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Modeling the impact of EVs in the Chinese power system: Pathways for implementing emissions reduction commitments in the power and transportation sectors

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ABSTRACT

The deployment of renewable electricity and electric vehicles (EVs) provides a synergistic opportunity to accelerate the decarbonization of both China's power and transportation sectors. Here, we evaluate the potential impacts of EVs by utilizing the SWITCH-China model designed to meet emissions constraints within its power sector while integrating the electrified transportation sector. We focus on how various EV stocks, and charging strategies (unmanaged versus smart charging) impact the power sector, in terms of generation and hourly grid operation, the capacity mix, and achieving the Paris Agreement goals. Large-scale deployment of EVs increases the need for generation capacity, while the implementation of smart charging requires 6.8%–14% less additional storage capacity. We calculate that power system integration costs to incorporate EVs range from \$228 - \$352 per EV. We show that a smart charging strategy saves between \$43 and \$123 per vehicle more annually in 2050 than a case with the same EV stock where the charging is unmanaged. Our results suggest that a 140 GW annual growth of renewables from 2020 to 2050, coupled with an aggressive EVs deployment using smart charging can put China solidly on a path to meet its ambitious carbon cap targets.

1. Introduction.

China committed to peak carbon emissions by 2030 and at least 20% of non-fossil fuel energy in total energy consumption by 2030 (Gambhir et al., 2015; Huo and Wang, 2012; Li and Yu, 2019) (NDRC, 2015a). The power sector is the largest source of CO_2 emissions in China at 3.55 $GtCO_2$/year in 2015, accounting for 38% of national CO_2 (International Energy Agency, 2018). CO_2 emissions from the Chinese transportation sector accounted for 9% of national emissions in 2014 (Gambhir et al., 2015). For comparison, transportation accounts for 34% of greenhouse gas emissions in the United States, with nearly 800 vehicles per 1000 inhabitants, compared to 173 cars in China and 505 cars in the EU (EPA, 2019). With on-road emissions having grown by a factor of roughly five since 2002, and with annual increases of 2.8%/year, the emissions from the transportation sector will reach 1.7 Gt CO_2 (20% of forecast total emissions) by 2050 (IEA, 2017).

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The national electricity demand of EVs was driven by the total EV stock, vehicle use intensity, vehicle energy efficiency, and the charging efficiency of batteries. China remains the world's largest electric car market, with accumulated 3.44 million electric cars by June 2019 (CPGPRC, 2019). China plans to deploy a total of 5 million EVs by 2020 (MIIT, 2012), and the corresponding sales target of new energy vehicles, including EVs and hydrogen vehicles, will be 25% of new sales by 2025 (MIIT, 2017). Electricity demand from EVs was predicted to reach nearly 290 TWh by 2030, and the increased penetration of EVs may become one of the driving factors to build new generation capacity (IEA, 2019). Besides, China is increasing investment in renewable electricity to transfer to a low carbon power system. Thus, electrification of the transportation sector is one promising way to improve the security of energy supply and to address climate targets through an accelerated transition towards sustainable energy resources. If coupled with a long-term capacity expansion model of the power system, the large-scale deployment of EVs would have a significant effect on the transportation and the power sectors (Richardson, 2013).

Many studies have investigated the pathway to decarbonize the power sector. Firstly, (He et al., 2016) proposed the SWITCH-China model to decarbonize China's power sector, and found that China could achieve the 2 °C target by optimizing the electricity generation mix. Ma et al. (2019) employed a structural decomposition analysis based on an input-output subsystem model to explore sources of emission increases in China's power sector from 2007 to 2015. They concluded that promoting the development of non-fossil energy power may make national CO_2 emissions peak and begin to decrease before 2030. Chen et al. (2018a) presented a capacity expansion model optimizing investment decisions and full-year, hourly power balances simultaneously, with considerations of storage technologies and policy constraints. Lastly (Lin et al. (2019)) developed an analytical model with four scenarios to examine the resource, economic, and institutional implications of replacing even retiring coal generation in China by 2040. They concluded that no new unabated coal was generated after 2020. All existing coal generation must be retired, at least by the end of its original depreciation schedule.

The rapid growth of EVs population could make the transportation sector a significant contributor to national CO_2 emissions. The future growth of vehicle stock, energy demand and CO_2 emissions from China's transportation sector are analyzed by (Gambhir et al., 2015; Huo and Wang, 2012; Li and Yu, 2019). (Ou et al., 2010) concluded that the implementation of measures that support high-efficiency electric vehicles could reduce 15.8% and 27.6% for life cycle energy demand and greenhouse gas emissions by 2050. Huo et al. (2010) found that more significant CO_2 reduction could be expected if technologies improve, and the share of non-fossil electricity increases significantly. Further, many studies focused on vehicle-grid integration (VGI) that links the transportation sector with the power sector to provide comprehensive benefits. Past studies indicate that VGI can provide the power system substantial flexibility, reduce peak demand, load balancing, frequency regulation, and participate in ancillary services. Xu et al. (2016) proposed three levels (provincial, municipal, and charging stations) PEV charging strategy to reduce system peak demand and charging costs. Zhang et al. (2017) established an aggregate model of vehicle-to-grid (V2G) fleet that forecasts energy and power constraints of the entire V2G fleet. In doing so, VGI could increase the penetration of renewable energy generation, and allow higher utilization of existing generation capacity and infrastructures. For instance, smart charging could reduce the peak demand and curtailment rates of renewable electricity (Chen et al., 2018b), and EVs have significant potential to participate demand response in a cost-efficient way (Jian et al., 2018), and reduce the need to build reserve capacity and generation capacity (Wolinetz et al., 2018).

The majority of the above studies focus either on the transportation sector, or on the power sector, but much more is needed to concretely describe the details of linking the transportation and the power sectors in long-term decarbonization planning.. This work aims to assess the large-scale deployment of EVs in China's power sector, considering differences in the mix of power generation and generation capacity, combined emissions and costs, transmission line capacity, and hourly operation of the grid. This work is expected to provide valuable insight about the possible environmental and economic benefits of EVs, and how to exploit the value of EVs by planning the power system and applying the charging strategy (unmanaged charging and smart charging strategies). This work focuses on the following questions: how would China's power system change given the large-scale deployment of EVs under more stringent CO_2 emissions constraints? How would the combined CO_2 emissions of the transportation and the power sectors? What are the integration costs and costs-saving to incorporate those changes in China's power system?

This study proposed a comprehensive evaluation path that utilizes the large-scale EVs to support the decarbonization process of China's power and transportation sector in a cost-efficient way. Based on the development path of EVs, this study first simulates the daily charging profile of EVs and temporal availability of EVs connecting the grid by the province through the Monte Carlo method. After that, we updated the SWITCH-China model that is a long-term capacity expansion model, and explored the pathway of the power system integrating the EVs under various scenarios with carbon emission constraints, charging strategies, participation rates, and EVs population from 2020 to 2050. Finally, the mixes of generation capacity and power generation, transmission capacity, and annualized costs of the power system, the combined emissions, and the levelized cost of driving (LCOD) of per EV are quantified.

The paper is organized as follows. Section 2 describes the SWITCH-China model, the transportation system, methodologies of simulating the charging dynamic of EVs, and scenarios definition. Sections 3 analyzes the scenario results from energy, economic, and environmental perspective. The discussion and conclusion are provided in Section 4.

2. Methodology, data and scenarios

Fig. 1 illustrates the updated SWITCH-China model structure with the newly integrated the transportation system component. This section begins with a description of the transportation system, continues with a breakdown of the SWITCH-China model, as well as the methodology behind the EV charging simulation, and ends with scenario definitions.

2.1. Transportation system model

The transportation system model simulates daily charging behaviors of EVs and charging availability connecting to the grid of EVs from 2020 to 2050, under different EV adoption and participation rates scenarios. The national daily charging profile and temporal availability of EVs were driven by the EV stock, driving patterns, vehicle use intensity, vehicle attributes, charging strategies, and participation rates of smart charging. The EV population are based on the same vehicles stock projections but differ in the share of EVs versus internal combustion engine vehicle (ICEV), as shown in Table 3. We summarize driving patterns and the vehicle use intensity (Supplementary Figure S1.4; Table S1.5) (BTRC, 2018), in which it is assumed that Beijing's driving behaviors are representative of other provinces. The EV attributes, including vehicle kilometer travel (VKT) (km/day), fuel economy (kWh/km), capacity (kWh), and charging efficiency, are presented in (Supplementary Table S1.4; Table S1.5). The charging strategies and participation rates of smart charging are introduced in Section 2.3. Finally, the outputs of the transportation system model are charging power boundaries (kW) and accumulated charging energy demand boundaries (kWh) (Section 2.3.3). These outputs are used to construct charging scenarios for EVs in the SWITCH-China model. Improvement of technologies, decreased vehicle use intensity, and high EV adoption scenarios are considered in our scenario. For instance, the fuel economy of private LDVs will decrease by 5% every ten years. The VKT of private LDVs will decrease over time, because the construction of highways and urban railways and

