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Distributed Optimal Batteries Charging Control for Heterogenous Electric Vehicles Fleet

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***Abstract*—Road vehicles are big consumers of energy and their transition to electricity supply rises a need for optimal charging control. We consider the case of electric vehicles fleet battery management process that utilizes the battery for supporting smart building operation. The paper presents a centralised and a distributed control method for cost-optimal battery management that include the electric vehicle battery model. Distributed control is used to achieve privacy and transparent charging costs for each vehicle while still achieving the same level of revenue as the centralised control. Here, the central operator acts only as a middle point in communication between various heterogeneous agents and coordinates them to respect global constraints. Charging stations themselves are entrusted to satisfy the local constraints. In this way, the privacy of the information related to specifications of charging station, users demands and behaviour pattern are kept. Most of all, the independence of vehicles and central operator is achieved. Distributed optimal batteries charging control for electric vehicles fleet is implemented by using an asymmetric projection algorithm. Management of electric vehicles fleet charging is considered as a part of the hierarchical building energy management where prices and constraints on cumulative fleet charging profiles are obtained from a higher-level instance. Given results show high matching with an equivalent centralised problem based on quadratic programming.**

***Index Terms*—Electric vehicle charging, Building energy management, Distributed control.**

I. Introduction

As energy production based on renewable resources requires flexibility on the consumers end, it is expected that the energy market will embrace volatile electricity prices. Introduction of microgrids with distributed power generation and storage units allows buildings to become active energy market participants [1], [2]. Till recently, solely a climate control was in the focus, as heating and cooling are one of the biggest energy consumers in a building. With the rapid growth of hybrid and electric vehicles (EVs) numbers, they are expected to become significant loads in the buildings energy system.

For the end-user, it is the most convenient that the vehicle is charged while parked, which is a motivation for including vehicles and corresponding batteries to a building microgrid suitable for application of advanced energy management approaches. Different approaches to the problem can be found, such as optimal power balancing [3], minimisation of charging cost [4] and also the overall building energy cost optimization when put to a coordinated operation [5] or multi-objective optimization [6].

Subsystems for ensuring building comfort are flexible energy consumers, which opens large possibilities in energy cost reduction. The same applies for vehicle charging. In addition, a microgrid with storage systems enables the reallocation of energy demand towards more cost-favourable conditions (tariffs). Coordinated operation of all the subsystems introduces significant opportunities for overall cost reduction of the building [7]. To this aim, the building systems are joined together as different levels of hierarchical energy management where vehicle charging stations are formed as subunits of the same level, i.e. as a multi-agent system with the central operator that accumulates information about vehicles and exchanges it with a higher hierarchy level. This reflects to significant implementation cost reduction since the equipment integration and required expert staff knowledge is identified as the most pronounced contributor of expenses [8]. It also enables dynamical reconfiguration of the topology to accept or release additional subunits, such as available electric vehicles. Additional gain is the elimination of sharing of the users private data, limited only to required knowledge of prices and consumption profiles.

The method considered here concentrates on battery charging and discharging assuming that higher control level will give required conditions for operation, foremost prices and energy flows constraints. Research focus is therefore put here to distributed control with game theory application and mutual bidding of individual (local) interests of the subunits of a complex system [9]. Used methodology iteratively solves primal and dual problems and converges to the optimum, which is also coinciding with Nash equilibrium from the game theory area, while respecting both local/individual and global/common constraints [10], [11].

Decentralised control used in this paper separates the decision making process by using the asymmetric projection algorithm (APA) proposed in [12] for achieving the independent vehicle decision making with respect to all the constraints. We utilize here the framework and apply it to heterogenous electric vehicle battery management as part of the building system in coordinated operation with building microgrid as a higher hierarchy level. The followed methodology is in this way readily expandable to the case where vehicles are owned by private persons and it is reasonable to expect that users will have specific constraints or want to make decisions themselves.

This paper is organised as follows. In Section II, a centralised optimal control problem with a corresponding model of vehicle battery dynamics is presented. Distributed battery charging and asymmetric projection algorithm as part of the hierarchical building energy management are given in Section III. Section IV presents and discusses simulation scenarios and results. Section V concludes the paper.

