

## A systematic comparison of various electric vehicle charging approaches

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### Abstract

The use of electric vehicles (EVs) has been on the rise. Most of the existing EV smart charging controls can be categorized into three approaches according to their optimization principles: individual, bottom-up and top-down. Until now, systematic comparison and analysis of the different approaches are still lacking. It is still unknown whether a control approach performs better than others and, if yes, why is it so. This study aims to fill in such knowledge gaps by conducting a systematic comparison of these three different control approaches and analyzing their performances in depth. A representative control algorithm will be selected from each control approach, then the selected algorithms will be applied for optimizing EV charging loads in a building community in Sweden. Their power regulation performances will be comparatively investigated. This study will help pave the way for the developments of more sophisticated control algorithms for EV smart charging.

### Introduction

To reduce the roadside carbon emission and greenhouse gas emissions, many governments and organizations have set targets and policies for promoting the utilization of electric vehicles (EVs) to replace the fossil fuel-based vehicles. In response to these targets and policies, a boost of the EV deployment has been witnessed in the past decades. The market statistics still showed strong momentum in the EV deployment despite the Covid pandemic. The number of EVs on the roads worldwide reached 10 million by the end of 2020 (IEA 2021). In Sweden, there was a 310% increase in the full battery EV number in 2020 (Kane 2021). With the large number of EV deployments, the massive EV charging loads are expected to impose great stress on the existing grid infrastructures.

To mitigate these problems and avoid the expensive upgrading of the existing power infrastructure, a resource-efficient and cost-effective way is to use the smart EV charging (i.e., charge EV in the periods with large renewable power production) to enhance the local power balance and electrical energy matching (Chaouachi et al. 2016). In other words, by properly scheduling the EV charging loads, the EV battery can be used as flexible energy storage to help regulate the electricity demands to match the renewable power production in the electric grid and thus improve the power supply quality (e.g., frequency regulation). Existing studies have proposed a

number of smart EV charging controls for such application (Mohamed et al. 2020). A comprehensive review of the various EV smart charging schemes, including the objectives, configurations and control algorithms, is provided in (Fachrizal et al. 2020). According to the optimization logic, most of these controls can be roughly categorized into three approaches: individual independent approach, bottom-up coordinated approach, and top-down coordinated approach (Huang et al. 2020). Both the bottom-up and top-down coordinated approaches are coordinated controls, which typically considers the optimization of multiple EVs' charging loads and takes the aggregated-level performance as the optimization target. The top-down coordinated approach typically conducts coordination from the aggregated-level and optimize multiple EVs' charging load simultaneously, while the bottom-up coordinated approach typically optimizes single EV's charging load sequentially to achieve the aggregated-level optimum. The individual independent approach typically considers the optimization of only one EV's charging load and takes the single-level performance optimization as the target.

Regarding individual independent approach, Cai et al. (Cai et al. 2019) developed an aging-aware model predictive control method. Dallinger and Wietschel (Dallinger and Wietschel 2012) proposed a stochastic model to determine the vehicle mobility behavior, an optimization model to minimize vehicle charging costs, and an agent-based electricity market equilibrium model to estimate variable electricity prices. Such control can balance the fluctuation of renewable energy sources in the grid. Regarding the bottom-up coordinated approach, in (Fachrizal and Munkhammar 2020) a centralized EV fleet charging control method is proposed for a residential building cluster. It optimizes the charging loads of EVs sequentially one by one based on the arrival time and departure time considering the interaction of individual EVs and photovoltaics (PV) power production. Similarly, in (Geth et al. 2010) a coordinated charging control for a number of EVs is proposed. In this control, a vehicle owner first indicates the point in time when the batteries should be fully charged. Then, the aggregator collects this information and calculates when each EV can start charging. The charging is optimized to be scheduled to the most economical period when the total demand (including the residential, industrial and EV consumption) is low. Regarding the top-down coordinated approach, Islam et al. (Shariful Islam et al. 2019) developed a correlated

probabilistic model for EV charging loads. In this probabilistic model, correlated samples are first generated, which contain various random variables associated with EVs, battery energy storage and PV. The generated samples are subsequently incorporated in the coordinated EV charging method to maximize quality of service while minimizing probability of voltage and current non-compliance.

Although existing studies have developed different control approaches for implementing smart EV charging, there is a lack of a systematic classification and comparison of these different approaches. Therefore, this study provides an overview of different control approaches, systematically compares their advantages and disadvantages and analyzes their performances in depth. The purpose is to have a deep understanding of the various control approaches, which will pave the way for the resource-efficient integration of the large EV load and PV power penetration in the future. In this study, a representative control algorithm will be selected for each control approach. The different control approaches are then compared based on a case building community in Sweden, and their performances are compared and analyzed systematically.

