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DAM PRICE-BASED MODEL PREDICTIVE CONTROL FOR SMART EV CHARGING UNDER GRID AND USER CONSTRAINTS

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ABSTRACT
The rapid deployment of Electric Vehicles (EVs) has significantly increased grid congestion, particularly in regions with limited capacity for infrastructure expansion where system operators no longer permit customers to extend grid connections. Dynamic energy pricing has emerged to incentivize consumers to optimize energy use through time-of-day tariffs. However, existing smart charging approaches typically optimize grid constraints, cost, or user preferences in isolation, with limited integration of these objectives. This paper proposes a cloud-based Model Predictive Control (MPC) framework for smart EV charging that simultaneously enforces grid power limits, minimizes charging cost, and satisfies user-defined requirements. The proposed method incorporates day-ahead market (DAM) electricity prices, real-time building load, photovoltaic (PV) forecasts, and EV user inputs within a multi-objective optimization problem solved using a receding horizon strategy. The approach is validated through both simulation and a real-world deployment in a commercial building with multiple EV chargers. Results show that the proposed strategy achieves charging cost reductions of up to 95% under favorable overnight pricing conditions and up to 87% in real-world operation with grid constraints, while maintaining user satisfaction. The findings demonstrate the practical feasibility and contribution of an integrated, cloud-based MPC approach for scalable, cost-efficient, and grid-compliant EV charging.
Keywords : *Electric Vehicles, Smart Charging, Day-Ahead Electricity Price, Charging Cost Optimization, Demand-Side Flexibility, Grid Compliance.*

1. Introduction

The integration of Electric Vehicles (EVs) and the Renewable Energy Sources (RES) in residentials, commercials, and industrial sectors and facilities have dramatically increased in the past few years due to their contribution in minimise the CO2 emissions and reducing dependence on fossil fuels. The RES generation fluctuates because it mainly depends on the weather conditions (Siddiqui et al., 2025), which increases the need for energy storage (Zhao et al., 2025). In Kazemtarghi et al., (2024), the traditional fixed-price charging methodology showed that the Charging Stations (CSs) become congested with EVs and the peak load increased significantly. This encouraged the energy suppliers to introduce dynamic hourly energy pricing where the energy price varies over the course of the day. This approach motivates the prosumers/consumers to optimise their energy usage to make the most of RES generation (improve the self-consumption), mitigate the stress on the grid and avoid the grid upgrades, and incentivizes minimizing the EVs' charging cost (Al-Saadi, Mathes, et al., 2022).

The global EV fleet has experienced rapid growth in recent years, with millions of new EVs added annually, leading to significant increases in electricity demand and peak load stress in distribution networks. In several European countries, EV penetration is already imposing constraints on low-voltage grids (Das et al., 2022), limiting the ability of Distribution System Operators (DSOs) to expand grid capacity without substantial infrastructure investments (Sevdari et al., 2022).

During the peak hours when the loads are high, the energy prices are high, which gives a chance to flexible loads, such as EVs to pause their charging temporarily until off-peak hours are reached where the energy prices are low and EVs can resume charging. This approach aims to flatten the load curve and optimizes the utilization of RES. This is the new energy management methodology that is based on controlling the demand-side (flexible loads) to match the generated energy unlike the traditional approach, which is based on controlling the generation to match the load (Opoku & Jochem, 2026). This paradigm aligns with demand response strategies, where flexible loads such as EVs are actively controlled to support grid stability and economic efficiency. Smart charging strategies have been widely studied, with recent review articles highlighting their role in demand response (Deb et al., 2022), grid flexibility, and renewable integration (Ayoade & Longe, 2024).

2. Literature Review

In the literature, there are many optimization techniques have been deployed for EV charging control and optimization (Kene & Olwal, 2023). For example, in Liikkanen et al. (2024), an EMS was developed to optimise the EV charging cost in a household with a PV system. The problem-based optimization was adopted to minimize EV charging cost against Spot market data of electricity prices. In (Kolawole & Al-Anbagi, 2019), a prediction and optimization model were developed which incorporates dynamic electricity prices and frequency regulation from both forecasting and real models into the objective function of the model to provide ancillary services to the system operator (Tsegaye et al., 2024). In (Qu et al., 2019), experimental analysis illustrated that the multi-objective electricity price optimization method can reduce the peak-valley load difference of the system and the cost input of operators. Using this method, the ability of users to respond to electricity prices was maximized, along with the regulation ability for users to access the power grid during different time periods. In (Ferretti & De Paola, 2025), smart EVs charging strategies based on machine-learning was deployed to unlock the flexibility of the connected EVs aiming to enable charging cost optimization and providing AS to the grid. In (Gong et al., 2021), EVs aggregated to participate in energy and regulation markets, thus cost of purchasing energy declined to fulfil EVs' charging requirements. An optimization model based on MPC is developed to estimate the energy and regulation prices as well as the EVs arrival. The validated results showed the effectiveness of the MPC in achieving a lucrative revenue while satisfying the charging preferences from EVs' owner.

However, these approaches often lack a comprehensive framework that simultaneously integrates economic, technical, and user-centric objectives. For instance, (Chandra et al., 2025) reported a 13.7% reduction in power losses using swarm optimization techniques. However, such approaches primarily focus on grid-level optimization without explicitly incorporating user-centric constraints or real-time pricing mechanisms.

Among many adopted solutions (Roth et al., 2020), smartly managed CSs present a robust method to bridge the gap between consumption and RES production over the course of the day, which alleviates the need for the stationary energy storage systems, and make the most of dynamic hourly pricing. The smart EV charging has been increasingly adopted in recent years due to its advantages, which offers reduced grid stress (Al-Saadi, Bhattacharyya, et al., 2022), optimise the charging cost, and provides Ancillary Services (AS) to system operators (Al-Saadi et al., 2021). Several studies have demonstrated the potential of smart charging to provide ancillary services and reduce system-level costs under uncertain conditions. These approaches highlight the capability of coordinated EV charging to support grid stability and reduce infrastructure requirements. However, they primarily focus on system-level objectives and often overlook the integration of user-defined charging constraints and real-time pricing signals within a unified optimization framework (Çelik & Ok, 2024).

Several studies have explored EV charging cost optimization using day-ahead market (DAM) pricing and local photovoltaic (PV) generation, demonstrating significant cost savings compared to uncontrolled charging (Hao, 2025). An Energy Management System (EMS) was developed with the aim of optimizing EV charging cost in a household with a small-scale photovoltaic (PV) system (Liikkanen et al., 2024). The charging cost was optimised against Nord Pool Spot market data of electricity prices. Based on self-consumption optimization, the PV surplus was used for EV charging. It was found that the yearly savings ranged between 25.4% and 51.9% compared with uncontrolled standard charging.

Model Predictive Control (MPC) has emerged as a powerful approach for EV charging due to its ability to handle multi-objective optimization problems while explicitly incorporating system constraints in a predictive framework. Unlike rule-based, heuristic, or static optimization methods, MPC continuously updates control actions based on real-time system states and forecasts, enabling adaptive responses to uncertainties in load demand, renewable generation, and electricity prices. This makes MPC particularly suitable for dynamic and uncertain environments such as EV charging systems integrated with RES and variable pricing signals. However, many existing MPC-based approaches focus primarily on cost minimization or grid services, without fully incorporating user-centric constraints or validating performance in real-world deployments.

