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Integrating EV Fleets and Renewable Sources into Building Energy Management with an Adaptive MPC Approach

Tesi di Laurea Magistrale in
Automation and Control Engineering - Ingegneria dell'Automazione e Controllo

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Abstract

Within the realm of Energy Management Systems (EMS) a novel approach using a Model Predictive Control (MPC) solution is proposed. This approach investigates the practicality of adopting Battery Management System (BMS)-aware techniques to regulate energy flows by utilizing a non-proprietary fleet of Electric Vehicles (EVs) as an optimal method for energy storage and utilization. Instead of considering uncertainty on factors such as varying electricity costs, energy usage, and storage availability, it focuses extensively on methodologies for the efficient employment of EVs while minimizing the impact of BMS limitations. The study first examines strategies to reduce battery wear in vehicles, thereby enhancing the effectiveness of each EV's use. Additionally, it scrutinizes potential responses of the BMS to manage uncertainties concerning power constraints. A novel solution is presented for the online learning of unfamiliar vehicles.

Keywords: EMS, MPC, EVs, BMS

Abstract in lingua italiana

L'obiettivo principale di questa tesi è lo sviluppo di un Model Predictive Control (MPC) per lo scheduling di operazioni ottimali nel contesto Energy Management System (EMS). Il caso studio considerato riguarda un'azienda dotata di un impianto fotovoltaico, dove sono noti a priori i consumi dell'edificio, i costi della tariffa elettrica a disposizione e la produzione energetica. Il risparmio energetico è ottenuto tramite l'accumulo ed utilizzo ottimale di energia all'interno di veicoli elettrici di privati, presenti all'interno del parcheggio e dell'azienda. L'analisi si concentra sugli effetti che la variabilità delle caratteristiche della flotta a disposizione può avere sullo scheduling. In particolare, il modello ottimizzato prende in considerazione il degrado delle batterie dovuto all'utilizzo predeterminato e i limiti di potenza imposti dai Battery Management System (BMS) di ogni veicolo. I risultati ottenuti evidenziano l'importanza di considerare specifici fattori, sia per garantire un uso efficiente delle risorse a disposizione sia per migliorare la soluzione ottimale individuata.

Parole chiave: EMS, MPC, EVs, BMS

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Introduction

In light of recent environmental challenges and subsequent policy decisions, the realm of EMS has garnered significant interest. The global push towards decarbonization and the imperative for electrification across nations have driven industries and service sectors to seek innovative solutions for sustainable and efficient energy use. The rise in electricity demand, propelled by carbon-neutral processes and the proliferation of EVs, has opened avenues for inventive approaches that have been under exploration in various contexts for years.

This thesis aims to contribute to this field by exploring effective strategies for employing electric vehicle fleets for Vehicle-to-Building (V2B) applications, focusing on the use of non-proprietary vehicles. By examining a generic company scenario, an MPC approach is developed to optimally manage the charging and discharging activities of these vehicles. The primary goal of this work is to enhance scheduling efficiency, ensuring the vehicles are used effectively while considering usage constraints.

The technical part of this thesis is divided into three main sections, each addressing a different aspect of the V2B system integration and optimization:

- **Development and Implementation of the V2B Algorithm:** This section focuses on the creation of a V2B algorithm that incorporates comprehensive data inputs. It includes an analysis of the potential savings over a 30-day trial period, highlighting the importance of historical consumption patterns and tariff fluctuations. Furthermore, it explores the implications of electric vehicle fleet configurations on the system, addressing the challenge of fleet variability.

- **Battery Degradation and Health Assessment:** Subsequently, the thesis will delve into the degradation of electric vehicle batteries within this operational framework. An assessment of battery wear will highlight the potential risks associated with unchecked usage, emphasizing the importance of integrating battery health considerations into the optimization process. This inclusion aims to demonstrate that minimal adjustments to operational strategies can mitigate adverse effects on battery longevity without compromising efficiency.

- **Adapting to BMS Constraints:** The final section will address the constraints imposed by BMS in EVs. Focusing on the limitations related to maximum power output as it varies with the battery's State of Charge (SOC), the study will initially examine the challenges of real-time scheduling due to uncertainties in BMS-imposed restrictions. Ultimately, the introduction of a machine learning algorithm designed to dynamically learn and adapt to the BMS's power constraints promises to refine scheduling decisions, enhancing the system's overall efficiency.

This thesis is structured to progressively tackle the complexities of utilizing electric vehicle fleets in EMS, from algorithmic development and economic analysis to technological and operational considerations, aiming to offer a comprehensive solution to the challenges of energy management and vehicle fleet utilization.

1 | Impact of Industry EMS on Key Stakeholders

This section explores the spectrum of stakeholders invested in the energy management solutions proposed in this thesis, highlighting the interdisciplinary interest spanning various sectors.

1. Government Organizations: Central to driving environmental policy, government entities have established ambitious goals to mitigate climate change through significant reductions in greenhouse gas emissions. By focusing on major energy consumers such as industries, this research supports governmental efforts to meet environmental targets effectively.

2. Community and Energy Providers: The transition towards greater electrification amplifies the demand for electricity, stressing the grid and necessitating reliable energy supply solutions. The advent of electric vehicles further complicates this scenario. This research aligns with the shift towards microgrids, proposing ways to integrate decentralized energy systems for improved sustainability and resilience.

3. Industry Sector: Recent global developments have spotlighted the vulnerabilities of energy-intensive industries to fluctuating energy costs and grid instability. This thesis presents intelligent energy resource management strategies as viable solutions to these challenges, emphasizing efficiency and sustainability in industrial operations.

By bridging the gap between theoretical research and practical application, this work contributes to a broader understanding of energy management's role in sustaining environmental, economic, and social well-being across these crucial sectors.

1.1. Government Organizations

The escalation of atypical weather phenomena across the globe, ranging from severe weather patterns to extreme snowfalls and temperature variations, has led to an accelerated governmental response. Under the European Climate Law enacted on June 30, 2021, [1] the European Commission has pledged to cut greenhouse gas emissions by at least 55% from 1990 levels by 2030, paving the way for climate neutrality by 2050 [2]. From 2016 to 2021, a yearly increment of 1.3% in energy-related emissions was observed [3], with industrial energy consumption accounting for approximately 24% and industrial processes for another 5%. Below (Figure 1.1) a historical perspective on these emissions is provided, tracing the trajectory of CO2 output over time.

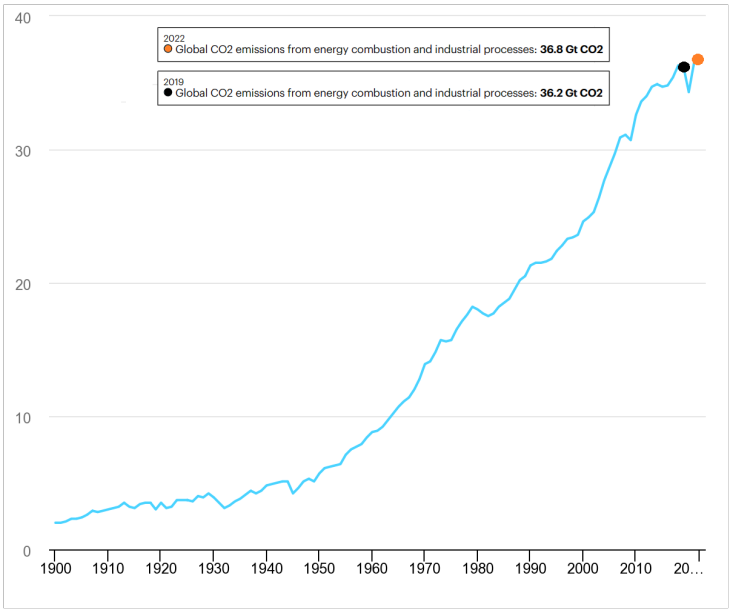


Figure 1.1: Global CO2 emissions from energy combustion and industrial processes 1900-2022 [4].

As depicted, despite an overall upward trend, the year 2022 has seen a divergence from this pattern [5]. According to recent analyses, while energy-related CO2 emissions grew by 0.9%, totaling 36.8 Gt, a concurrent reduction of 102 Mt in emissions from industrial processes was recorded. This divergence indicates progress in industrial sustainability practices and underscores the importance of continued research and development in this area. It emphasizes the crucial role the industrial sector plays in reaching environmental goals and the significant impact governmental policies can have on this pursuit.

1.2. Community and Energy Providers

The growing dependence on electricity is placing increasing demands on the electric grid. The move towards electrification and decreased fossil fuel use is critical for achieving carbon neutrality. However, it is crucial to recognize that the challenges faced by energy providers in this transition are significant and their preparedness should not be taken for granted. According to the Stated Policies Scenario (STEPS), global electricity demand is forecasted to rise by 5,900 terawatt-hours (TWh) by 2030, and even more, reaching over 7,000 TWh, under the Announced Pledges Scenario (APS) [6]. This increase is comparable to the current combined electricity consumption of the United States and the European Union. The transportation sector is anticipated to be a major contributor to this surge, with the electric car market share expected to grow from about 8% in 2021 to 32% under STEPS and close to 50% under APS by 2030 [7]. Goldman Sachs Research projects (Figure 1.2) that electric vehicle sales could rise to approximately 73 million units by 2040, a significant jump from the 2 million sold in 2020. This increase would see electric vehicles making up 61% of all car sales globally, with projections of over 80% in many developed countries.

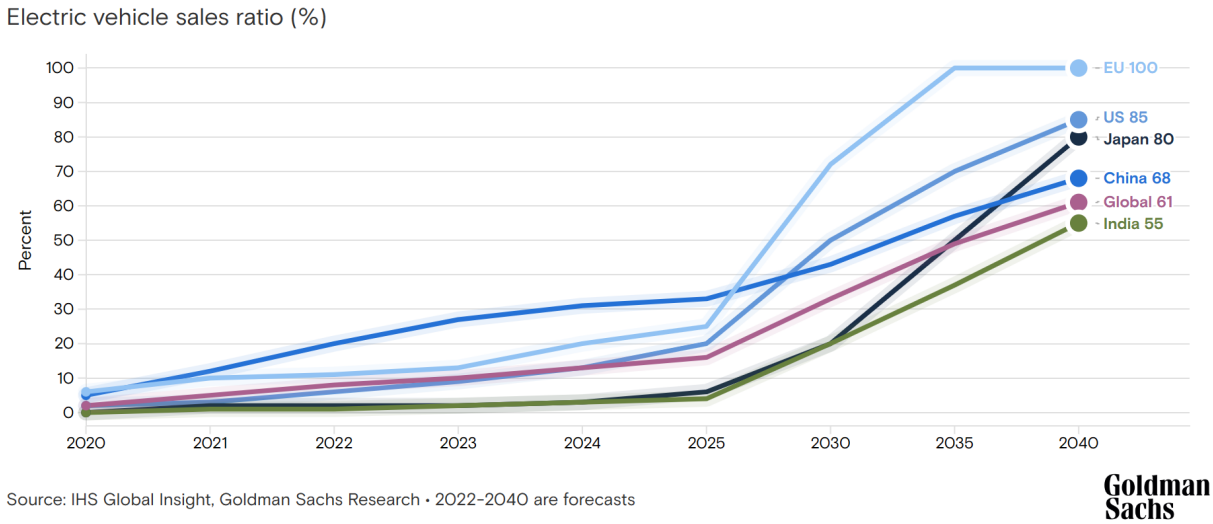


Figure 1.2: Forecasted acceleration in the shift to electric vehicles [8]

The uptick in electricity demand poses challenges for the power grid, which could impact the consistent supply of electricity. The rising popularity of electric vehicles adds to this challenge, as charging requirements further increase electricity demand. Taking into account the average daily driving distance in the USA, which is 37 miles [9], and an energy-efficient vehicle consuming 0.25 kWh per mile, the daily energy requirement per

vehicle is 9.25 kWh. This is substantial when compared to the average daily energy use of an American individual, about 28.8 kWh [10], suggesting that electric vehicles could lead to a 35% increase in daily energy consumption per driver. This issue is not necessarily a question of power plant capacity; countries with smaller power infrastructures, such as Italy, are deemed capable of meeting these demands [11]. The variability in electricity demand presents a complex challenge for providers [12, 13], as Transmission System Operators must plan for next-day delivery based on predicted demand in the Day-Ahead Electricity Market (DAM) [14]. Power generators submit bids at various prices, and the grid activates them in ascending order of cost until supply meets demand, setting the wholesale price at the last power plant's marginal cost [15].
For residential customers, several electricity tariffs are available. Fixed plans involve a consistent unit price throughout the contract term, buffered against wholesale price fluctuations. On the other hand, variable ones (Table 1.1) fluctuate with the wholesale market, encouraging energy use when prices dip, known as Time-of-Use (ToU) tariffs. ToU pricing can offer improved price signals, decrease grid losses, stimulate innovation, and bolster electrification efforts when paired with digital technologies like smart meters [16].

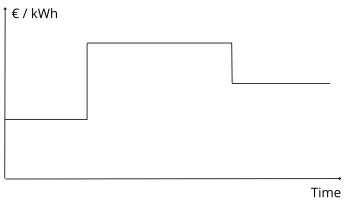
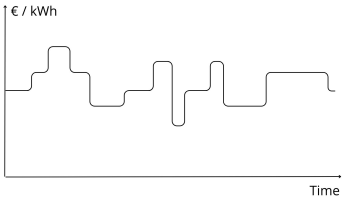
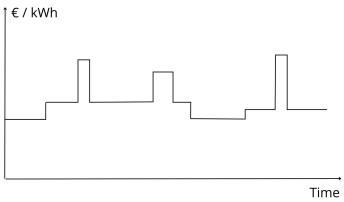
Static ToU pricing		The cost of electricity fluctuates based on the time of day, with generally lower prices during nighttime and weekends, and higher prices during daytime hours.
Real ToU pricing		The cost of electricity fluctuates following the national electricity demand, highlighting periods of increased consumption and times of notably low usage.
Critical peak pricing		Combining elements from the other two, it emphasizes both peaks and typical consumption.

Table 1.1: Primary Time-of-Use pricing options availableles.

In conclusion, the adoption of fixed-rate plans by individual consumers presents challenges for two key reasons:

1. In various instances, the scheduling flexibility of non-essential appliances, such as washing machines, dishwashers, and heating systems, allows for potential advantages with dynamic pricing.
2. Optimal utility for energy operators is realized when consumer demand aligns with off-peak periods, suggesting a positive societal impact through the use of dynamic pricing in this context.

Recognizing the increasing significance of dynamic pricing in the future, the identified challenge persists. Managing unexpected spikes in energy demand during specific daily intervals poses difficulties for operators in accurately forecasting energy needs in advance. A proposed solution involves leveraging communication protocols to facilitate continuous communication between providers and consumers through smart meters. Upon resolving this challenge, the examination of local energy control through systems like microgrids would emerge as a crucial solution for energy providers.

1.3. Industry sector

Energy conservation is a primary concern for energy-intensive industries, which include manufacturing companies and large enterprises that rely heavily on electricity for machinery operation and environment conditioning. Recent global occurrences such as the SARS-COVID-19 pandemic and the conflict in Ukraine have led to significant disruptions in energy pricing and electrical grid stability.
The pandemic has forced many heavy electricity consumers to halt or reduce their operations due to public health policies, shifting the consumption pattern towards residential use as people work from home. This shift has caused notable changes in electricity demand profiles and introduced new complexities in power system management, compounded by the unpredictability of pandemic progress and policy responses [16].

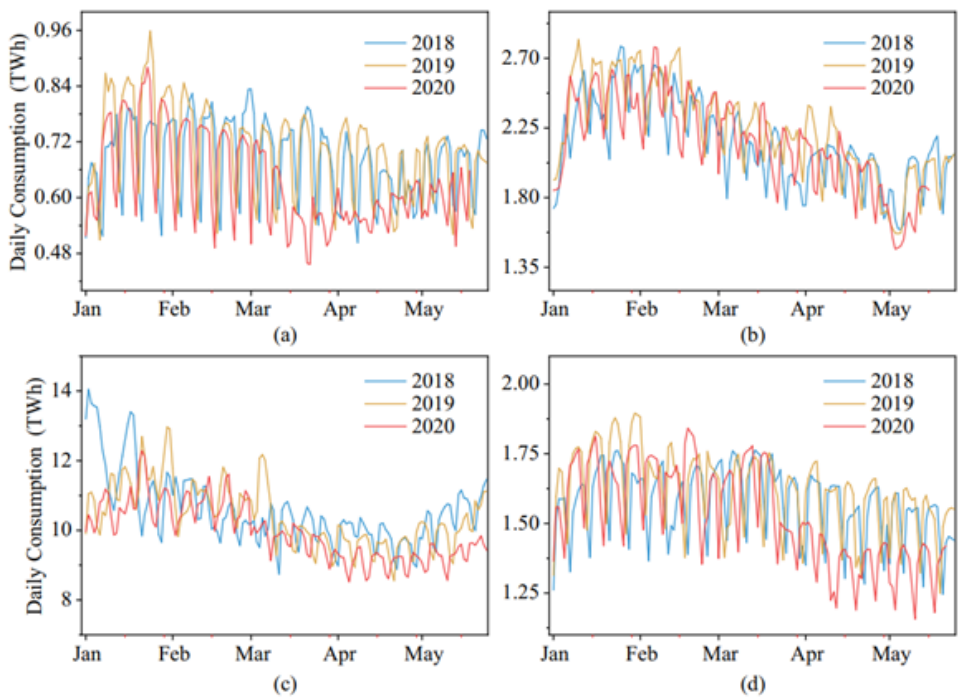


Figure 1.3: Variations in daily electricity consumption across (a) Italy, (b) Japan, (c) U.S. and (d) Brazil [17].

The industrial sector has seen a downturn in electricity usage due to production halts. In China, the construction and manufacturing industries experienced a 12% decrease in demand (Figure 1.3), while the United States anticipated a 20% reduction in 2020 [18]. In contrast, residential electricity demand has risen, with some European countries witnessing up to a 40% increase (Figure 1.3). This imbalance challenges the power system's

equilibrium, which depends on accurate load forecasting, especially in regions reliant on coal with lengthy unit commitment decisions.
The equilibrium of the power system relies on a multi-stage generation scheduling process, covering multi-day ahead planning, day-ahead scheduling, intra-day rolling dispatch, and real-time dispatch. As previously described, these procedures heavily lean on precise load forecasts, particularly in regions dominated by coal, where decisions on unit commitment must span extended periods. The sudden onset of the COVID-19 pandemic and swiftly evolving anti-epidemic policies intensify the uncertainty in load demand, heightening the complexities of load forecasting [19].

Concerning the war in Ukraine, it proved to be problematic as well. With the escalation in natural gas costs, electricity production from power plants has incurred heightened expenses, impacting various sectors. This has prompted numerous scientists and researchers to endeavor to predict the consequences of the war across diverse areas, encompassing the economy, business, ecology, and food [20, 21]. Preceding the conflict, the EU relied on Russian gas for approximately 45% of its imports and around 40% of its gas consumption (Figure 1.4).

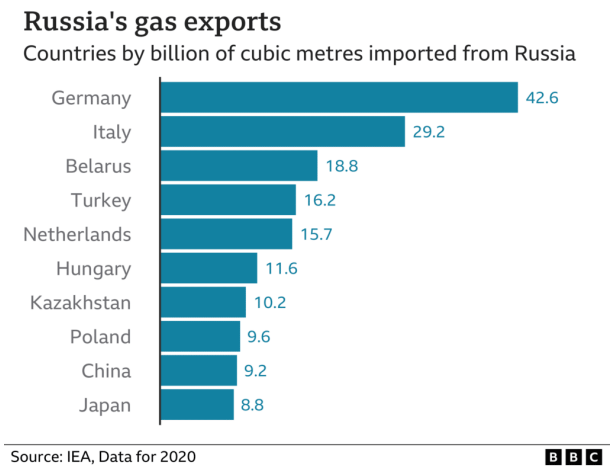


Figure 1.4: Dependence on Russian gas exports to Europe [22].

This necessitates the identification of strategies for optimizing consumption within a corporate context. Fundamentally, this involves endeavors to diminish energy consumption while maintaining the building's throughput. The underlying rationale for this approach is rooted in the potential reduction of energy expenditure through the strategic planning of consumption following energy tariffs.

2 | Approaches for Smart Energy Consumption in Industries

Before exploring the solution proposed in this document, it is essential to acknowledge a range of diverse strategies that have been employed to tackle energy management issues. These strategies vary widely in their approach, scope, and effectiveness, underscoring the complexity of optimizing energy consumption within industrial infrastructures. This section aims to provide a brief overview of these strategies, setting the stage for a deeper discussion on the necessity and uniqueness of the approach presented herein.

1. **Evaluating Internal Modification Strategies:** One prevalent approach involves the internal restructuring of energy usage processes within industrial facilities. This can include, for example, upgrading to energy-efficient machinery, implementing strict operational schedules to minimize idle power consumption, or optimizing heating, ventilation, and air conditioning (HVAC) systems for better energy use. The advantages of such strategies are immediately evident in reduced operational costs and enhanced energy efficiency. However, their limitations are equally significant, primarily due to high upfront investment costs and potential disruptions to existing production processes. This discussion elucidates the need for alternative or complementary solutions that can offer broader, more cost-effective benefits.

2. **The External Perspective:** Contrasting with the internal focus, the approach discussed in this study expands the perspective to external energy flow management. By integrating smart grid technologies, renewable energy sources, and advanced monitoring systems, this strategy aims to control both the inflow and outflow of energy to and from the industrial site. This not only addresses the immediate concerns of energy efficiency and cost but also contributes to the larger goal of sustainable energy use. The synergy between internal modifications and external energy flow management creates a holistic solution, enhancing the overall energy system's effectiveness without compromising on individual process efficiencies.

It's important to note that, in principle, both solutions can be implemented within a

structure without conflicting with each other. By referencing different components of the structure, these two techniques complement rather than impede one another. The integration and synchronization of both approaches result in the ultimate energy system, enabling individuals to extract the maximum potential from their building. A critical factor for stakeholders is the initial investment required for implementing smart energy solutions. While concerns about upfront costs are valid, the long-term benefits—ranging from substantial energy savings to improved sustainability—often outweigh these initial expenditures. This chapter concludes with a detailed cost-benefit analysis of the proposed solution, demonstrating its superiority over traditional energy management practices.

2.1. Communication Protocols For Demand Response

Investigating for efficient energy use within industrial settings, the role of advanced communication protocols becomes indispensable. These protocols form the backbone of effective demand-side management (DSM) solutions, facilitating a dynamic and responsive approach to energy consumption. Engaging in the Day-Ahead Market (DAM) allows industrial energy consumers to anticipate energy prices, adjusting their consumption in response to hourly fluctuations [23]. This anticipation is made possible through smart meter infrastructure, yet the lack of standardized Demand Response (DR) programs across different regions poses a challenge to broad implementation. Customized to meet local structural and regulatory demands, these programs require significant integration efforts, hindering widespread customer participation.

The diversity in DR programs, while adaptive, necessitates an overarching framework to reduce complexity and foster wider adoption. The implementation of these systems traditionally involves incorporating new software or control mechanisms into the existing grid infrastructure—a process that is not only time-consuming but also meets resistance due to the need for extensive testing and community acceptance [24]. Thus, the call for standardized templates for DR program models is clear. Such templates would streamline the adoption process, making it more accessible for customers and encouraging broader engagement by reducing the technical and administrative barriers currently faced.

Figure 2.1: OpenADR Logo. Trademark owned by OpenADR Alliance. Used under fair use for academic purposes [25].