## Methods

This section first introduces the basic idea of different control approaches. Then, one control method will be proposed for each control approach, and the detailed implementation of each control method will be described.

### Basic idea of different control approaches

Fig. 1 presents the schematics of three typical EV fleet control approaches for balancing power in the building sector: individual independent approach, bottom-up coordinated approach, and top-down coordinated approach. Both the bottom-up and top-down approaches are coordinated controls, which take the aggregated-level performance optimization as the target. While the individual independent approach takes the single-level performance optimization as the target. In the individual independent approach, the optimization of individual EV's charging rates is conducted independently considering neither the other EVs' charging load nor the aggregated one (see Fig. 1a). As a result, different EVs may charge at the same period, leading to the "avalanche effect (Kühnbach et al. 2021)" (i.e., creating new peak power loads for the power grid). In the bottom-up coordinated approach, the charging rates of individual EVs are optimized one by one in a sequence based on the arriving time to the charging station, and the optimization of each single EV's operation is performed based on the aggregated results of the earlier optimized EVs (see Fig. 1b). The optimization is based on the arrival time. Since the bottom-up coordinated approach takes the aggregated-level performances as the optimization target, the performances at the aggregated-level are superior to the individual independent approach. However, due to a lack

of global coordination, the optimization from bottom-up coordinated approaches may not produce the global optimum solution. Similar to the bottom-up coordinated approach, the top-down coordinated approach takes the aggregated-level performance directly as the optimization objective. The charging rates of individual EVs are coordinated simultaneously to achieve the optimized performance at the aggregated-level (see Fig. 1c). Since all the EVs are optimized at the same time, the computational load could be much higher compared to the other two approaches. In some existing controls (Usman et al. 2016), to reduce the number of variables to be optimized, the charging rates of EVs are fixed. The optimizer only needs to search for the charging time slots and thus reduces associated computational complexity. With fixed charging rates, the optimization performances might not be the optimal. Table 1 summarizes the three different approaches and compares their pros and cons.

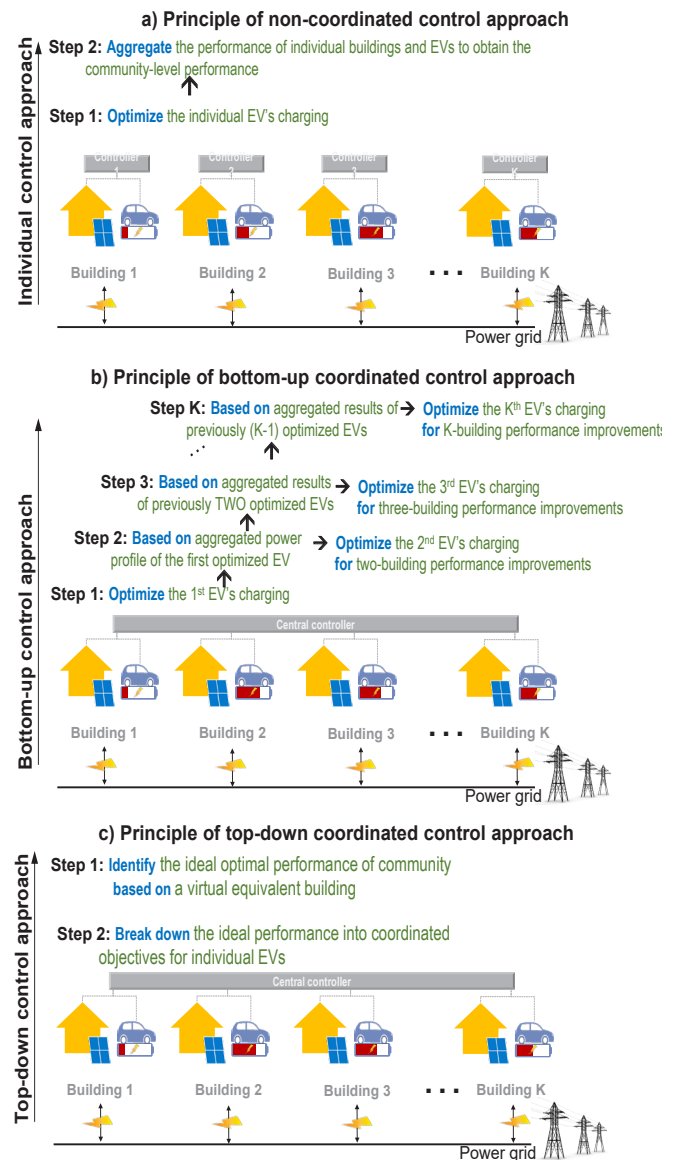


Figure 1 Schematics of three different control approaches for EV fleets in the building sector.

