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Exploring the Potential Benefits of V2B for Industrial Applications

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Executive Summary

This study investigates the feasibility of integrating Vehicle-to-Building (V2B) technology into industrial demand response applications as part of the Biflex research project. It quantifies the cost savings associated with V2B-enhanced fleet management compared to a baseline of non-smart charging, unidirectional smart charging, and V2B charging scenarios. By modeling an industrial facility equipped with a fleet of electric vehicles (EVs) and typical operational loads, the analysis evaluates potential financial benefits, profitability thresholds, and the flexibility of energy usage across varying electricity tariffs and demand response incentives. Additionally, the study explores the multifaceted advantages of V2B applications, including reductions in CO_2 emissions and enhancements in self-sufficiency. Through this analysis, the findings underscore the potential of V2B systems to optimize energy management, improve economic performance, and contribute to sustainability goals within the industrial sector. The comparative analysis showed that these strategies reduce costs by 14.98% for V2B, while also decreasing CO_2 emissions by 13.31% and increasing self-consumption rates by 20.60%.

Keywords: Smart Charging, Energy Management, Energy Storage Sytems, Sustainable Energy, V2H & V2G

1 Introduction

The transition to zero emissions is essential for tackling urgent challenges like climate change, air quality, and sustainable development. Greenhouse gas emissions, primarily CO_2 from fossil fuels, are the main drivers of climate change. Achieving zero emissions can significantly reduce these gases, stabilizing global temperatures and mitigating severe impacts such as extreme weather, rising sea levels, and biodiversity loss.

Emissions from vehicles and industries contribute to air pollution, leading to serious health issues, including respiratory diseases and premature deaths. Moving towards a zero-emission landscape would result in cleaner air and improved public health outcomes, ultimately lowering healthcare costs [1].

This transition aligns with international agreements like the Paris Agreement [2], promoting sustainable development and encouraging investment in renewable energy technologies and green jobs. Furthermore, reducing reliance on fossil fuels enhances energy independence, shielding nations from price fluctuations and geopolitical conflicts.

In this context, electric vehicle (EV) batteries have emerged as a pivotal component in modern energy management systems (EMS). These batteries not only serve as energy storage for vehicles but can also act as a flexible energy resource for buildings. Bidirectional charging capabilities allow EVs to draw energy from the grid and return excess energy back to it, aiding in grid stability and demand management. By facilitating the storage and discharge of surplus renewable energy, EVs enhance the integration of green energy sources, ultimately contributing to a sustainable and resilient energy future [3].

Additionally, the ability of EVs to store and discharge surplus renewable energy such as solar or wind enhances the integration of these sources into the grid. By mitigating issues related to intermittency, bidirectional charging ensures that excess energy generated during peak production can be stored and utilized later [4]. From an economic perspective, users of bidirectional charging can benefit from dynamic electricity pricing. Charging vehicles during off-peak hours when electricity is cheaper and selling energy back to the grid during high-demand periods can lower overall energy costs and provide an additional revenue stream for EV owners.

Moreover, the active participation of EVs in energy systems through bidirectional capabilities supports decarbonization goals. By facilitating the use of cleaner, renewable energy and decreasing reliance on fossil fuels, EVs contribute significantly to broader climate objectives. In emergencies or outages, bidirectional charging allows EVs to provide energy to buildings or homes, enhancing energy resilience and security. This capability is crucial during disasters or grid failures, providing a vital energy source when traditional systems are compromised [5].

An important motivation for this study is to explore the relationship between emissions and price optimization, especially in the context of V2B applications. While these applications do not explicitly aim to reduce emissions, they can contribute to emission reductions indirectly by optimizing energy consumption. Moreover, the solution proposed in this paper operates behind the meter, highlighting its potential for localized energy management and increased efficiency.

1.1 Vehicle-to-Building (V2B)

The interaction between a large building and a bidirectional electric vehicle (BEV) is commonly termed Vehicle-to-Building (V2B). This concept encompasses sizable residential, commercial, and industrial structures [6]. Dossow and Kern expand on this by defining Vehicle-to-Building (V2B) specifically for commercial and industrial contexts as "Vehicle-to-Business" (V2B) [7].
Literature indicates that V2B presents multiple advantages, spanning economic, technical, and environmental aspects. As previously mentioned, V2B can yield financial gains through reducing peak loads and enhancing power factors [6]. Borge-Diez et al. emphasize peak shaving as a significant benefit of V2B, which lowers costs by minimizing the building's maximum peak load [8]. Another method for decreasing electricity expenses is utilizing V2B for strategic energy procurement, which entails storing energy when prices are low and consuming it when prices rise [8].
Additionally, boosting the proportion of renewable energy sources, like photovoltaic (PV) systems, is recognized as a noteworthy benefit of V2B, as stated by Borge-Diez et al. [8]. The energy storage capabilities of BEV batteries allow them to hold excess energy during times of high production and low demand for later use. Borge-Diez et al. also point out that V2B can serve as a backup power source during outages [8]. A further major advantage of V2B is its potential to cut CO_2 emissions [6].
Moreover, Thompson and Perez highlight the postponement of infrastructure capital expenses and the reduction of operational costs as other important factors [6]. By integrating these applications, V2B can lead to various benefits, such as enhancing the global grid's efficiency, lowering emissions, and improving the energy efficiency of buildings, which ultimately results in reduced electricity costs [8]. It is important to recognize that these benefits hinge on the proper implementation of V2B.