II. Battery charging model and cost

From the perspective of high-level energy management systems, vehicle charging is described through the dynamics of its battery. Batteries are modelled via state-of-charge (SoC) dynamic equation:

$$x^i_{k+1} = x^i_k + \frac{1}{C^i}\left(\frac{1}{\eta^i_{dch}}E^i_{dch,k} + \eta^i_{ch}E^i_{ch,k}\right), \quad (1)$$

where $k \in \mathbb{Z}$ is the sampling time index, C, E and η denote storage capacity, energy and efficiency, respectively. Electric vehicles are indexed with i. Energy and efficiency are separated to discharging and charging components, $E^i_{dch} \leq 0$ and $E^i_{ch} \geq 0$, which avoids high calculation complexity of a mixed-integer problem formulation under some mild assumptions [1]. Equation (1) is reformulated into state-space representation suitable for model predictive control (MPC) standard form:

$$x^i_{k+1} = A^i x^i_k + B^i u^i_k, \quad (2)$$

where x^i_k is a vehicle batteries SoC vector, $u^i_k = [E^i_{ch,k},\ E^i_{dch,k}]^\top$ is a vector of energies, exchanged between the microgrid and the charger, from time instant k to $k+1$, while A^i and B^i are corresponding model matrices. The sampling time for the model discretisation should be large enough to disregard the transients on energy links, but smaller or equal to the sampling times of price and behaviour predictions.

Chargers are bidirectional, connected to the buildings microgrid and are considered in the building energy management strategy. A control system decides when and in which amount to charge or discharge the battery, meaning to buy or sell energy from/to the microgrid link towards the chargers. The goal of the charging/discharging control system on the vehicle is to minimise the charging cost under the given constraints. There are multiple constraints related to storage capacity, power ratings and microgrid link towards the chargers.

Microgrid connection capacity is put in the constraints form:

$$P_{min}T_s \leq u^F_k \leq P_{max}T_s, \quad (3)$$

where $u^F_k = \sum_{i=1}^N u^i_k$ is the total EV fleet consumption in time step k, N is the number of vehicles in the fleet and T_s is the sampling time period. If vehicle i is not connected to the microgrid in the moment k, then energy $u^i_k = 0$. Limits P_{max} and P_{min} are the maximum power that charging system can take from (P_{max}, positive sign) and give back to (P_{min}, negative sign) the microgrid. The system is often designed not to withstand the peak operation of all chargers at the same time. Furthermore, each charger has own individual constraints. Power ratings of individual chargers form constraints:

$$u^i_{min} \leq u^i_k \leq u^i_{max}, \quad (4)$$

where u^i_{min} and u^i_{max} are 0 if the vehicle is not connected to the charger. To avoid damage or rapid degradation of the car battery, SoC is only permitted to be inside the recommended working limits, i.e. in any time instant, the following constraint has to be satisfied:

$$x^i_{min} \leq x^i_k \leq x^i_{max}. \quad (5)$$

If the vehicle is leaving the charging station at the time instant k, then the state x_k has to be equal to x_{final}, making sure that the vehicle need is met. In a form of constraints that is:

$$x^i_k = x^i_{final}, \quad \text{if} \quad k \in z^i, \quad (6)$$

where z^i are instants at which the vehicle gets disconnected from the charger. The conditions (2), (3),(4),(5) and (6) form an overall set of constraints that should be satisfied while minimising the cost function.