However, these approaches often fail to fully exploit the flexibility of EV charging when simultaneously considering grid constraints, dynamic pricing, and user-defined requirements. Smart charging strategies can be applied across residential, commercial, and public charging infrastructures. Similar approaches have been applied in public charging infrastructures using intraday market trading, showing moderate cost reductions compared to static pricing schemes (Wahsh et al., 2024), around 8% of charging costs could be reduced compared to purchasing all the required energy from the energy supplier. Nevertheless, these methods often achieve limited savings and the existing studies are validated in simulation environments, with limited real-world demonstrations under practical operating conditions (Christensen et al., 2025). This limitation further emphasizes the need for experimentally validated and integrated control strategies for smart EV charging.

2.1. Research Gap

Most existing studies address EV smart charging objectives in isolation, such as cost optimization using DAM prices, grid constraint management, or user satisfaction (Meisenbacher et al., 2021). In some cases, dual-objective formulations are considered, for example combining cost optimization with ancillary services or battery degradation (DeForest et al., 2018). However, limited work has addressed the simultaneous integration of cost optimization, grid constraints, and user preferences within a unified control framework, particularly in real-world deployments (Pless et al., 2020). Furthermore, many existing studies rely solely on simulation environments, lacking validation under practical operating conditions (Powell et al., 2022). This gap highlights the need for integrated, scalable, and experimentally validated smart charging solutions.

2.2. Contribution

This paper proposes a cloud-based MPC framework for multi-objective EV charging that integrates day-ahead market pricing, grid constraints, and user preferences. The approach is validated through both simulation and real-world deployment, demonstrating its effectiveness in reducing charging costs while ensuring grid compliance and user satisfaction.

3. Methodology

A commercial building equipped with 5 AC chargers, each with two 11kW charging ports (total 10 ports total). The EV charged overnight and employees' EVs parked throughout the daytime with varying energy demands and plug-in durations. The building is connected to a constrained grid with a power limit of 68kVA. A cloud-based control approach has been deployed to control the EV chargers and comply with grid constraints. The overall system and the control algorithm are described in the subsections below in more details.

3.1. System Architecture

The residential and commercial buildings consume a significant energy i.e., roughly 30–40% of final global energy consumption and a comparable share of energy-related CO_2 emissions. In 2019, the buildings sector globally consumed around 30% of global final energy consumption and accounted for about 28% of energy-related CO_2 emissions (*Perspectives for the Clean Energy Transition – Analysis*, 2019). According the International EnergyAgency (IEA) report (*Greenhouse Gas Emissions from Energy Use in Buildings in Europe*, 2024), buildings in Europe were responsible for roughly 34% of CO_2 emissions from energy use (*Greenhouse Gas Emissions from Energy Use in Buildings in Europe*, 2024).

These figures indicate the importance of business buildings in the energy transition, and provide an enormous decarbonisation potential in the sector. Governments worldwide, particularly in Europe, are offering some incentives and legislation to integrate RES such as PV systems and to improve the energy efficiency.

In this work, a commercial building of around 50kW of peak consumption is considered. Due to the high EV integration in the Netherlands five chargers need to be integrated. The challenge is due to the high congestion in the Distribution System Operator (DSO) grid, the DSO is unable to upgrade the grid connection. The smart charging idea comes up as a solution: to comply with the contracted grid power, make the most of dynamic energy prices to reduce charging costs, and meet user preferences.

The building of 50kVA is integrated within smart meters for online energy monitoring, PV system of 20.72 kWp, 5 AC chargers. Real-time grid data and PV data were gathered via Modbus communication protocol and stored in the gateway at 15-minute intervals. Concurrently, real-time EV charger data were directly transmitted to a cloud database utilizing the Open Charge Point Interface (OCPI) protocol. Fig. **1** shows the Energy and Data (E&D) diagram for the system. The system components with their types are explained here:

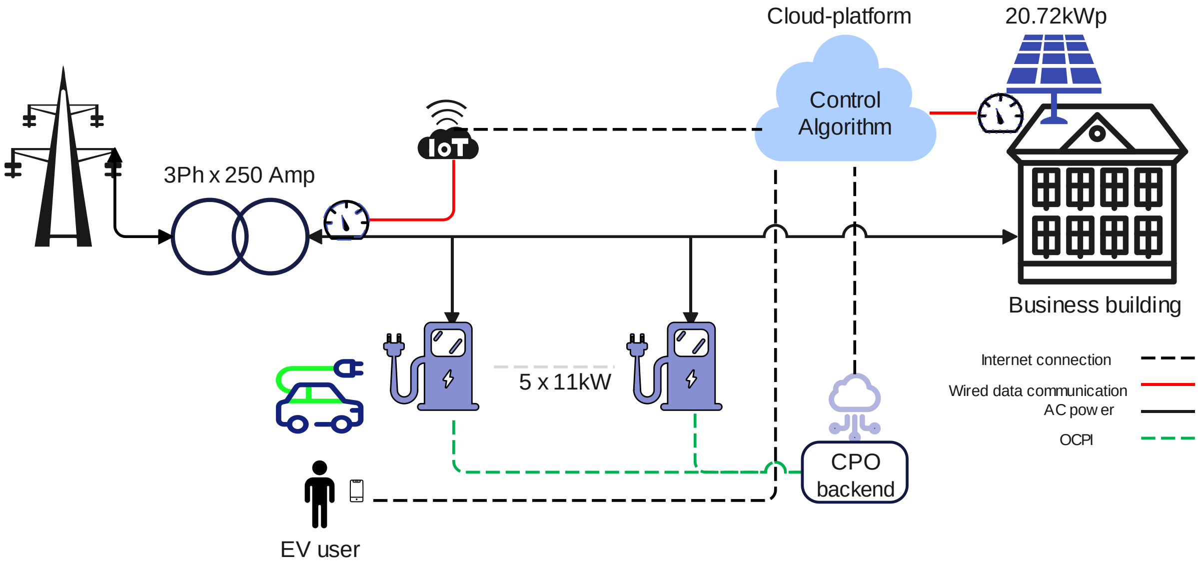

Fig. 1. E&D diagram for system components of business building.

- Grid connection: 3-phase connection of 3Ph x 250 Amp. The contracted power is 68kVA. The energy contract is based on dynamic energy price.
- Building: it is a commercial building. It has various non-flexible loads. The average load of the building is around 50kW.
- Gateway: The gateways from Bliqvanger brands are connected to the internet via Wi-Fi. It receives real-time data from the smart meters, and sent it to the cloud platform.
- Smart Meters (SMs): two SMs of Eastron SDM630 were installed. The SM measures the real-time voltages and currents in each phase and the power flow. The meter exchanges its information with the gateway which in turns exchange the information with the cloud platform.
- EVs chargers: five identical chargers were installed on the site. Each charger has two sockets, each of 11kW. Each charger has a SIM card with unique number and connected to the internet. The chargers exchange their information bidirectionally with the Charge Point Operator (CPO) backend based on Open Charge Point Interface protocol (OCPI). The charging power level of the chargers could be adjusted through their power electronics components from 0-11kW.
- CPO backend: the CPO backend receives the real-time data from the chargers and send the control power setpoints to the chargers. The backend has API used to exchange the data with the cloud platform bidirectionally. In this work, the CPO operates by the chargers' provider/manufacturer.

