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Optimal Energy Transactions for Bidirectional Charging Stations Enabling Grid Ancillary Services

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***Abstract*— This paper proposes a novel control algorithm to use bidirectional charging of electric vehicles (EVs) in the framework of vehicle-to-grid (V2G) technology for optimal energy transaction and investment. The energy storage components of an electric charging station, including the buffers of energy, provide the opportunity to sell energy to or buy energy from a smart grid that not only improves the stability and power quality of the grid but also offers the possibility to the charging station owner and the EV drivers to benefit from the trades in the energy market financially. Therefore, a model predictive controller (MPC) is developed to maximize the profit of the charging station and satisfy the EVs minimum state of charge (SOC) requirement while participating in incentive-based ancillary programs of the grid. The proposed algorithm changes the energy investment in the components when the price of energy changes with time, especially the price of the grid's energy, to keep the optimality of the energy shares. The simulation results confirm the effectiveness of the proposed control strategy.**

I. INTRODUCTION

Nowadays, the effect of greenhouse gas emissions on our environment has undeniably increased as the temperature of the earth persistently rises, resulting in drought, polar ice melting, and sea level rise. A considerable amount of carbon dioxide is emitted into the atmosphere as a result of transportation vehicles [1]. However, the technology of EVs is an environmentally friendly approach to deal with the problem of CO_2 emission in the transportation sector [2]. In fact, merging new technologies and innovations gives the opportunity to develop EVs as a new alternative for the transportation sector with higher quality, higher capacity, and lower price. One of the most important structures for implementing grid-connected EVs is the V2G structure (Fig. 1), where there is a bidirectional energy flow between the EVs and the grid.

Bidirectional charging stations, which are currently under development, provide flexibility to the smart grids to use the capability of charging/discharging EVs to improve grid performance. Smart grids that use V2G technology with renewable energy resources (RERs) can cope with the problems originating from the unreliability of renewable resources such as solar and wind energy. In other words, V2G technology enables EVs to actively contribute to enhancing power grid performance by participating in ancillary services. Basically, this technology is an exchange of energy, data, and financial transactions among EVs, aggregators, and the power grid to make a stable balance between demand and supply [1]. The incentive-pricing plans proposed by the spot market for charging stations of EVs and EV owners motivate them to participate in demand response (DR). According to these plans, car drivers can charge their batteries during off-peak demand at a low price and sell energy to the grid at a higher price during on-peak demands to gain profit [3].

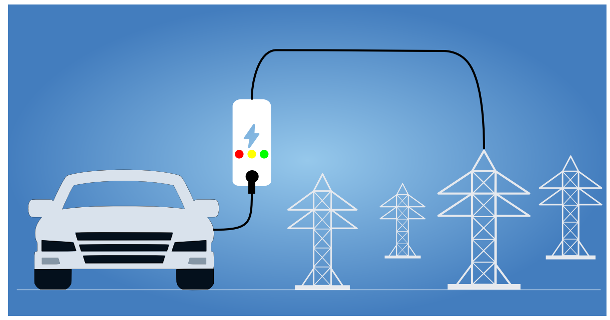

Fig. 1. Vehicle-to-grid (V2G) technology proposes using electric vehicles (EVs) as energy consumers and suppliers. It allows EVs to act as mobile energy storage units that can be used for a range of ancillary services, such as balancing the grid, managing peak demand, providing back-up power during grid outages, etc.

Looking into the state-of-the-art V2G technology, various control strategies have been utilized to integrate EVs in smart grids and DR programs. In [4], a strategy for managing EVs flexibility in local energy communities is suggested. The proposed approach allows an optimized and fair management of V2G participants in DR programs. A modern scheme proposed in [5] makes a balance between power production and consumption by motivating EVs to participate in energy trading programs. Additionally, a consortium blockchain-based strategy has been adopted to deal with problems arising from the security and privacy protection of online transactions between EVs and the grid. Also, a managing scheme of EVs in smart grids has been suggested in [6] to reliably and optimally participate in DR using a peak-clipping method. A dynamic complex network model of energy networks with V2G technology is proposed in [7], where EVs are considered energy transporters, coupling demand side management dynamics of different districts of the grid.

In [8], a scalable DR technique is suggested to manage EVs in smart grids to decrease overall procurement costs for a retailer bidding to the day-ahead and spot market. Besides, an optimal V2G pricing strategy based on game theory is proposed in [9], where the game factors are assumed

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to be the EV users' and gird aggregators' factors. Two energy management strategies suggested by [10] include V2G technology in the smart grid, where energy supply and demand forecasts and market prices are used in a multi-agent system framework.