*Table 1 Comparison of different EV fleet charging approaches.*

<p><b>Individual independent approach</b> (Cai, Zhang et al. 2019) (Dallinger and Wietschel 2012)</p> <p><b>Principle:</b> The optimization of individual EV charging rates is conducted separately without considering the other EVs' charging load. Then, the individual EV charging loads are aggregated to obtain the aggregated-level performance.</p> <p><b>Pros:</b> Easy to implement</p> <p><b>Cons:</b> 1. The aggregated level performance is not optimized. 2. New demand peaks may occur when individual EVs take the same action (e.g., shift demand to the same period)</p>
<p><b>Bottom-up coordinated approach</b> (Fachrizal and Munkhammar 2020) (Usman, Knapen et al. 2016)</p> <p><b>Principle:</b> The charging rates of individual EVs are optimized one by one in a sequence, and the optimization of each single EV's operation is performed based on the aggregated results of the earlier optimized EVs</p> <p><b>Pros:</b> Better performance at aggregated level than individual independent approach</p> <p><b>Cons:</b> 1. Due to a lack of global coordination, the optimization from bottom-up coordinated approaches may not produce the global optimal solution. 2. High computational load.</p>
<p><b>Top-down coordinated approach</b> (Shariful Islam, Mithulananthan et al. 2019) (Nayak et al. 2019) (van der Kam and van Sark 2015) (Huang et al. 2020) (Weckx and Driesen 2015)</p> <p><b>Principle:</b> The aggregated level performance is used as the optimization objective. The charging rates of individual EVs are coordinated to achieve the best performances at the aggregated-level.</p> <p><b>Pros:</b> Optimized performance at aggregated-level.</p> <p><b>Cons:</b> 1. It requires the controller to know/forecast the expected future arrival time in the building for all EVs, as the scheduling also considers the EVs that have not arrived yet. 2. The computational complexity increases with the number of EVs.</p>

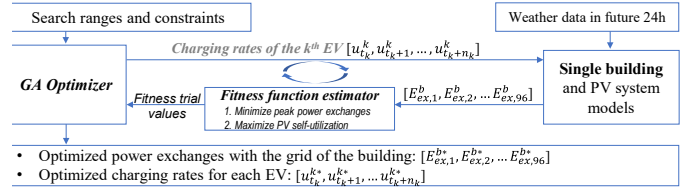
### Representative control algorithm for each approach

This section presents the selected EV charging control for each approach, including the control logic and detailed mathematical modelling. Note this study only considers the unidirectional power flow, i.e., the G2V (grid to vehicle) mode. The EVs can only be charged. The bidirectional power flow, i.e., G2V2G (i.e., grid to vehicle to grid) is not considered.

#### Algorithm for individual control

Fig. 2 presents the selected control method for the individual independent approach. This control is implemented for each individual EV considering the single building's (i.e., the building whether the EV gets power from) demand and renewable power production. Considering the computation speed and ability to find optimal solutions, Genetic Algorithm (GA), an evolutionary optimization algorithm, is used in the control. Note that other algorithms are also applicable for different controls, as long as the computational loads are acceptable. In each iteration, a set of alternatives (in this study the alternatives refer to EV charging loads) will be produced by the GA optimizer. These alternatives will then be imported into the building and PV system model for calculating the power exchanges with the grid in each timestep. Then, the power exchanges in each timestep will be imported into the fitness function to evaluate the fitness values of the alternatives. The alternatives with good

fitness values will be selected and used for producing the alternatives in the next generation. The iteration will continue until the optimal solutions are found. Since there is existing toolbox available for implementing the GA optimization in Matlab and Python, this study will not go into details about the mathematics of GA. For more details about the GA, please refer to (Yang 2021).