1.2 Optimal Energy Management and Smart Charging for EVs

Numerous Vehicle-to-Building (V2B) smart charging strategies have been proposed in the literature [9, 10, 1, 11]. In [12], the study explores interactions between the smart grid, aggregators, and EVs, focusing on coordinated charging while considering uncertainties in fleet behavior, electricity prices, and regulations. Smart charging for EVs focuses on strategies and algorithms aimed at minimizing costs while maximizing efficiency and reliability in the charging process. It involves coordinating the energy consumption of EVs with the availability of renewable energy sources, time-of-use electricity rates, and the overall demand on the smart grid.
Key elements include flattening of the load, which helps stabilize the demand of the grid by charging EVs during off-peak hours or when renewable energy is abundant, and cost minimization, achieved by optimizing charging times based on electricity prices. Real-time data from EVs, the grid, and other sources plays a critical role in forecasting energy demand and adjusting charging schedules [13].
Additionally, uncertainty management addresses unpredictable factors like fleet behavior and fluctuating electricity prices. Smart charging is often integrated into demand response programs, where EV owners

are incentivized to charge during optimal times or reduce their load in response to grid conditions. Effective communication systems between EVs, aggregators, and the smart grid are essential for ensuring the smooth operation of these energy management strategies [14].
In the scope of this paper, we have developed an advanced charging algorithm specifically for V2B applications within industrial fleets. This algorithm will be comprehensively detailed in the Methodology section.

2 Methodology

In this section, we will define the methodological framework used to investigate the integration of electric vehicles into building energy systems via V2B technology specifically for industrial applications. This includes system architecture, data sources, simulation and optimization techniques, scenarios considered, and performance metrics for evaluation. This structured approach aims to provide clarity on how the V2B model is developed to improve energy management and sustainability in commercial buildings.

2.1 System architecture

The system architecture consists of multiple interconnected components, with the optimization module serving as the central element. The optimization module operates on the basis of real-time and forecasted data acquired via the EMS, including building load profiles, local renewable generation (e.g., photovoltaic systems), electricity pricing signals, and grid constraints. Utilizing this information, the optimization algorithm generates bidirectional charging schedules that incorporate V2B functionality, thereby enabling electric vehicles to operate not only as flexible loads but also as distributed energy storage units capable of discharging energy back to the building infrastructure behind the meter.

The charging schedules computed by the optimization process are transmitted to the EMS, which acts as the supervisory control layer. The EMS subsequently communicates the operational commands to the individual charging stations, ensuring the coordinated execution of both charging and discharging activities. This hierarchical control framework facilitates intelligent energy management at the building level, allowing for improved self-consumption of renewable energy, peak load reduction, and enhanced flexibility in demand-side operations. The integration of V2B capabilities further strengthens the role of electric vehicles as active components within the local energy ecosystem, contributing to the overall sustainability and efficiency of the energy system. An overview of the operational framework and capabilities of the *OptiCharge* system is presented in Figure 1.

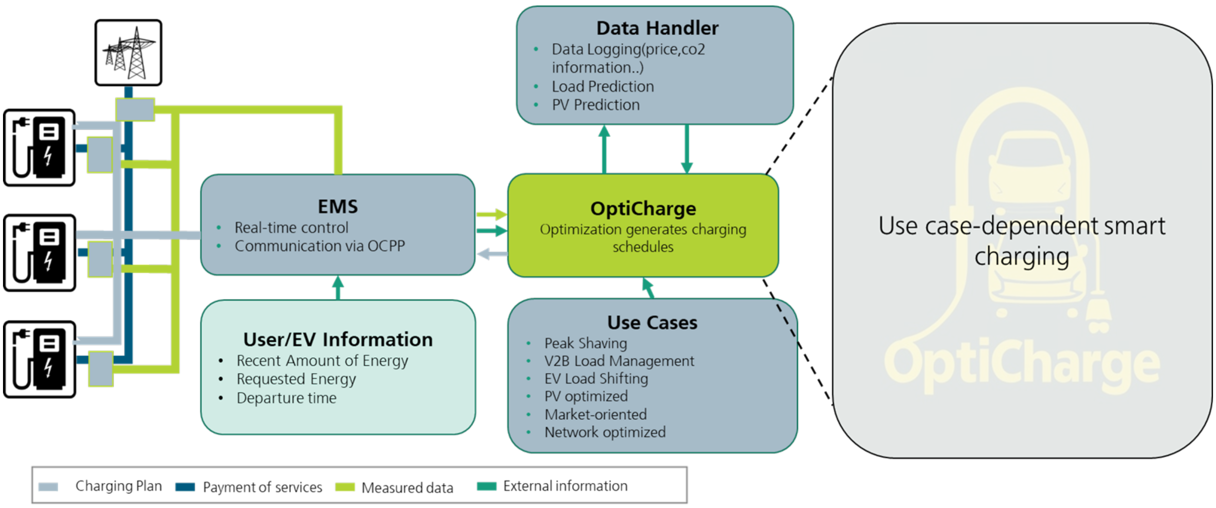


Figure 1: Diagram illustrating the operational principles of possible the system

2.2 Scenarios

This paper compares three scenarios:

- **Baseline Scenario:** A non-smart charging strategy in which EVs begin charging at maximum power upon connection and continue until fully charged.