In this paper, we consider a charging station that includes a buffer and several EVs to design an MPC for managing energy transactions between the storage components and the grid such that the benefit of the charging station is maximized while the charging station can contribute to the energy spot market. The energy investment in the players (the buffer, the EVs, and the grid) is made to maximize the benefit of the charging station, and this investment is updated when the energy tariffs for selling to/buying from the players change. In fact, the price of energy sold or bought by the grid and the price of energy sold to/bought from the EVs are not constant with time. Therefore, the proposed optimal control strategy updates the energy investment in the players while considering the incentive-based plans proposed by the energy spot market (ancillary services) and the minimum state of charge (SOC) that the EVs should have before leaving the charging station. Hence, the paper is targeting the following steps to deal with this complex problem successfully:

- Modeling the buffer and the battery for prediction purposes
- Define a cost function that describes the wealth of the charging station in terms of energy investments
- Formulating the constraints arising from energy flow and distribution, the EVs minimum SOC requirement, and the spot market primary service

The organization of the paper is as follows: Section II describes the storage components' models in the charging station. Section III provides detailed information about the proposed methodology, which formulates the cost function and the corresponding constraints, concluding the whole optimization problem formulation for MPC at each sample time. The simulation results are demonstrated in section IV, and the article concludes in section V.

II. MODELING AND CHARGING STATION SETUP

The proposed model for the electric vehicle battery and the architecture of the charging station are described in two subsections as follows.

A. Battery model

This subsection describes the model of the battery and buffer used in the charging station setup. A lithium-ion battery can be modeled in a discrete form as follows [11], [12]:

$$\dot{x} = \frac{\eta}{C} I \tag{1}$$

where x is the SOC of the battery, η is the efficiency of the battery, C is the capacity of the battery, and I is the current injected into ($I > 0$) or taken from ($I < 0$) the battery. In the case of buffer, the capacity C is considerably more than the EVs battery. The goal is to develop a control-oriented hybrid model of the batteries such that the three different modes of charging/discharging/standby are captured. It is vital to note that each car's battery produced by a car manufacturer has an optimal charging power profile, usually expressed in terms of SOC. The vehicles are charged based on this power characteristic to avoid any possible inefficiency or damage caused by the inappropriately injected current into the battery. Therefore, it is assumed that these power profiles are used to charge and discharge the vehicles, meaning that knowing the SOC of a battery, the corresponding power for charging and discharging is read from the profiles.

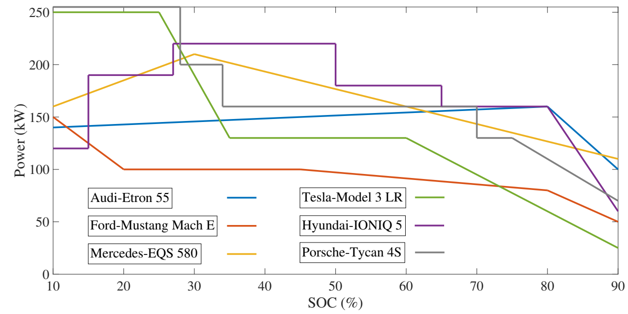

Fig. 2. Power charging profiles of six different EVs [13].

The mathematical description of the current injected into/taken from a battery can be written as follows:

$$I = \delta_1 f_c(x) + \delta_2 f_d(x) \tag{2a}$$

$$\delta_1 + \delta_2 \leq 1, \quad \delta_{1,2} \in \{0, 1\} \tag{2b}$$

where δ_1 and δ_2 are binary variables for charging and discharging, respectively. The charging current $f_c(x)$ and discharging current $f_d(x)$ are functions of SOC and are extracted from the charging power profiles. It is important to note that currently, car manufacturers only provide charging power profiles but not discharging power profiles. Since this paper has targeted a futuristic control algorithm for the bidirectional charging of EVs and the discharging profile $f_d(x)$ is also required, it is assumed that this profile is given. The proposed hybrid model of the batteries can also be used for the buffer in the charging station. Fig. 2 demonstrates approximately batteries' charging profiles in terms of SOC for different EV manufacturers.

For design purposes, it is required to model the current from the grid I_G using binary variables for buying energy from or selling energy to the grid. Therefore, the grid current I_G is described using a pair of binary variables and a pair of continuous variables as follows:

$$I_G = \delta_{1G} I_1 + \delta_{2G} I_2 \tag{3a}$$

$$\delta_{1G} + \delta_{2G} \leq 1, \quad \delta_{1G}, \delta_{2G} \in \{0, 1\} \tag{3b}$$

where it is assumed that $I_1 \geq 0$ and $I_2 \leq 0$ and both are continuous variables. While δ_{1G} is 1, the current is injected into the grid from the charging station, and in the case δ_{2G} is 1, the current flow is from the grid side to the charging station.