Enter Open Automated Demand Response (OpenADR Figure 2.1), a beacon of innovation in the realm of DR protocols. Known for its open-standard and non-proprietary nature, OpenADR facilitates seamless communication between demand response services and energy consumers, ranging from individual buildings to comprehensive systems like microgrids. This protocol not only simplifies the initiation of demand-side management programs but also ensures the effective management of energy resources, potentially averting shortages.

OpenADR operates through a structured framework (Figure 2.2) where communication occurs primarily between two entities: the Virtual Top Node (VTN) and the Virtual End

Node (VEN). The VTN serves as a centralized controller, managing the VENs—which represent the connected resources—through messages that inform and motivate without exerting direct control.

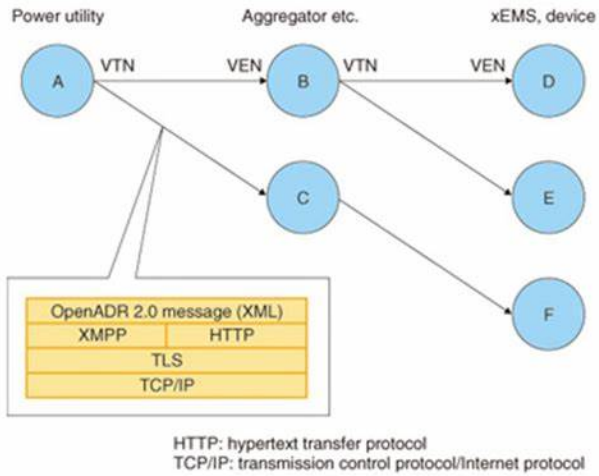


Figure 2.2: OpenADR framework [26].

Key services within OpenADR include:

- **Event Service (EiEvent):** This crucial service communicates detailed energy-related messages, such as energy prices and demand response event details, allowing participants to plan and adjust their energy consumption efficiently.
- **Report Service (EiReport):** It enables feedback from client systems, providing valuable data on real-time consumption, resource availability, and system performance back to the VTN.
- **Opt Service (EiOpt):** Through this service, VENs inform the VTN of their availability or resource commitment to an event, enhancing the planning and execution of DR strategies.
- **Registration Service (EiRegisterParty):** This initial step ensures a smooth information exchange between VTN and VEN, establishing a foundation for interoperable communication.
- **Poll Service (OadrPoll):** A vital service for simpler devices, enabling them to stay updated with the latest information without supporting extensive messaging capabilities.

The communication protocol can operate over various connections, including existing

broadband Internet connections, cloud-based control systems, or dedicated connections like cellular modems. The main transport mechanism is HTTP, where VENs pull information from VTNs, constituting a REST implementation.
By standardizing communication protocols like OpenADR, the energy sector can significantly enhance the effectiveness and scalability of demand response programs.

2.2. Enhancing Energy Efficiency through ISO 50001

Establishing that issues related to the instability of the load on the electrical grid can be resolved using innovative communication technologies, we can assume that energy tariffs are known with good precision by individual consumers. What remains is to explore the possible opportunities for energy control that must be based on these prices.
One of the forefront innovations in today's energy landscape is the development of microgrids. These decentralized energy systems, capable of generating, managing, and distributing energy across various locales, present a novel solution to harmonize energy demand with supply on a local scale. Private individuals and industries can set up similar systems with solar panels, energy storage, and communication with the grid. While these last systems may not handle the energy exchange between buildings, they can impact the issue of matching energy demand with supply from a local point of view.

ISO 50001 [27] emerges as a cornerstone in this context, offering a systematic framework for organizations, including those operating microgrids, to enhance their energy efficiency. Originating from the European norm EN 16001, ISO 50001's establishment in 2012 marked a significant step towards global energy sustainability. This standard delineates the criteria for an EMS, catering to all types of organizations eager to reduce their energy consumption, minimize greenhouse gas emissions, and achieve economic savings. By focusing on strategic energy planning, ISO 50001 encompasses the management of diverse energy sources, ranging from electricity and gas to hot water and oil products.
This standard provides a framework for managing energy performance and optimizing energy costs, supporting organizations in reducing their environmental impact. Each company is unique, making it challenging to have a one-size-fits-all set of requirements. That's why the application of the standard should be tailored to the specifics of each organization. Certification can be obtained if all requirements are met. It is based on the PDCA (Plan-Do-Check-Act) cycle, a framework for continuous improvement (Figure 2.3).

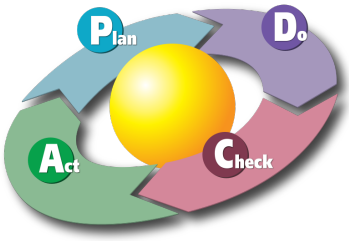


Figure 2.3: Plan Do Check Act cycle [28].

Plan

The first step in establishing an EMS is to recognize the external factors that could affect its performance. This includes understanding how climate conditions, legal requirements, and the specifics of energy suppliers might influence the reliability of services and set potential limits on energy use. These factors play a critical role in either enhancing or challenging the effectiveness of the EMS.
It is also crucial to define the roles and responsibilities within the organization to support the EMS. The primary responsibility falls on the top manager, who ensures the EMS's goals and scope are clearly defined and upheld. This individual is tasked with:

- Implementing an energy policy aimed at continuous improvement in energy performance.
- Integrating the EMS into existing business processes.
- Allocating the necessary resources, including funding, staff, and equipment, for the EMS's operation.
- Monitoring the system to confirm that it meets its targets.

An energy management team complements the top manager's efforts by focusing on the planning activities that drive better energy performance. This team, representing various organizational sectors impacting energy use, reports to the top manager on energy performance issues and outcomes. They also ensure that team members are either skilled in energy management or receive the necessary training. The energy management team is also responsible for carrying out an energy review, which is a comprehensive process that includes:
The team is tasked with developing and conducting an energy review, which involves several key steps:

1. **Analysis of Energy Usage:**
    - Conduct an in-depth analysis to identify all forms of energy used, such as electricity, natural gas, and water.
    - Assess both historical and current energy consumption patterns, aiming for an understanding that covers significant timescales to factor in seasonal and periodic changes.
    - Standardize measurements (e.g., using tonnes of oil equivalent) for consistency, although ISO 50001 does not mandate a specific unit.

2. **Identification of Significant Energy Uses:**
    - Determine the key areas of energy use within the organization to prioritize efforts and resource allocation effectively. These areas are characterized by their substantial impact on total energy consumption or significant potential for performance improvement.
3. **Identification of Opportunities for Improvement:**
    - Pinpoint potential enhancements in energy performance, including equipment upgrades, procedural changes, or the utilization of waste energy.
    - Evaluate these opportunities through technology monitoring, expert consultations, and benchmarking, prioritizing based on factors like energy savings, investment returns, and complexity.

The culmination of this review is an estimation of future energy consumption and usage, taking into account the planned improvements.

Do

A baseline serves as a critical reference point for measuring the organization's performance improvement over time. It consists of the recorded energy consumption levels over a predetermined period, enabling the organization to track progress and evaluate the effectiveness of implemented measures.
The organization must systematically collect, measure, monitor, and analyze key operational data that significantly impacts energy performance. This includes managing processes with high energy demand through strategic planning, implementation, and control. Operational controls might involve documented procedures or guidelines for managing systems and equipment with substantial energy use. Examples include implementing energy-saving devices like valve flow controls and automated switches, which help mitigate energy performance fluctuations due to human factors. Maintenance, expertise, and clear communication with employees are also vital for enhancing energy efficiency.

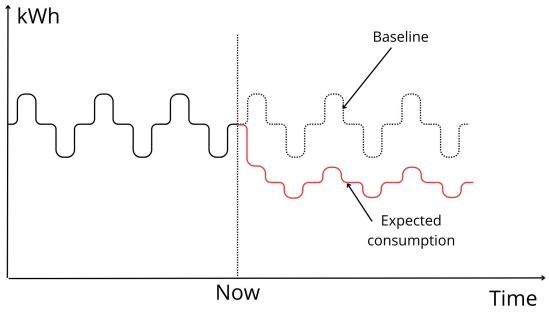


Figure 2.4: Baseline vs expected consumption.

The focus extends to optimizing buildings and equipment for energy conservation, balancing cost considerations against the effectiveness of energy-efficient technologies. Strategic changes—such as modifying product formulations to reduce energy consumption or adopting innovations that utilize waste energy—can significantly impact. The integration of energy generators, smart meters, and automated systems plays a crucial role in monitoring and improving energy performance. Moreover, programming equipment for optimal energy efficiency, especially during peak usage, and aligning operational processes with their intended functions contribute to substantial energy savings.

Check

The organization must decide what to monitor, the monitoring frequency, and how to evaluate the success of energy management measures against set objectives. Internal audits are critical for assessing high-consumption areas, evaluating the effectiveness of recent changes, and ensuring compliance with the EMS requirements. Identifying qualified auditors, setting a regular inspection schedule, and focusing on improvement opportunities rather than just non-conformities are essential steps in this process. ISO 19011 provides valuable guidelines for conducting these inspections.

Act

Any detected non-compliance, whether identified by an inspector or reported by an external customer, requires prompt correction. This involves fixing technological faults and determining systemic corrective actions to prevent recurrence. The organization must demonstrate ongoing improvement in its energy management practices, acknowledging that continuous, uninterrupted enhancement is not feasible but striving for consistent progress over time.

In practice, the primary motivation for companies to implement an EMS is to enhance their competitiveness, with the secondary goal of reducing energy consumption and related costs. Notably, by 2016, Italy had emerged as the world's third-highest country in terms of EMS certifications [29], illustrating a significant commitment to energy efficiency. During the initial obligation period, which began in December 2015, particularly within the plastic sector, the Italian National Agency for New Technologies, Energy and Sustainable Economic Development (ENEA) observed a marked preference for ISO 50001 and monitoring systems among the proposed interventions, representing 15% of 1051 initiatives. The attractiveness of ISO 50001 largely stems from its relatively short payback period of less than two years, a feature also reflected in energy audits within the ceramic sector that reported an average payback of less than 1.5 years. Further evidence from the 2016 FIRE-CEI-CTI survey supports this, revealing that 70% of participants noted a payback time of under three years for their ISO 50001 EMSs, with an 85% success rate in achieving return on investment expectations [30].

Subsequent research efforts [31, 32] have focused on proposing bespoke solutions aimed at minimizing industrial process waste and boosting operational efficiency. One significant study highlights the advantage of using both smart and traditional Building Energy Management Systems (BEMS) [33]. Conventional BEMS typically rely on pre-set logic or simple control algorithms to manage heating and cooling based on fixed schedules or set points, often overlooking real-time changes in occupancy, weather conditions, or energy pricing. In contrast, smart BEMS employ sophisticated optimization algorithms and data analytics to dynamically adjust building operations, taking into account real-time data such as occupancy schedules, weather patterns, energy prices, and historical energy usage. This approach not only results in substantial energy savings but also significantly reduces CO2 emissions.

The impact of implementing smart BEMS was demonstrated in two scenarios: one involving a commercial office building predominantly heated by natural gas and another focusing on a residential scenario with electricity as the primary energy source. Despite the lower consumption profiles typical of these settings compared to industrial environments, the office building scenario experienced a significant 29.6% reduction in CO2 emissions and a 29.9% decrease in space-heating demand. Similarly, the residential scenario saw a 28.2% drop in CO2 emissions and a 28.6% reduction in space-heating demand, showcasing the effectiveness of smart BEMS in enhancing energy efficiency across diverse settings.

A study on these applications [34] underscores a burgeoning interest in optimizing energy consumption within industrial sectors, pointing towards a significant contemporary focus. This interest spans various domains, notably within manufacturing systems, assembly lines, and the development of energy conservation policies and strategies. It also

encompasses the integration of renewable energy sources into manufacturing systems. Researchers have delved into diverse methodologies, from greedy randomized multi-objective adaptive search metaheuristics for scheduling tasks on individual machines [35, 36] to employing decomposition-based heuristic methods and epsilon-constraint methods that consider energy tariffs while prioritizing energy-intensive machines for optimization [37, 38]. The coordination of machinery—whether in series or parallel configurations, and across various types—features prominently, leveraging sophisticated techniques for enhanced synchronization.

In sum, there's been considerable exploration into methods that can directly modify industrial operations to cut down on energy costs. Yet, this area presents several challenges:

- Customization is key, as each company's context varies significantly. This necessitates forming specialized teams, which entails additional expenses.
- Aligning with fluctuating energy price tariffs to optimize machine operation schedules while aiming to minimize costs can jeopardize meeting product delivery schedules due to the constraints on operation times. Production throughput emerges as a paramount concern, as highlighted in these analyses, with the integration of machines and material handling equipment (MHE) being crucial for maintaining throughput [39, 40].
- The hesitancy towards investments with slow returns is palpable among companies, discouraging them from adopting new technologies or machinery that could potentially improve energy efficiency but at a significant upfront cost.

Accredia's report sheds light on the perception of ISO certifications within industries, revealing that while 74% of surveyed entities recognize the importance of these certifications for their business image, only a mere 10% consider them from the perspective of energy cost reduction [41]. This indicates a recognition of the potential benefits of adhering to energy standards in enhancing efficiency; however, a readiness to undertake substantial modifications is lacking. For many, the prospect of adjusting production processes, equipment, and algorithms presents an unfeasibly high risk and set of conditions, deterring significant shifts towards energy optimization.

2.3. Energy storage solutions

The strategic management of energy storage solutions has become a focal point for both external entities concerned with CO2 emissions and electricity demand, and end-users aiming to reduce their electricity costs. Despite the potential benefits, a common hurdle for end-users is the reluctance to make upfront investments due to the uncertainty surrounding the return on investment. Viewing the energy system from an external perspective offers a simplified approach by treating the system as a Black-Box, focusing on inbound and outbound energy flows without delving into the intricacies of each process within the system.
The core of this strategy lies in the adoption of electricity storage systems, specifically rechargeable batteries, to capitalize on the optimal timing for energy procurement from the grid and its subsequent use. "Optimal" in this context refers to purchasing energy at lower prices during off-peak hours and utilizing it during peak demand periods, thus ensuring a more efficient energy distribution and management within the facility.

2.3.1. Energy Storage Solutions for Renewable systems

Energy storage becomes particularly crucial for buildings with access to renewable energy sources like photovoltaic systems or wind turbines, which face the challenge of inconsistent energy production throughout the day. The introduction of an energy storage solution mitigates this issue by storing excess energy produced during peak generation times for later use, thus overcoming the limitations posed by the variability of weather conditions. However, the decision to install energy generation and storage systems is often made by individual entities based on their specific needs, leading to two potential outcomes based on daily weather conditions:

- **Undersized plant:** All the generated energy is utilized by the building, making the addition of a storage system redundant. The focus shifts towards managing reduced consumption.
- **Oversized plant:** Surplus energy can be stored for future use, optimizing energy consumption and cost-efficiency.

Recent studies have explored the distribution and optimization of on-site generated energy. For instance, real-time control strategies have been employed to manage the energy usage of machine tool components with flexibility in response to renewable energy availability [42, 43]. Such approaches have demonstrated economic benefits in manufacturing systems powered by renewable sources. Additionally, the optimization of production schedules in

facilities with an on-site wind power supply has been investigated, employing stochastic optimization to balance energy costs and production efficiency [44]. This evolving landscape of energy management underscores the significance of integrating storage solutions and renewable energy sources into the broader energy system, presenting opportunities for enhanced efficiency and sustainability in industrial and residential settings.

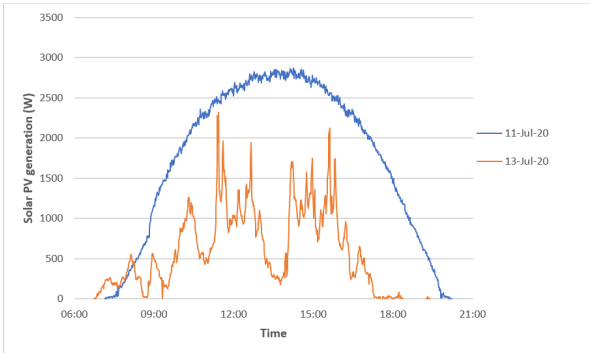


Figure 2.5: Traditional solar PV generation vs household consumption [45].

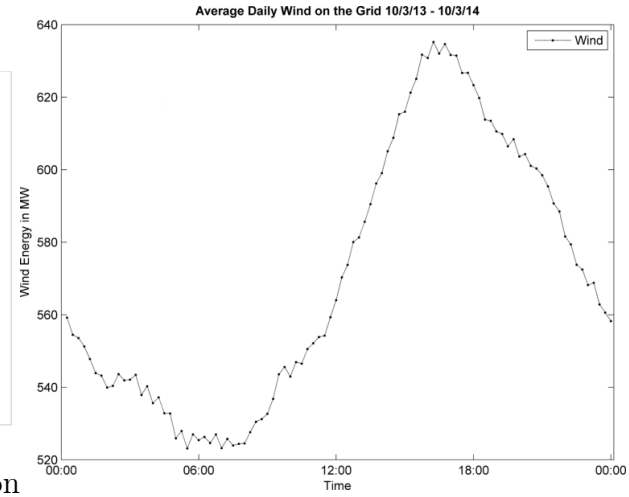


Figure 2.6: Wind energy generation in Irelands for a year [46].

The focus of primary research in the field of energy management often centers on the optimal use of surplus energy, with many studies exploring the integration of energy tariffs to maximize savings and efficiency [41, 47, 48]. For instance, the use of wind turbines (Figure 2.6) and photovoltaic units (Figure 2.5) has been proposed to assist facilities in participating in interruptible and curtailable demand response programs, using stochastic programming to determine the ideal capacity for renewable sources to maximize utility savings annually [49]. Furthermore, analytical models and dynamic control schemes have been developed to create demand-responsive production schedules and reduce power demand in manufacturing systems, demonstrating the potential of aligning production processes with energy tariffs [50, 51]. In addition, data-driven approaches and neural networks have been applied to optimize production schedules in response to real-time pricing, showcasing the advantages of intelligent manufacturing systems under demand response scenarios [48, 52].

2.3.2. Optimizing Energy Costs through Smart Consumption

Adjusting energy consumption to coincide with energy tariffs offers significant benefits, particularly in cost savings on electricity bills. The strategic use of batteries allows for

energy to be purchased during low-cost periods and consumed when grid prices are unfavorable, optimizing the overall energy expenditure [53]. Despite the clear advantages of implementing battery storage systems, the adoption rate among businesses remains low, primarily due to the high initial investment costs associated with such systems. While rechargeable batteries can endure numerous charge and discharge cycles, making them a long-term solution, the cost implications, especially for systems requiring significant storage capacity, remain a barrier.

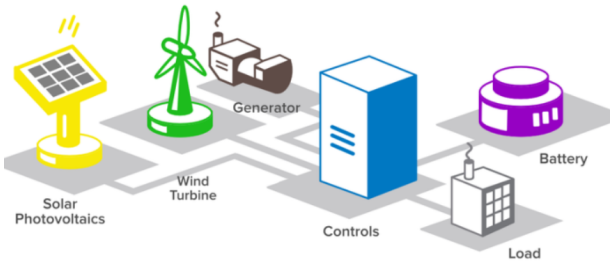


Figure 2.7: Components of a building energy management system [54].

The literature also highlights the cost of Battery Energy Storage Systems (BESS) (Figure 2.7) as a crucial factor affecting their deployment. Oversizing BESS not only increases investment costs but may also introduce technical challenges to the grid infrastructure [55]. Research efforts have thus been directed towards identifying cost-reduction strategies for BESS, aiming to make them more economically viable for self-consumption and ancillary services [56–60]. The costs related to BESS are influenced by a variety of factors, including technology choice, application specificity, geographic location, initial investment, and ongoing maintenance [55]. Moreover, considerations such as BESS degradation, power losses, and State of Charge (SOC) are critical to understanding and mitigating the costs associated with BESS deployment [61]. Efficiently integrating BESS into energy management systems requires a deep understanding of these various cost-influencing factors and optimizing them within modeling frameworks to minimize both investment and operational expenses.

3 | Electric vehicle battery

In exploring alternatives to traditional stationary battery storage, electric vehicles (EVs) present a compelling solution due to their substantial onboard battery capacity. This capacity can be harnessed for energy storage when the vehicle is parked and connected to a charging station. By employing scheduling algorithms, it's possible to determine the optimal times for charging and discharging the EV's battery during periods of inactivity. Nonetheless, this innovative approach introduces several challenges that must be addressed:

- **Variable Owner Schedule:** The unpredictability of a vehicle owner's return complicates the scheduling of charging and discharging cycles. Even in seemingly straightforward scenarios such as parking meters, the disconnection of the vehicle from the charger might not coincide with the end of the allocated time slot. To mitigate the impact of such unpredictability, it becomes crucial to incorporate usage constraints to bolster the system's resilience against unexpected events.

- **Charging Limitations:** The scenario where a vehicle needs to be left charging introduces additional complexities, particularly concerning the charging rate. If the vehicle owner returns sooner than anticipated and finds the vehicle not fully charged, it could pose significant inconvenience. While high-speed superchargers could potentially alleviate this issue, their effectiveness is contingent upon the vehicle's initial state of charge and may not be feasible with lower-power charging solutions.

- **Battery Management System (BMS) Constraints:** The operation of an EV's battery is governed by its Battery Management System (BMS), which varies significantly across different makes and models, and is influenced by the battery's current state. The BMS plays a pivotal role in ensuring the battery's longevity and safety by preventing misuse. Consequently, any external control over the vehicle's charging and discharging must be carefully calibrated to align with the BMS's parameters, which could limit the flexibility of such energy storage solutions.

Given these considerations, the following chapter will delve into the current landscape

of EV-based energy storage applications, examining their implementation across various settings. This exploration will include an analysis of BEMS to identify existing challenges and limitations within this innovative energy conservation strategy. Building on this foundation, the thesis will propose a novel approach designed to address these identified gaps, offering a fresh perspective on leveraging electric vehicles for energy storage and management.

3.1. EV implementations in EMS

The transformative potential of electric vehicles (EVs) within the transportation sector, a notable contributor to energy consumption and air pollution, has garnered significant attention in recent scholarly work [62]. Transitioning from traditional combustion engines to EVs emerges as a strategic approach to curtail greenhouse gas emissions, aligning with broader environmental sustainability goals [63–65]. EVs distinguish themselves through electric propulsion systems and energy storage capabilities, facilitated by recharging through grid electricity, brake energy recuperation, and renewable sources like photovoltaic and wind power, alongside dedicated recharging stations [66]. Presently, EVs in the market span across three main categories (Figure 3.1): Battery Electric Vehicles (BEV), Plug-in Hybrid Electric Vehicles (PHEV), and Hybrid Electric Vehicles (HEV), each with distinct operational characteristics [67].