- PV system: the system of 20.72kWp, and inverter capacity of around 16kW AC. Though the inverter has built-in meter, a smart meter has installed to measure the real-time energy data and sent it to the gateway.
- Cloud platform receives the real-time data from the chargers through the CPO platform, and from the gateways. The platform is integrated with PV forecasting algorithm and MPC algorithm to control the flexible loads i.e., EVs chargers. Based on the real-time measurements, the MPC algorithm generates control signal of power setpoints to be sent to the chargers through the CPO. The cloud platform operates by the Energy Service Provider (ESP). The MPC algorithm will be explained with more details in section 2.3.
- EV user: the EV user enters their charging preferences into a dedicated webpage. The user inputs are taken as input to the control algorithm in the cloud-platform.
- The system operates in a centralized cloud-based architecture, where EV chargers, building load meters, and PV generation systems transmit real-time data to a cloud controller. The controller processes this information with day-ahead market (DAM) prices and user inputs to compute optimal charging schedules. The resulting charging setpoints are then communicated back to the EV chargers at each control interval. This architecture enables scalable coordination of multiple charging points while ensuring real-time adaptability.

3.2. MPC Formulation

This study focused on cloud-based EV control with the aim of optimise the charging cost, minimise the stress on the grid, and meet the EV user preferences. A business building situated in the south-east of the Netherlands was selected for demonstration purposes. This area has grid congestion issues, where the upgrades of the grid connection are not possible.

The demonstration included installing 5 AC chargers, each with two 11kW sockets. The real-time data from the chargers, grid balance, and PV inverter— were collected via the gateways using the Modbus protocol and communicated to the cloud-based platform. These data were input to the optimization algorithm along with the grid constraints, dynamic electricity price, and EV user preferences. The MPC methodology was employed as an optimization control technique, designed to achieve the above-mentioned goals. The MPC is a sophisticated control algorithm that determines an optimal solution (power setpoint) by minimizing a predefined objective function while adhering to specified constraints, all based on a mathematical model.

The grid constraint is mainly represented by the contracted power limit of 68kVA. The five chargers have total power of (5*2*11kW) 110kW, besides the building max consumption with reaches 50kW. Therefore, the total consumption of the building should be limited to around 68kW. The demand-side management was deployed to maintain the total load within the contracted power limit.

3.2.1. MPC Optimization Formulation

In this work, cloud-based MPC was developed in Python, predicting optimal output power setpoints over a predefined horizon and updating them in real time. The prediction horizon, which represents a future prediction interval, is set by MPC to optimise the predicted values (PV generation, and load building) and minimize errors within 15min timeframe. At each time step, only the first control input value from the optimization set is utilized as the current control input. This iterative process ensures that the values of the control input are optimised for cost function minimization and comply consistently with the given grid constraints and users' preferences. In (Hermans et al., 2024), the MPC proofed its effectiveness to manage the demand side of EVs loads to match the power supply in a grid connected microgrid to comply with the rated power limit set for large buildings. The system achieved a 59% of daily grid peak power reduction.

In this work, the EV charging optimization problem is formulated as a multi-objective MPC problem. At each time step, the controller solves an optimization problem over a finite prediction horizon N (24 hours), with a time discretization step Δt (15min).

$$min\sum_{t=1}^{N} C_t . P_t^{EV} . \Delta \mathrm{t}$$

where $C_t$represents the electricity price at time step t, and $P_t^{EV}$is the aggregated EV charging power.
Subject to the following constraints:

Grid constraint:

$$P_t^{EV} + P_t^{load} - P_t^{PV} \leq P^{max}$$

P_t^{load} is the load of the building. P^{max} is the max reachable power according to the grid contracted power.

Charging power limits:

$$0 \leq P_{i,t}^{EV} \leq P_i^{rated}$$

$P_i^{rated}$is the rated power of the ith charger i.e. 11kW.

State of Charge (SoC) dynamics:

$$SoC_{i,t+1} = SoC_{i,t} + \eta . P_{i,t}^{EV} . \Delta \mathrm{t}$$

$SoC_{i,t}$is the SoC of the ith EV, and η is the efficiency.

User requirement constraint:

$$SoC_{i,t_{dep}} \geq SoC_i^{req}$$

where t_{dep}represents the user departure time, and SoC_i^{req} is the required SoC from the user.

The optimization is solved in a receding horizon manner, where only the first control action is applied at each step before updating the system states and resolving the problem.

Fig. **2** shows the MPC flowchart for smart EV charging control. The input data acquisition, cost-optimizing control computation under constraints, and closed-loop feedback are illustrated.

3.2.2. User Constraint Modeling

The EVs users have access to a webpage to insert their preferences, which are then communicated to the cloud-platform as input to the MPC. The EV user preference is vital to be taken into account to provide the best service to the EV users, which encourages more people to consider EVs as an alternative option to fuel cars. The EV user preferences include many options, see Table 1, such as charging cost optimization (Yes/No), charge an EV with XkWh during the first N hour(s) of parking, choosing charging profile (Yes/No), and session duration where the parking time and the leaving time should be inserted by the EV user. If the EVs users does not enter their preferences into dedicated website, then the default setting will be considered. The default settings are illustrated in Table 1, which could be modified based on the user preferences.

Table 1- Features of the EV charging optimization based on EV user preference.

Parameters	EV user preference	Default setting
Charging cost optimization	Yes/No	True
Energy transfer (XkWh) during the first N hour(s)	XkWh, N hours	10
Total needed energy (kWh)	Y	20
Choose charging profile	Yes*/No	No
Session duration	Yes**/No	Yes 12 h
Max charging power (kW)	Insert max charging power	11

*True/option, insert the charging power profile.
**True/option, insert parking time and leaving time.

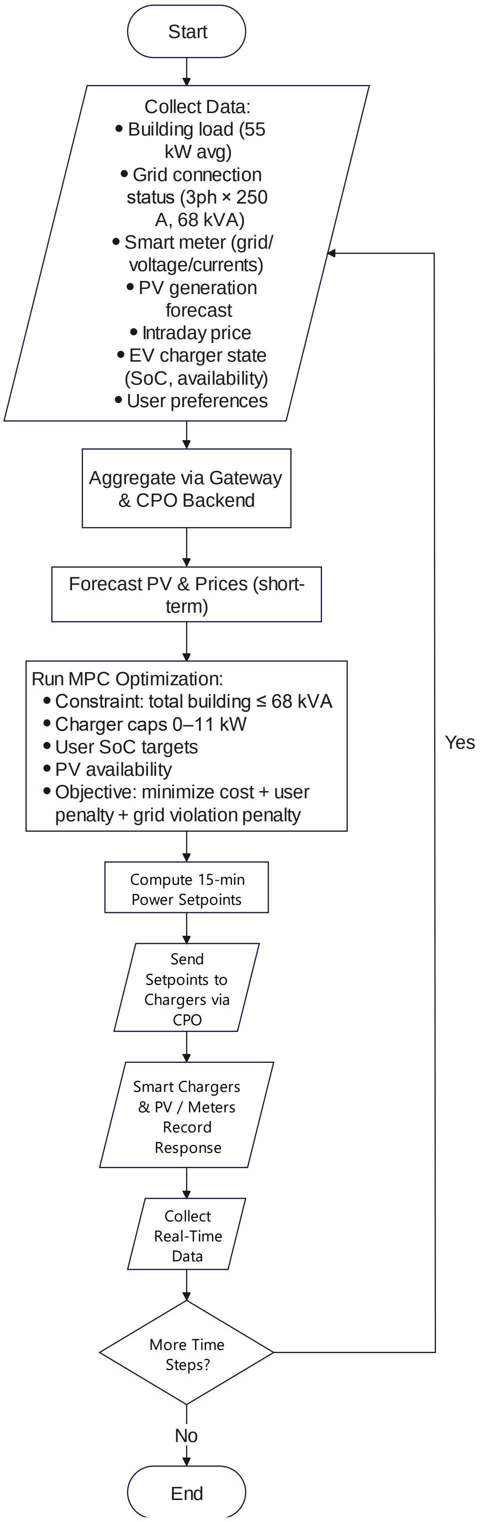

Fig. 2. MPC flowchart for smart EV charging control—showing input data acquisition, cost-optimizing control computation under constraints, and closed-loop feedback.