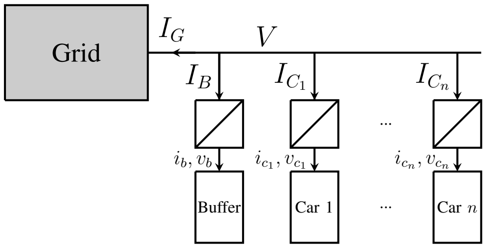

Fig. 3. The charging station architecture.

B. Charging station structure

The architecture of the charging station with the corresponding converters for charging and discharging the batteries is illustrated in Fig. 3. It is assumed that the charging station includes one buffer and n EVs connected to the same bus with the same voltage V, and the converters (chargers) supply the compatible currents to these components. The buffer, as a battery with significant capacity compared to the cars' battery, can provide benefits to the charging station since the charging station operator is able to buy energy from the grid or cars and sell it at a higher price to the grid or cars. In other words, this component is not only an active player when a primary or secondary service is sent from the spot market to the charging station but also gives the opportunity to make economic energy transactions.

III. CONTROLLER SYNTHESIS

The goal of the proposed control algorithm is to maximize the financial benefit of the charging station by exploiting bidirectional charging while not only contributing to the spot market through demand response but also satisfying the requirements of the EVs. In other words, the charging station should make an optimal energy transaction between the grid, the buffer, and the EVs using bidirectional charging while participating in demand response and ensuring a minimum level of SOC before the cars leave the charging station. MPC, as an optimal controller with the capability of predicting the future behavior of the system, is designed to maximize the benefit of the charging station and to satisfy the constraints originating from Kirchhoff's law and the minimum SOC requirement. The following two subsections elaborate on the cost function and the constraints of the optimization problem. The goal is to set the charging/discharging currents of the buffer and the EVs optimally.

A. Cost Function

Utility maximization refers to the process of making decisions to allocate resources in a way that maximizes an individual's / investor's overall satisfaction or wealth. In the context of finance, it involves choosing investments or assets that provide the highest expected utility, e.g. financial wealth, taking into account factors such as risk tolerance, time horizon, and personal preferences [14]. In financial decision-making, utility maximization is significant in portfolio management and investment choices. Investors seek to maximize their benefits by selecting investments or assets with the highest expected return. Suppose an investor starts with some initial endowment and wants to invest its wealth into m different assets. Let u_t^i denotes the number of shares of asset i owned by the investor at time t. It is also assumed that the price of asset i is described by p_t^i at each time. Then, the investor's wealth at each sample time is as follows [15]:

$$W_t = \sum_{i=1}^{m} u_t^i \; p_t^i. \tag{4}$$

u_t^i is also called a "portfolio" in the literature of financial mathematics, and the goal of utility maximization, also known as "portfolio optimization", is to choose these portfolios such that the highest expected wealth for a given level of risk is achieved.

In this paper, the charging station wealth is defined by the energy investment in the buffer, the EVs, and the energy sold to the grid. Specifically, the charging station operator can make energy transactions among the grid, the EVs, and the buffer. The benefit of the charging station should be maximized by conducting energy transactions concerning the price of energy in the grid and spot market, as well as the price of energy stored in the buffer and the vehicles. It is assumed that the amount of electrical energy (portfolios) bought from the grid, the buffer, and the EVs at time t is u_b^G, u_b^B, and $u_b^{C_i}$ in MWh, respectively. Also, the electrical energy sold to the grid, the buffer, and the EVs are described by u_s^G, u_s^B, and $u_s^{C_i}$, respectively. Then, the resulting financial wealth J_t is given by:

$$\begin{aligned} J_t = {} & u_b^G M_b^G + u_s^G M_s^G + u_b^B M_b^B + u_s^B M_s^B \\ & + \sum_{i=1}^{n} (u_b^{C_i} M_b^{C_i} + u_s^{C_i} M_s^{C_i}) \end{aligned} \tag{5}$$

where M_b^* and M_s^* are the prices for buying from and selling to the players at time t, respectively. The core idea of the energy transactions between the grid, the buffer, and the EVs is to buy energy from the players with lower energy prices (M_b^*) and sell it to the players with higher energy prices (M_s^*) such that the benefit of the charging station is maximized. Therefore, energy transactions lead to a higher financial wealth for charging stations. Bidirectional charging provides the opportunity to exploit the capacity of the buffer and the cars' battery to make energy transactions such that the financial wealth of the charging station increases. This means choosing u_b^*/u_s^* and adapting these selections with respect to the prices M_b^*/M_s^* by shifting the energy shares from one player to the others to boost the whole wealth J_t.