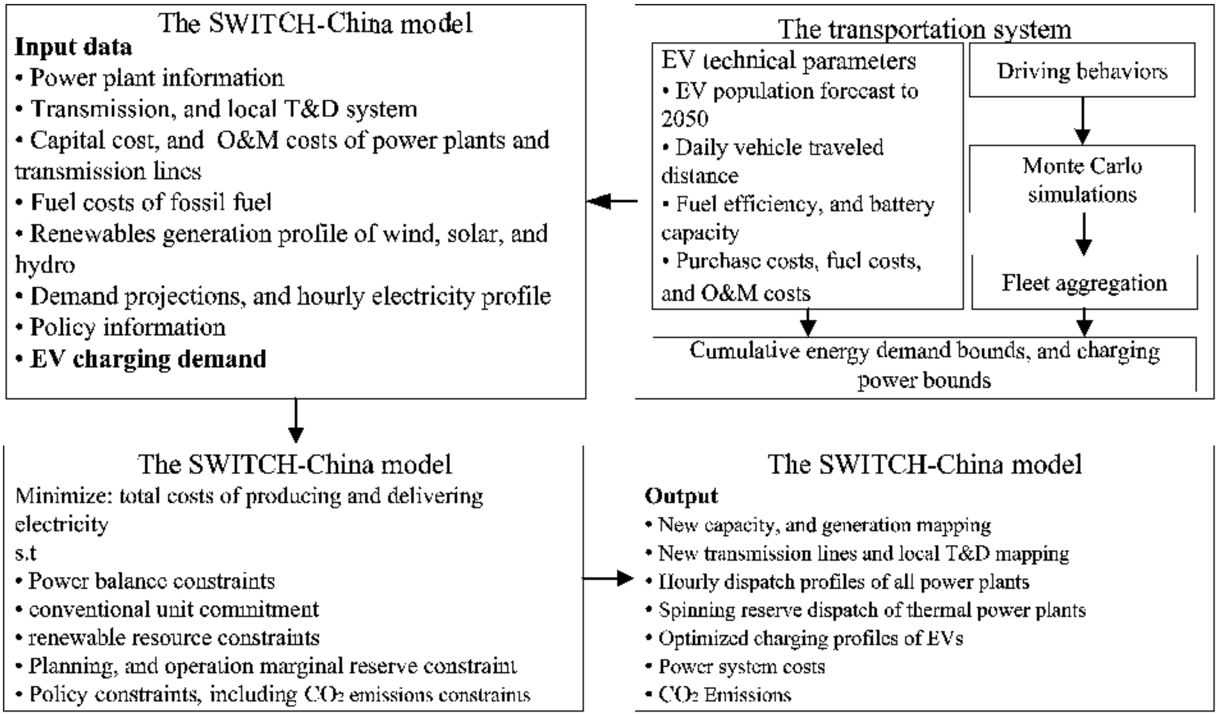

Fig. 1. Schematic diagram of the Switch-China model integrated with the transportation system.

the difference in people's choices of transport mode to fulfill their changing travel needs (Huo et al., 2012). The vehicle stocks of private LDVs, commercial LDVs (taxis, business LDVs), trucks, buses (public transport, heavy duty passenger buses) will be 557.7 million, 24.5 million, 36.5 million and 4.4 million by 2050, respectively. The EV populations will reach roughly 349 million (Huo and Wang, 2012), with a corresponding energy demand of 698.9 TWh (5.8% of total electricity demand in 2050) in the aggressive EV scenario, as shown in Table 1.

2.2. The SWITCH-China model

The SWITCH-China model is a capacity expansion planning tool of the power system. It optimizes capacity expansion of conventional and renewable generation technologies, storage systems, and transmission systems coupled with hourly load demand and renewable energy output profiles while meeting the projected electricity demand from 2020 to 2050 (He et al., 2020; Johnston et al., 2019; Sanchez et al., 2015). To comprehensively study the impacts of integrating the power system in its current state with an electrified transportation sector, and to project towards future decarbonization, the SWITCH-China model is adopted to simulate the electricity power system in both spatial and temporal resolution. For the temporal resolution, the optimization horizon is divided into four investment periods: 2016–2025, 2026–2035, 2036–2045 and 2046–2055. Specifically, the SWITCH-China model run with 12 months per period, two days per month, and six sampled hours per day. Geographically, the model divides the entire power system into 32 load zones that can be connected through existing inter-provincial transmission lines. The SWITCH-China model simultaneously optimizes investment decisions and operation dispatch decisions to minimize the total costs of producing and delivering electricity, while satisfying a series of constraints that includes power balancing constraints, convention unit commitment, renewable resource constraints, planning and reserve marginal constraints, and policy constraints, as shown in Fig. 1. The detailed information is shown in the Appendix. A and supplementary information.

Table 1
The electricity demand of EVs (TWh).

Scenario	2020	2030	2040	2050
Moderate EV Scenario	27.6	111.7	235.5	374.7
Aggressive EV Scenario	27.6	191.0	429.5	698.9

2.3. Model charging dynamics for EVs in China

2.3.1. Charging dynamics of EVs in China

The daily charging profile of EVs mainly depends on arrival time, and departure time from a charging station, VKT, state of charging (SOC), charging strategies, and the availability of charging infrastructure. We investigate the driving behaviors of vehicles through existing literature (BTRC, 2018; Chen et al., 2018b; Jian et al., 2018; Sun et al., 2014; Xu et al., 2016). The probability distribution arrival/departure times for private LDVs, buses, taxis, commercial LDVs are summarized in (Supplementary Table S1.4; Table S1.5).

The average daily travel distance of buses is roughly 160 km and should remain constant through to 2050, and the normal operation time of buses starts between 05:30–06:00 and ends between 22:00–23:00. Taking a BYD K8 bus as an example, the maximum mileage of electric buses is roughly 180–200 km after charging 8 h during the night. It is reasonable to assume that the charging periods of electric buses are most likely to be 10:00–16:30 (daytime) and 23:00–05:30 (nighttime).

In China, driver shift duration and daily frequency (a single driver or two drivers who trade-off) significantly influence EV charging dynamics. Fifty-five percent of taxis are driven by individual drivers, while forty-five percent of taxis are driven by two drivers. The average daily distance of taxis with a single driver is nearly 240 km, and it is 400 km for taxis with two drivers (Sun et al., 2014). The shift start/end usually occurs at 06:00 and 18:00. Drivers must charge before they shift the taxis to guarantee the SOC is enough for the next driver. It is assumed that one charge per day for taxis with a single driver occurs between 20:00 and 22:00. For the taxi with two drivers, it is assumed that taxis will charge between 2:00 to 4:00, and between 11:30 and 14:30.

Electric light-duty commercial vehicles (LDCV) are often part of a company or government fleet. China had the largest electric LDCV fleet worldwide (138,000 vehicles) in 2018. The average daily travel distance of LCVs is 40–50 km, and the normal operation time of LCVs is from 9:00–18:00. The parking distribution is derived from studies (Jian et al., 2018).

According to a statistical analysis of private cars (BTRC, 2018), most people use vehicles in Beijing to commute, leaving home between 6:00 and 9:00 and arriving at their workplace between 07:00 and 10:00. Detailed information can be found in Supplementary. Figure S1.4. The average daily travel distance of private LDVs is roughly 40 km, which translates to the daily electricity consumption of 4.5 kWh - 9 kWh.

2.3.2. Unmanaged charging

It is assumed that an EV starts charging as soon as it is plugged in the grid under the unmanaged charging scenario. The accumulated energy demand is a fixed trajectory where the lower energy bound is equal to upper energy bound. Flexible charging is not allowed since the charging profiles have to strictly follow the accumulated energy demand trajectory.

2.3.3. Smart charging

Smart charging can occur in a centralized way through aggregators that directly controls the charging behaviors of EVs without the involvement of EV owners. When EVs participate in the smart charging program, their end of energy demand is treated as a required energy target. This requirement ensures that the presence of charging management will have no impact on the mobility of EVs. The following EVs are regarded as the controllable EV 1) electric buses at night; 2) private LDVs parked in lots at workplaces during the daytime; 3) private LDVs parked at homes during the nighttime; 4) single-driver taxis parked when off-duty, while all other EV types are regarded as unmanaged EVs. The charging flexibility of a given EV can be modeled by its accumulated charging demand bounds and charging power bounds. This is similar to the methodology (Chen et al., 2018b; Zhang et al., 2017). It is assumed that controllable EVs plugged-in at the same time with unmanaged EVs, but the aggregators can control the time of active charging and charging power as long as their end of energy demand is the same with that of the unmanaged charging.

Fig. 2 illustrates the daily aggregated cumulative charging demand bounds. The upper energy bound corresponds to unmanaged charging when active charging begins immediately. The lower energy bound corresponds to delaying active charging until the last possible moment while still reaching the same energy target. Within the boundaries of these two curves, any increasing trajectory can be achieved by managing charging behaviors while still meeting the energy target, charging power limits of EVs. In contrast, the fixed boundary represents unmanaged charging that does not allow the use of any flexibility measures. Smart charging allows for the possibility to delay charging while delivering the same amount of energy as unmanaged charging by the end of the day.

2.3.4. Integrating EVs charging load into the SWITCH-China model

Virtual storage is created in each province to represent the aggregated charging profile and charging availability of EVs. The charging energy demand is aggregated to a charging trajectory between two cumulative charging demand bounds that determine how much charging power can be dispatched in a given time. The daily aggregated charging loads are scaled to construct monthly profiles by repeating the full day of hourly charging loads. Similarly, the monthly charging loads and constraints are scaled to create an annual data set for the SWITCH-China model. Notably, there are no differences in the charging behaviors of EVs across each province, but there are differences in the EV population. Finally, the feasible trajectories of charging power are regarded as inputs in the SWITCH-China model by province, and period.