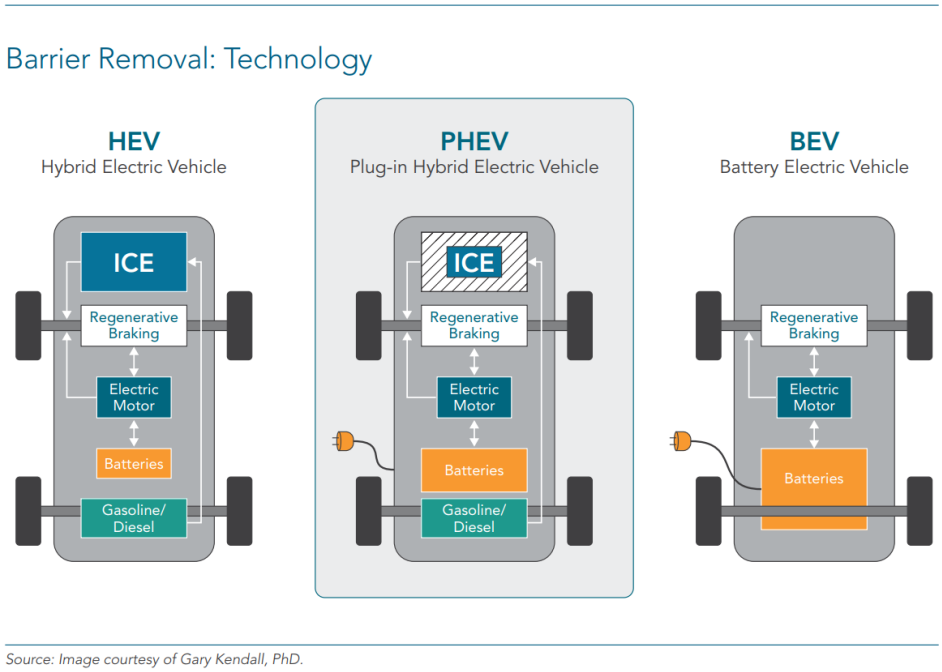


Figure 3.1: Comparison of Hybrid, Plug-in Hybrid, and Battery Electric Vehicle Technologies [68].

Explorations into leveraging EV batteries for energy storage have opened up novel avenues in energy management, particularly through vehicle-to-grid (V2G), vehicle-to-building (V2B), and vehicle-to-vehicle (V2V) applications. V2G technology, for instance, allows EV batteries to provide ancillary grid services by managing charging and discharging

activities in alignment with peak grid demands. This approach is increasingly relevant, with projections indicating a surge in EV energy demand to 1.1 PWh by 2030 [8]. V2B applications view the EV as a mobile energy storage unit, facilitating energy distribution within buildings throughout the day. Meanwhile, V2V focuses on the bidirectional energy transfer among vehicles, a concept gaining traction with the anticipated increase in EV ownership. Notably, given that vehicles are parked and idle for the majority of the day, their potential utility as mobile energy storage assets presents a promising opportunity for energy optimization [69].

3.1.1. Control Strategies for Bidirectional EV Charging

Several studies delve into the specifics of EV charging control, with research addressing the challenges of three-phase independent control and proposing strategies for bidirectional DC grid-connected modules within a V2G framework [70]. These strategies (Figure 3.2) involve sophisticated control mechanisms, including cross-DC dual closed-loop control for charging and discharging, underscoring the complexity and potential areas of investigation in charging infrastructure technology.

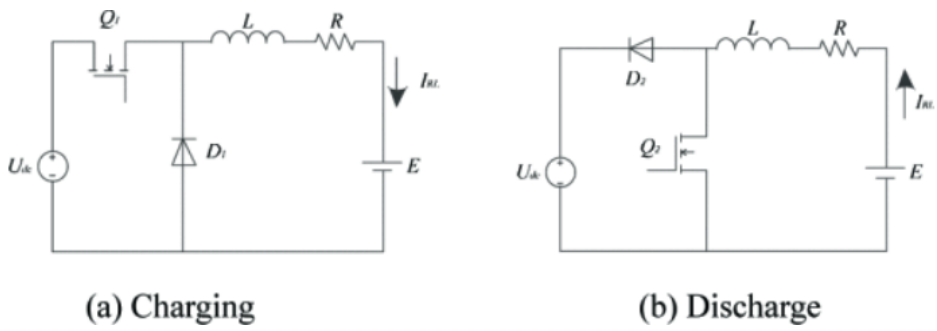


Figure 3.2: Equivalent circuit diagram of bidirectional buck-boost topology during charging and discharging [70]

On the scheduling front, recent advancements include the development of dynamic rolling prediction methods utilizing deep long short-term memory (LSTM) algorithms for accurate V2G capacity forecasting [71]. This enhances the decision-making process for V2G scheduling, optimizing the integration of EVs with grid operations. Moreover, algorithms for coordinating EVs and distributed energy resources in a V2G context aim to adjust charging and discharging activities to align with grid demand fluctuations, showcasing the capacity of V2G technology to stabilize grid operations and promote economic and environmental benefits [72–74]. Furthermore, the introduction of bi-directional smart

charging controllers emphasizes the importance of maintaining battery health, ensuring protection against potential risks such as overload and overvoltage [75].

3.1.2. Innovations in Vehicle-to-Everything Energy Management

The exploration of Vehicle-to-Vehicle (V2V) energy sharing has introduced innovative frameworks and strategies for managing electric vehicle (EV) energy transactions. A notable study by Shurrab et al. [76] presents an energy management framework for V2V interactions, focusing on intelligent energy allocation. This framework integrates considerations for energy trading prices, EV-specific parameters, and key concerns such as individual rationality, user privacy, and security. Its primary objective is to deliver cost-efficient V2V energy solutions, aiming to enhance user satisfaction, social welfare, and meet energy demands efficiently. Koufakis et al. [77] explore algorithms to optimize EV charging schedules by leveraging real-time data, addressing uncertainties in renewable energy production, and employing virtual demand concepts to influence present and future EV charging scenarios (Figure 3.3). Their findings highlight the potential of these strategies to minimize charging costs and boost the integration of renewable energy sources.

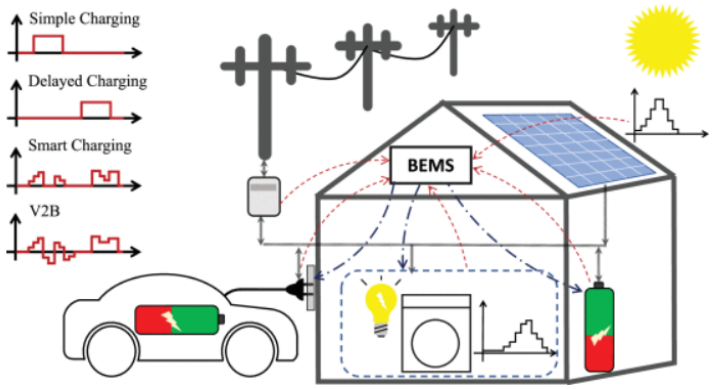


Figure 3.3: Smart building microgrid with V2B, PV generation and BESS [78]

In the context of Vehicle-to-Building (V2B), several studies have ventured into temporal optimization problems using linear programming to identify the most favorable charging and discharging intervals for EVs equipped with V2B and V2G capabilities [79–84]. These studies take into account a range of decision variables, including EV charging/discharging rates, hourly energy prices, and purchases, aiming for optimized energy management within microgrid environments. [79] underscores the importance of renewable energy sources, advocating for stateflow-based energy management approaches and emphasizing the pivotal role of EVs in stabilizing power supply systems. Tidjani et al. [80] and

Dagdougui et al. [81] propose solutions to moderate building peak loads and minimize economic regulation costs of smart buildings by harmonizing the operational capacities of EVs with other energy-demanding assets.
Moreover, considerations around battery degradation have been integrated into the optimization framework by some researchers, revealing that despite the associated costs, V2B applications can yield substantial net profits, especially when EVs are parked for extended periods [83–86]. Alternative perspectives, such as those presented by Leippi et al. [87] and studies focusing on multi-objective scheduling models [88], aim to balance cost savings against battery wear, using Pareto analysis to navigate the trade-offs.
Overall, the utilization of EVs in a Vehicle-to-Everything (V2X) (Figure 3.4) context offers a spectrum of benefits across various services, including reactive power compensation, voltage regulation, frequency control, and energy arbitrage. These applications not only contribute positively to grid stability and efficiency but also offer advantages to vehicle owners and the broader stakeholder community [89], showcasing the multifaceted value of EV integration into energy management systems.

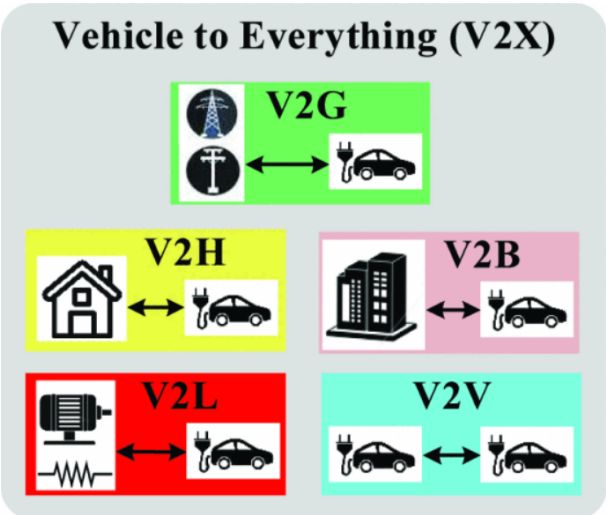


Figure 3.4: V2X applications: vehicle to vehicle (V2V), vehicle to home (V2H), vehicle to building (V2B), vehicle to load (V2L), and vehicle to grid (V2G) [89].

Summarizing all the benefits delineated in the assorted research studies under scrutiny, this document's proposed system aims to amalgamate diverse applications of electric vehicles to optimize advantages. These encompass:

- **Cost Savings and Grid Support:** By capitalizing on the Vehicle-to-Grid (V2G) capabilities, the system promotes efficient energy acquisition during periods of lower costs. It aims to refine EV charging schedules, leverage renewable energy sources

more effectively, and explore the potential for bidirectional energy transactions. This approach not only facilitates cost savings for EV owners but also contributes to grid stabilization and efficiency.

- **Battery Availability:** Central to the system is the strategic coordination of EV presence within parking spaces to maximize battery utilization. Vehicle-to-Vehicle (V2V) energy sharing becomes a crucial component, allowing for the redistribution of stored energy among vehicles without necessitating the sale of excess power back to the grid or risking battery depletion. This strategy ensures that EV owners can return to a fully charged vehicle, possibly by receiving energy from others, optimizing convenience and efficiency.
- **Optimized Energy Utilization:** The system employs advanced algorithms and methodologies to fine-tune the use of energy stored in EV batteries. By incorporating strategies from Vehicle-to-Building (V2B) applications, it determines the most advantageous moments to draw energy from the grid versus utilizing the stored reserves, ensuring optimal energy use and reducing dependency on external power sources.
- **Maximizing Electric Vehicle Potential:** Acknowledging the reality that EVs spend a significant portion of their time idle, the proposed system seeks to unlock this untapped potential. A critical aspect of this endeavor is addressing the feasibility and desirability of allowing external access to the vehicle's battery for energy management purposes. This includes careful consideration of issues related to battery wear, the provision of adequate compensation for EV owners who participate, and ensuring the overall convenience and attractiveness of the service.

By amalgamating these approaches, the proposed system aims to harness the full potential of electric vehicles not just as modes of transportation but as integral components of a smarter, more sustainable energy infrastructure.

3.2. BMS challenges

The exploration of energy management applications has seen a wide array of innovative solutions tailored to diverse contexts, each aiming to optimize outcomes through specialized techniques. Amidst these developments, the focus has significantly shifted towards devising complex algorithms designed to yield superior energy management results. Despite this progress, a critical aspect often overlooked in research involves the role of the Battery Management System (BMS) associated with electric vehicle (EV) batteries. The BMS serves a fundamental purpose in protecting the battery from misuse, ensuring its longevity and safety. This oversight in external assumptions about battery operations can lead to simulations that starkly contrast with real-world outcomes. The authority of the BMS to restrict or modify operations means that any external intervention without its consent could potentially misalign with actual battery behavior.
Addressing this gap requires a nuanced understanding of battery degradation models and the specific logic embedded within the BMS, which varies from one vehicle to another. This variability underscores the necessity of incorporating detailed knowledge of charging and discharging protocols into energy management planning to align closely with the actual capabilities and limitations dictated by the BMS.

3.2.1. Physical Limitations of Battery Technologies

It's essential to recognize the diversity of battery technologies employed in EVs, each with distinct characteristics that affect their suitability and performance (Table 3.1):

- **NiCad**: Known for its high life cycle, low internal resistance, and ability to sustain high load currents, NiCad batteries are prevalent in power tools, two-way radios, and biomedical equipment. Their resilience and reliability make them a viable option for demanding applications.
- **SLA**: SLA batteries offer a cost-effective solution for situations where energy density is not a primary concern. Their affordability and reliability find relevance in a range of applications, despite the compromises in volume and weight efficiency.
- **Lithium**: Lithium-based batteries, despite being the most costly option among the common battery types, stand out for their high energy density and cell voltage. These characteristics render them particularly suitable for portable electronic devices and EVs, where minimizing size and weight is crucial.

	NiCad	NiMH	SLA	Lithium
Technology Age (since): this reflects the maturity of the technology.	1950	1990	1970	1991
Cycle Life: denotes the total number of complete charge and discharge cycles that a rechargeable battery can endure before experiencing a reduction of 20% of total capacity.	1500	500	200 - 300	500 - 1000
Energy Density (Wh/kg): indicates the amount of energy relative to the battery's weight.	40 - 60	60 - 80	30	165
Internal Resistance (ohm): higher resistance indicates greater internal losses (lower efficiency).	100 - 300	200 - 800	<100	300 - 500
Load Current (A): load current capabilities determined by chemistry and manufacturing processes.	>2C	0.5-1C	0.2C	2C
Cell Voltage (V): voltage of each individual cell in the battery pack	1.2	1.2	2	3.6
Operating Temperature (°C)	-40 to +60	-20 to +60	-20 to +60	-20 to +60
Cost ($/g)	50	70	25	100

Table 3.1: Battery technology comparison

In the landscape of electric vehicles (EVs), the trajectory of battery technology significantly influences their development and market penetration. Nickel-Cadmium (NiCad) batteries, once prevalent for their durability and rechargeability, have fallen out of favor due to environmental and operational drawbacks. Specifically, cadmium's environmental impact and the memory effect, which reduces battery capacity if not fully discharged before recharging, pose significant issues. The current frontrunner in the EV battery space is Lithium-Ion (Li-ion) technology, celebrated for its superior energy density, efficiency, and extended operational lifespan. These attributes render Li-ion batteries the most favored choice for modern electric vehicles, offering enhanced range and performance

capabilities.[90].

3.2.2. Components and Challenges in EV Batteries

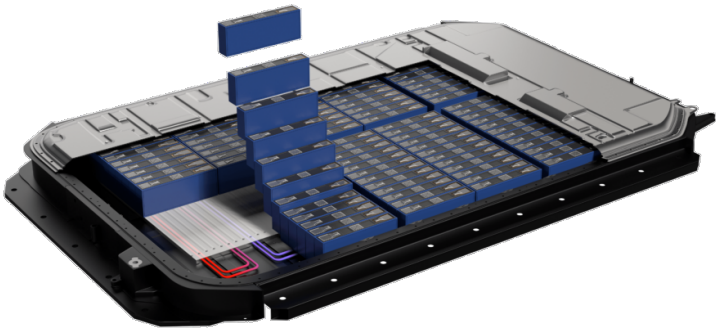


Figure 3.5: EV battery disassembly [91].

Delving into the specifics of battery pack assembly, involves the strategic organization of cells in series and parallel arrangements to meet designated voltage and current specifications (Figure 3.5). Serial connections amplify the voltage, whereas parallel configurations boost current capacity. This modularity in design introduces challenges including safety concerns, thermal management, and the inherent complexity of battery architecture [92, 93].

Operational hurdles abound in the utilization of batteries within EVs. Each cell in a battery pack must operate within predefined limits for current, voltage, and temperature to avert operational failures. A notable risk is thermal runaway, a condition exacerbated in lithium-based batteries, where unchecked internal temperature rises can lead to reduced battery life and increased fire risk [94]. Effective thermal management strategies are imperative, incorporating cooling systems to avert overheating and heating mechanisms to offset performance dips in cold conditions [95].

Cell imbalance presents another challenge, arising from voltage disparities among fully charged cells within a pack. These imbalances, stemming from manufacturing variances or disparate usage patterns, necessitate cell balancing techniques to even out voltage levels, thereby maintaining the efficiency and longevity of the battery pack [96].

Integrating a Battery Management System (BMS) into each EV is essential to mitigate risks associated with thermal runaway, ensure operational integrity, and extend the lifespan of the battery pack[92]. The BMS serves as a critical interface, interpreting sensor data to facilitate informed operational decisions and manage cell balancing effectively. It oversees essential parameters such as cell voltage, current, temperature, and impedance, employing sophisticated methodologies for evaluating battery conditions including state-space models, neural networks, and symbolic/fuzzy logic, aimed at assessing the state of health (SOH) and state of charge (SOC) under diverse operational scenarios [97].

3.2.3. Advanced Operations and Strategic Role of the BMS

Implementing a BMS in each EV is therefore essential to prevent physical damage, performance degradation, and the dangers associated with thermal runaway . The BMS acts as an intermediary, interpreting sensor data and operational responses to inform decision-making and predict battery conditions. It requires a certain sampling rate, authority over switching for cell balance management, a comprehensive detection system, and a coordinated protection circuit approach. Ongoing research and development are imperative to refine control over battery operations, considering parameters such as total and individual cell voltage, current, temperature, impedance, and even smoke detection. The evaluation of battery conditions involves complex methodologies, including state-space models, neural networks, and symbolic/fuzzy logic, to determine SOH and SOC under various operational circumstances.
The BMS's accuracy in estimating SOC is particularly crucial, as it directly influences charging regulation and cell balancing efficacy [98]. The following block diagram illustrates the components of a BMS (Figure 3.6):

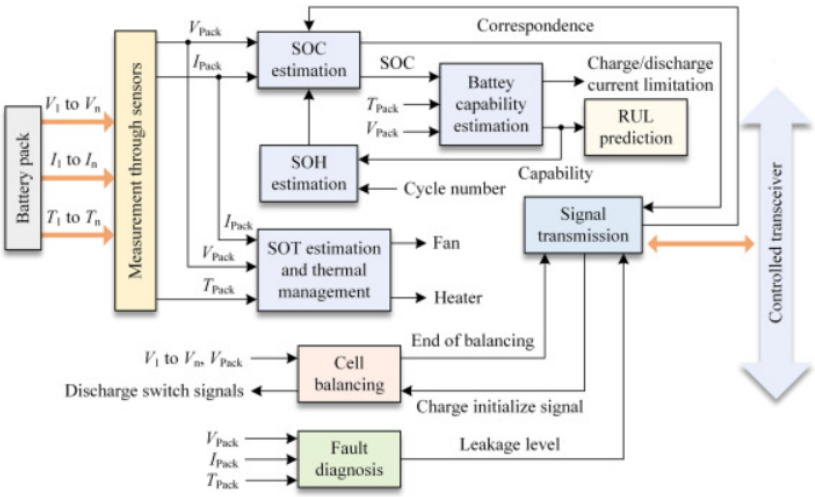


Figure 3.6: Flowchart of Battery Management System Functions [99].

- The sensing block records battery parameters at multiple points, producing digital signals for the estimation of the battery state.
- Thermal management activates fans or heaters as required to maintain optimal temperature conditions.
- The capacity estimation block calculates charge/discharge current limitations using specialized algorithms.

- Multi-dimensional constraints imposed by a cell equalizer correct overcharge or discharge irregularities.
- The fault diagnosis block is designed to ensure the safety of the battery system.
- Lastly, the controlled transceiver block orchestrates the communication of information, enabling data transmission.

After identifying the real-time issues a BMS must monitor for optimal battery utilization, additional factors must be taken into account to manage long-term battery decay. The primary degradation factors are known as "calendar aging" and "cyclic aging." Calendar aging is the gradual decline of the battery's condition over time, regardless of its operational use, such as the effects of charging, discharging, and actual driving. This type of aging typically develops over longer durations (about 9-10 months) and is well-documented in numerous studies [100, 101]. Short-term research on calendar aging often relies on scenarios that are not easily replicated outside of controlled environments, particularly regarding temperature—a crucial factor that varies from 20-40°C in the long term to 60°C in the short term for measurable outcomes [101]. It's noted in empirical studies that calendar aging can exacerbate the deterioration of battery performance as the level of charge increases. For instance, references like Figure 3.7 indicate that despite regular charge and discharge cycles, vehicles spend most of the time (80-90%) stationary throughout the day. Laboratory results, conducted at a constant high temperature of 60°C, reveal the profound impact of calendar aging on battery health over time and SOC levels when the vehicle is not in operation.

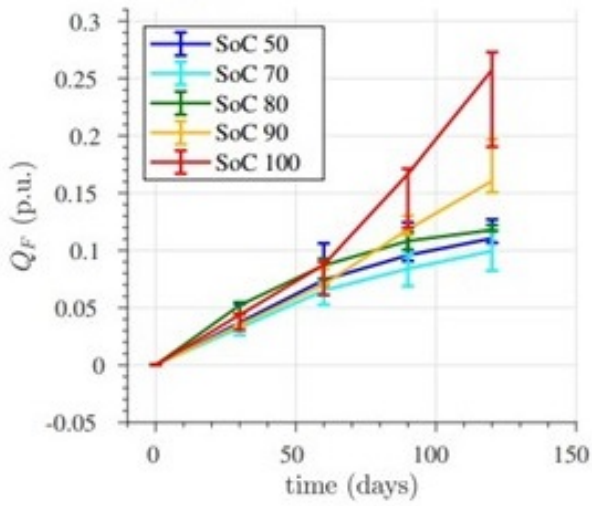


Figure 3.7: Qf is the capacity fade on percentage, tests were conducted in the laboratory with a constant temperature of 60°C [101].

Since many degradation models overlook the calendar aging factor, it will not be the focus of this research. Instead, the emphasis will be placed on cyclic aging, which has a more pronounced impact on battery wear and tear through the charge and discharge cycles associated with vehicle operation. Discharging poses a greater risk than charging because the battery, being engineered to supply power to an electric motor, is more vulnerable to high-demand operations. Consequently, this research will prioritize cyclic aging as the key factor in battery degradation analysis. Regarding cyclic aging, the BMS greatly affects charging behavior to mitigate rapid battery degradation [102]:

- **Maximum Power:** The BMS might restrict charging power reflecting cell condition, temperature, and overall battery status. Intelligent charging algorithms need to incorporate these limitations.
- **Cell Balancing Time:** Active balancing by the BMS during charging could prolong charge duration. Intelligent scheduling should account for this extra time.
- **Temperature Profiles:** BMS modulates charge power in response to temperature changes. Intelligent charging should adapt to daily temperature fluctuations.
- **Battery Aging:** The BMS strives to reduce battery wear. Intelligent charging algorithms should avoid excessive charging and discharging that could hasten aging.

The specifics of these algorithms are broad and varied, as each EV and manufacturer will have different protocols based on the vehicle and brand requirements. For example, considering the relationship between maximum power and the current SOC, we can attribute this to physical factors [103]:

- **Internal Resistance:** The internal resistance of a battery increases as it discharges, restricting the flow of current and thus power output.
- **Voltage Drop:** A lower SOC corresponds to a lower battery voltage. Since power is directly proportional to voltage, a drop in voltage means a drop in power.
- **Heat Management:** High outputs of power produce heat. At lower SOCs, it becomes harder to dissipate this heat, limiting the power that can be delivered.
- **Battery Chemistry:** Different battery chemistries show different power behaviors at various SOC levels.