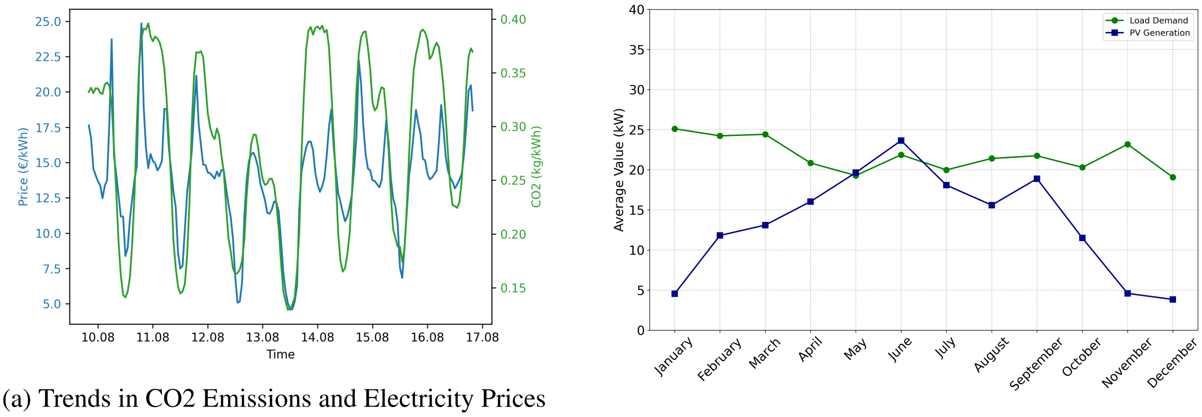
- **Smart Unidirectional Scenario:** A price-optimized unidirectional smart charging strategy, where EVs charge during off-peak periods to minimize costs.
- **V2B Scenario:** A bidirectional charging strategy where EVs are charged during periods of low electricity prices or excess generation, and discharge stored energy to support building loads during peak demand or high-price periods.

Table 1: Simulation Parameters

Parameter	Description	Value / Range
Simulation horizon	Total simulation period	1 year (15-min resolution)
Optimization horizon	One optimization period	1 day or when a new EV arrived
Annual PV production	Energy generated by PV system	117.59 MWh/year
Building load profile	Annual building electricity demand	190.64 MWh/year
Number of EVs in fleet	Total electric vehicles considered	5 vehicles
Battery capacity (EV)	Energy capacity per vehicle	90 kWh
Charging power	Max-Min charging rate per EV	11-4.2 kW (AC)
Discharging power (V2B)	Max-Min discharging rate per EV	11-4.2 kW
Battery efficiency	Charging efficiency	88%
PV utilization strategy	Priority of PV energy usage	Building load $\rightarrow$ EV charging
Tariff structure	Electricity pricing model	Day-Ahead + Taxes

2.2.1 Data Sources

Several datasets play crucial role in this application, including an industrial load profile that captures the electricity demand of an industry over time, reflecting variations driven by operational activities. This profile includes key elements such as the base load from continuous operations (e.g., lighting and machinery). For this study, the load profile is generated using the Synpro tool developed by Fraunhofer ISE [15]. A total load of 190 MWh/a and PV generation of 117 MWh/a were calculated to model a typical energy profile of a small manufacturing facility, characterized by a 73 MWh/a deficit. This scenario provides a relevant basis for investigating V2B integration, where bidirectional electric vehicles serve as flexible storage units to support building loads during PV shortfalls. The setup enables the assessment of V2B strategies for enhancing self-sufficiency, reducing grid dependency, and improving energy resilience in industrial contexts with limited renewable capacity. The analysis also incorporates day-ahead electricity prices and CO_2 values for 2023, which are generated with energy charts from Fraunhofer ISE [16]. The 'Fleet Profile Generator' tool developed by Fraunhofer ISE was used to generate year-long driving profiles for 5 EVs, based on input data provided by Fraunhofer ISI [17].



(a) Trends in CO2 Emissions and Electricity Prices 2023 Germany

(b) Monthly Average Load and PV Output

Figure 2: Data sources for the case study

Figure 2a presents the relationship between CO2 emissions (in kg/kWh) and electricity prices (in € / kWh) over a randomly selected week. The analysis reveals that fluctuations in CO2 emissions, which reflect the environmental impact of energy production, often exhibit similar trends to changes in electricity prices, influenced by market dynamics and demand. Notably, periods of increased CO2 emissions, often associated with higher fossil fuel generation, correspond with spikes in electricity prices. As previously mentioned, in this paper, we will investigate whether emission reductions can be achieved without incorporating CO2 time series into the objective function, while prioritizing PV usage and implementing price-optimized charging strategies in our case study.

2.3 Charging Discharging Strategy

The charging schedule strategy in all scenarios employs different methodologies; however, these approaches converge on several common objectives. Primarily, the overarching goal is to maximize self-sufficiency. Consequently, when PV generation is available, the charging strategy prioritizes external loads before utilizing solar energy for charging.

In the contexts of smart charging and V2B configurations, an additional objective emerges: the minimization of electricity costs. Within the V2B framework, we take advantage of the flexibility afforded by directional charging. The expected outcome is that during periods of high electricity demand and elevated pricing within the optimization horizon, we can discharge energy stored in electric vehicles to satisfy the load requirements. It is critical to ensure that EVs reach their target state of charge (SoC) by the conclusion of the optimization period.

