The impact of electric vehicle charging schemes in power system expansion planning

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Abstract

This study analyzes the impacts of the massive electrification of vehicles on the power system expansion planning and operation for the year 2030. For this purpose, a long-term generation and transmission expansion co-optimization model is used, which captures the hourly operational dynamics of the system by means of the use of representative days. This is relevant since smart charging schemes for Electric Vehicles (EVs) are available, and their benefits are intertwined with the hourly available generation (especially solar), the level of demand, and the transmission capacity. Private and public EVs' demand is considered through five main scenarios, which differ in the number of EVs and the charging strategies used (*i.e.*, upon-arrival charging or smart charging). The analysis is illustrated using the Chilean power grid. The numerical results show that a massive penetration of EVs in the Chilean power generation system will heavily encourage solar power capacity investments. Furthermore, smart charging allows for an additional increase in the solar power installed, leading (in the Chilean case) to an extra 2.4% increase in solar power generation and an additional 2.5% decrease in fossil fuel-based generation, which was commonly used to offer flexibility to the system. These effects are diminished if a high-enough level of solar power is not feasible. In addition, some sensitivity analyses are made in order to identify the specific influences of some of the model parameters.

Keywords: Power system expansion planning; Electric vehicles; Smart charging; Solar power; Flexibility

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Nomenclature:

Acronyms and abbreviations:
CO_2: carbon dioxide
EV: electric vehicle
GDP: gross domestic product
GHG: greenhouse gases
ICEV: internal combustion engine vehicle
NCRG: non-conventional renewable generation
PV: photovoltaic
RoR: run-of-river
SEN: *Sistema Eléctrico Nacional* (Chilean National Electric System)

Sets:
B: set of buses in the power system
C: set of candidate transmission lines
C_b^+: set of candidate transmission lines that end at bus *b*
C_b^-: set of candidate transmission lines that start at bus *b*
D: set of representative days
DG: set of dispatchable generation technologies (i.e., DRG, Coal, Natural Gas, and Diesel)
DRG: set of dispatchable renewable generation technologies (Biomass, large Hydro, Geothermal)
G: set of generation technologies
H: set of hours
L: set of existing transmission lines
L_b^+: set of existing transmission lines that end at bus *b*
L_b^-: set of existing transmission lines that start at bus *b*
$NCRG$: set of non-conventional renewable generation technologies (i.e., $VRG \cup DRG$, with no large Hydro)
VRG: set of variable renewable generation technologies (Solar, Wind, Run-of-River Hydro)

Parameters:
CB_c: susceptance in candidate line c (μS)
CE_c: ending bus of candidate line c
$CF_{c,d}^{max}$: maximum power flow through candidate line c during day d (MW)
CS_c: starting bus of candidate line c
CT: carbon tax cost per ton of CO_2 produced (US$/t$CO_2$)
$D_{b,d,h}$: demand in bus d for day d at hour h (MW)
$D_{b,d,h}^{EV}$: electric private vehicle demand in bus d for day d at hour h (MW)
$D_{b,d,h}^{EVT}$: electric taxi vehicle demand in bus d for day d at hour h (MW)
$D_{b,d,h}^{EVTS}$: electric bus (public transportation) demand in bus d for day d at hour h (MW)
DW_d: weight (i.e., probability of occurrence) of representative day d
$EF_{g,b}$: CO_2 emission factor for generation technology g in bus b (tCO_2/MWh)
EVS: share of electric vehicles participating in smart charging schemes
GCF_g: annual capacity factor for dispatchable technology g
GIC_g: annualized investment cost of generation technology g (US$/MW)
LB_l: susceptance in existing line l (μS)
LBU: reserve requirements as a percentage of the demand level
LE_l: ending bus of existing line l
$LF_{l,d}^{max}$: maximum power flow through existing line l during day d (MW)
LIC_c: annualized investment cost of candidate line c (US$)
LS_l: starting bus of existing line l
M: large number
$OC_{g,b}$: operational cost of generation technology g in bus b (US$/MWh)
$P_{g,b}$: initial installed capacity of generation technology g in bus b (MW)
$P_{g,b}^{max}$: maximum power capacity of generation technology g that can be installed in bus b (MW)
$R_{g,b}^{down}$: ramp down for generation technology g in bus b
$R_{g,b}^{up}$: ramp up for generation technology g in bus b
RBU: reserve requirements as a percentage of the variable renewable generation level
$RCF_{g,b,d,h}$: capacity factor for generation technology g from subset VRG in bus b for day d at hour h
REQ: renewable energy quota required in the power system
$VoLL$: value of lost load (US$/MWh)
δ^{max}: maximum phase angle (Rad)

