The Impact of Evolving Energy Prices in Smart Charging: An Empirical Study with Data from Norway

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***Abstract*—Smart charging of electric vehicles (EVs) has emerged as a strategy to lower the cost for vehicle owners, while also shifting their demand to low consumption hours. As the volatility of energy prices has increased, an important question is how different charging strategies are affected by the price trends. This paper conducts an empirical study using hourly data on the energy prices perceived in Norway during 2019-2024. By means of a scheduling model which minimizes the cost of charging, we compute EV owners' costs and energy losses for several charging strategies using different degrees of flexibility. The results show that the value of flexibility for EV owners has increased over the years and that the optimal schedule of charging has shifted from night to midday hours on weekends.**

***Index Terms*—Electric vehicles, Energy consumption, Power grids, Smart devices**

I. INTRODUCTION

As the penetration of electric vehicles increases, charging strategies are becoming important not only for the budget of vehicle owners, but also for the power grid operators to keep an efficient use of the grid. In response, several smart charging approaches have emerged in recent literature, as reviewed in [1] and [2]. These smart charging approaches rely on the owners offering flexibility to charge their vehicles during some hours within a time interval. Then, an optimal schedule of charging is devised over this time interval, often supported by a digital platform. The optimization process seeks to minimize the cost of charging for the owner, which typically coincides with low consumption periods. In this way, not only the vehicle owner benefits from a lower cost of charging, but also the power grid may benefit from a peak-shaving effect and lower energy losses [1]. This cost-minimizing approach, which is supposed to promote better grid operation, is common in Norway. It is supposed to address power grid challenges associated with EV integration, such as increased energy losses and voltage fluctuations, which can occur when charging is uncontrolled [3,4].

Building on this, smart charging platforms have gained popularity in countries such as Norway, Sweden, Denmark, and the Netherlands, proving in practice that vehicle owners can effectively save costs. For example, an empirical study in Norway, the country with the highest plug-in car segment market share worldwide, has recently reported that non-users of smart charging technologies tend to use a simpler plug-and-charge strategy, which leads them to pay about 18% higher costs than the smart charging users [5].

As energy prices have entered into evolving trends during the last years [6], a relevant question to address is how the more volatile pattern of prices can affect smart charging. Empirical literature on this matter using recent price trends is scarce. Among the exceptions, [7] conducted a simulation study using data from Norway and found that smart charging has led to greater cost savings since the beginning of the energy price crisis. However, such study focused only on cost savings and did not consider potential trends in associated energy losses. Also, the flexibility in that study was restricted to pre-defined charging session intervals. To bridge the gap, in this paper, we conduct an empirical study using real data on the hourly energy prices perceived during the last six years in a relevant area of the Norwegian electricity market. For a representative fleet of vehicles and their respective charging needs, we implement an optimization model that retrospectively computes minimal cost schedules of charging for different degrees of flexibility. To exploit flexibility opportunities, we allow for charging sessions to be delayed over multiple days instead of the more restricted setting used by [7]. We also compute the cost of the non-flexible plug-and-charge strategy, which serves as basis to assess the value of flexibility. Our results show that the larger fluctuations in hourly energy prices in recent years have amplified the cost differences between flexible and non-flexible charging strategies. On the other hand, as the low prices have become less consistent with the night periods, our results also show that the minimum cost schedules of charging are shifting from night to midday hours on weekends.

The rest of this article is organized as follows. In Section II, we outline the modeling approach and data. In Section III, we present the results of different charging strategies and compare them in terms of costs and energy losses. We conclude with a brief discussion and final remarks in Section IV.

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II. MATERIALS & METHOD

We consider a fleet of EVs, accounting for variations in battery size, daily travel range, and grid connection time—the time horizon for which an EV is plugged in. Each EV travels a randomly determined daily distance, consuming a corresponding amount of battery capacity, which conveys recharging needs in time. Using a mathematical programming framework, we model various charging strategies based on plug-in time and charging flexibility. By comparing these strategies, we analyze charging costs and the associated energy losses in the electricity transmission system.

In the following, we define different charging strategies. The strategies prescribe different schedules of charging over certain time periods. Since our study is retrospective in time, the energy prices per time period are given. The strategies then differ in terms of flexibility, varying from fully flexible to plug-and-charge, as defined below.

