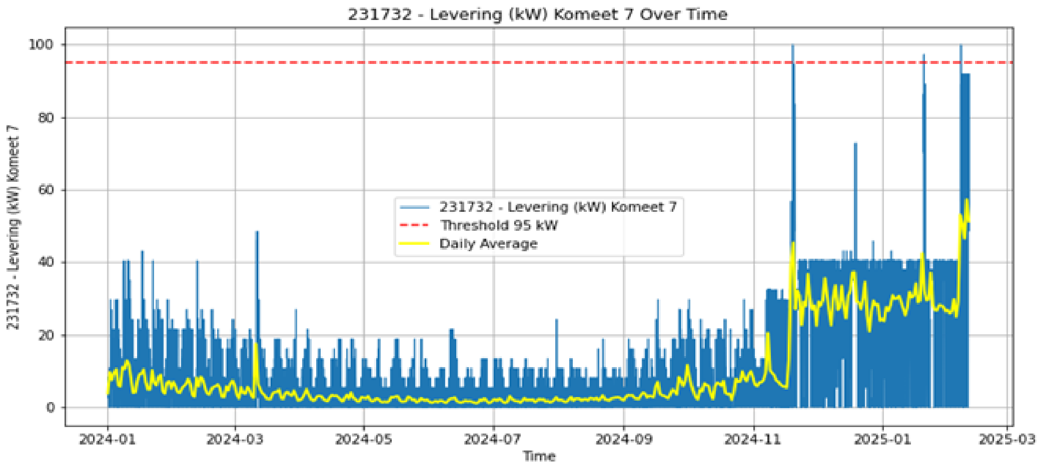

Figure 3: Power demand profile 2024

Due to a number of demand side changes in 2024 this baseload is not directly usable as a benchmark for future predictions. The most important ones are the following:

- The temporary connection of a part of the warehousing normally connected to the grid connection of the second location. This occurred during the months with higher solar exposure, namely from May till November
- The operations of a battery temporarily applied for the sole purpose of peak shaving, active from the beginning of November
- The activation of a new warehousing at the primary location on the 15th of November

In order to create a baseload profile usable in simulations the following calculations were performed on the original baseload:

- The battery activity in both directions is retrospectively subtracted in the opposite direction
- The difference between grid feed-in and solar generation is calculated and added to the baseload.
- A multiplication value was calculated by dividing averages for the month of January 2025 to that of January 2024. Due to low solar exposure, these months represented a reasonably accurate comparison.

This provided the following baseload profile, which is used as input to the optimization model presented in Chapter 6. As visible, the peaks of this power profile often exceed the current grid limitation of 105 kW. Even though the addition of PV production solves this in many cases, off-season peaks still exceed the limitations imposed by the DSO. For viable future operations these peaks must be alleviated, either by battery operations or increased grid power.

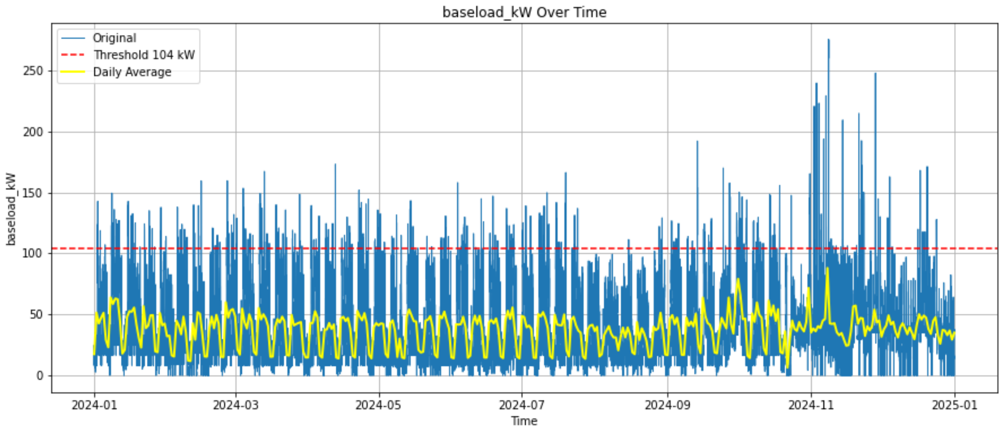

Figure 4: Recalculated power demand profile 2024

3.4 Benchmark Vehicle: EV-1

EV-1 refers to the first operational heavy-duty electric vehicle (HDEV) integrated into the Bakker Warehousing fleet, commissioned in November 2024. This vehicle serves as a benchmark case for operational and performance analysis due to the availability of high-resolution telemetry data.

Through the Volvo Connect platform [32], a comprehensive set of operational parameters can be exported, including energy consumption, trip profiles, and charging statistics. This facilitates a detailed evaluation of the vehicle's real-world usage patterns and efficiency. Currently, EV-1 is exclusively deployed for a dedicated client and is required to charge at that client's own facilities. The information relating to the charging infrastructure, control logic, and energy supply configuration of the client's site are not accessible for this study, all benchmark analyses are based solely on the internal vehicle data retrieved from Volvo Connect.

As a result, the performance evaluation of EV-1 in this thesis is based solely on vehicle-side energy dynamics and operational behaviour.

3.5 Current Stationary Battery Operation

At the present time, Bakker Warehousing leases a stationary lithium-ion battery energy storage system (BESS) from Kenter (the metering company), rated at 500 kW with a nominal C-rate of 0.5C. This system is configured purely as a local buffer to mitigate grid connection violations and does not participate in market-based energy transactions. The battery is operated under a fixed leasing agreement and is primarily used for grid compliance rather than active energy management.

The control logic is configured to activate the battery only in response to violations of the contracted grid transfer capacity (GTV). Once the instantaneous site demand exceeds this threshold, the battery discharges to prevent incurring penalties from the distribution system operator (DSO). Following such an event, the system automatically recharges to 80% state-of-charge (SoC), independently of electricity market conditions. This control strategy does not incorporate dynamic price signals or state-of-charge optimisation.

As a result, the battery currently serves as a static grid buffer within the site's energy system.

A recent example of its operation is shown in Figure 5, illustrating the SoC behaviour over a representative three-month period.

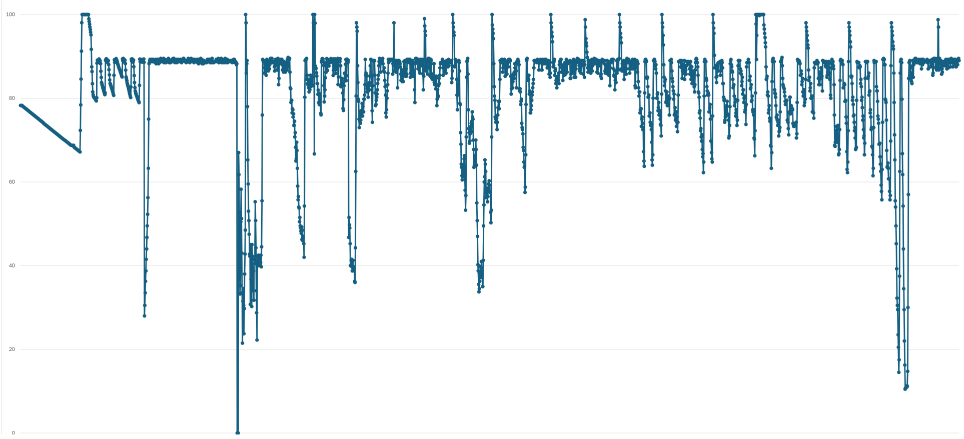

Figure 5: Kenter battery SoC of the 3 months

4 Methodology

The electrification of heavy-duty logistics operations introduces a complex interplay between energy supply constraints, infrastructure constraints, and fleet requirements. To assess the technical and economic feasibility of deploying phased charging infrastructure at the Bakker Warehousing site a scenario-based modelling approach grounded in cost optimization is applied. The methodology provides insight in the preparations and construction of this model which aims to incorporate real-world data to simulate phased electrification across four distinct deployment scenarios, enabling robust comparative assessment of different design choices in order to systematically address the research question and its supporting sub-questions.

The three sub-questions are restated here for clarity:

- **SQ1:** How can energy infrastructure and site-level EMS architectures be designed to support modular, phased deployment of HDEV charging while adapting to changing fleet sizes and grid constraints?
- **SQ2:** How does the operational role and value of battery energy storage systems (BESS) evolve across different electrification phases, and how can they be operated to optimize the balance between charging support, market participation, and grid limitation management?
- **SQ3:** How can retroactively generated EV demand profiles based on real diesel telemetry be used to evaluate charging feasibility, EMS coordination, and investment decisions under realistic operational constraints?

The proposed approach directly responds to six research gaps (G1–G6), derived from the literature review and organized into two thematic groups: (1) realism and system design feasibility (G1–G3), and (2) EMS architecture and integration pathways (G4–G6). Each modelling step is designed to address one or more of these gaps, forming a coherent research strategy that connects component-level control logic with depot-level feasibility under operational and grid-related constraints.

As a first step, the methodological focus lies on adapting existing infrastructure and fleet data to support phased electrification. This involves two elements: the derivation of electric vehicle (EV) charging demand profiles based on historical diesel operations (i), and (ii) the modelling of the physical system, incorporating total operations with limitations such as grid capacity and charger ratings. Together, these elements establish a realistic baseline against which future electrification strategies can be evaluated. They form the foundation for addressing the first sub-question—concerning phased system deployment—and Research Gap G2, which highlights the lack of scenario realism in many EMS studies.

To enable robust scenario-based evaluation of electrification strategies, the simulation framework is structured around four distinct deployment phases. Each phase represents a stepwise increase in infrastructure capacity, electrified fleet share, and operational complexity. The phases are defined as follows: the *Current Phase* reflects present-day conditions at Bakker Warehousing, with limited electrification under existing grid constraints; the *Intermediate Phase* introduces a moderate fleet expansion under improved—but still constrained—grid conditions, with a total site import capacity of 600 kW. This limit mirrors the peak power of the charging infrastructure yet must be used to accommodate all facility operations, meaning that the charging system competes with baseload and other internal demands. As a result, it remains an active constraint and represents a realistic scenario where system conditions have improved but not yet been fully resolved. The *Final Phase* assumes near-full depot electrification with high charging throughput and relatively unconstrained peak access. Lastly, the *Future Phase* explores long-term scaling potential, including high energy turnover exceeding 100% electrifiable potential and maximum grid limitations. This phased structure provides a clear basis for evaluating how system design and operational control must adapt over time.

G2: Retroactive electrification to construct realistic demand profiles. A key challenge in modelling EV fleet operations is the absence of granular charging demand data that reflects actual logistics behaviour. Existing studies often rely on assumed duty cycles or synthetic demand estimates, limiting the realism of subsequent optimization results. This study addresses this gap by introducing a bottom-up approach that converts historical diesel route data into time-resolved EV charging demand, enabling the formulation of realistic operational constraints for scenario analysis.

4.1 Generation of EV Charging Demand from Diesel Route Data

To translate historical logistics operations into realistic EV charging demand, this study uses a retroactive electrification method based on actual route records. Each recorded trip is assigned a State-of-Charge (SOC) requirement by multiplying the route distance by an average energy consumption factor derived from a benchmark Volvo FME truck. A corresponding charging window is defined between the vehicle's depot arrival and next departure. Charging power is calculated as the required energy for a full recharge divided by the available idle time.

Sessions are filtered for technical feasibility: routes are excluded if the average required power exceeds charger capabilities or if the SOC need exceeds 80% of battery capacity. The result is a dataset of realistic, technically feasible charging sessions that reflects the electrifiable share of the 2024 route history and serves as the primary input for all subsequent simulation and optimization runs.

Benchmark vehicle and energy consumption factor. The Volvo FME truck used for this analysis has a 540kWh battery and is operational at a site similar in profile to the case study depot. Through the Volvo Connect portal [32], its average energy use of 1.37kWh/km was determined under typical freight operation conditions and applied uniformly across all vehicles and routes for demand synthesis.

Window derivation and charging power. For each vehicle and day, the available charging window is defined by the interval between depot arrival and departure. These timestamps are extracted directly from the fleet's route logs. The total charging energy required is calculated by multiplying the previous trip distance by the benchmark consumption factor. To determine the average required charging power, this energy is divided by the available idle time (i.e., duration of the depot stay). This calculation yields a time-bound charging session that is realistic in both temporal and energetic dimensions.