In study [104], multiple vehicles demonstrated varying average charging powers when the SOC changed (Figure 3.8):

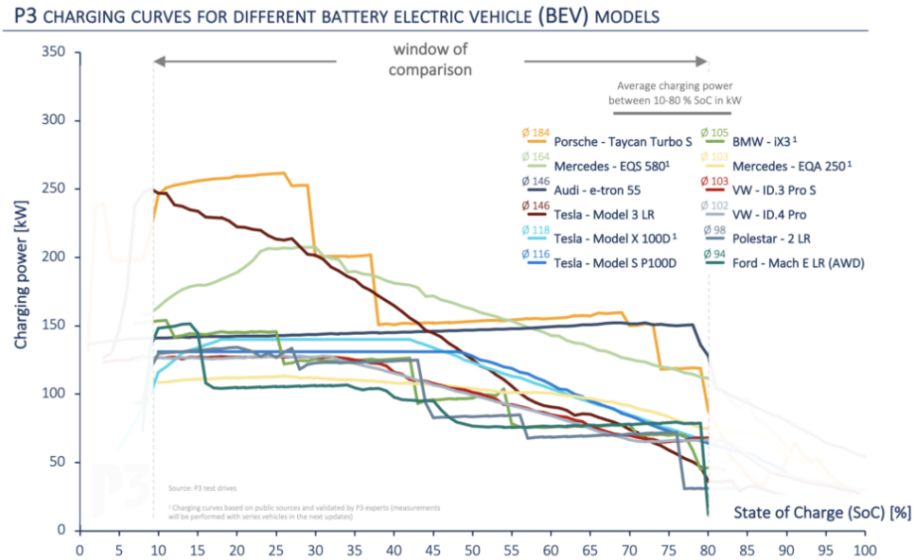


Figure 3.8: Comparison of maximum charging power about SOC for various EVs models [104].

Research such as that documented in [103] has explored solutions for optimizing the charging process at stations, addressing similar challenges. However, forecasting the constraints imposed by the BMS proves to be challenging, as this type of detailed information is often not exchanged between the vehicle and the charging station. In scenarios where advanced communication protocols are employed, like the Combined Charging System (CCS), a dynamic negotiation is established between the charger and the vehicle. This involves the vehicle providing updates on its battery status, including SOC, temperature, and maximum power capability, while the charger communicates its available capacity, making use of V2G capabilities [105]. Nonetheless, in the context of scheduling challenges, understanding the complexity of the system and, hence, future power constraints is crucial to ensuring the solution remains viable.

4 | Introduction to the Optimization Challenge

This section introduces a semi-realistic scenario to explore the complexities of an optimization challenge. The scenario involves a metallurgical factory outfitted with solar power capabilities and a parking lot equipped with electric vehicle chargers. Crucial data such as vehicle availability, energy consumption, solar energy production, and energy pricing are derived from real-world datasets and are assumed to be precise for simulation. The task of optimizing the factory's energy savings is assigned to a digital controller. This optimization focuses on the strategic timing of battery charging and discharging rather than altering the factory's core operational processes. The objective is to store energy when costs are minimal and utilize it during periods of higher prices. To achieve this, a Model Predictive Control (MPC) algorithm is employed. This algorithm leverages accurate forecasts of daily energy consumption and production, vehicle fleet availability, and energy price variations. It introduces increasing levels of complexity to the problem and evaluates the outcomes through several stages:

1. Initially, the focus is on maximizing savings by using the vehicle fleet as a flexible energy storage system, strategically distributing stored energy at times of maximum benefit. The integration of energy-sharing capabilities among vehicles (V2V), with the building (V2B) adds a layer of versatility, enhancing the system's efficiency and adaptability.

2. Subsequently, the strategy incorporates considerations for minimizing operational wear and thermal variance, aiming to reduce potential degradation. An energy incentive, calculated based on the battery's cost, is introduced to avoid risky operations and optimize battery use in EVs, thereby providing a more attractive solution for EV owners.

3. The strategy culminates by integrating minimum and maximum power constraints as dictated by the BMS, employing an online learning methodology to assess performance across diverse operational scenarios.

4.1. Defining the Scenario

This section outlines the scenario utilized to investigate the optimization challenge, centered around an industrial facility in southern Germany. The facility's energy consumption and PV system generation data, spanning from November 29, 2015, to October 11, 2017 (a total of 682 days), is modeled using a specific dataset [106]. For simulation purposes, the focus is narrowed to the year 2016, with the data adjusted to align with the year 2020 and shifted by two days. This manipulation ensures the days of the week match between the energy data and the EV data, available solely for 2020. Conversion of the kWh readings to kW enables a series of energy consumption analyses. Preliminary statistical analysis for the first two months yielded (Table 4.1):

	Maximum	**Minimum**	**Average**	**Median**	**St. Dev.**
Consumption (kWh)	673.377	199.502	447.302	497	148.782

Table 4.1: Daily Consumption and Generation Statistics

From this analysis, two key insights emerge:

1. Given that the EV fleet, belonging to the factory's workforce, is mainly present during daylight, the outfitted PV plant will essentially reduce net energy consumption.
2. The daily variability in energy consumption (Figure 4.1) reflects the patterns of a small business [107]. This variability directly impacts potential daily savings. For this study, which concentrates on fleet applications, the consumption profile is incremented to better study differences in fleet characteristics.

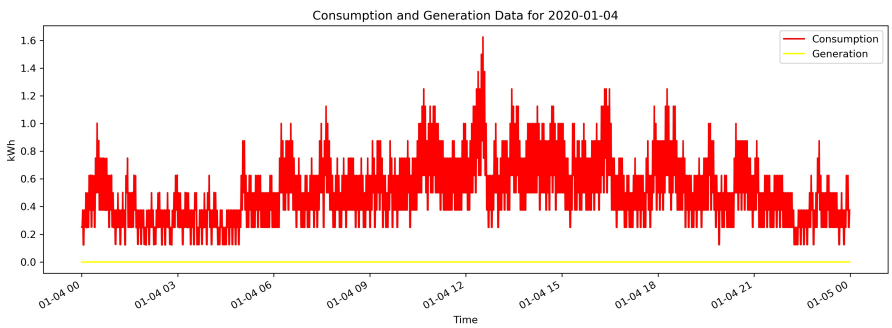


Figure 4.1: Typical daily energy consumption and photovoltaic generation pattern.

The EV fleet is represented using data from the National Renewable Energy Lab (NREL) [108], tracking around 400 Electric Vehicles over four to five years (2016-2021). This

data sheds light on EVs and driver behaviors at workplace charging stations, essential for understanding vehicle availability and charging patterns. The study focuses on the year 2020, with vehicle presence ranging from 1 to 31 on a typical day (Figure 4.2).

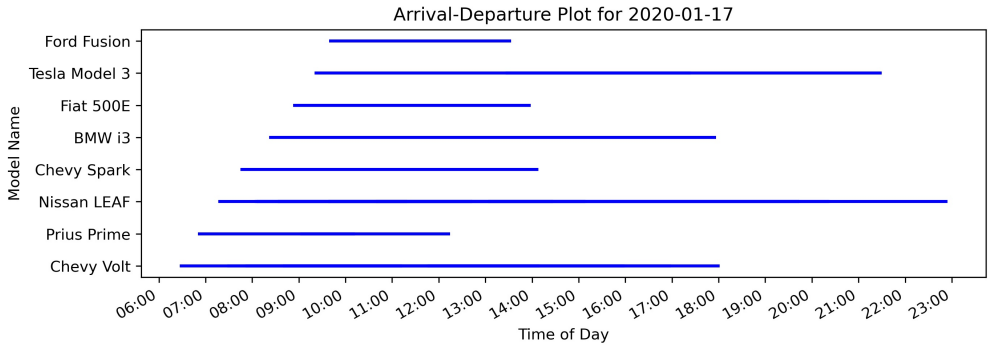


Figure 4.2: Typical daily presence of the fleet.

The variability in vehicle presence and composition is a key factor in our analysis, allowing for a comprehensive evaluation of the optimization algorithm across varied scenarios. This examination aims to pinpoint the algorithm's strengths and weaknesses by observing its performance under different conditions. For this study, the focus is exclusively on data from 2020, with the vehicle count fluctuating between 1 to 31 on any given day. We leverage specific information for each vehicle type (Figure 4.3) identified during this period to ensure a detailed and accurate assessment.

	Capacity (kWh)	Max Power (kW)	Price ($)
Chevy Bolt	65.0	50.0	26500.0
Chevy Volt	72.0	7.2	34395.0
BMW i3	42.2	50.0	44450.0
Chevy Spark	19.0	50.0	13400.0
Jaguar I-Pace	90.0	100.0	69900.0
Fiat 500E	42.0	6.6	33460.0
BMW X5E	26.0	7.4	66900.0
Honda Clarity	17.0	6.6	33400.0
Prius Prime	14.0	3.8	28220.0
Tesla Model 3	79.0	250.0	39990.0
Nissan LEAF	62.0	100.0	32620.0
Ford Fusion	8.0	3.8	36450.0
Audi A3 E-Tron	9.0	7.2	39100.0
BMW 530e	23.0	7.4	57200.0
Ford C-Max	7.6	3.8	24120.0
Mitsubishi iMiEV	16.0	3.3	23995.0
Scion iQ EV	12.0	50.0	31800.0
Tesla Model S	80.0	270.0	79990.0
Mitsubishi Outlander	13.8	7.4	36295.0
Kia Soul EV	64.0	100.0	33950.0
Chrysler Pacifica Hybrid	16.0	10.0	39995.0
Smart Car	17.6	22.0	23900.0
Ford Focus Electric	50.0	6.6	29120.0
Tesla Model X	100.0	250.0	89990.0
Hyundai Kona EV	65.8	75.0	37390.0
Cadillac ELR	17.1	15.5	75000.0

Figure 4.3: Current market EV characteristics considered.

The analysis also incorporates energy price data sourced from the Australian Energy Market Operator (AEMO) [109]. This dataset provides detailed insights into electricity demand and pricing in Victoria, Australia, offering 30-minute snapshots throughout 2020. Price fluctuations ranged from 0.04 €/kWh to 0.2 €/kWh, averaging around 0.11 €/kWh (Figure 4.4). This pricing data plays a crucial role in our optimization strategy, allowing for nuanced financial analysis and strategic planning based on real-world energy cost variations.

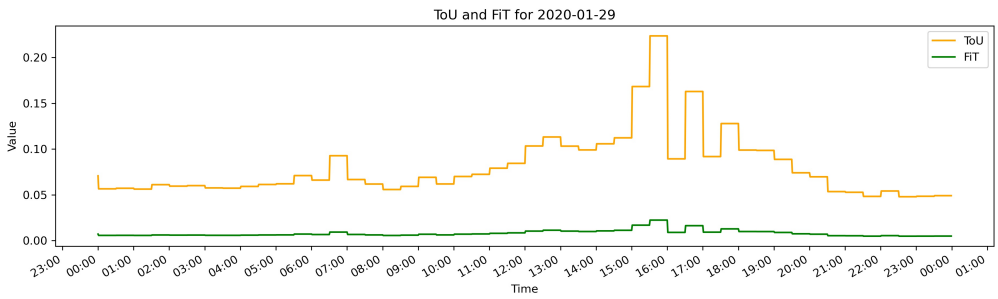


Figure 4.4: Typical daily electricity prices.

4.2. EMS MPC Framework

The development of the MPC will focus primarily on managing the inflow and outflow of energy and data within the company. This strategy intentionally avoids delving into the detailed structure of the company or its specific operational processes and machinery. By doing so, it maintains a flexible approach to managing the company's daily energy needs. The central challenge addressed by the MPC is to achieve a balance among the energy consumed and generated by the facility, including energy storage and the charging requirements of the vehicles. The discrete-time MPC formulation, based on the general dynamics of the system, is given by the equation:

$$x_{k+1} = f(x_k, u_k)$$

where the state vector X and the control vector U are defined as follows:

$$X = \begin{bmatrix} SOC_1^1 & SOC_2^1 & \cdots & SOC_T^1 \\ SOC_1^2 & SOC_2^2 & \cdots & SOC_T^2 \\ \vdots & \vdots & \ddots & \vdots \\ SOC_1^N & SOC_2^N & \cdots & SOC_T^N \end{bmatrix} \tag{4.1}$$

$$U = \begin{bmatrix} P_1^{1+} - P_1^{1-} & \cdots & P_T^{1+} - P_T^{1-} \\ P_1^{2+} - P_1^{2-} & \cdots & P_T^{2+} - P_T^{2-} \\ \vdots & \ddots & \vdots \\ P_1^{N+} - P_1^{N-} & \cdots & P_T^{N+} - P_T^{N-} \end{bmatrix} \tag{4.2}$$

The evolution of the system's state is described by a linear relationship that models the change in the SOC for each time step:

$$SOC_{t+1}^i(P_t^{i+}, P_t^{i-}) = SOC_t^i + (P_t^{i+} - P_t^{i-})\frac{\Delta}{60}t$$

where the terms are defined as:

- P_t^{i+}: the charging power to the EV i at time t.
- P_t^{i-}: the discharging power from the EV i at time t.

Given the variability in the availability of vehicles, each car is assigned its planning horizon based on its presence. To accommodate this, the system must adhere to certain hard

constraints. For each vehicle i the SOC and the net charging power $(P_t^{i+} - P_t^{i-})$ are defined as follows, taking into account the vehicle's availability (S^i):

$$SOC_t^i = \begin{cases} SOC_t^i & \text{for t} \in S^i \\ 0 & \text{otherwise} \end{cases} \qquad P_t^{i+} - P_t^{i-} = \begin{cases} P_t^{i+} - P_t^{i-} & \text{for t} \in S^i \\ 0 & \text{otherwise} \end{cases} \tag{4.3}$$

Here, S^i represents the time intervals during which vehicle i is available. To maintain consistency, initial and final SOC values are aligned with the vehicle's arrival state:

$$SOC_0^i = SOC_{fin}^i = SOC_{\text{init}}^i$$

The cost function, integral to the MPC's optimization process, is formulated as:

$$J = \sum_{k=0}^{N-1} \left(x_k^T Q x_k + u_k^T R u_k \right) + x_N^T P x_N$$

This cost function takes into account the instantaneous power balance, reflecting the interplay between internal consumption, PV generation, and the energy interactions with the vehicle fleet:

$$c_t(P_t^{i+}, P_t^{i-}) = (P_t^{\text{load}} - P_t^{\text{PV}} + P_t^{+}(P_t^{i+}) - P_t^{-}(P_t^{i-}))\frac{\Delta t}{60} \tag{4.4}$$

In this context:

- P_t^{PV} and P_t^{load} represent the power generated by the PV system and consumed by the building at time t, respectively.
- c_t: quantifies the net consumption, integrating building consumption, PV generation, storage interactions, and vehicle charging/discharging.
- Δt: denotes the sampling interval.

For managing a fleet, the total charging and discharging power at any moment is the aggregate of the respective powers for all available vehicles:

$$\begin{cases} P_t^{+} = \sum_i^N P_t^{i+} & \text{for t} \in S^i \quad (4.5a) \\ P_t^{-} = \sum_i^N P_t^{i-} & \text{for t} \in S^i \quad (4.5b) \end{cases}$$

Within the operational day, the number of vehicles (N) present and their energy transactions play a critical role. The energy cost, varying hourly, directly influences the economic aspect of energy management. The optimization of this cost function is crucial for minimizing expenses, taking into account that energy can be both purchased and sold, with the selling price generally lower than the buying price. The following maximization function determines the current cost of energy transactions:

$$C_t(P_t^{i+}, P_t^{i-}) = \max_{P_t^{i+}, P_t^{i-}} \left(c_t(P_t^{i+}, P_t^{i-}) \cdot \pi_t^+, \quad c_t(P_t^{i+}, P_t^{i-}) \cdot \pi_t^- \right) \tag{4.6}$$

where:

- C_t: represents the energy expense at time t in euros.
- π_t^+ and π_t^-: denote the purchase and selling prices of electricity at time t, respectively, in €/kWh.

This maximization ensures the selection of the most economical operation mode—whether consuming energy or feeding it back into the grid. As a result, the overall cost function for the vehicle fleet's energy transactions is defined as:

$$J(P_t^{i+}, P_t^{i-}) = \sum_{t}^{T} C_t(P_t^{i+}, P_t^{i-})$$

The objective of the MPC is to identify the optimal sequence of charging and discharging actions (P_t^{i+}, P_t^{i-}) that minimizes this cost:

$$\underset{P_t^{i+}, P_t^{i-}}{\operatorname{argmin}} J(P_t^{i+}, P_t^{i-})$$

Finally, the following constraints ensure that charging and discharging processes are appropriately managed, avoiding any operational conflicts and adhering to the physical limits of the vehicle's charging infrastructure:

$$\begin{cases} P_t^{i+} \cdot P_t^{i-} = 0 & \text{for t} \in S^i \quad \text{for i} \in N & (4.7) \\ 0 \leq P_t^{i+} \leq P_{MAX} & \text{for t} \in S^i \quad \text{for i} \in N & (4.8) \\ 0 \geq P_t^{i-} \geq P_{MIN} & \text{for t} \in S^i \quad \text{for i} \in N & (4.9) \end{cases}$$

4.3. V2B Considerations

This section will describe the initial phase of research, which explores the concept of utilizing EV fleets as energy storage systems within a V2B framework. The focus is on determining the maximum potential savings without imposing constraints, providing a benchmark for the optimization problem. The study will take into account various factors such as daily energy consumption, price fluctuations, fleet availability, and initial energy levels. The primary aim is to investigate the effectiveness of using an EV fleet for energy storage, initially by analyzing how the algorithm performs across different daily consumption patterns and energy tariffs (Figure 4.5). Subsequently, a single consumption profile and energy cost will be selected for in-depth analysis and application in further stages of the research:

	Int_t	Tot_cars	Tot_SOC kWh	Tot_Empty_SOC kWh	New_cost €	Savings%
2020-01-23	05:45 - 21:00	27.0	1441.2	319.8	123.782	76.83%
2020-01-31	06:30 - 21:15	17.0	909.2	233.4	1536.231	59.65%
2020-01-30	06:30 - 20:30	26.0	1508.2	318.9	297.617	40.14%
2020-01-28	06:15 - 19:00	27.0	1580.2	335.3	28.144	36.94%
2020-01-04	13:15 - 23:00	1.0	62.0	17.0	1621.813	35.39%
2020-01-27	06:30 - 19:45	28.0	1574.2	363.0	14.085	22.23%
2020-01-22	06:00 - 23:00	25.0	1315.2	223.9	91.952	20.38%
2020-01-29	06:15 - 18:30	21.0	1161.2	217.9	86.125	19.05%
2020-01-07	06:15 - 21:00	29.0	1521.2	315.2	22.386	17.78%
2020-01-20	07:00 - 15:15	1.0	62.0	36.0	9.351	12.82%
2020-01-24	06:15 - 23:30	25.0	1377.2	290.2	115.417	11.54%
2020-01-17	06:30 - 23:00	20.0	1091.2	199.8	52.23	10.33%
2020-01-21	06:45 - 21:45	28.0	1394.2	323.8	21.961	10.0%
2020-02-04	09:00 - 21:15	8.0	438.2	131.4	13.701	7.8%
2020-02-03	05:30 - 18:15	17.0	1010.0	205.7	13.359	7.49%
2020-01-03	06:15 - 19:45	21.0	1131.0	247.6	65.651	7.43%
2020-01-16	06:00 - 21:45	25.0	1370.2	317.3	55.922	7.04%
2020-01-15	05:30 - 20:45	28.0	1405.2	336.6	86.429	6.64%
2020-01-14	06:00 - 21:15	30.0	1637.2	350.7	48.498	6.27%
2020-01-10	06:30 - 19:15	23.0	1120.2	269.4	92.956	5.77%
2020-01-06	06:15 - 22:30	31.0	1697.2	392.1	18.031	4.89%
2020-02-05	06:15 - 23:00	18.0	989.2	240.4	70.911	4.85%
2020-01-02	06:00 - 20:45	19.0	983.0	228.3	68.214	4.47%
2020-01-08	06:00 - 22:30	23.0	1208.2	225.5	77.079	4.32%
2020-01-09	06:00 - 21:15	29.0	1558.2	317.4	99.72	3.19%
2020-01-13	06:00 - 20:15	26.0	1408.2	324.0	68.523	3.06%
2020-01-05	12:00 - 21:45	1.0	62.0	14.9	9.453	2.15%
2020-01-12	11:15 - 21:00	1.0	62.0	17.2	23.487	1.2%
2020-01-26	10:15 - 20:00	1.0	62.0	8.7	32.44	0.84%
2020-01-11	08:45 - 21:45	2.0	134.0	22.4	78.246	0.55%

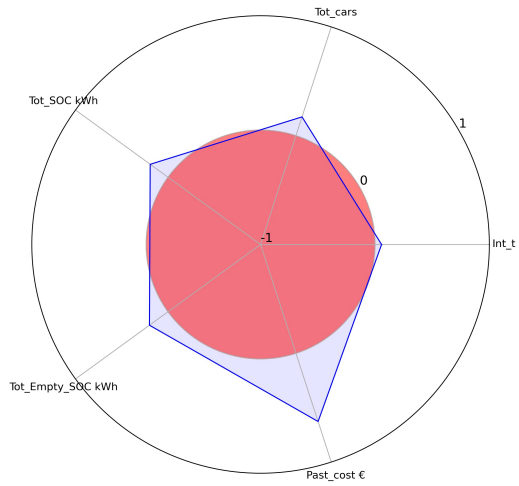
Figure 4.5: V2B Scheduling with fleet information.

- **Int_t:** This represents the time interval during which the fleet is active. It begins with the arrival of the first vehicle and concludes with the departure of the last vehicle.
- **Tot_cars:** The total count of vehicles present on that particular day.
- **Tot_SOC kWh:** The aggregate SOC of all vehicles present on that day.
- **Tot_Empty_SOC kWh:** The combined empty SOC for all vehicles upon their

arrival at the parking lot.

- **Past_cost €:** The total energy cost for that day, calculated over the period **Int_t**, without the inclusion of energy storage.
- **New_cost €:** The revised total energy cost for the same period with the implementation of energy storage.
- **Savings %:** The percentage of cost savings compared to the **Past_cost**.

The table is organized in descending order based on the 'Savings%' column. Cells in light blue highlight the days with the maximum value for the respective column. Whereas, cells in gray highlight the days with the minimum value for the respective column.
The impact of several parameters like number of vehicles, time interval of availability and total space for conservation of energy seems to be none or not congruent. Also, to have a complete analysis fluctuations of prices of each should be considered since savings could come from them. To understand this better, a correlation analysis is proposed:



- Only **Past_cost €** column exhibits a positive correlation with the amount of money saved, suggesting that days with higher past costs tend to result in greater savings.
- This implies that an increase in the industry's energy consumption on any given day correlates with a higher potential for cost savings.
- The influence of other factors appears to be minimal, which may be attributed to variables not captured in the current optimization model, as the optimizer consis-

tently identifies solutions regardless of daily fluctuations.