*Figure 2 Selected optimization logic for the individual control approach.*

The detailed mathematical modelling is introduced below. In each timestep, the charging rates ( $u^k$  (kW),  $0 < u^k < u_{limit}^k$ , in which  $u_{limit}^k$  (kW) is the maximum charging rate) of the  $k$ th EV should meet the following two constraints,

$$0 \leq SOC_{0,k} \times CAP_k + (u_{t_k}^k + u_{t_{k+1}}^k + \dots + u_{t_{k+n_k}}^k) \times \tau \leq CAP_k \quad \text{where } i=1,2,\dots, n_k, \quad (1)$$

where  $SOC_{0,k}$  (%) is the initial state of charge when the  $k$ th EV arrives at the charging port;  $CAP_k$  (kW·h) is the capacity of the  $k$ th EV battery;  $t_k$  is the arrival time of the  $k$ th EV at the charging port;  $n_k$  is the parking duration; and  $\tau$  is the simulation interval (15 minutes in this study).

In order to meet the travelling needs of the next trip, the EV battery should be charged to a user-specified level ( $SOC_{1,k}$ ) before they depart the charging port. This constraint is expressed by the equation below,

$$SOC_{0,k} \times CAP_k + (u_{t_k}^k + u_{t_{k+1}}^k + \dots + u_{t_{k+n_k}}^k) \times \tau \geq SOC_{1,k} \times CAP_k. \quad (2)$$

In Eq (2), when  $SOC_{1,k}$  equals 1, it represents that the EV users require the EV battery to be fully charged before they depart the charging port. In this strategy, minimizing the peak power exchanges with the grid is used as the optimization target. Following this control goal, a fitness function is determined, as expressed by (Salom et al. 2011)

$$J_{grid} = \min(E_{peak}^b), \quad (3)$$

where  $E_{peak}^b$  (kW) is the peak power exchange of the building with the grid.  $E_{peak}^b$  (kW) in Eq. (3) is calculated by the two equations below.

$$E_{ex,i}^b = E_{d,i}^b + u_i^k - E_{s,i}^b. \quad (4)$$

$$E_{peak}^b = \max(|E_{ex,1}^b|, |E_{ex,2}^b|, \dots, |E_{ex,96}^b|) \quad (5)$$

In Eq. (4),  $E_{d,i}^b$  (kW) and  $E_{s,i}^b$  (kW) are the power demand and renewable power supply of the individual building in each simulation interval (i.e., 15 minutes), respectively.  $u_i^k$  (kW) is the charging load of the  $k$ th EV parked in the building in the  $i$ th simulation step.  $E_{ex,i}^b$  (kW) is the power exchange with the grid of the building in each simulation interval considering the EV charging load. Note there are

96 simulation steps in each day (96=24 hours × 4 simulation-steps/hour), as the simulation timestep is 15 minutes (see Eq. (5)). The outputs of GA search are the optimal charging loads ( $[u_{t_k}^{k*}, u_{t_{k+1}}^{k*}, \dots, u_{t_{k+n_k}}^{k*}]$  (kW)) for the kth EV to meet the control targets.

### Algorithm for bottom-up control

Fig. 3 presents the selected control method for the bottom-up coordinated approach. This control is implemented for each individual EV in a sequence considering the aggregated-level power demand and renewable power production. Again, the GA algorithm will be used in the control optimization. The detailed mathematical modelling is introduced below.

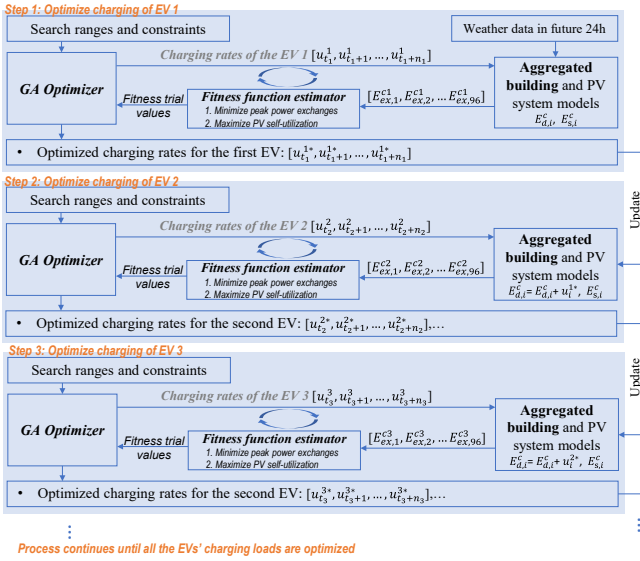


Figure 3 Selected optimization logic for the bottom-up control approach.