Route filtering and electrifiability thresholds. Not all routes can be feasibly electrified given current charger capabilities and operational constraints. Therefore, a pre-processing filter is applied to remove infeasible sessions from the baseline demand set. Two criteria are used:

- **Power constraint:** The required average charging power must not exceed 350 kW for the intermediate, final and future electrification cases. For the current phase this limit is set at 50 kW. These thresholds correspond to the physical limitations of the site and installed charging hardware.
- **Energy constraint:** The required energy must not exceed 80% of the vehicle's total battery capacity (i.e., 432 kWh). This 20% margin serves as a buffer to ensure operational robustness and reduce the risk of stranding as well a buff to decrease battery degradation, which is more profound at lower states of charge. It reflects real-world planning practice and aligns with typical fleet-level safety policies.

Sessions that fail either criterion are excluded from the electrification scenario. The result is a defensible subset of historical operations that could have been realistically served by electric vehicles, under site-specific constraints.

Fleet selection and deployment phases. Four deployment phases are defined to represent the gradual electrification of the fleet under evolving GTV constraints. The *current phase* reflects the present-day site limitation of 105kW GTV, with limited electrification enabled by low-power depot charging for a small subset of technically feasible vehicles. In the *intermediate phase*, the GTV is increased to 600kW, allowing the electrification of approximately 50% of the filtered fleet. The *final phase* assumes a GTV of 1200kW and supports the full electrification of all feasible vehicle routes under depot-based charging. Lastly, the *future phase* explores a scenario in which electrification demand exceeds the current fleet baseline—reaching 150% of the original energy demand—and the GTV is further increased to 1700kW. A detailed description of the assumptions and system configurations used in each phase is provided in the next section.

4.2 Electrification Phases: Simulation Setup across Four Deployment Scenarios

As mentioned, in order to evaluate the performance of charging strategies under evolving infrastructure and electrification levels four deployment phases are defined. These phases reflect increasing grid connection capacity (GTV), charger availability, and fleet electrification intensity. Together, they form the structural basis for the scenario modelling framework applied throughout the remainder of this thesis.

Current configuration. The current phase reflects the site's existing GTV limit of 105 kW. A small subset of electric vehicles—five in total—is selected based on their suitability for low-power depot charging. Each vehicle is limited to 50 kW of charging power, with a total site-wide cap of 100 kW. This is based on the fact that it would be unable to exceed the grid limitation without the demands of other loads. These values represent an electrification strategy that can be deployed immediately without upgrading the contracted grid connection. The selection of these vehicles and the derivation of feasible charging sessions are detailed in Section 6.

Intermediate configuration. In the intermediate phase, the contracted GTV is increased to 600 kW, enabling more extensive depot charging. Approximately 50% of the total electrifiable energy demand—based on the filtered diesel route dataset—is selected for electrification. This setup represents a transitional scenario in which infrastructure is expanded in line with moderate fleet electrification targets. Vehicle selection is based on their cumulative contribution to energy demand, ensuring that high-impact routes are prioritized.

Final configuration. The final phase models full deployment of electric vehicles under upgraded infrastructure. The entire filtered dataset of technically feasible EV charging sessions is included, representing complete fleet electrification. The GTV is expanded to 1200 kW, allowing for greater simultaneity in charging events and increased scheduling flexibility. This scenario serves as the primary reference for evaluating long-term performance, cost efficiency, and EMS coordination strategies.

Future configuration. The future phase explores an extended electrification scenario in which the total charging demand reaches 150% of the baseline full-fleet energy requirement. This demand increase is constructed by time-shifting a subset of existing vehicle sessions by six hours, thereby introducing overlapping demand without relying on synthetic or externally sourced routes. The previously used EVs are retained, but their shifted charging windows represent intensified operational requirements. The GTV is set to 1700 kW, matching the site technical connection limit and allowing assessment of grid stress and flexibility under extreme conditions.

Temporal structure and session splitting. Charging demand is discretized into 15-minute intervals, aligned with the MILP model's resolution and the day-ahead electricity market structure. In the EMS-integrated scenario, charging sessions that span multiple days are automatically split: energy demand falling outside the current day's optimization window is deferred and appended to the following day's demand list. This ensures temporal consistency while preserving session integrity.

Slack interpretation and diagnostic use. Slack variables are introduced in the optimization model to explicitly capture infeasibility, but their role differs between model types. In the exogenous profile models which are explained in detail in the next subsection, slack is applied only on EV charging power, enabling the model to register undelivered EV energy when grid import limits or resource conflicts make full delivery impossible. This allows hard-charging windows to be enforced while still ensuring solver feasibility. In contrast, the endogenous EMS-integrated models apply slack to the overall system energy balance, absorbing residual infeasibility across all controllable flows (EV, battery, grid) in any time step.

In both cases, slack energy is penalized at an artificially high rate (€1.000/kWh), ensuring it activates only when no feasible alternative exists. Crucially, these penalty costs are excluded from the reported operational costs in the results; they serve purely as a diagnostic signal. Total slack values therefore quantify infeasibility and inform the operational success metric, while preserving meaningful cost comparisons between scenarios.

While this step secures the realism of EV charging demand based on historical operations, it does not yet evaluate how different charging behaviours interact with physical system constraints. The next phase addresses this by applying multiple charging control strategies—ranging from low to high complexity—to the same demand profiles. This enables a structured comparison of strategy effectiveness, feasibility, and system impact across deployment stages. In doing so, it directly responds to Research Gap G3, which highlights the lack of comparative studies on real-world charging control strategies under constraint-aware conditions.

G3: Strategy comparison across deployment phases. By simulating the same charging demand under three control strategies and multiple battery sizes, the model enables a structured evaluation of how system intelligence affects energy cost, renewable energy use, and feasibility. This approach helps clarify when and where more advanced charging logic becomes valuable, and how it interacts with other system levers such as BESS. The outcomes provide a benchmarking foundation for evaluating the marginal value of EMS-based charging coordination in the next modelling phase.

4.3 Charging Control Logic and Strategy Benchmarking

As a second step, the methodological focus turns to evaluating how charging control strategies influence operational feasibility and energy system performance under real-world constraints. This dimension addresses Research Gap G3, which highlights the lack of structured comparisons across realistic charging strategies in existing EMS literature. It also provides a foundation for later EMS integration by establishing baseline behaviour across a spectrum of system intelligence levels.

Building on the previously derived EV charging demand profiles, this phase treats the charging profiles as exogenous—i.e., fixed time series inputs to the optimization problem—allowing for consistent benchmarking across scenarios. The charging strategies are organized according to increasing system maturity:

- **FAST:** Vehicles charge at the maximum allowable power immediately upon arrival. No temporal coordination or cost awareness is applied. In the visualization, this results in tall, narrow spikes of charging demand aligned with vehicle arrival times.
- **SPREAD:** Charging is evenly distributed across the available time window. This basic strategy reflects rudimentary load management without market interaction. The profile appears as low, flat blocks of charging activity that span the full duration of each window.
- **SMART:** Charging demand is shifted to the lowest-cost intervals within each charging window based on day-ahead electricity prices. Although price-aware, this strategy remains pre-processed and external to the optimization. In the plot, this produces irregular, staggered charging blocks concentrated in the lowest-cost periods.

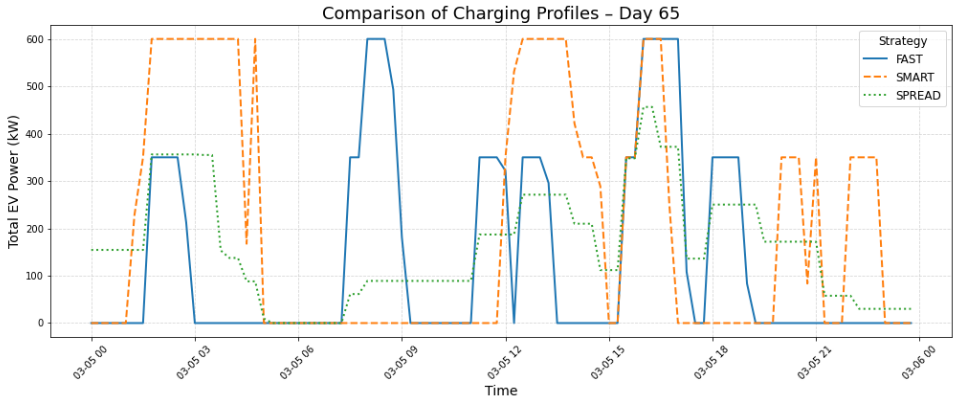

Figure 6: Charging profile comparison

All three strategies are evaluated across the current, intermediate, final, and future configurations as explained in section 4.2. This showcases the influence of the application of more complex charging strategies across the four deployment phases. The resulting scenario matrix enables robust benchmarking and supports the identification of strategy-dependent trade-off's in terms of peak shaving, cost, and feasibility. While these exogenous strategies are less flexible than fully integrated smart charging, they are widely applicable in early deployment phases and form a crucial reference point for later EMS-based coordination. The next step in the integration of battery systems in the power balance equation to compare the influence of energy storage on different charging strategy applications in both the intermediate and final phase of electrification.

G1: Operational value of BESS. By simulating daily energy flows across multiple battery configurations and charging strategies, the model reveals the role of BESS in improving cost efficiency, peak shaving, and charging feasibility. The combination of rolling-horizon optimization and high-resolution inputs ensures that temporal dynamics—such as price signals, PV variability, and EV demand—are accurately represented. This enables a robust evaluation of when and where BESS becomes economically or operationally valuable.

Sub-question 2: How can BESS be operated to optimize charging, grid interaction, and market participation? The scenario analysis provides direct insights into the optimal dispatch of BESS under varying conditions. It shows how battery behaviour adapts to site constraints, market signals, and charging logic, offering answers to the second sub-question. Together with the charging strategy benchmarks, this forms a comprehensive evaluation of the system-level role of storage prior to full EMS integration.

4.4 Battery Storage Integration and Site-Level Energy Optimization

The integration of battery energy storage marks a critical step in enabling cost-effective and grid-compliant electrification at scale. While previous sections treated EV charging demand as an exogenous load to be scheduled under fixed system constraints, this stage incorporates on-site storage as an active resource that dynamically buffers mismatches between energy supply, demand, and grid capacity.

The battery system is modelled as a controllable asset that participates in 15-minute site-level power balancing. At each timestep, it may charge using surplus PV or low-cost grid energy, discharge to support EV charging or baseload, or remain idle depending on operational constraints and electricity prices. Key applications include:

- **Peak shaving:** Discharging during high-demand intervals to reduce contracted grid import violations and monthly peak charges.
- **Energy arbitrage:** Charging when prices are low and discharging during peak-rate periods to increase energy revenue.
- **Solar mismatch mitigation:** Temporarily storing PV surplus and reallocating it to EV charging windows that occur outside of this generation.

Battery capacities of 500 kWh and 1000 kWh are evaluated in the intermediate through future phases with sizing adjusted to reflect increasing electrification demand. These values reflect feasible near-term and long-term deployment scenarios for logistics depots. Both systems are constrained by realistic operational parameters:

- **Power rating:** 0.5C, yielding 250kW and 500kW maximum charge/discharge power respectively.
- **State-of-Charge bounds:** Enforced between 20% and 90% to account for degradation-aware operation.
- **Daily cycling:** Limited to two full cycles per day, reflecting long-term wear constraints in depot-scale applications.

Battery dispatch is co-optimized with grid import/export and fixed EV charging demand using the rolling-horizon MILP model described in more detail in the next chapter. To isolate the value of storage, each battery-enabled scenario is benchmarked against a counterpart simulation with identical charging profiles and system conditions but without battery application. This direct comparison reveals under what conditions BESS improves economic and operational performance, including peak reduction, PV self-consumption, and cost savings across the four electrification phases.

Sub-question 3: What types of operational control strategies can ensure HDEV availability while staying within the technical and economic boundaries of local grid constraints and route schedules? This final modelling phase internalizes EV charging control within the energy system optimization to explore the value of fully coordinated scheduling. By co-optimizing EV charging alongside battery dispatch and grid interaction, the model simulates the functionality of an integrated Energy Management System (EMS). This allows for dynamic allocation of charging power based on evolving system conditions, providing insights into how coordination can improve delivery feasibility, reduce energy costs, and better utilize available flexibility. The outcomes directly answer the third sub-question and complete the progression from fixed-demand benchmarking to full-system control.