A conventional centralised approach takes all the constraints within the same problem formulation and minimises the cost function. Two types of cost functions are considered here, linear and quadratic. The optimisation problem for achieving the smallest charging cost is formed as a linear program (LP):

$$\begin{aligned} J :=& \min_{\mathbf{u}} \mathbf{c}^\top \mathbf{u}, \\ \text{s.t.} \quad & (2), (3), (4), (5), (6), \end{aligned} \quad (7)$$

or quadratic program (QP):

$$\begin{aligned} J :=& \min_{\mathbf{u}} \tfrac{1}{2}\mathbf{u}^\top Q \mathbf{u} + \mathbf{c}^\top \mathbf{u}, \\ \text{s.t.} \quad & (2), (3), (4), (5), (6), \end{aligned} \quad (8)$$

where $c \in \mathbb{R}^N$ is a price vector containing prices for all vehicles in one interval, Q is a multiplication factor of vehicles consumption influence on the price and in this case it can be set to a constant value. In the simulation scenarios, $Q = \frac{C}{N}$ is chosen, where C is a small arbitrary constant determining the significance of the quadratic term and N is the number of vehicles. Bold notation stands for vectors stacked over the prediction horizon n.

The microgrid takes into account the grid energy price and its other subsystems when forming the price towards the chargers. The energy exchange price c^F, can be forwarded by the microgrid as a volatile market electricity price or transformed to shift the battery charging process towards the overall building cost-optimum . Volatile energy market electricity prices can be found at e.g. European Power Exchange company portal [13]. It is assumed that grid price for energy is equal for buying and selling, which may not be the case in practice. It serves as an amortisation that compensates increased battery expenditure due to a higher number of charging cycles [2]. Consequently, the price vector is composed of two components:

$$c^\top = [c_{ch}, c_{dch}]^\top, \quad (9)$$

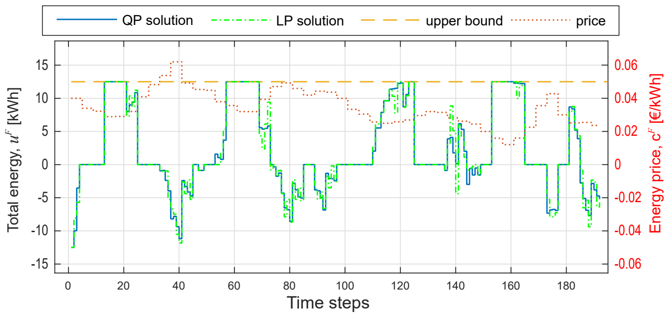

Fig. 1. Result comparison of LP and QP for a fleet with 25 vehicles.

where $c_{ch} = c^F + c_{bat,ch}$ and $c_{dch} = c^F + c_{bat,dch}$.

From Fig. 1, which shows simulations of the total energy exchanged with the microgrid (u_k^F) for $N = 25$ vehicles, it can be seen that there is no significant difference in overall energy consumption plan between the LP and QP for a small quadratic term Q. Simulation runs for two days with a time step $T_s = 15$ min. The vehicles are selling the energy when the price is high and anticipated disconnecting time is far, while buying energy when the price is low or imposed by system constraint for fully charged battery (x^i_{final}) when disconnecting. This shows that a simpler LP performs as good as QP and therefore it is sufficient for the centralised case. Still, the QP is presented as it can be transformed to an equivalent distributed formulation and it satisfies conditions for distributed algorithm convergence [12].

III. Hierarchical building energy management

A. Microgrid control

The proposed methodology uses two basic approaches: distributed optimal control among subunits of the same subsystem and hierarchical optimal control between different levels (subsystems). Hierarchical control is proposed in [7] and here extended with iterative distributed control of vehicle batteries charging as shown in Fig. 2.

In particular, we consider here microgrid as a higher hierarchy level that provides prices and joint constraints for the distributed control problem. The microgrid optimisation problem is simply formed as minimisation of cost for energy exchange with the grid, E_{G}:

$$J^{\mu *}(\mathbf{u}^F) := \min_{\mathbf{u}^\mu} \sum_{k=0}^{n-1} c_{g,k} E_{\mathrm{G},k}, \tag{10}$$
$$\text{s.t.} \quad \begin{aligned} &\mathbf{G}^\mu \mathbf{u}^\mu \leq \mathbf{w}^\mu + \mathbf{F}^\mu \mathbf{u}^F, \\ &E_{\mathrm{G},k} = u_k^F + \mathbf{1}_d^\top d_k^\mu + \mathbf{1}_u^\top u_k^\mu, \end{aligned}$$

where $\mathbf{G}^\mu$, $\mathbf{w}^\mu$ and $\mathbf{F}^\mu$ are microgrid constraints, $\mathbf{d}^\mu$ is a vector of energy productions of different generation units in the microgrid, $\mathbf{u}^\mu$ is the microgrid control variable and $\mathbf{1}_d$ and $\mathbf{1}_u$ are appropriately sized vectors of ones.