3.2.3. Implementation and Data Flow

The simulation environment as well as the cloud-based algorithm were implemented in Python. This includes the modelling of all system components in the business building as shown in Fig. **1**. This is done in the pandapower library for power flow analysis and a custom MPC module for optimization. On the other hand, for the cloud-based control, the real-time data were collected and inputted to the objective function. The objective function was formulated to minimise EV charging costs and constraints included user preferences and grid limits. The system components were modelled as follows:

- Building load: modeled as a non-flexible load.
- RES generation (PV): modeled as a negative load to the building consumption. The used data are 24-hour-ahead forecast from the TSO.
- EV chargers: modeled as flexible loads with upper limits of 11 kW per socket (five chargers, 10 ports in total).
- User preferences: collected from the web interface and introduced as hard constraints in the optimization problem.
- Grid connection: represented by a contracted maximum import limit of 68 kVA, with stricter limits (80 kW and 50 kW) applied in specific scenarios to test grid compliance.
- DAM prices: hourly DAM prices from Nord Pool were used as inputs for the cost optimization.

For the system components described above, historical data were utilized for the simulation studies, while measured data collected from the demonstration site were used for the real-world demonstration. Data processing and optimization procedures were implemented using Python libraries, including NumPy, Pandas, and SciPy (specifically the optimization module).

The MPC controller operates at discrete time intervals (e.g., 15 minutes), using updated forecasts of electricity prices, building load, and PV generation. Communication between system components is achieved via a cloud-based platform, where data is exchanged through standardized communication protocols. The computational problem is formulated as a convex optimization problem and solved using a quadratic programming (QP) solver, ensuring fast convergence suitable for real-time operation.

3.3. Electricity Pricing

The DAM is a segment of the electricity market where participants (buyers and sellers) trade the electricity on an hourly bases where the auction matches supply and demand for the next day. The prices determined in a single daily auction that starts at 12:00 and ends at around 12:45 CET. The DAM provides a clear price schedule for the next 24 hours, which is used by generators, suppliers, ESP, and many large consumers to plan production, consumption, and trading strategies. The DAM electricity prices and volumes are binding for the delivery day, unless later altered via intraday trading. In many European countries, it is possible to trade electricity on the energy trading market shortly before delivery on the intraday electricity market. At the public charging stations, intraday trading can minimise EV charging costs (*Nord Pool | Day-Ahead Prices*, n.d.), (Bjørndal et al., 2025).

In (Naharudinsyah & Limmer, 2018), EV charging cost was optimised using intraday electricity prices and DAM prices in the German market. The results showed that the intraday EVs charging costs were reduced by around 8% compared with DAM. In the Netherlands, the DAM showcases a complex pricing structure with hourly fluctuations, which is influenced by various factors. The hourly energy price includes a spot price. This varies constantly at an hourly resolution, alongside additional elements that may fluctuate yearly and vary based on individual grid connections and electricity purchase and sales agreements. These supplementary elements typically include electricity and value-added taxes, purchase and sells margins, as well as transmission and distribution costs as mentioned in (*Nord Pool | Day-Ahead Prices*, n.d.).

To gather data for this work, DAM electricity prices were sourced from Nord Pool (*Nord Pool | Day-Ahead Prices*, n.d.) via an API. Notably, this source provides reliable hourly electricity price data for the Netherlands, enabling optimization strategies to be implemented at an hourly resolution. Leveraging the obtained spot prices, the cost of charging EV was accurately determined (Massana et al., 2025). The hourly prices were used as input to the MPC to minimise EV charging cost while respecting the user preferences and grid constraints.

3.4. RES and LOAD Forecasts

Based on the MPC, to optimise over a certain horizon, forecasts of load and RES (PV) generation are assumed to be available, such as those from the Transmission System Operator (TSO) in the Netherlands, which provide 24-hour-ahead power forecasts (Li et al., 2025). Concerning the load forecast, deep recurrent neural network (RNN) with long short-term memory (LSTM), based on (Li et al., 2025), was used and adapted to the cloud platform.

4. Scenarios and Use Cases Under Study

Three scenarios were considered in this work; the real-world demonstration results were compared with the simulation results obtained from Pandapower. In this work, the standard charging sessions are based on simulation only, while the smart charging sessions are both simulation-based and real-world demonstration-based.

4.1. Baseline Scenario Definition

To evaluate the performance of the proposed MPC strategy, a baseline scenario is defined based on uncontrolled EV charging, where vehicles begin charging immediately upon connection at maximum power until the required SoC is reached. The cost savings reported in this study are calculated relative to this baseline scenario, providing a consistent reference for assessing the effectiveness of the proposed optimization framework.

4.2. Cost Saving Scenario: Simulation-Based

The standard charging and the smart charging scenarios were simulated taking into account the DAM price. In this scenario, it was assumed that there is no grid power limit, and EV user preferences are limited to the required transferred energy. The charging sessions were started overnight where the DAM price and load of the building are low.

4.3. Grid Compliance Scenario

This scenario includes two use cases, 80kW and 50kW of the grid limit. The 80kW grid limit use case is simulation-based as it is exceeding the actual grid limit 68kW. The idea of this use case is to compare the results with the previous scenario and to test the control algorithm before deployment in the real-world demo. The second use case in this scenario is demonstrated in real-world taking into account the grid limit of 50kW, which is within the actual grid limit i.e., 68 kW. Both use cases were demonstrated overnight when the DAM and the building energy consumption are low.

4.4. Users' Preferences Scenario: Real-World Based Demo

When the EVs are charged overnight, the users' preferences are limited to the required transferred energy to the EVs. While when the EVs are charges during the day, then there are many preferences need to be taken into account (as listed in **Table 1**) particularly during the day the building load and the DAM price are much higher than overnight. This third scenario includes three use cases during the day to charge EVs with energy demands of 24kWh, 14kWh, and 27kWh, respectively. In this real-world demo, the focus was on testing the capability of the cloud control system to meet EV users' preferences and comply with the actual grid limit.

5. Results and Discussion

In this study, three scenarios are presented. The first scenario is focusing on the cost saving. The second scenario is focusing on the grid compliance, and the third scenario is focusing on the EVs users' preferences. In these three scenarios, the DAM price was taken into account and EV users' preferences were considered. In the first scenario, it has assumed that there is not grid limit to compare the case if the grid connection were expanded with the actual grid limit, which is presented in the second scenario.

The proposed MPC strategy is evaluated using both simulation and real-world deployment scenarios. The system consists of five EV chargers (dual-socket chargers) connected to a building with a constrained grid capacity of 50 kW. The controller operates with a time resolution of 15 min and utilizes DAM prices for scheduling.

5.1. Cost Savings Scenario: Simulation-Based

As discussed previously, the general aim of this work is to optimise the EVs charging cost taking advantages of the dynamic electricity price, offer a solution to minimise the stress on the grid by avoiding grid upgrades which is not possible due to DSO grid congestion, and to meet the EVs users' preferences.