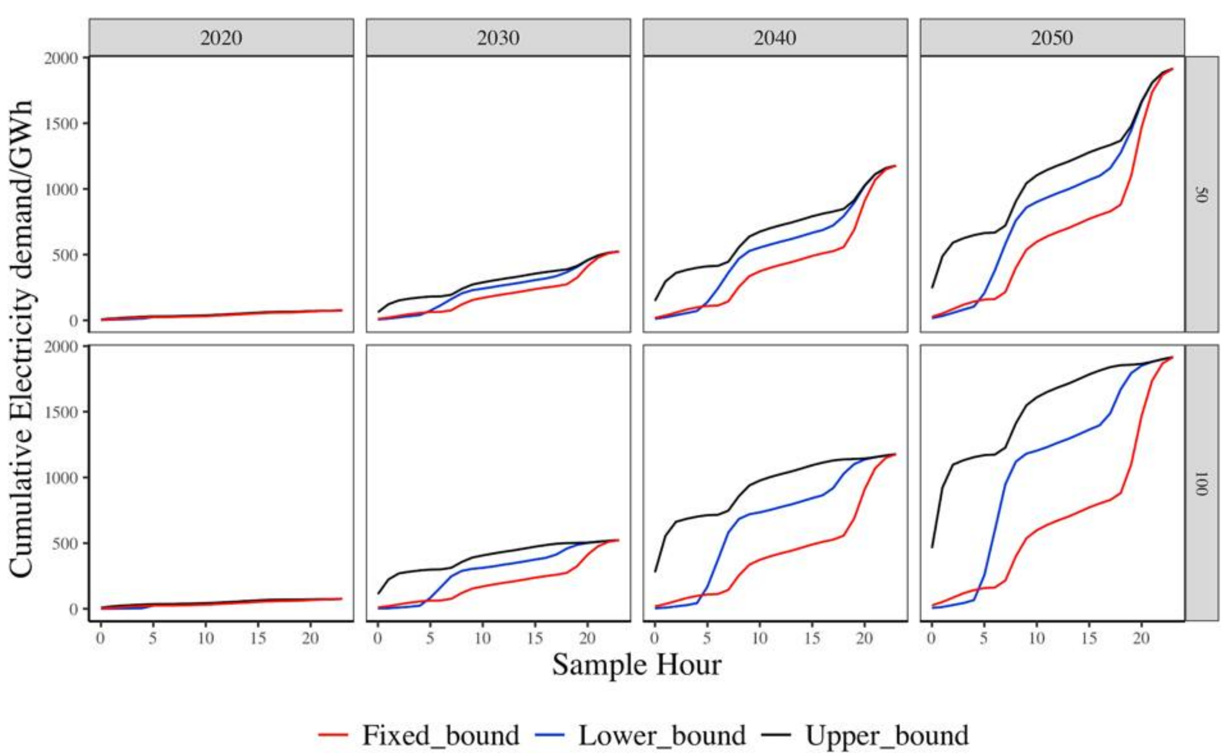

Fig. 2. Average Energy Demand Bounds on Cumulative Charging Trajectories under Aggressive EV Adoption Scenario with Different Participation Rates. The participation rate in smart charging also has effects on the energy demand curve, so we set up two scenarios: a 50% participation rate of EVs and a 100% participation rate of EVs. The 50% means that only one half of EVs are available to do the smart charging mode, and a 100% means that all EVs can do smart charging mode. Although the participation rate of smart charging is different, the cumulative charging demand at the end of the day is the same.

2.4. Scenario descriptions

Our scenarios form an assessment of the impacts of decarbonizing the power sector while varying nationwide EVs deployment from 2020 to 2050, as shown in Table 2. Within the EVs component to our analysis, our variables of interest include EV adoption levels, charging strategy, the participation rate in smart charging, and carbon emissions constraints. The scenarios are: First, business as usual (BAU), which assumes the continuation of existing policies and future renewable cost trends. Second, carbon cap constraints (C70), which implies a carbon cap of 70% lower than the 2014 emissions level by 2050, as shown in Table 4. Third, carbon cap constraints with EV adoption scenario (C70-EV), which assumes different EV adoption levels and charging modes scenarios. Notably, the "C70" scenario is consistent with the $2^{\circ}C$ scenario during given the assumption that other sectors reduce their emissions in parallel with the CO_2 reductions from the power sector, as shown in Table 4. This is also consistent with China's recent announcement of achieving carbon neutrality by 2060. Annual car ownership prediction is based on (Huo and Wang, 2012). The EV adoption scenarios are based on the same vehicles stock projections but differ in the share of EVs versus internal combustion engine vehicles (ICEVs), as shown in Table 3. The aggressive EV deployment target in 2050 is similar to the assumptions in (NDRC, 2015b), and the EV target for the moderate EV deployment scenario is nearly half as much as the aggressive EV deployment scenario. To better understand the benefits of smart charging, the different participation rates of smart charging scenarios are used to explore how to coordinate aggressive EVs and the power sector towards the decarbonization of the power system.

Table 2
Scenario descriptions.

	Business as usual (BAU)	Carbon cap constraints (C70)
Research periods	Base year: 2016; Investment period: four investment periods with every ten years	
Existing policies	The Chinese "Five-year plan" from 2016 to 2020; No new coal-fired power plants after 2020	
Future renewable cost trends	The rapid decrease in capital costs of renewable energy (solar, wind) and storage system. The detailed information is shown in the supplementary.	
Carbon emissions constraints	No	70% reduction in electricity sector emissions from 2014 level by 2050 (IEA, 2017)
EV adoption levels	No	Moderate EV ("MEV") deployment scenario: around 174 million EVs will come in the road by 2050. Aggressive EV ("AEV") deployment scenario: around 349 million EVs will come in the road by 2050.
Charging modes	No	Unmanaged charging ("UC"): EVs charge immediately after being plugged into the grid. Smart charging ("SC"): Power system operator directly optimizes EV's charging time and power.
Participation rates	No	The Participation rate of 50% of smart charging (PR50): 50% controllable EVs can participate in smart charging program. The Participation rate of 100% of smart charging (PR100): 100% controllable EVs can participate in smart charging program.

Note: The scenario names are the "BAU", "C70", "C70-MEV-UC", "C70-MEV–SC–50", "C70-MEV–SC–100", "C70-AEV–SC–50", "C70-AEV-UC", and the "C70-AEV–SC–100" scenario. For instance, the "C70-MEV-UC" scenario is the scenario that uses carbon emissions constraints, moderate EV adoption level, and an unmanaged charging strategy. The "C70-MEV–SC–100" scenario is the scenario that uses carbon emissions constraints, moderate EV adoption level, and a 100% participation rate of smart charging.

Table 3
Projected Electric Vehicle Stock Sizes (million units).

Scenario	Type	2020	2030	2040	2050
Moderate Scenario	Private LDVs	3.77	39.03	99.72	167.31
	Buses	0.29	0.53	0.83	1.2
	Taxis	0.15	0.35	0.62	0.97
	Commercial LDVs	0.44	2.12	3.34	4.42
Aggressive Scenario	Private LDVs	3.77	78.06	199.44	334.62
	Buses	0.29	0.64	1.11	1.55
	Taxis	0.15	0.7	1.23	1.94
	Commercial LDVs	0.44	4.23	6.67	11.04

Table 4
National CO_2 Emissions Targets for the Power Sector (million tons CO2).

Scenario	2020	2030	2040	2050
BAU	–	–	–	–
C70	3780	3524	2046	1322

3. Results

3.1. Annual grid impacts

3.1.1. Installed capacity and generation

Fig. 3 shows that the cumulative installed capacity by energy source in 2050. Across scenarios, solar PV dominates generation capacity: the largest installed capacity, at 3114 GW (44.2% of total capacity), occurring in the "C70-AEV-UC" scenario, compared with 187 GW (6.7% of total capacity) in the "BAU" scenario. The second most used technology is wind, with capacity between 788 GW (28% of total capacity) in the "BAU" scenario and 1922 GW (25.6% of total capacity) in the "C70-AEV-UC" scenario. Capacity of hydropower plants does not expand because of resource limitations, so hydropower remains stable at 316 GW in all scenarios. As a baseload energy source, nuclear is competitive in our scenarios because of its high capacity and zero-emissions. However, nuclear capacity accounts for less than 6% of total capacity considering public security concerns. The capacity limits of nuclear is consistent with nuclear development trend in (IEA, 2015). There is a significant reduction in coal capacity from 1140 GW in the "BAU" scenario to 656 GW in the "C70" scenario by 2050. The rest of the coal capacity is used to provide for backup usage. The large-scale renewables electricity leads to dramatically increase in storage capacity from 32 GW in the "BAU" scenario to 551 GW-717 GW in the scenarios with "C70" and both with and without EVs, in order to incorporate flexibility in utilizing variable renewable resources. For instance, the ratio of solar capacity to storage capacity is roughly 5:1 ("C70"), which suggests that the installed capacity of storage increases as the CO_2 emissions constraints strengthen. Similarly, gas-fired generation capacity goes up sharply in the last period to meet the strong CO_2 emissions constraints, though fuel price of natural gas is higher than coal price over the period.

Fig. 4 shows the annual generation by energy source in 2050. In the "BAU" scenario, most of the energy generated in 2050 comes from coal (60% of total generation), while in the "C70" scenarios, coal generation makes up less than 6% of total generation, in order to satisfy reductions in CO_2 emissions. In contrast, under the "C70" scenarios, the total non-fossil generation, at around 9000 TW-hours (TWh), accounts for about 64% of total generation by 2050. The share of gas-fired generation capacity relative to the total installed capacity increases from zero in the "BAU" scenario to 13.2% in the "C70" scenario, which suggests that gas-fired plants will be competitive compared with coal generation, coming from a lower CO_2 emissions intensity and a higher flexibility in gas.

The obvious impact of smart charging is on the quantity and type of installed capacity and generation. For the generation capacity, charging strategies has a negligible impact on the renewable capacity, as applying smart charging would reduce the need for new generation capacity by

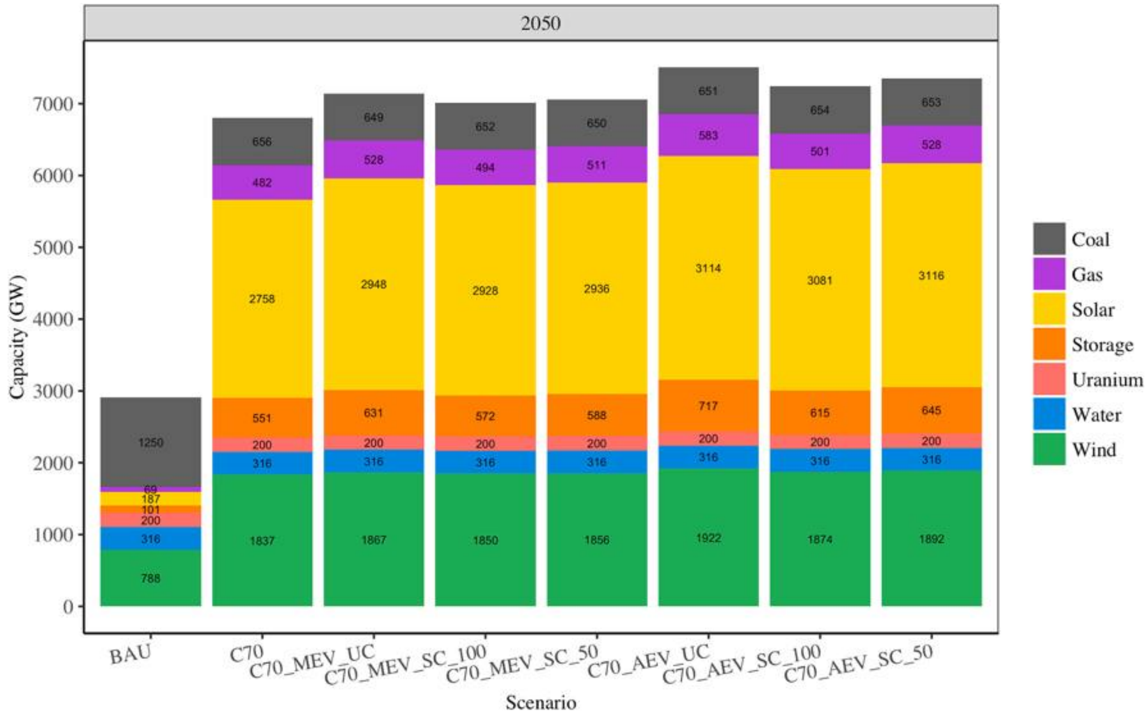

Fig. 3. The cumulative electricity capacity by energy source in 2050.