In Figure 3, we present example simulation results and the V2B performance of the optimization system. Different colors represent different EVs. The right y-axis displays dynamic electricity price information, while the left y-axis shows power in kW. The bottom of the graph indicates time and includes color coding for the presence duration of each corresponding EV. The price sensitivity performance of *OptiCharge* is clearly illustrated. Simulation results for 01.01.2023 has been given for 3 different use cases in the Appendix.

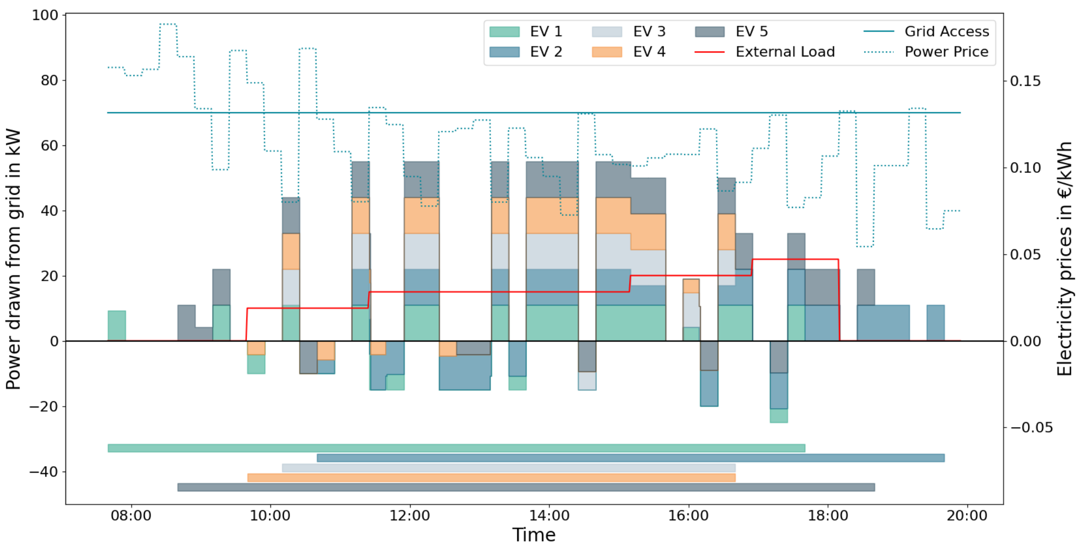


Figure 3: Illustration of the V2B charging and discharging process.

The objective of this illustration is to demonstrate the sensitivity of the charging strategy and its effectiveness in minimizing cost. The electricity prices presented do not reflect real-world values; they are provided solely to illustrate how charging and discharging behavior is influenced by price signals. In the results section, cumulative results and savings over one year are given, incorporating actual electricity pricing data.

The study aims to provide clear guidelines for industries considering V2B integration. It will identify the conditions under which V2B becomes economically viable, offering a roadmap for industries to leverage emerging energy technologies.

In this study, the optimization process utilizes *OptiCharge*, an advanced optimization tool developed by Fraunhofer ISE, which employs a Mixed-Integer Linear Programming (MILP) solver to obtain efficient and precise solutions of optimization problem. This optimizer can be operated based on various input parameters which are presented in Section 2.1 and is designed to minimize electricity costs. Simultaneously, it ensures that the energy requirements of EVs are met prior to their departure times. For V2B use-case, *OptiCharge* optimizes charging during low-cost periods and discharging during high-cost periods. Due to its modular architecture, it can be seamlessly integrated with existing Energy Management Systems (EMS).

As displayed in Figure 1, *OptiCharge* offers more scenarios beyond the scope of this study, which could be integrated in the future. The controller utilizes information from the EVs connected to the system. Each EV has a specific amount of energy requested and an available energy amount, which can be described as the initial SoC and target SoC, considering the corresponding battery size of the EV.

MILP formulation:

$$
\begin{aligned}
\min_{C,p,soc,\lambda^{ms},\lambda^{ts},\lambda^{l}} \quad & \sum_{b=0}^{B-1}\sum_{t=0}^{T-1} p_{b,t}\cdot\theta_{b,t}\cdot\Delta t + \sum_{c=0}^{C-1}\sum_{t=0}^{T-1}\lambda_{c,t}^{ms}\cdot z_{c,t}^{ms} \\
& + \sum_{c=0}^{C-1}\left(\lambda_c^{ts}\cdot z_c^{ts} + t\_soc_c^{overshoot}\cdot z_c^{ts\_overshoot}\right) + \sum_{t=0}^{T-1}\lambda_t^{l}\cdot z^{l} \qquad (1) \\
\text{subject to} \quad & \sum_{b=0}^{B-1} p_{b,t} = \sum_{c=0}^{C-1}(C_{c,t}-D_{c,t}) + L_t - \lambda_t^{l},\ \forall t\in T.
\end{aligned}
$$