The first scenario is simulation-based with the aim of charging cost optimization, assuming the grid constraint has no limit, and EVs' user preferences are limited to the amount of the needed transferred energy. The smart charging sessions are demonstrated in simulation environment besides the standard charging. The 10 charging sessions arranged to start simultaneously overnight from 20:00 to 06:00, as shown in Fig. **3**. The standard charging sessions started immediately at maximum charging power i.e., 11kW. The transferred energy for each charger is illustrated in Table 2. This results in a peak-load of the building around 130kW, 110kW of charging power plus 20kW from the building load for the standard and smart charging, respectively. On the other hand, the smart charging sessions started when the electricity price is low and stop or the charging power levels get less when the electricity price is high. The maximum charging power reached around 90kW when the electricity price at lowest level i.e., 12 €/MWh. Then decreased slightly as the electricity price is getting high, and then fully stopped as the needed transferred energy has transferred. This results in high decreases in charging cost compared to the standard charging. The total charging cost of the standard charging sessions is 47,5 € while for the smart charging sessions is 2,14 €. This huge saving amount of 45,3 € or 95.48 % thanks to the smart charging control. These results highlight the importance of flexibility in EV charging as a key enabler for demand-side participation in modern power system.

It is important to note that the highest cost savings (up to 95%) are observed under specific overnight scenarios characterized by low electricity prices and high flexibility in charging schedules. In such cases, the controller shifts the majority of the charging load to low-price periods, resulting in substantial cost reductions. Therefore, these savings are primarily driven by favorable price differentials rather than solely by the optimization algorithm. In contrast, under daytime conditions with tighter user constraints and reduced flexibility, the cost savings are more moderate, reflecting the trade-off between user requirements and economic optimization.

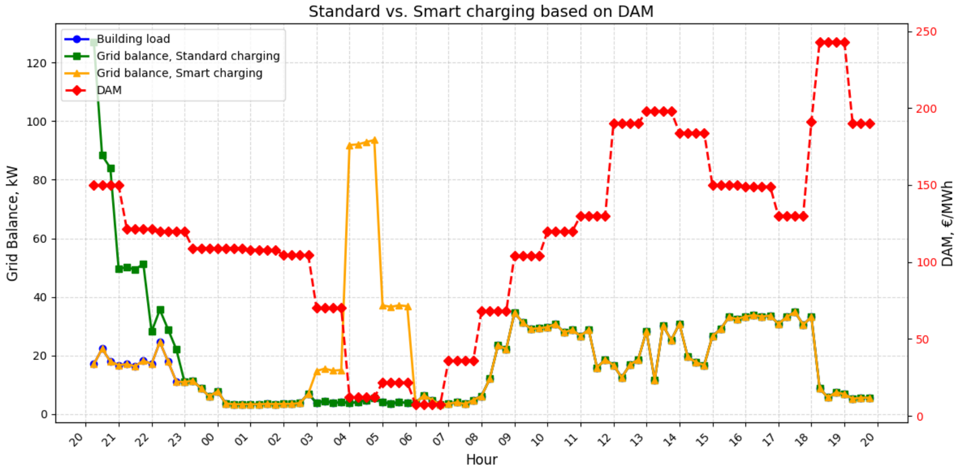

Fig. 3. Power flow of the standard charging versus smart charging, simulation-based.

Table 2 - Standard charging versus smart charging: charging cost optimization, simulation-based.

Chargers	Transferred Energy (kWh)	Charging Time (min)		Charging cost (€)		Saving (€)
		Standard	Smart	Standard	Smart	
Charger 01, A	5,5	30	60	1,98	0,066	1,914
Charger 01, B	5,5	30	60	1,98	0,066	1,914
Charger 02, A	5,5	30	60	1,98	0,066	1,914
Charger 02, B	5,5	30	60	1,98	0,066	1,914
Charger 03, A	11	60	60	3,96	0,132	3,828

Charger 03, B	11	60	60	3,96	0,132	3,828
Charger 04, A	11	60	60	3,96	0,132	3,828
Charger 04, B	22	120	120	7,92	0,23826	7,68174
Charger 05, A	22	120	120	7,92	0,23826	7,68174
Charger 05, B	33	180	180	11,88	1,00826	10,87174
				47,52	2,14478	45,37522

As can be seen in Table 2, the smart charging sessions took longer than the standard charging in case of transferring 5,5kWh to the EVs while when transferring 11kWh, 22kWh, and 33kWh, the charging periods are the same. This is mainly because of the DAM electricity price changes every one hour. So, when the energy transferred is 5,5kWh, the smart charging starts to charge with power of 5,5kW for an hour at lowest DAM price i.e., 12 €/MWh, while when the needed transferred energy is 11kWh, 22kWh, and 33kWh, the charging starts at lowest DAM price at maximum charging power i.e.,11kW, which is the same as the case of the standard charging so it takes the same charging time with less charging cost. These findings give incentives to the EVs users to schedule their charging, which is aligned with the study reported in (Wang et al., 2025).

5.2. Grid Constraint Performance

Two use cases are presented here, one is simulation-based with grid limit of 80kW, and one is demonstrated in real-world with 50kW of grid limit. In both use cases, the standard charging sessions were simulated and compared with the smart charging sessions.

In addition to cost optimization, the proposed MPC framework effectively enforces grid constraints by ensuring that the total power demand does not exceed the predefined grid capacity limit. Throughout both simulation and real-world operation, no violations of the 50 kW grid constraint were observed.

The controller dynamically adjusts EV charging power in response to variations in building load and PV generation, demonstrating stable and reliable operation. The receding horizon nature of the MPC ensures smooth control actions without abrupt changes in charging power, contributing to system stability.

5.2.1. Use Case 1: 80kw Grid Limit: Simulation-Based

Another scenario has simulated, taking the grid constrain into consideration i.e., around 80kW and optimise the smart charging against the DAM. The standard charging scenario has no difference compared with the previous scenario as the EVs start their charging immediately after the EVs connected to the charger with no grid connection limit. In the previous scenario, the grid connection limit reached 90kW in case of smart charging, while in this scenario the 80kW limit should compliance. The difference is only 10kW and it is expected not to see big difference. The 10 smart charging sessions have simulated, the results are shown in Fig. **4**.

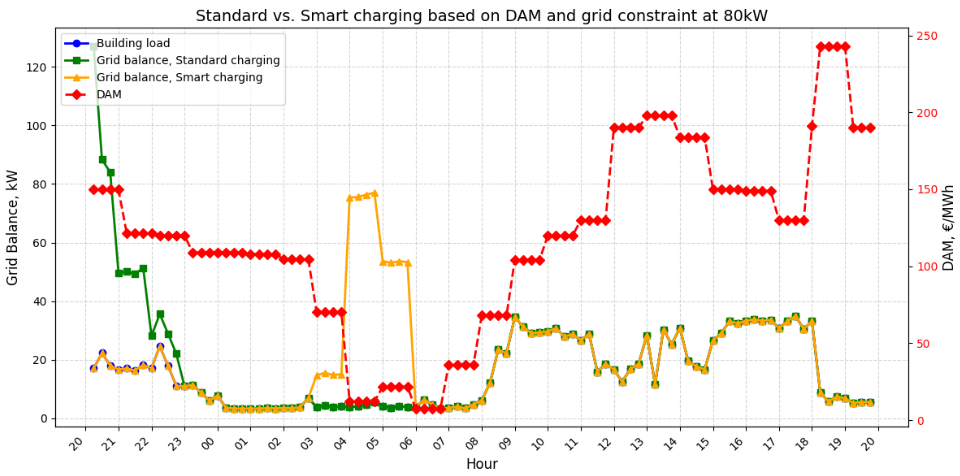

Fig. 4. Power flow of the standard charging versus smart charging, simulation based.