A. *Modelling charging Strategies*

We define two types of charging strategies: "Plug-and-Charge" and "Flexible Charging". Under the plug-and-charge strategy, the car starts charging immediately when plugged in. Under flexible charging, the EV owner specifies a charging amount and an interval of time. Then the actual charging process can take place at any time(s) over this interval. We define different flexible strategies, according to different degrees of flexibility. First, a fully flexible strategy allows charging to occur at any time during the time horizon. Other flexible strategies restrict the interval of times at which the charging can occur; thus we refer to them as time-restricted flexible strategies.

Let T be the set of time periods (hours) over a given time horizon, for instance, a whole year. To compute the schedule of charging for the flexible strategies, we formulate a linear programming model, where the decision variable x_t represents the energy charged during hour t, defined for every t in T. The energy price for charging on time t is π_t. The objective function aims at minimizing the cost of charging C throughout the time horizon, that is:

$$C = \min_{x} \sum_{t \in T} \pi_t x_t \qquad (1)$$

The charging amount x_t is limited to the maximum power that the charging device can deliver, which we refer to as P^{max}. Recharging can take place while the car is connected to the charging device, for which we define the set of time periods $T^{plug\text{-}in}$. The car cannot charge at times outside this time interval. Note that the set T is defined to capture the whole time horizon including discharging, and the set $T^{plug\text{-}in}$ is defined to capture different grid connection times of the EV. Therefore, the different degrees of flexible charging strategies can be captured by adjusting the elements contained in the set $T^{plug\text{-}in}$. The charging rate must be non-negative. Thus, the domain of variable x_t is restricted as follows:

$$0 \leq x_t \leq P^{max} \ \forall \ t \in T^{plug-in} \qquad (2)$$

Let d_t be the battery consumption because of driving on time t. Let SOC_t be the status of charge (SoC) of the battery on time t. The SoC describes the status of the battery as a fraction of the overall battery size. The battery size of the car is denoted by B. Then, the computation of SOC_t from one to another period is given by constraints (3) below.

$$SOC_{t+1} = SOC_t + x_t/B - d_t/B \ \forall \ t \in T \qquad (3)$$

The SoC always has a lower limit, which helps car owners avoid range anxiety. For this analysis, we assume car owners use 20% of their battery capacity as the lower bound. The natural upper limit is 100%.

$$0.2 \leq SOC_t \leq 1 \ \forall \ t \in T \qquad (4)$$

Within these two main strategies (Flexible and Plug-and-Charge), we test several sub-strategies. The sub-strategies differ by different sets of plug-in times $T^{plug\text{-}in}$, as seen in Table 1. Therefore, we call these strategies time-restricted flexible strategies. As a benchmark sub-strategy to evaluate the lowest costs of charging possible, we introduce a sub-strategy called "Fully Flexible", where the car can be charged at any time.

Table 1. Plug-in times of different charging sub-strategies.

Sub-strategy	$T^{plug\text{-}in}$
Worktime	Workdays 08:00 – 16:00
Afternoon	Workdays 17:00 – 21:00
Night	Workdays 21:00 – 07:00
Sunday	Saturdays 21:00 – Mondays 07:00
Fully Flexible	Anytime

B. *Data*

To retrieve the charging schedule under different charging strategies, we implement the linear programming model (1)-(4) and conduct a computational study for a set of 1000 cars. This set of cars computes a Norwegian fleet based on data from [8], a digital platform storing public data in Norway. The dataset contains 258,863 registered electric vehicles in Norway. In our computation, the proportion of each car model corresponds to the corresponding market share. For instance, our car fleet contains 105 VW Golfs, which is equivalent to 10.5% that this vehicle represents in the dataset. Each of the charging strategies is applied to each of the 1000 cars. We assume that all cars commute to work daily, whereby the daily commuting distance is sampled out of a skewed normal distribution. The distribution parameters are estimated from the percentiles of the daily commuting distance presented in [9]. The arrival times of each car are sampled from a truncated normal distribution, with a mean of the respective arrival time and a standard deviation of $\sigma = 1$. As electricity efficiency data for these models, we use data from the Worldwide Harmonized Light Vehicles Test Procedure (WLTP). To charge a car, the car owners use a charging device that can power P^{max} = 7.4 kW. When analyzing the costs of charging and energy losses in the electricity transmission system we conduct our analysis on data from the Norwegian NO5 bidding zone, derived from [10]. As price data, we use the day-ahead price, and as load data the actual total load in the system.