B. Constraints

The proposed control algorithm should maximize the financial wealth of the charging station by finding the optimal portfolios, i.e., the energy investments, while considering the constraints caused by energy flow in the system and SOC of the batteries, as well as the demands from the spot market. Based on Kirchhoff's law, the current from the grid must be equal to the injected current into the buffer and the cars' battery:

$$I_G + I_B + \sum_{i=1}^{n} I_{C_i} = 0 \quad (6)$$

where I_G is the current injected into the grid, I_B, and I_C are the injected currents into the buffer and the cars' battery, respectively. It is important to mention that the direction of the currents in the case of discharging is the reverse of what is shown in Fig. 3. The energy invested in the buffer or the EVs and the energy shifted to the grid can be expressed mathematically as follows:

$$u^*_{b/s} = \int_0^t V(\tau) I_*(\tau) d\tau \quad (7)$$

where V is considered a constant in this paper. Moreover, the level of SOC of the EVs is not allowed to be any desired value because using the battery out of the standard recommended range might damage the battery or cause non-optimal usage. Therefore, the following constraint is imposed on the EVs battery and the buffer at each sample time t:

$$\alpha_j \le x_{j,t} \le \beta_j \quad (8)$$

where $j \in \{B, C_i\}$ and α_j and β_j are the lower and upper bounds on the SOCs ($x_{j,t}$), respectively. This inequality ensures the safe and reliable operation of the batteries in the charging station. The car manufacturers usually consider the range of 10%-90% or 20%-80% as an optimal operating range for the EVs.

Bidirectional charging also provides the opportunity for charging stations to participate in DR programs. As mentioned in Section I, the DR services provided by the charging station can be formulated in terms of power planning or energy consumption programs. In the case of primary services, the charging station is supposed to reduce power consumption supplied by the grid or even provide power to the spot market. This flexibility provided by the charging station in terms of power reduction can be expressed by:

$$P_{\min} \le P_B + P_C \le P_{\max} \quad (9)$$

where $P_{\max}$ and $P_{\min} < 0$ are respectively the upper bound and lower bound on the power consumption of the charging station. When a primary demand is received from the spot market, which usually asks for a power reduction for 30s, the charging station can either limit its power consumption to $P_{\max}$ or even provide power to the grid by discharging the storage components. This power provision is one of the main advantages of bidirectional charging in the charging station.

One of the most important constraints in the design procedure of the MPC is to provide the minimum SOC required by the EV drivers before leaving the charging station. The energy transactions between the charging station and the grid, as well as the ancillary service provision, should not affect the requested SOC by the driver at the time he/she wants to take the EV from the charging station. It is assumed that the time for picking up the EVs is known in advance. Therefore, it is necessary to direct the EVs SOC above a threshold set by the drivers. The strategy adopted in this paper for taking the final SOC into account is to add the following soft constraint to the optimization problem formulation using a slack variable:

$$x_C(T) + \delta \ge S_0 \quad (10)$$

where T is the end time of the prediction horizon, S_0 is the minimum required SOC and $\delta \ge 0$ is the slack variable. When the EVs connect to the charger in the charging station, $X_C(t)$ has low levels of SOC. Therefore, δ gets higher values to satisfy the constraint (10). When time is approaching the time specified by the EV drivers for picking up the car, the controller should set the charging power of the EVs such that the minimum required SOC is satisfied on time.

C. Optimization Problem Formulation

The goal of the predictive controller is to find the optimal currents injected into/taken from the buffer and the EVs' battery such that the financial benefit of the charging station is maximized. Referring to Eq. (1)-(3), the optimization problem is a mixed-integer linear programming (MILP). Since the detailed explanation of the cost function and the constraints has been completed in the last two subsections, the whole optimization problem of MPC can be formulated as follows:

$$\max_{\delta,\Delta_1,\Delta_2,\xi,I_1,I_2,I_G} \sum_{t=1}^{N} J_t - \gamma_t \cdot \delta \quad (11a)$$