As can be seen in Fig. **4**, in the smart charging scenario, when the energy cost reaches its minimum value i.e., 12 €/MWh, the chargers power limited to be around 72kW, plus the load of the building, the total reached consumption is around 77kW. The total cost of the smart charging sessions is around 2,11€ compare with the standard charging which costs around 47,5€. The total saving is 45,4€ or 95.54%, as listed in Table 3. This slight disparity from the first scenario is due to not much change of the maximum reached power in the first scenario i.e., 90kW and the maximum power limit in the 2nd scenario i.e., 80kW. As the power difference increases, the difference gets higher as demonstrated in the 3rd scenario.

In this scenario the charging sessions took longer to achieve the most optimum charging cost optimization, as illustrated in Table 3, this is due to the grid compliance limit.

Table 3 - Standard charging versus smart charging: charging cost optimization, simulation-based.

Chargers	Transferred Energy (kWh)	Charging Time (min)		Charging Time (min)		Saving (€)
		Standard	Smart	Standard	Smart	
Charger 01, A	5,5	30	60	1,98	0,066	1,914
Charger 01, B	5,5	30	60	1,98	0	1,98
Charger 02, A	5,5	30	60	1,98	0,066	1,914
Charger 02, B	5,5	30	60	1,98	0,066	1,914
Charger 03, A	11	60	120	3,96	0,18513	3,77487
Charger 03, B	11	60	120	3,96	0,18513	3,77487
Charger 04, A	11	60	120	3,96	0,066	3,894
Charger 04, B	22	120	120	7,92	0,23826	7,68174
Charger 05, A	22	120	120	7,92	0,23826	7,68174
Charger 05, B	33	180	180	11,88	1,00826	10,87174
				Total cost (€)	Total cost (€)	Total saving (€)
				47,52	2,11904	45,40096

5.2.2. Use Case 2: 50kw Grid Limit: Real-World Based Demo

In this use case, the actual grid constraint and the charging cost optimizations have taken into account. This scenario unlike the previous simulated ones, this use case has demonstrated in real-world with 10 charging sessions and the grid constraint limit was considered to be 50kW, which is within the limit of the actual grid limit i.e., 68kW. The simulated standard charging is the same as the previous first scenario. The smart charging has to fulfil the needed transferred energy based on EVs user preferences in optimum cost besides complying with the grid constraint. The real-time data of PV system, grid balance, and the charging sessions have communicated to the cloud-platform. The results are shown in Fig. **5**. The maximum reached power around 47kW between 05:00 and 05:45 due to low charging cost at this period, then the power dropped sharply to be around 3,7kW due to fulfilments of the needed transferred energy and slight gradual increase of the DAM price. These findings are align with the reported results in (Hao, 2025), where the smart EV charging minimise the stress on the grid, where the total power losses reduced by 13.7%. These results are aligned with the mentioned findings in (Hermans et al., 2024), where the smart charging minimised the average daily peak by 59%.

This scenario showed that the charging sessions time increases due to decrease in the charging power because of the grid limit, as listed in

Table **4**. Furthermore, for the same reason, the saving of the charging has declined compared with the previous two scenarios. In this use case, an 87.45% saving was achieved compared with 95% range obtained before. This saving could even decline significantly when the charging sessions occur during the day where the DAM are high and the building load is higher than the overnight load which gives fewer manoeuvres for cost optimization.

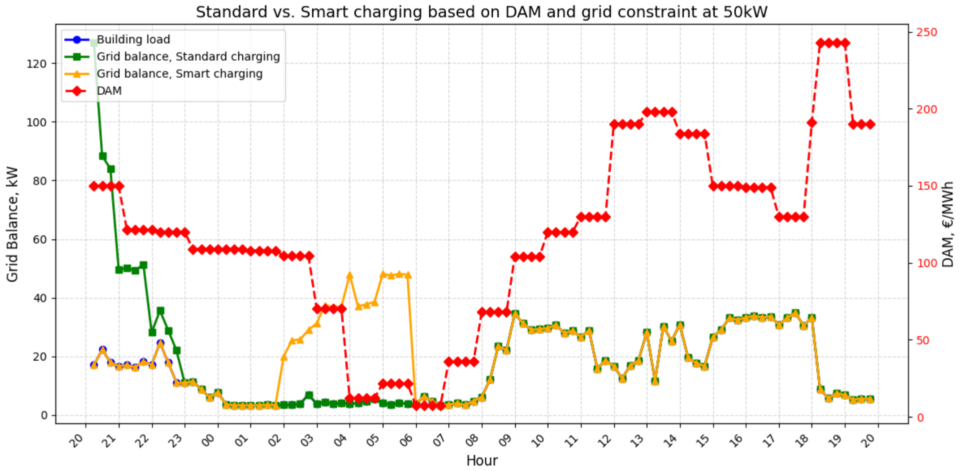

Fig. 5. Simulated standard charging sessions versus real-world demonstration of the smart charging scenarios.

Table 4 - Simulation-based standard charging versus real-world smart charging.

Chargers	Transferred Energy (kWh)	Charging Time (min)		Charging Time (min)		Saving (€)
		Standard	Smart	Standard	Smart	
Charger 01, A	5,5	30	60	1,98	0,066	1,914
Charger 01, B	5,5	30	60	1,98	0,11913	1,86087
Charger 02, A	5,5	30	60	1,98	0,066	1,914
Charger 02, B	5,5	30	60	1,98	0,066	1,914
Charger 03, A	11	60	120	3,96	0,18513	3,77487
Charger 03, B	11	60	120	3,96	0,18513	3,77487
Charger 04, A	11	60	120	3,96	0,451	3,509
Charger 04, B	22	120	180	7,92	1,463715	6,456285
Charger 05, A	22	120	180	7,92	1,197845	6,722155
Charger 05, B	33	180	180	11,88	2,15743	9,72257
				Total cost (€)	Total cost (€)	Total saving (€)
				47,52	5,95738	41,56262

The results presented for both use cases mentioned are aligned with the reported findings in (Boubaker et al., 2025), where the optimization of the EV charging and discharging schedules in distribution networks was optimised, focusing on the needs of EV aggregators and household EV users. A multi-objective framework for EV demands response in power systems, optimizing charging and discharging schedules while considering grid connection limit and EV users' preferences as constraints were proposed. To this end, the framework employs a V2G approach. The proposed model, centred on aggregators and EV users, tackles issues such as power loss reduction, voltage profile enhancement, and optimal EV charging and discharging scheduling to maximize system performance. For this aim, a multi-objective optimization based on using a linear weighted sum technique deployed to simultaneously address the framework objectives. The optimization problem was tackled based on a metaheuristic swarm intelligence algorithm, while the Red Deer Algorithm (RDA), is utilized to determine the timings of the optimal EV charging and discharging. The study simulates various residential EV loads with different charging powers modelled in IEEE 69-bus system. The aim was to analyse the grid impact of EV integration during peak and off-peak hours and to determine the optimal power flow for charging control. The results showed that the smart EV charging significantly alleviated average EVs load demand without overloading the distribution grid's power flow, while maintaining an optimised voltage profile.

5.3. Users' Preferences Scenario: Real-World Based Demo

In this scenario, three use cases are presented based on real-world demonstration. One use case for an employee working in the business building and two use cases for visitors. Both uses cases demonstrated how the cloud-based controller meets EV users' preferences. The demonstrated scenarios were compared with the simulated standard charging sessions.