Variables:
$cf_{c,d,h}$: power flow in candidate line c during day d at hour h (MW)
$ef_{l,d,h}$: power flow in existing line l during day d at hour h (MW)
$LS_{b,d,h}^{out}$: EV load displaced from bus b during day d at hour h (MW), due to load shifting schemes
$LS_{b,d,h}^{in}$: EV load allocated to bus b during day d at hour h (MW), due to load shifting schemes
$NonS_{b,d,h}$: lost load in bus b during day d at hour h (MW)
$r_{g,b,d,h}$: reserve provided by generation technology g in bus b during day d at hour h (MW)
$q_{g,b,d,h}$: power output by generation technology g in bus b during day d at hour h (MW)
X_c: binary variable that is equal to 1 if candidate line c is built, and 0 otherwise
$Y_{g,b}$: new installed capacity of generation technology g in bus b (MW)
$\delta_{b,d,h}$: phase angle in bus b during day d at hour h (Rad)

1. Introduction

CO_2 emissions have been steadily rising during the last decades. In the year 2018, the transportation sector was responsible for more than a fourth of the total greenhouse gas (GHG) emissions worldwide [1]. To face this challenge, Electric Vehicles (EVs) have been proven to be a cleaner, more silent, and more energy efficient alternative to internal combustion engine vehicles (ICEVs) to combat climate change. The environmental and economic impacts of EVs are especially positive when their electricity consumption comes from renewable energy sources (RES) [2]. Because of this, they become a particularly attractive alternative in the case of countries with a large RES potential, as is the case of Chile [3]. Even though EVs present many benefits, they also face a variety of challenges in their adoption, and these have been widely studied in order to promote their acceptance [4-8]. Some of the main barriers are their higher prices, compared to ICEVs, and the so-called range anxiety, which is the fear of running out of power given the inferior range in the first EV models [9]. It has been proven that the availability of a public charging infrastructure is a reliable way to diminish range anxiety and increase EV sales [10]. Because of this, optimal charging infrastructure deployment strategies have been thoroughly studied [5,11-18].

Most EVs use Li-ion batteries, considered as the most promising technology for the near future, given its high energy density, high efficiency and long lifespan. This technology however is expensive, which is the main reason for EVs higher capital costs [8]. Nonetheless, Li-ion battery prices have shown a downward trend in recent years, which has resulted in falling prices for EVs. Due to these falling costs, some authors argue that, in the early 2020's, EVs will become competitive in terms of their investment cost compared to ICEVs and sales should rapidly increase [19,20]. In the meantime, a variety of measures (categorized as monetary and non-monetary) have been taken to promote EV adoption. Monetary incentives focus on reducing the cost for the consumer and include financial help, tax exemptions, free access to toll roads, free parking, and free use of charging stations. Non-monetary incentives include the availability of public charging infrastructure, allowing the use of bus lanes, and the use of zero-emission zones [4]. Several governments are partaking in these measures, and some have even set target years for sales bans of ICEVs, such as France, Ireland, Norway, United Kingdom, among others [21]. Considering these future trends, it becomes evident that power system expansion planning models need to incorporate EVs into their forecasts, as they could significantly affect the peak load depending on their charging patterns, along with other effects. Besides the evolving deployment of EVs, RES technologies have also been subject to a reduction in costs, due to technological investments and production learning curves [19]. The costs per kilowatt of solar Photovoltaic (PV) panels have exponentially fallen, which has allowed a rapid increase in the number of approved solar projects. This has induced continuous modifications in generation portfolio forecasts for regions with a high potential for solar energy.

