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Electric vehicle charging in China's power system: Energy, economic and environmental trade-offs and policy implications

Ying Li [a,*], Chris Davis [b], Zofia Lukszo [a], Margot Weijnen [a]

[a] Faculty of Technology, Policy and Management, Delft University of Technology, Jaffalaan 5, 2600 GA Delft, The Netherlands
[b] Center for Energy and Environmental Sciences (IVEM), University of Groningen, Nijenborgh 4, 9747 AG Groningen, The Netherlands

HIGHLIGHTS

- We investigate the energy, economic and environmental implications of deploying EVs for China's power system by 2030.
- EVs outperform gasoline-powered vehicles in terms of average fueling costs.
- Controlled EV charging given the expected 2030 capacity portfolio results in more CO_2 emissions than uncontrolled charging.
- Controlled charging has absolute advantages in mitigating the peak load and facilitating RES generation.
- Controlled (dis)charging will not reduce CO_2 for China without generation decarbonization and CO_2-influenced dispatch.

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ABSTRACT

This work investigates different scenarios for electric vehicle (EV) deployment in China and explores the implications thereof with regard to energy portfolio, economics and the environment. Specifically, we investigate how to better deliver the value of EVs by improving designs in the power system and charging strategies, given expected developments by 2030 in both the power system and EV penetration levels.

The impact of EV charging is quantified by applying an integrated transportation-power system model on a set of scenarios which represent uncertainties in charging strategies. We find that deploying EVs essentially shifts the use of gasoline to coal-fired power generation in China, thus leading to more coal consumption and CO_2 emissions of the power system. Economically, EVs outperform gasoline-powered vehicles in terms of average fueling costs. However, the impact of EVs in terms of CO_2 emissions at the national level largely depends on the charging strategy. Specifically, controlled charging results in more CO_2 emissions associated with EVs than uncontrolled charging, as it tends to feed EVs with electricity produced by cheap yet low-efficiency coal power plants located in regions where coal prices are low. Still, compared with uncontrolled charging, controlled charging shows absolute advantages in: (1) mitigating the peak load arising from EV charging; (2) facilitating RES generation; and (3) reducing generation costs and EV charging costs. Hence, in light of this trade-off of controlled charging with the goals of energy security, economic efficiency and reducing environmental impacts, policy interventions in the Chinese power system should opt for controlled charging strategies in order to best realize the benefits of EVs. Accordingly, this paper proposes that increasing the use of cleaner forms of electricity generation, such as RES power and gas power, and establishing energy efficiency and CO_2 emission regulations in power dispatch are critical for China. Lastly, this work illustrates what the optimized charging profiles from the power system perspective look like for different regions. These results can inform Chinese policy makers in creating a better integration of the transportation and the power system.

1. Introduction

The transportation sector accounts for about half of the oil consumption in China, and is the fastest growing contributor to national greenhouse gas (GHG) emissions [1]. To improve the security of energy supply and address climate change, a transition of the transportation sector towards low-carbon and sustainable energy resources is needed [2]. One possible strategy is to electrify transportation through using electric vehicles (EVs), and the Chinese government has been making substantial efforts in this aspect [3]. However, whether EVs are low-carbon and sustainable

* Corresponding author.
E-mail address: y.li-6@tudelft.nl (Y. Li).

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for China compared with conventional vehicles is an open question, as the benefits from deploying EVs is highly dependent on the fuel consumption, costs and CO_2 emissions associated with electricity generation [4]. Given substantial differences in the regional generation portfolios and the expanding inter-regional transmission grid in China, a comprehensive assessment is needed to evaluate the value of deploying EVs in such a large-scale and complicate power system [5].

Furthermore, the implications of EVs are largely influenced by charging strategies. Most studies indicate that uncontrolled EV charging entails a series of challenges for the investments in and the operation of the power system [6]. For instance, it may require additional generation capacity [7] and upgrading of the existing power grid [8]. Accordingly, demand response of EVs has been proposed to cope with this. The key idea behind the EV demand response is that with certain mechanisms, EVs' charging (and discharging) can be controlled as a dispatchable load or as an energy storage system to coordinate with the power system operation [7]. Based on various controlled charging strategies, many benefits can be expected from EV demand response. For instance, studies show that EVs can provide ancillary services in the electricity market [9,10], manage the intermittency issues of RES generation [11,12], and mitigate the need for grid expansion [13,14]. The questions left here are how the implications of EVs are affected by different charging strategies, and which charging strategy would be more suitable in light of the characteristics of China's power system.

In short, this work aims to assess the implications of deploying EVs in the Chinese power system considering regional differences in generation portfolio and the constraints of inter-regional transmission grid capacity, and investigate the influences of the contextual power system and charging strategies on the value of EVs. The results of this work are expected to inform policy makers regarding the possible benefits and threats associated with EV deployment, and how to better exploit the promises of EVs by improving designs in the power system and charging strategies. Specifically, this work will answer three questions: (1) what are the implications of EV deployment in China from the energy portfolio, economic efficiency and environmental sustainability perspectives? (2) to what degree can the implications of EVs be affected by charging strategies? and (3) what can be improved in the power system and charging strategies to better deliver the value of EVs?

Although many studies assessing the value of EVs have been conducted in the literature, this paper distinguishes itself in two main areas. First of all, this paper distinguishes itself by providing a comprehensive evaluation of the value of EVs in China from the combined perspectives of energy portfolio, economic efficiency and environmental sustainability. We argue that these three perspectives are all desirable for policy designs to achieve an effective and efficient low-carbon transition in the long-term. Hence, this work can provide well-rounded policy evaluations of the value of EVs with regard to the different aspects and trade-offs involving goals related to these perspectives. However, the existing literature has omitted certain perspectives of the three, which might lead to biased policy decisions. For instance, [1,5,15,16] only focused on the environmental aspect of deploying EVs; [7,12,17–20] focused more on energy portfolio effects especially for the integration for renewable energy; other studies, such as [21,22], focused more on a mix of two perspectives. Also, there are studies of EVs focusing on their impact on the distribution and transmission grids, such as [13,14]; and other studies focusing more on aspects of the electricity market, such as [9,23].

Additionally, this paper distinguishes itself by developing a new integrated transportation-power system model, which enables a better quantification of the value of EVs. First, the model can statistically estimate the temporal availability of EVs connecting to the grid. This addresses the lack of accurate driving data which has been identified as a key issue in creating EV-grid models [6]. Additionally, the model enables the simulation of power system operation with a high temporal and spatial resolution. Temporally, the model simulates power system operation on an hourly basis, which can estimate what types of power plants are reacting to the changes in EV load. Because of this, the model is better in terms of evaluation accuracy when compared with life-cycle assessment methods (e.g. [1,21]), or with methods assuming a fixed generation portfolio or a given merit order (without considering start-up constraints of power plants) for EV charging (e.g. [5,15,24]). Spatially, the Chinese power system is modeled as a six-region power system, which incorporates the constraints of inter-regional transmission capacity and the differences in regional generation portfolio by technology. In particular, this work highlights the influence of inter-regional power exchange on the value of EVs given the fact that it might shift EV-associated regional power supply to interconnected regions [4]. This shift is likely to be more significant in China in light of its mismatches of distribution between power resources and electricity demand as well as the fast expanding inter-regional transmission grid [25]. However, existing model-based studies for the Chinese case, such as [17,20], fail to take this into consideration. Hence, this model enables a more accurate estimation of the value of EVs, and can provide a theoretical reference for the methods that can be used in studies that model the integration of EVs into the power system.

The model is applied to a set of scenarios which represent the Chinese power system by 2030 with different charging strategies. The Chinese power system consists of six regional power systems, whose diversity in generation portfolio and grid connections enables us to explore the implications of EVs with different power systems. Further, four charging strategies are modeled, including: (1) two uncontrolled charging strategies which allow EV users to charge freely, yet differ in the accessibility of EV charging infrastructures; and (2) two controlled charging strategies in which EV charging is optimized from the power system operators' perspective, with one strategy where EVs can also discharge back into the grid when needed.

This paper is organized as follows. Section 2 introduces the transportation-power system model. Section 3 presents the scenario definitions and the key data used in this work. Section 4 analyzes the scenario results regarding the energy-economic-environmental implications of EVs. Section 5 discusses the policy implications of the scenario results and how to better deliver the value of EVs for real applications. The final conclusions are provided in Section 6.

2. Research methods

2.1. An integrated transportation-power system model

This paper develops an integrated transportation-power system model to quantify the interactions between EVs and the power system. The framework of the model is shown in Fig. 1. Specifically, the transportation model calculates the electricity demand of EVs, statistically estimates the availability of EVs connecting with the grid, and defines the strategies of using EVs. The statistic estimation method used in our transportation model can be useful for similar studies, since the lack of accurate driving data has been identified as a key issue in creating useful EV-grid models [6]. Specifically, the possible strategies of using EVs in this work are: (1) using EVs as loads (only charging) or as an energy storage system (both charging and discharging); and (2) having EVs' charging and discharging controlled by the power system operator or by EV owners [26].

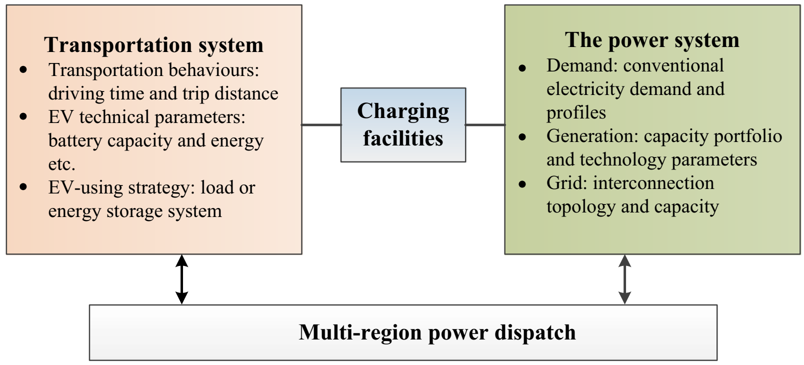


Fig. 1. The schematic diagram of the integrated transportation-power system model used in this work. The arrows represent the directions of power flows.

With the data from the transportation model as inputs, the power dispatch model computes how power plants across regions can be optimally dispatched in response to hourly load changes arising from EV charging considering technical, constraints of the power system (e.g. ramping and transmission constraints). The power dispatch model here is expressed as a multi-region unit commitment (UC) optimization problem. Note that the inter-regional power exchange here is constrained by market-based net transfer capacity of the transmission grid rather than physical power flows. Instead of using the conventional mixed-integer UC optimization, this work adopts the clustered integer approach in [27] to group power plants by generation technology, which largely reduces the amount of commitment state variables in the UC optimization. Accordingly, the cluster integer based optimization method enables us to model detailed power system operation with less computational efforts, which makes our model applicable for the simulation of large-scale power systems.

2.2. Transportation system model

This part mainly introduces how the model estimates EVs' temporal availability which determines how many EVs are connected to the grid at a given time. It is desirable to simulate EVs' availability using realistic patterns that mimic people's actual travel behaviors. However, comprehensive travel behavior data for EVs are unavailable yet. This work therefore builds a statistical transportation model based on actual travel survey data in the Netherlands to estimate EVs' temporal availability in China. Hereby we assume that: (1) EV driving patterns are similar to those of conventional cars; and (2) the driving time does not differ much between regions.

First, as a proxy to generate travel patterns, the Mobiliteitsonderzoek Nederland (MON) survey data for the year 2008[1] was used (see more details in Appendix A). To perturb the model and simulate expected variability in the number of EVs available for each hour of the day, kernel density estimates [28,29] were constructed to represent the probability density function of the percentage of EVs available at each hour. The motivation for using kernel density estimates is that they allow for the creation of probability density functions which closely mirror variations in the actual data. The approach is similar to that of creating a probability density function using histogram data, except that every observation in the data is represented as a normal distribution, and all of these normal distributions are then summed to arrive at the final probability density function. With these probability density functions, we can then create synthetic data that has characteristics similar to that of the real data.

This paper creates kernel density estimates per hour and type of day (weekday or weekend), as shown in Fig. 2. What we can see with this is that our data is able to capture patterns in the survey data that cannot be represented with a normal distribution. In several of the figures, the distributions are seen to be skewed to one side or bimodal (e.g. 9 pm on weekends, 3 pm on weekdays).

For illustrative purposes, Fig. 3 shows the estimated temporal availability of EVs in connecting to the grid on an hourly basis for two days. Generally, we can observe that about 80–90% of the entire fleet are available to connect with the grid, which is validated by the observations from the National Household Travel Survey of the U.S in 2009.[2] In addition, on weekdays, the variability of EV availability tends to be much lower, especially during rush hours in morning and evening. On weekends, people are less constrained to a particular schedule and the range of temporal availabilities is much greater.