5.3.1. USE Case 1

In this use case, the EV user preferences (an employee working within the business building) were indicated as shown in Table 5, the controller ensures transfer of a 10kWh during the first 5 hours of session. The smart charging session took in total around 9 hours from 08:00 till 17:00, the total energy transferred during this time is 24kWh. It can be observed from Fig. **6** that during the first two hours the energy price is significantly high i.e., between 320-400 €/MWh, which makes the controller limited the charging rate to be lower i.e., 2kW. After 13:30, when the energy price started to fall below 320€/MWh, the charging power increased gradually. The maximum reached power is 4.2kW when the energy price noticeably dropped to its minimum value i.e., 240 €/MWh. Using this strategy, as much as 2.06€ of charging cost was saved compared with the reference charging, which means the charging cost was minimised by 28.6%, which is consistent with the results obtained in previous studies (Naharudinsyah & Limmer, 2018). On the other side, the standard charging took around 2.1hours to meet the EV user preferences in terms of energy transfer i.e., 24kWh. The maximum charging power during the standard charging is set to be 11kW. The adopted approach not only optimise the charging cost but also minimise the stress on the grid particularly in the Netherland where the grid congestion become a problem. The comparison between the standard and smart charging is explained in Table 6.

Table 5 - EV user preferences, first charging session.

Parameters		EV user preference
Charging cost optimization		True
Energy transfer (XkWh) during the first N hour(s)		10kWh, 5hours
Total needed energy (kWh)		24
Choose charging profile		False
Session duration	Parking time	08:00
	leaving time	17:00
Max charging power (kW)		10

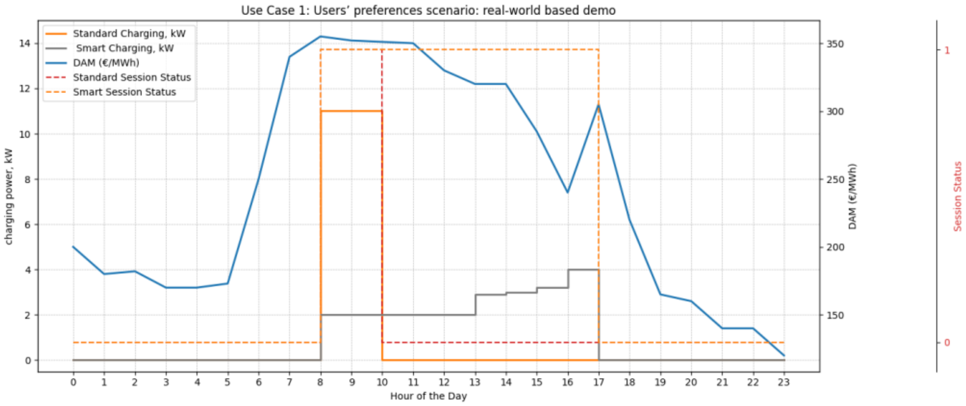

Fig. 6. Smart and standard charging profiles.

Table 6 - Smart charging versus standard charging.

Characteristics	Standard charging	Smart charging
Charging cost optimisation	✕	☑
Session duration (h)	2.1	9
Transferred energy (kWh)	24	24
Control the transferred energy	✕	☑
Transferred energy during the 1st 5 hours	24	10
Max charging power (kW)	11	4.2
Charging cost (€)	7.2	5.14

5.3.2. USE Case 2

In this use case, the EV user (a visitor) preferences were selected as shown in Table 7. The smart charging session took in total around 2.53 hours from 08:15 till 11:08, the total energy transferred during this time is 14kWh. As can be observed in Fig. **7**, although the energy price is significantly high i.e., 400-440 €/MWh, the charging power is considerably high i.e., around 9kW. This is to meet the EV user preferences i.e., transfer of 9kWh during the first hour of parking time. Afterwards, the charging completely stopped, and the charging power dropped severely to be 0kW. Then, when the energy price fell slightly below 400 €/MWh after 10:00, the charging power jumped to be around 5kW. Based on this approach, as much as 0.95€ was saved during this charging session, which means the charging cost improved by up to 30.2% compared with the standard charging, which is in line with the outputs obtained in (Naharudinsyah & Limmer, 2018). On the other side, the standard charging took around 1.25 hours to meet the EV user preferences in terms of energy transfer i.e., 14kWh with maximum charging power of 11kW. The comparison between the standard and smart charging is explained in Table 8.

Table 7 - EV user preferences, second charging session.

Parameters		EV user preference
Charging cost optimization		True
Energy transfer (XkWh) during the first N hour(s)		9kWh, 1hour
Total needed energy (kWh)		14
Choose charging profile		False
Session duration	Parking time	08:15
	Leaving time	11:08
Max charging power (kW)		11

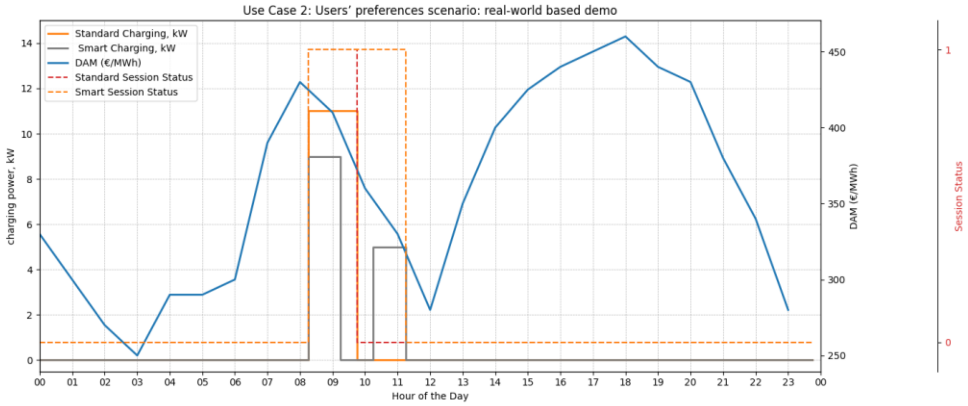

Fig. 7. Smart and standard charging profiles.

Table 8 - Smart charging versus standard charging.

Characteristics	Standard charging	Smart charging
Charging cost optimisation	✕	☑
Session duration (h)	1.25	2.53
Transferred energy (kWh)	14	14
Control the transferred energy	✕	☑
Transferred energy during the 1st 5 hours	14	10
Max charging power (kW)	11	9
Charging cost (€)	3.14	2.19

5.3.3. USE Case 3

In this use case, the EV user (a visitor) preferences were selected as shown in Table 9. The smart charging session took in total as much as 9 hours from 09:30 till 14:30, the total energy transferred during this time is considerably high i.e., 27kWh. As can be seen in Fig. **8**, when the energy price is noticeably high i.e., above 240 €/MWh, the charging power is limited to be the minimum i.e., 2kW. After 12:00, the energy price relatively dropped under 240€/MWh, then the charging power increased accordingly. The maximum reached charging power 11kW, when the energy price fell substantially to a minimum value i.e., 200€/MWh, as presented in Table 10. Guided by this approach, as much as 1.78€ was saved during this charging session, which means the charging cost was optimised by over 22.8%, which is correlated with the previous studies' results (Rosado et al., 2023). On the other side, the simulated standard charging took around 2.2 hours to meet the EV user preferences in terms of energy transfer i.e., 27kWh with maximum charging power of 11kW. The comparison between the standard and smart charging is explained in Table 10.