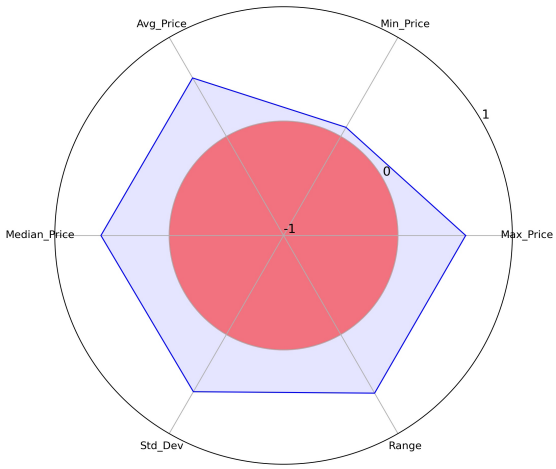
Further investigation is required to unpack the nuanced impact of these less influential factors, especially considering the complexity of daily energy tariffs and consumption patterns (Figure 4.6):

	Max_Price	Min_Price	Avg_Price	Median_Price	Std_Dev	25th_Percentile	75th_Percentile	Range	Savings%
2020-01-23	2.652	0.035	0.224	0.055	0.6174	0.047	0.076	2.617	76.83%
2020-01-31	13.064	0.029	1.539	0.094	3.4347	0.069	0.24	13.035	59.65%
2020-01-30	1.805	0.043	0.185	0.067	0.3121	0.051	0.215	1.762	40.14%
2020-01-28	0.307	0.048	0.086	0.071	0.0551	0.055	0.092	0.259	36.94%
2020-01-04	14.7	0.031	1.283	0.049	3.8084	0.044	0.073	14.669	35.39%
2020-01-27	0.127	0.038	0.061	0.051	0.0228	0.048	0.065	0.089	22.23%
2020-01-22	0.188	0.015	0.059	0.048	0.0339	0.039	0.074	0.173	20.38%
2020-01-29	0.224	0.048	0.08	0.069	0.0344	0.058	0.094	0.176	19.05%
2020-01-07	0.113	0.033	0.056	0.05	0.0153	0.048	0.061	0.079	17.78%
2020-01-20	0.365	0.039	0.073	0.066	0.0448	0.058	0.072	0.326	12.82%
2020-01-24	0.098	0.042	0.063	0.061	0.0137	0.052	0.07	0.055	11.54%
2020-01-17	0.064	0.018	0.042	0.042	0.0097	0.037	0.048	0.046	10.33%
2020-01-21	0.083	0.043	0.053	0.049	0.0088	0.048	0.056	0.04	10.0%
2020-02-04	0.063	0.026	0.042	0.042	0.0057	0.039	0.044	0.037	7.8%
2020-02-03	0.066	0.036	0.048	0.048	0.007	0.043	0.052	0.03	7.49%
2020-01-03	0.091	0.043	0.059	0.057	0.0128	0.049	0.067	0.048	7.43%
2020-01-16	0.086	0.038	0.049	0.048	0.0073	0.045	0.05	0.048	7.04%
2020-01-15	0.076	0.031	0.054	0.052	0.0089	0.049	0.06	0.046	6.64%
2020-01-14	0.081	0.039	0.052	0.05	0.0075	0.048	0.054	0.042	6.27%
2020-01-10	0.081	0.024	0.055	0.05	0.0138	0.049	0.062	0.058	5.77%
2020-01-06	0.061	0.032	0.048	0.049	0.007	0.047	0.052	0.029	4.89%
2020-02-05	0.058	0.036	0.046	0.047	0.005	0.043	0.049	0.022	4.85%
2020-01-02	0.08	0.039	0.058	0.057	0.0101	0.049	0.064	0.041	4.47%
2020-01-08	0.06	0.038	0.051	0.051	0.0053	0.048	0.056	0.022	4.32%
2020-01-09	0.059	0.037	0.048	0.049	0.0045	0.046	0.049	0.022	3.19%
2020-01-13	0.061	0.005	0.045	0.047	0.0091	0.043	0.049	0.055	3.06%
2020-01-05	0.049	0.022	0.041	0.041	0.0047	0.038	0.045	0.027	2.15%
2020-01-12	0.051	0.034	0.042	0.041	0.0046	0.038	0.047	0.017	1.2%
2020-01-26	0.085	0.044	0.058	0.052	0.0116	0.05	0.06	0.042	0.84%
2020-01-11	0.057	0.038	0.048	0.048	0.0042	0.044	0.049	0.019	0.55%

Figure 4.6: V2B Scheduling with statistical tariffs data.

- **Max_Price/Min_Price:** Represents the highest and lowest electricity prices reached each day.
- **Avg_Price:** This average price for the day serves as a reference point for all the day's prices.
- **Median_Price:** The median price helps to normalize the average if there are outliers present.
- **Std_Dev:** The standard deviation is used to measure the variation or dispersion of the data set.
- **25/75th Percentile:** This percentile indicates the value below which a certain percentage of observations fall, providing insight into the data distribution.
- **Range:** This is the difference between the maximum and minimum values, showing the spread of the prices.

Reorganizing the data to highlight 'Savings%' reveals that, in practical scenarios, the potential for savings is more strongly influenced by energy tariffs than the sheer number of vehicles available. This indicates that to observe a more pronounced dependency on fleet-related factors, a scenario with higher energy consumption may be necessary.

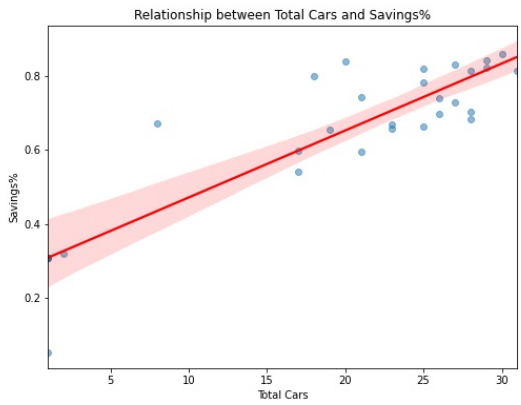


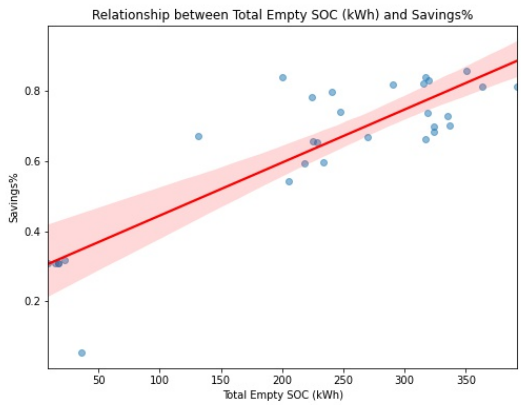
- There is a nearly perfect linear relationship between the amount of savings and the variability of energy prices, as indicated by the standard deviation.
- Correlation analysis of all statistical measures of energy tariffs suggests a substantial positive effect on the potential savings, highlighting the importance of tariff fluctuations over the number of available EVs for saving costs.

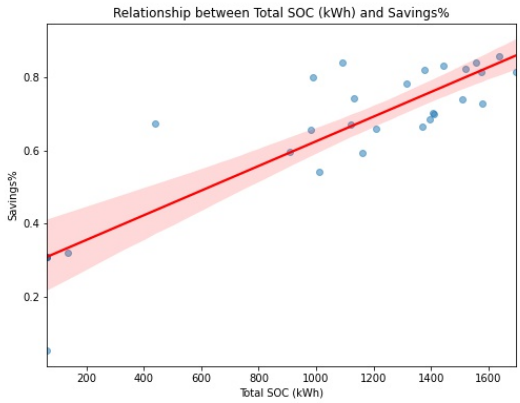
Considering these findings and the focus of this study on the fleet of EVs, a single date with significant energy consumption and high price variability was selected—January 31, 2020. On this date, the high energy demand necessitates the use of a large number of vehicles, coupled with a significant standard deviation in energy tariffs:

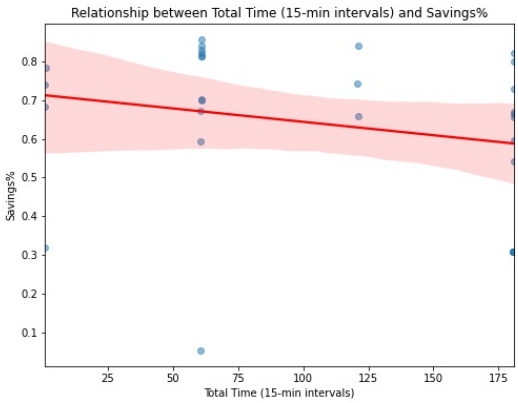
	Int_t	Tot_SOC kWh	Tot_Empty_SOC kWh	Savings%
2020-01-14	06:00 - 21:15	1637.2	350.7	85.71%
2020-01-09	06:00 - 21:15	1558.2	317.4	84.0%
2020-01-17	06:30 - 23:00	1091.2	199.8	83.92%
2020-01-23	05:45 - 21:00	1441.2	319.8	83.04%
2020-01-07	06:15 - 21:00	1521.2	315.2	82.1%
2020-01-24	06:15 - 23:30	1377.2	290.2	81.97%
2020-01-27	06:30 - 19:45	1574.2	363.0	81.38%
2020-01-06	06:15 - 22:30	1697.2	392.1	81.3%
2020-02-05	06:15 - 23:00	989.2	240.4	79.8%
2020-01-22	06:00 - 23:00	1315.2	223.9	78.28%
2020-01-03	06:15 - 19:45	1131.0	247.6	74.17%
2020-01-30	06:30 - 20:30	1508.2	318.9	73.96%
2020-01-28	06:15 - 19:00	1580.2	335.3	72.88%
2020-01-15	05:30 - 20:45	1405.2	336.6	70.11%
2020-01-13	06:00 - 20:15	1408.2	324.0	69.8%
2020-01-21	06:45 - 21:45	1394.2	323.8	68.34%
2020-02-04	09:00 - 21:15	438.2	131.4	67.27%
2020-01-10	06:30 - 19:15	1120.2	269.4	66.94%
2020-01-16	06:00 - 21:45	1370.2	317.3	66.38%
2020-01-08	06:00 - 22:30	1208.2	225.5	65.77%
2020-01-02	06:00 - 20:45	983.0	228.3	65.5%
2020-01-31	06:30 - 21:15	909.2	233.4	59.65%
2020-01-29	06:15 - 18:30	1161.2	217.9	59.42%
2020-02-03	05:30 - 18:15	1010.0	205.7	54.21%
2020-01-11	08:45 - 21:45	134.0	22.4	31.96%
2020-01-05	12:00 - 21:45	62.0	14.9	30.93%
2020-01-12	11:15 - 21:00	62.0	17.2	30.93%
2020-01-26	10:15 - 20:00	62.0	8.7	30.88%
2020-01-04	13:15 - 23:00	62.0	17.0	30.83%
2020-01-20	07:00 - 15:15	62.0	36.0	5.35%

Upon repeating the optimization for various fleet configurations, the data, while more orderly than before, does not show a direct correlation between the maximum value of individual parameters and the highest savings. This suggests that each parameter's influence on the outcome differs, implying a complex interplay between various factors affecting savings:






Relationship between Total SOC (kWh) and Savings%
Savings%
Total SOC (kWh)
0.2
0.4
0.6
0.8
200
400
600
800
1000
1200
1400
1600


Relationship between Total Time (15-min intervals) and Savings%
Savings%
Total Time (15-min intervals)
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
25
50
75
100
125
150
175

4.4. Battery Degradation and Temperature Assessment

This stage focuses on evaluating the effects of various processes on electric vehicles, particularly how they contribute to battery degradation. This deterioration is accounted for in our model by first translating it into financial terms and then into an energy equivalent. Consequently, battery storage is envisioned as a service offered by individuals aiming for financial compensation, which involves retaining extra energy in the battery at the end of the day. The cost associated with battery degradation is determined by monitoring changes in the SOH due to operational activities [110].

$$R^i(P_t^{i+}, P_t^{i-}) = B^i \cdot \sum_t^T \Delta SOH(P_t^+, P_t^-)\%_t^i$$

$$SOH\% = \frac{Q_{cur}}{Q_0} \times 100$$

where:

- R^i: energy reward for storage service in vehicle i.
- B^i: battery cost in vehicle i, taken as 30% of the vehicle cost.
- Q_{cur}: current maximum capacity.
- Q_0: Nominal maximum capacity.
- $\Delta SOH(P_t^+, P_t^-)\%_t^i$: Variation of the battery's SOH for EV i at time t.

The SOH value, ranging between 0 and 1, indicates the end of the battery's usable life, typically when its rechargeable capacity falls below 80% of its original capacity. This value is calculated based on the following equation:

$$\Delta SOH\%_t^i = \beta \cdot e^{\left(k_T \cdot \frac{(T_t^i - T_{ref})}{T_t^i} \cdot k_{DOD} \cdot DOD_t^i + k_{C_{ch}} \cdot Cch_t^i + k_{C_{dch}} \cdot Cdch_t^i\right)}$$
$$\cdot \left[1 + b_{mSOC} \cdot mSOC_t^i \cdot \left(1 - \frac{mSOC_t^i}{2 \cdot mSOC_{ref}}\right)\right] \cdot \left(FEC_t^i\right)^{a_{opt}}$$

Parameters highlighted in light blue are empirically derived fitting parameters specific to the use of electric batteries. Lithium-ion batteries, with technologies such as LMO (lithium manganese oxide), LFP (lithium iron phosphate), NMC (lithium nickel manganese cobalt oxide), and NCA (lithium nickel cobalt aluminum oxides), are currently

considered the most suitable due to their longevity and performance advantages. Specifically, NMC batteries are chosen for our model based on their efficacy in high-demand operations and frequency response, as suggested by recent studies [110, 111].

Parameters	β	k_T	T_{ref}	k_{DOD}	k_{Ch}	k_{Cch}	b_{mSOC}	$mSOC_{\text{ref}}$	a_{opt}
Values	0.001673	21.6745	293	0.022	0.2553	0.1571	-0.0212	42%	0.915

The variables that are crucial in the analysis of battery degradation in vehicles include:

- T_t^i : This is a key determinant of battery life since chemical reactions within the battery accelerate at higher temperatures, thus affecting its performance. Important points to consider are:

  1. Vehicles arriving at a parking lot after long journeys may experience significant increases in internal temperature. Information about this can be obtained from onboard sensors (Figure 4.7), indicating that the condition of each vehicle varies and requires tailored management strategies for charging and discharging cycles [112].

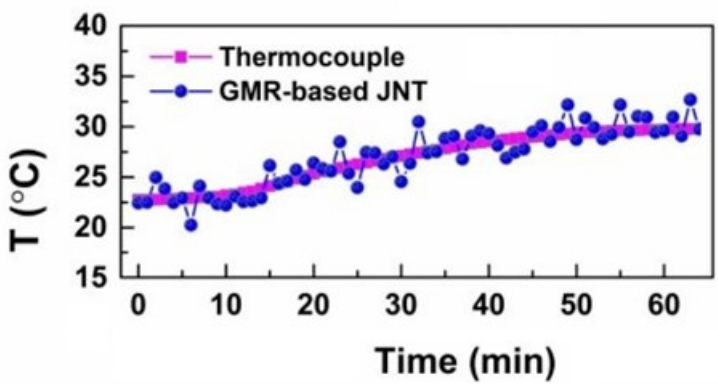


Figure 4.7: Measured temperature of a vehicle while driving.

However, the dataset utilized in this study lacks direct information on the initial temperatures of the vehicles. Therefore, for this analysis, we approximate the initial temperature of each vehicle to be equal to the ambient temperature. Recognizing that ambient temperature can fluctuate daily, we adopt a simplification by assuming a constant ambient temperature for all vehicles across all days under consideration. This approach allows us to maintain focus on the

primary objectives of the study while acknowledging the limitations imposed by the available data.

2. The act of charging or discharging batteries within the parking environment can also lead to temperature rises. A model that accurately represents the impact of these activities on temperature is essential for effective management.

$$T_t^i = T_{t-1}^i + (P_{th,t-1}^i + Q_{gen,t-1}^i - h \cdot A \cdot (T_{t-1}^i - T_{atm})) \cdot C_{th} \cdot \Delta t \cdot k$$

$$\begin{cases} P_{th,t}^i = \dfrac{P_t^{i+} - P_t^{i-}}{t_{eff}} \cdot eff \\ Q_{gen,t}^i = \dfrac{P_t^{i+} - P_t^{i-}}{R_{ref} \cdot t_{eff}} \cdot (1 - eff) \\ Q_{ext,t}^i = h \cdot A(T_t^i - T_{atm}) \end{cases}$$

Parameters	Values
h	50
A	1.5
C_{th}	360000
R_{ref}	0.005
eff	0.85

This approach is rooted in thermal dynamics and heat transfer principles, employing the lumped capacitance model for simplified analysis of systems where temperatures change over time but are uniformly distributed [113]. However, the model does not incorporate temperature control measures, which are critical for maintaining temperatures within optimal ranges through the use of heating, ventilation, and air conditioning (HVAC) systems [114] (Figure 4.8):

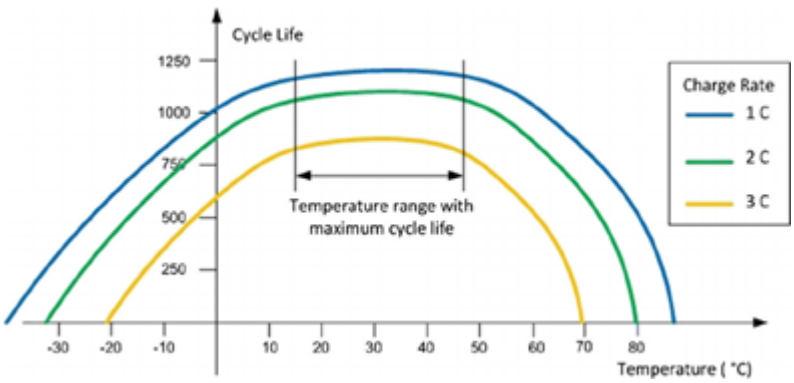


Figure 4.8: Optimal operational temperature EV battery.

To mitigate these variations' impact, a scaling factor k is introduced, albeit at the expense of increased approximation error.

- **DOD: Depth-Of-Discharge**, This measures the difference between the initial and final SOC over a charge and discharge cycle. The model initially does not factor in battery degradation for charging, assuming degradation only during discharging, which effectively doubles its perceived impact. This is based on the assumption that energy use aligns with a charging process, even if not perfectly synchronized with the cycle:

$$DOD_t^i = SOC_{t-1}^i - SOC_t^i \tag{4.10}$$

- C_{ch}, C_{dch}: These rates indicate the speed at which a battery charges or discharges about its total capacity. A 1-C rate, for example, means a battery can fully charge or discharge in one hour:

$$C_{ch,t}^i = \frac{P_t^{i+}}{Q_0}, \quad C_{dch,t}^i = \frac{P_t^{i-}}{Q_0} \tag{4.11}$$

- $mSOC$: The battery's performance is influenced not only by its charging and discharging activities but also by its initial and final SOC. The average or middle SOC, is calculated between two consecutive states SOC_{t-1} and SOC_t, is an important parameter in this context:

$$mSOC_t^i = \frac{SOC_{t-1}^i + SOC_t^i}{2} \tag{4.12}$$

- FEC: This parameter represents a complete charge and discharge cycle, calculated as twice the DOD to include both charging and discharging phases ($2 \cdot DOD$) (the 2 accounts for both charging and discharging phases). This parameter, along with the exponent (a_{opt}), accounts for the full charge and discharge functionality of the considered technology.

This document proposes testing a new algorithm, where the usage cost of an EV will be taken into account by an optimizing system. This system aims to compensate owners for leaving more energy in their EVs by the day's end. The main goal of this algorithm is to enhance the usage of the electric vehicle. The control system is designed to evaluate the risk (and associated costs) of each action, promoting the efficient use of the EV's battery (Figure 4.9):

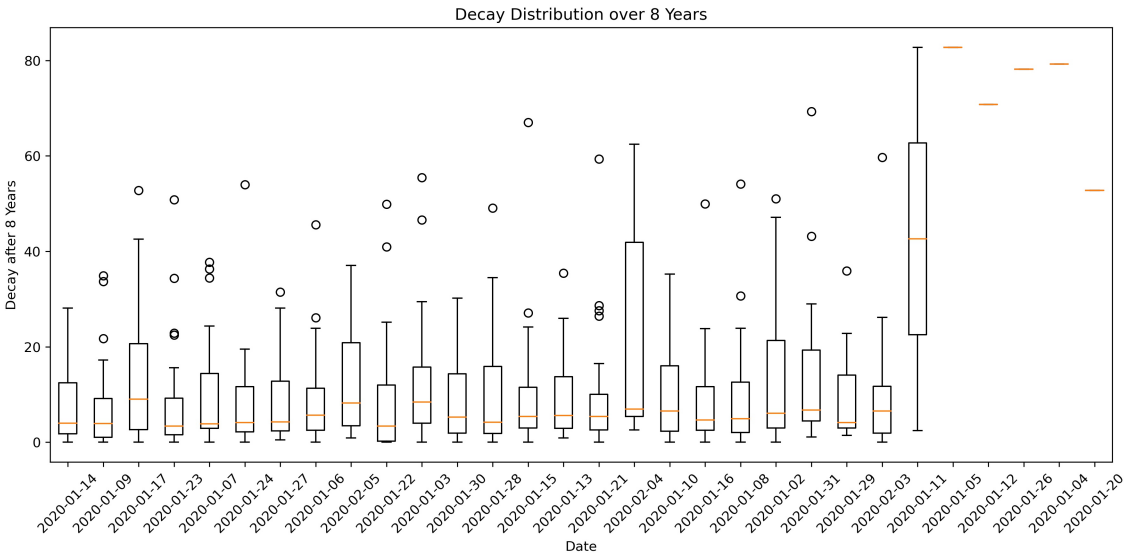


Figure 4.9: Decay distribution over fleet vehicles after 8 years of fixed use.

A box plot is utilized to examine the effects of this algorithm. This type of graphical representation uses boxes to denote the interquartile range (IQR), encompassing the central 50% of the data, where most data points are found. The median is shown by a line inside the box, while the lines extending from the box's ends represent variability outside the upper and lower quartiles. Outliers, or data points significantly different from the rest, are depicted as dots or circles beyond these lines. The data are organized in descending order of savings observed in a previous table, indicating that dates with higher savings experienced less vehicle damage, likely due to the fleet's favorable condition.
Conversely, on the right side, finding an optimal solution was more challenging, requiring intensive use of the available batteries. This outcome is concerning since, according to standard EV battery warranties, batteries should last at least eight years with an SOH above 80%. However, projecting daily usage over eight years reveals that most vehicles would exceed the 20% SOH decline.

The document then shifts focus to modifying the objective function imposing the following constraint:

$$(SOC^i_{fin} = SOC^i_{in} + \frac{\Delta SOH^i \cdot B^i}{\pi^+})$$

This innovative approach enables the system to internalize the cost associated with the SOH decay of each vehicle through its impact on the SOC. By doing so, it elegantly merges the considerations for monetary expenses related to energy consumption and the degradation costs due to vehicle usage. This integration means that instead of having to delicately balance or weigh the financial cost against the SOH decay of the vehicles, the

latter is effectively encapsulated within the former.
The resulting model simplifies decision-making for the industry: it allows for the extensive use of the EV fleet as required, without the primary focus on minimizing vehicle degradation. This adjustment implies that any negative impact on a vehicle's SOH, which would necessitate additional costs, is automatically factored into the overall cost calculation. Thus, if the operational necessity dictates, the industry can opt to use the EVs extensively, accepting the higher operational costs as a trade-off for immediate utility, without directly optimizing against SOH degradation. From the new simulation is resulting (Figure 4.10):

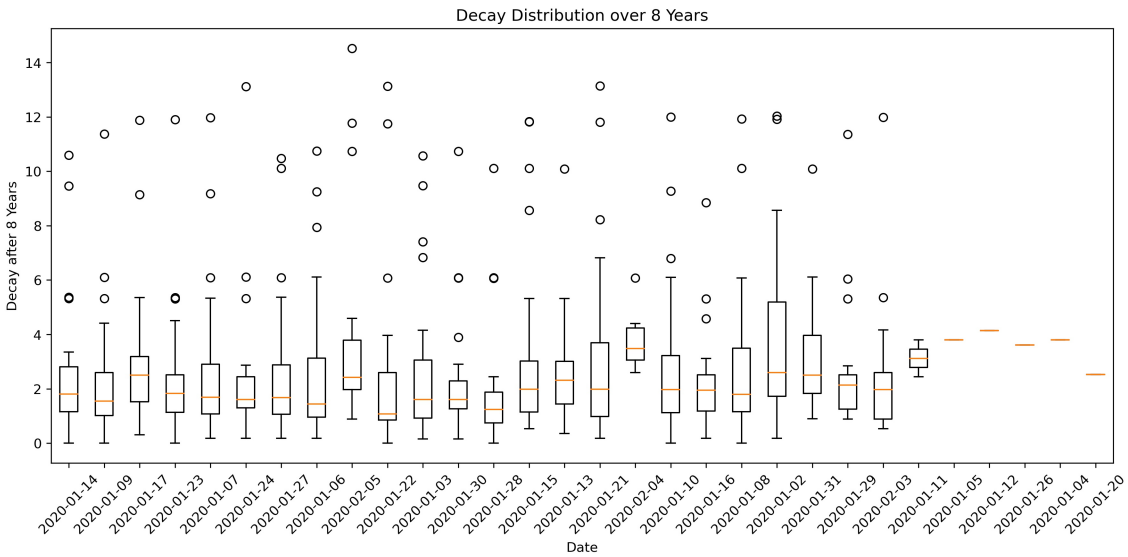


Figure 4.10: Decay distribution over fleet vehicles after 8 years of minimized use.