Long-term electric power system expansion planning is a complex task, which needs to consider economic, environmental, technical and social aspects in its modelling. One of the most elusive aspects of the associated models is that they should strive to anticipate to technological developments and behavioral changes in their respective populations. Some of these factors are frequently ignored, such as the effect that a massive uptake of EVs could have in future energy demand, which nonetheless, could be significant.

Several studies have been carried out in recent years to anticipate to this transition, both including an increased amount of RES generation and considering the effects of EVs in the energy sector. One of the most common approaches when modelling EVs focuses on the power demand increase they would cause [7,22] and the planning modifications this implies, analyzing both generation expansion [23,24] and transmission expansion [25,26]. There are also some studies that focus on both simultaneously [27,28]. Although EVs will bring an increase in power demand, most of these studies agree on the fact that this on itself is not their most relevant impact. As mentioned earlier, a more important issue is the EV charging pattern and drivers' consumer behavior. The charging pattern will determine whether EVs will add load to the peak hours or not, if they could help to reduce energy curtailments, and if they will charge during low price hours. In absence of incentives, charging takes place upon arrival at a destination, in the workplace or at home, depending mainly on the availability of charging stations [29-31]. This charging pattern can be described as upon-arrival charging. On the other hand, optimizing and allocating EV loads to specific hours is known as smart charging [32]. Optimizing the charging patterns of vehicles has many advantages, starting with the usage of cheaper generation technologies, to making the best of the positive feedback between EVs and solar generation [33-35], up to the possibility for EVs to offer flexibility to the system and displace some more polluting flexibility providers [36]. Because of these benefits of an optimized charging pattern, an adequate incentive system has also been a matter of study, since these type of schemes critically depends on customer acceptance [37]. A more sophisticated application of EVs providing flexibility for the system comes in the way of Vehicle-to-Grid (V2G) programs. This considers that EVs are able to inject energy into the grid as well, usually under the presence of an aggregator [38-40]. In this way, EVs are able to provide more flexibility than under smart charging schemes. In theory, this means an even larger reduction in operational costs [41]. Some downsides of this concept are the need for bi-directional chargers, some inconvenience for users, and battery lifespan degradation, among others [42,43]. Some authors have made observations of the fact that many V2G studies rely heavily on strong assumptions when considering EVs discharge efficiency, such as in [44], where the authors refer to multiple works, finding that only a few of them have empirically obtained efficiency values. These efficiencies were dramatically lower than those used as assumptions in other works. As a result of this, many of the more optimistic economic evaluations could be inaccurate and would require a re-evaluation in terms of the actual V2G benefits.

Chile, as a country with large RES potential, is an interesting case study to analyze. Some works related to EVs applied to the Chilean case focus mostly on the distribution grid [45-47], or on small scale economic evaluations [48]. It has not been studied how the upcoming EV penetration in Chile will affect the system expansion, or how the share of solar power in the grid could benefit from the flexibility provided by smart charging. Nonetheless, solar power has a very high potential in Chile, as some other studies confirm [49].

The present study analyzes the impacts of a massive electrification of vehicles on the power system expansion planning, using a long-term generation and transmission expansion co-optimization model. The proposed model considers both public and private EV demand, which is implemented in the hourly operation of the system. Smart charging schemes allow the model to better take advantage of the particularities of the resulting generation portfolio. The benefits are studied in terms of total costs, marginal costs, and emission levels, among others. Real vehicle travel patterns in urban areas of Chile were used as input, along with demand forecasts for each power bus and the historical hourly capacity factors of different RES power plants. Most of these factors were conveyed into the model through representative days, obtained using clustering techniques and data from a year of real operations. Given the concerns mentioned when implementing V2G schemes, the study focuses on smart charging, with only a sensitivity test implementing a V2G exercise. There are some similar works applied to different regions, such as Germany [24] and Portugal [36]. However, none of these studies consider a co-optimization of generation and transmission expansion planning and use real vehicle travel patterns. In addition, [36] does not consider transmission expansion at all and consists of a technical feasibility optimization, instead of an economic one. Meanwhile [24] is applied to a region with a high potential for wind power, instead of solar. These last authors in fact state in their conclusions that different regions will present different results in terms of the generation technology benefited from EV integration. In this sense, this study also serves as an economic optimization of the integration of EVs in a power system in a region with high solar potential, as well as numerous hydro generation sources.