2.3. Power system model: multi-region power dispatch

Many unit commitment (UC)-based power dispatch models incorporating EVs have been developed in the literature, such as [11,14,26]. Most studies express the model as a mixed-integer linear programing (MILP) problem, in which binary variables, [0, 1], are used to indicate the commitment state and the start-up actions of generation units. However, applying the MILP approach for the large Chinese power system is computationally constrained as the combinatorial commitment states explode quickly with the number of generation units. To find a balance between computational ease and accuracy in practice, the work adopts the clustered integer approach developed in [27,30] to reduce the amount of variables in the UC model. The key idea of the clustered integer approach here is to group generation units by technology, so that the commitment state for technology g with N_g units can be expressed as an integer varying from 0 to N_g, representing how many units of this group are turned on. The dimension of combinatorial commitment states with the clustered method is $N_g + 1$, which is much lower than that resulting from the mixed-integer method.[3]

A detailed mathematical formulation of the clustered-integer unit commitment (CIUC) model is presented in Appendix C, mainly based on the work in [11,17,31–35]. In particular, [33] develops a UC model incorporating energy storage system and transmission capacity constraints, which provides the basic framework of the UC model in this work. The research in [27,30,31] provides insights into the applications of the clustered integer approach to UC models, and the work in [11,17,34,35] presents more details about integrating EVs into UC models.

[1] http://www.scp.nl/Onderzoek/Bronnen/Beknopte_onderzoeksbeschrijvingen/Mobiliteitsonderzoek_Nederland_MON.

[2] http://nhts.ornl.gov/download.shtml.

[3] The dimension of combinatorial commitment states with the mixed-integer method is 2^{N_g}.

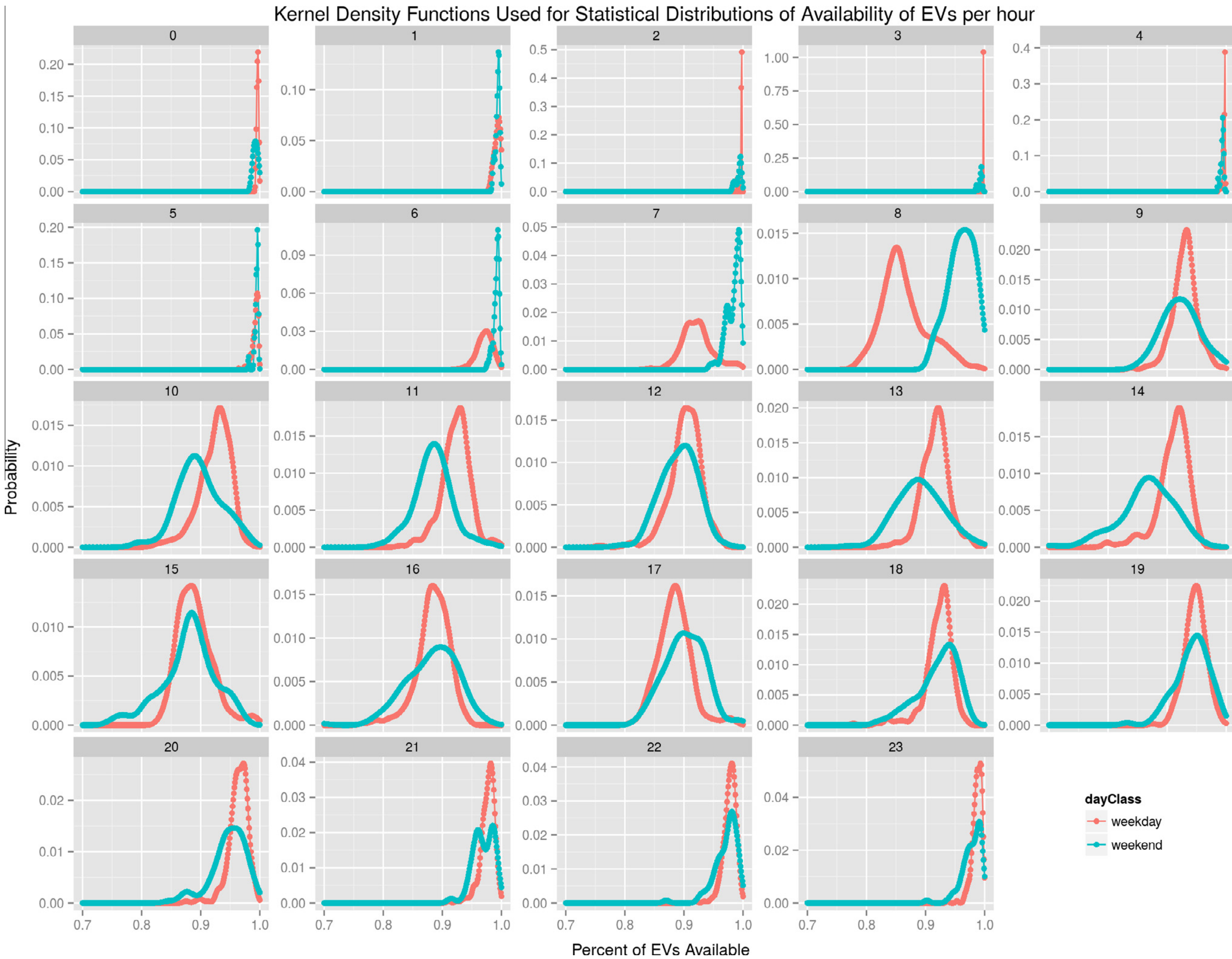


Fig. 2. Kernel density estimates of EVs' temporal availability per hour on weekdays and weekends.

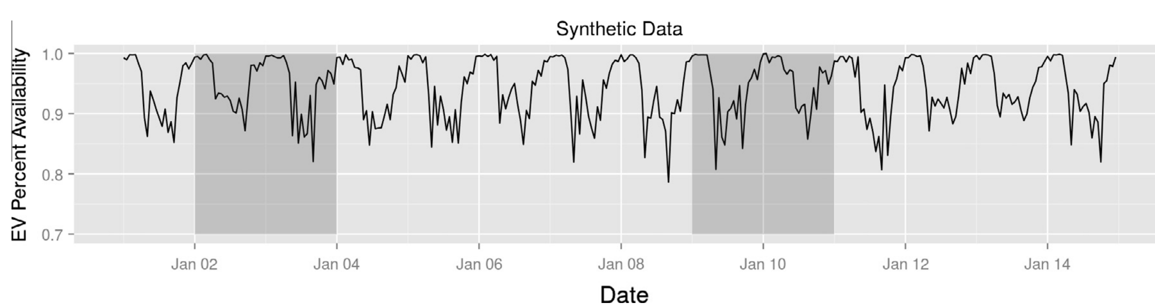


Fig. 3. Illustrative time series data showing EVs' temporal availability in connecting to the grid, calculated by sampling kernel density estimates. Note that the periods during the weekend are highlighted in gray boxes and other periods are weekdays.

3. Scenario definitions and data collection

3.1. Scenario definitions

This work chooses the year of 2030 as the baseline scenario to depict the expected future power system in China. The 2030 scenario is chosen mainly because it has the most accessible data about the planning for the regional generation portfolios and the inter-regional transmission grid development in China. More detailed explanations about the data of this baseline scenario are shown in Section 3.2. This work focuses on studying the influences of the power system and charging strategies on the value of EVs. The diversity of these six regional power systems in generation portfolios and grid interconnections enables us to compare the influences of different regional power system contexts on the value of EVs. In this way, only one scenario variable is used in this work, namely the charging strategy. Depending on the role and the controllability of EVs from the power operators' perspective, four types of charging strategies are defined in the scenarios, as shown in Table 1.

Specifically, the home charging and random charging are defined to indicate the cases when no artificial control is imposed

Table 1
The settings of charging strategies for different scenarios.

Scenario	Charging strategy	EVs		Explanations
		Role	Controllability	
1	Home charging	Load	Uncontrolled	EVs are charged after returning home without delay, the time of staying home is from 6 pm to 8 am the next day
2	Random charging	Load	Uncontrolled	EVs are free to be charged whenever parked, until their batteries are full
3	Controlled charging	Load	Controlled	EVs' charging is optimally dispatched by the power system operator
4	Vehicle to grid (V2G)	ESS	Controlled	Both EVs' charging and discharging are optimally dispatched by the power system operator

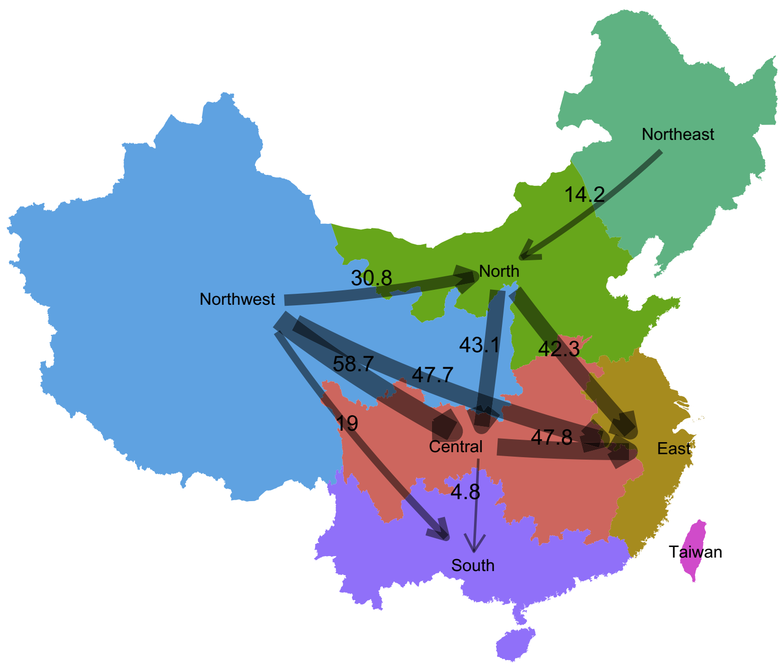


Fig. 4. The planning of inter-regional transmission grid by 2030. Note that the numbers close to the links indicate transmission capacity (in GW), and the arrows reflect main directions of power flows.

to EV charging, so that EV users are free to charge whenever they have access to charging facilities. For the home charging strategy, the access to charging facilities is constrained at home. However, the random charging represents a situation where charging facilities are widely spread so that EVs can be charged whenever parked without any delay.

For illustrative purposes, the energy and charging power of EVs with home charging and random charging under different charging power rates are illustrated in Appendix D.1. For the home charging, the energy stored in EVs steadily decreases during the day as EVs are only able to charge after returning home at 6 pm. Home charging generates a large peak early in the evening, and the peak reaches a plateau based on the maximum rate imposed by the charging infrastructure. For random charging, the flexibility of vehicles to charge when parked is enough to ensure that the entire EV fleet remains at a high state of charge (SOC). The charging profiles for the home charging and random charging are exogenous parameters for the model, while the profiles of controlled charging and V2G are optimized with the model.

3.2. Key data of the baseline scenario

3.2.1. The power system

3.2.1.1. Inter-regional transmission grid. The Chinese power system is comprised of six inter-connected regional power systems, and the geographical distribution of these six regions is shown in Fig. 5. To meet the fast growing electricity demand along the east coast of China and to facilitate the renewable energy development in the North, Northwest and Northeast (three North) regions, China planned an ambitious expansion of the inter-regional transmission grid capacity. As shown in Fig. 4, the total inter-regional transmission capacity will be expanded from 47.40 GW in 2012 to 308.40 GW in 2030. Moreover, the expansion is mainly for the transmission lines starting from the Northwest, North and Central, ending with the East and South. The data in this figure are adapted[4] from [25]. The rate of transmission loss and cost slightly differ between transmission lines depending on the type of lines (e.g. AC or DC), voltage level and line length etc. This work adopts average values of energy loss and transmission cost based on the data in [36] mainly to reflect the length of transmission lines (see Appendix D.2).

[4] The following changes have been made when adapting the data from [25]. First, this work integrates Tibet into the Northwest power system to fit the six region-based power system structure in China. Second, the planned cross-border transmission capacity is assumed as a negative demand for the importing regions. For instance, with regard to the cross-border transmission grid between Myanmar and the South, a negative power demand which equals the amount of this cross-border transmission capacity is imposed to the South power system. This assumption does not affect the meaning of the results, as the cross-border imported capacity is quite negligible compared with the regional electricity demand in China.