4.5 Integrated Charging Optimization and EMS Coordination

As a final step, the methodological focus shifts toward embedding electric vehicle (EV) charging control within the energy system optimization itself. This stage transitions from static, predefined charging profiles to fully integrated scheduling logic, whereby charging power is co-optimized alongside battery dispatch and grid interaction within a Mixed-Integer Linear Programming (MILP) framework. The goal is to evaluate whether a coordinated Energy Management System (EMS)—one that internalizes charging decisions—can improve delivery feasibility, reduce energy costs, and better utilize available flexibility. This phase directly supports the third sub-question, which asks what types of operational control strategies can ensure heavy-duty EV availability while respecting technical and economic constraints. It also addresses Research Gaps G4–G6, which collectively call for route-aware EMS modelling, benchmark comparisons across constraint regimes, and quantified value propositions for coordination.

G4: Route-integrated EMS feasibility. To answer whether EMS coordination can improve operational feasibility under route constraints, this study implements a formulation where vehicle-specific arrival windows, state-of-charge requirements, and charging power limits are enforced as hard constraints within the optimization. Charging power is treated as a decision variable—rather than an exogenous profile—enabling the solver to exploit dynamic trade-offs between grid import, PV surplus, battery use, and price signals. This endogenous approach is tested under the same conditions as previous exogenous strategies, enabling direct comparison. The key metric is not just total energy delivered, but whether charging sessions that failed under exogenous profiles (due to high demand or conflicting schedules) can now be accommodated through smart scheduling.

G5: Future deployment and relaxed constraint regimes. Once the feasibility benefits of EMS coordination are established under constrained conditions, the next question is whether those benefits persist in more flexible, future-proof settings. To explore this, the integrated EMS model is evaluated under relaxed grid import limits and uncongested charging infrastructure. This allows for assessment of EMS value under a future deployment phase—one in which technical constraints are no longer the primary bottleneck. The comparison focuses on cost savings, peak load flattening, and improved allocation of renewable energy. In doing so, it tests whether EMS remains a relevant operational tool even after structural grid limitations are addressed.

G6: Monetized value of coordination. Finally, this phase quantifies the operational benefits of EMS coordination by translating them into economic and policy-relevant outcomes. Across all scenarios key performance indicators including energy cost, peak import power and slack use are tracked to quantify operational impact. This allows the study to assess the marginal value of EMS adoption in both euros and kilowatt-hours. The resulting trade-off's offer concrete guidance on whether the implementation of advanced EMS logic is justified by its coordination benefits.

Together, these modelling efforts enable a comprehensive evaluation of smart charging coordination within realistic heavy-duty depot operations. They provide not only technical answers to sub-question 3, but also insight into when and why EMS adoption may be warranted. The mathematical implementation and structural details of this integrated EMS framework are presented in the next section.

To operationalize the main research question, three supporting sub-questions have been formulated in the first Chapter. These sub-questions break down the overarching challenge of phased, modular, and grid-aware electrification into discrete analytical problems that can be addressed through simulation and optimization. Each sub-question is directly linked to a dedicated segment of the modelling architecture and scenario matrix. In this way, the sub-questions act as the methodological scaffolding that structures the simulation logic, the comparative strategy, and the performance evaluation.

The research design therefore treats each sub-question not only as a component of the broader research objective, but also as a guiding axis along which model scenarios, system configurations and electrification phases are explored.

5 System Modelling and Optimization Framework

This chapter outlines the mathematical formulation and implementation of the optimization framework used to simulate energy flows and control strategies at the depot level. The system is defined as a deterministic, mixed-integer linear program (MILP) that allocates energy between grid import/export, battery storage, and EV charging. The model seeks to minimize total system cost while respecting physical constraints on power flow, battery operation, and grid capacity. Key structural components include time-discretized input data, a cost-based objective function, operational constraints, and a daily rolling horizon to reflect temporal dynamics. Outputs from the model are used to evaluate performance across scenarios with varying infrastructure setups, charging strategies, and coordination levels.

5.1 Modelling Approach

The system is modelled as a deterministic, time-discretized optimization problem with 15-minute resolution, aligned with the structure of European day-ahead electricity markets and the metering granularity of site-level energy data. The optimization is formulated as a mixed-integer linear program (MILP) and implemented in Python using the CVXPY 1.4.1 interface with the ECOSBB solver. ECOSBB is specifically chosen for its ability to handle models with negative revenues, enabling realistic representation of export during periods of negative electricity prices without requiring artificial curtailment.

A rolling-horizon structure is applied: each simulation day is optimized independently, reflecting the daily publication of day-ahead prices. State-of-charge (SOC) continuity is enforced across days, such that each day begins with the final SOC of the previous day. To ensure feasibility under strict physical and operational constraints (e.g., charger limits, grid import capacity), slack variables are introduced on EV charging only. These are penalized at €1000/kWh but excluded from cost metrics, serving purely as diagnostics to identify infeasible delivery conditions.

Full-year simulation is performed as a looped sequence of daily runs, balancing temporal accuracy with computational tractability. The modular model structure allows for extension, scenario switching, and transparent parameter tuning. EMS-integrated scheduling logic is introduced in the following chapter.

5.2 Model Inputs and Objective Function

- **PV generation** profiles (15-minute intervals).
- **Baseload demand** profiles from metering data.
- **Day-ahead market prices**, including separate import and export rates.

Table 1: Notation used in the optimization model

EV Charging Variables	
$P^{\text{EV}}_{t,i}$	Charging power assigned to EV session i at time t [kW]
S^{EV}_{i}	Slack energy for EV session i, used to quantify infeasibility [kWh]
P^{EV}_{t}	Total EV charging power at the depot during timestep t [kW]
Grid Power Variables	
G^{imp}_{t}	Power imported from the grid at timestep t [kW]
G^{exp}_{t}	Power exported to the grid at timestep t [kW]
Battery Variables	
$P^{\text{batt,ch}}_{t}$	Battery charging power at timestep t [kW]
$P^{\text{batt,dis}}_{t}$	Battery discharging power at timestep t [kW]
SOC_t	State-of-charge of the battery at timestep t [kWh]
σ^{ch}_{t}	Binary variable: 1 if battery is charging at t, 0 otherwise
σ^{dis}_{t}	Binary variable: 1 if battery is discharging at t, 0 otherwise
Cost and Market Parameters	
p^{buy}_{t}	Electricity import price at timestep t [€/kWh]
p^{sell}_{t}	Electricity export price at timestep t [€/kWh]
C^{deg}	Battery degradation cost per unit of throughput [€/kWh]
C^{peak}	Peak demand charge (monthly) [€/kW]
System Parameters and Constraints	
L_t	Site baseload at timestep t [kW]
P^{PV}_{t}	PV generation at timestep t [kW]
E^{batt}_{t}	Total battery throughput at timestep t [kWh]
Post-processing and Sustainability Metrics	
HBE_t	Renewable fuel credits (Hernieuwbare Brandstofeenheden) generated at t
$P^{\text{PV}\to\text{batt}}_{t}$	PV energy stored in the battery at t [kWh]
$P^{\text{batt}\to\text{EV,green}}_{t}$	Green battery energy delivered to EVs at t [kWh]
SOC^{green}_{t}	Virtual SoC representing green (PV-origin) energy in battery at t [kWh]

- **EV charging demand** profiles, either fixed (FAST, SPREAD, SMART) or decision variables in EMS-integrated cases.
- **EV route-based sessions**, derived from historical logs.

The model minimizes total system cost per day where the following calculation is made for each of the 96 timesteps:

$$\min \ C_{\text{total}} = \sum_{t} \left[p^{\text{buy}}_{t} \cdot G^{\text{imp}}_{t} - p^{\text{sell}}_{t} \cdot G^{\text{exp}}_{t} + c_{\text{deg}} \cdot E^{\text{batt}}_{t} \right] + \frac{c_{\text{peak}}}{30} \cdot \max(G^{\text{imp}}_{t}) \tag{1}$$

5.3 System Constraints

1. Power Balance: Ensures energy demand and supply are balanced at each time step.

$$G^{\text{imp}}_{t} + P^{\text{PV}}_{t} + P^{\text{batt,dis}}_{t} = L_t + P^{\text{EV}}_{t} + G^{\text{exp}}_{t} + P^{\text{batt,ch}}_{t} \tag{2}$$

2. Battery SOC Dynamics: Updates the battery state-of-charge based on charging/discharging activity and efficiency losses.

$$SOC_{t+1} = SOC_t + \Delta t \cdot (\eta_{\text{ch}} P^{\text{batt,ch}}_{t} - \frac{1}{\eta_{\text{dis}}} P^{\text{batt,dis}}_{t}) \tag{3}$$

3. SOC Limits: Keeps the battery SOC within minimum and maximum allowable levels to preserve physical safety and battery health.

$$SOC_{\min} \leq SOC_t \leq SOC_{\max} \tag{4}$$

4. Charge/Discharge Mutual Exclusivity: Prevents simultaneous charging and discharging of the battery.

$$\sigma_t^{\text{ch}} + \sigma_t^{\text{dis}} \leq 1, \quad \sigma_t^{\text{ch}}, \sigma_t^{\text{dis}} \in \{0, 1\} \tag{5}$$

5. Battery Power Constraints: Limits the power of charging/discharging to the battery's rated capacity.

$$0 \leq P_t^{\text{batt,ch}} \leq C_{\text{batt}} \cdot \sigma_t^{\text{ch}} \tag{6}$$
$$0 \leq P_t^{\text{batt,dis}} \leq C_{\text{batt}} \cdot \sigma_t^{\text{dis}} \tag{7}$$

6. Grid Import/Export Limits: Respects the technical connection limits of the depot.

$$0 \leq G_t^{\text{imp}} \leq G^{\text{imp,max}} \tag{8}$$
$$0 \leq G_t^{\text{exp}} \leq G^{\text{exp,max}} \tag{9}$$

7. Battery Cycling Limit: Constrains battery usage to a maximum of two full cycles per day to reflect manufacturer limitations and preserve lifespan.

$$\sum_t \Delta t \cdot (P_t^{\text{batt,ch}} + P_t^{\text{batt,dis}}) \leq 4 \cdot C_{\text{batt}} \tag{10}$$

8. Endogenous EV Charging Constraint: For EMS cases, ensures required energy is delivered within the allowable window.

$$\sum_t \Delta t \cdot P_t^{\text{EV}} = E_{\text{required}}, \quad 0 \leq P_t^{\text{EV}} \leq P^{\text{EV,max}}, \quad t \in [t_{\text{arr}}, t_{\text{dep}}] \tag{11}$$

5.3.1 Output Metrics

For each scenario, the following key performance indicators (KPIs) are computed and compared per 15 minute interval:

- **EV Energy Delivered** (kWh): total energy successfully delivered to the EV fleet.
- **Grid Import** (kWh) and **Grid Export** (kWh): total site energy imported from and exported to the grid.
- **Peak Grid Import** (kW): maximum grid import power observed, relevant for peak charge costs.
- **Battery Throughput** (kWh): total energy cycled through the battery (combined charge and discharge).
- **Average Battery SOC** (%): average state-of-charge of the battery over the simulated period.

- **Import and Export Unit Prices** (€/kWh): average prices for imported and exported energy.
- **Total Import Cost** (€) and **Total Export Revenue** (€): aggregated monetary flows due to grid interaction.
- **Total Cost per km** (€/km): overall system cost normalized by fleet distance.
- **Total System Cost** (€): net total cost, including grid energy, battery degradation, and peak penalties.

5.4 Optimization flowchart

Figure 7 provides a visual overview of the complete optimization framework, highlighting the key input data streams, system constraints, and resulting outputs. It illustrates how arrival-based EV demand, base load, PV generation, and market pricing are combined within a rolling optimization procedure to minimize system-wide energy costs. The green block labelled: *Exogenous charging optimization* becomes part of the central system optimization whenever EV charging is treated endogenously, in which case charging decisions are directly integrated into the solver logic instead of using fixed demand profiles.