In the bottom-up coordinated approach, the optimization is based on the aggregated-level power demand and PV power production. The power demand ( $E_{d,i}^c$  (kW)) and PV power production ( $E_{s,i}^c$  (kW)) of the community in the  $i^{\text{th}}$  simulation step are calculated by aggregating single building's power demand and PV power production.

$$E_{d,i}^c = \sum_{j=1}^n E_{d,i}^{b,j} \quad (6)$$

$$E_{s,i}^c = \sum_{j=1}^n E_{s,i}^{b,j} \quad (7)$$

Eqs. (6) and (7) shows the calculation of the aggregated-level power demand and PV power production of all the  $n$  buildings. The peak power exchange of the whole building community with the grid  $E_{peak}^c$  (kW) is calculated by

$$E_{peak}^c = \max(|E_{ex,1}^c|, |E_{ex,2}^c|, \dots, |E_{ex,96}^c|) \quad (8)$$

where  $E_{ex,i}^c$  (kW) is the power exchange with the grid of the whole building community considering the EV charging load in the  $i^{\text{th}}$  simulation step. In each iteration, the calculation of  $E_{ex,i}^c$  is updated by adding the previously optimized EV charging load.

$$\text{1st step - EV 1: } E_{ex,i}^c = E_{d,i}^c - E_{s,i}^b \quad (9)$$

$$\text{2nd step - EV 2: } E_{ex,i}^c = E_{d,i}^c + u_i^{1*} - E_{s,i}^b \quad (10)$$

$$\text{3rd step - EV 3: } E_{ex,i}^c = E_{d,i}^c + (u_i^{1*} + u_i^{2*}) - E_{s,i}^b \quad (11)$$

⋮

Eqs. (9) to (11) shows the calculating of the power exchange with the grid ( $E_{ex,i}^c$  (kW)) in each iteration. The fitness function for the optimization strategy (i.e., minimize the peak power exchanges with the grid) is depicted by

$$J_{grid} = \min(E_{peak}^c) \quad (12)$$

The process will continue until all the EVs being optimized in the building community.

### Algorithm for top-down control

Fig. 4 presents the selected control method for the top-down coordinated approach. This control is implemented for all the EV simultaneously considering the building-aggregated-level power demand and renewable power production. Again, the GA algorithm will be used in the control optimization.

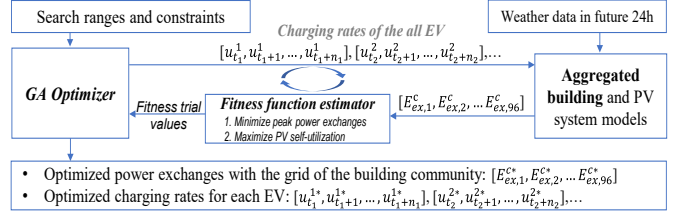


Figure 4 Selected optimization logic for the top-down control approach.

The fitness function for the control strategy is the same as the bottom-up coordinated approach, as depicted by Eqs. (12). While the calculation of the power exchange with the grid of the building community ( $E_{ex,i}^c$  (kW)) in each timestep should consider all the EV charging load, see the equation below,

$$E_{ex,i}^c = E_{d,i}^c + (u_i^1 + u_i^2 + u_i^3 + \dots) - E_{s,i}^b \quad (13)$$

The top-down control requires the controller to know/forecast the expected future arrival time in the building for all EVs, as the scheduling also considers the EVs that has not arrived yet. It then produces the optimal charging loads of all the EVs in one simulation. The outputs are the optimized charging loads of all the EVs  $[u_{t_1}^{1*}, u_{t_1+1}^{1*}, \dots, u_{t_1+n_1}^{1*}]$ ,  $[u_{t_2}^{2*}, u_{t_2+1}^{2*}, \dots, u_{t_2+n_2}^{2*}]$ , ...

This study will compare the above-mentioned three control algorithms, as well as a benchmark scenario without any smart EV charging control, i.e., the EVs are charged at rated charging rate once they are plugged into the charging station, as mostly used nowadays.

## Results

A building community located in Ludvika, Dalarna region of Sweden is used for analysis in this study. There are three separate buildings in the studied building community. In the case studies, a summer week was selected to test the different control approaches. Considering the different driving patterns in workdays