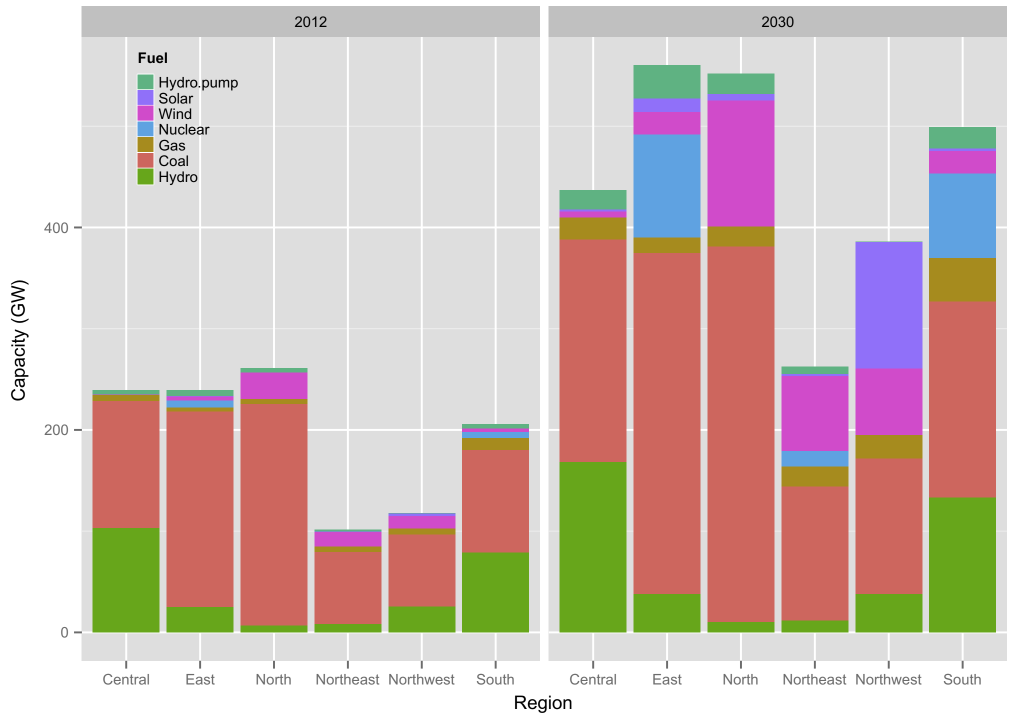


Fig. 5. The regional generation portfolios in 2012 and the estimated regional generation portfolios in 2030. Note that the data of 2012 are mainly from [40] and the estimations of 2030 are compiled by the authors based on the projections in [25,41–44].

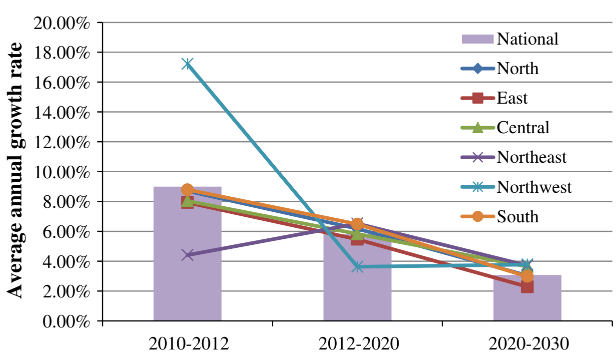


Fig. 6. The projected growth rates of electricity demand during 2012–2030 for the nation and the six regions. Data source: [25,44]. Note that the bars show the national average annual growth rates, while the lines with markers represent the regional average annual growth rates.

3.2.1.2. Regional generation portfolio. China's energy policies have been based on central planning which is regularly issued on a five-year basis, so that an official planning for the mid-term generation portfolio by 2030 is not available. Hence, this work reviews the projections in the literature to gain an overall picture of the possible generation capacity expansion in China. The review scope covers projections by key organizations in China (e.g. China Electricity Council [37], National Energy Administration [38]), literature [25,36] and international associations (e.g. International Renewable Energy Agency [39]) etc. With all the resources, the authors summarize the evolution of generation portfolio during 2012–2030 as follows. In terms of the absolute amount of generation capacity, coal power will still be the largest till 2030, followed by hydro, wind and nuclear. In terms of the installed capacity growth during 2012–2030, solar power will be the largest, followed by nuclear power, wind power and pumped hydro storage. The derived 2030 regional generation portfolios are illustrated in Fig. 5, in which the generation portfolio of year 2012 is also depicted to show the evolution of the regional generation portfolios from 2012 to 2030. More details about the data regarding the economic and technical performance of regional power technologies, regional fuel prices and RES meteorological data are shown in Appendix D.3.

3.2.1.3. Electricity demand. Fig. 6 shows the projections for the national and regional electricity demand growth by 2030. In general, the demand growth rate decreases over time considering the slowdown of economy development, from 5.80% during 2012–2020, to 3.08% during 2020–2030. The regional growth rate differs by region. In general, the most developed regions (e.g. the North, East, South and Central) are in line with the national trend. However, for the Northwest, a big drop in demand growth is expected during 2012–2020, and then the growth becomes more stable during 2020–2030. In contrast, the demand in the Northeast is more likely to have a slight increase during 2012–2020. The demand profiles of the regional power systems are mainly referred to those of the European countries, more details are shown in Appendix D.4.

3.2.2. Transportation system

3.2.2.1. EV penetration level. The number of EVs[5] deployed in China by 2014 was about 1.19 million, which is less than 1% of the conventional vehicles [45]. However, given the strong incentives from governments to promote EV deployment [46], the number of EVs is expected to increase fast in the coming years. According to the National Development and Reform Commission, the number of EVs by 2030 is expected to account for about 28% of the vehicles in China [47]. With this penetration level, the expected amount of regional EV deployment in 2030 is shown in Table 2, which is

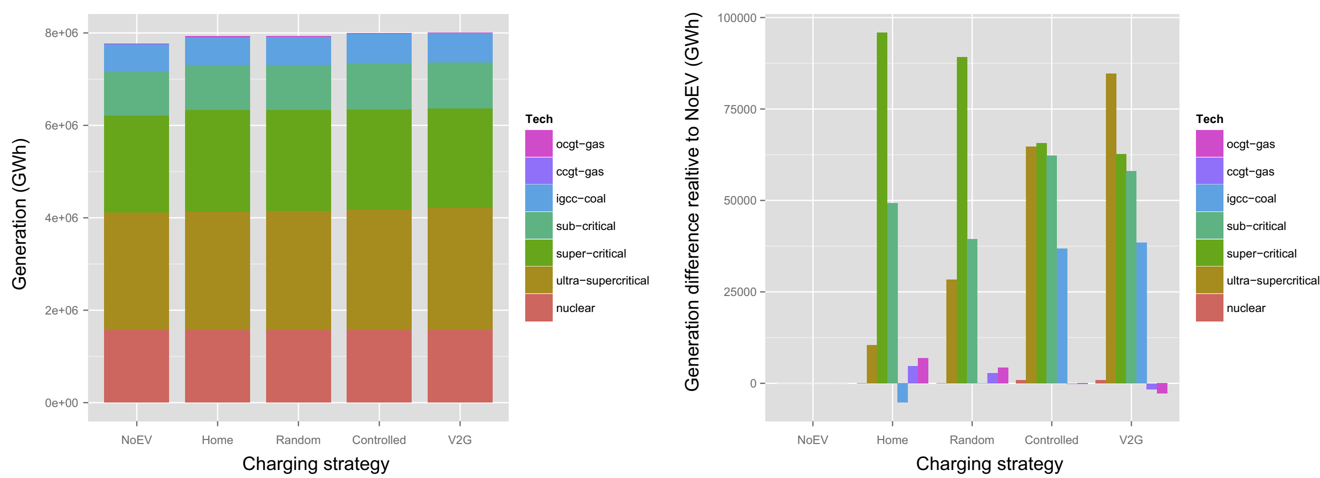
[5] The electric vehicles here include normal passenger cars and buses.

Table 2
The expected amount of EVs for different regions in 2030.

Regions	North	East	Central	Northeast	Northwest	South	National
Amount [million]	8.21	6.65	5.71	2.85	2.12	5.08	30.61

Table 3
EV-related parameters for in this work.

Parameters	$SOC_{min,max}$	Battery energy	Driving power	Energy efficiency	Power conversion efficiency	Charging power rate
Data	20%, 90%	25 kW h	10 kW/h	0.25 kW h/km	90%	3 kW



(a) The absolute amount of non-RES generation by technology.

(b) The differences in non-RES generation by technology, relative to the "NoEV" case.

Fig. 7. The national non-RES generation with different EV charging strategies.

estimated based on the provincial vehicle ownership of vehicles in China at the end of 2012.

3.2.2.2. Transportation data and EV-related parameters. The temporal transportation data regarding to what percentage EVs are driving on the road or parked are calculated with the kernel density estimation method, as we explained in Section 2.2. The time series data regarding EVs' availability in connecting to the grid based on the kernel density estimates are shown in Fig. B.18, which are validated by the actual survey data in Fig. A.17. More EV-related parameters are shown in Table 3.

4. Result analysis

4.1. Energy portfolio

The energy portfolio is analyzed with respect to three aspects: fossil fuel consumption, RES generation, and the non-served load which to some extent reflects power supply security. The results of the national generation mix generally show that deploying EVs mainly affects the non-RES generation yet has very limited impact on RES generation, as will be discussed below.

4.1.1. Non-RES generation mix and fossil fuel consumption

Fig. 7 shows to what degree the non-RES generation (including fossil fuel-based generation and nuclear generation) changes with the EV charging strategy. Compared with the "NoEV" case, deploying the planned amount of EVs increases the national non-RES generation by 2.08%-3.10%. This additional coal consumption is quite low relative to the huge amount of electricity demand in China. Moreover, controlled charging strategies result in more non-RES generation than uncontrolled charging strategies. Specifically, the V2G charging leads to the highest increase in non-RES generation and the home charging results in the least increase (see Fig. 7a).

Without controlled EV charging, deploying the planned amount of EVs increases coal consumption of the power supply by around 3%, and controlled charging strategies increase coal consumption further by around 1% (see Fig. 9). Fig. 7b shows where the additional non-RES generation under the controlled charging strategies comes from. There are two economic mechanisms which lead to increased amounts of electricity generation from coal plants. Although seemingly paradoxically, they favor both high and low-efficiency coal-fired power plants yet in different regions.

First, in comparison with uncontrolled charging, in many parts of the country, controlled charging leads to more generation from high-efficiency coal-fired power technologies (e.g. ultra-supercritical and integrated gasification combined cycle), which in turn reduces the use of low-efficiency coal power technologies and the use of quick-reacting yet expensive gas power which has higher fuel costs.

However, we find that controlled charging also facilitates the sub-critical (low-efficiency) coal generation, which seems contradictory. Fig. 8 shows that the additional sub-critical coal generation with controlled charging strategies is from the North and Northwest. What is happening here is that the low coal prices make the marginal costs of sub-critical power even lower than that of high-efficiency coal-fired power plants in other regions. The same reasoning explains the increase in the super-critical coal generation in the North and Northwest.

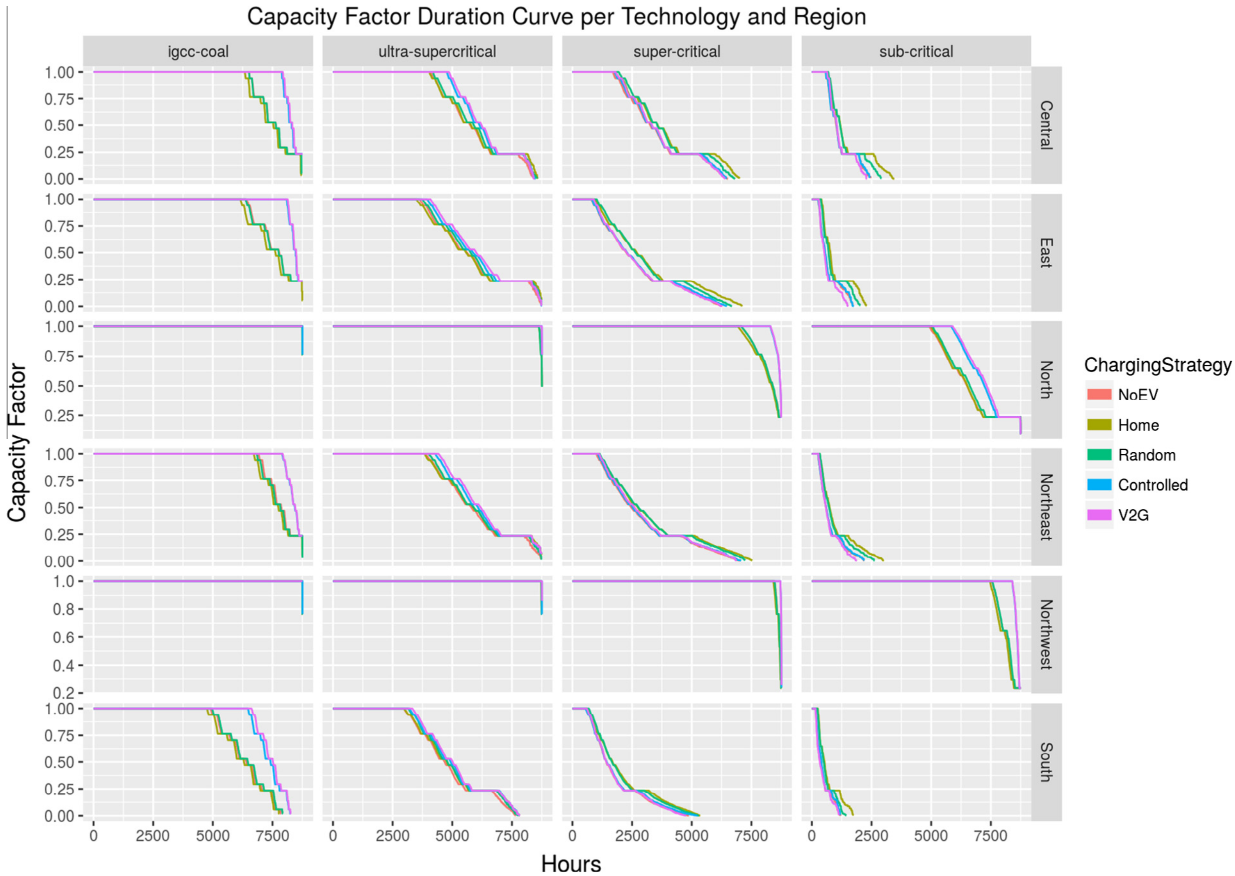


Fig. 8. The capacity factor duration curve for each fossil fuel-based technology and for each region with different charging strategies. Note that the generation efficiency of the four technologies in this figure descends from left to right.