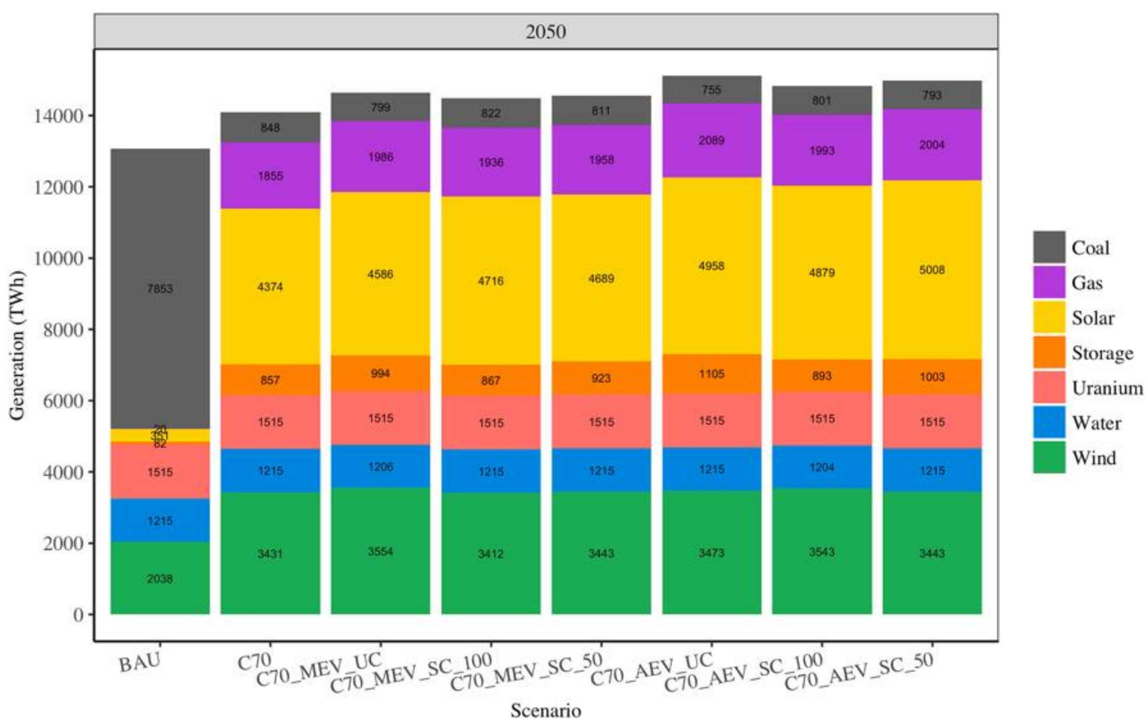

Fig. 4. The electricity generation by energy source in 2050.

around 1% relative to unmanaged charging scenarios. In contrast, under the "C70-MEV" scenario, imposing smart charging with a 100% participation rate would decrease storage capacity by around 9% by 2050, compared with the unmanaged charging strategy. Under the "C70-AEV", storage capacity would decrease further to 615 GW by 2050, 14% lower than the unmanaged charging strategy. Similarly, we find that smart charging also builds 3%–14% less gas-fired power capacity, resulting from a lower peak load than in the unmanaged charging scenarios. Furthermore, a 100% participation rate in smart charging builds less capacity than a 50% participation rate of smart charging.

From a national generation perspective, compared with the "C70" scenario across the different EV adoption level, deploying EVs would increase the national generation by 2.8%–7.2%, which is larger than just the forecasted EV charging demand due to transmission losses and charging efficiency losses. Moreover, smart charging strategies result in less generation than unmanaged charging. This is mainly coming from a reduction in storage generation and gas generation. Specifically, under the "C70-AEV–SC–100" scenario, the smart charging leads to the highest reduction by around 19% compared with unmanaged charging.

3.1.2. Electricity transmission system

Fig. 5 shows the cumulative inter-provincial/regional transmission line capacity by period. One of the major challenges to integrate RE, and a motivation for the development of cross-provincial transmission, is that the RE resources are located far from the load centers, such as the eastern coastal region. As source-rich areas are not able to consume all of what they generate locally, this enhances the need for cross-provincial transmission. To decarbonize China's power sector and to meet higher load demand along the east coast of China, transmission line capacity needs to be expanded aggressively. Under the "C70" scenario, the cumulative transmission capacity increases from 736 GW in 2020 to 1774 GW in 2050, around 44% higher than in the "BAU" scenario by 2050. While the large-scale deployment of EVs would lead to increasing transmission capacity by about 3.3%–5.4% relative to a "No EV" scenario, charging strategies have a negligible impact on transmission line capacity expansion. With the construction of more ultra-high voltage UHV transmission lines, inter-regional and inter-provincial transmission could play a great role in the integration of RE into a resource-load-unbalanced area.

In contrast, charging strategies have a significant impact on local T&D capacity. As shown in Fig. 6, under the "C70-MEV–SC–50" scenario, systems need to build 345 GW of local T&D capacity, which is 7.5% lower than in the unmanaged charging scenario. Furthermore, if there is a 100% participation rate in smart charging, the system further builds even less 13.5% local T&D capacity, at 13.5% less than in the unmanaged charging. Similar results also occur in the aggressive EV adoption scenario. This is because smart charging would result in a reduction in the evening peak electricity demand as described in Section 3.2.

3.1.3. Combined CO_2 emissions

A comparison of national CO_2 emissions of the power sector and the transportation sector, as shown in Table 5 and Table 6. There is a significant reduction in CO_2 emissions in the "C70" scenario: the 2050 emissions level under the "BAU" scenario is at around 6.7187 billion tons CO_2 (41% above the 2014 level), and the 2050 emissions level under the "C70" scenario is at 1.322 billion tons CO_2 (70% below the 2014 level). The main reason is that non-fossil generation increases from 27.6% in the "BAU" scenario to 64% in the "C70" scenario. Notably, the SWITCH-China model minimizes total costs by following trajectories of carbon emission constraints. Therefore, the carbon budget is the same under the same carbon emission constraints no matter what EV deployment scenarios are used. However, the CO_2 emissions from the transportation sector would have a significant reduction resulting from switching from internal combustion engine vehicles (ICEVs) to EVs. Under various EVs adoption levels, if these EVs are alternating by gasoline-driven vehicles, the gasoline-driven vehicles will emit corresponding CO_2 emissions. For instance, the moderate EVs adoption level would make a substantial contribution to reducing CO_2 emissions of about 380.2 Million ton (Mt) from the transportation sector. The aggressive EV adoption level further reduces CO_2 emissions around 725.3 Mt. Thus, across the board, large-scale deployment of EVs can significantly decrease overall CO_2 emissions of the power and transportation sectors in the future.

Table 7 show the comparison of CO_2 emission intensity (kg CO_2/MWh) of the power system by 2050. The CO_2 emissions intensity of the power system decrease from 476.9 kg CO2/MWh under the "BAU" scenario to 93.65 kg CO_2/MWh under the "C70" scenario. First, the

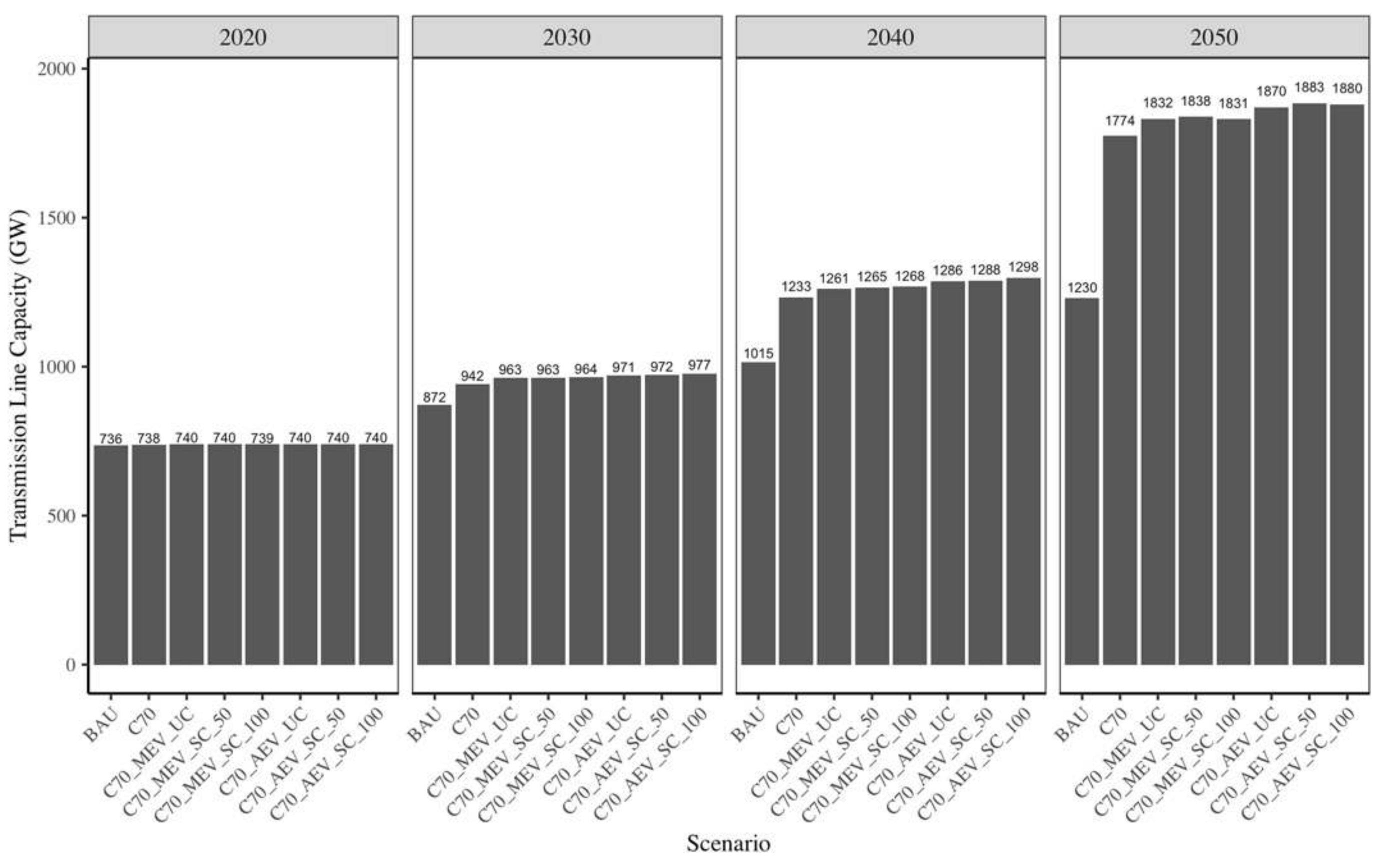

Fig. 5. Cumulative Transmission Line Capacity by Scenario over the Period. The transmission line capacity accounts for voltage level above 500 kV, including inter-provincial/regional transmission lines.