Upon analyzing the latest results, it is evident that decay has decreased compared to previous measurements. Furthermore, concerning the cost savings difference in respect of the optimal quantities found previously without considering decay:

Min Δ Savings	Max Δ Savings	Median Δ Savings
-0.000115%	-1.74207%	-0.004031%

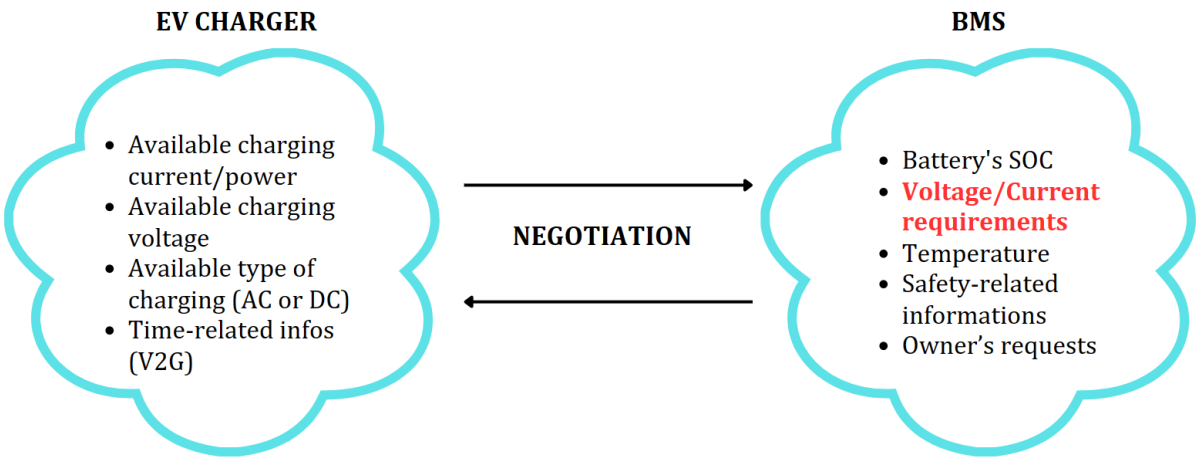
Therefore simulations showed a significant reduction in battery degradation and little changes in savings, indicating controlled operations can positively impact. However, these experiments also suggest that prioritizing company savings leads to a preference for using vehicles with cheaper batteries and lower service costs. This cost-centric vehicle selection, evident from the scattered outliers in the box plot, highlights the need for alternative

solutions, such as negotiation algorithms allowing each vehicle to set its usage price. Such strategies could make the system more appealing to EV owners.

4.5. BMS implementation

The next phase involves integrating the BMS into our evaluation. As discussed in previous sections, the main limitation to an EV battery's usable power does not stem from the availability of chargers but rather from the battery's inherent capacity limitations. It's important to acknowledge that batteries usually support much lower power levels than those offered by EV chargers, with the capacity depending on the battery's condition. Key factors such as the SOC, temperature, and SOH significantly influence the charger's immediate power output. This is especially relevant when optimizing charging and discharging schedules for efficient energy storage, requiring detailed consideration of the battery's current status and potential limitations. Here, the BMS is crucial, aiming to protect the battery in real-time. It focuses on conforming to existing safety standards rather than predicting battery behavior, which suggests that establishing a communication link between the BMS and the charger could introduce initial implementation challenges. The discussion shifts to how the BMS limits operations based on the SOC, suggesting an adaptable maximum power level that varies with the vehicle's SOC.

An initial step might involve simulating a scenario where a fixed maximum and minimum power limit is set for each vehicle, but the MPC operates based on wrongly estimated limits. To align the simulation closer to reality, a feedback loop is proposed where each BMS informs the MPC of the actual power limit, which might adjust the applied power. In typical scenarios where a charger connects to an EV, specific details like maximum and minimum power levels may not be readily available, as outlined in the previous chapter. However, current limits are communicated between the charger and the EV through a negotiation process, in line with the IEC 62196 standard:



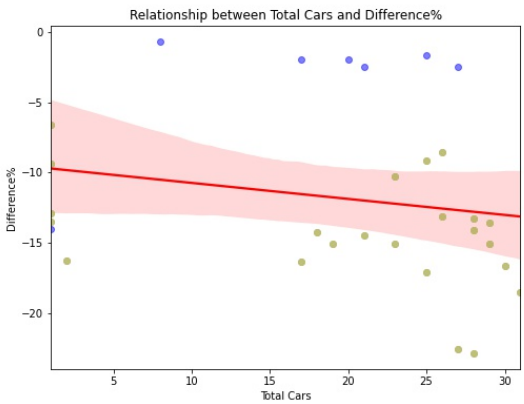
This negotiation enables the continuous update of information to the controller, providing

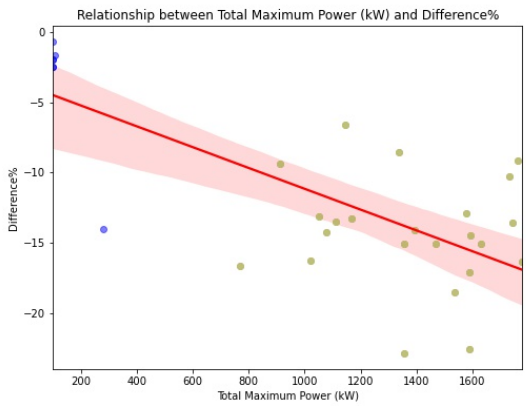
insights into the battery's operational limits based on the current SOC. The controller can use this information to more accurately predict the system's actual performance.
Two scenarios are considered:

1. **Overestimation of limits by 50%:** Here, the MPC schedules operations that the system cannot support because the assumed limits are higher than the actual limits. The results indicate significant variability in savings, dependent on each fleet's condition:

Min Δ Savings	Max Δ Savings	Median Δ Savings
-0.65606%	-22.871353%	-13.519534%

This analysis underscores the complex interplay between the BMS and the EV charging strategy, highlighting the necessity of accurate data and real-time communication to optimize energy management and safeguard battery health. A regression model could further illustrate these variations:





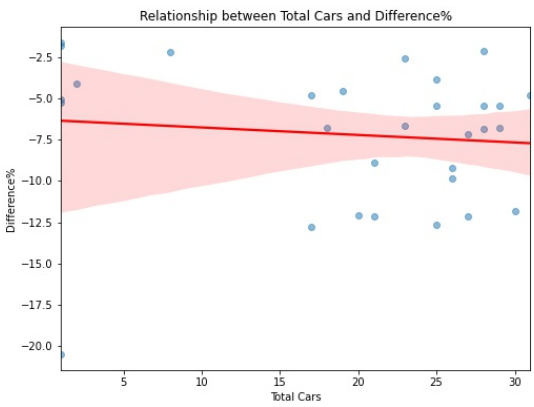
These findings are not straightforward and thus very intriguing. On one hand, it might seem that having a larger fleet would allow for easier correction of any discrepancies from the previous operation due to the increased number of vehicles available. However, the results indicate the opposite effect. This contradiction likely arises because the windows for optimal operation are brief, and any failure to execute precisely within these windows significantly impacts savings. There is also a difference between the yellow and blue points, with the yellow point representing fleets on which the total available power is higher than a specific quantity. This further clarifies that even with a large number of vehicles, the savings difference can

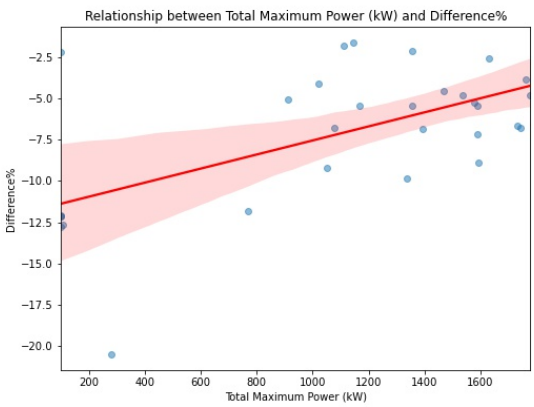
be lower in scenarios where the maximum power available is less, hence reducing the margin of error. Therefore, as anticipated, the greater the overestimation of power, the larger the error. Nonetheless, even with a high number of vehicles, optimal energy purchase, sale, and usage are crucial. Missing these optimal moments leads to lost savings.

2. **Underestimation of limits by 50%:** In this scenario, the MPC schedules operations that the real system will not need to adjust, as the operations do not exceed the actual limits:

Min Δ Savings	Max Δ Savings	Median Δ Savings
-1.611636%	-20.502902%	-6.078723%

The results show a higher minimum savings case, indicating that the optimal solution is consistently worse than in the previous scenario, but with a lower maximum and median savings, suggesting that non-truncated responses generally perform better:

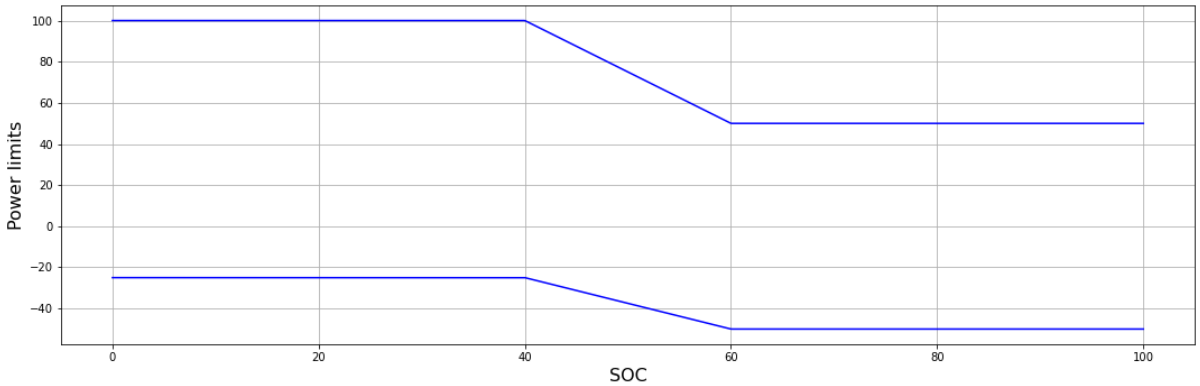




This outcome points to a clear dependency on fleet parameters, with an increase in available power typically reducing losses relative to the optimal case. However, the number of vehicles does not seem to significantly affect the loss or gain in savings, suggesting a certain threshold of fleet size beyond which additional vehicles do not contribute to improved energy management efficiency.

In the absence of empirical data to accurately depict real-world behavior, this study utilizes simulations to replicate response curves similar to those observed in experiments by

P3 Group. These simulations are designed to further elucidate the dynamics of charging, employing a variety of models to simulate maximum and minimum power levels:



These models include simple linear and nonlinear behaviors, as well as complex step curves, with parameters randomly assigned to each vehicle to simulate a scenario of high variability. The methodology assumes a fixed understanding by the MPC of the maximum and minimum power levels, set at the median value of the entire curve. The simulation results are as follows:

Min Δ Savings	Max Δ Savings	Median Δ Savings
-0.033436%	-6.609356%	-2.416485%

These findings imply that a full understanding of the BMS's simulated responses concerning maximum and minimum power across the SOC spectrum isn't crucial for obtaining satisfactory outcomes. A median value can adequately inform the effective deployment of the vehicle as a BESS.

However, it's critical to recognize that these are simulation models, and real-world performance may differ depending on the variable SOC. This variability presents a considerable challenge for the scheduling system, which necessitates precise knowledge of usage conditions about the current SOC. The fact that changes in the system's states also lead to variations in the bounds related to the system's inputs necessitates the incorporation of an additional complexity layer. Now, it must be acknowledged that scheduled operations will alter the future boundaries of these operations. As a result, dynamic constraints must be introduced:

$$\begin{cases} 0 \leq P_t^{i+} \leq P_{MAX}(SOC) & \text{for t} \in S^i \qquad \text{for i} \in N \qquad (4.13) \\ 0 \geq P_t^{i-} \geq P_{MIN}(SOC) & \text{for t} \in S^i \qquad \text{for i} \in N \qquad (4.14) \end{cases}$$

To adapt to these continuously changing conditions, an adaptive corrective strategy employing the Online Kernel Regression technique is utilized, ensuring that charging and discharging operations are optimized in real-time based on the latest data [115, 116].

Online Kernel Regression is an algorithm in machine learning that predicts values without relying on a predefined form (non-parametric). It updates its predictions by considering one piece of data at a time. This quality makes it especially useful when data is received in a sequence and the model must adjust in real-time. Through this method, the model continually learns and adapts to new information without starting the learning process over.
To predict a new output $\hat{y}$ for an input x, Online Kernel Regression computes a sum weighted by the kernel function across all known inputs and the new one:

$$\hat{y}(x) = \sum_{i=1}^{n} \alpha_i K(x, x_i)$$

where:

- α_i are the learned weights.
- x_i are the previously seen input vectors.
- n is the number of previously seen data points.

At the heart of this technique is the kernel function, which quantifies how similar two input vectors are. This function allows the algorithm to interpret the input data in a higher-dimensional space without directly transforming it, facilitating the identification of intricate data patterns.
An example of a kernel function is the Laplace Kernel, used for the proposed simulation and expressed as:

$$K(x, x') = \exp\left(-\frac{\|x - x'\|}{\sigma}\right)$$

where:

- x and x' are two input feature vectors.
- $\|x - x'\|$ is the L1 norm (Manhattan distance) between the vectors.
- σ is a positive scale parameter that controls the width of the kernel.

Upon receiving a new data point, the algorithm uses a weighted sum of kernel-derived similarities between this point and all previous ones to predict its target value. These weights are fine-tuned over time to decrease the error in prediction, often through a

gradient descent method.
The prediction error for a new point is defined as

$$e_{new} = y_{new} - \hat{y}_{new}$$

With a new data point $(x_{\text{new}}, y_{\text{new}})$, the algorithm updates the weights α to reduce this new point's prediction error. This update depends on a loss function, typically squared error loss:

$$L(y_{\text{new}}, \hat{y}(x_{\text{new}})) = (y_{\text{new}} - \hat{y}(x_{\text{new}}))^2$$

The update rule incorporates a learning rate η, which may decrease over time to adjust the model more finely with accumulated data and can include regularization to prevent overfitting.

Including a decay factor, the rule for updating weights at time t is:

$$\eta_t = \frac{\eta_0}{1 + \delta t}$$

where η_0 is the initial learning rate and δ is the decay rate.

Incorporating the forgetting factor, the weight update rule at time t becomes:

$$\alpha_i^{(new)} = \lambda \alpha_i + \eta_{new} e_{new} K(\mathbf{x}_{new}, \mathbf{x}_i)$$

This ensures older data points gradually lessen in influence, and the learning rate's decrease slows weight adjustments, promoting nuanced model modifications.
Online Kernel Regression's adaptability to different kernel functions allows it to be tailored to capture diverse data similarities, influencing how well the model can learn and generalize.

The concluding simulations involve executing MPC to find the optimal schedule every 15 minutes and applying Online Kernel Regression every minute to upload its knowledge of the limits (Figure 4.11).

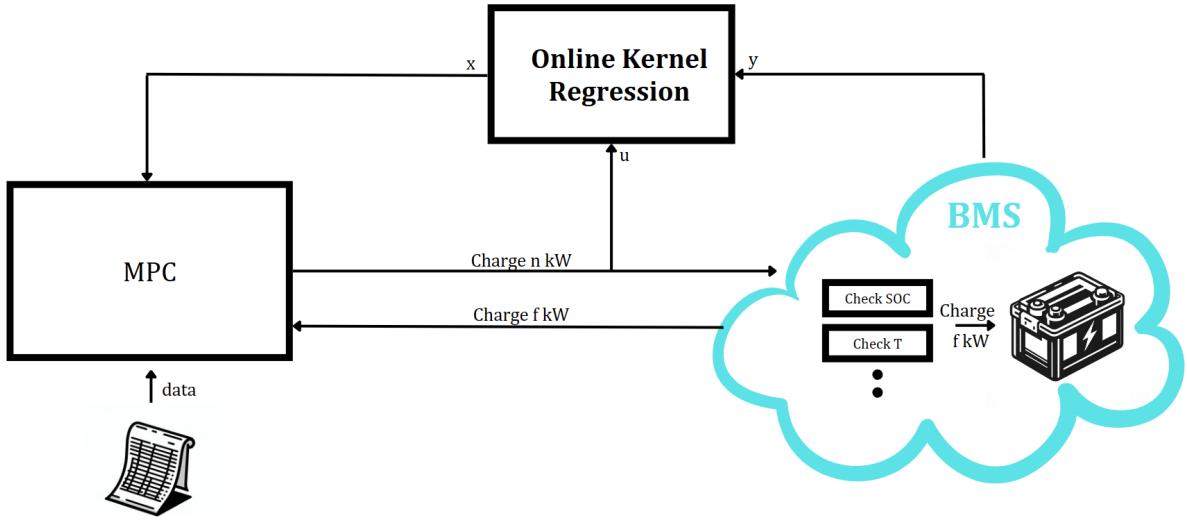
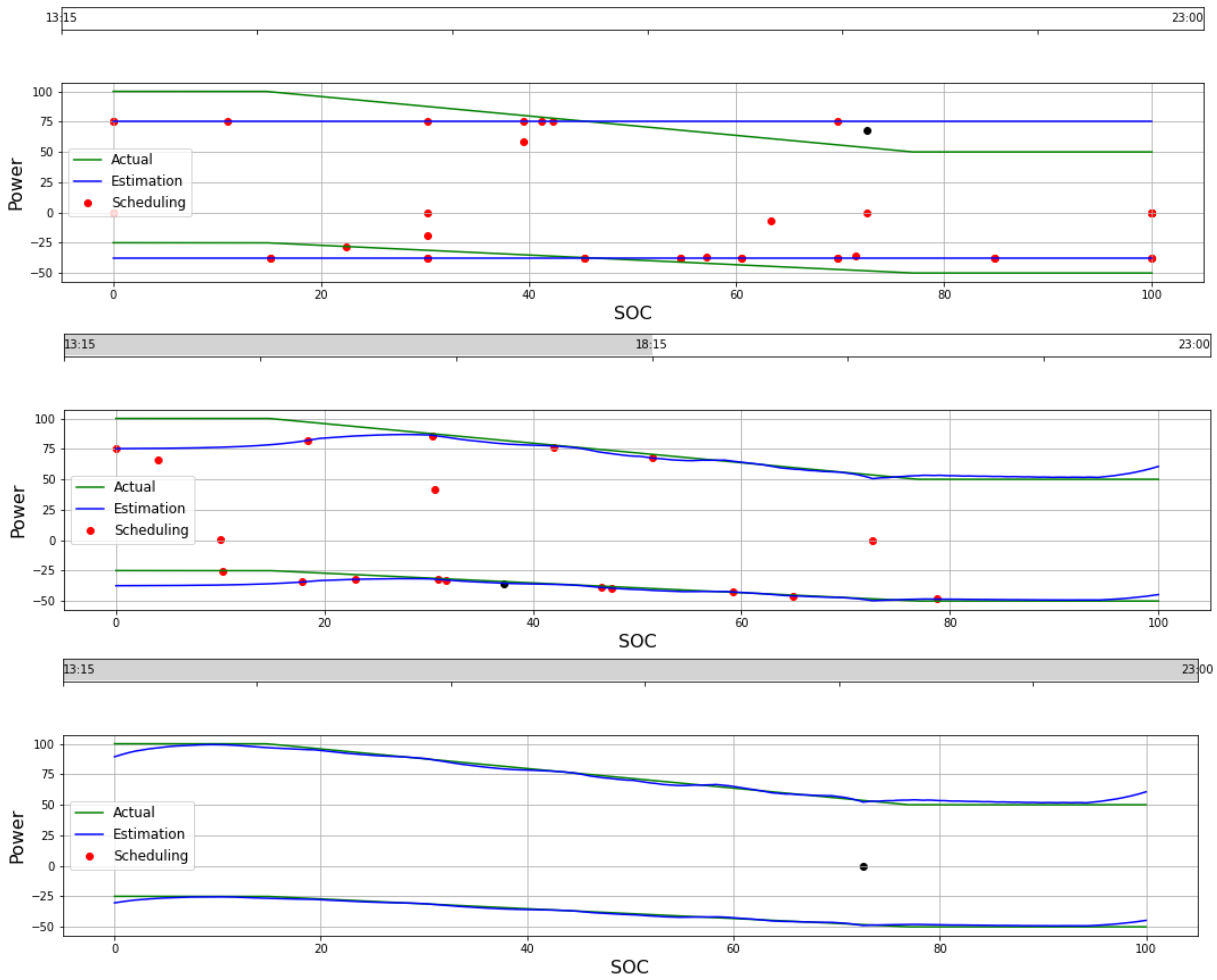


Figure 4.11: Online control scheme with OKR.

The final outcomes illustrate that an online approach is beneficial for understanding the intricate behavior of the SOC and, as a result, approaches the optimal solution more closely. By adapting in real time to new data, this method allows for a dynamic and flexible understanding of SOC behaviors, enhancing the ability to predict and adjust to changes effectively. This capability is crucial for applications requiring precise energy management and optimization, demonstrating the value of online learning algorithms in achieving near-optimal performance in complex systems.