These changes in inter-regional power exchange with charging strategies are further validated in Fig. 10, which shows that: (1) with uncontrolled charging, the amount of power exported from the North and from the Northwest is much lower than that in the "NoEV" case; while (2) the power exported from the North and from the Northwest largely increases if uncontrolled charging is used.

4.1.2. RES generation

Table 4 shows to what degree the use of RES (both wind and solar) generation changes with the EV charging strategies. In general, EV charging has a negligible impact on the use of RES generation. Still, comparing amongst the charging strategies, we find that controlled charging facilitates more RES generation than uncontrolled charging. Specifically, V2G performs a bit better than the controlled charging in terms of mitigating the curtailment of RES generation. Furthermore, home charging also performs better than random charging, given the fact that wind power generation (especially for the three North regions) is higher in the night than in the daytime.

4.1.3. Non-served load

Fig. 11 shows to what degree the amount of non-served load changes with different charging strategies. Clearly, uncontrolled charging strategies largely increase the amount of non-served load, which is mainly due to the EV charging load overlapping with the peak load of the reference power system ("NoEV"). Amongst two uncontrolled strategies, the random charging is slightly better than the home charging. In contrast, controlled charging strategies can largely mitigate the non-served load arising from EV charging. In particular, the V2G strategy can even reduce the non-served load of the reference power system ("NoEV").

4.2. Economic implications

Table 5 shows to what degree the generation costs of the national power supply change with the charging strategies. First, deploying the planned amount of EVs increases the variable generation costs of the national power system by 3.36–5.46%. Specifically, the home charging leads to the highest increase in the costs, and the V2G results in the lowest increase. Additionally, compared with home charging, the random charging reduces the additional costs of the power system arising from EV charging by 23.08%. This implies that without controlling EV charging, developing more accessible and widely distributed charging facilities can help mitigate the additional costs for EV charging more than charging facilities clustered at home. Furthermore, relative to the home charging, both the controlled charging and V2G can reduce the additional costs for EV charging by more than 30%.

Fig. 12 explains what contributes to the changes in generation costs, by decomposing the total costs into different types including fuel costs, non-served (Nos) load costs,[6] operation and maintenance (OM) costs, start up costs and transmission costs. It shows that the controlled charging strategies can largely reduce the fuel costs, non-served load costs and the start up costs of the power system

[6] Nos load cost represents the economic penalty for non-served load, which is assumed to be 1 million $/GW in this work.

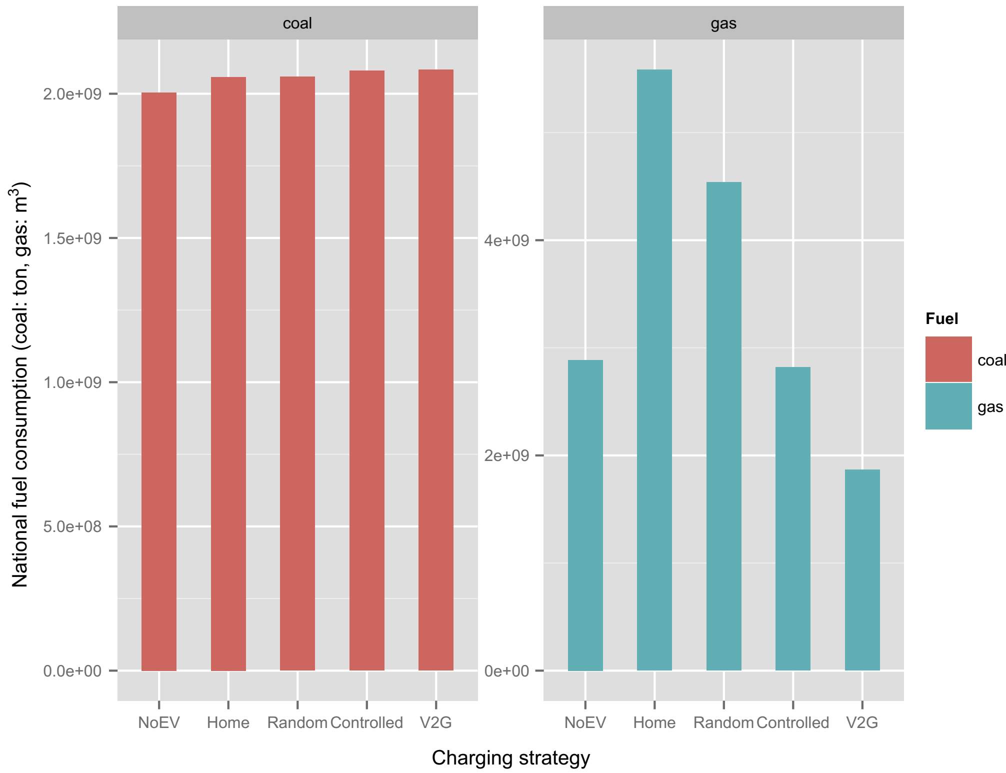


Fig. 9. The coal and gas consumption for the power supply with different charging strategies.

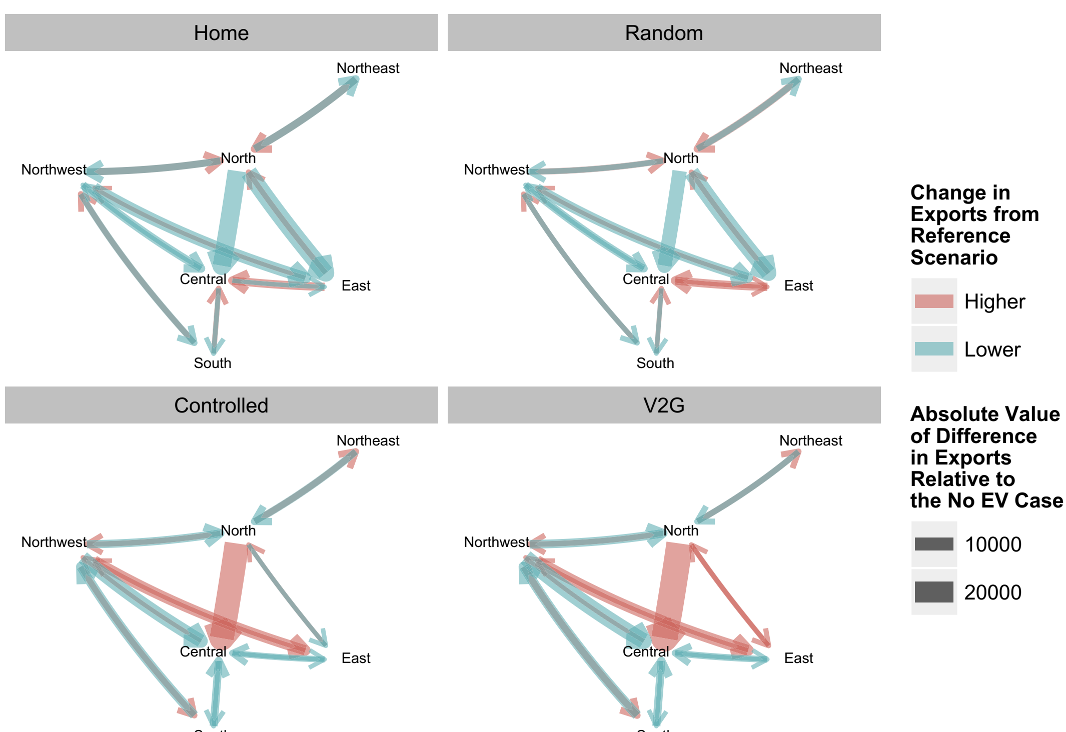


Fig. 10. The differences in the exported power between regions with different charging strategies, relative to the "NoEV" case. The arrow shows the direction of net power exchange between regions. The pink color shows the amount of exported power is higher than the "NoEV" case, the blue shows the opposite. The width of the line represents the absolute amount of the power exchange between regions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

for EV charging, while they increase the OM costs and transmission costs. This is in line with what we analyzed in Section 4.1: relative to the uncontrolled charging strategies, the controlled charging strategies facilitate the utilization of high-efficiency coal generation, increase inter-regional load exchange and mitigate the non-served load around the peak load periods.

Table 4
The curtailment rate of RES generation of the national power system. Note that wind and solar means the summation of wind and solar generation.

	Curtailment rate of RES generation (%)		
	Solar	Wind	Wind and solar
NoEV	0.0007	0.0493	0.0400
Home charging	0.0008	0.0459	0.0373
Random charging	0.0007	0.0504	0.0409
Controlled charging	0.0000	0.0020	0.0016
V2G	0.0000	0.0090	0.0007

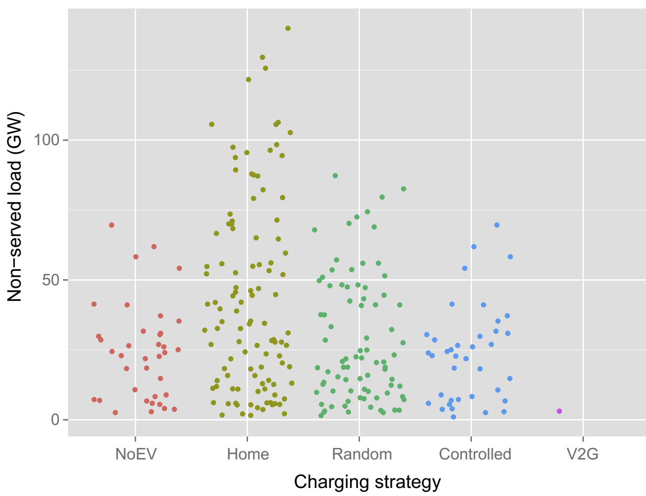


Fig. 11. The national non-served load with different charging strategies.

More importantly, home charging leads to the highest increase in fuel costs of the power system, as it clusters EV charging during peak load hours when costly yet quick-reacting gas power plants have to be dispatched. In addition, home charging results in the highest increase in the non-served load costs of the power system given the fact that the maximum generation capability of the system is insufficient to accommodate the clustered peak demand from EV charging. Compared with home charging, random charging can slightly reduce the additional fuel costs, and largely reduces the non-served load cost associated with EV charging. This is mainly due to random charging spreading the clustered load from EV charging over a longer time period. More specifically, the controlled charging can constrain the additional non-served load costs for EV charging to zero. The V2G charging can even reduce the non-served load costs for the reference power system (without EVs), which implies it increases the flexibility of the power system by allowing EVs to feed power back to the grid, and thus can mitigate the non-served load of the reference power system.

Given the inter-regional power exchange, it is hard for us to figure out the real generation costs associated with EVs for each region. Instead, we use the average generation costs at the national level in comparison with the costs of gasoline-driven vehicles, as shown in Fig. 13. In general, the average generation cost of EVs ranges from 0.013 to 0.022 $/km, which is much lower than that of gasoline-driven vehicles. Taking the home charging as the

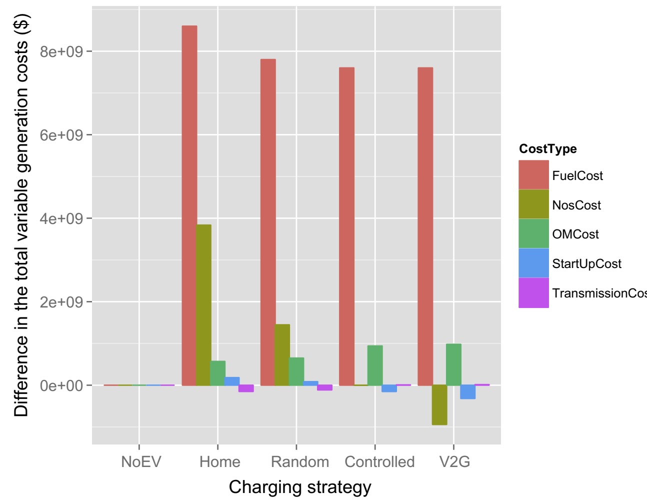


Fig. 12. The differences in costs of the national power system between the EV cases and the "NoEV" case. Note that the "NoEV" case here is seen as the reference, so that the difference to itself is zero.