Table 2: Optimized Variables

Variable	Description
$C_{c,t}$	Charging power for EV c at time t (continuous)
$D_{c,t}$	Discharging power for EV c at time t (continuous)
$C_{c,t}^{binary}$	Binary charging variable for EV c at time t
$D_{c,t}^{binary}$	Binary discharging variable for EV c at time t
$p_{b,t}$	Power drawn from band b at time t (continuous)
$soc_{c,t}$	State of charge of EV c at time t (continuous)
$\lambda_{c,t}^{ms}$	Slack for minimum SoC of EV c at time t
λ_c^{ts}	Slack for target SoC of EV c at departure
λ_t^{l}	Slack for external load l at time t

$$0 \leq p_{b,t} \leq p_b^{max},\ \forall b \in B, t \in T \tag{2}$$

$$soc_{c,t_0^c} = soc_c^0 \tag{3}$$

$$soc_c^{min} - \lambda_{c,t}^{ms} \leq soc_{c,t} \leq 1,\ \forall c \in C, t \in T \tag{4}$$

$$soc_c^d - \lambda_c^{ts} + t\_soc_c^{overshoot} \leq soc_{c,t},\ \forall c \in C, t \in T \tag{5}$$

$$0 \leq \lambda_{c,t}^{ms} \leq soc_c^{min},\ \forall c \in C, t \in T \tag{6}$$

$$0 \leq \lambda_c^{ts} \leq soc_c^d,\ \forall c \in C \tag{7}$$

$$0 \leq t\_soc_c^{overshoot} \leq 1 - soc_c^d,\ \forall c \in C \tag{8}$$

$$C_{c,t}^{binary} \cdot C_c^{min} \leq C_{c,t} \leq C_{c,t}^{binary} \cdot \min(C_c^{max}, C_t^{max}),\ \forall c \in C, t \in T \tag{9}$$

$$D_{c,t}^{binary} \cdot D_c^{min} \leq D_{c,t} \leq D_{c,t}^{binary} \cdot \min(D_c^{max}, D_t^{max}),\ \forall c \in C, t \in T \tag{10}$$

$$C_{c,t}^{binary} + D_{c,t}^{binary} \leq 1,\ \forall c \in C, t \in T \tag{11}$$

$$C_{c,t}^{binary} \in [0,1],\ \forall c \in C, t \in T \tag{12}$$

$$D_{c,t}^{binary} \in [0,1],\ \forall c \in C, t \in T \tag{13}$$

$$soc_{c,t+1} = soc_{c,t} + \frac{\Delta t}{E_c^{bat}}(\eta_c \cdot C_{c,t} - \frac{1}{\eta_c} D_{c,t}),\ \forall c \in C, t \in T \tag{14}$$

Table 3: Parameters

Parameter	**Description**
Δt	Coarse time step length
C	Number of EVs
B	Number of power bands
T	Horizon length
L_t	External load at time t
C_c^{max}, D_c^{max}	Max. (dis-)charging power for EV c
C_c^{min}, D_c^{min}	Min. (dis-)charging power for EV c
$\theta_{b,t}$	Pricing coefficients for band b
soc_c^{min}	Min. SoC limit for EV c
t_c^0, t_c^d	Arrival and departure times for EV c
soc_c^0, soc_c^d	Initial and target SoC for EV c
E_c^{bat}	Battery size for EV c
η_c	Inverter efficiency for EV c

2.3.1 Performance Criteria

Self Consumption:

Self consumption quantifies the proportion of locally generated energy (e.g., from a photovoltaic (PV) system) that is directly utilized within the system. It reflects how efficiently the system uses its own renewable energy generation and can be expressed as:

$$\text{Self Consumption (\%)} = \frac{E_{\text{PV\_used}}}{E_{\text{PV\_generated}}} \quad \text{where } E_{\text{PV\_used}} = E_{\text{Building Load}} + E_{\text{EV Charging}} \tag{15}$$

Total electricity cost and carbon emission:

In a dynamic charging process, both total electricity cost and total carbon emissions can be expressed using the same mathematical structure because of their shared underlying principle: they represent cumulative results at the end of the simulation with time-dependent effects of energy consumption and time series values. Specifically, both metrics quantify the impact of charging energy E_t at each time step t, weighted by a corresponding time-varying signal.

Let the total impact J of EV charging over a horizon T be calculated as:

$$J = \sum_{t=1}^{T} \alpha_t \cdot E_t \tag{16}$$

where:

- T: total number of time intervals,
- α_t: time-dependent signal at time t (e.g., price or emission factor),
- E_t: energy charged at time t (in kWh).

2.4 Simulation Framework

In the realm of EMS and charging station applications, the necessity for a robust simulation framework arises from the need to thoroughly assess the performance of control algorithms over a long-term simulation period. Such a framework enables the efficient modeling of complex interactions and dynamics within the system, allowing for optimization processes to be conducted within a limited timeframe such as 6, 12 or 24 hours. This capability is critical for generating reliable data that informs decision-making, ultimately enhancing the efficacy and resilience of energy management strategies in real-world applications.
For this study, the annual simulation results for each scenario were generated using the simulation framework developed by Fraunhofer ISE [18]. The simulation framework not only facilitates the straightforward implementation of control algorithms over annual simulations, but also enables a comprehensive economic analysis.
The overall structure of the framework and its integration with *OptiCharge* is illustrated in Figure 5.