The problem (10) can be more complex to include different layers of pricing such as reduction of maximum power, announced day-ahead profile following or intra-day deviations as energy market incentive as described in [14].

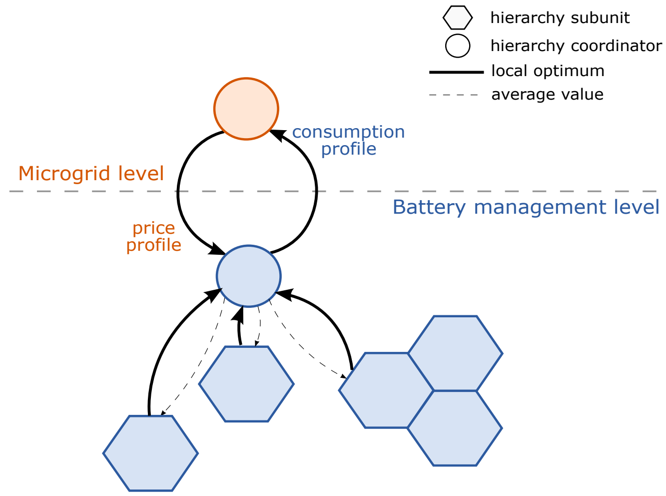

Fig. 2. Proposed methodology of distributed optimal control with dynamic reconfiguration of problem structure for building microgrid and battery charging problems.

The microgrid and fleet charging/discharging problems are connected through the vehicles coupling constraints:

$$\mathbf{G}^F \mathbf{u}^F \leq \mathbf{w}^F, \tag{11}$$

which are constraints of the critical region of multi-parametric solution (10) [7].

B. Distributed control for vehicles charging/discharging

Although the centralised vehicles charging/discharging problem requires no iterations and the considered problem is fairly easy to solve, it is only employable when all vehicles are part of a single microgrid with known configuration, mutually compatible and open components with a consistent information exchange protocol and legally well-arranged framework. This is possible only for a large fleet operator as e.g. a transportation and logistics company. In practice, this is a minority of cases and the control algorithm should require minimum information exchange between the agents and a central coordinator while taking into account individual objectives, local and global constraints. With distributed battery charging, a vehicle only sends a required energy value to the central system. This way it preserves privacy of its data but also the final charging price will be more transparent as it is not imposed by external higher system, but rather decided by the vehicle itself.

Distributed optimisation for vehicles separates a single problem in two parts: central operator and local agents. That way every subsystem takes care of its own constraints. Central operator is an intermediary entity that collects the overall energy demand. It provides a demand feedback to each individual agent and makes sure that coupling constraints are satisfied. Each vehicle bases its decision on the information it has and adjusts own charging/discharging strategy. The behaviour of vehicles that interact in the described configuration is coinciding with Nash equilibrium from the game theory area. Game theory states that, when choosing a strategy, a player takes into account that other players will act in their best interest as well. In the end, the optimal strategy for everyone is met at the point called Nash equilibrium.

To solve a decentralised optimisation problem, we use here an algorithm initially proposed in [12]. The algorithm belongs to the class of asymmetric projection algorithms and it is developed for aggregative games characterised by a separable quadratic cost function and linear coupling constraints. Convergence of the algorithm is obtained for any population size and in the presence of both local and coupling constraints. That means that the algorithm is suitable for converting a centralised QP into an equivalent decentralised problem.