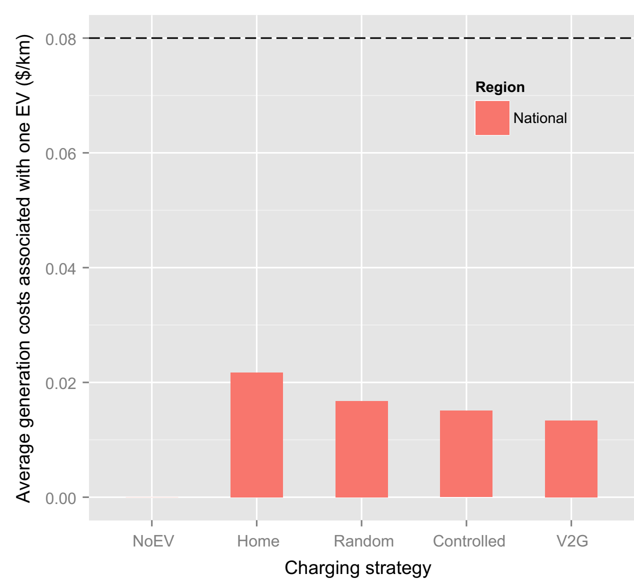


Fig. 13. The average generation costs associated with EVs with different charging strategies. The horizontal line represents the average costs of gasoline-driven vehicles with assumptions that the fuel consumption of gasoline-driven vehicles are 8 L/100 km, and the gasoline price is $1/L.

Table 5
The total variable generation costs of the national power supply with different charging strategies.

	Charging strategy	Total operating cost (billion $)	Cost difference relative to NoEV	Cost difference relative to home charging
NoEV	No charging	238	Reference	–
No control	Home charging	251	+5.46%	Reference
	Random charging	248	+4.20%	−23.08%
Imposing control	Controlled charging	247	+3.78%	−30.77%
	V2G	246	+3.36%	−38.46%

Table 6
The total CO_2 emissions of the national power system with different charging strategies.

	Charging strategy	Total CO_2 emissions (Gt)	Additional emissions caused by EV charging	Difference of the additional emissions
NoEV	No charging	3.651	Reference	–
No control	Home charging	3.755	+2.77%	Reference
	Random charging	3.754	+2.74%	−1.09 %
Imposing control	Controlled charging	3.789	+3.63%	+31.05%
	V2G	3.793	+3.74%	+35.02%

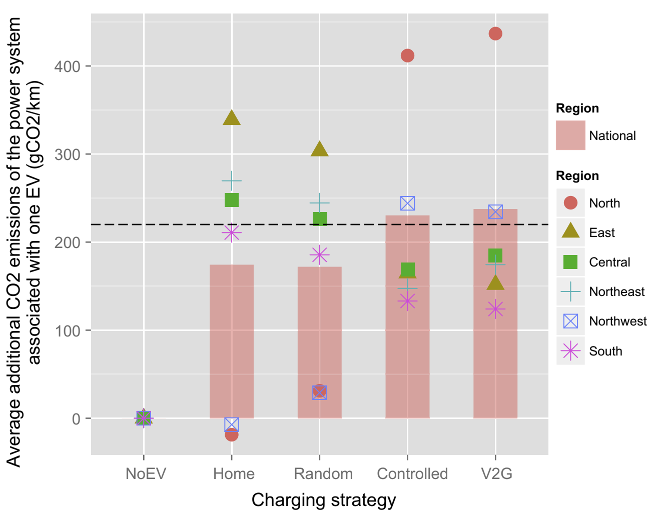


Fig. 14. The average CO_2 emissions of the power system associated with EVs in different regions. The horizontal line represents the average CO_2 emissions of gasoline-driven vehicles, which is assumed to be 220 g/km based on [15]. Note that the value of *y* axis does not represent the absolute amount of CO_2 emissions for regional EV charging, given the fact that the changes of CO_2 emissions for a given region can be caused by the EV charging in this region or the EV charging in interconnected regions.

reference, the controlled charging strategies can reduce the average generation costs of EVs per km by around 41% maximum.

4.3. Environmental implications

Table 6 shows that deploying the planned amount of EVs results in increased CO_2 emissions of the national power system from 2.74% to 3.74%, which equals about 0.103–0.142 Gt. In particular, imposing controls on EV charging brings more CO_2 emissions than uncontrolled charging. For instance, taking home charging as the reference case, controlled charging and V2G charging increase the additional CO_2 emissions of the power system arising from EV charging by around 31% and 35%, respectively. With regard to uncontrolled charging strategies, random charging slightly lowers the CO_2 emissions associated with EV charging compared to home charging.

Fig. 14 shows to what degree the average CO_2 emissions of the power system in different regions change with the various EV charging strategies. First, at the national level, the average CO_2 emissions associated with one EV without controlled charging are about 172–174 gram/km,[7] which is around 20% less than gasoline-driven vehicles; and the random charging results in less CO_2 emissions than home charging although to a negligible degree. Compared with the uncontrolled charging strategies, imposing control on EV charging increases the average CO_2 emissions associated with EVs beyond the level of gasoline-driven vehicles. For instance, with the controlled charging, the CO_2 emissions associated with one EV are about 230 g/km, around 4.5% higher than gasoline-driven vehicles. Further, the V2G strategy results in more CO_2 emissions than the controlled charging.

However, the environmental implications of EVs largely vary between regional power systems. First, Fig. 15 shows the CO_2 intensity of regional power supply when EV is charging and discharging. Generally, it shows that regardless of the charging strategy, the North and Northwest have the highest CO_2 emission intensity for EV charging, while the South has the lowest. This reflects that the CO_2 emissions associated with EVs highly depend on the regional generation portfolio.

Interestingly, in the context of inter-regional grid connections, there is a shift of CO_2 emissions between regions especially for the controlled charging scenarios, as shown in Fig. 14. For instance, for the East, Northeast, Central and the South regions, imposing controlled charging strategies can largely reduce the CO_2 emissions associated with EVs below the level of gasoline-driven vehicles. However, the impact of controlled charging has the opposite effect for the North and Northwest regions. Particularly, in the South, EVs always have lower CO_2 emissions than gasoline-driven vehicles and imposing controlled charging strategies reduces the average CO_2 emissions associated with EVs to around 124–133 gCO_2/km, which is 40–44% lower than gasoline-driven vehicles. Clearly, the CO_2 emissions associated with EV charging are shifted from the regions where coal prices are high to those where coal prices are low, facilitated by the inter-regional transmission networks. This is in line with the shift of the power supply for EV charging as shown in Fig. 10. As analyzed above, the additional CO_2 emissions in the regions with cheap coal are mainly from low-efficiency technologies. This reflects a defect in the power system design regarding pursuing economic benefits yet neglecting concerns about the CO_2 emissions of various coal technologies across regions.

5. Discussion of the results and policy implications

To better understand the results of this paper for real applications, this section first summarizes the value of EVs regarding the energy portfolio (security of supply), economics and the environment for the Chinese power system, and elucidates the general comparisons between EVs and gasoline-powered vehicles in Section 5.1. Furthermore, in Section 5.2, this paper provides a general rule of thumb for policy makers regarding the performance of the four charging strategies, and discusses what policy efforts are needed to better deliver the promises of EVs. In Section 5.3, this paper shows what optimal charging profiles from the power system perspective look like, with the purpose of guiding policy designs for the implementations of demand response programs in reality.

5.1. The value of EVs regarding energy portfolio, economics and the environment

From an energy perspective, deploying EVs basically shifts gasoline consumption to coal-based electricity generation. Specifically,

[7] The yearly driving distance in this car is 19520.02 km, and the yearly CO_2 emissions associated with one car are about 3.35–4.64 ton.

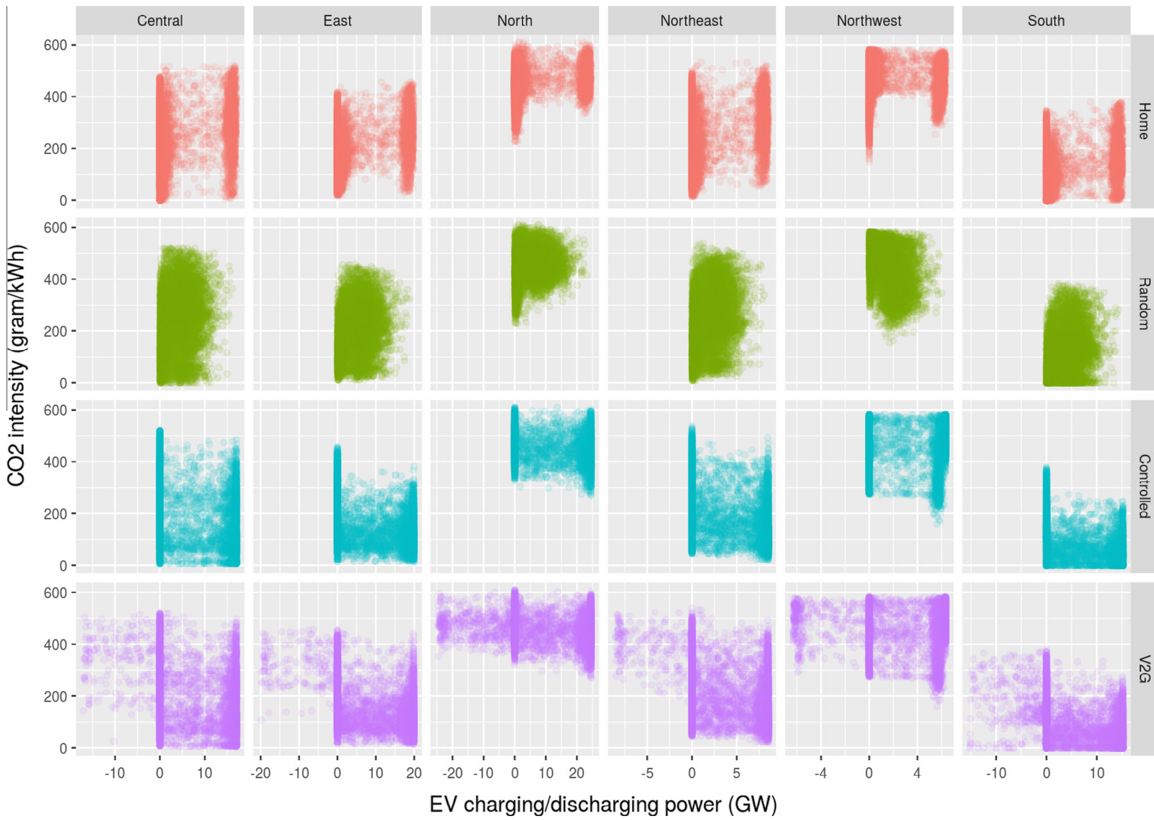


Fig. 15. The average CO_2 emission intensity of regional generation when EV is charging or discharging on an hourly basis.

Table 7
The ratings for charging strategies based on the implications of EVs in comparison with gasoline-fueled vehicles under a given charging strategy. The "+" represents that EVs outperform gasoline-powered vehicles, while the "–" represents the opposite, and the amount of "+"/"–" are relative between charging strategies.

Aspect	Indicator	Uncontrolled charging		Controlled charging	
		Home Charging	Random charging	Controlled charging	V2G
Energy	(1) Coal consumption	–	– –	– – –	– – – –
	(2) RES generation	++	–	+++	++++
	(3) Non-served load	– –	–	+	++
Economic	(1) Generation costs/EV fueling costs	+	++	+++	++++
Environment	(1) CO_2 emissions	+	++	–	– –

deploying the planned amount of EVs increases coal consumption of the national power system by around 3–4% which is about 0.06–0.08 Gt. This additional coal consumption can save China about 48 GL gasoline consumption in the transportation sector. Furthermore, deploying the planned amount of EVs has a very limited impact on promoting the integration of RES energy with the given power system. Additionally, deploying EVs can benefit or threaten power supply security in terms of the amount of non-served load, depending on the charging strategy. Specifically, uncontrolled charging increases the amount of non-served load as it tends to cluster the EV charging load with the peak load in the reference power system. However, to what degree that uncontrolled EV charging increases the non-served load depends on a combination of EV penetration levels, charging power rates and inter-regional grid connections. On the other hand, controlled charging strategies can constrain the additional peak load arising from EVs, and the V2G strategy can even reduce the peak load of the reference power system.

From an economic perspective, deploying the planned amount of EVs increases the variable generation costs of the power system by around 3.36–5.46%. Controlled charging strategies outperform uncontrolled charging strategies in terms of the generation costs, as they can shift EV charging from peak load hours to off-peak load hours. With the shift, EV charging can be fueled by cheap coal generation, and the clustering of the EV charging load with the peak load of the power system is avoided. On average, the generation/fueling cost of EVs is 0.013–0.022 $/km, which is around 75% lower than with gasoline-driven vehicles. Although the average fueling costs of EVs might slightly vary depending on the differences between the coal price and gasoline price, it indeed sends a clear incentive for consumers as they can save substantially on fuel costs when using EVs instead of gasoline-powered vehicles.