$$\text{s.t.} \quad X_{t+1} = X_t + T_s \cdot (A\ U_t) \quad (11b)$$

$$U_t = \Delta_1 F_c(X_t) + \Delta_2 F_d(X_t) \quad (11c)$$

$$\tilde{\Delta}_1 + \tilde{\Delta}_2 \le \mathbf{I}_{n+2} \quad (11d)$$

$$\text{Eq.}\,(3), (6) - (10) \quad (11e)$$

where γ_t is a positive time-varying coefficient, $\xi = [X_1 \cdots X_{N+1}]$, $X_t = [x_{B,t}\ x_{C_1,t} \cdots x_{C_n,t}]^T$, the matrices including only binary variables are:

$$\begin{cases} \Delta_{1C} = \text{diag}(\delta_{1C_1}, \ldots, \delta_{1C_n}) \\ \Delta_{2C} = \text{diag}(\delta_{2C_1}, \ldots, \delta_{2C_n}) \\ \Delta_1 = \text{diag}(\delta_{1B}, \Delta_{1C}) \\ \Delta_2 = \text{diag}(\delta_{2B}, \Delta_{2C}) \\ \tilde{\Delta}_1 = \text{diag}(\delta_{1G}, \Delta_1) \\ \tilde{\Delta}_2 = \text{diag}(\delta_{2G}, \Delta_2) \end{cases} \quad (12)$$

Also, the state vectors, input vectors, and charging profile vectors are as follows:

$$\begin{cases} \xi = [X_1 \ldots X_{N+1}] \\ X_t = [x_{B,t}\ x_{C_1,t} \ldots x_{C_n,t}]^T \\ I_C = [I_{C_1} \ldots I_{C_n}]^T \\ U = [I_B\ I_C^T]^T \\ F_{c,C} = [f_{c,C_1} \ldots f_{c,C_n}]^T \\ F_c = [f_{c,B}\ F_{c,C}^T]^T \\ F_{d,C} = [f_{d,C_1} \ldots f_{d,C_n}]^T \\ F_d = [f_{d,B}\ F_{d,C}^T]^T \end{cases} \quad (13)$$

It is also assumed that $\tilde{A} = \text{diag}(\frac{\eta_{C_1}}{C_{C_1}}, \cdots, \frac{\eta_{C_n}}{C_{C_n}})$, and $A = \text{diag}(\frac{\eta_B}{C_B}, \tilde{A})$. The binary variables δ_{1*} and δ_{2*} are respectively defined for charging and discharging the buffer and the EVs or buying energy from/selling energy to the grid. Also, η_B and η_{C_i} are the efficiency coefficients of the buffer and the EVs, and C_B and C_{C_i} are the capacity of the buffer and the EVs, respectively. $f_{c,*}$ is the charging profile of the buffer/EVs, while $f_{d,*}$ is the discharging profile. Finally, the sampling time is noted by T_s. Since this paper aims to capture primary ancillary services as described in (9), the sampling time is considered in order of 1s.

It is vital to note that the algorithm in this paper is proposed for the charging station shown in Fig. 3, where a buffer and n EVs have been connected to the charging station. The motivation for exploiting charging/discharging power profiles is not only because it provides an optimal and safe method for bidirectional energy provision but also because it reduces the computational burden of the MPC. When the amount of power for charging/discharging is defined based on the SOC of the EVs or the buffer, then the controller does not need to seek the optimal charging/discharging currents. The MPC specifies whether the component should be charged, discharged, or in standby mode, meaning no current enters or leaves the storage component. This leads to faster decision-making where mostly the binary variables in Δ_1 and Δ_2 play a role in computation. As a result, the computation resources can be used to implement the proposed algorithm on charging stations with more charging points (more EVs). The implementation of primary service requests is accomplished through changing $P_{\max}$ and $P_{\min}$ with time. In other words, it is assumed that the whole power consumption of the charging station is not more than $P_{\max}$ at each time, and simultaneously, the power provision by the charging station is not more than $|P_{\min}|$. During 1 day (24 hours), depending on the grid condition, the spot market might ask for changing the upper and lower bounds accordingly to improve the grid stabilization.

IV. SIMULATION RESULTS

Two main simulation scenarios have been considered for this paper to demonstrate the performance of the proposed controller. In the first scenario, it is supposed that the price of energy is constant with time, and the performance of the MPC is investigated under primary demand. In the second scenario, the energy price is changed to see its effect on the decision-making strategy. The charging station architecture is shown in Fig. 3, and it is assumed that 20 EVs have been connected to the charging points in the charging station. The charging power profile of the EVs is also shown in Fig. 4, where an approximation of the Tesla Model 3 P AWD - 2021 charging power profile is used [16]. It is also assumed that the power profile for discharging is the minus of the power profile for charging ($f_d = -f_c$). Without loss of generality, it is assumed that the buffer is also charged with the same trend as the EVs, and only the profile is scaled by 20 (20x) in the power axis such that it is able to provide energy for the whole EVs, if necessary. The sampling time is also chosen $T_s = 1\,$s, and the prediction horizon is $t_p = N \times T_s = 15\,$s.