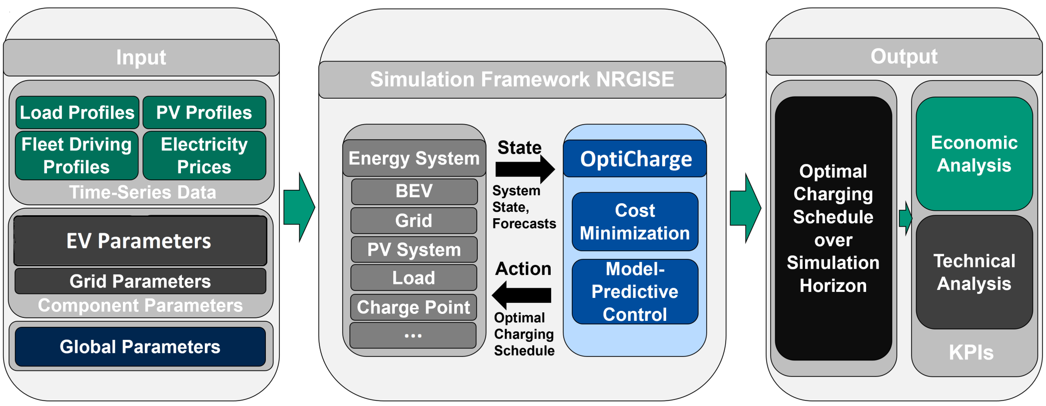


Figure 4: Architecture of the simulation framework [18].

3 Results

To provide a more comprehensive analysis, we conducted a detailed evaluation of the optimizer using the simulation framework presented in Section 2.4. Our analysis specifically targeted the year 2023, during which we employed real-world data pertaining to PV genration, load demand, pricing and CO2 information, as specified in Table 1. The results of this investigation were systematically obtained and are comprehensively illustrated in Table 4. This approach allows for a robust understanding of the optimizer's performance under realistic conditions, thereby contributing valuable insights into its efficacy and operational characteristics. The total cost values represent the total amount of electricity paid for during the year.

Table 4: Annual performance comparison of three EV charging strategies (one-year results).

Scenario	**Total Cost (k€)**	**CO_2 Emissions (tonne)**	**Self Consumption(%)**
Baseline (Non-Smart)	32.08	41.30	68.46
Unidirectional Charging (Price-Optimized)	30.54 (-4.80 %)	39.48 (-4.38 %)	72.83 (+5.99 %)
V2B	27.28(-14.98 %)	35.80 (-13.31 %)	86.24 (+20.60 %)

The implementation of a smart charging strategy, optimized for fluctuations in electricity prices, resulted in a 4.80% reduction in total costs, decreasing from 32.08 k€ to 30.54 k€. Concurrently, this strategy led to a 4.38% decrease in CO_2 emissions, reducing emissions from 41.30 tonnes to 39.48 tonnes. Furthermore, the self-consumption rate exhibited a notable increase of 5.99%, indicating enhanced efficiency in the utilization of locally generated energy.

The V2B charging strategy demonstrated the most significant improvements across all assessed metrics. This strategy achieved a 14.98% reduction in total costs, lowering expenses to 27.28 k€. Additionally, it resulted in a 13.31% decrease in CO_2 emissions, reducing emissions to 35.80 tonnes. Importantly, self-consumption increased substantially by 20.60%, reaching 86.24%.

It is important to note that the optimization of CO_2 reduction was not explicitly included in the objective function, as the model primarily utilized time series data for price information. However, the implementation of smart charging algorithms still yielded a reduction in CO_2 emissions as a result of the optimized scheduling. This indicates that even when CO_2 reduction is not a direct objective, the integration of smart charging strategies can lead to significant environmental benefits.

These values are directly dependent on the case study parameters chosen; in this analysis, we selected a scenario where the industrial demand for energy exceeds that generated by photovoltaic (PV) systems. This context emphasizes the importance of flexible charging strategies in managing energy demand and optimizing resource utilization.

The results underscore the considerable potential of bidirectional charging in enhancing both the economic and environmental performance of EV charging systems while maximizing the utilization of on-site energy resources. In general, this analysis highlights the positive impact of V2B systems on both economic performance and sustainability outcomes, confirming the value of flexible energy management solutions in improving overall system efficiency.

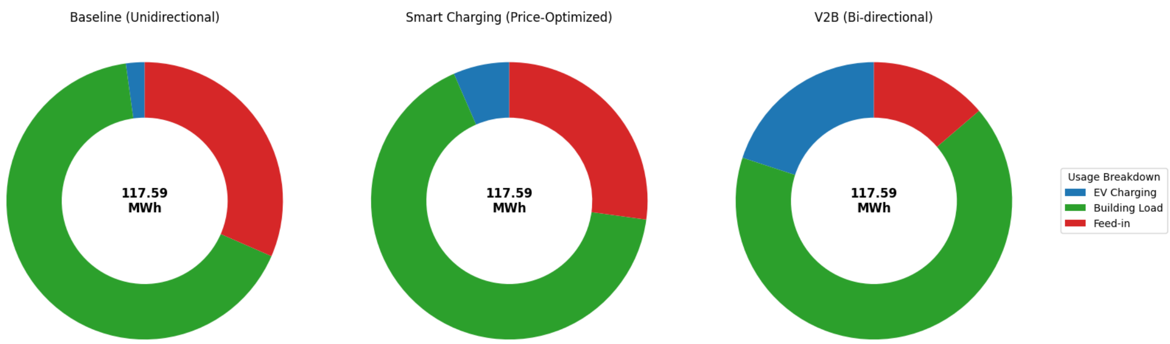


Figure 5: Annual PV Usage distribution for different scenarios

4 Conclusion

This study has demonstrated the significant benefits of advanced electric vehicle charging strategies, particularly focusing on smart unidirectional and V2B charging systems. The comparative analysis revealed that the implementation of V2B resulted in a significant 14.98% reduction in total cost, a 13.31% decrease in CO_2 emissions, and a 20.60% increase in self-consumption rates.