From an environmental perspective, deploying EVs increases the CO_2 emissions of the power system by around 2.74–3.74%. Specifically, with uncontrolled charging strategies, the CO_2 emission associated with EVs is around 172–174 g/km, which is 20% less than gasoline-driven vehicles. Imposing controlled charging strategies increases the CO_2 emissions associated with EVs by around 31–35% than uncontrolled charging, which makes gasoline-powered vehicles outperform EVs in such cases.

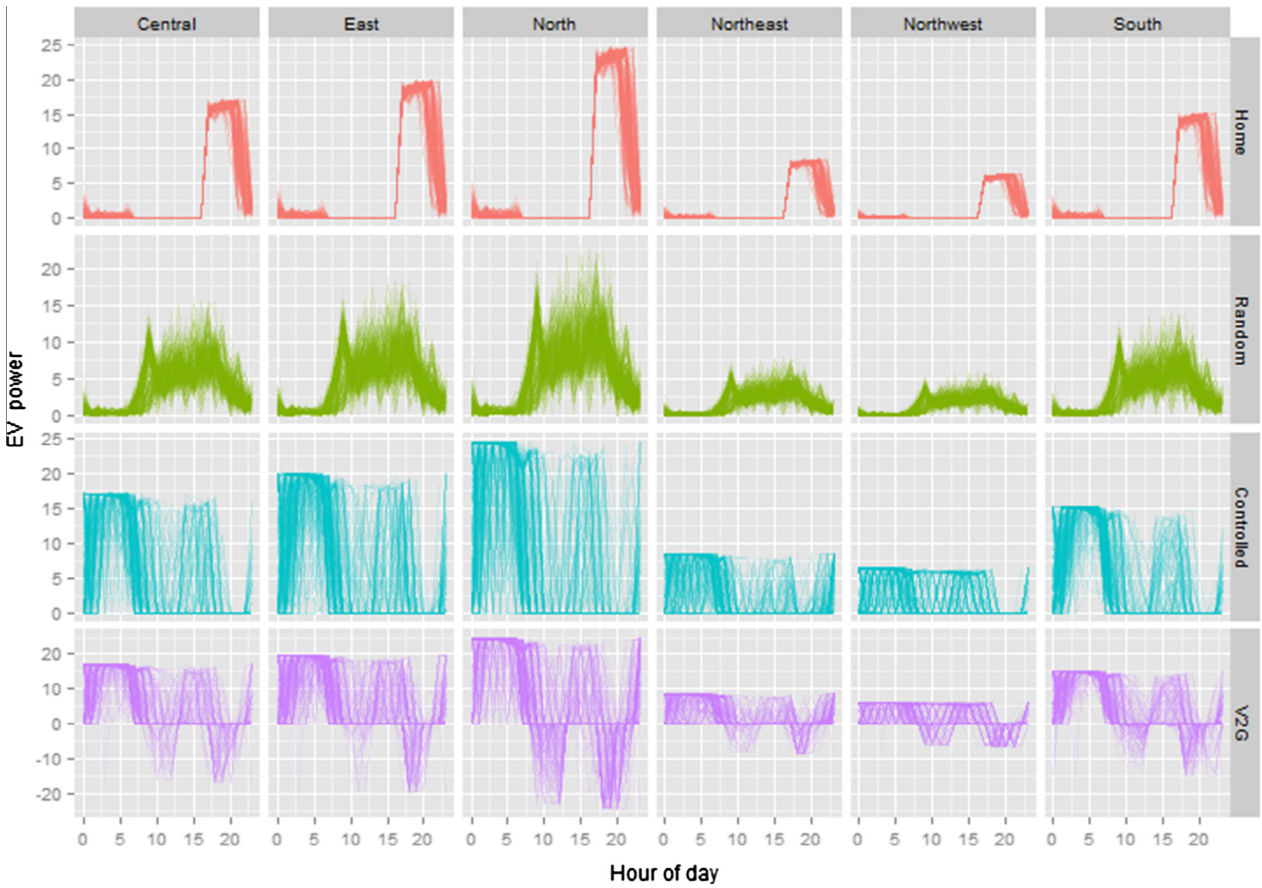


Fig. 16. The optimal daily EV charging profiles for each regional power system with different charging strategies in the whole year.

Aside from the national power system, this paper finds that the implications of EVs largely vary between regional power systems. This paper highlights that given the inter-regional power exchanges, how good deploying EVs is in an environmental sense not only depends on where EVs charge, but also depends on the interconnected regions. In the context of inter-regional transmission connections, there is a clear shift of coal generation and CO_2 emissions associated with EVs to the regions where fuel prices are cheap (e.g. the North and Northwest). In the North and Northwest, we see a situation where the high-efficiency coal-fired power plants are already operating at full capacity, and due to the low fuel prices, the low-efficiency coal-fired power plants are actually favored in the merit order over higher-efficiency coal plants in other regions. Meanwhile, this shift reduces the energy consumption and CO_2 emissions for the regions (e.g. the Central and East) which mainly import power for EV charging. This also reminds us that it would be one-sided to rate regions for EV deployment based on their regional generation portfolios. Still, when inter-regional power exchange for EV charging is negligible compared with regional power supply, the implications of EVs mainly depend on the regional generation portfolio. This has been exemplified by the South power system which shows the largest potential of using EVs in mitigating CO_2 emissions for all charging strategies, due to it has the cleanest generation mix amongst all regions.

5.2. Policy implications for EV charging strategies

To provide a general rule of thumb for policy makers to evaluate the performance of the four charging strategies, we rate the charging strategies based on the energy, economic and environmental implications of EVs under a given charging strategy in comparison with gasoline-fueled vehicles, as described in Table 7.

In general, controlled charging strategies outperform uncontrolled charging ones in terms of: (1) improving power supply security (indicated by mitigating non-served load); (2) facilitating RES generation; and (3) reducing generation costs and EV fueling costs. Amongst the two controlled charging strategies, V2G slightly performs better in both mitigating non-served load and facilitating RES generation yet to a limited degree. Although seeking the best charging strategy with a full cost-benefit analysis is out of the scope of this paper, we argue that controlled charging itself might be sufficient for most regional power systems in bulk energy management unless RES generation is excessive. Uncontrolled charging strategies especially the home charging pose a threat to power supply security, which should be avoided in reality. The random charging is slightly better than the home charging in mitigating the clustering of EV load with the peak load of the reference power system, while it is not an attractive option considering the fact that huge capital costs are needed for developing charging infrastructure in this case.

In short, Table 7 shows a trade-off of using controlled charging strategies in the Chinese power system, between the benefits above and the cost of more coal consumption and more CO_2 emissions. We summarize the following two main aspects regarding the power system designs that lead to this trade-off. Accordingly, policy attentions are needed for these aspects to improve the performance of controlled charging strategies in delivering the potential of EVs especially with regard to environmental benefits.

First, the dominance of coal power and its absolute economic competitiveness relative to gas power prohibits controlled charging strategies from delivering the potential of EVs. Specifically,

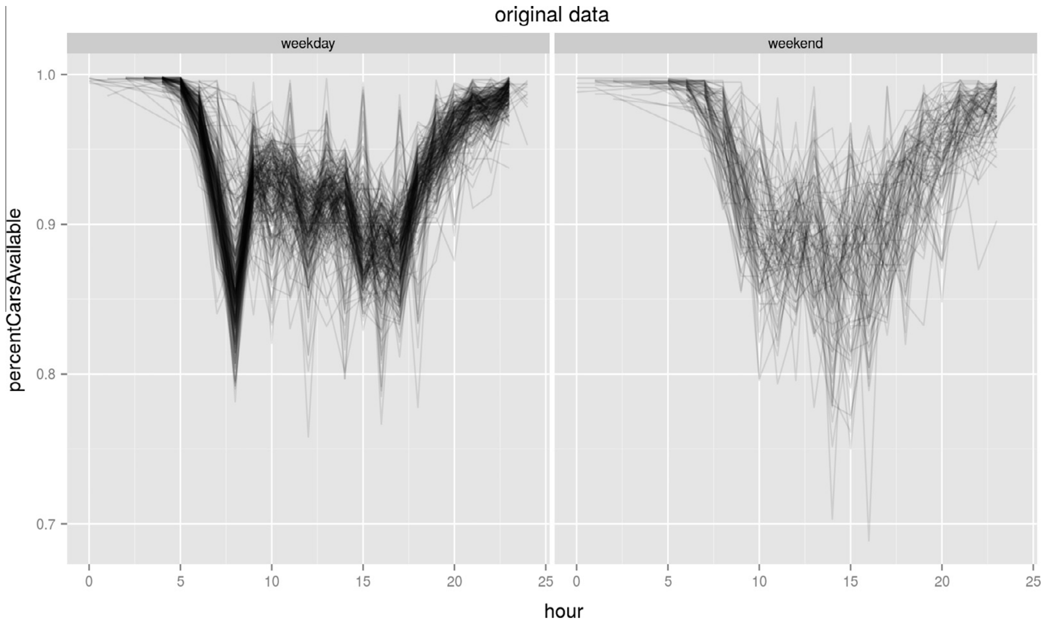


Fig. A.17. Calculations of EV availability per hour on weekdays and weekends, based on actual survey data.

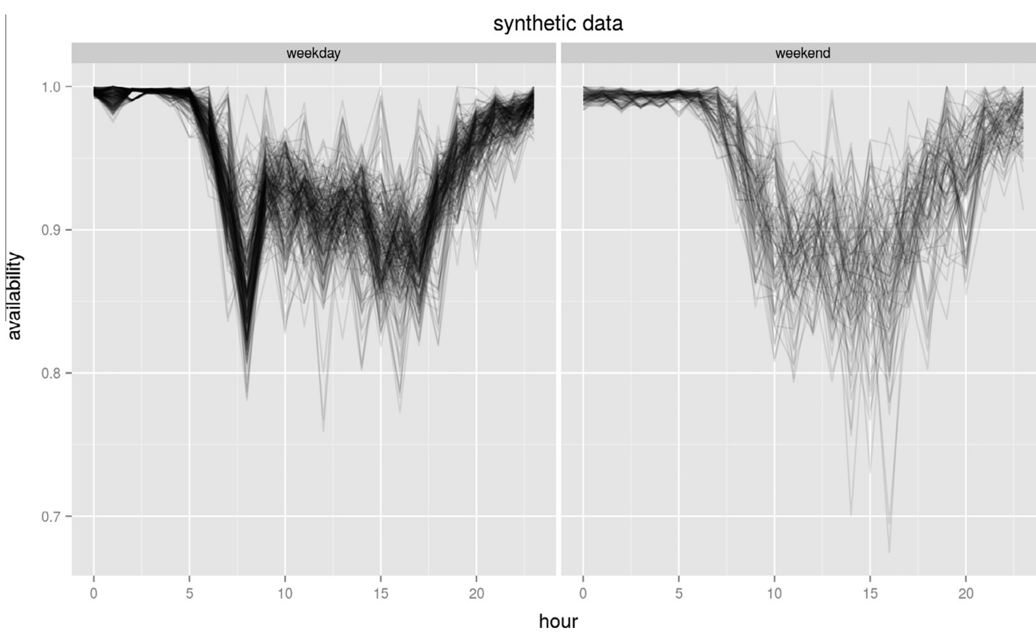


Fig. B.18. Kernel density estimates of EV availability per hour on weekdays and weekends.

with the given 2030 power system, once least-cost oriented controlled charging is imposed, coal-fired electricity generators would be the cheapest marginal units to react to EV load. Possible solutions for changing this are making improvements to designs of the power system by increasing the use of RES energy or other less CO_2 intensive generation especially including gas power. With regard to RES power, China has so far made substantial progress in promoting wind and solar power capacity. However, the use of gas in the power system is still quite limited. Given the huge gap between the coal price and gas price in China, reforms on the gas market will be critical to lower the gap and thus improve the cost competitiveness of gas-fired generation [48]. Otherwise, controlled charging strategies entail more coal consumption and more CO_2 emissions, especially for the regions where coal prices are low.

Second, in the context of the inter-regional transmission network, the large variations of regional fuel prices facilitate controlled charging strategies to use more cheap yet low-efficiency coal generation in the regions where fuel prices are low (e.g. the North and Northwest), especially when energy efficiency and CO_2 emission-related regulations are absent. This further undermines the attractiveness of controlled charging strategies in saving the environment. Hence, regulations that discriminate against low-efficiency and dirty coal generation technologies across regions are required to complement economic-based electricity dispatch principles. Possible solutions for this include CO_2 pricing, energy efficiency-incorporated electricity dispatch mechanisms (e.g. the pilot energy-saving dispatch mechanism in China [49]), etc.