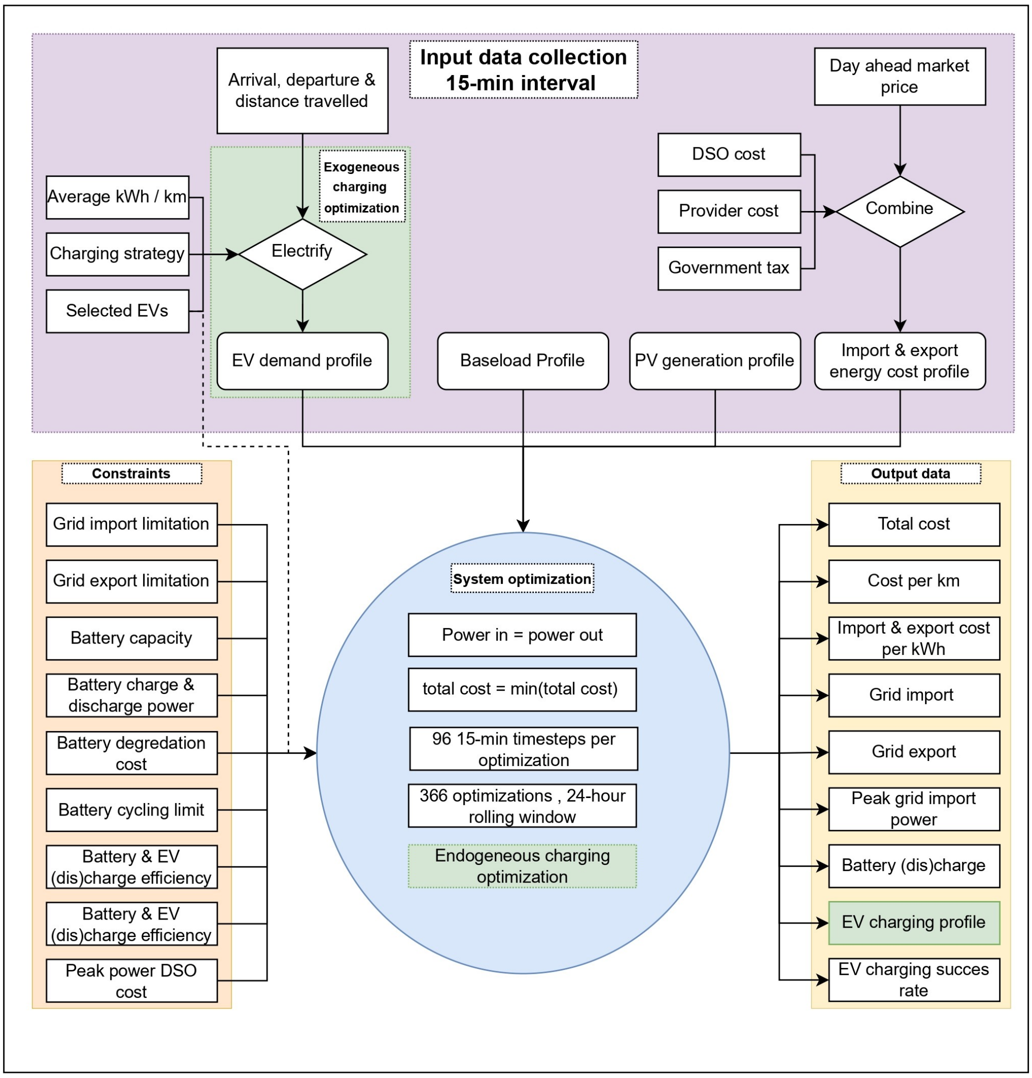

Figure 7: Optimization flowchart

6 Results and Discussions

This chapter presents the results of the simulation framework developed in Chapters 4 and 5. Each subsection corresponds directly to a modelling component introduced in the methodology and progressively builds evidence to evaluate the proposed research sub-questions. The results are structured to align with the staged complexity of the model: from basic electrification and charging strategies to battery integration and EMS coordination.

The chapter begins with an analysis of route electrifiability based on historical diesel operations. It then examines charging control strategies across four deployment phases: current, intermediate, final, and future. Next, the impact of battery integration is quantified across all phases and charging strategies. Finally, the added value of integrated energy management (EMS) is assessed and compared to smart charging under fixed profiles.

6.1 EV Charging Demand Derived from Diesel Routes

To quantify the expected increase in electricity demand from heavy-duty fleet electrification this section applies the route-to-demand modelling approach introduced in Section 4.1. Using historical diesel fleet data from 2024, each route is retroactively electrified using a representative HDEV configuration, thereby generating realistic charging demand profiles anchored in actual operations. The feasibility of electrification is assessed for each route based on total distance until return to the Bakker Warehousing depot and the average power needed to recharge the consumed electricity during the following idle time. Notable, all trips under 30 km are excluded, as these typically represent repositioning manoeuvres and not core transport tasks.

In the current scenario, charging is restricted to an average power of 50 kW. Under this constraint, **54%** of the routes exceed the allowable power threshold and are considered infeasible for electrification. In 8 the distribution of route frequency is showcased for the current scenario. For this calculation, all EV demands have been subjected to electrification to determine the electrification potential of each individual EV, each represented by a different colour.

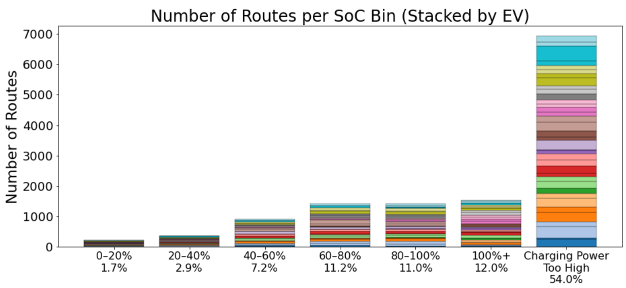

Figure 8: Frequency of routes per SoC bin intermediate scenario

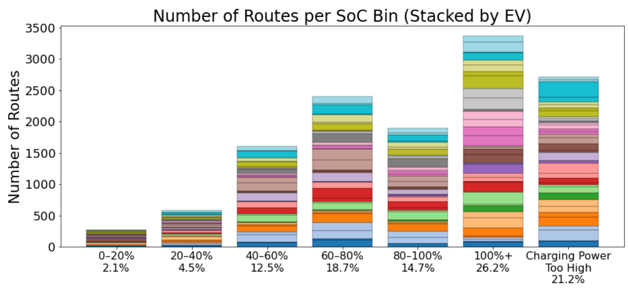

Figure 9: Frequency of routes per SoC bin final scenario

The outcome of the scenario's with upgraded an charger power of 350 kW is visualized in figure 9 , which displays the frequency of routes categorized by their estimated state-of-charge (SoC) impact on an HDEV battery system. The bins range from 0–20% up to greater than 100%. The SoC bins and corresponding route frequencies are as follows: 0–20% (2,1%), 20–40% (4,5%), 40–60% (12,5%), 60–80% (18,7%), 80–100% (14,7%), and >100% (26,2%).

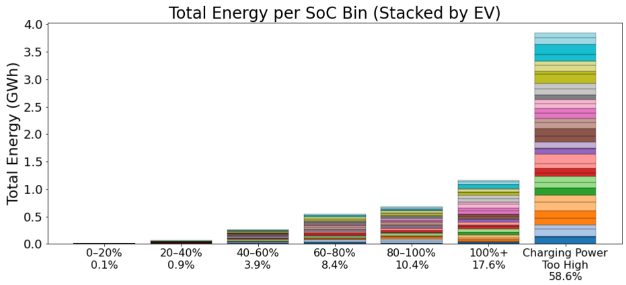

Figure 10: Total energy used per SoC bin intermediate scenario

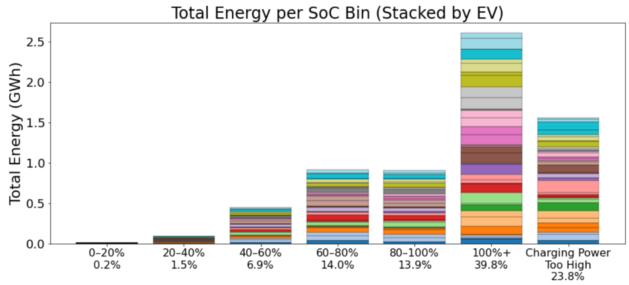

Figure 11: Total energy used per SoC bin final scenario

While frequency gives insight into route distribution, it does not directly correlate with the total energy demand. Longer routes contribute disproportionately to the aggregate electricity consumption, and therefore energy-weighted analysis is required. This is visualized by figures 10 and 11, 50 kW and 350 kW maximum charger power respectively. From an operational risk perspective, only routes consuming up to 80% SoC are deemed eligible for electrification; this constraint minimizes the risk of stranding vehicles due to unforeseen delays or deviations. The SoC bins and corresponding route frequencies are as follows: 0–20% (0.2%), 20–40% (1.5%), 40–60% (6.9%), 60–80% (14.0%), combining into a total of **22.6%** of electrifiable routes. This corresponds to approximately 1.5 GWh of required energy. The 60–80% and 80–100% SoC bins account for the largest shares of total energy use, comprising 13.9% and 39.8% respectively. Unelectrifiable routes make up 23.8% of total energy. This value represent an approximate decrease of 58% of routes that require an average charging power that exceeds system capabilities relative of to the intermediate scenario. This showcases the need for scalable system limitations in later phased of electrification. These routes can also, partly, be electrified by rearranging idle times and are therefore a good example of the influence of adapting scheduling constraints (i.e. idle time) from diesel and electric vehicles planning before integrating additional charging infrastructure.

The route analysis forms the basis for subsequent modelling of fleet-wide charging demand profiles and the assessment of battery and charging system integration strategies. From this electrified demand, the best electrifiable trucks for both the current and future system operations are extracted. For the current phase, these are routes that require <80% of the total SoC as well as an average charging power of <50 kW. For the other scenario, the average power threshold is increased to 350 kW. Results are visualized by the top 5 trucks in each selection below.

Table 2: Electrifiability top 5 EVs in current and future phases

Current Phase			**Final Phase**		
EV File	**Electrifiable (kWh)**	**Electrifiable (%)**	**EV File**	**Electrifiable (kWh)**	**Electrifiable (%)**
EV 06-BTN-1	51.563	43,01	EV 04-BRN-2	85.563	61,26
EV 19-BPB-5	44.984	34,83	EV 62-BLH-5	84.494	58,82
EV 04-BRN-2	44.716	32,43	EV 79-BPH-4	82.495	44,50
EV 66-BTN-8	44.461	39,54	EV 19-BPB-5	80.837	61,19
EV 62-BLH-5	44.015	31,37	EV 16-BSX-2	79.587	50,30

These results offer valuable insights into the under-explored topic of retroactive simulation of fleet electrification, as mentioned in research gap 3. By establishing the technical feasibility of converting diesel routes into battery-electric operations, they form the empirical foundation for the selection of EV charging demands used in subsequent scenario modelling. Moreover, this data, in combination with the existing energy data from PV and baseload offer insight into the reasoning behind sub-question 1: **How can existing energy systems and infrastructure on the user side of the grid connection be adapted to facilitate modular and phased deployment of EV charging systems so that the system can grow alongside fleet electrification?**

In the following section, the selected EV demands are translated into independent charging profiles, as described in Section 4.3. This transformation marks the next modelling step toward inclusion in the system-wide cost optimization framework.

6.2 Profile Generation: Exogenous Charging Allocation

The charging strategies evaluated in this study are divided into two categories: exogenous and endogenous profile generation. In the exogenous case, charging profiles are constructed prior to system optimization using greedy heuristics that allocate power independently for each vehicle based on arrival and departure windows, required energy, and maximum site limits. While this approach aligns with decentralized or rule-based charging systems, it introduces a critical drawback: charging feasibility is not guaranteed, even when individual sessions comply with the filtering rules.

Due to competition for limited site power—especially under strict grid constraints—sessions that are individually feasible may become undeliverable when multiple EVs overlap in time. This results in a mismatch between filtered and actually delivered energy, particularly under high congestion or with aggressive filtering thresholds.

In contrast, endogenous profiles are co-optimized with system constraints and objectives (e.g. in EMS-integrated scenarios), but these will be discussed separately. Here, we focus only on the delivery performance of the exogenous strategies (FAST, SMART, SPREAD) across phases.