Although optimization of CO_2 reduction was not explicitly included in the objective function, the findings suggest that smart charging algorithms can still yield environmental benefits through optimized scheduling. This highlights the potential for indirect positive impacts on sustainability outcomes, even when CO_2 reduction is not a primary objective.

The results are contingent upon the specific case study parameters selected, particularly the scenario where industrial energy demand exceeds the energy generated by PV systems. This context underscores the importance of flexible charging strategies in effectively managing energy demand and optimizing the use of locally generated resources.

In general, the findings of this study reinforce the value of integrating innovative charging strategies within energy management systems of buildings. By enhancing both economic performance and sustainability objectives, these strategies can play a crucial role in advancing the transition to a more sustainable energy future. Future research should continue to explore the varying impacts of different energy management solutions across diverse scenarios to further demonstrate their potential benefits.

Acknowledgments

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Presenter Biography

Since 2020, Robert Kohrs has been the Head of the Department of “Smart Grids” at Fraunhofer ISE. Previously, from 2013 to 2020, they led the “Smart Grid ICT” group and managed the “Communication Networks and e-Mobility” team from 2011 to 2013. He began their career at Fraunhofer ISE as a researcher and project manager (2009–2011) after earning a PhD in semiconductor detectors for high-energy particle physics at the University of Bonn in 2008. They hold a Diploma in Physics from the same university (2002).