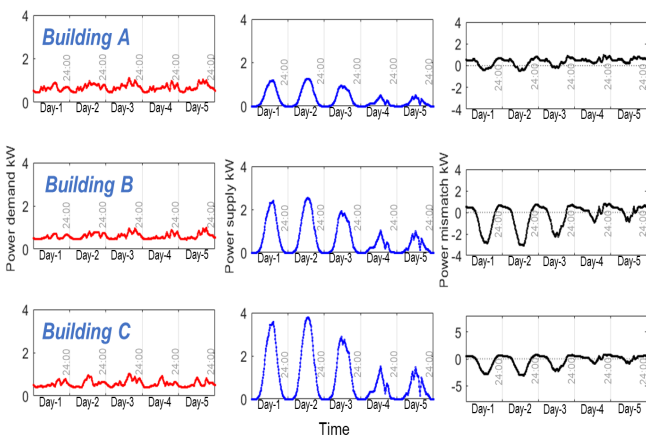
and weekends (the EVs might not be parked in the community during weekend daytime), this study only considers the five workdays for simplicity. The weather data of Ludvika was used for modelling the local PV power productions. Table 2 summarizes the EV information used for the simulation. Considering the uncertainty in the EV usage (e.g., the EVs could be used more in some days), the initial SOC in each day are set differently. The time interval of simulation was set to 15 mins with the purpose of improved accuracy.

*Table 2 Configuration of EVs for the simulation in the workdays of the selected week*

	Capacity	Limit		
EV 1	53 kW·h	12 kW	Arrive	$\sim N(6:00, 10^2)$
			Depart	$\sim N(14:00, 10^2)$
			Initial SOC	$\sim N(40\%, 5\%^2)$
EV 2	39 kW·h	12 kW	Arrive	$\sim N(8:00, 10^2)$
			Depart	$\sim N(16:00, 10^2)$
			Initial SOC	$\sim N(40\%, 5\%^2)$
EV 3	32 kW·h	12 kW	Arrive	$\sim N(10:00, 10^2)$
			Depart	$\sim N(17:00, 10^2)$
			Initial SOC	$\sim N(40\%, 5\%^2)$

**Power demand and supply information**

Fig. 5 displays the power demand, PV power generation, and electricity mismatch in each timestep (i.e., 15 minutes interval) during the workdays in a typical summer week for the three buildings. The electricity demand only includes the domestic electricity loads (i.e., lighting, washing machine, TV, etc.). The trends of PV power production of the three buildings are similar, since the solar irradiation is nearly the same for the three buildings. As Building C has the largest roof area, more PV panels can be installed on its roof. Thus, it has the largest average PV production. Power mismatch of each building is calculated as the deviation between its power demand and renewable generation in each timestep. A positive value of power mismatch indicates insufficient renewable generation (and thus grid power is needed), while a negative value of power mismatch indicates excessive renewable generation (and thus selling electricity to the grid is needed).



*Figure 5 The power demand, PV power generation and power mismatch in each timestep during the weekdays in the selected summer week for the three buildings*

Note this study only conducts simulation for five days. This is because of two reasons: (1) One week simulation can already reveal the characteristics of each control approach. (2) The computational load will increase exponentially if the simulation is conducted for a full year. To increase the optimization performance, this study used a simulation timestep of 15 minutes. In other words, there are 4 variables to be optimized in each hour. In the optimization, the average number of variables to be optimized for each EV is 32 (i.e., 8 hours parking period on average in each day). Considering the large number of variables to be optimized, in the GA optimization, the number of generations is set as 8000, and the population size is set as 10000. The genetic algorithm is coded in Matlab.

**Energy performance comparison**

Fig. 6 compares the energy flow of the whole building community under different EV charging approaches. The bars represent the power flow of PV system, building demand and EVs, respectively. And the blue curve with marks represents the power mismatch, which is deviation between the total power demand and total power production. The power mismatch will be adjusted by the power grid and thus can be interpreted as the energy exchanges with the grid. When EV charging loads are not included, in Day-1 to Day-3, since the total PV power production is much larger than the community electricity demand, the peak power exchanges are caused by the large renewable power exports to the grid. While in Day-4 and Day-5, the peak power exchanges are caused by the large power demand due to the insufficient PV power production.

Fig. 6(a) is the case when there is no EV smart charging. Since the EVs are charged immediately at the rated charging rates after they are connected to the charging ports, large EV charging loads are observed near the arrival time of each EV (e.g., see Day-1 to Day-5). While when there are multiple EVs being charged simultaneously, large peak demands will be produced (e.g., see the large peak loads in Day-3 and Day-4). As can be seen in Day-1, Day-2 and Day-3, there are both large PV power exports to the grid and large demand penetration on the grid. Fig. 6(b) shows the performance under the individual control approach. Compared to the no EV smart charging case, the large charging loads are more evenly distributed in periods with large PV power production, and thus the large power demands are avoided. As can be seen in Day-1, Day-2 and Day-3, the peak power exchanges are caused by the PV power exports. The large power demands in Day-4 and Day-5 are also significantly shaved. Since there is a lack of coordination among different EVs' charging loads, there are large fluctuations in the power exchanges (e.g., see the large PV power exports in Day-1 and Day-2). Fig. 6(c) presents the performance under the bottom-up control approach. The bottom-up control implements coordination of the EV charging loads, i.e., shift the