To show the price pattern of an average day in this region, we calculate the average of each year's day-ahead electricity prices and then scale the values by dividing each price point by its respective yearly average. Figure 1 shows this scaled day-ahead electricity price on weekdays. A typical price pattern appears for all years, with peaks during morning and afternoon periods. As one can see from the figure, the pattern is more pronounced in recent years (2021-2024) than in previous years (2019,2020). Especially 2024 was characterized by extremely high peak prices, with prices at 08:00 o'clock in the morning at 144% of the year's average price.

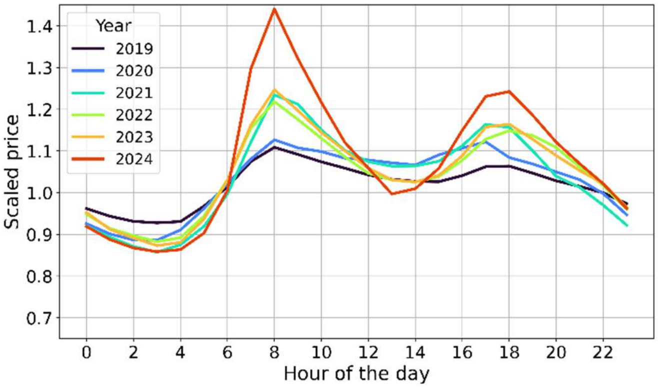

Figure 1: Scaled electricity price on weekdays.

A similar trend is observed on weekends, where weekdays exhibit progressively higher peak prices, while weekends show progressively lower valley prices, as illustrated in Figure 2. Notably, overall electricity prices on weekends are significantly lower than those on weekdays.

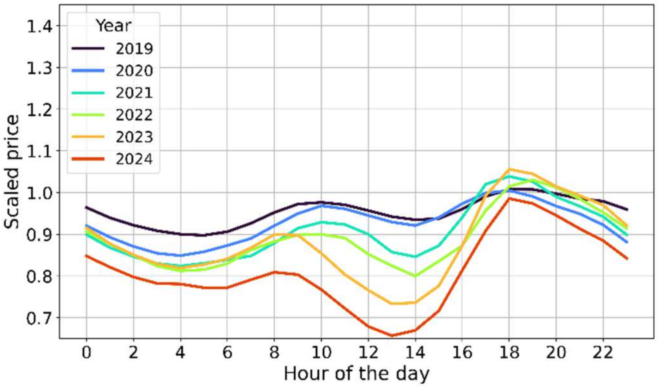

Figure 2: Scaled electricity price on weekends.

III. RESULTS

A. Costs of Charging

First, we present the fleet's charging schedule under the "Fully Flexible" strategy, which results in optimal costs. This schedule provides insights into changes in the optimal charging approach. Figure 3 shows the average electricity consumption mapped on weekdays and hours, whereby a warmer color indicates a higher average.