Table 9 - EV user preferences, third charging session.

Parameters		EV user preference
Charging cost optimization		True
Energy transfer (XkWh) during the first N hour(s)		False
Total needed energy (kWh)		27
Choose charging profile		False
Session duration	Parking time	08:00
	leaving time	17:00
Max charging power (kW)		10

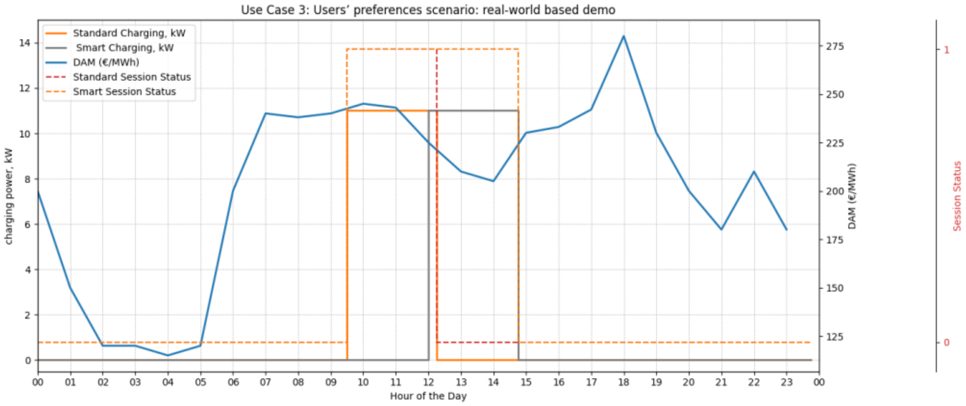

Fig. 8. Smart and standard charging profiles.

Table 10 - Smart charging versus standard charging.

Characteristics	Standard charging	Smart charging
Charging cost optimisation	False	True
Session duration (h)	2.2	5
Transferred energy (kWh)	27	27
Control the transferred energy	False	True
Max charging power (kW)	11	11
Charging cost (€)	7.8	6.02

5.4. Sensitivity Analysis

To further evaluate the robustness of the proposed approach, a qualitative sensitivity analysis is conducted with respect to key factors such as electricity price variability, user parking duration, and grid capacity limits. The results indicate that higher price volatility leads to increased cost-saving potential, as the controller can better exploit price differences. Conversely, shorter parking durations reduce flexibility and limit optimization performance. Similarly, stricter grid constraints increase the importance of coordinated charging but may reduce achievable cost savings due to limited scheduling flexibility.

5.5. Comparison With Literature

Compared to previous studies, the proposed approach demonstrates competitive or superior performance in terms of cost reduction and grid constraint enforcement. While prior works report cost savings typically ranging between 10% and 50% depending on the scenario, the higher savings observed in this study are attributed to the integration of DAM pricing, real-time system constraints, and user preferences within a unified MPC framework. Furthermore, unlike many existing studies that rely solely on simulation, this work validates the approach through real-world deployment, enhancing its practical relevance and applicability.

5.6. Discussion

Overall, the results demonstrate that the proposed MPC-based smart charging framework provides a flexible and effective solution for managing EV charging in grid-constrained environments. The integration of economic, technical, and user-centric objectives enables a balanced trade-off between cost efficiency and operational constraints. The results also indicate that the proposed approach performs particularly well under high price volatility conditions, where scheduling flexibility can be fully exploited.

However, under constrained scenarios (e.g., daytime charging with strict user requirements), the optimization potential is reduced, highlighting the inherent trade-off between user satisfaction and economic objectives. The findings suggest that the effectiveness of smart charging strategies is highly dependent on external factors such as price variability and user behavior. Therefore, future large-scale deployments should consider stochastic modeling of these uncertainties. Additionally, the scalability of the proposed approach makes it suitable for integration into larger EV fleets and smart grid applications.

6. Future Work

The extent of this study demonstrated the effectiveness of smart charging based on cloud control to reduce the charging cost and the ability to minimise the stress on the grid. This is a scalable solution could be applicable over local and wide geographical areas, where EV charging could be controlled within households and/or within buildings, and public charging stations. The EV capacity could be aggregated to provide AS to the system operator and contribute to system stability by adopting the coordinated smart charging. However, some limitations are worth noting. Although the EV chargers were controlled effectively, a slight delay between sending the power setpoint and the execution by the charger was observed. This could have implications only in case of providing primary ancillary services to the grid. Future work should therefore include follow-up work designed to evaluate whether the delays are causing an issue for system operators in case of primary ancillary services provision.

This work makes use of the DAM price, which gives the ability to make most of the RES generation and allows high EV penetration. The periods where the DAM electricity price is high, this is due to low-RES generation in the system, and due to limited availability of the energy storage systems to store the generated energy at peak hours. Accordingly, the energy prices are being low during high-RES generation.

By considering the EV charging cost optimisation, the self-consumption of the local RES optimised at the residential and commercial buildings could help to integrate more EV chargers at their facilities with no need to upgrade the grid-connection. In addition, the improvements noted in this study showed the cost saving due to the smart charging is high compared to the standard charging and the total savings could increase significantly.

Future research should focus on extending the proposed framework to larger-scale EV fleets and integrating additional sources of uncertainty, such as stochastic EV arrival patterns and renewable generation variability. Furthermore, the incorporation of V2G capabilities and advanced forecasting techniques could enhance system flexibility and economic performance. Addressing communication delays and evaluating their impact on fast-response ancillary services also remains an important direction for future work.

7. Conclusion

This study addressed the challenge of integrating grid constraints, cost optimization, and user preferences within a unified smart EV charging framework, which is insufficiently explored in existing literature.

This work demonstrated the effectiveness of a cloud-based MPC framework for multi-objective EV charging, validated through both simulation and real-world deployment. EV chargers, acting as a smart power electronics interface, dynamically adapted their output power in response to the DAM price and grid signals, ensuring effective demand response without compromising users' requirements. The proposed approach is particularly relevant for regions facing grid congestion and limited infrastructure expansion. These results reinforce the potential of integrating advanced control algorithms directly into power electronics systems to achieve flexible and scalable smart grid solutions.

Cost savings of up to 95% were achieved under favorable overnight pricing conditions, while more realistic savings of up to 30% were observed during daytime operation with tighter constraints. The cloud-based control system showed its ability to aggregate a number of EVs to provide AS to the system operator and gave some extra financial incentives for the EVs users. Furthermore, the smart charging system has avoided the need to upgrade the grid connection. The smart charging took more time to fulfil the transferred energy requirement. However, the users' preferences were collected through a dedicated webpage and used as input to the MPC to prioritize user satisfaction. The more the user uses the EV daily, the more cost-effective the optimization becomes compared with the uncontrolled standard charging approach. The results also showed that depending on daily fluctuations in the electricity prices, it is sometimes more beneficial to sell the PV power rather than use it to charge the EV and instead charge the EV with grid electricity at night.

Despite these promising results, several limitations should be acknowledged. The performance of the proposed approach depends on the availability of accurate forecasts for electricity prices, building load, and renewable generation. Additionally, the demonstrated system scale is limited to a small number of chargers, and further validation is required for larger deployments.

The proposed framework provides practical value for energy service providers and grid operators by enabling cost-efficient and grid-compliant EV charging without requiring infrastructure upgrades. From a theoretical perspective, this work contributes to the development of integrated multi-objective control strategies for demand-side flexibility in smart grids. The scalability and adaptability of the proposed approach make it a promising solution for future energy systems with high EV penetration.

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