Approach	Min Δ Savings	Max Δ Savings	Median Δ Savings
Fixed Knowledge	-0.033436%	-6.609356%	-2.416485%
Average Starting Point	-0.029143%	-6.240192%	-2.195646%

Regarding the estimation of curves, we present an example involving a vehicle as follows:



In these diagrams, the color coding is defined as:

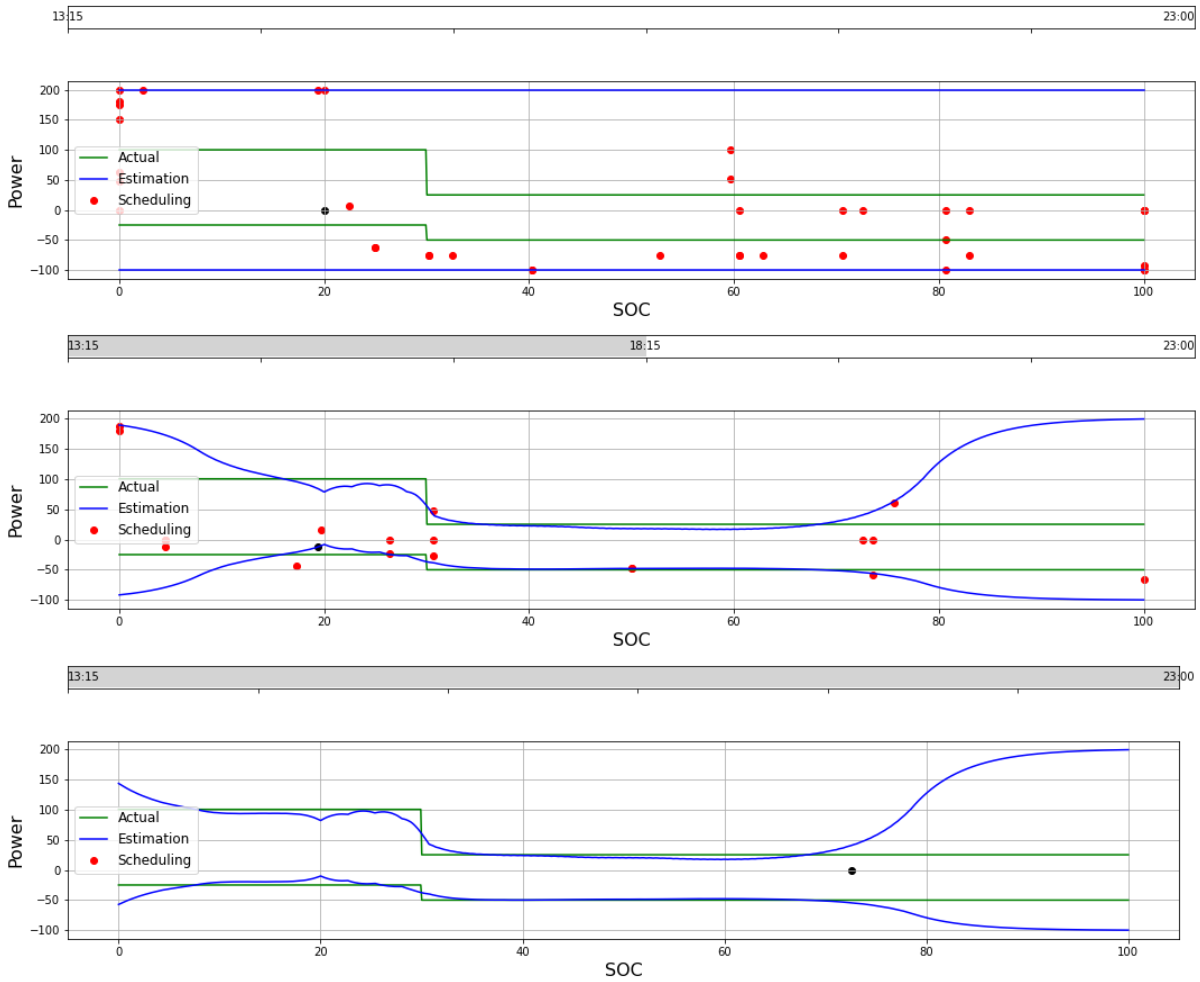
- Blue lines depict the estimated current range of maximum and minimum power capacities.
- Green lines illustrate the actual limits of maximum and minimum power.
- Red dots indicate the power planned for charging/discharging at specific times along the horizon.

The goal of this visualization is to assess the accuracy of the fitting process, its operational requirements, and the consequences of initial scheduling errors that exceed the green line constraints. Assuming an average starting condition aids the learning process by minimizing the occurrence of incorrect scheduling. In terms of the learning mechanism, introducing 15 new data points at every optimization step significantly benefits the system. Nonetheless, similar to all machine learning models, the challenge here is not solely the volume of data but also its quality (usefulness). The quality in this context

heavily relies on vehicle utilization since acquiring new data about boundary conditions requires reaching a new SOC. Consequently, in a broad scenario, having a large fleet may not be advantageous due to reduced utilization per vehicle. However in this scenario, as evidenced by the outcome following decay minimization (Figure 4.10), only a few vehicles are considered daily. Lastly, when dealing with a more complex curve for learning purposes, the estimation may not always align closely with the actual curve.
Building on the foundation of earlier tests that commenced from a positive outset, the final experiments shift focus to what can be termed as the worst-case scenario. This scenario, as unveiled in the initial tests, is characterized by significantly overestimated limits. The commencement with initial values of Pmax and Pmin being set at a 200% increase yields the following results, presented in a table format:

Approach	Min Δ Savings	Max Δ Savings	Median Δ Savings
Fixed Knowledge	-0.033436%	-6.609356%	-2.416485%
Average Starting Point	-0.029143%	-6.240192%	-2.195646%
+200% starting point	-0.562459%	-24.001422%	-9.274811%

As anticipated, the optimization outcomes have significantly deteriorated, indicating a pronounced dependence on the starting conditions. Notably, even though the median loss does not exceed a 10% reduction in savings, possessing minimal information about the specific vehicle—such as the variation in power during charging—could substantially aid the system in achieving a solution nearly identical to the optimal one. This observation underscores the machine learning algorithm's heightened reliance on the precision of data.


13:15
23:00
Power
Actual
Estimation
Scheduling
SOC
13:15
18:15
23:00
Power
Actual
Estimation
Scheduling
SOC
13:15
23:00
Power
Actual
Estimation
Scheduling
SOC

5 | Comprehensive Testing

This section details the exhaustive testing methodology employed throughout the analysis, which underpinned the decisions and insights discussed earlier.

The approach to our research workflow was not to directly target the topics discussed within the research from the outset. Instead, it involved a methodical examination, starting with the foundational elements of our hypotheses. By rigorously testing various facets, we incrementally focused on areas of greater significance. This systematic exploration facilitated a deeper understanding of the subject matter, allowing for a refined analysis of the core themes. We then moved to examine aspects that were of paramount interest, based on preliminary findings.

Several of these intermediate results, which were pivotal in shaping the course of our investigation, are presented in the subsequent chapter. This iterative process not only ensured thorough scrutiny but also helped in identifying and prioritizing areas with the most impactful insights.

5.1. Investigating Low Consumption Patterns

The initial phase of our research centered on analyzing actual household energy consumption data collected in our dataset. This examination was particularly focused on identifying patterns of EV decay over the initial timeframe of 30 days with different consumption and energy price profiles:

	Tot_cars	Int_t	Max_En	Min_En	Median_En	Median_Dec_8y%	Savings%	Decay_Savings%
2020-01-23	27.0	05:45 - 21:00	0.55	-0.0	0.02	4.47%	81.39%	81.38%
2020-01-31	17.0	06:30 - 21:15	0.86	-0.0	0.003	4.32%	78.12%	78.12%
2020-01-30	26.0	06:30 - 20:30	0.19	-0.0	0.0	1.96%	54.31%	54.29%
2020-01-28	27.0	06:15 - 19:00	0.23	0.0	0.0	2.17%	50.74%	50.67%
2020-01-27	28.0	06:30 - 19:45	0.54	-0.0	0.0	1.45%	37.97%	37.44%
2020-01-04	1.0	13:15 - 23:00	1.03	1.03	1.03	10.76%	36.13%	36.12%
2020-01-20	1.0	07:00 - 15:15	0.55	0.55	0.554	8.65%	33.67%	33.41%
2020-01-29	21.0	06:15 - 18:30	1.0	-0.0	0.0	2.73%	28.94%	28.89%
2020-01-07	29.0	06:15 - 21:00	1.93	0.0	0.0	2.33%	26.59%	26.08%
2020-01-22	25.0	06:00 - 23:00	1.18	-0.0	0.0	3.01%	25.33%	25.25%
2020-02-04	8.0	09:00 - 21:15	0.87	-0.0	0.001	4.98%	20.55%	20.34%
2020-01-24	25.0	06:15 - 23:30	3.52	-0.0	0.786	6.66%	18.63%	17.52%
2020-02-03	17.0	05:30 - 18:15	0.49	-0.0	0.0	3.78%	16.51%	16.28%
2020-01-21	28.0	06:45 - 21:45	2.21	-0.0	0.0	1.35%	16.44%	14.78%
2020-01-17	20.0	06:30 - 23:00	3.57	-0.0	0.25	5.76%	15.04%	14.15%
2020-01-16	25.0	06:00 - 21:45	2.23	-0.0	0.107	6.06%	13.03%	12.35%
2020-01-03	21.0	06:15 - 19:45	0.98	0.0	0.0	2.0%	11.91%	11.83%
2020-01-14	30.0	06:00 - 21:15	1.69	0.0	0.09	1.91%	11.13%	10.11%
2020-01-15	28.0	05:30 - 20:45	1.81	-0.0	0.007	2.93%	10.62%	10.08%
2020-01-10	23.0	06:30 - 19:15	0.2	-0.0	0.0	4.95%	9.36%	9.34%
2020-01-05	1.0	12:00 - 21:45	2.98	2.98	2.982	8.04%	8.09%	6.75%
2020-01-02	19.0	06:00 - 20:45	0.04	-0.0	0.0	2.35%	6.81%	6.8%
2020-01-06	31.0	06:15 - 22:30	1.2	-0.0	0.0	1.16%	6.55%	5.76%
2020-02-05	18.0	06:15 - 23:00	2.22	0.0	0.009	4.16%	6.52%	6.1%
2020-01-08	23.0	06:00 - 22:30	1.71	0.0	0.0	2.18%	6.42%	6.28%
2020-01-09	29.0	06:00 - 21:15	3.17	0.0	0.036	2.97%	5.63%	4.86%
2020-01-13	26.0	06:00 - 20:15	1.77	-0.0	0.0	3.74%	5.49%	5.26%
2020-01-12	1.0	11:15 - 21:00	3.72	3.72	3.723	10.8%	4.52%	3.87%
2020-01-26	1.0	10:15 - 20:00	0.8	0.8	0.802	6.6%	2.41%	2.11%
2020-01-11	2.0	08:45 - 21:45	1.37	0.94	1.156	10.02%	2.02%	1.87%

This analysis unveiled that, due to the relatively low energy transfer to each vehicle, the rates of energy decay and battery utilization were minimal, even in scenarios devoid of specific decay minimization strategies. Such findings underscore the inherent efficiency in energy consumption within the analyzed context, which proved to be a crucial baseline understanding for our study.

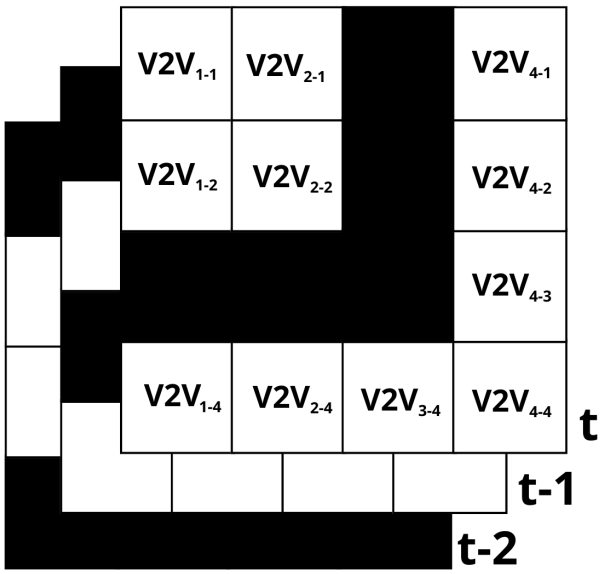
Given the primary objective of our research—to critically assess fleet utilization under a spectrum of operational constraints and limitations—we proceeded to escalate the energy consumption figures by a factor of 50. This adjustment was strategically made to simulate a consumption profile akin to that of a metallurgical factory, thereby imposing a more challenging yet realistic scenario for our study. This escalated consumption model aims to offer insights into the potential complexities and challenges of fleet utilization when subjected to stringent limits and constraints.

By aligning the consumption profile more closely with high-demand industrial scenarios, we aimed to delve deeper into the nuances of energy management and efficiency in contexts that significantly strain existing resources. However, to ensure the study remained

grounded in scenarios of practical significance, we decided against further increasing the consumption levels to mimic an even more energy-intensive facility. This decision allows us to maintain a focus on applications and implications that are directly relevant and applicable to the real-world challenges faced by fleets today, particularly in high-demand but realistic operational environments.

5.2. V2V Implementation

Prior to finalizing our approach, we undertook a preliminary assessment aimed at quantifying the financial benefits of energy exchange on an individual vehicle basis. This assessment also included a robust set of constraints specifically designed to optimize energy sharing among vehicles:



The theoretical framework for facilitating these energy exchanges was articulated through the construction of an antisymmetric matrix. Within this matrix, diagonal elements were designated to represent power transactions with the industry, while the off-diagonal elements—and their inversely indexed counterparts—were used to denote energy transfers between vehicles. For instance, an element $V2V_{1-2}$ illustrates the energy transferred from vehicle 1 to vehicle 2, and conversely, $V2V_{2-1}$ signifies the reverse flow of energy, effectively capturing the bidirectional nature of these transactions.

Despite the initial success of our approach, the final adaptation of the algorithm took a notably different direction. Rather than evaluating the financial savings associated with each vehicle individually and subsequently combining these savings with the energy transactions between vehicles through the antisymmetric matrix, we opted for a holistic analysis. This involved considering the aggregate sum of power exchanges across the entire fleet. This methodological pivot, although seemingly subtle, marked a significant enhancement in our analysis:

	Int_t	Tot_cars	Tot_SOC kWh	Tot_Empty_SOC kWh	V2B_New_cost €	V2V_New_cost €	V2B_Savings%	V2V_Savings%	V2V_Solutions	V2B_Solutions
2020-01-23	05:45 - 21:00	27.0	1441.2	319.8	121.443	121.443	81.39%	81.39%	1	2
2020-01-31	06:30 - 21:15	17.0	909.2	233.4	850.758	850.758	78.12%	78.12%	1	3
2020-01-30	06:30 - 20:30	26.0	1508.2	318.9	243.339	243.366	54.31%	54.3%	1	2
2020-01-28	06:15 - 19:00	27.0	1580.2	335.3	26.422	26.422	50.74%	50.74%	1	3
2020-01-27	06:30 - 19:45	28.0	1574.2	363.0	13.236	13.236	37.97%	37.97%	1	3
2020-01-04	13:15 - 23:00	1.0	62.0	17.0	1618.33	1618.33	36.13%	36.13%	1	2
2020-01-20	07:00 - 15:15	1.0	62.0	36.0	9.348	9.348	33.67%	33.67%	1	2
2020-01-29	06:15 - 18:30	21.0	1161.2	217.9	83.486	83.486	28.94%	28.94%	1	4
2020-01-07	06:15 - 21:00	29.0	1521.2	315.2	21.604	21.604	26.59%	26.59%	1	3
2020-01-22	06:00 - 23:00	25.0	1315.2	223.9	88.252	88.252	25.33%	25.33%	1	2
2020-02-04	09:00 - 21:15	8.0	438.2	131.4	12.681	12.681	20.55%	20.55%	1	2
2020-01-24	06:15 - 23:30	25.0	1377.2	290.2	109.175	109.175	18.63%	18.63%	1	2
2020-02-03	05:30 - 18:15	17.0	1010.0	205.7	12.726	12.726	16.51%	16.51%	1	2
2020-01-21	06:45 - 21:45	28.0	1394.2	323.8	21.446	21.446	16.44%	16.44%	1	3
2020-01-17	06:30 - 23:00	20.0	1091.2	199.8	50.799	50.799	15.04%	15.04%	1	2
2020-01-16	06:00 - 21:45	25.0	1370.2	317.3	53.458	53.458	13.03%	13.03%	1	2
2020-01-03	06:15 - 19:45	21.0	1131.0	247.6	64.711	64.711	11.91%	11.91%	1	2
2020-01-14	06:00 - 21:15	30.0	1637.2	350.7	47.691	47.691	11.13%	11.13%	1	3
2020-01-15	05:30 - 20:45	28.0	1405.2	336.6	84.221	84.221	10.62%	10.62%	1	3
2020-01-10	06:30 - 19:15	23.0	1120.2	269.4	91.943	91.943	9.36%	9.36%	1	2
2020-01-05	12:00 - 21:45	1.0	62.0	14.9	9.382	9.382	8.09%	8.09%	1	2
2020-01-02	06:00 - 20:45	19.0	983.0	228.3	67.526	67.526	6.81%	6.81%	1	3
2020-01-06	06:15 - 22:30	31.0	1697.2	392.1	17.992	17.992	6.55%	6.55%	1	3
2020-02-05	06:15 - 23:00	18.0	989.2	240.4	70.199	70.199	6.52%	6.52%	1	3
2020-01-08	06:00 - 22:30	23.0	1208.2	225.5	75.964	75.964	6.42%	6.42%	1	3
2020-01-09	06:00 - 21:15	29.0	1558.2	317.4	98.296	98.296	5.63%	5.63%	1	2
2020-01-13	06:00 - 20:15	26.0	1408.2	324.0	67.527	67.527	5.49%	5.49%	1	4
2020-01-12	11:15 - 21:00	1.0	62.0	17.2	23.25	23.25	4.52%	4.52%	1	2
2020-01-26	10:15 - 20:00	1.0	62.0	8.7	32.348	32.348	2.41%	2.41%	1	2
2020-01-11	08:45 - 21:45	2.0	134.0	22.4	77.371	77.371	2.02%	2.02%	1	2

This enhanced approach resulted in a noticeable uptick in the quality of solutions over various testing days, underscoring the efficacy of simplifying the energy exchange strategy. By comparing the V2B method—which incorporates the finalized formula to aggregate power exchanges by the vehicles—with the initial V2V strategy utilizing the antisymmetric matrix, it became evident that the streamlined approach substantially improved the algorithm's ability to find viable solutions.

Given the anticipated increase in algorithmic complexity, driven by considerations such as energy decay and power exchange limits, adopting this simplified method emerged as the most prudent course of action. This decision was fortified by the empirical evidence showcasing the streamlined strategy's superior efficiency and its capability to foster more effective solutions across varied operational scenarios.

5.3. Strategic Decay Minimization Negotiation

To optimize vehicle performance and operational costs, a negotiation framework was devised to address a multi-objective problem. The primary goal was to identify a strategy that minimizes vehicle battery decay while adjusting the decay weights during the optimization process. The results of implementing this strategy for a single vehicle are presented in the following table:

Weight	Decay %	Savings %
+ 0%	0.0004397357	50.74%
+ 10%	0.0003738347	50.73%
+ 20%	0.0003189172	50.69%
+ 30%	0.0002724485	50.63%
+ 40%	0.0002326182	50.55%
+ 50%	0.0001980987	50.46%
+ 60%	0.000167894	50.35%
+ 70%	0.0001414229	50.22%
+ 80%	0.000117553	50.17%
+ 90%	9.63568e-05	50.08%
+ 100%	7.72801e-05	49.94%

However, a notable challenge in this approach was the complexity involved in effectively representing the interests of each vehicle owner. Although the strategy was successful in reducing battery decay, which is directly linked to the lifecycle and performance of the vehicle, it also decreased the costs associated with energy compensation for battery degradation. To add a layer of decision-making, owners were required to choose their preferred level of decay, thus introducing a more corporate-oriented strategy. This pivot necessitated further exploration into the negotiation dynamics, an area ripe for future research that is particularly interested in the interplay between economic incentives and stakeholder preferences.

5.4. Pricing Effects on Vehicle Utilization

To deepen our understanding of how pricing strategies impact battery utilization, a series of experiments was conducted under different pricing assumptions.

Experiment 1: Uniformly Low Vehicle Pricing: Initially, a scenario was created where all vehicles were assigned a uniformly low price point:

	Tot_cars	Int_t	Max_En	Min_En	Median_En	Median_Dec_8y%	Savings%	Decay_Savings%
2020-01-23	27.0	05:45 - 21:00	0.0	0.0	0.0	1.644e-18%	81.39%	81.39%
2020-01-31	17.0	06:30 - 21:15	0.0	0.0	0.0	1.593e-18%	78.12%	78.12%
2020-01-30	26.0	06:30 - 20:30	0.0	0.0	0.0	1.593e-18%	54.31%	54.3%
2020-01-28	27.0	06:15 - 19:00	0.0	0.0	0.0	1.542e-18%	50.74%	50.74%
2020-01-27	28.0	06:30 - 19:45	0.0	0.0	0.0	1.593e-18%	37.97%	37.97%
2020-01-04	1.0	13:15 - 23:00	0.0	0.0	0.0	2.055e-18%	36.13%	36.13%
2020-01-20	1.0	07:00 - 15:15	0.0	0.0	0.0	1.747e-18%	33.67%	33.67%
2020-01-29	21.0	06:15 - 18:30	0.0	0.0	0.0	1.542e-18%	28.94%	28.94%
2020-01-07	29.0	06:15 - 21:00	0.0	2.368e-15	0.0	1.387e-18%	26.59%	26.59%
2020-01-22	25.0	06:00 - 23:00	0.0	0.0	0.0	1.490e-18%	25.33%	25.33%
2020-02-04	8.0	09:00 - 21:15	0.0	0.0	0.0	1.799e-18%	20.55%	20.55%
2020-01-24	25.0	06:15 - 23:30	0.0	0.0	0.0	1.542e-18%	18.63%	18.63%
2020-02-03	17.0	05:30 - 18:15	0.0	0.0	0.0	1.387e-18%	16.51%	16.51%
2020-01-21	28.0	06:45 - 21:45	0.0	0.0	0.0	1.465e-18%	16.44%	16.44%
2020-01-17	20.0	06:30 - 23:00	7.105e-15	1.693e-12	0.0	1.696e-18%	15.04%	15.04%
2020-01-16	25.0	06:00 - 21:45	0.0	0.0	0.0	1.542e-18%	13.03%	13.03%
2020-01-03	21.0	06:15 - 19:45	0.0	0.0	0.0	1.387e-18%	11.91%	11.91%
2020-01-14	30.0	06:00 - 21:15	2.268e-13	0.0	0.0	1.593e-18%	11.13%	11.13%
2020-01-15	28.0	05:30 - 20:45	7.105e-15	2.451e-12	0.0	1.439e-18%	10.62%	10.62%
2020-01-10	23.0	06:30 - 19:15	0.0	0.0	0.0	1.644e-18%	9.36%	9.36%
2020-01-05	1.0	12:00 - 21:45	0.0	0.0	0.0	2.055e-18%	8.09%	8.09%
2020-01-02	19.0	06:00 - 20:45	0.0	0.0	0.0	1.542e-18%	6.81%	6.81%
2020-01-06	31.0	06:15 - 22:30	0.0	0.0	0.0	1.490e-18%	6.55%	6.55%
2020-02-05	18.0	06:15 - 23:00	0.0	0.0	0.0	1.799e-18%	6.52%	6.52%
2020-01-08	23.0	06:00 - 22:30	0.0	0.0	0.0	1.439e-18%	6.42%	6.42%
2020-01-09	29.0	06:00 - 21:15	6.632e-13	6.132e-12	0.0	1.542e-18%	5.63%	5.63%
2020-01-13	26.0	06:00 - 20:15	7.105e-15	5.855e-12	0.0	1.516e-18%	5.49%	5.49%
2020-01-12	1.0	11:15 - 21:00	0.0	0.0	0.0	2.055e-18%	4.52%	4.52%
2020-01-26	1.0	10:15 - 20:00	0.0	0.0	0.0	2.055e-18%	2.41%	2.41%
2020-01-11	2.0	08:45 - 21:45	0.0	0.0	0.0	1.773e-18%	2.02%	2.02%

The results from this experiment indicated a consistent but reduced battery utilization across the fleet compared to the baseline scenario, suggesting that lower vehicle pricing leads to more even but overall diminished utilization.