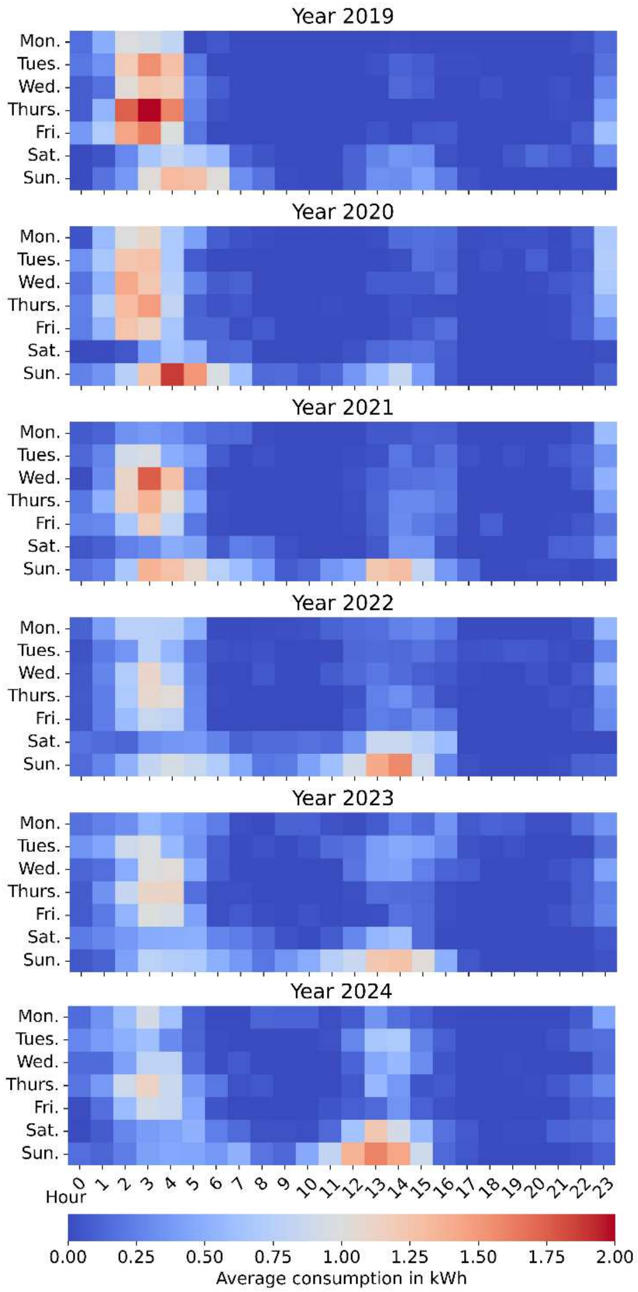

Figure 3: Average electricity consumption under the Fully Flexible charging sub-strategy.

It shows that while there is almost no charging during daytime on workdays in 2019, the average amount charged at this time has increased in recent years. Overall, the optimal charging behavior has shifted from a night-focused charging behavior (2019-2021) to a Sunday night and afternoon behavior (2022-2024). This shows how the optimal charging schedule can shift in response to changes in electricity prices, with prices that were once lowest at night now being lowest during the weekend.

Let C_1 and C_2 be the cost of charging by two different strategies. To compare the costs associated with these two strategies, we calculate the relative difference ΔC as $\Delta C = (C_1 - C_2)/C_2$. Table 2 presents the ΔC between "Fully Flexible" and time-restricted flexible sub-strategies. The data show that the cost difference relative to the "Fully Flexible" sub-strategy (benchmark) has increased across all flexible sub-strategies over time, making cost-minimal charging increasingly challenging. While nighttime charging resulted in near-optimal costs in earlier years (2019, 2020), it has deviated significantly from optimality in recent years (2022, 2023). However, focusing on weekend charging instead of weekdays leads to costs closer to optimal levels, providing an incentive to delay charging to weekends, especially in recent years.

Table 2: ΔC between time-restricted flexible and fully-flexible sub-strategy

YEAR	WORKTIME	AFTERNOON	NIGHT	SUNDAY
2019	16 %	16 %	4 %	4 %
2020	35 %	33 %	8 %	9 %
2021	34 %	37 %	14 %	9 %
2022	40 %	54 %	24 %	17 %
2023	49 %	65 %	33 %	21 %
2024	43 %	67 %	30 %	15 %

Comparing the time-restricted flexible charging strategy to the corresponding plug-and-charge strategy, it becomes evident that the value of flexibility has increased over time, with the ΔC showing a growing trend (Table 3). The data also highlight that the value of flexibility is strongly influenced by the EV's connection time, particularly in recent years. While EV owners saved between 8–16% by switching from plug-and-charge to flexible charging in 2019, this savings range expanded substantially to 38–77% in 2024.

Table 3: ΔC between time-restricted flexible and corresponding plug-and-charge strategy.

YEAR	WORKTIME	AFTERNOON	NIGHT	SUNDAY
2019	12 %	8 %	16 %	13 %
2020	20 %	21 %	38 %	26 %
2021	33 %	26 %	33 %	32 %
2022	43 %	24 %	45 %	42 %
2023	50 %	30 %	48 %	52 %
2024	77 %	38 %	56 %	54 %

B. *Energy losses in the transmission system*

Since regulations in Norway mandate that the grid operator is responsible for covering the economic consequences of energy losses, it is important to study how the different charging strategies of EV owners affect the energy losses. Energy losses (PL) can be approximated using a simple formula: $PL = k\ (P/V)^2$. Whereby, k is a constant reflecting the resistance of the grid, P represents the power in the grid, and V is the voltage. In our computations, we use parameter values $V = 300$ kV and $k = 0.2$. Note that the latter one is in line with estimations from the literature (see [11]). Given our focus on energy losses attributed to charged EVs, we calculate the increase in energy losses. To calculate this, we calculate the energy losses based on the load without cars and the new power load based on the charging of EVs. As energy losses increase quadratically with consumption, higher peak consumption has a significant impact on this figure. Note that these energy losses are approximate estimates for the cable. These figures are intended for comparison purposes rather than to provide an exact value. A more accurate estimation could also account for losses in other parts of the system and employ a more precise estimation method.