The rest of the paper is organized as follows. Section 2 provides a description of the proposed model. Section 3 gives an overview of the Chilean power system, along with the information and method used in the determination of accurate representative days. This section also presents the main case studies and sensitivity analyses considered. Section 4 presents the numerical results for all scenarios, along with the results for the sensitivity analyses. Section 5 discusses the numerical results. Finally, Section 6 concludes the paper.

2. Power generation and transmission expansion planning model

Some authors [50-52] have shown the importance of co-optimizing generation and transmission expansion decisions due to the strong interactions between both processes. Accordingly, the proposed model co-optimizes power generation and transmission expansion planning decisions, while taking rational expectations of the power market operation.

The planning of the generation and transmission expansion is formulated as a mixed-integer linear programming (MILP) problem. The objective of the model is to minimize both investment and operational costs. Investment costs are related to new power generation capacity installed and new transmission lines installed; meanwhile, operational costs consider hourly operations of generating units, CO_2 emission taxes and loss of load. The model considers an hourly resolution in each bus of the power system. The construction of new lines is seen as a discrete decision (through the use of integer variables) and the target year is set to be far enough in the future as to allow the construction of these investment decisions. The model considers hourly EV demand coming from private vehicles, electric taxis, and electric buses, as well as the option of smart charging for some of these.

2.1. Mathematical model formulation

2.1.1. Model assumptions and conditions

The main assumptions and general conditions used in the model formulation are presented here. A perfectly competitive market is assumed. The rationale for this assumption is that, although market power has been a continuous concern of power system operators worldwide, there are currently several tools and processes implemented in order to eliminate, or at least mitigate, market power. Accordingly, market power is rather limited in current power systems; so, the perfectly competitive market assumption is relatively realistic and common in power systems literature [27,28,49,52-58]. Since, under the perfect competition assumption, the decentralized profit maximizing problem is equivalent to the vertically-integrated (centralized) cost minimization problem, this work deals with the latter problem.

The proposed model is static (one-shot) in the sense that investment decisions are not annually modeled. On the contrary, a target year (far enough in the future to allow generation and transmission investments to be fully implemented) is considered. Accordingly, new generation capacity is considered as a continuous variable, since it is assumed that power generation capacity will be optimally built in the long run. This assumption agrees with the idea that this paper primarily focuses on the impacts of a massive electrification of vehicles in long-term power systems expansion planning.

As mentioned earlier, generation and transmission expansion planning is formulated as a MILP problem. The linearity of the model guarantees that the solutions found are truly the global optimal solutions. To keep the model's linearity, generation marginal costs are assumed constant, using a linear approximation of the actual operation cost curves. In addition, the model's linearity is also a consequence of making a DC approximation of both Kirchhoff's Currents Law (energy balance constraint) and Kirchhoff's Voltages Law; as well as a consequence of ignoring power transmission losses.

The model is deterministic (although the reader might consider that it accounts for uncertainty through the use of representative days, as explained in Section 3.3). Regarding the vehicles, for simplicity, this work refers only to battery EVs (i.e., hybrid vehicles are not considered).

2.1.2. Objective function

The objective function minimizes total annualized system costs in terms of: new lines to be built, new generation capacity to be installed, operation of generating units, carbon taxes, and non-supplied energy. As detailed in (1), investment costs consider the sets of candidate lines (C), buses (B), and generation technologies (G). Regarding investment decisions, X_c is an integer variable representing if candidate line c is built, while LIC_c is the annualized investment cost associated with the construction of candidate line c. $Y_{g,b}$ is a decision variable representing the amount of new capacity built of generation technology g in bus b in MW, while GIC_g represents the annualized investment cost per MW of built capacity of generation technology g in US$/MW. Operational costs consider the sets of generation technologies, buses, representative days (D) and hours (H). $q_{g,b,d,h}$ is a decision variable representing the amount of power in MW produced by generation technology g in bus b during day d at hour h. DW_d is the weight associated with the representative day d. This weight is used for turning a few representative days into a full year of operation, accounting for the same level of demand, while representing an accurate distribution of how frequent a type of day is during a year. $OC_{g,b}$ is the variable cost per MWh of energy produced by generation technology g in bus b, expressed in US$/MWh. $EF_{g,b}$ is the CO_2 emission factor associated with the operation of generation technology g in bus b, measured in tCO_2/MWh, while CT is the carbon tax per ton of CO_2 emitted, expressed in US$/$tCO_2$. $VoLL$ represents the value of lost load, and it is the cost incurred in when the system does not have enough generating power output to satisfy demand, measured in US$/MWh. $NonS_{b,d,h}$ represents the amount of lost load in bus b during day d at hour h, measured in MW.