Experiment 2: High Vehicle Pricing: Subsequently, an experiment was set up where the vehicle prices were fixed at a significantly higher rate:

	Tot_cars	Int_t	Max_En	Min_En	Median_En	Median_Dec_8y%	Savings%	Decay_Savings%
2020-01-23	27.0	05:45 - 21:00	2.586	0.1898	1.404	7.9%	81.39%	81.09%
2020-01-31	17.0	06:30 - 21:15	2.385	0.08298	0.4412	8.4%	78.12%	78.11%
2020-01-30	26.0	06:30 - 20:30	2.098	0.08098	0.5072	4.59%	54.31%	54.13%
2020-01-28	27.0	06:15 - 19:00	2.414	0.08196	1.161	4.39%	50.74%	47.21%
2020-01-27	28.0	06:30 - 19:45	4.009	0.6333	1.203	4.65%	37.97%	30.47%
2020-01-04	1.0	13:15 - 23:00	4.55	4.55	4.55	13.11%	36.13%	36.12%
2020-01-20	1.0	07:00 - 15:15	3.788	3.788	3.788	11.59%	33.67%	32.45%
2020-01-29	21.0	06:15 - 18:30	1.695	0.08101	0.7275	5.37%	28.94%	28.2%
2020-01-07	29.0	06:15 - 21:00	2.977	0.3292	1.445	4.9%	26.59%	20.58%
2020-01-22	25.0	06:00 - 23:00	1.416	0.08096	0.9249	5.47%	25.33%	24.57%
2020-02-04	8.0	09:00 - 21:15	1.507	0.08103	0.5141	8.54%	20.55%	19.73%
2020-01-24	25.0	06:15 - 23:30	4.744	0.08068	1.938	9.21%	18.63%	16.99%
2020-02-03	17.0	05:30 - 18:15	1.168	0.1625	0.5066	5.62%	16.51%	13.82%
2020-01-21	28.0	06:45 - 21:45	2.96	0.6447	1.352	6.54%	16.44%	10.09%
2020-01-17	20.0	06:30 - 23:00	2.248	0.08132	1.286	9.54%	15.04%	13.72%
2020-01-16	25.0	06:00 - 21:45	2.155	0.0	0.9055	6.79%	13.03%	11.51%
2020-01-03	21.0	06:15 - 19:45	1.527	0.1894	0.4999	4.63%	11.91%	11.01%
2020-01-14	30.0	06:00 - 21:15	2.62	0.09463	1.438	6.25%	11.13%	7.31%
2020-01-15	28.0	05:30 - 20:45	4.397	0.08104	1.385	5.9%	10.62%	8.25%
2020-01-10	23.0	06:30 - 19:15	1.169	0.0	0.4971	5.3%	9.36%	8.74%
2020-01-05	1.0	12:00 - 21:45	4.043	4.043	4.043	12.32%	8.09%	6.6%
2020-01-02	19.0	06:00 - 20:45	0.9099	1.596e-11	0.3632	5.0%	6.81%	6.23%
2020-01-06	31.0	06:15 - 22:30	0.0	0.0	0.0	0.0%	6.55%	0.0%
2020-02-05	18.0	06:15 - 23:00	1.983	0.08082	0.7843	7.03%	6.52%	5.6%
2020-01-08	23.0	06:00 - 22:30	1.807	0.0	0.8478	4.86%	6.42%	5.31%
2020-01-09	29.0	06:00 - 21:15	3.999	0.3694	1.429	6.55%	5.63%	3.42%
2020-01-13	26.0	06:00 - 20:15	1.708	0.1622	0.9261	5.87%	5.49%	4.09%
2020-01-12	1.0	11:15 - 21:00	3.791	3.791	3.791	13.53%	4.52%	3.92%
2020-01-26	1.0	10:15 - 20:00	2.413	2.413	2.413	10.02%	2.41%	2.03%
2020-01-11	2.0	08:45 - 21:45	1.139	1.062	1.1	11.51%	2.02%	1.89%

This test revealed a pronounced effect of vehicle pricing on battery utilization patterns, potentially leading to differential cost savings influenced by the varying prices of the vehicles.

Experiment 3: Equalizing Battery Decay: The final experimental setup aimed to normalize decay across all vehicles:

	Tot_cars	Int_t	Max_En	Min_En	Median_En	Median_Dec_8y%	Savings%	Decay_Savings%
2020-01-23	27.0	05:45 - 21:00	0.0	0.0	0.0	0.0%	81.39%	0.0%
2020-01-31	17.0	06:30 - 21:15	0.0	0.0	0.0	0.0%	78.12%	0.0%
2020-01-30	26.0	06:30 - 20:30	0.0	0.0	0.0	0.0%	54.31%	0.0%
2020-01-28	27.0	06:15 - 19:00	0.0	0.0	0.0	0.0%	50.74%	0.0%
2020-01-27	28.0	06:30 - 19:45	0.0	0.0	0.0	0.0%	37.97%	0.0%
2020-01-04	1.0	13:15 - 23:00	2.922	2.922	2.922	11.6%	36.13%	36.12%
2020-01-20	1.0	07:00 - 15:15	2.015	2.015	2.015	8.71%	33.67%	33.09%
2020-01-29	21.0	06:15 - 18:30	0.0	0.0	0.0	0.0%	28.94%	0.0%
2020-01-07	29.0	06:15 - 21:00	0.0	0.0	0.0	0.0%	26.59%	0.0%
2020-01-22	25.0	06:00 - 23:00	0.0	0.0	0.0	0.0%	25.33%	0.0%
2020-02-04	8.0	09:00 - 21:15	0.3763	0.3763	0.3763	5.02%	20.55%	19.99%
2020-01-24	25.0	06:15 - 23:30	0.0	0.0	0.0	0.0%	18.63%	0.0%
2020-02-03	17.0	05:30 - 18:15	0.0	0.0	0.0	0.0%	16.51%	0.0%
2020-01-21	28.0	06:45 - 21:45	0.0	0.0	0.0	0.0%	16.44%	0.0%
2020-01-17	20.0	06:30 - 23:00	0.0	0.0	0.0	0.0%	15.04%	0.0%
2020-01-16	25.0	06:00 - 21:45	0.0	0.0	0.0	0.0%	13.03%	0.0%
2020-01-03	21.0	06:15 - 19:45	0.0	0.0	0.0	0.0%	11.91%	0.0%
2020-01-14	30.0	06:00 - 21:15	0.0	0.0	0.0	0.0%	11.13%	0.0%
2020-01-15	28.0	05:30 - 20:45	0.0	0.0	0.0	0.0%	10.62%	0.0%
2020-01-10	23.0	06:30 - 19:15	0.0	0.0	0.0	3.63%	9.36%	8.49%
2020-01-05	1.0	12:00 - 21:45	1.666	1.666	1.666	8.21%	8.09%	7.48%
2020-01-02	19.0	06:00 - 20:45	0.0	0.0	0.0	0.0%	6.81%	0.0%
2020-01-06	31.0	06:15 - 22:30	0.0	0.0	0.0	0.0%	6.55%	0.0%
2020-02-05	18.0	06:15 - 23:00	0.0	0.0	0.0	0.0%	6.52%	0.0%
2020-01-08	23.0	06:00 - 22:30	0.0	0.0	0.0	0.0%	6.42%	0.0%
2020-01-09	29.0	06:00 - 21:15	0.0	0.0	0.0	0.0%	5.63%	0.0%
2020-01-13	26.0	06:00 - 20:15	0.0	0.0	0.0	0.0%	5.49%	0.0%
2020-01-12	1.0	11:15 - 21:00	1.884	1.884	1.884	10.96%	4.52%	4.19%
2020-01-26	1.0	10:15 - 20:00	1.144	1.144	1.144	7.34%	2.41%	2.23%
2020-01-11	2.0	08:45 - 21:45	0.6297	0.6297	0.6297	10.02%	2.02%	1.95%

The outcomes here underscored the intricacies involved when multiple vehicles are considered, showing that striking a balance between battery utilization and cost savings becomes more complex as the number of vehicles increases.

Each of these experiments sheds light on the multifaceted nature of battery utilization. Specifically, they highlight how vehicle pricing can significantly influence the economics of battery usage and, by extension, the overall energy management within a vehicular fleet. The nuanced findings from these tests are crucial for developing pricing strategies that optimize battery life and cost efficiencies in real-world applications.

5.5. Impact of Initial Conditions on OKR Efficacy

The robustness of the proposed online approach, as discussed in the main body of the research, was assessed by testing under various initial conditions. Specifically, the initial power levels for the experiments were set at two distinct starting points: one at the average historical value and the other at a value 200% higher than the actual observed levels. These initial settings were chosen to simulate a range of operational scenarios that could significantly affect the performance and outcomes of the approach.

The tests were performed with both a simplex and a more complex curve to forecast future trends and behaviors. This dual-faceted testing methodology was intended to evaluate the flexibility and adaptability of the online approach under differing circumstances. The results are as follows:

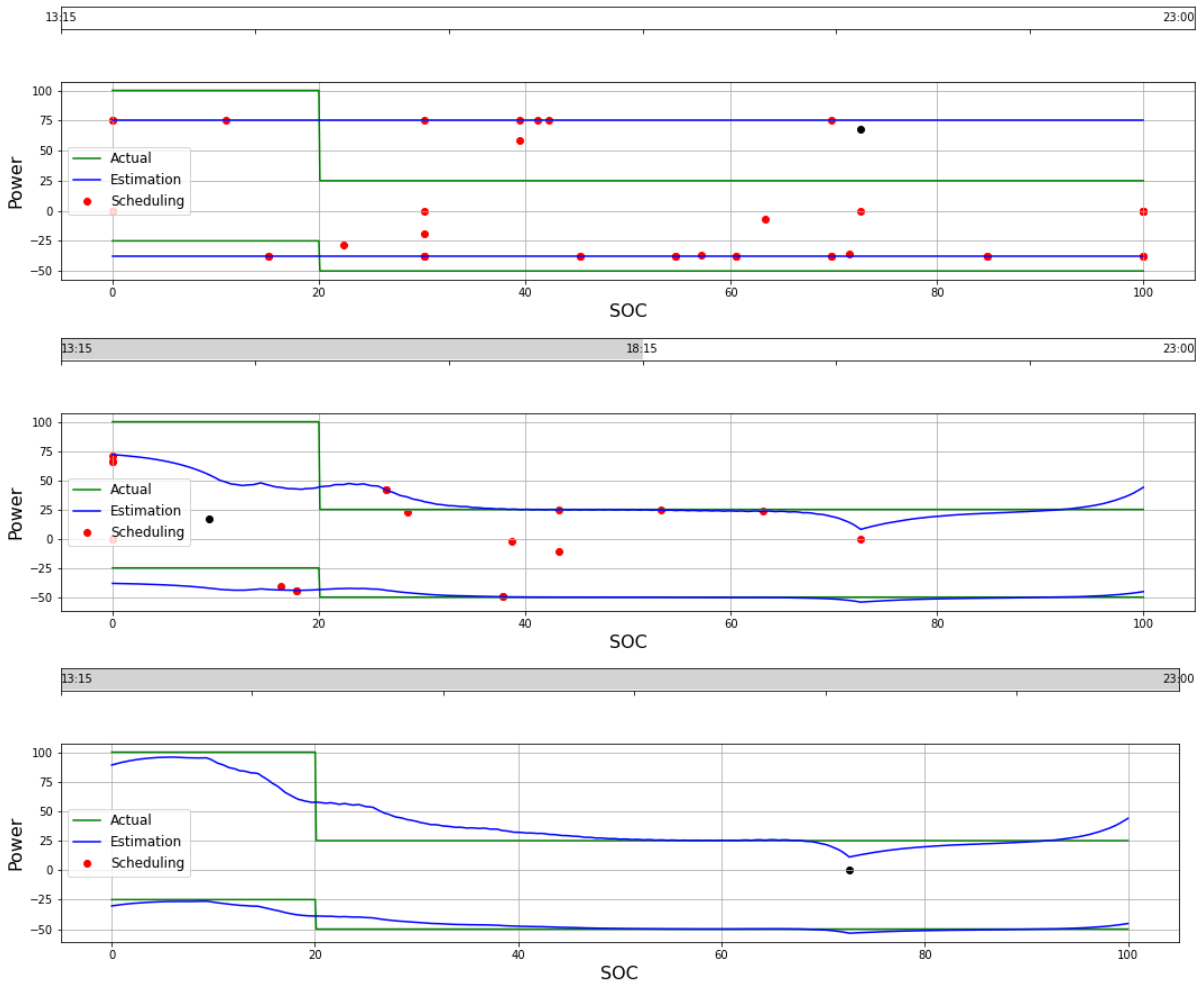


Figure 5.1: Results with initial power levels set at average value using a complex curve estimation.

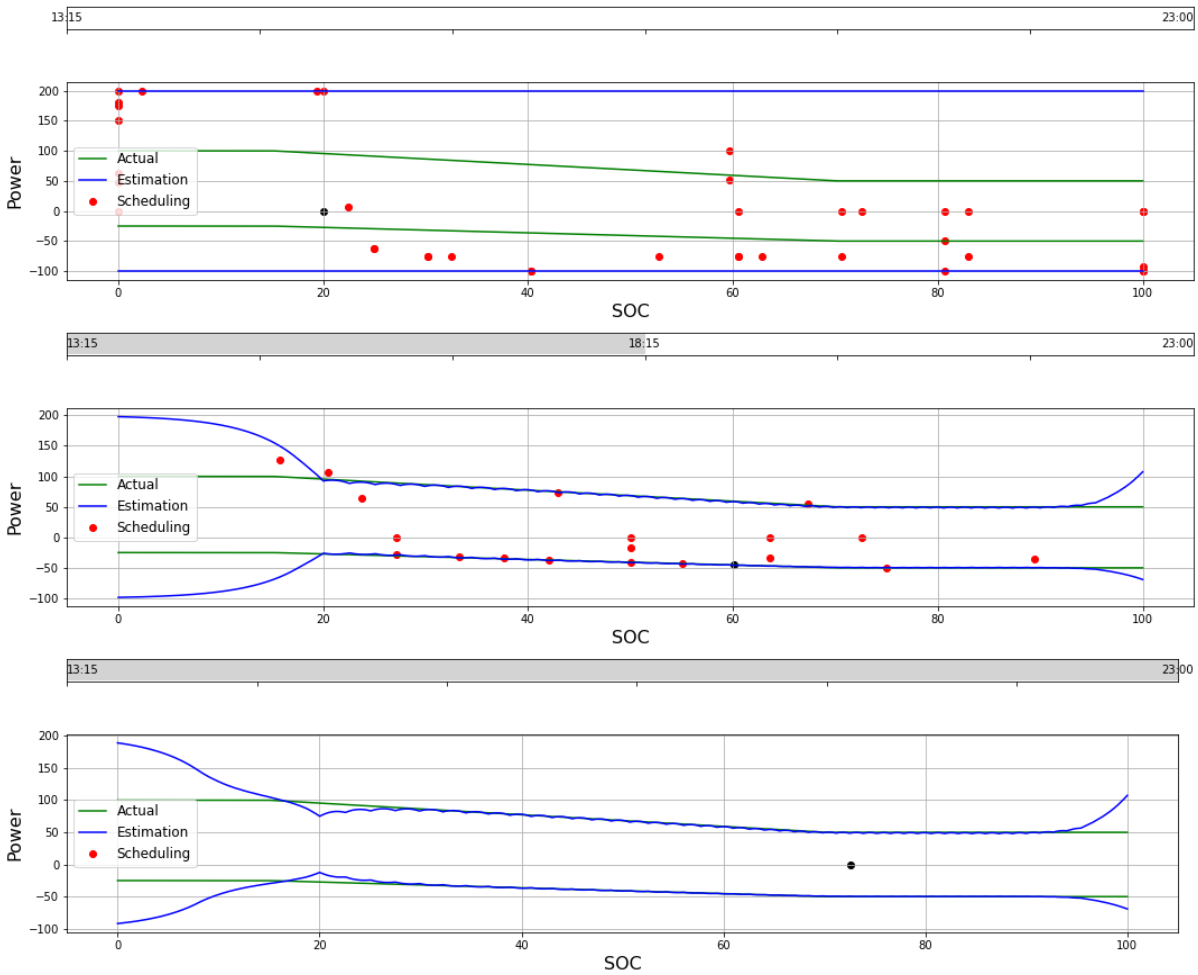


Figure 5.2: Results with initial power levels set at 200% higher value using a simple curve estimation.

6 | Conclusions and Future Developments

Conclusions emphasize the importance of understanding vehicle characteristics for effective control in intelligent vehicle systems applications. The research findings underscore the necessity of incorporating various factors, such as decay and power limits, to simulate specific behaviors accurately.
The analysis of decay estimation demonstrates that maintaining control over vehicle usage can significantly enhance performance without considerably compromising the objective function, regardless of the fleet's configuration. Conversely, unregulated usage can lead to substantial battery degradation. Moreover, simulations of BMS reveal that power limitations—both maximum and minimum—profoundly affect the cost function. Therefore, employing these vehicles requires acknowledgment of the dynamic variability of these parameters, which are influenced by the SOH, temperature, and SOC. The data indicate that adjustments based on current SOC can mitigate some effects, but given the variability among vehicles, adopting adaptive learning techniques for dynamic control adjustment and scheduling optimization is advisable.

Looking ahead, one area ripe for further exploration involves the management of vehicle temperatures. Temperature estimation is significantly affected by the HVAC systems, which vary from vehicle to vehicle. As temperature plays a critical role in the decay function and impacts BMS limits, improving its estimation is pivotal for the efficient control of these vehicles. The research suggests that accurately estimating temperature is vital for achieving optimal control, as it influences crucial operating parameters.
In the context of energy management systems, possessing a comprehensive understanding of the system is crucial. The opportunities for optimal intervention are fleeting, and inaccuracies in parameter estimation could result in missed opportunities for efficient energy management. Therefore, future studies should focus on developing more sophisticated models and control strategies that account for the intrinsic variability of vehicle systems. This approach will enhance the precision of control operations and contribute to the overall efficiency and sustainability of intelligent vehicle fleets.

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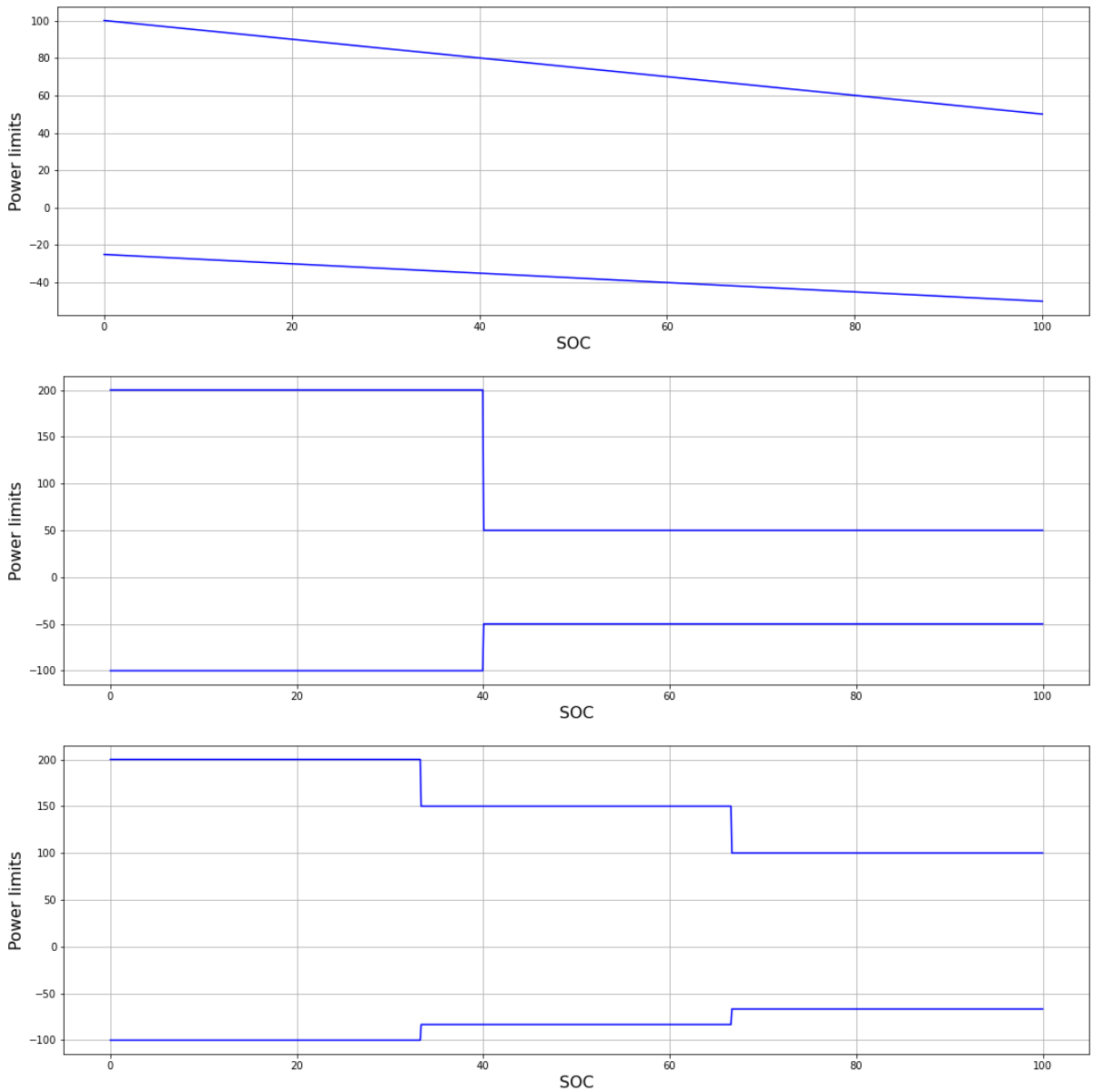
A | Appendix A



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List of Symbols

Variable	Description	SI unit
$\boldsymbol{P_t^{i+}}$	charging power to EV i at time t	kW
$\boldsymbol{P_t^{i+}}$	discharging power from EV i at time t	kW
$\boldsymbol{SOC_t^t}$	energy in EV i at time t	kWh
$\boldsymbol{c_t}$	net consumption at time t	kWh
$\boldsymbol{C_t}$	energy expense at time t	€
$\boldsymbol{J}$	total expenses	€
$\boldsymbol{T_t^i}$	temperature in EV i at time t	K
$\boldsymbol{DOD_t^i}$	Depth-Of-Discharge in EV i at time t	%
$\boldsymbol{C_{ch,t}^i}$	charging rate in EV i at time t	$s^{-1}(C)$
$\boldsymbol{C_{dsch,t}^i}$	discharging rate in EV i at time t	$s^{-1}(C)$
$\boldsymbol{mSOC_t^i}$	average SOC in EV i at time t	%
$\boldsymbol{FEC_t^i}$	Full-Equivalent-Cycle in EV i at time t	constant
$\boldsymbol{P_{MAX}(SOC_t^i)}$	maximum charging power for EV i given its SOC at time t	kW
$\boldsymbol{P_{MIN}(SOC_t^i)}$	minimum discharging power for EV i given its SOC at time t	kW

List of Acronyms

Acronym	Full name and description
MPC	Model Predictive Control
EV	Electric Vehicle
BMS	Battery Management System
V2B	Vehicle to Building
SOC	State of Charge
ToU	Time of Use
DAM	Day-Ahead Electricity Market
APS	Announced Pledges Scenario
STEPS	Stated Policies Scenario
HVAC	Heating, Ventilation, and Air Conditioning
DR	Demand Response
BESS	Battery Energy Storage System
BEMS	Building Energy Management System
MHE	Material Handling Equipment
PDCA	Plan-Do-Check-Act
LSTM	Long Short-Term Memory
BEV	Battery Electric Vehicles
PHEV	Plug-in Hybrid Electric Vehicles
HEV	Hybrid Electric Vehicles
V2G	Vehicle to Grid
NiCad	Nickel-Cadmium
CCS	Combined Charging System
IQR	Interquartile Range

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