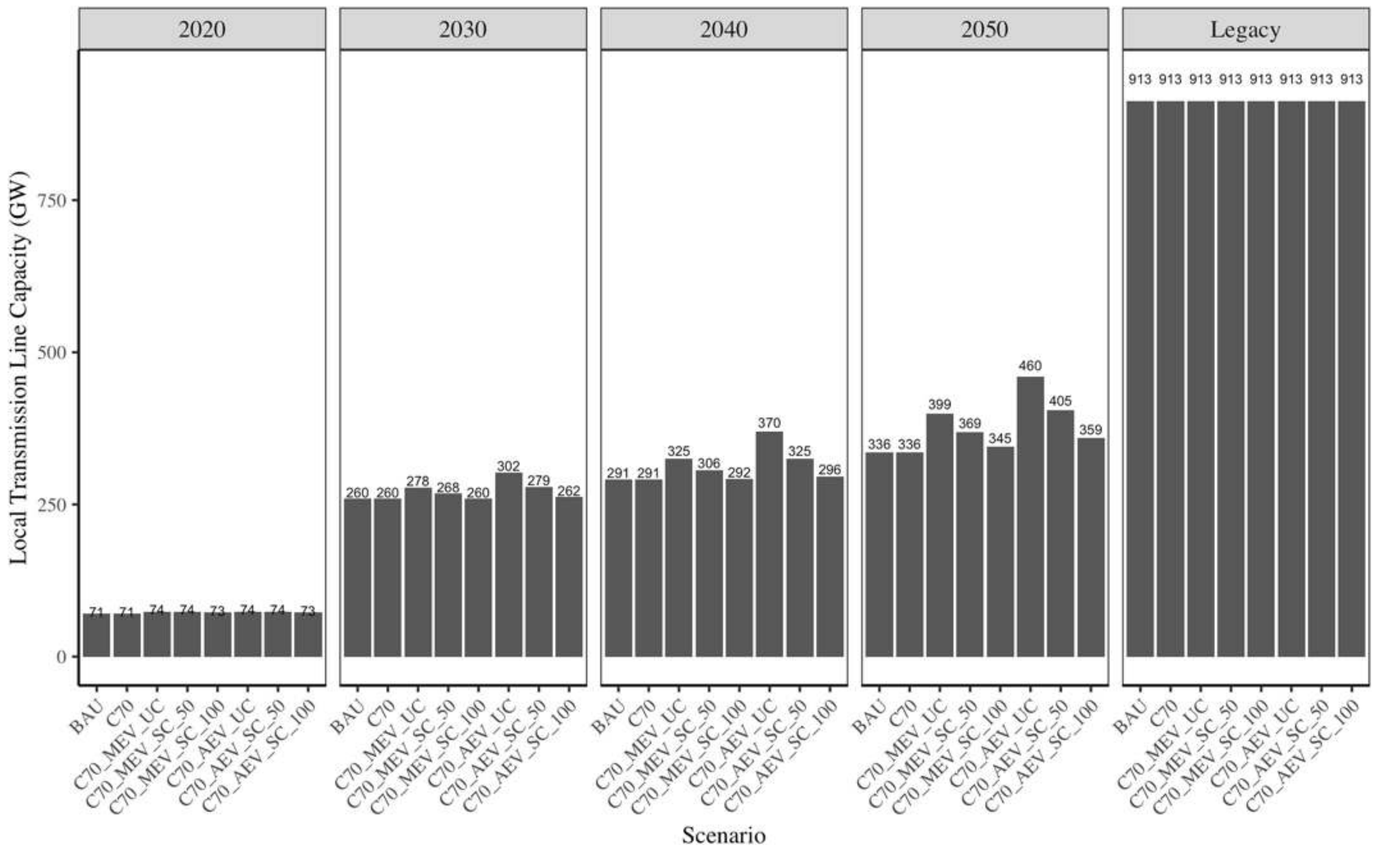

Fig. 6. New Local Transmission and Distribution Capacity by Scenario over the Period. The local transmission and distribution (T&D) system is built to serve the peak load in each period. The item "legacy" presents the existing local transmission and distribution capacity. This figure shows that how much local T&D capacity need to be built in each period, rather than cumulative capacity by period.

Table 5
National CO_2 Emissions from the Transportation Sector (Billion ton CO_2).

EV adoption levels	2020	2030	2040	2050
Moderate	0.0301	0.1300	0.2469	0.3802
Aggressive	0.0301	0.2337	0.4635	0.7253

Note: Under the EV adoption levels, it is assumed that these EVs are alternating by gasoline-driven vehicles, the gasoline-driven vehicles then will emit corresponding CO_2.

Table 6
National CO_2 Emissions from the Power Sector (Billion ton CO_2).

Scenario	2020	2030	2040	2050
BAU	4.056	4.330	5.374	6.7187
C70	3.780	3.524	2.046	1.322

Table 7
Average CO_2 emissions of the power system in 2050 (kg/MWh).

Charging strategy	Participation rate/%	BAU	C70-MEV	C70-AEV
No EV	0	476.9	93.65	93.65
No control	0	–	90.16	87.36
Smart charging	50	–	90.70	88.11
	100	–	91.14	89.96

national power generation would increase resulting from additional electricity demand of EVs as described in Section 3.1.1. Thus, deployment of EVs would decrease CO_2 emission intensity than does in the "No EV" scenario. Second, a smart charging would bring more CO_2 emission intensity than that under the unmanaged charging scenario. For instance, under the "C70-MEV-UC" scenario, smart charging with 50% and 100% participation rate increases CO_2 emission intensity by around 2.1% and 3.5%, respectively. Because a smart charging results in a more stable national load profile, facilitating the coal generation by alternating gas generation, and reducing storage generation. This would lead to less national generation compared with unmanaged charging scenario, as described in Section 3.1.1. Therefore, the CO_2 emission intensity would increase resulting from imposing smart charging on EVs.

Table 8 show the comparison of the power system CO_2 emissions intensity (g CO_2/km) per EV. At the national level, the CO_2 emission intensity per kilometer of EV are 10.84–11.23 g CO_2/km, which is significantly less than the intensity of CO_2 emissions for gasoline-driven vehicles (132 g CO_2/km). On the other hand, a higher participation rate

Table 8
Average CO_2 emissions of the power system associated with EV and ICE vehicle (g CO_2/km).

Charging strategy	Participation rate/ %	BAU	C70-MEV	C70-AEV	ICEV[a]
No EV	0	57.23	11.24	11.24	132
No control	0	–	10.82	10.48	–
Smart charging	50	–	10.88	10.57	–
	100	–	10.94	10.80	–

[a] By 2050, most electricity vehicle costs are approximately equal to ICE drivetrains, at $14200. It is assumed that lifetime of gasoline-driven vehicles is 12 years, and the VKT of EVs and ICEVs is 13,600 km, and fuel consumption of EVs and ICEVs are 12 kWh/100 km and 6 L/100 km, respectively, and that the gasoline price is 1 $/L, as a base fuel scenario. The fuel emission factor of gasoline is 2.2 kgCO_2/L. The O&M costs of EVs and ICEVs are account for 8% of purchase costs (Gambhir et al., 2015).

in smart charging strategy EVs results in higher CO_2 emissions intensity for the same level of EV adoption. For instance, in the “C70-MEV-UC” scenario, the CO_2 emissions intensity associated with EVs are 10.84 g/km, which is 3.6% lower than the value in the “C70-MEV–SC–100” scenario. The CO_2 emissions intensity of vehicle highly correlates with the CO_2 emissions intensity of the power system, so the impacts of charging strategies on CO_2 emissions intensity of one vehicle are similar to CO_2 emissions intensity of the power system.

3.1.4. Combined costs

Table 9 shows to what degree the annualized costs of the power sector change with the carbon emissions constraints, charging strategies, and participation rates in a smart charging. Firstly, as EVs are integrated into the power sector, annualized costs increase by 3.0–9.6% in 2050 as capacity and generation increase to meet the additional charging demand of EVs. Specifically, an unmanaged charging strategy leads to the larger increase in the annualized costs, while a smart charging strategy with a 100% participation rate results in the lowest total costs, and a smart charging with a 50% participation rate also helps to mitigate the additional costs. Notably, in order to meet the carbon emissions target, we find that by 2050 China’s power system costs will be at 98.6 $/MWh under the “C70” scenario, 49.3% higher than in the “BAU” scenario. Moreover, system average energy costs will be at 108.1 $/MWh as a result of infrastructure needs to match an aggressive deployment of EVs, as shown in Table 10. This cost includes a largely carbon-free electricity sector, whose benefits are very large compared to the ‘electricity only’ BAU scenario.