5.3. Moves towards demand response programs

In short, better fulfilling the benefits of EVs requires a cleaner power supply, and a healthy electricity dispatch which concerns economic, energy and emission issues. In addition to improving designs of the power system, the question of how to guide the charging behaviors of EV consumers as optimized/controlled is also of high interest for policy makers. Fig. 16 shows the differences in EVs' daily charging profiles between uncontrolled charging and controlled charging strategies. For instance, the home charging peaks between 6 pm and 11 pm, while the random charging often peaks right after morning and noon traffic-rush hours. However, with controlled strategies, charging at 11:00 pm–7:00 am and at 2:00–4:00 pm is expected from the power system perspective; moreover, the V2G distinguishes itself by discharging to the grid at the noon and evening peak load times. To shift the EV charging profile from uncontrolled ones to the optimized ones, incentives for EV consumers are needed. The incentives can be delivered by various demand response programs, such as designing EV-specific electricity rates (e.g. time of use (TOU) electricity tariff), and developing new business models between utilities, EV aggregators and EV consumers to facilitate centralized EV charging management. Accordingly, given the fixed categorized electricity price between utilities and consumers in China today, institutional changes regarding electricity tariffs/contracts between the involved actors are required.

Another interesting point in Fig. 16 is that with a given controlled charging strategy, the patterns of daily charging profiles are quite similar between regions although the amount of charging/discharging power are region-specific depending on the EV penetration levels. This implies that the EV demand response programs among the regions can be functionally similar to each other.

6. Conclusions

This work has investigated the implications of deploying EVs for China's power system with regard to energy, economics and the environment, and explored how to better deliver the value of EVs by improving the designs in the power system and charging strategies, given the expected power system and EV penetration levels in 2030. The results are quantified mainly based on an integrated transportation-power system dispatch model which distinguishes itself with two key features. First, the model adopts the kernel density estimates approach to statistically determine the temporal availability of EVs connecting to the grid. Second, it applies the clustered integer approach to reduce the amount of variables in the unit commitment model. This allows us to capture more technical details regarding the six regional power systems and their inter-regional transmission connections, which are used for modeling EV-incorporated power dispatch in China. Furthermore this approach allows us to work with increased model details in a computationally efficient manner.

The scenario results show that at the national level, deploying EVs basically shifts gasoline consumption to coal-based electricity generation. Although this can save the transportation sector in terms of dependency on oil, it comes with the cost of more coal consumption and more CO_2 emissions of the power system. Accordingly, EVs outperform gasoline-powered vehicles in terms of average fueling costs. However, how good EVs are in terms of CO_2 emissions at the national level largely depends on the charging strategy. Specifically, controlled charging results in more CO_2 emissions associated with EVs than uncontrolled charging, as it tends to feed EVs with cheap yet low-efficiency coal generation in the regions with low coal prices. This might be counter-intuitive, but what is happening is that the high-efficiency coal generation in the North and Northwest is already operating at full capacity. Due to the inter-regional transmission connections in China and the differences in coal prices among regions, the low-efficiency coal generation in the North and Northwest actually is more economically attractive and thus favoured in the merit order over high-efficiency coal generation in other regions with higher fuel prices. Still, compared with uncontrolled charging, controlled charging shows absolute advantages in: (1) mitigating the peak load arising from EV charging; (2) facilitating RES generation; and (3) reducing generation costs and EV charging costs.

Hence, in light of the trade-offs of controlled charging between energy security, economic efficiency and environmental destruction, policy efforts that improve designs of the power system are required to better use controlled charging strategies in delivering the promises of EVs for China. Accordingly, this paper proposes that increasing generation with lower or zero CO_2 emission rates, such as RES power and gas power, are fundamental to make EVs more clean. In addition, establishing energy efficiency and CO_2 emission-concerned regulations for power dispatch is also helpful to discriminate against cheap yet dirty coal generation across regions. More importantly, this work illustrates what the optimized charging profiles from the power system perspective look like, which provides insights into the directions for designs of demand response programs for EV users.

The methods we developed for the Chinese case can be used as a template for similar studies in other countries. Other countries, especially the ones with coal-intensive generation or with large cross-border transmission capacity, can learn lessons from the Chinese case. They should be aware that deploying EVs does not necessarily bring benefits for the environment or for energy security, even though it might come with economic savings for the power system. Accordingly, coordinating the development of clean electricity generation with EV deployment is needed to make EV more sustainable. In addition, given the high temporal flexibility of EVs connecting to the grid, it is crucial that the EV battery recharging system is designed to deliver the promises of EVs both for power system operations and the environment in the most affordable way. As power systems worldwide vary in their technical implementations, the model used in this work can be easily adapted to cope with the specifics of power systems in other countries than China.

Still, it should be noted that the results of this paper are based on the statistical estimation method, the optimization-based power dispatch model and four predefined charging strategy scenarios, and thus the designs and assumptions related may affect the results of this paper. First, the statistically estimated results regarding the availability of EVs connecting to the grid can only represent the behaviors of EV users with certain probabilities rather than the real behaviors. Second, the parameters used in the model are subject to high uncertainties, which could affect the results of this work. In particular, simplifications and estimations of the average values for typical types of generation technologies across regions were made. Moreover, the parameters regarding the future state of the Chinese power system and the transportation system are mainly obtained from the literature. The future, however, is highly uncertain, and better scenarios which incorporate more of the dynamics of future developments of the Chinese context should be created. Also, the hourly-based power dispatch model only considers the value of EVs for the power system in bulk power management, while neglecting the roles of EVs in other fields, such as for ancillary services (e.g. frequency regulation). Third, the scenarios of charging strategies defined in our work typically represent four possibilities based on two scenario variables: (1) whether the development of EV

Table C.8
The sets and indexes.

Sets and indexes	Specifications
R, r	The set and index of regions, note that this work only simulates one region
G, g	The set and index of power technologies
S, s	The set and index of ESS technologies
T, t	The set and index of time
G^{Res}	The subset of G, which represents RES power technologies
G^{Fossil}	The subset of G, which represents fossil fuel-based power technologies
$G^{Non(fossil\&Res)}$	The subset of G, which represents non-fossil fuel and non-RES based power technologies, here it refers to nuclear

Table C.9
The decision variables.

Decision variables	Specifications [units]
$P_{r,g,t}$	The power output of technology g in region r at time step t in region r [MW]
$SU_{r,g,t}$	The amount of generation units of technology g that start up at time step t in region r, $[0,1,\ldots,n_g]$
$SD_{r,g,t}$	The amount of generation units of technology g that shut down at time step t in region r, $[0,1,\ldots,n_g]$
$UC_{r,g,t}$	The amount of generation units of technology g that are committed/on at time step t in region r, $[0,1,\ldots,n_g]$
$P^{Nos}_{r,t}$	The demand that are not met by supply at time step t in region r [MW]
$P^{Im}_{r,r',t}$	The power imported from region r' to region r at time step t [MW]
$P^{Ex}_{r,r',t}$	The power exported from region r to region r' at time step t [MW]
$P^{Gen}_{r,s,t}$	The power generated from ESS technology s at time step t in region r [MW]
$P^{Sto}_{r,s,t}$	The power stored to ESS technology s at time step t in region r [MW]
$P^{Cur}_{r,g,t}$	The curtailed power for RES technology g at time step t in region r [MW]
$P^{Cha}_{r,t}$	The charging power of EVs at time step t in region r [MW]
$P^{Dis}_{r,t}$	The discharging power of EVs at time step t in region r [MW]

charging facilities is constrained at home or widely distributed in public places; and (2) whether EV users can coordinate EV charging with power system operation. However, there might be more mixed scenarios relevant for real practice. The above research limitations should be addressed in future work.

Appendix A. Processing of the transportation data

This survey covers over 30,000 people, each of whom had their travel patterns recorded for a day. The following techniques were applied to pre-process the MON data. As the survey data only records the trips rather than the total population of vehicles, an estimation about the total population of vehicle was made based on the number of distinct cars observed in the data traveling during a particular day of the week. In addition, the power dispatch is simulated on an hourly basis, and the departure and arrival times from the survey data are also rounded to the nearest hour. Fig. A.17 shows after the data has been normalized, the estimated availability of EVs per hour and type of day. Each line represents a single day.

Appendix B. Validation of the transportation data from kernel density estimates

Fig. B.18 shows the EV availability for each day on an hourly basis, which is constructed by sampling from the kernel density estimates (KDE). The data from the KDE are validated as they show the similar pattern with the real survey data in Fig. A.17.

Table C.10
The parameters.

Parameters	Specifications [units]
$c^{Fuel}_{r,f}$	The price for fuel f in region r [\$/Joule]
$\delta_{g,f}$	The consumption intensity of technology g for fuel f [Joule/MWh]
$c^{O\&M}_{g}$	The variable operation and maintenance costs per power unit of technology g [\$/MW]
$c^{Startup}_{g}$	The start up costs of technology g [\$ per time]
c^{Nos}_{g}	The penalty for per unit of unmet power demand g [\$/MW]
$n_{r,g}$	The number of generation units of technology g in region r
$D^{Con}_{r,t}$	The conventional power demand in region r at time t [MW]
p^{min}_{g}, p^{max}_{g}	The minimum and maximum power output of generation technology g, respectively [MW]
$p^{Ava}_{r,g,t}$	The available power output of generation technology g in region r at time t [MW]
$\triangle p^{Upmax}_{g}, \triangle p^{Downmax}_{g}$	The maximum ramping up and down power of generation technology g in one time step [MW]
c^{Tran}	The transmission cost per unit of power [\$/MWh]
e^{loss}	The energy loss intensity per transmission distance [MW/km]
$d_{r,r'}$	The distance between region r and r' [km]
$p^{Lntc}_{r,r'}$	The net transfer capacity of line between region r and r' [MW]
$\eta^{Gen}_{s}, \eta^{Sto}_{s}$	The generation and storage efficiency of storage technology s [%]
$p^{Ava}_{r,s}$	The total installed capacity of ESS technology s in region r [MW]
$E^{Hadd}_{r,s,t}$	The natural rainfall energy added to the reservoirs of hydro pump storage [MWh]
$p^{Dri}_{r,t}$	The power output required for driving in region r at time step t [MW]
$\eta^{Dri}, \eta^{Cha}, \eta^{Discha}$	The power efficiency for EV driving, charging and discharging [%]
$p^{EVrated}_{r}$	The maximum power output of EV at one time step [MW]

Appendix C. The description of the clustered integer unit commitment model

This part first introduces the mathematical formulation of the power dispatch model, followed by explanations regarding the lists of sets, decision variables and the parameters of the model.

C.1. Objective function

The objective function is to minimize the total variable generation costs (C^{Var}) of the system over one year, including fuel cost (C^{Fuel}), operation and maintenance cost ($C^{O\&M}$), start-up cost ($C^{Startup}$), non-served energy cost (C^{Nos}) and transmission cost (C^{Tran}), as listed in Eq.(C.1). The specifications of the costs are provided as follows.

$$\min C^{Var} = C^{Fuel} + C^{O\&M} + C^{Startup} + C^{Nos} + C^{Tran} \tag{C.1}$$

$$C^{Fuel} = \sum_{r\in R}\sum_{g\in G}\sum_{t\in T}\sum_{f\in F} P_{r,g,t} * \Delta t * \delta_{g,f} * c^{Fuel}_{r,f} \tag{C.2}$$

$$C^{O\&M} = \sum_{r\in R}\sum_{g\in G}\sum_{t\in T} P_{r,g,t} * \Delta t * c^{O\&M}_{g} \tag{C.3}$$

$$C^{Startup} = \sum_{r\in R}\sum_{g\in G}\sum_{t\in T} SU_{r,g,t} * c^{Startup}_{g} \tag{C.4}$$

$$C^{Nos} = \sum_{r\in R}\sum_{t\in T} P^{Nos}_{r,t} * \Delta t * c^{Nos}_{r} \tag{C.5}$$

$$C^{Tran} = \sum_{r\in R}\sum_{r_c\in R}\sum_{t\in T} P^{Ex}_{r,r_c,t} * \Delta t * c^{Tran} \tag{C.6}$$

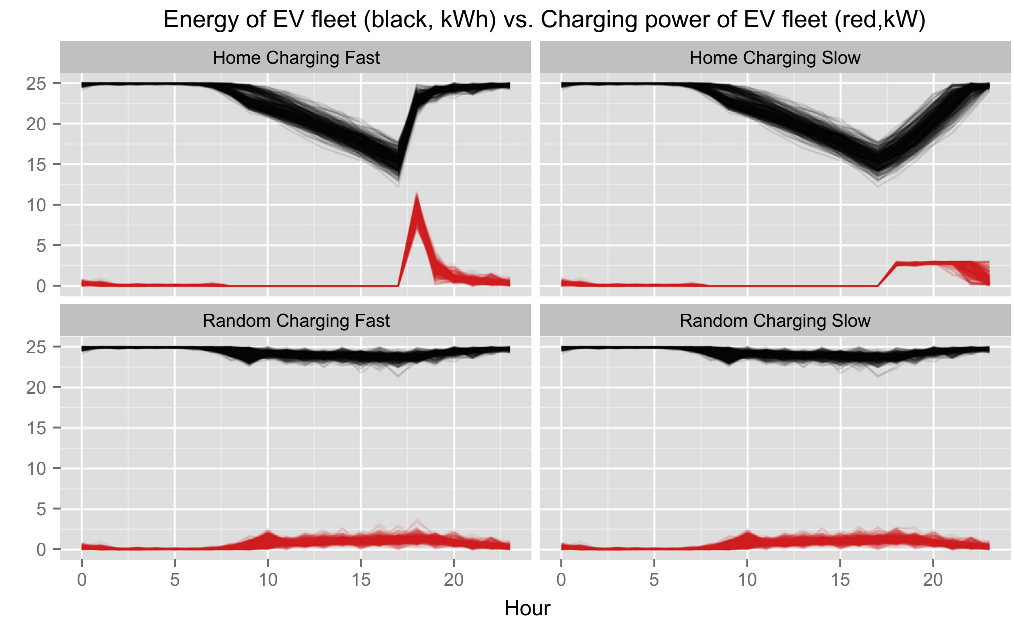


Fig. D.19. The charging power and energy of EV fleet for the random and home charging strategy with different charging power rates. For illustrative purposes, the fast charging power rate in the figure is assumed to be 12 kW and the slow rate is 3 kW.