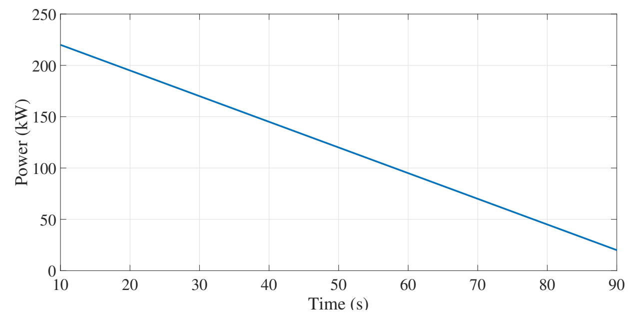

Fig. 4. Power charging profile of the EVs.

1) Scenario 1: In this scenario, the buffer and the EVs have different initial SOCs. The price of energy for the grid, buffer, and EVs are chosen $M_b^G = 1440$ c.u./MWh, $M_s^G = 360$ c.u./MWh, $M_b^B = 2160$ c.u./MWh, $M_s^B = 2160$ c.u./MWh, $M_b^{C_i} = 2160$ c.u./MWh, $M_s^{C_i} = 2160$ c.u./MWh, respectively, where "c.u." stands for "currency unit". It is assumed that these prices are constant during normal operation; however, they are changed during the primary demand. The price of buying and selling energy for the grid, the buffer, and the EVs are, respectively, $M_b^G = 360$ c.u./MWh, $M_s^G = 14400$ c.u./MWh, $M_b^B = 1080$ c.u./MWh, $M_s^B = 720$ c.u./MWh, $M_b^{C_i} = 1080$ c.u./MWh, $M_s^{C_i} = 720$ c.u./MWh. Based on these prices, during the primary demand, the charging operator can buy energy from the EV drivers and the buffer with 1080 c.u./MWh and sell it to the grid with 14400 c.u./MWh. Also, for the EV drivers, it makes sense to sell energy to the charging station because the price of selling to the station is more than buying. Starting from different initial conditions, it is more beneficial to charge the buffer and the EVs because the price of buying energy from the grid is much less than the price of selling energy to the buffer and EVs. Therefore, the controller makes the transactions in order to absorb energy into the buffer and the EVs, leading to an increase in the SOCs, as shown in Fig. 5. As the SOCs increase, the charging powers of the storage components reduce. The primary demand is received three times during the charging phase: $t = 600\,$s, $t = 900\,$s, and $t = 1200\,$s, and lasts $30\,$s each time. The spot market demands to reduce the power consumption of the charging station to $P_{\max} = -3.32$ MW, $P_{\max} = -2.82$ MW, and $P_{\max} = -2.38$ MW, respectively, meaning some energy should be transferred from the grid to the charging station ($P_{\max} < 0$). Therefore, the MPC stops receiving energy from the grid and changes the direction of energy flow into the grid, reducing the storage components SOC during the demand intervals (see Fig. 5). When the demand is received, the EVs and the buffer have levels of SOC that require a specific power for discharging. In fact, these components cannot take any continuous value of electrical power, resulting in certain levels of power injection from the buffer and EVs to the power grid. At the end of the simulation (50 min), as shown in Fig. 5 for four selected EVs, the storage components are filled with maximum SOC (90%).

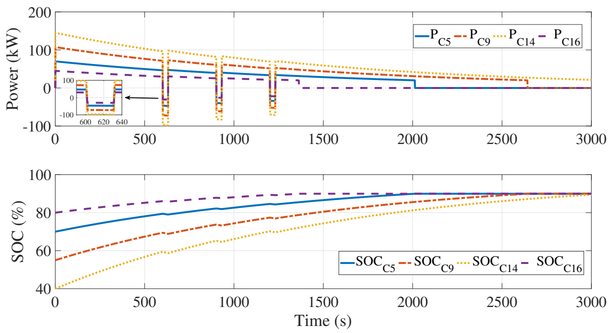

Fig. 5. The power profiles and SOCs in Scenario 1.