Fig. 7 explains what contributes to the changes in total costs. A carbon emission constraints scenario would change the costs structure that switch from coal fuel costs to more capital costs. The fuel costs of coal decrease 331.4 billion in the “BAU” scenario to 28.3 billion in the “C70” scenario. The capital costs from solar, wind and storage account for 33.3% of total costs by 2050 in the “C70” scenario, compared with 9% in the “BAU” scenario. From cost-saving of smart charging perspective, compared with unmanaged charging, smart charging costs 9–24 $ billion less annually in the moderate EV adoption scenario, even 27–40 $ billion less annually in 2050 in the aggressive EV adoption scenario. The cost reduction is mainly driven from a decrease in fuel costs, capital costs of storage, solar and gas-fired power plants, and local T&D build costs. For instance, smart charging would result in a reduction in fuel costs of gas, at 6.9 billion (30.9% of total cost reduction) in the “C70-MEV–SC–100” scenario compared with the “C70-MEV-UC” scenario. This is consistent with the results in Section 3.1.1: compared with unmanaged charging, smart charging decreases the utilization of gas-fired generation and of storage capacity. Besides, storage capital costs (2.3 billion), local T&D costs (6.4 billion), and solar capital costs (1.6 billion) contribute to the left cost reductions. It is notable that unmanaged charging leads to an increase in fuel costs, because the EVs charging peak occurs within peak load hours, when gas-fired power plants with a quick start-up and flexible ramping are to be dispatched. In contrast, smart charging can offset the charging demand to off-peak hours in order to smooth the load profile. Thus, this suggests that increasing the flexibility of the power system by optimizing the charging demand of EVs can significantly reduce annual system costs.

Table 9
Annual total costs of the power sector by 2050.

EV adoption levels	Charging strategies	Participation rates/%	Power sector costs/ Billion USD	Additional costs caused by EVs charging	Difference of the additional costs
BAU	BAU	BAU	800.0	–	Reference
C70-No EV	–	–	1194.1	Reference	+49.3%
Moderate	No control	–	1253.0	+4.9%	Reference
	Smart charging	50	1240.3	+3.9%	−1.0%
		100	1230.7	+3.1%	−1.7%
Aggressive	No control	–	1308.5	+9.6%	Reference
	Smart charging	50	1282.3	+7.4%	−2.0%
		100	1264.9	+5.9%	−3.3%

Table 10
Average energy costs of the power system across the scenarios in 2050.

EV adoption levels	Charging strategies	Participation rates/%	Power sector costs/ $2016/ MWh	Additional costs caused by EVs charging	Difference of the additional costs
BAU	BAU	BAU	66.07	–	Reference
C70-No EV	–	–	98.63	Reference	+49.3%
Moderate	No control	–	103.50	+4.9%	Reference
	Smart charging	50	102.45	+3.9%	−1.0%
		100	101.66	+3.1%	−1.8%
Aggressive	No control	–	108.08	+9.6%	Reference
	Smart charging	50	105.92	+7.4%	−2.0%
		100	104.48	+5.9%	−3.3%

Given an EV deployment scenario, it is necessary to figure out the combined costs from both the power system and the transportation sector in order to analyze the cost benefits of EVs versus ICEVs and cost benefits of smart charging versus unmanaged charging. We define the annual system integration costs as the cost of integrating a particular amount of EVs. As shown in Table 11, the annual integration costs of the power system range from 211 to 352 $ per EV across various EV adoption levels and participation rates. One notable metric for analyzing the tradeoff between smart charging and unmanaged charging is the implementation costs of a smart charging that is the cost of the on-board metering device and the wireless interconnection. We observe that the reduction in system integration costs of power system is always higher than the implementation cost for smart charging strategy. For instance, incorporating a smart charging strategy decreases integration costs by 12.2–29.6% relative to an unmanaged charging strategy, and the saving costs per vehicle decrease as the participation rates in smart charging grows. Therefore, strategies that prioritize saving system costs should deliver subsidies to drivers who participate in smart charging programs, and should build both more charging infrastructure and upgrade local transmission systems to improve the ability for EVs to respond to demand, ultimately increasing their market share.

Another way we can summarize the economic impact of EV adoption is by using the updated levelized cost of driving (LCOD) ($/km) of per EV in comparison with the LCOD per gasoline-driven vehicle (See Appendix B). As shown in Table 12, in all unmanaged charging scenarios, EVs have a 2.05%–2.25% higher LCOD than ICEVs in the base fuel price scenario, whereas the LCOD of EVs is roughly 4.4% lower than for ICEVs in the high fuel price scenario. More importantly, imposing smart charging strategies rather than an unmanaged charging strategy decreases the LCOD of per EV by 1.4–4.3%. From a practical perspective, it may be difficult to reach a level of participation in which a power system operator has full control of the charging of EVs, representing a 100% smart charging participation rate. Under a 50% smart charging participation rate, EV owners are guaranteed a contracted time to charge EVs. Thus, utilizing a smart charging with a 50% participation rate would probably be more convenient and cost effective to implement in reality.

3.2. Hourly grid impacts

Fig. 8 and Fig. 9 illustrate hourly dispatch in 2050 across the “C70-AEV-UC” and “C70-AEV–SC–100” scenarios. The results are similar to other scenarios: generally, the generation capacity expansion can meet

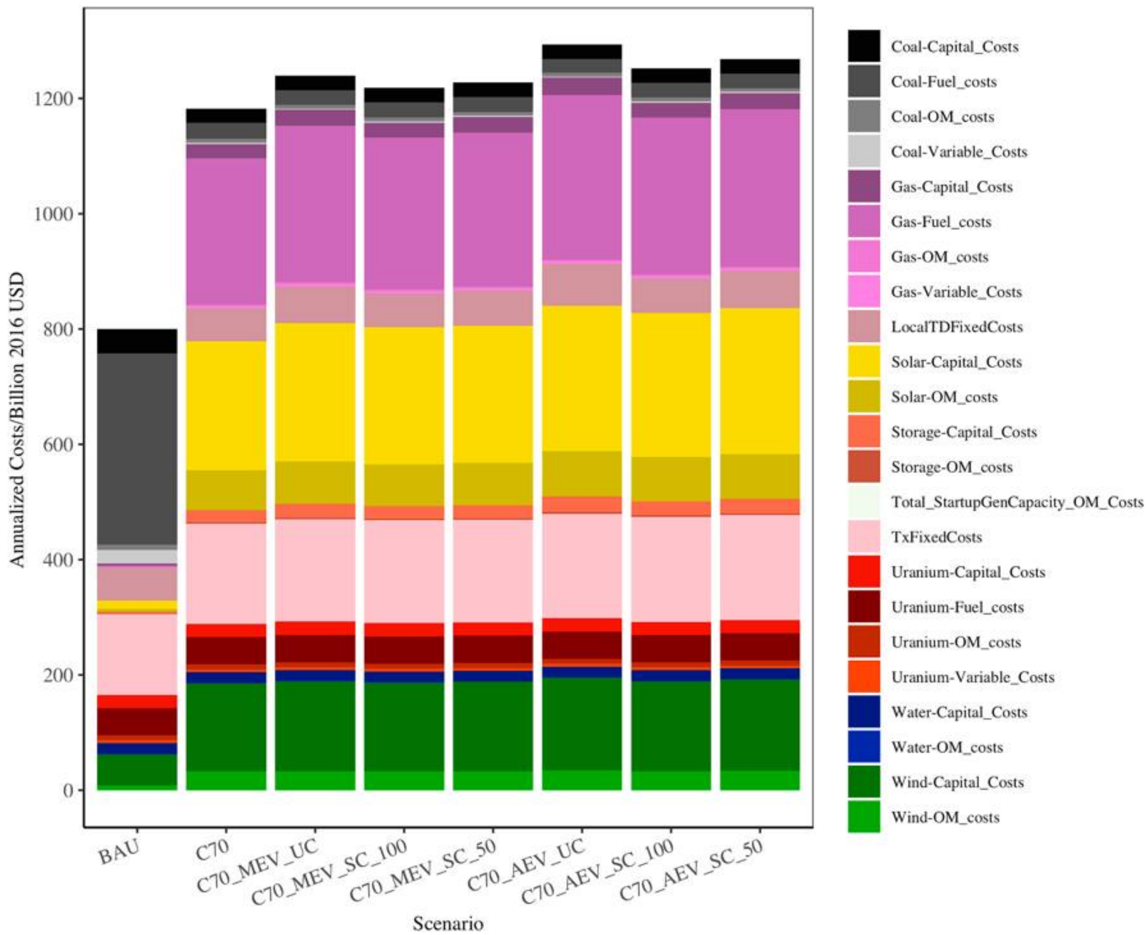

Fig. 7. Total Annualized Costs in 2050. The total annualized cost is the discounted sum of the investment costs for new generators and transmission lines, the O&M costs, the fixed O&M costs for transmission lines and distribution systems, the variable costs, the start-up costs and the fuel costs.

Table 11
Annualized Integration Costs of the Power System Per EV in 2050 ($/EV-year)[a].

Charging strategy	Participation rate/%	C70-MEV	Additional costs caused by smart charging/%	C70-AEV	Additional costs caused by smart charging/%	Implementation cost[b]
No control	0	352	reference	338	reference	0
Imposing control	50	300	−12.2	258	−21.0	9
	100	211	−34.9	220	−29.6	18

[a] The integration costs are come from additional generation capacity, generation, transmission lines and fuel consumption.
[b] Costs for smart charging US$ 150 from Göransson et al., 2010). Ten-years lifetime of EVs assumed. Discount rate of 4% assumed.

Table 12
Levelized Cost of Driving for one EV and one ICE Vehicle in 2050 ($/km)[c].