The solution is obtained by iterating the steps from Algorithm 1 to convergence. In every iteration, first step is for central operator to calculate the average demand and send it back as a feedback. Second and third part are formed similarly to a step in the constrained gradient descent, where $\tau > 0$ is a gradient step and $\prod$ is a projection on the feasible solutions hyperplane. Projection to a set of constraints finds a point x, best approximating the initial point y, in a set χ. This is expressed as a QP, minimising the euclidean second norm:

$$\textstyle\prod_{\chi} \mathbf{y} = \arg\min_{\mathbf{x}\in\chi} \parallel \mathbf{y} - \mathbf{x} \parallel_2 . \tag{12}$$

Function $\mathcal{F}^i(\mathbf{u}^i_{(k)}, \sigma_{(k)})$ is the gradient of the cost function. The cost for one vehicle i, singled out from (8), can be rewritten as $J^i(\mathbf{u}^i, \mathbf{u}^{-i}) = (\mathbf{C}^i\sigma + \mathbf{c}^i)^\top \mathbf{u}^i$ and its gradient is:

$$\mathcal{F}^i(\mathbf{u}^i_{(k)}, \sigma_{(k)}) = \bigtriangledown_{\mathbf{u}^i} J^i(\mathbf{u}^i, \mathbf{u}^{-i}) = (\mathbf{C}^i\sigma + \mathbf{c}^i)^\top, \tag{13}$$

where $-i$ index refers to all the remaining vehicles apart from the considered one, i.

Additional cost term $\mathbf{G}^{F^\top}_{(:,i)}\lambda_{(k)}$ depends on the influence of agent i in the coupling constraint and on the multiplier λ. It is securing respect of the global constraint. The scheme differs from the standard gradient projection since λ depends on both current and previous strategy, with factors $\mathbf{G}^F\mathbf{u}_{(k)}$ and $\mathbf{G}^F\mathbf{u}_{(k+1)}$. Matrices $\mathbf{G}^F$ and $\mathbf{w}^F$ are describing the coupling constraint (11).

Each vehicle has its own set of local constraints χ. They are not related and can be diverse, e.g. different capacity, link limits, SoC at the disconnection time. To achieve the same flexibility with centralised control, the coefficients of constraints should be checked when a vehicle connects and changed if needed.

Although the convergence is guaranteed, in practical terms to speed up the computation it is enough to be in the close proximity of the optimum. The algorithm output is considered converged if maximum distance in two steps is smaller than ε_{toll}:

$$\parallel \mathbf{u}_{(k+1)} - \mathbf{u}_{(k)} \parallel \leq \varepsilon_{toll}. \tag{14}$$

If ε_{toll} is small enough, i.e. in simulation results $\varepsilon_{toll} = 0.1$, the computational error will be significantly smaller than the precision of vehicle charging equipment. Another factor influencing the computation speed is gradient step τ. It is simply taken as a small constant and because of that there is a trade-off between size of ε_{toll} and τ.

Algorithm 1 Asymmetric projection algorithm (APA) [12]

Initialisation: Set $k = 0$ and $\tau > 0$. Each agent i has initial input $\mathbf{u}^i_{(0)}$, the central operator sets $\lambda_{(0)} \in \mathbb{R}^m_{\geq 0}$.

Iterate to convergence

Step 1: Central operator average update

$$\sigma_{(k)} \leftarrow \frac{1}{N}\sum_{i=1}^{N} \mathbf{u}^i_{(k)};$$

Step 2: Local individual strategy update

$$\mathbf{u}^i_{(k+1)} \leftarrow \textstyle\prod_{\chi^i}[\mathbf{u}^i_{(k)} - \tau(\mathcal{F}^i(\mathbf{u}^i_{(k)}, \sigma_{(k)}) + \mathbf{G}^{F^\top}_{(:,i)}\lambda_{(k)})];$$

Step 3: Central operator multiplier update

$$\lambda^i_{(k+1)} \leftarrow \textstyle\prod_{\mathbb{R}^m_{\geq 0}}[\lambda_{(k)} - \tau(\mathbf{w}^F - 2\mathbf{G}^F\mathbf{u}_{(k+1)} + \mathbf{G}^F\mathbf{u}_{(k)})].$$