Table 3: Energy Delivery Performance of Exogenous Charging Strategies

Phase	**Required Energy (kWh)**	**FAST (%)**	**SPREAD (%)**	**SMART (%)**
Current	229,105	99.21%	99.43%	98.98%
Intermediate	625,200	99.96%	100.00%	99.86%
Final	1,266,626	99.38%	99.96%	99.17%
Future	1,891,826	99.81%	99.99%	99.56%

All exogenous strategies perform robustly in energy delivery, exceeding 98.9% across all phases. However, slight differences emerge based on the temporal spread of each profile. SMART charging delivers marginally less energy in congested phases due to its tendency to concentrate power usage in cost-effective time slots, occasionally leading to contention. FAST and SPREAD show better delivery rates due to either early charging (FAST) or broader allocation (SPREAD), with the latter achieving full delivery in the intermediate, final and future scenario's, adjusting slightly for rounding errors.

6.3 Charging Strategy Benchmarking Across Deployment Phases

As described in Section 4.3, charging profiles are constructed using both exogenous heuristic approaches (FAST, SPREAD, SMART) and endogenous optimization within the EMS-integrated setup. The results presented here explicitly evaluate these approaches, testing the practical feasibility and economic outcomes of these profiles under realistic system constraints. By comparing the operational success and system costs, these results directly address research sub-question 3, providing insight into the effectiveness of different charging strategies under constrained grid conditions.

To understand the performance impact of charging strategies under different infrastructure constraints, the SMART, FAST, and SPREAD profiles were simulated for each deployment phase without battery storage. This provides a consistent baseline for evaluating the incremental value of battery integration and coordinated EMS control.

Each profile was pre-constructed based on heuristics introduced in Section 4.3 and executed in the absence of a battery system. Charging feasibility and economic outcomes are compared using two key performance metrics: (1) *Operational Success*, which quantifies the fraction of requested energy that was infeasible due to system constraints (captured as slack relative to grid import), which reflects how well the optimizer was able to deliver energy based on the predefined profile, and (2) *Cost per km (€)* which represents the combination of grid import fees and grid export revenue divided by the amount of electrically driven kilometres. In addition, financial indicators such as import/export prices, total cost and peak import power are reported for each case.

Current Phase

Table 4 shows that none of the three charging strategies achieves a full 100% energy delivery rate in the current scenario. Among them, the SPREAD strategy attains the highest operational success at 97,2% due to its smoother, less volatile distribution of charging. Notable differences emerge in cost-related performance. SMART charging results in the lowest total cost (€-9.067) and the lowest cost per kilometre (€-0,0548), reflecting its ability to align charging with favourable electricity prices. FAST yields slightly higher energy delivery but comes with increased cost per kilometre, indicating that its lack of temporal targeting undermines cost-efficiency. SPREAD, while significantly more reliable, provides the highest total cost.

Table 4: Strategy Performance – Current Phase

Strategy	Operational Success (%)	Peak Grid Import (kW)	Import €/kWh	Export €/kWh	Cost per km (€)	Total Cost (€)
FAST	92,3%	105	0,1232	0,0554	–0,0257	–4.260
SPREAD	96,2%	105	0,1191	0,0555	–0,0172	–2.849
SMART	92,0%	105	0,1112	0,0580	–0,0548	–9.067

Intermediate Phase

As shown in Table 5, the energy system becomes noticeably less constrained with the increased grid limitation of 600 kW peak power, albeit this capacity is shared across a larger number of vehicles. Although overall charging success improves, both FAST and SMART strategies still fall short of a 100% delivery rate. SMART continues to outperform the alternatives economically, achieving the lowest cost per kilometre (€ 0,0534) and reducing total system cost by more than € 15.000 compared to FAST. Notably, the SPREAD strategy results in no slack but incurs the highest cost (€ 41.514), highlighting its inability to leverage low-price charging windows effectively. The fact that all strategies reach exactly 600kW of peak import indicates that the grid constraint remains a binding limitation in this phase. Even for SPREAD, this suggests that the absence of slack does not imply an optimal solution, but rather reflects the saturation of available capacity. This outcome reinforces that minimizing infeasibility alone does not guarantee cost-optimal performance.

Table 5: Strategy Performance – Intermediate Phase

Strategy	**Operational Success (%)**	**Peak Grid Import (kW)**	**Import €/kWh**	**Export €/kWh**	**Cost per km (€)**	**Total Cost (€)**
FAST	99,2%	600	0,1172	0,0558	0,0867	39.545
SPREAD	100,0%	600	0,1186	0,0538	0,0910	41.514
SMART	98,2%	600	0,0979	0,0605	0,0534	24.350

Final Phase

In the final phase (Table 6) increased grid and infrastructure capacities eliminate all slack, indicating that the system is no longer constrained by hard power limits. This is further supported by the fact that the observed peak grid import values remain below the available grid capacity, meaning the optimizer operates fully within feasible bounds. As a result, charging decisions are now primarily driven by cost optimization within the structure of each strategy. In this context, SMART again delivers the lowest total cost (€ 75.510) and the lowest cost per kilometre, due to its ability to align charging with favourable price periods. While SPREAD achieves perfect delivery, it does so at a significantly higher cost (€ 114.461), suggesting limited exploitation of price variability. FAST performs intermediately. The strong cost performance of SMART under unconstrained conditions reaffirms the advantage of price-sensitive, temporally flexible charging strategies.

Table 6: Strategy Performance – Final Phase

Strategy	**Operational Success (%)**	**Peak Grid Import (kW)**	**Import €/kWh**	**Export €/kWh**	**Cost per km (€)**	**Total Cost (€)**
FAST	100,0%	781	0,1138	0,0549	0,1151	108.449
SPREAD	100,0%	756	0,1157	0,0512	0,1207	114.461
SMART	100,0%	781	0,0919	0,0665	0,0826	75.511

Future Phase

The **Future Phase** results in **Table 7** confirm and amplify earlier trends. With the grid import ceiling expanded to 1,700 kW—far exceeding the observed peak import values—the system operates entirely within unconstrained limits. As route electrification also increases, full energy delivery is achieved across all strategies, with no slack present. However, the economic spread between strategies continues to grow: SMART remains the most cost-efficient at €130.066, while SPREAD incurs the highest total cost (€180.955). FAST performs in between. Despite the system's increased scale and flexibility, only the SMART strategy consistently aligns charging with low-price periods, reinforcing the value of temporally adaptive, price-aware control in large-scale electrified logistics.

Table 7: Strategy Performance – Future Phase

Strategy	Operational Success (%)	Peak Grid Import (kW)	Import €/kWh	Export €/kWh	Cost per km (€)	Total Cost (€)
FAST	100,0%	1.096	0,1136	0,0534	0,1293	178.256
SPREAD	100,0%	985	0,1153	0,0478	0,1310	180.955
SMART	100,0%	1.096	0,0896	0,0676	0,0946	130.066

6.4 Battery System Impact Across Charging Strategies

This section quantifies the role of battery storage in multi-objective optimization, directly addressing research sub-question 2 outlined in Section 2.8. Specifically, results presented here demonstrate how battery storage contributes simultaneously to vehicle charging feasibility, market participation, and grid limitation management under varying deployment phases. These insights, derived directly from the methodological framework described in Section 4.4, provide a clear basis for optimal battery sizing and integration strategies.

To evaluate the role of stationary battery energy storage systems (BESS) in enhancing electrification performance, we compare system metrics for each strategy with and without integrated storage. The benchmark scenario for each phase is the 0 kWh battery case, presented in the previous subchapter. Battery capacities of 500 kWh and 1.000 kWh are then introduced to quantify the impact on operational feasibility, cost, and market participation. All simulations are conducted per phase (Current, Intermediate, Final, Future), enabling a structured assessment of the value added by BESS integration under progressively more demanding conditions.

Metrics such as operational success, energy prices, cost per kilometre, and total system cost are analysed to reveal the trade-off's between battery size, control strategy, and infrastructure utilization.

Current Phase

As shown in **Table 9**, none of the baseline strategies (FAST, SPREAD, SMART) achieve full EV energy delivery in the current phase. While feasibility is already relatively high, significant slack remains—especially for FAST and SMART—highlighting the limitations of grid-only operation. Battery integration effectively reduces this slack while simultaneously improving economic performance.

The first battery increment (500 kWh) primarily improves feasibility, increasing operational success by an average of 4,5 percentage points across all strategies. The second increment

(1.000 kWh) yields only marginal additional feasibility gains (on average +0,2 percentage points), but continues to improve costs—albeit to a lesser extent.

Across all strategies, the initial 500 kWh battery reduces total system cost by:

Table 8: Total Cost Reduction per Battery Size Increment – Current Phase

Strategy	**0 kWh → 500 kWh**	**500 kWh → 1.000 kWh**
FAST	€ 9.422	€ 8.711
SPREAD	€ 10.504	€ 8.606
SMART	€ 9.279	€ 8.078

While both battery sizes deliver clear economic benefits, the largest improvements stem from the first step. This confirms that a moderate storage capacity already addresses most feasibility constraints and unlocks the bulk of cost reduction. Additional capacity mainly deepens market interaction, but with diminishing returns. Even FAST charging, despite its limited temporal flexibility, benefits considerably—highlighting the broad value of battery integration under constrained grid conditions.

Table 9: Battery Impact – Current Phase

Strategy	**Operational Success (%)**	**Import €/kWh**	**Export €/kWh**	**Cost per km (€)**	**Total Cost (€)**
FAST (No Battery)	92,3%	0,1232	0,0554	–0,0257	–4.260
FAST – 500 kWh	98,8%	0,1085	0,0669	–0,0825	–13.682
FAST – 1.000 kWh	99,0%	0,1040	0,0822	–0,1350	–22.393
SPREAD (No Battery)	96,2%	0,1191	0,0555	–0,0172	–2.849
SPREAD – 500 kWh	98,8%	0,1065	0,0669	–0,0803	–13.353
SPREAD – 1.000 kWh	98,8%	0,1034	0,0818	–0,1321	–21.959
SMART (No Battery)	92,0%	0,1112	0,0580	–0,0548	–9.067
SMART – 500 kWh	95,8%	0,1023	0,0717	–0,1108	–18.346
SMART – 1.000 kWh	95,8%	0,1007	0,0862	–0,1596	–26.424

Intermediate Phase

In the intermediate electrification phase, EV charging demand increases substantially compared to the current phase. Battery integration proves critical: it eliminates all remaining feasibility issues across all strategies. Operational success reaches 100% for all cases, with zero slack observed. As such, the system is no longer constrained by technical feasibility, and the key differentiator becomes economic performance.

Table 10: Total Cost Reduction per Battery Size Increment – Intermediate Phase

Strategy	**0 kWh → 500 kWh**	**500 kWh → 1.000 kWh**
FAST	€ 11.428	€ 10.784
SPREAD	€ 12.294	€ 10.309
SMART	€ 9.678	€ 9.728

While all strategies benefit substantially from the first battery increment, gains from 500 kWh to 1.000 kWh are more modest and similar across strategies. This suggests diminishing economic returns from additional storage capacity, particularly once feasibility is resolved. Notably, SMART derives slightly more benefit in the second step than in the first, highlighting the overlap between SMART and battery operations.

Interestingly, the marginal benefits of storage are somewhat less pronounced in SMART than in FAST or SPREAD when considered relative to the strategies' inherent intelligence. This suggests a partial functional overlap between battery operations and the SMART strategy's own scheduling capabilities. In contrast, FAST and SPREAD — which lack temporal flexibility — benefit more independently from battery support, as the battery becomes the primary mechanism for aligning energy flows with favourable market conditions.