Charging strategy	Participation rate/%	C70-MEV	LCOD difference relative to ICEV[a]/%	C70-AEV	LCOD difference relative to ICEV[a]/%	ICEV[a]	ICEV[b]
No control	0	0.2089	2.25	0.2085	2.05	0.2043	0.2185
Imposing control	50	0.2055	0.62	0.2033	−0.48	–	–
	100	0.1999	−2.13	0.2008	−1.71	–	–

[a] By 2050, most electricity vehicle costs are approximately equal to ICE drivetrains, at $14200. It is assumed that the lifetime of gasoline-driven vehicles is 12 years, that the VKT is 13,600 km, and fuel consumption of EVs and ICEVs are 12 kWh/100 km and 6 L/100 km, respectively, that the gasoline price is $1/L, as a base fuel scenario. The O&M costs of EVs and ICEVs are account for 8% of the purchase costs (Gambhir et al., 2015).
[b] Fuel price forecasting ranges from $0.65/L to $1.4/L by 2050 (U.S. EIA, 2019). Here, we use the fuel price of $1.4/L as a high fuel price scenario.
[c] The LCOD of per vehicle calculates how much it costs to drive a vehicle per kilometer over the vehicle's life. The LCOD of per vehicle includes purchase costs, fuel/electricity costs, O&M costs, integration costs of power system and supporting infrastructure costs from transportation sector.

electricity demand growth and peak demand. On the one hand, renewable energy generation profiles vary throughout the year due to seasonal patterns. Wind generation tends to be higher during the winter and the spring and lower during the mid-to-late summer. Monthly solar outputs are highest in the summer months because of maximized daylight. Hydropower has more production during the summer and the fall due to China's precipitation patterns. With a restrictive carbon cap, renewable energy resources dominate generation mixes and generation

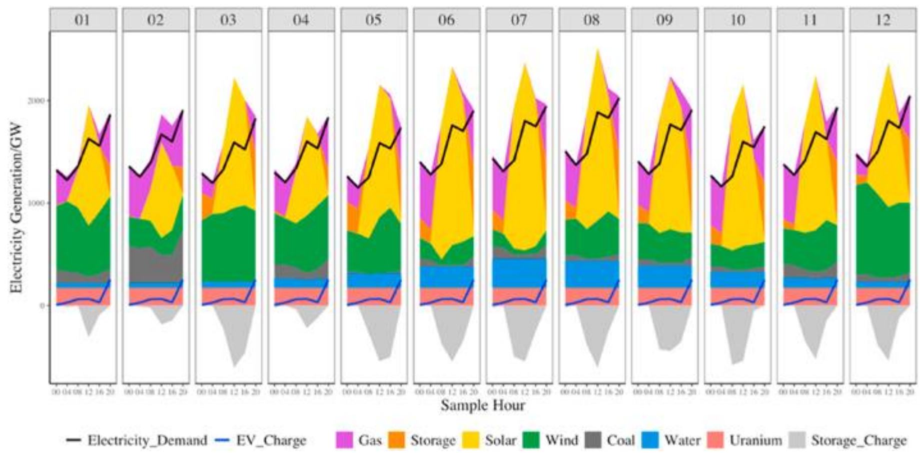

Fig. 8. Hourly Dispatch Schedule in "C70-AEV-UC" Scenario in 2050. The figure depicts 6 h per day, two days per month, and twelve months. Each vertical line separates the months, each of which contains one days. Total generation exceeds load because of local distribution transmission, transmission line losses, storage charge and discharge losses.

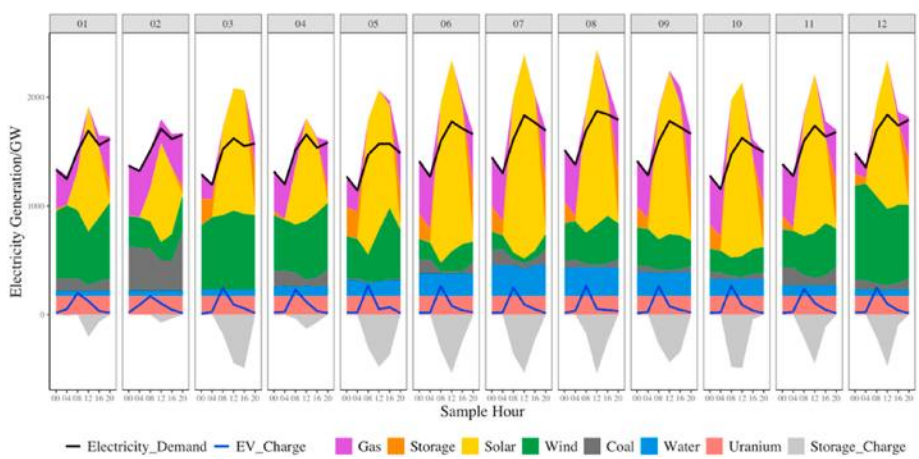

Fig. 9. Hourly dispatch schedule in "C70-AEV–SC–100" scenario in 2050.

capacity mixes. This dramatically changes electricity power system operating characteristics, such as load balancing and ramping flexibility. In the "C70" scenario, large-scale storage systems (8.8% of total generation capacity) are deployed to improve nighttime flexibility and to smooth the output timing of renewables. Gas-fired plants are attractive for providing flexibility in the absence of solar because of their relatively low capital cost, a high degree of efficiency, operational flexibility, and lower CO_2 emissions factors (kg CO_2/kWh), despite having a higher fuel price than coal.

Though the charging demand of EVs accounts for less than 6% of electricity demand in 2050, charging behaviors of EVs have notable impacts on grid operation in terms of the peak load demand and load rate. Most of unmanaged charging power occurs during 17:30–24:00, when private EVs plug in at home, which significantly increases national peak demand. As shown in Table 13, under the moderate EV adoption level, peak load increase by 5.2%. In contrast, with a 100% participation rate of smart charging, peak load only increases by 1.3%. This pattern is even more pronounced at the aggressive EV adoption levels, where additional peak demand would be only 3% of national peak demand, compared with 12.5% given an unmanaged charging scenario, resulting in a more stable baseload and a reduction in the need for additional generation capacity and local T&D capacity. It is worth pointing out that a higher participation rate in smart charging would result in a larger reduction in peak load and a higher increase in the system load rate.

These results suggest that the EV charging power, as a flexible load, has a significant technical potential for optimizing hourly grid

Table 13
Peak and valley demand, and load factor of the power system in 2050.

Scenario	Peak load/GW	Difference/%	Valley load/GW	Difference/%	Load rate/%	Difference/%
BAU	1817.7	Reference	1122.8	Reference	80.3	Reference
C70	1817.7	0	1122.8	0	80.3	0
C70-MEV-UC	1911.9	5.2	1143.6	1.9	78.5	−2.2
C70-MEV–SC–50	1863.6	2.5	1131.9	0.8	80.5	0.2
C70-MEV–SC–100	1842.1	1.3	1131.1	0.7	81.5	1.5
C70-AEV-UC	2044.3	12.5	1151.6	2.6	75.2	−6.4
C70-AEV–SC–50	1918.5	5.5	1135.2	1.1	80.1	−0.2
C70-AEV–SC–100	1873	3	1143.6	1.9	82.1	2.2

operation. If smart charging is successfully applied, EV charging can increases the power system load rate and reduce the peak demand. Developing generation plants with the high performance of flexibility, efficiency and low CO_2 emissions factors are crucial to providing backup or generation in the absence of renewable energy.

4. Conclusions and policy implications

Previous literature, including (Gambhir et al., 2015; Hao et al., 2015; Hartmann and Özdemir, 2011; Li et al., 2016), describes the economic and environmental benefits of smart charging. However, most prior works either do not fully consider or over-simplify the additional power system costs to support a large-scale EV integration, as well the changes required in grid operation to sustain a low-carbon energy mix. The effect of this omission is that limiting factors stemming from the simultaneous implementation of both strategies may restrict the reported benefits of each. This paper has investigated the impacts on China's power system of deploying EVs at large scale, in terms of power generation and hourly grid operation, generation capacity mix, environmental impacts, and economic impacts. We have also explored how to better improve both the value of and synergies of the electricity sector and the transportation system. Using the SWITCH-China model, we quantify the least-cost pathway towards both meeting future CO_2 emissions constraints and also meeting additional demand set by the deployment of EVs by optimizing capacity expansion, hourly generation dispatch and instantaneous EV charging.

We find that, in order to achieve a 70% carbon emissions reduction from the emissions level in 2014 by 2050, the following measures are needed: (1) A rapid deployment in solar and wind capacity. An average annual growth rate of 86 GW of solar and 54 GW of wind from 2020 to 2050 will meet emission targets by 2050. (2) A coal capacity phase-out. With the forecasted decrease in coal capacity factor observed in high carbon cap scenarios, phasing out around 43% of coal capacity over the next three decades may be necessary. (3) Additional grid flexibility. As the proportion of solar and wind capacity rises, more flexible generation resources, such as gas-fired plants and storage systems, or more flexible loads that can quickly ramp up or down will be needed to ensure system electricity load balance.

The Chinese government is working on a timeline for the development of EVs through 2030. Given the large-scale EV deployment pathway we consider – around 340 million EVs in 2050 in the aggressive EV adoption scenario, such large-scale deployment of EVs would provide solid environment benefits. Moreover, by 2050, EVs outperform gasoline-driven vehicles in terms of average CO_2 emissions per kilometer at national level, almost a tenth of the emissions coming from gasoline-driven vehicles. As a consequence, although we see that in aggressive EV adoption scenario, the power system's CO_2 emissions are at around 61.06–62.87 Mt per year by 2050, we note that this offsets CO_2 emissions by about 725.3 Mt from transportation sector. Thus, it can be concluded that an aggressive EVs deployment scenario would significantly decrease overall CO_2 emissions in the future.

If this development of EVs is coupled with existing decarbonization efforts within the power system, China can pave the way now to succeed in meeting its ambitious targets within the next decades. To initiate this transition, we find that by 2050 China's power system costs will be at 98.6 $/MWh, 49.3% higher than in the "BAU" scenario, in order to satisfy carbon cap constraint. Moreover, system costs will be at 108.1 $/MWh as a result of infrastructure needs to match a large-scale deployment of EVs. In fact, a large development of EVs to alternate gasoline-driven vehicles will require considerable additional investment in the short-term for both the transportation sector and the power sector, as levelized costs of driving (LCOD) of gasoline-driven vehicles are expected to be lower than EV in the short-term. However, over the 2050 horizon, EVs will become cost-competitive to gasoline-driven vehicles, the LCOD of EVs reaching even lower levels than gasoline-driven vehicles. Therefore, a large-scale deployment of EVs, coupled with more aggressive carbon cap transition of power sector, is a most likely cost-effective option to meet China's ambitious carbon cap target for both power sector and transportation sector in the future.