IV. Simulation results

The described algorithms are applied to the case of a fleet consisting of 25 vehicles. Each vehicle has assumed availability and starting SoC for the moment it is connected to the charger. Vehicle connection and disconnection times are assigned randomly in the time of the day people usually come from and go to work. In simulation results, vehicle initial SoC when connecting to the system is a random number from interval $[0.2, 0.8]$, while SoC is limited to $[0.2, 0.9]$. Other limitations are power ratings as 3.5 kW for individual device link and 50 kW for overall energy consumption of a fleet. The efficiency of the charging and discharging are assumed to be $\eta_{ch} = 0.9$ and $\eta_{dch} = 0.75$. Capacity of the battery is set to $C = 10$ kWh. At the moment when leaving the charging station, the vehicle SoC is required to be equal to 0.9, i.e. fully charged battery. Charging and discharging battery amortisations are used as $c_{bat,ch} = 0.004$ €/kWh and $c_{bat,dch} = -0.007$ €/kWh.

All results show simulation for a two-day period with a time step $T_s = 15$ min and prediction horizon 6 hours, $n = 24$. Receding horizon principle is used. Simulations are performed using MATLAB and LP and QP optimization problems are solved with CPLEX solver [15].

In Fig. 3, results of LP for one vehicle in a centralised system are presented. All local constraints are satisfied. Availability of EV is a binary variable indicating when a vehicle is connected to the charger. In the figures, it is scaled for better visual representation. Similar solution is obtained for QP with a small quadratic term, as it is shown before. Both LP and QP try to use maximal individual energy as often as they can and secure overall energy consumption under limits by arranging charging intervals between vehicles.

The distributed control algorithm secures the global constraints in a different way. Before the communication between the central operator and agents starts, the vehicle is not aware of the existence of other agents. As a result, it adjusts its own strategy only with respect to the provided grid energy price. Solving a LP with only local constraints yields locally optimal battery charging. After that, through exchange of information with a central operator, the battery

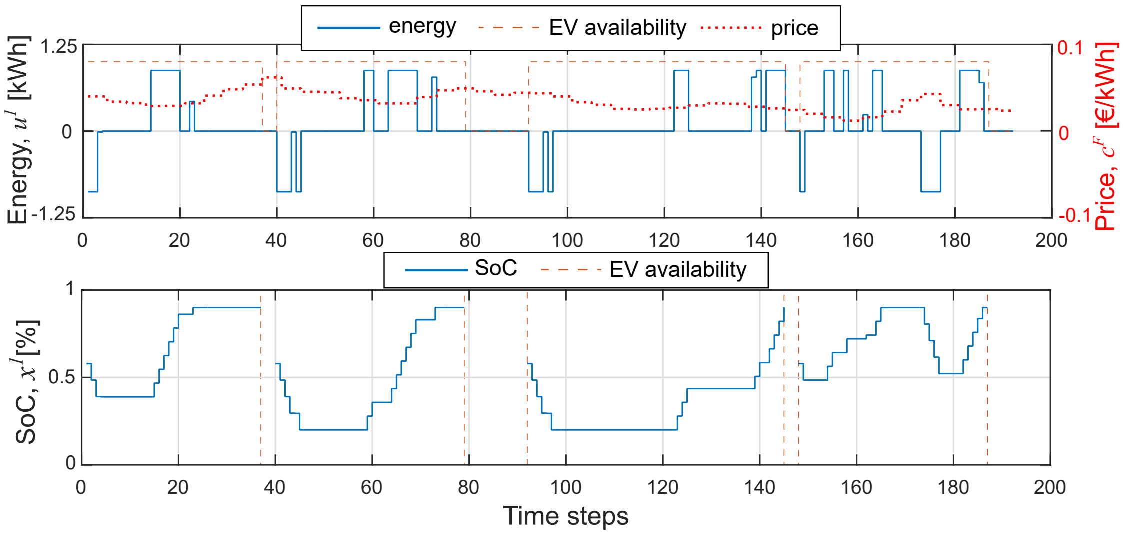

Fig. 3. Results from LP for the selected vehicle $i = 1$.