Table 11: Battery Impact – Intermediate Phase

Strategy	Operational Success (%)	Import €/kWh	Export €/kWh	Cost per km (€)	Total Cost (€)
FAST (No Battery)	99,2%	0,1172	0,0558	0,0867	€ 39.545
FAST – 500 kWh	100,0%	0,1092	0,0694	0,0616	€ 28.117
FAST – 1.000 kWh	100,0%	0,1015	0,0863	0,0380	€ 17.333
SPREAD (No Battery)	100,0%	0,1186	0,0538	0,0910	€ 41.514
SPREAD – 500 kWh	100,0%	0,1081	0,0648	0,0640	€ 29.220
SPREAD – 1.000 kWh	100,0%	0,1020	0,0827	0,0414	€ 18.911
SMART (No Battery)	98,2%	0,0979	0,0605	0,0534	€ 24.350
SMART – 500 kWh	100,0%	0,0926	0,0773	0,0322	€ 14.672
SMART – 1.000 kWh	100,0%	0,0893	0,0940	0,0108	€ 4.944

Final Phase

In the final phase, all configurations reach 100% operational success, indicating that feasibility constraints have been fully resolved. As such, differences between strategies are purely economic. FAST and SPREAD benefit strongly from battery integration, reducing total cost by €14.848 and €17.476 respectively between the baseline and 1.000 kWh configurations. In contrast, SMART shows minimal cost improvement — and even a slight increase from 500 to 1.000 kWh — suggesting a functional overlap between its internal price-optimization logic and battery operation. This implies that, beyond a certain scale, battery capacity becomes redundant within already optimized scheduling strategies.

Table 12: Total Cost Reduction per Battery Size Increment – Final Phase

Strategy	0 kWh → 500 kWh	500 kWh → 1.000 kWh
FAST	€ 12.278	€ 10.949
SPREAD	€ 12.679	€ 10.711
SMART	€ 7.139	€ 9.439

Interestingly, the SMART strategy displays a larger incremental gain from 500 to 1.000 kWh than from 0 to 500 kWh — a reversal of earlier trends. This can be explained by the battery power constraint: in the model, the battery's maximum charge and discharge power scales with its capacity (e.g., 250 kW for 500 kWh, 500 kW for 1.000 kWh). Once all EV charging and site operations are feasible, the second 500 kWh primarily enhances the battery's ability to exploit short-term price volatility, providing faster and deeper arbitrage opportunities. In other words, while the first 500 kWh supports operational alignment, the second increment unlocks the full economic potential of battery-driven market optimization.

Table 13: Battery Impact – Final Phase

Strategy	**Grid Import (kWh)**	**Import €/kWh**	**Export €/kWh**	**Total Cost (€)**
FAST (0 kWh)	1.161.487	0,1138	0,0549	€ 108.449
FAST – 500 kWh	1.129.281	0,1080	0,0705	€ 96.171
FAST – 1.000 kWh	1.153.550	0,1020	0,0900	€ 85.222
SPREAD (0 kWh)	1.188.292	0,1157	0,0512	€ 114.461
SPREAD – 500 kWh	1.147.948	0,1085	0,0603	€ 101.782
SPREAD – 1.000 kWh	1.163.167	0,1032	0,0792	€ 91.071
SMART (0 kWh)	1.152.954	0,0919	0,0665	€ 75.511
SMART – 500 kWh	1.202.039	0,0885	0,0854	€ 68.372
SMART – 1.000 kWh	1.270.602	0,0859	0,1027	€ 58.933

Future Phase

In the final projected stage of electrification, grid-only scenarios begin to show their technical and economic limits. Notably, SMART charging without storage struggles to keep import costs competitive, despite moderate export gains. Battery integration becomes essential not just for cost minimization, but also to cap peak grid import power and ensure sustained operational flexibility.

Table 14: Total Cost Reduction per Battery Size Increment – Future Phase

Strategy	**0 kWh → 500 kWh**	**500 kWh → 1.000 kWh**
FAST	€ 12.576	€ 11.309
SPREAD	€ 12.984	€ 11.130
SMART	€ 10.610	€ 9.520

Integrating a 500 kWh battery yields immediate gains: total cost drops by € 12.576 for FAST, € 12.984 for SPREAD, and € 10.610 for SMART. These gains reflect improved import cost control and modest export benefits. A further upgrade to 1.000 kWh continues this trend, though with slightly reduced marginal gains. SMART benefits the most from this second increment, saving an additional € 9.520, due to expanded arbitrage capacity now that simultaneous operation with grid import is no longer restricted. This final setup delivers the lowest system cost across all simulations: € 109.936.

Table 15: Battery Impact – Future Phase

Strategy	**Grid Import (kWh)**	**Import €/kWh**	**Export €/kWh**	**Total Cost (€)**
FAST (No Battery)	1.756.765	0,1136	0,0534	€ 178.256
FAST – 500 kWh	1.711.373	0,1092	0,0668	€ 165.680
FAST – 1.000 kWh	1.720.336	0,1045	0,0863	€ 154.371
SPREAD (No Battery)	1.714.972	0,1153	0,0478	€ 180.955
SPREAD – 500 kWh	1.673.097	0,1096	0,0555	€ 167.971
SPREAD – 1.000 kWh	1.679.032	0,1048	0,0749	€ 156.841
SMART (No Battery)	1.753.052	0,0896	0,0676	€ 130.066
SMART – 500 kWh	1.770.000	0,0869	0,0892	€ 119.456
SMART – 1.000 kWh	1.835.138	0,0849	0,1078	€ 109.936

These improvements form the foundation for the next step: coordinated energy scheduling through EMS integration.

6.5 Comparative Assessment of EMS vs. Decentralized Control

This section assesses the impact of EMS integration in facilitating modular and phased deployment of EV charging infrastructure. By evaluating scenarios both with and without EMS, these results demonstrate explicitly how existing infrastructure—when managed through coordinated energy strategies—can effectively adapt and scale alongside increased fleet electrification. This analysis builds directly on the methodological approach described in Section 4.5.

To assess the added value of full system coordination, the EMS-integrated strategy is benchmarked directly against the SMART strategy. Both approaches share a cost-optimizing logic, making use of energy prices, PV generation, and battery storage to minimize system expenditure. However, EMS integration distinguishes itself by coordinating all controllable energy flows—across EVs, battery, and the grid—in a unified optimization framework, whereas SMART charging calculates EV charging externally. This comparison helps quantify the additional benefit of holistic control at different levels of electrification.

Four comparative tables are presented for the *Current*, *Intermediate*, *Final*, and *Future* phases. Each table is placed directly after the corresponding SMART result table in the battery impact subsection. The results are grouped by battery size (0, 500 and 1.000 kWh) and list SMART and EMS strategies side by side, enabling direct evaluation of improvements in import cost, export revenue, total system cost, and operational success.

Current Phase

In the current phase, the primary value of EMS coordination lies in guaranteeing full operational success across all battery capacities, especially in the scenario without energy storage solutions. While the SMART strategy still results in under delivery of up to 8 %, the EMS-integrated approach eliminates all slack and ensures complete energy delivery. This increase in reliability is particularly critical in early deployment stages where grid performance and contractual obligations are sensitive to shortfalls.

In addition to this operational advantage, EMS coordination also leads to notable cost reductions. At 0 kWh, total system cost improves by more than €1.500 compared to SMART. With increasing battery capacity, the financial gains compound: the 500 kWh EMS scenario saves over €3.600 and the 1.000 kWh case exceeds €4.200 in additional savings. These results underscore that even in small-scale deployments, centralized coordination offers tangible improvements in both reliability and cost-effectiveness. That said, these financial gains are likely smaller than the investment and operational costs of integrated EMS operations. They can be employed, but from either a feasibility perspective or as preparation for further incorporation at later stages.

Table 16: EMS Integration vs. SMART – Current Phase

Strategy	**Peak Grid Import (kW)**	**Operational Success (%)**	**Import €/kWh**	**Export €/kWh**	**Total Cost (€)**
SMART – 0 kWh	105	92,0 %	0,1112	0,0580	€ -9.067
EMS Integrated – 0 kWh	105	100,0 %	0,1065	0,0596	€ -10.579
SMART – 500 kWh	105	95,8 %	0,1007	0,0717	€ -18.346
EMS Integrated – 500 kWh	105	100,0 %	0,0971	0,0741	€ -22.025
SMART – 1.000 kWh	105	95,7 %	0,1023	0,0862	€ -26.424
EMS Integrated – 1.000 kWh	105	100,0 %	0,0987	0,0882	€ -30.704

This performance becomes even more compelling when placed in the context of the following simulation setup: although the grid import ceiling remains at 105 kW—reflecting the constraints of the Current Phase—the demand profile corresponds to the Intermediate Phase, in which roughly 50 % of the total electrifiable fleet is activated. This shift is enabled by relaxing two filtering constraints: increasing the maximum per-session charging power from 50 kW to 350 kW, and raising the allowable site limit from 100 kW to 600 kW during route screening. These adjustments raise the system-wide EV energy demand from 229 MWh to 625,MWh—an increase of 273 %—while keeping infrastructure limits constant, creating an extremely constrained transition scenario.

Within this setup, EMS coordination proves essential to maintaining feasibility. With 1.000 kWh of storage, EMS achieves a successful energy delivery rate of 90,3 %, compared to just 72,9 % under SMART with the same battery size—a 17,4 percentage point gain. Even without storage, EMS reaches 81,8 % delivery, more than double the 39,6 % achieved by SMART. These results highlight the ability of an EMS to resolve power allocation conflicts across concurrent charging sessions—something heuristic strategies fail to do under increased restrictiveness.

While EMS strategies exhibit higher total cost and cost per kilometre, these outcomes are a direct consequence of improved feasibility. More energy delivered means less PV export, and therefore higher net system cost. However, the rise in cost per kilometre remains limited—e.g., from –0,0006 to 0,0094 in the 1.000,kWh case—while enabling a dramatic increase in operational success. This confirms that EMS integration is not just economically viable under extreme constraints; it is a prerequisite for scaling delivery without structural overdesign.

Table 17: EMS vs SMART – Current phase limitations with future EV charging demands

Battery Capacity	**Successful Energy Delivery (%)**	**Total Cost per km (€)**	**Total Cost (€)**
SMART – 0 kWh	39,6 %	–0,0205	–9.330
SMART – 500 kWh	67,4 %	0,0056	2.562
SMART – 1.000 kWh	72,9 %	–0,0006	–252
EMS – 0 kWh	81,8 %	0,0324	12.098
EMS – 500 kWh	89,8 %	0,0242	9.894
EMS – 1.000 kWh	90,3 %	0,0094	3.856

Intermediate Phase

In the intermediate phase, increased electrification pushes the 600 kW grid import ceiling to its operational limits. While the SMART strategy falls just short of full energy delivery—especially at 0 kWh and 1.000 kWh capacities—EMS integration succeeds in delivering 100 % of the demand across all battery sizes within the same constraint. This illustrates the advantage of unified coordination, even under tight system limits.

Beyond reliability, EMS also yields significant cost reductions. At 0 kWh, it improves system cost by nearly €2.700 compared to SMART. At 500 kWh, the savings exceed €5.000, and in the 1.000 kWh scenario, EMS lowers the total cost by more than €5.900—turning a positive cost in SMART into a net-negative result. Even under identical grid access, EMS logic produces a more efficient and cost-effective outcome.

Table 18: EMS Integration vs. SMART – Intermediate Phase

Strategy	**Peak Grid Import (kW)**	**Operational Success (%)**	**Import €/kWh**	**Export €/kWh**	**Total Cost (€)**
SMART – 0 kWh	600	98,2 %	0,1135	0,0605	€ 24.350
EMS Integrated – 0 kWh	600	100,0 %	0,1065	0,0629	€ 21.640
SMART – 500 kWh	600	99,9 %	0,1007	0,0773	€ 14.672
EMS Integrated – 500 kWh	600	100,0 %	0,0971	0,0798	€ 9.636
SMART – 1.000 kWh	600	99,9 %	0,1023	0,0940	€ 4.944
EMS Integrated – 1.000 kWh	600	100,0 %	0,0987	0,0956	€ -976

Final Phase

In the Final Phase, both strategies already deliver full energy demand without slack, but EMS integration still proves more economical. At 1.000 kWh capacity, EMS saves over €8.500 annually over SMART and increases export revenue per kilowatt-hour. This shows how tighter coordination yields tangible cost reductions even when slack is no longer an issue.