In terms of generation capacity mix, power generation, and hourly grid impacts, the decarbonization process of China's power system needs more flexible generation to incorporate renewables on a large scale. When coupled with EV charging demand, unmanaged charging results show that times of charging demand from EVs correlate with times of evening peak demand on the national level. The peak load would increase substantially, which has a significant impact on the synergistic operation between gas-fired plants, storage systems and solar PV, as described in Section 3.2. This increase in peak load cannot be satisfied without additional investments in generation capacity, especially gas-fired power plants and storage with high flexibility. Yet, with the increasing amount of EVs, fluctuations in power system operation increase, so it is imperative to investigate how to shift EV charging demand to times of low national demand. In contrast, optimizing EV charging to serve the grid in a way that would defer the construction of new generation capacity and diminish the growth in electricity demand is already possible. If smart charging is done, charging demand rises in the off-peak time to avoid additional peak demand and to reduce the need for power generation from gas-fired power plants and storage in the times of evening peak demand during the absence of solar generation. The electricity demand in moderate EV adoption scenarios can be met without additional generation capacity at 100% participation in smart charging. Therefore, even with a low participation rate in smart charging, using EVs as grid support can have favorable effects on the load rate.

The difference in system total cost savings between smart charging and unmanaged charging suggests that smart charging provides total cost reductions in all the scenarios that we explored. Annually, China's power system can save total costs between $9 to $75 billion by managing EVs with smart charging by 2050. The introduction of managed charging reduces the average costs per EV between $43 to $123 annually. Therefore, between 3% and 9.6% of total costs are avoided annually by managing EV charging behavior, compared with an unmanaged charging strategy. Strategies that prioritize saving system costs should deliver subsidies to drivers who participate in smart charging programs, should build more charging infrastructure, and should upgrade local transmission systems to improve the ability for EVs to respond to demand, ultimately increasing their market share.

Our method has several limitations. Although it accounts for how smart charging, market share of EVs and decarbonization policies of the power system affect the Chinese power sector's long-term generation capacity and transmission line expansion, system costs, this method does not predict the stock of EVs, which is an exogenous input, and it ignores the difference in driving behaviors between different provinces. Similarly, it does not account for how the time-of-use electricity prices affect the EVs users' response to participate in the smart charging program. Other generation technologies, like nuclear, hydro power, geothermal, and biomass, may need more uncertainty to the application of available technologies. Forecasting fuel price and capital costs of generation technologies may change decisions to install new technologies over time. Electricity demand forecasts and capital cost assumptions are embedded with uncertainties. Other growing policy methods, such as a carbon tax which has already been launched in some pilot cities, as well as a national renewable portfolio standard (RPS) target set for 2020 and 2030, may add more complex power sector interactions. In the future, we plan to include more uncertainty analyses. Future works of the SWITCH-China will also consider the synergies of a carbon tax, RPS targets, and demand response. Other reason for this paper is to make all of the tools needed for other researchers, policy makers, and industrial companies to interrogate additional scenarios. We are examining a range of policy and market cases that focus on an expansion of the RPS scenario, and will release a set of papers focused on the emerging carbon market, job creation scenarios in the evolving energy sector, and on models that are stochastic and based on uncertainties in future energy demand, technology costs, and regional power pool connections.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Bo Li: Data curation, Formal analysis, Methodology, Software, Writing - original draft, Writing - review & editing. **Ziming Ma**: Data curation, Formal analysis, Software, Writing - review & editing. **Patricia Hidalgo-Gonzalez**: Investigation, Software, Writing - review & editing. **Alex Lathem**: Data curation, Software. **Natalie Fedorova**: Data curation, Formal analysis, Software, Writing - review & editing. **Gang He**: Data curation, Software, Writing - review & editing. **Haiwang Zhong**: Critical revision of the article, Investigation, Writing - review & editing. **Minyou Chen**: Critical revision of the article, Project administration, Funding acquisition, Writing - review & editing. **Daniel M. Kammen**: Critical revision of the article, Supervision, Funding acquisition, Project administration, Resources, Writing - review & editing.

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Appendix D. Supplementary data

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The supplementary is available on https://1drv.ms/w/s!AnfdntpX-yxegYEYSnMWQtnG0svRRg.

Appendix. A. The SWITCH-China Model

The SWITCH model is a capacity expansion and dispatch model of the power system. Using the SWITCH-China model, we model the entire Chinese power system. The model is a linear program to minimize the sum of all investment and operation costs, including (1) capital costs of new and existing generators; (2) fixed O&M costs of all generators; (3) variable costs of all generators; (4) fuel costs; (5) transmission lines costs, and local transmission and distribution (T&D) costs; (6) fixed O&M costs of new and existing transmission lines, and local T&D.

The model has five basic constraints: power balance constraints, conventional unit commitment constraints, generation technologies resources constraints, planning and operation marginal reserves constraints, and policy constraints. Extending the conventional unit commitment model, the SWTICH-China model considers the optimization dispatch for EV charging, as well as carbon emission constraints, natural resource limits of renewables. Reserve margin targets are provided by thermal plants, big hydro power plant and storage units. The planning reserve requires that enough power plant and transmission capacity are built to provide a capacity reserve margin. Additionally, the spinning reserve requirement is calculated as a percentage of load plus a percentage of intermittent generation in each balancing area in each hour. We use a simple and flexible model of spinning reserves that tracks the state of unit commitment and dispatched capacity to ensures that the generation fleet has enough up- and down-ramping capacity to satisfy reserve requirements. The unit commitment module is a prerequisite for spinning reserves. The detailed formulation of the SWITCH-China model is shown in supplementary.

The model data inputs, including power plants information, transmissions, capital costs of generation technologies assumptions, O&M costs of generation technologies assumption, capital costs of transmissions and local T&D assumptions, O&M costs of transmissions and local T&D assumptions, fuel costs, demand projection assumptions, renewables electricity generation profiles are based on (He et al, 2016, 2020). Besides, the update to the SWITCH-China model is shown in supplementary.

Appendix. B. The calculation of emissions and costs for both transportation sector and power sector

The charging demand of EVs is calculated by aggregating different vehicle types in each year:

$$ED_{y,m} = \sum_{model} \frac{Stock_{y,m} \times VKT_{y,m} \times FE_{y,m}}{Charge_{y,m}}$$

where, $ED_{y,m}$ (kWh) represents energy demand of EVs of type m in year y; $Stock_{y,m}$ represents vehicles stock of EVs of type m in year y; $VKT_{y,m}$ $(units)$ represents annual vehicle travel distance stock of EVs of type m in year y; $FE_{y,m}$ (km/kWh) represents fuel economy of EVs of type m in year y; $Charge_{y,m}(\%)$ is charging efficiency of EVs of type m in year y, assuming to be 95% in all periods.

In order to compare the costs savings and emissions differences in both the power sector and transportation sector. We created two EVs deployment scenarios that are based on the same vehicles stock projections but differ in the share of EVs versus ICEVs.

The emissions TE in period y from each vehicle type i and each drive-train type j are calculated as follows:

$$TE_y = \sum_i \sum_j p_i d_i s_{i,j} e_{i,j} f_j$$

where, p_i is the stock of vehicle type i, d_i is the vehicle kilometers travel of vehicle type i, $s_{i,j}$ is the share of drive-train type j for vehicle type i, $e_{i,j}$ is the energy consumption per unit travel distance of drive-train type j for vehicle type i, f_j is the co2 emission per unit energy consumption of drive-train type j.

The levelized cost of driving of conventional vehicles and EVs are shown as follow (Hao et al., 2015):

$$LCOD = \frac{PC + AC + \sum_{i=1}^{n} \frac{(FC_i + OM_i + IC_i)}{(1+dr)^{i-1}}}{\sum_{i=1}^{n} VKT_i}$$

where, *LCOD* is the levelized cost of driving of vehicles ($/km); *PC* is the vehicle purchase cost; FC_i is the fuel cost at vehicle age *i*; OM_i is the O&M cost at vehicle age *i*; IC_i is power system integration costs at vehicle age *i*. *AC* is the charging infrastructure cost (only for EVs); *dr* is the discount rate; VKT_i is annual vehicle travel distance at vehicle age *i*.

The detailed calculations of LCOD are formulated as follows:

$$FC = FE \cdot FP \cdot VKT$$

$$IC = PIC + SCC$$

where, *FE* is fuel efficiency of vehicle (L/100 km for ICEV or kWh/100 km for EV); *FP* is fuel price ($/L for ICEVs or $/kWh for EVs), and electricity price is used by average energy costs from the SWITCH-China model; *PIC* is the additional power system costs per EV as the cost of integrating a particular amount of EVs; *SCC* is the implementation costs of smart charging.

Data input	Major assumption	Notes
Vehicle cost estimate	By 2050 most electric vehicle costs are approximately equal to the ICE vehicle, at $14200.	Gambhir et al. (2015)
O&M costs	8% of the purchase costs for EVs and ICEVs.	Gambhir et al. (2015)
Fuel efficiency	EVs 12 kWh/100 km. Gasoline-driven vehicles 6 L/100 km	Gambhir et al. (2015)
Vehicle kilometer travel distance	ICEVs and EVs13600 km per year	Huo et al. (2012)
Vehicle median lifetime	12 years (ICEVs), 10 years (EVs).	Gambhir et al. (2015)
Fuel CO_2 emissions factor	Gasoline 2.2 $kgCO_2$/L	Gambhir et al. (2015)
Fuel price	Gasoline 1$/L. High fuel price of gasoline scenario 1.4 $/L. Electricity price is average energy costs, as shown in Table 10.	U.S. EIA (2019)
EVs charging infrastructure costs	Charging infrastructure $150 per EV. Additional power system costs per EV is shown in Table 11. Implementation costs of smart charging $150 per EV.	(Göransson et al., 2010; Jian et al., 2018)
Discount rate	4%	

Appendix. C. The formulation of smart charging of EVs

The mathematical formulation of EV's flexibility is shown below:

$$0 \leq P_t^e \leq P_t^{max}\ ,\ \forall t \in T$$

$$E_t^{lower} \leq \sum_{\tau=1}^{t} \Delta\tau \times P_\tau^e \leq E_t^{upper}$$

where, *T* is the number of time interval; *t* is the duration in hours; P_t^{max} is the maximum aggregated charging power of the entire fleet at time *t*; E_t^{lower} and E_t^{upper} represents respectively the lower and upper boundaries for the aggregated energy demand of the entire fleet by time *t*, respectively; The first Equation only allows charging within the maximum aggregated charging power constraints, and does not allow the of energy back to the grid. The second Equation asserts that the cumulative charging energy must be between the upper and lower energy boundaries.

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