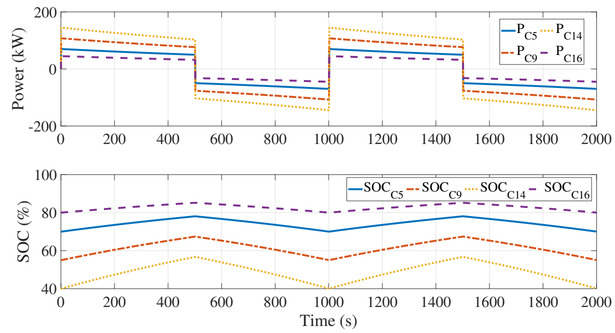

Fig. 7. The power profiles and SOCs in Scenario 2.

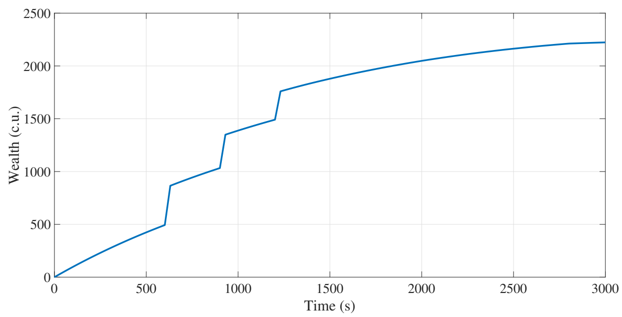

Fig. 6. Wealth function in Scenario 1.

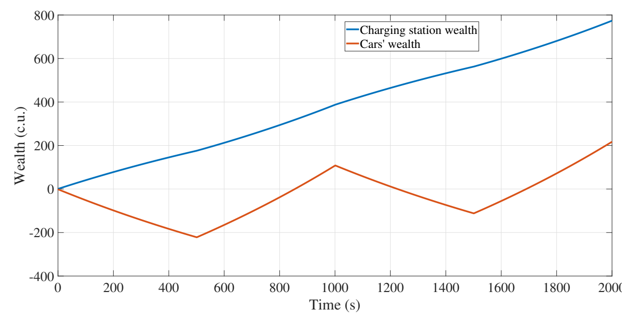

Fig. 8. Wealth function in Scenario 2.

The wealth function of the charging station is illustrated in Fig. 6, where it rises continuously with time. However, during the primary demand intervals, the slope of the increment increases because the reward for primary demand participation is considerable enough to motivate the charging station operator to discharge the EVs and the buffer shortly.

2) Scenario 2: The effect of changing energy prices is investigated in this scenario, where the prices of energy are changed noticeably. The buffer and the EVs have different levels of SOC at the beginning, and there are two sets of tariffs. The first set of prices is $M_b^G = 480$ c.u./MWh, $M_s^G = 120$ c.u./MWh, $M_b^B = 720$ c.u./MWh, $M_s^B = 840$ c.u./MWh, $M_b^{C_i} = 720$ c.u./MWh, $M_s^{C_i} = 720$ c.u./MWh, while the second set is $M_b^G = 360$ c.u./MWh, $M_s^G = 1440$ c.u./MWh, $M_b^B = 1080$ c.u./MWh, $M_s^B = 720$ c.u./MWh, $M_b^{C_i} = 1080$ c.u./MWh, $M_s^{C_i} = 720$ c.u./MWh. Starting from the initial condition, it is more beneficial to charge the buffer and the EVs because the price of buying energy from the grid is less than the price of selling energy to the buffer and the EVs. Therefore, the controller makes the transactions to shift the energy from the grid to the buffer and the EVs, resulting in SOC increment between $t = 0\,$s and $t = 500\,$s, as shown in Fig. 7. Then, in the second period from $t = 500\,$s to $t = 1000\,$s, the second energy tariff is applied, which results in discharging the storage components into the grid. The charging station operator buys energy from the EVs and the buffer at a cheaper price (1080 c.u./MWh) and sells it to the grid at a higher price (1440 c.u./MWh). Accordingly, the controller discharges the buffer and the EVs, shifting energy from the charging station back to the grid between $t = 500\,$s and $t = 1000\,$s. As the SOCs increase, the charging powers of the storage components reduce (Fig. 7). The two sets of tariffs are applied again in the same order between $t = 1000\,$s and $t = 2000\,$s, and the same trends for the power and SOCs are observed. The levels of SOC for EVs are the same at $t = 0\,$s, $t = 1000\,$s, and $t = 2000\,$s.