Table 19: EMS Integration vs. SMART – Final Phase

Strategy	Peak Grid Import (kW)	Operational Success (%)	Import €/kWh	Export €/kWh	Total Cost (€)
SMART – 0 kWh	781	100,0 %	0,1191	0,0665	€ 75.511
EMS Integrated – 0 kWh	781	100,0 %	0,1118	0,0684	€ 72.928
SMART – 500 kWh	853	100,0 %	0,1034	0,0854	€ 68.372
EMS Integrated – 500 kWh	981	100,0 %	0,0987	0,0893	€ 61.252
SMART – 1.000 kWh	1.064	100,0 %	0,1065	0,1027	€ 58.933
EMS Integrated – 1.000 kWh	1.200	100,0 %	0,0987	0,1052	€ 50.565

Future Phase

In the future phase system pressure increases, and while both strategies continue to deliver energy effectively, EMS maintains lower import volumes and further improves the financial outcome. The 1.000 kWh EMS case again outperforms SMART significantly, saving over €5.800 and achieving the lowest cost per kilometre of all strategies. Such margins justify system-level EMS implementation under high-electrification scenarios.

Table 20: EMS Integration vs. SMART – Future Phase

Strategy	Peak Grid Import (kW)	Operational Success (%)	Import €/kWh	Export €/kWh	Total Cost (€)
SMART – 0 kWh	1.096	100,0 %	0,1191	0,0676	€ 130.066
EMS Integrated – 0 kWh	1.096	100,0 %	0,1118	0,0710	€ 126.490
SMART – 500 kWh	1.166	100,0 %	0,1034	0,0892	€ 119.456
EMS Integrated – 500 kWh	1.297	100,0 %	0,0971	0,0960	€ 114.826
SMART – 1.000 kWh	1.380	100,0 %	0,1065	0,1078	€ 109.936
EMS Integrated – 1.000 kWh	1.547	100,0 %	0,0987	0,1125	€ 104.131

6.7 Summary of Results

The simulation results across four deployment phases demonstrate a clear progression in system coordination needs, feasibility challenges, and economic trade-off's. As electrification intensifies—from pilot-scale deployment to full-fleet operation—the system's ability to reliably deliver energy no longer relies on support systems as the grid limitations are no longer active constraints. instead, these systems can cost optimize, allowing for a lower overall cost per kilometre.

Heuristic charging strategies such as FAST, SPREAD, and SMART perform robustly in the Current Phase, where total electrification is limited to five vehicles and aggregate charging demand remains relatively modest. Despite the tight 105 kW grid import ceiling, all three strategies achieve over 93,8% EV energy delivery, with SMART reducing total system cost by over €4.500 with respect to fast charging due to favourable price alignment. However, as fleet electrification expands and grid import rises to 600 kW in the Intermediate Phase, the system becomes less congested and delivery competition decreases. Under these conditions, SMART charging is still the most cost-effective heuristic—exhibits with measurable slack of up to 1,8%. However, this is solved when paired with a 500 kWh battery.

Battery storage consistently improves system resilience and reduces operational costs across all phases, especially when co-timed with low-price grid energy and high PV output. Yet, while stand-alone battery deployment provides tangible benefits—particularly in peak shaving and export optimization—it is not a stand-alone solution for feasibility. As system grid limitations become less constraining cost optimization becomes the main driver of the battery systems. This generates on average around €10.000 per 500 kWh annually over all strategies and sizes.

In contrast, EMS-integrated coordination ensures both full delivery and further cost reductions across all scenarios. Even in low-demand phases with significant charging overlap and limited import headroom, EMS consistently achieves close to a 100% operational success. This underscores a critical feasibility insight: while batteries support the system, it is EMS coordination that ultimately ensures system reliability under stress. From a feasibility perspective, the EMS emerges as the more decisive enabler of high-electrification operations—unlocking the full potential of batteries, grid connection, and PV generation through system-wide optimization.

These findings establish a clear case for phased implementation: initial deployment feasibility is best achieved though ems integration. However, with a route planning that minds charging restriction and a battery storage system this can also be achievable. For a future-proof cost-efficient operation an integrated EMS will benefit both growth planning and cost effectiveness. The following chapter interprets these outcomes in the context of real-world implementation, investment timing, and strategic planning for depot-scale electrification.

6.6 Phase-Based System Evaluation

Current Phase

The Current Phase operates under a strict 105 kW import ceiling, yet achieves high operational success across all charging strategies. This is not due to relaxed system conditions, but because of deliberately constrained electrification: only five carefully selected vehicles are included, each filtered for both energy and power feasibility. Under these conditions, heuristic strategies such as SMART and SPREAD achieve over 93,8 % energy delivery, and SMART in particular delivers significant cost reductions (up to €4.500 annually when compared to FAST) by aligning charging with low-cost time slots.

Battery deployment further enhances performance in this phase. A 500 kWh system paired with SMART logic reduces slack, flattens peak import, and improves both import cost and export value. In contrast, full EMS coordination offers only marginal additional benefit — a few percentage points in operational success and roughly €1.500–€4.000 in extra savings. Given the modest demand and high solver complexity, EMS investment is not yet economically justified.

However, early EMS preparation is strategically sound. Establishing modular infrastructure, compatible data flows, and preliminary control logic now reduces risk in future phases where feasibility margins narrow. The recommended implementation path is therefore battery deployment with SMART scheduling, supplemented by modular EMS readiness.

Intermediate Phase

In the Intermediate Phase, fleet electrification increases substantially and the grid ceiling rises to 600 kW. While this allows more energy throughput, the number of concurrent charging sessions increases sharply, causing the system to remain congested. SMART charging begins to show its limits: despite using the same economic logic as EMS, it fails to fully deliver energy in all cases. Slack reaches up to 1,83 %. However, this can be soled by incorporating a 500 kWh battery.

In contrast, EMS-integrated setups deliver 100 % of energy across all battery sizes while also improving cost performance by over €6.000 annually compared to SMART. These improvements stem from coordinated control over charging timing, battery dispatch, and export opportunities — capabilities beyond the scope of heuristic scheduling.

This phase therefore marks a turning point: EMS becomes economically attractive, and can be developed more due to the increased number of charging session. Prior investments in SMART routing and battery infrastructure pay off by enabling seamless EMS integration with minimal structural upgrades.

Final Phase

In the final phase, full fleet electrification is introduced under a relatively unconstrained 1.200 kW import ceiling. All fixed-profile strategies — FAST, SPREAD, and SMART — achieve 100 % operational success, even without battery integration. This marks a clear shift from earlier phases: technical feasibility is no longer a limiting factor, and economic optimization becomes the primary focus.

Among the fixed strategies, SMART without storage already outperforms FAST and SPREAD by a significant margin, reducing system cost from €108.449 (FAST – No Battery) to €75.511. Adding battery storage further improves this result, with SMART – 1.000 kWh lowering the total cost to €58.933, and EMS Integrated – 1.000 kWh pushing it down to €50.565.

The cost advantage of EMS narrows in this high-throughput regime due to flattened price spreads and saturated arbitrage opportunities. However, EMS still offers incremental benefits through granular coordination, allowing finer exploitation of flexible charging slots and export timing. Its role thus evolves: from feasibility enabler in constrained phases to economic fine-tuner and future-proofing mechanism in high-demand settings.

Future Phase

The Future Phase reflects full-fleet electrification under a 1.700 kW import ceiling and peak throughput conditions. Among fixed strategies, SMART without storage already outperforms FAST and SPREAD, reducing system costs from €178.256 (FAST – No Battery) to €130.066. Adding storage improves this further: SMART – 1.000 kWh lowers the total to €109.936, and EMS Integrated – 1.000 kWh pushes this to €104.131 — the lowest cost across all configurations.

While all EMS-integrated strategies maintain 100 % operational success, the improvement no longer stems from feasibility recovery alone. SMART charging also performs robustly under these conditions, achieving the highest export rate of €0,1078/kWh and a strong baseline. Instead, the performance gap is driven by EMS's superior optimization of energy flows: pre-charging storage, aligning exports with peak prices, and reallocating power between overlapping sessions.

The incremental cost reductions show that battery upgrades continue to provide consistent savings, especially under EMS coordination. For example, the SMART strategy reduces costs by €10.610 when moving from 0 to 500 kWh, and by €9.520 from 500 to 1.000 kWh (Table 14). These nearly equal gains challenge the notion of diminishing returns and underscore the steady value of adding capacity. EMS integration improves upon this further, achieving the lowest total cost of €104.131 in the 1.000 kWh configuration.

As system throughput scales and overlapping sessions increase, coordinated control logic becomes critical — not just to optimize cost arbitrage, but to ensure robust and efficient operation across all time windows.

In summary, EMS integration is no longer just a tool for feasibility — it is a structural requirement for optimal system operation in high-demand scenarios. Strategic rollout should plan for EMS coordination alongside battery deployment to capture these final-stage improvements.

6.7 Discussion of Key Findings

The phased simulation study reveals how charging feasibility, cost-efficiency, and system control interact across increasingly complex operational conditions. Three key dynamics emerge: (1) the economic hierarchy of charging strategies under different grid and fleet constraints, (2) the role of battery storage in reducing marginal charging cost, and (3) the critical value of EMS coordination in maintaining feasibility and optimizing €/km performance as demand scales.

Cost per kilometre as the primary economic benchmark. While multiple indicators—total system cost, import/export value, peak shaving—were tracked, cost per kilometre emerged as the most interpretable and decision-relevant metric. This value translates system behaviour into a tangible operational expense. In the Current Phase, SMART charging combined with a 1.000 kWh battery delivered a cost of € –0,1596/km, nearly doubling the cost-effectiveness of grid-only operation (–0,0548/km). SPREAD and FAST, by contrast, remained above –0,08/km even with storage, highlighting the importance of temporal price alignment.

As electrification expands, this cost gap widens. In the Intermediate Phase, EMS coordination reduces cost per kilometre to below € 0,05/km, while SPREAD and FAST hover around € 0,09/km—even with storage. In the Final and Future phases, EMS becomes the only configuration capable of both delivering all required energy and keeping cost per kilometre near € 0,08/km. Non-integrated setups exceed € 0,13/km, reflecting increased energy cost, lost arbitrage, and local infeasibility.

Battery storage improves but cannot guarantee low-cost feasibility.

Battery integration led to clear cost reductions across all phases, particularly when deployed in tandem with EMS coordination. In unconstrained settings, batteries reliably lowered import costs and improved export arbitrage. However, in the Current Phase, where grid capacity is actively constrained at 105 kW, standalone battery systems proved insufficient to fully resolve infeasibility.

Even at 1.000 kWh, SMART-based dispatch could not avoid slack entirely — e.g., SMART with 1.000 kWh incurred 4,2% of slack and a cost of €–26.424, whereas the EMS-integrated 1.000 kWh setup completely resolved infeasibility and reached a lower cost of €–30.704. This illustrates a crucial insight: in some cases congestion cannot be solved by battery size alone — control logic is essential.

Across later phases, where import capacity is relaxed, batteries consistently contributed over €10.000 per 500 kWh in annual system savings — provided that dispatch was aligned with market signals and system constraints.

EMS coordination ensures feasibility and unlocks cost optimization. Though EMS integration greatly improves feasibility in heavily constrained scenario's, the added monetary value of EMS is most evident in high-demand phases. In the Intermediate Phase, EMS reduced cost per kilometre by over € 0,03 compared to SMART + battery, while also eliminating delivery slack entirely. By the Final and Future phases, it was the only strategy that simultaneously delivered all required energy and maintained low cost. This dual performance—cost and feasibility—is not achieved by any other configuration. Finding the optimal moment for integration is therefore dependant on the main objective, either feasibility improvement or monetary gain.

Notably, EMS coordination also improved export revenue by aligning battery discharge and grid export with price peaks. It consistently reduced peak grid import, though this was not the dominant cost driver. Rather, its greatest economic value lies in its ability to shift charging away from expensive intervals and absorb operational pressure without requiring oversizing of batteries or grid infrastructure.

Strategy selection is phase-sensitive. In early phases, battery-supported SMART charging is economically sound, with cost per kilometre already below conventional diesel benchmarks. However, as the fleet and energy throughput increase, the difference in €/km relative to the integrated strategy increases. In the Final and Future phases, SPREAD and FAST incur significantly higher cost per kilometre—often exceeding € 0,13/km. EMS, by contrast, scales efficiently: it preserves low cost, adapts to infrastructure, and absorbs complexity, reaching a cost per km of 0,92€ even without a battery system.

Having interpreted the system's performance across deployment phases, the following roadmap outlines concrete implementation actions aligned with infrastructure upgrades and electrification targets.