charging load of an EV to avoid overlapping with the charging load of previously optimized EVs, and thus the peak power exchanges are reduced compared to the individual control approach. The fluctuation of peak power exchanges is also smaller (e.g., see the large PV power exports in Day-1 and Day-2). Fig. 6(d) shows the performance under the top-down control approach. There are obvious limits of the peak power exchanges with the grid. As can be seen in Day-1 and Day-2, the peak energy exports are well limited to specific values in a long period, and in Day 4, the peak power demand is well limited to a specific value during the daytime. This is because the top-down control implements a global coordination of all the EVs' charging load and takes the community-level aggregated performances directly as the control target. It is capable of identifying the global optimum.

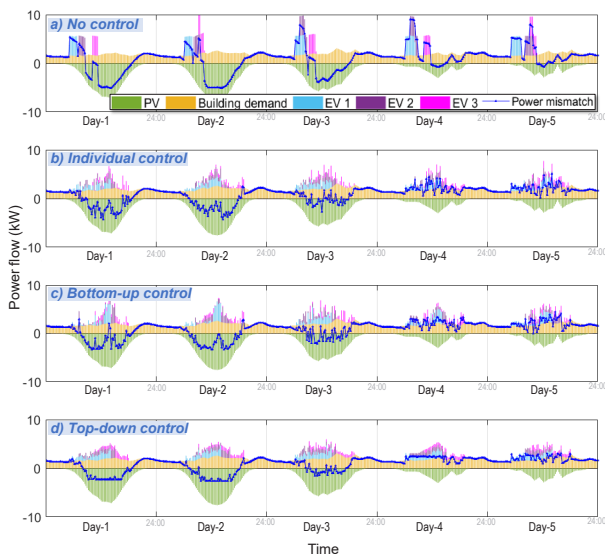


Figure 6 Power flow of the building community and EVs under different EV control approaches (a) No control, (b) Individual control, (c) Bottom-up control, and (d) Top-down control.

To have a more straightforward look into the performances of different control approaches, the daily peak power exchanges with the grid are calculated and compared, as shown in Fig. 7. The performance improvements (i.e., the reduction in the peak power exchanges) compared with the reference case (i.e., no smart charging) are also calculated in each day and presented in Fig. 7. As can be seen, all the three controls can significantly reduce the daily peak power exchanges with the grid. The individual control reduces the daily peak power exchanges by 15% to 65% compared to the reference case. The bottom-up control performs better than the individual control in reducing the peak power exchanges. It can reduce the daily peak power exchanges by 38% to 71% compared to the reference case. The top-down control performs the best among all the control approaches, and it can reduce the daily peak power exchanges by 48% to 73% compared to the reference case in the studied week. Table 3 summarizes the daily peak

power exchanges under different control approaches and the relative performance improvements.

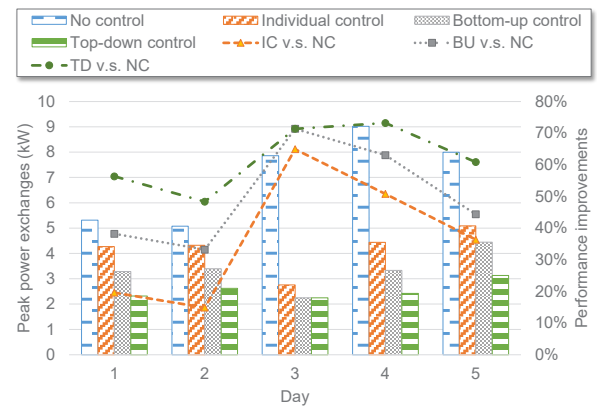


Figure 7 Comparison of the daily peak power exchanges with the grid and the relative performance improvement under different control approaches. (IC: individual control; BU: bottom-up control; TD: top-down control)

Table 3 Summary of the daily peak power exchanges under different control approaches and the relative performance improvements.