The wealth of the charging station, as shown in Fig. 8, is steadily increasing with time. However, the rate of increase is different in each of the 500 s intervals. The benefit of the grid with the first set of tariffs is 360 c.u./MWh if the energy is sold to the buffer and 240 c.u./MWh if it is sold to the EVs, while in the second mode, the benefit for buying from the buffer and selling to the grid is 360 c.u./MWh, and for buying from the EVs and selling to the grid is also 360 c.u./MWh. Therefore, with the second set of tariffs, the benefit of the charging station is greater, and the slope of wealth increment is more than the first set (Fig. 8). The controller makes the energy transactions to maximize the benefit of the charging station by charging and discharging EVs and the buffer. The SOC levels of the EVs at the end of the simulation are the same as at the beginning of the simulation (Fig. 7). The wealth of EV drivers decreases when they buy energy from the charging station, but it increases when they sell it back to the charging station. The gain of selling to the charging station (1080 c.u./MWh) is more than buying (720 c.u./MWh), and in a cycle of charging and discharging the net benefit is positive (360 c.u./MWh). Therefore, the EV drivers benefit from the energy transactions despite having the same levels of SOC at the end of the simulation.

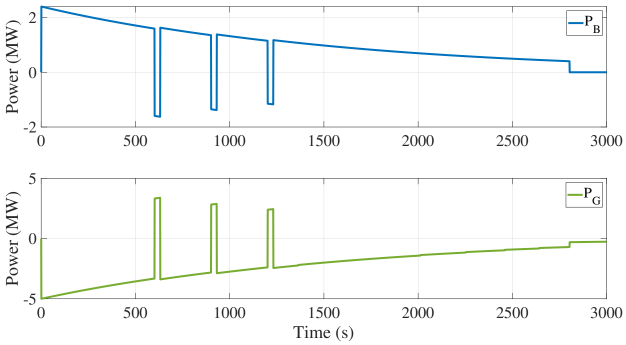

Fig. 9. Buffer and grid power profiles in Scenario 1.

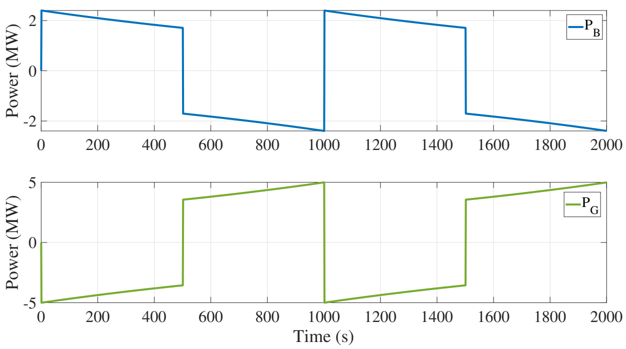

Fig. 10. Buffer and grid power profiles in Scenario 2.

3) The buffer and grid analysis: The power profiles of the buffer and the grid for the two scenarios are shown in figures 9 and 10. In the first scenario, the power consumption of the buffer starts with a value more than 2 MW and decreases with time (Fig. 9). When the primary demands are received three times ($t = 600\,\mathrm{s}$, $t = 900\,\mathrm{s}$ and $t = 1200\,\mathrm{s}$), the direction of energy flow is changed and energy is sent from the buffer (and also EVs) to the grid. Therefore, its power consumption gets negative values three times, each of them lasts for 30 s. This storage component fully discharges at the end of the simulation. The power provided by the grid starts from 5 MW, and its absolute value decreases with time. When the charging station participates in DR three times, the grid receives energy, and as a result, its power consumption jumps above zero, as shown in Fig. 9. This power provision contributes noticeably to the reserve market for frequency stabilization. The power profiles of the buffer and the grid in the second scenario are shown in Fig. 10. The buffer charges twice and discharges twice during the simulation. When the first set of energy tariffs is applied in this scenario, the charging station operator buys and stores energy in the buffer. On the other hand, when the second tariff is applied, it sells energy to the grid at a higher price, leading to more gains. The grid provides almost 5 MW at the beginning of the simulation, and its power profile fluctuates with time. The set of energy tariffs changes three times, which results in these power jumps in reverse of the buffer (Fig. 10). The proposed algorithm changes the direction of energy flow according to the set of energy tariffs to maximize the benefit.

V. CONCLUSIONS

A control algorithm for charging/discharging storage components of an electric charging station, including a buffer and several EVs, was proposed in this paper to optimally make energy transactions between the charging station and the grid while contributing to the primary services originating from the spot market. It was shown that the proposed strategy could choose the energy portfolios according to energy price variation and DR with an optimal energy supply to the EV. This work was completed in the scope of the DeRIVE project denoted by 01MV22014B and funded by the German Federal Ministry of Digital Infrastructure and Transport (BMDV).

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