Table D.11
The energy loss and transmission cost of inter-regional transmission lines [25,36].

Transmission line		Energy loss	Transmission cost
From	To	(%/GW)	($/GW h)
North	East	2.53	2400.00
North	Central	3.50	3320.16
Northeast	North	2.48	2352.57
Northwest	North	2.94	2788.93
Central	East	2.61	2475.89
Northwest	East	6.28	5957.31
Northwest	Central	5.01	4752.57
Central	South	3.33	3158.89
Northwest	South	7.67	7275.89

C.2. Constraints

The power dispatch optimization is subject to the following constraints. Eq. (C.7) shows the power supply should be continuously balanced with the demand at each time period. As the RES power generation is exogenously determined depending on the given installed capacity and meteorological data, $P^{Cur}_{r,t}$ is added to allow for RES generation curtailment. EV works similarly to energy storage system (ESS), the charging and discharging power of EVs represented by $P^{Cha}_{r,t}$ and $P^{Dis}_{r,t}$, respectively, are optimally dispatched.

The power output of different types of generation units are shown in Eqs. (C.8), (C.10)–(C.12), in which $n_{r,g}$ is the amount of units in the clustered group of technology g in region r. Eq. (C.9) represents the dynamics of commitment states for the units which are of a given technology, g. When considering a group of units, the power output can change from ramping up/down for some of the units, and from starting up and shutting down of some other units in a simultaneous way [32]. Therefore, we formulate the ramping up and down constraints for a clustered group of fossil fuel-based generation units as shown in Eqs. (C.13) and (C.14), respectively, in which $\triangle p^{Upmax}_{r,g}$, $\triangle p^{Downmax}_{r,g}$ represents the maximum up and down capacity of a unit in one time step. The ramping up and down constraints for normal power plants (e.g. nuclear) are shown in Eqs. (C.15) and (C.16), respectively. Eq. (C.18) shows that the

Table D.12
The fuel price data used in this work. The data are compiled by the authors with sources of [36,50–52]. The percentage value within the bracket shows the variation of coal price and natural gas price relative to the benchmark region, in which the North and Northwest are the benchmark region for coal and gas price, respectively.

Regions	Coal price ($/ton)		Gas price($/m^3)	
	2012	2030	2012	2030
North	64.00 (Ref.)	76.55	0.3584 (+40%)	0.4278
East	112.00 (+75%)	133.97	0.3880 (+52%)	0.4641
Central	112.00 (+75%)	133.97	0.3552 (+39%)	0.4249
Northeast	96.00 (+50%)	114.83	0.3232 (+26%)	0.3866
Northwest	51.20 (−25%)	61.24	0.2560 (Ref.)	0.3062
South	128.00 (+100%)	153.11	0.3632 (+42%)	0.4344

Table D.13
The annual average wind capacity factor calculated by the authors.

Region	North	East	Central	Northeast	Northwest	South
Average capacity factor	0.29	0.29	0.27	0.31	0.25	0.29

exported power between regions must be lower than the net transfer capacity, and the relations between exported power and imported power between two given regions are shown in Eq. (C.17). Eqs. (C.19)–(C.21) show the inter-temporal dynamics of the energy in ESS with withdrawing and injecting power over the course. Similar to the constraints for energy storage system, the energy and power constraints of EV are formulated in Eqs. (C.22)–(C.24).

$$\sum_{g\in G} P_{r,g,t} - \sum_{g\in G^{Res}} P^{Cur}_{r,g,t} + \sum_{s\in S}\left(P^{Gen}_{r,s,t} - P^{Sto}_{r,s,t}\right) = D^{Con}_{r,t} + \left(P^{Cha}_{r,t} - P^{Dis}_{r,t}\right) - P^{Nos}_{r,t} \tag{C.7}$$

$$U_{r,g,t} * p^{min}_{g} \leqslant P_{r,g,t} \leqslant U_{r,g,t} * p^{max}_{g}, \forall g \in G^{Fossil} \tag{C.8}$$

$$U_{r,g,t} = U_{r,g,t-1} + SU_{r,g,t} - SD_{r,g,t}, \forall U_{r,g,t}, SU_{r,g,t}, SD_{r,g,t} \in [0,1,2,,,n_{r,g}] \tag{C.9}$$

$$P_{r,g,t} = p^{Ava}_{r,g,t}, \forall g \in G^{Res} \tag{C.10}$$

$$P^{Cur}_{r,g,t} \leqslant p^{Ava}_{r,g,t}, \forall g \in G^{Res} \tag{C.11}$$

$$0 \leqslant P_{r,g,t} \leqslant p^{Ava}_{r,g,t}, \forall g \in G^{Non(fossil\&Res)} \tag{C.12}$$

Table D.14
The key technical and economic parameters of fossil fuel-based generation units. Data source: [56,31].

Technology	Capacity of a single unit	Unit availability	Maximum power output	Minimum power output	Ramp up[a]	Ramp down	Efficiency of power output	Emission factor	Start up cost	OM cost	Fuel consumption
Unit	GW	%	%	%	%	%	%	ton/GW h	$/time	$/GW/hour	GJ/GW h[b]
small-coal	0.25	0.99	0.85	0.20	0.10	0.10	0.90	882.00	16,800	3995.43	9270.00
sub-critical	0.30	0.99	0.85	0.20	0.09	0.09	0.90	770.28	20,000	4000.00	8095.80
super-critical	0.60	0.99	0.85	0.20	0.12	0.12	0.90	686.00	25,200	4109.59	7210.00
ultra-supercritical	1.00	0.99	0.85	0.20	0.20	0.20	0.90	574.28	33,600	4680.37	6035.80
igcc-coal	1.00	0.99	0.85	0.20	0.20	0.20	0.90	548.80	11,760	3082.20	5356.00
ccgt-gas	0.50	0.99	0.85	0.20	0.40	0.40	0.90	240.00	11,760	2283.11	9552.50
ocgt-gas	0.50	0.99	0.85	0.20	0.50	0.50	0.90	240.00	9408	2283.11	8406.20
nuclear	0.80	0.99	0.90	0.50	0.04	0.04	0.90	0	50,400	5538.81	0
wind	0	1	0	0	0	0	0	0	0	0	0
solar	0	1	0	0	0	0	0	0	0	0	0
hydro	0	1	0	0	0	0	0	0	0	0	0
coal-biomass	0	1	0	0	0	0	0	0	0	0	0
gas-biomass	0	1	0	0	0	0	0	0	0	0	0

[a] The ramp up and ramp down capability is relative to the capacity of a single unit.
[b] The conversion factor used here is 1 ton coal = $20.6*E+10$ Joule, and 1 m^3 gas = $3.82*E+07$ Joule.

Table D.15
The match between EU countries and the regions in China for the reference of demand profile data.

No.	Regions in China	Data source + adaptations	Reasons for matching
1	North	Germany	High peaks both in winter and Summer
2	East	Italy	Averagely high for the whole year, and demand is generally higher in summer than winter
3	Central	Italy	Averagely high for the whole year, and demand is generally higher in summer than winter
4	Northeast	Denmark	High demand in winter
5	Northwest	France + 2 h delay	Low demand profiles and time lag caused by long distance from the east
6	South	Italy	Averagely high for the whole year, and demand is generally higher in summer than winter

$$P_{r,g,t}-P_{r,g,t-1}\leqslant\left(U_{r,g,t}-SU_{r,g,t}\right)*\triangle p_g^{Upmax}+SU_{r,g,t}*max\left(\triangle p_g^{Upmax},p_g^{min}\right)-SD_{r,g,t}*p_g^{min},\forall g\in G^{Fossil} \tag{C.13}$$

$$P_{r,g,t-1}-P_{r,g,t}\leqslant\left(U_{r,g,t}-SU_{r,g,t}\right)*\triangle p_g^{Downmax}+SD_{r,g,t}*max\left(\triangle p_g^{Downmax},p_g^{min}\right)-SU_{r,g,t}*p_g^{min},\forall g\in G^{Fossil} \tag{C.14}$$

$$P_{r,g,t}-P_{r,g,t-1}\leqslant\triangle p_g^{Upmax},\forall g\in G^{Non(fossil\&Res)} \tag{C.15}$$

$$P_{r,g,t-1}-P_{r,g,t}\leqslant\triangle p_g^{Downmax},\forall g\in G^{Non(fossil\&Res)} \tag{C.16}$$

$$P_{r,r',t}^{Im}=P_{r,r',t}^{Ex}\left(1-e^{loss}*d_{r,r'}\right),\forall r'\in R_r \tag{C.17}$$

$$P_{r,r',t}^{Ex}\leqslant p_{r,r'}^{Lntc} \tag{C.18}$$

$$E_{r,s,t}=E_{r,s,t-1}-P_{r,s,t}^{Gen}/\eta_s^{Gen}+P_{r,s,t}^{Sto}\eta_s^{Sto}+E_{r,s,t}^{Hadd} \tag{C.19}$$

$$E_{r,s,t}^{min}\leqslant E_{r,s,t}\leqslant E_{r,s,t}^{max} \tag{C.20}$$

$$0\leqslant P_{r,s,t}^{Gen},P_{r,s,t}^{Sto}\leqslant p_{r,s}^{Ava} \tag{C.21}$$

$$SOC_{r,t}=SOC_{r,t-1}-p_{r,t}^{Dri}/\eta^{Dri}+P_{r,t}^{Cha}\eta^{Cha}-P_{r,t}^{Dis}/\eta^{Dis} \tag{C.22}$$

$$SOC_{r,t}^{min}\leqslant SOC_{r,t}\leqslant SOC_{r,t}^{max} \tag{C.23}$$

$$0\leqslant P_{r,t}^{Cha},P_{r,t}^{Dis}\leqslant p_r^{EVrated} \tag{C.24}$$

C.3. Nomenclatures

See Tables C.8–C.10.

Appendix D. Key explanations and data for this work

D.1. Explanations regarding the home charging and random charging

See Fig. D.19.

D.2. Transmission-related data

See Tables D.11 and D.12.

D.3. Generation-related data

The wind speed data is provided in the form of surface flux data which is composed of two vector components at a 10 meter height with a six-hour interval [53]. Further processing for wind speed data is done, including spline interpolations to adjust to hourly wind speed data, and converting wind speed to wind power based on wind turbine model E-33 [54]. The average capacity factor of wind power in the six regions is further calibrated with the historical capacity factors in [55], and is shown in Table D.13. The calculation of solar PV production is mainly based on the PVWatts calculator from NREL,[8] which can automatically identify the solar resource data at or near a given location. For each regional power system, a location is chosen to represent the average solar resources for the region. The hydro power in this work mainly represents run of river plants whose generation highly depends on the amount of natural rainfall inflows and vary largely between seasons. The average annual utilization of hydro power generation in China is about 0.4 [50]. Depending on the abundance of hydro resources, this work categorizes the six regions into two groups, namely abundant and scarce. Specifically, the North and Northwest have relatively lower rainfalls so that they are assumed to be in the group of scarce, other regions are abundant in hydro. The hourly hydro power availability is assumed to be the same for a given month. The average hydro power availability for each month is illustrated, and the variation of monthly hydro generation availability, which is mainly based on the data of Guangxi province in the South [48] (see Table D.14).

D.4. Demand-related data

We do not have access to the data of regional demand profiles of the Chinese power system. Therefore, this paper refers to the data of four EU member states including Germany, France, Denmark and Italy to represent the regional demand profiles in China.[9] These four countries are chosen mainly because they show a large diversity in seasonal electricity demand, which is similar to the regional power systems in China. This work matches the reference of demand profile data between EU countries and the regional power systems in China as shown in Table D.15. It should be stressed that the assumptions regarding demand profile data here do not affect the meaning and validity of the results in this work based on a set of sensitivity validation we did. In turn, the method here can provide reference value for the studies that are also confronting with the lack of data issues.

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