Table 4 shows the energy losses associated with integrating a single EV into the electrical grid under various plug-and-charge strategies. While no clear trend over time is observed, significant differences between strategies are evident. This is expected, as the energy consumption curve in NO5 remained stable from 2019 to 2024, and the plug-and-charge behavior has not changed during this period, as it is not influenced by external factors such as electricity prices. Plug-and-charge during worktime causes higher energy losses than during afternoons, which in turn causes more losses than nighttime. In particular, Sunday results in the least losses.

Table 4: Energy Losses in kWh per EV for different plug-and-charge sub-strategies (per year).

YEAR	WORKTIME	AFTERNOON	NIGHT	SUNDAY
2019	17.7	17.4	16.7	16.0
2020	18.3	18.1	17.4	16.8
2021	18.9	18.6	18.0	17.5
2022	18.1	17.9	17.3	17.0
2023	18.0	17.7	17.2	16.8
2024	18.7	18.6	18.0	17.5

In contrast, under a time-restricted flexible charging strategy (Table 5), the dynamics change. There is no clear order of strategies causing energy losses. However, the four categories can be grouped into two groups of energy losses. Charging during worktime and the afternoon causes considerably higher energy losses than charging during the night or on Sundays.

Table 5: Energy Losses in kWh per EV for different time-restricted flexible strategies (per year).

YEAR	WORKTIME	AFTERNOON	NIGHT	SUNDAY
2019	15.5	15.3	13.7	13.8
2020	17.0	16.7	14.9	14.8
2021	16.7	16.5	14.9	15.3
2022	16.7	16.4	14.9	15.0
2023	16.0	16.1	14.7	15.1
2024	16.7	16.4	14.9	15.2

A comparison of Table 5 and Table 2 reveals that in 2019 and 2020, a charging sub-strategy that resulted in low costs also led to low energy losses. However, this is not necessarily the case in more recent years. For example, since 2021, the "Sunday" sub-strategy has resulted in lower charging costs than "Night," but has also led to higher energy losses. Similarly, since 2022, the "Worktime" sub-strategy has produced lower costs but has also been associated with higher energy losses. This indicates that while the approach of cost-minimal charging will promote grid-efficient operation (as outlined in the introduction) it has its limitations.

Another key observation is that every time-restricted flexible charging sub-strategy results in lower energy losses compared to any plug-and-charge sub-strategy. This indicates that even if an EV owner switches from one plug-in time to another, energy losses will decrease as long as the charging strategy shifts from plug-and-charge to flexible.

IV. Discussion & Conclusion

This article has studied the impact of recent energy price trends on charging costs for EV owners and energy losses, subject to a variety of charging strategies. Computing the schedule of charge for a Norwegian EV fleet from 2019 to 2024, we examine how charging strategies evolve over time. Our findings show that the connection time (sub-strategy) of an EV significantly affects the cost difference between plug-and-charge and flexible charging strategies. Over the years, the cost difference between these strategies has increased, with flexible charging becoming increasingly beneficial. This shows how the new volatilities in the electricity market are reflected in an increasing value of flexibility for EV owners. Regarding energy losses, switching from plug-and-charge to flexible charging also results in reduced losses. Our study further underscores the importance of EV connection time as a key factor in both charging costs and energy losses, emphasizing the need to consider this aspect when evaluating strategies. Notably, in recent years, sub-strategies that lead to lower costs do not always correspond with lower energy losses.

From a policy perspective, promoting flexible charging is advisable, as it reduces energy losses. An incentive system could encourage EV owners to adopt flexible charging. Given the increasing cost savings for owners, the shift to flexible charging may occur naturally. Moreover, both EV owners and transmission system operators benefit more from flexible charging during off-peak times, such as nights and Sundays, rather than during work hours or the afternoon. Since some flexible charging sub-strategies do not align with energy loss reductions despite providing cost savings, a time-dependent or dynamic grid fee could help ensure that cost-minimal charging also minimizes energy losses. Ensuring that this relation always holds would improve transparency and provide clarity for private households.

Future research could focus on strategies to reduce overall charging costs, including energy loss expenses in other parts of the transmission system, such as conductors and transformers. Alternatively, research could explore pricing strategies for aggregators to support goals like renewable energy integration, as discussed in [12]. Lastly, given the involvement of multiple stakeholders, studying methods to coordinate energy consumption more effectively while considering all their interests remains a crucial area for further investigation.

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