Controls	Day-	1	2	3	4	5
No control (Benchmark)	Peak power exchanges (kW)	5.3	5.1	7.9	9.0	8.0
	Individual control	4.3	4.3	2.8	4.4	5.1
	Relative improvement %	20	15	65	51	36
Bottom-up control	Peak power exchanges (kW)	3.3	3.4	2.3	3.3	4.4
	Relative improvement %	38	33	71	63	44
Top-down control	Peak power exchanges (kW)	2.3	2.6	2.3	2.4	3.1
	Relative improvement %	56	48	71	73	61

### Computational performances comparative analysis

The computational loads of the three controls are also compared. Table 4 compares the total computational performances for the five-day simulation considering three EVs with a simulation timestep of 15 minutes. The simulation was conducted on a computer with 128.0 GB installed RAM and AMD Ryzen Threadripper 3990X 64-Core Processor 2.90 GHz. In the GA search engine, the number of generations is set as 8000, and the population size is set as 10000. In the individual control and bottom-up control, as the EV charging loads are optimized one by one, the average number of variables to be optimized simultaneously is 32 (i.e., an average parking period of 8 hours a day and 4 variables in each hour). The call times of GA engine of these two controls are both 15 (i.e., 3 EVs in each day and 5 days in total). While for the top-down control, the average number of variables to be optimized in each optimization increased to 96 (i.e., an average parking period of 8 hours a day, 4 variables in each hour and 3 EVs), but the call times of GA engine reduced to 5 (i.e., 5 days). The total computing time for the individual

control, bottom-up control and top-down control are 8 hours, 6.5 hours and 10.8 hours, respectively. The ability to converge is assessed by checking while the optimized solutions become stable after several repeated optimization. If the required number of repetitions to reach a stable solution is large, the convergence ability is poor. The ability to converge is poorer in top-down control compared to the other two controls, since the total number of variables to be optimized is three times the number in the other two controls. This means the optimization might need to be implemented multiple times to obtain a converged global optimum. Note with the increase of the EV number, the computing complexity of top-down control will increase dramatically in each call of the GA engine, which may deteriorate the optimization results. While for the individual control and bottom-up control, the computing load in each call of GA engine will not change much.

The total computing time for the non-coordinated control, bottom-up coordinated control and top-down coordinated control are 5~8 hours, 5~8 hours and 9~12 hours, respectively. Note that due to the randomness in selecting the initial population and mutation of child populations, the time required for implementing GA can be different when running it multiple times for the same problem. The values in the table only provide a rough reference about the computational loads. The call times of the GA engine and the variables to be optimized in each simulation are more influential on the final required time.

*Table 4 Comparison of the computational performances of the three approaches considering three EVs in a typical summer week (five workdays).*

Controls	Average number of variables to be simultaneously optimized	Call times of GA engine	Computational load (hour)	Ability to converge
Individual control	32	15	8	Good
Bottom-up control	32	15	6.5	Good
Top-down control	96	5	10.8	Poor

## Conclusions

This study has classified existing EV smart charging control methods into three categories according to (i) whether there is coordination, and (ii) how coordination is conducted. For each control approach, a control algorithm has been selected using the GA algorithm, and their performances have been systematically compared in different aspects. The comparison reveals how different ways of coordination affect the demand response performances of EV smart charging. The control objective minimizing the peak power exchanges with the grid has been considered in the comparison. A case building community located in Dalarna County of Sweden with three EVs has been used for the case studies

and comparison. The major findings are summarized as follows.

- Both the two coordinated controls, i.e., bottom-up and top-down controls, can achieve much better control performances at the aggregated-level compared to the individual control. The individual control reduces the daily peak power exchanges by 15%~65% compared to the reference case, while the two coordinated controls reduce it by 38%~71% and 48%~73%, respectively.
- The top-down control approach can achieve better control performance than the bottom-up control. This is because the top-down control is able to coordinate the operation of all EVs considering the constraints during the full optimization period. While, with the combined effects of a non-optimal start and the accumulation of the ‘biased’ subsequent optimization, bottom-up control approach cannot lead to global optimum like the top-down control approach.
- Despite the good optimization performances, the computation complexity in one call of GA search engine is much larger in the top-down control, as the large the number of parameters to be optimized simultaneously. As a result, with the increase of EV number, the computing complexity in single optimization increases significantly. This will make it difficult to converge and identify the global optimum.

The results from this study suggest that decision makers need to make a balance between the control performances and the computational complexity. If the number of EVs is substantially large, bottom-up coordinated approach can achieve near-optimum performances with good convergence ability. While if the number of EVs is relatively small, the top-down coordinated approach is a better alternative, which can converge and identify the global optimal solutions. The idea of top-down coordinated approach, which directly takes the aggregated-level performances as the optimization target, can find the global optimal solutions.

The conclusions related to the different ways of coordination can be applied to different countries, as the methods are generic.

This study considers simple scenarios of EV mobility patterns and did not consider the EV battery degradation due to the smart charging. Future work will use more sophisticated EV usage models to investigate the EV smart charging benefits.

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