Appendix – Additional Simulation Results

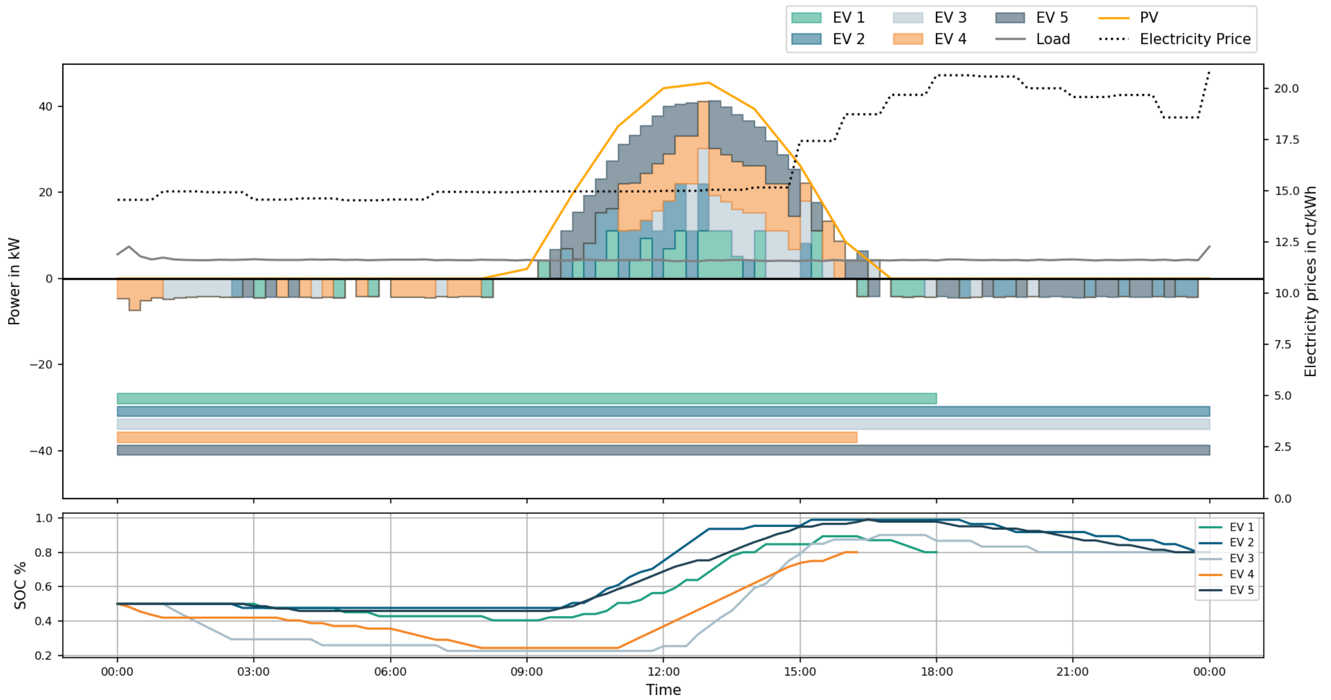

Figure 6: Charging Schedule, Connection Status, and SoC of EVs for V2B Case

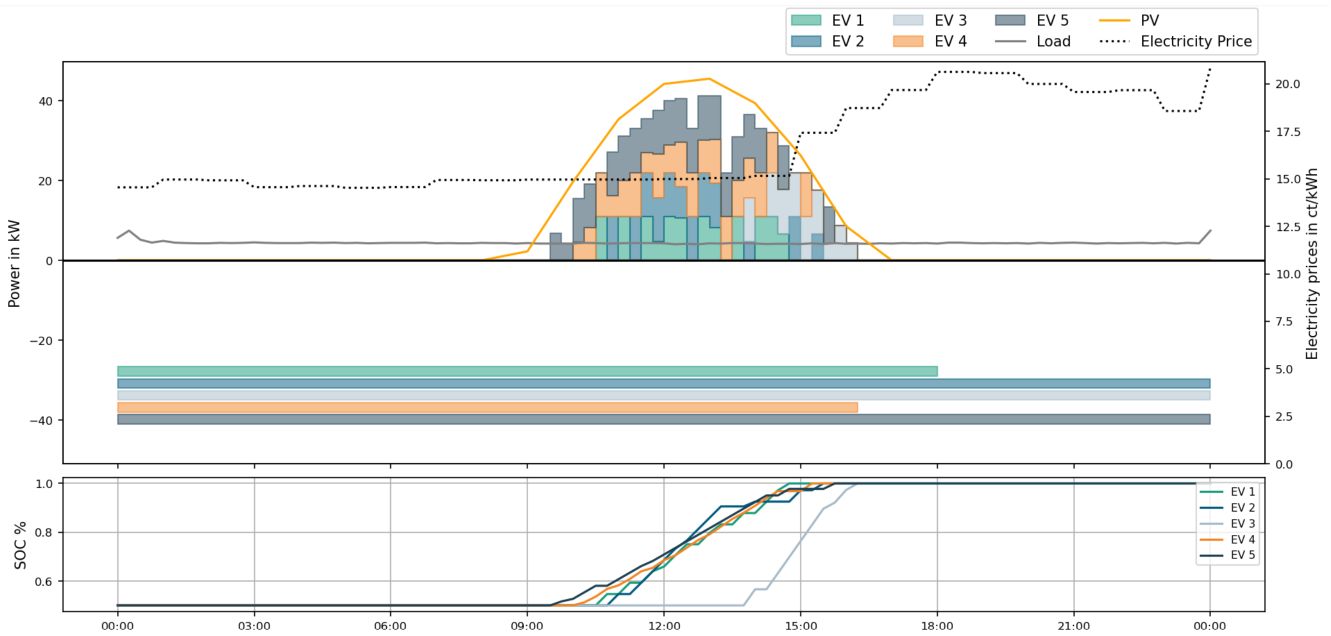

Figure 7: Charging Schedule, Connection Status, and SoC of EVs for Unidirectional Smart Charging Case

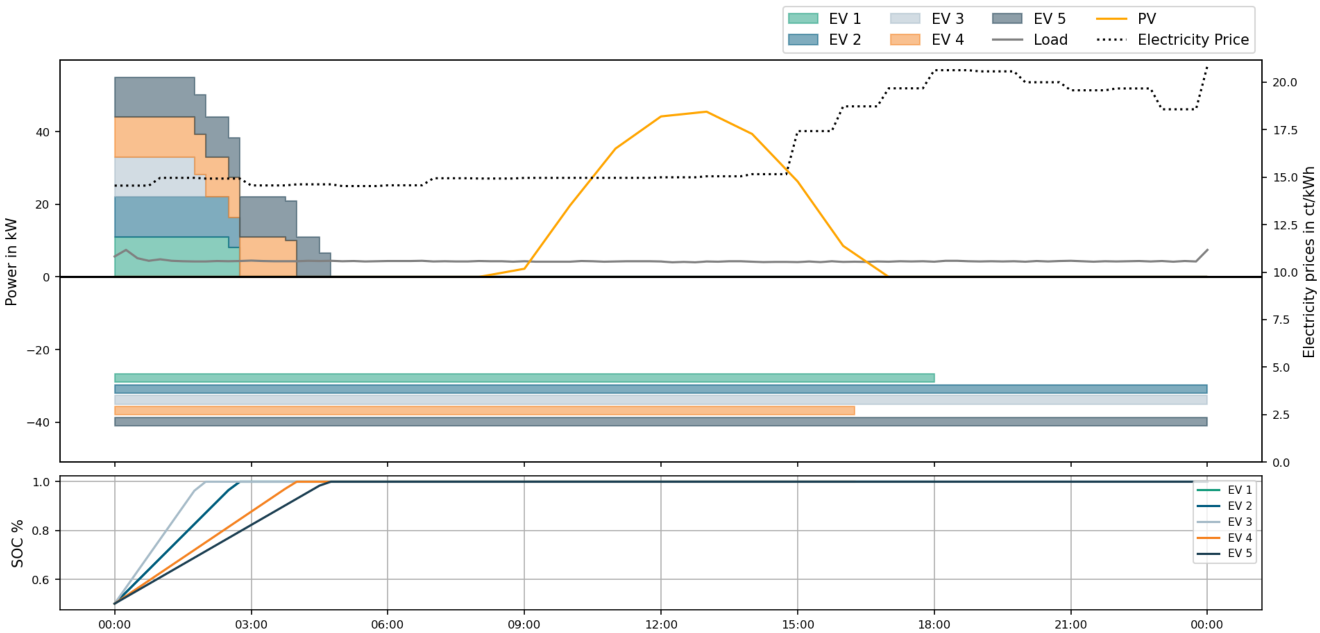

Figure 8: Charging Schedule, Connection Status, and SoC of EVs for Uncontrolled Charging Case