7 Conclusions and recommendations

This chapter reflects on the main outcomes of the simulation study and assesses their broader implications for system design, operational decision-making, and policy alignment. The discussion synthesizes technical findings with practical considerations for implementation at Bakker Warehousing, while the recommendations outline concrete next steps for scaling, integration, and future research.

7.1 Fleet Electrification Roadmap

This roadmap translates the simulation insights into a practical deployment strategy for Bakker Warehousing. It aligns technology decisions—battery sizing, charging logic, and EMS coordination—with two structural transition points: (1) the scheduled grid import upgrade in 2027, and (2) the gradual electrification of the entire heavy-duty vehicle fleet.

The phases below are defined not by simulation constraints, but by real-world implementation triggers. Each phase recommendation balances operational feasibility with cost per kilometre performance, ensuring that investments scale proportionally with system complexity.

Phase 1 (2025–2027): Low Electrification, Grid-Limited Operation

During this initial phase, depot charging is constrained by the existing 105 kW grid import limit. To preserve feasibility, electrification is limited to a small subset of vehicles selected based on route energy and power demand. SMART charging logic—relying on day-ahead price signals—is sufficient for managing depot-level charging.

To reduce cost and increase flexibility, a 500–1.000 kWh battery can be deployed. Simulation results show that this pairing reduces cost per kilometre from €–0,026 to as low as €–0,1596, while also increasing export earnings. EMS coordination is not yet economically necessary, but preparatory steps are strongly recommended. These include deploying modular charger control hardware, aligning data architecture with future EMS compatibility, and increasing the amount of metering points.

Recommendations:

- Electrify 10–15% of the fleet using filtered, low-energy-demand routes.
- Deploy 500–1.000 kWh battery for peak shaving, solar mismatch mitigation and market arbitrage.
- Use SMART charging; defer EMS implementation until Phase 2.
- Begin EMS-readiness infrastructure (control/data pathways, monitoring).

Phase 2 (2027–2030): Grid Upgrade and Intermediate Electrification

With the contracted import capacity increasing to 600 - 1.700 kW in 2027, electrification of 40–70% of the fleet becomes technically feasible. Simulation results show that heuristic strategies such as SMART + battery still incur slack (up to 1,83 %) and cost per kilometre rises above €0,08. In contrast, EMS-integrated coordination eliminates slack and brings €/km below €0,05. The economic break-even point for EMS investment is likely found in this phase, with cost savings exceeding €6.000/year and operational reliability guaranteed even during congestion periods.

Recommendations:

- Expand electrification to all filtered feasible routes with power requirements of upto 350 kW.
- Scale battery capacity to 1.000 kWh to accommodate higher overlap.
- Deploy full EMS platform to optimize charging, battery, and export schedules.
- Prioritize economic KPIs: cost per kilometre and import €/kWh.

Phase 3 (2030+): Full Fleet Electrification and Intelligent Coordination

In this final phase, the entire depot fleet is electrified, and aggregate energy throughput peaks. Seasonal demand spikes, limited charger simultaneity, and potential PV curtailment make tight coordination essential. EMS integration is no longer a cost optimization tool—it becomes the system's backbone.

Only EMS-integrated setups maintain 100% delivery and keep €/km under €0,10 across all scenarios. Heuristic strategies exhibit measurable slack and total cost differences of over €20.000 annually. Moreover, EMS unlocks future capabilities such as V2G, dynamic fleet prioritization, and participation in congestion management schemes.

Recommendations:

- Electrify 100% of all feasible routes.
- Maintain or expand battery capacity beyond 1.000 kWh, linked to EMS logic.
- Integrate advanced EMS modules for market participation and V2G readiness.
- Optimize cost per kilometre and total system cost under full electrification

7.2 Guidelines for Extended Applicability

While the electrification strategies discussed in this thesis are broadly relevant to comparable logistics operations within the Netherlands, the analysis is specifically tailored to the operational characteristics, system constraints, and strategic outlook of Bakker Warehousing. When applying these findings to other contexts, the following considerations should be taken into account:

- **Grid connection timeline:** At the time of writing, Bakker Warehousing remains on the waiting list for an increase in grid connection capacity, with the projected upgrade date at the end of 2026. However, in cases where grid limitation increase is applied for at current time the waiting period is a significantly longer period. Under such conditions, early deployment of a coordinated Energy Management System (EMS), supported by a sufficiently sized Battery Energy Storage System (BESS), becomes critical. As demonstrated in Table 17, rapidly increasing EV demand without either a grid upgrade or operational EMS infrastructure leads to a sharp decline in delivery feasibility.

- **PV generation availability:** The presence of a large on-site photovoltaic (PV) system at Bakker Warehousing enhances the effectiveness of the BESS during congested hours by allowing it to recharge using surplus solar energy. In scenarios lacking such PV capacity, the BESS becomes more reliant on grid availability and may be unable to recharge sufficiently during low-demand periods. This reduces its ability to buffer grid limitations and increases the risk of infeasibility.
- **Demand profiles based on diesel operations:** The EV charging demand profiles in this study are derived from historical diesel fleet operations. These are not optimized for electric vehicle usage and therefore present a conservative case. In deployments where EV scheduling and routing can be designed from the ground up, charging and duty cycles can be aligned more effectively with available energy, turning vehicles into part of the flexibility solution rather than the constraint. In such cases, it is recommended to first simulate the energy system without EV load, and then incrementally integrate optimized EV demand to assess feasibility and performance.

7.3 Grid Capacity Strategy

Grid import capacity is a central constraint in depot electrification planning, shaping both feasibility and cost outcomes. During the Current Phase, the contracted import limit of 105 kW tightly bounds all energy delivery, requiring deliberate under-electrification to maintain feasibility. From 2027 onward, the planned upgrade to a 1.700 kW contracted capacity (GTV) removes this immediate bottleneck, enabling expanded fleet electrification.

However, simulation results show that even in the fully electrified Future Phase, actual peak import rarely exceeds 600–1.400 kW. This suggests that immediately contracting the full 1.700 kW may lead to systematic overcapacity and unnecessary expenditure. At the current distribution tariff of €2,2233 per kW per month, each 100 kW of unused capacity represents over €2.600 annually in avoidable cost—adding up to more than €18.000 per year if the full headroom remains unused.

In this context, a more flexible capacity strategy should be considered. If the full GTV will not be utilized until the late 2020s or early 2030s, it may be economically prudent to contract only a partial increase initially—e.g. 1.400–1.500 kW—and expand further only when demand justifies it. This approach becomes particularly attractive when viewed through the lens of national grid congestion policy: full resolution of structural congestion in Friesland is not expected before 2032.

By negotiating a capacity reservation or staged extension with the DSO (Liander), Bakker Warehousing could possibly secure the right to expand when needed, while freeing short-term grid headroom for other regional demands. This improves systemic efficiency without compromising the company's long-term growth potential.

Recommendations:

- Maintain the 2027 upgrade, but consider contracting only 900 - 1400 kW initially, depending on the projected growth phases
- Use EMS-monitored peak data to determine the optimal timing for future capacity expansion.
- Collaborate with the DSO to reserve future GTV expansion rights while supporting short-term regional congestion relief.

7.4 Answering the Research Questions

To conclude the analysis, this section provides explicit answers to the three supporting sub-questions and the overarching research question formulated in Chapter 2. Each question is rephrased for clarity and aligned with the findings presented in Chapters 6 and 7.

Sub-question 1:

How can the design of energy infrastructure and EMS architectures enable a modular and scalable deployment of HDEV charging systems under evolving grid limitations and fleet expansion?

Answer: The results show that phased deployment of HDEV charging infrastructure can be made highly feasible when supported by a complex system architecture that adapts to changing grid constraints and electrification levels. In early deployment stages, feasibility can be maintained by selecting electrifiable routes based on power and energy thresholds, supported by heuristic charging strategies and moderate storage. Should the EV demand increase rapidly without a corresponding rise in grid limitation an integrated EMS can be applied to support the battery system to achieve a high delivery success rate. As the contracted import capacity and number of EVs increase, the complexity of overlapping charging windows and grid congestion calls for centralized EMS coordination. The findings confirm that EMS logic can support constrained system more effectively that stand-alone battery systems, increasing both the resilience of the system and the returns on investments.

Sub-question 2:

In what ways does the role of battery energy storage evolve throughout different deployment phases, and how can its operation be optimized to balance charging support, market participation, and grid constraint management?

Answer: Battery energy storage systems (BESS) fulfil distinct roles across the electrification trajectory. In the early phase, BESS serves as a technical buffer that supports feasibility by mitigating peak import violations and bridging temporal mismatches between PV availability and EV charging. As system flexibility increases, the battery shifts toward a cost-optimizing role, supporting arbitrage and solar mismatch mitigation under EMS control. Simulation results show that the first 500 kWh of storage often resolves most feasibility issues, while additional capacity (up to 1.000 kWh) primarily enhances economic performance. However, the full value of storage—both operational and financial—is only unlocked under EMS coordination. Without integrated control, the battery's dispatch remains suboptimal, particularly under constrained grid or market conditions.

Sub-question 3:

How does the use of retroactively generated EV demand—based on real diesel fleet operations—enhance the evaluation of charging feasibility, EMS coordination strategies, and infrastructure investment planning?

Answer: By reconstructing EV charging demand from historical diesel operations, this study incorporates route-level variability, idle window constraints, and realistic energy needs into the modelling framework. This bottom-up approach enables the simulation to detect infeasibility risks that synthetic profiles typically obscure—such as overlapping charging sessions or site-level power conflicts. It also allows for more precise filtering of electrifiable routes, which forms the basis for phase-specific deployment planning. Moreover, the use of diesel-based EV profiles supports the evaluation of EMS logic under real-world scheduling constraints, enabling a more accurate assessment of operational benefits for all modular systems. The methodology thus enhances both the technical validity and investment relevance of the simulation outcomes.

Main Research Question:

How can grid-aware and modular EV charging strategies be leveraged to support the phased deployment and operational management of depot-scale infrastructure, enabling reliable and cost-effective electrification of heavy-duty vehicle fleets under logistical and grid constraints?

Answer: The study demonstrates that modular EV charging infrastructure, when coupled with progressively integrated modular energy systems, offers a viable pathway toward full-fleet electrification under active grid constraints. In early deployment phases, filtered vehicle selection and battery-buffered SMART charging can ensure high delivery feasibility at relatively low cost. However, as electrification intensifies, EMS integration becomes essential in preventing the need for costly grid oversizing. By dynamically allocating energy across EVs, battery, and the grid, EMS coordination enhances operational control, increases system robustness, and reduces energy costs beyond what is achievable with heuristic strategies. The results show that EMS consistently outperforms fixed-profile charging approaches in both energy delivery and cost-per-kilometre metrics, particularly under high congestion. Therefore, a phased strategy combining filtered deployment, scalable storage, targeted grid upgrades, and staged EMS activation constitutes a future-proof approach to reliable and economically efficient electrification.

Final Reflection

This thesis demonstrates that the electrification of a heavy-duty vehicle fleet in a grid-constrained depot is not only technically feasible, but also economically viable. Through simulation-based scenario analysis, the study identified how battery storage, smart charging, and EMS coordination interact under varying grid and fleet configurations. The results show that early-stage limitations can cause infeasibility. However, that the support of EMS integrated systems with storage solutions can mitigate this. The combination of EMS and battery storage becomes increasingly cost effective as system complexity grows, and ins therefore also a future-proof investment, shifting it's focus from feasibility management to cost optimization.

The recommendations presented here offer a practical, phased roadmap for Bakker Warehousing to deploy a future-proof charging system aligned with operational goals, cost efficiency, and external policy constraints. As the broader energy and logistics systems evolve—through market liberalization, emission zones, or grid reinforcement—the foundations laid by this study will support scalable adaptation and long-term competitiveness.

Disclaimer on the use of AI tools

In the preparation of this thesis, *ChatGPT* by OpenAI has been employed as a supportive tool for two distinct purposes:

1. **Textual and Structural Support:** to assist in the academic rewriting of self-authored sections, language refinement, and the generation of general feedback on written content.
2. **Modelling and Programming Support:** to assist with the design, debugging, and optimization of Python-based models used throughout this thesis.

All content and code generated with the help of this tool have been critically reviewed, tested, and validated by the author to ensure correctness, contextual appropriateness, and compliance with academic standards.

The final responsibility for the scientific integrity, structure, and content of this thesis lies solely with the author.

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