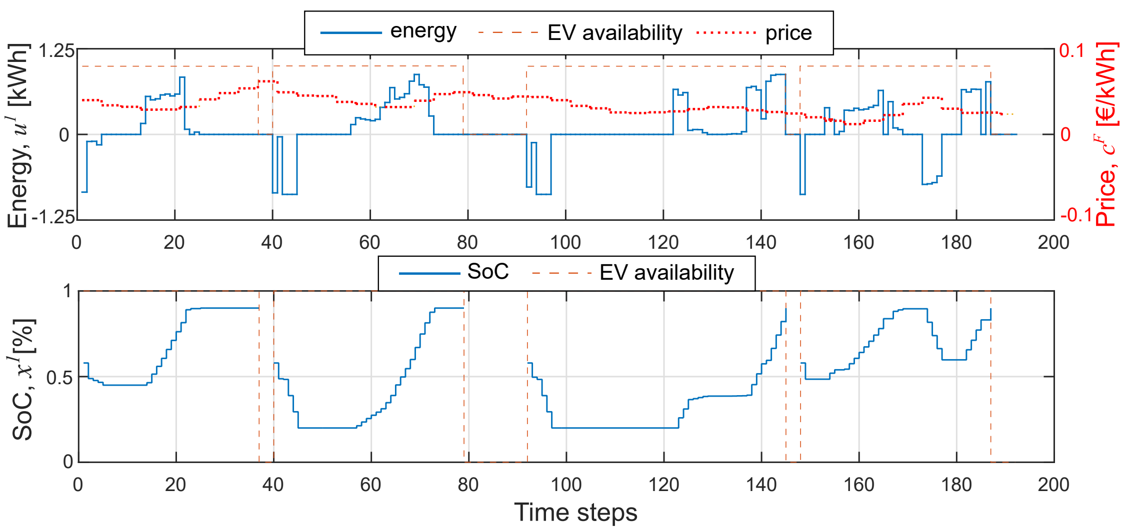

Fig. 4. Results from APA for the selected vehicle $i = 1$.

Fig. 5. Result comparison for APA and QP.

charging strategy is corrected towards the common, global optimum. In most cases, vehicles lower their demand and, at the end, they altogether achieve optimal average consumption to the price profile. Now individual charging is performed through more periods, but with lower amount of energy that grows towards the end of charging process.

Figure 4 shows simulation results for the same vehicle as in Fig. 3. Although the individual charging is slightly different, overall energy consumption for distributed control almost perfectly matches the centralised case. Comparison of schedule u^F computed using QP and APA is shown in Fig. 5. The figure shows that finally the cost of the charging is the same, but there is a small difference in how the cost is distributed among vehicles. Precisely, in distributed control vehicles tend to be closer to average and therefore their costs are more evenly distributed. The difference between QP and APA can be explained by accumulation of the difference in SoC as a consequence of termination criteria that stops the APA algorithm before the full convergence.

V. Conclusion

In this work, a coordinated control between a building microgrid and electric vehicles fleet chargers is considered. Decomposition of a microgrid and chargers into two hierarchy levels, and then their connection with communication via price-consumption profiles enables independence of different subsystems. That means the vehicle charging can be controlled separately from other building systems. The goal of both centralised and decentralised control observed in this paper is the same; minimising the cost of vehicle charging with respect to constraints. Vehicles are modelled via state of charge of their batteries and a set of constraints gathers local and global constraints, i.e. users needs, grid and local link limitations.

Distributed control achieves the same level of revenue while keeping the privacy by a minimum exchange of information. Overall cost of all observed results, computed with different control algorithms, is almost the same with minor differences. However, there is a difference in individual charging plans. Centralised control tends to use maximum energy more often and divides low price intervals among vehicles while with decentralised control charging periods last longer and use energy closer to an average demand. In addition to that, final charging price is more transparent as it is not imposed but decided by the vehicle itself. To make it possible, every vehicle needs to have a suitable equipment, which can be a limitation, while centralised control has no limits when it comes to a central operator computer system power and size. It is computationally less demanding and fairly easy to solve, but it is only employable when all vehicles are part of a single microgrid with known and well-arranged framework.

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