$$\text{Min} \sum_{c\in C} X_c * LIC_c + \sum_{b\in B}\sum_{g\in G} Y_{g,b} * GIC_g + \sum_{g\in G}\sum_{b\in B}\sum_{d\in D}\sum_{h\in H} DW_d * q_{g,b,d,h} * (OC_{g,b} + EF_{g,b} * CT) + \sum_{b\in B}\sum_{d\in D}\sum_{h\in H} VoLL * DW_d * NonS_{b,d,h} \quad (1)$$

2.1.3. Energy balance constraint

The energy balance constraint is formulated as in (2).

$$\sum_{g\in G} q_{g,b,d,h} + \sum_{l\in L_b^+} ef_{l,d,h} - \sum_{l\in L_b^-} ef_{l,d,h} + \sum_{c\in C_b^+} cf_{c,d,h} - \sum_{c\in C_b^-} cf_{c,d,h} + LS_{b,d,h}^{out} = D_{b,d,h} + D_{b,d,h}^{EV} + D_{b,d,h}^{EVT} + D_{b,d,h}^{EVTS} - NonS_{b,d,h} + LS_{b,d,h}^{in} \ : \ \forall\, d \in D, h \in H, b \in B \quad (2)$$

Eq. (2) presents the energy balance equation (i.e., Kirchhoff's Current Law) for each bus of the power system, linearized as in [59]. This considers generation at each bus, power flow through existing and candidate lines (both incoming and outgoing), power demand, and loss of load. In certain cases, this includes EV loads and displacement of load due to smart charging. EV loads consider the efficiency of chargers.

2.1.4. Transmission constraints

The transmission network constraints can be formulated as in (3) - (7).

$$-\delta^{max} \le \delta_{b,d,h} \le \delta^{max} \quad : \quad \forall\, b \in B, d \in D, h \in H \quad (3)$$

$$ef_{l,d,h} = LB_l * \left(\delta_{s,d,h} - \delta_{k.d.h}\right) \ : \ \forall\, d \in D, h \in H, l \in L, s \in LS_l, k \in LE_l, s \ne k \quad (4)$$

$$-M*(1-X_c) \leq cf_{c,d,h} - CB_c * \left(\delta_{s,d,h} - \delta_{k.d.h}\right) \leq M*(1-X_c) : \forall\, d \in D, h \in H, c \in C, s \in CS_c, k \in CE_c, s \neq k \quad (5)$$

$$-LF_{l,d}^{max} \leq ef_{l,d,h} \leq LF_{l,d}^{max}:\ \forall\, l \in L, d \in D, h \in H \quad (6)$$

$$-CF_{c,d}^{max} * X_c \leq cf_{c,d,h} \leq CF_{c,d}^{max} * X_c :\ \forall\, c \in C, d \in D, h \in H \quad (7)$$

Eq. (3) sets the limits for phase angles. Eqs. (4) and (5) correspond to the linear DC approximation of Kirchhoff's Voltage Law to compute power flows through both existing and candidate lines [59]. Eqs. (6) and (7) limit the power flow through both existing and candidate lines according to their technical thermal limits.

2.1.5. Generation constraints

The generation constraints are formulated as in (8) - (13).

$$q_{g,b,d,h} \leq RCF_{g,b,d,h} * (P_{g,b} + Y_{g,b})\ :\ \forall\, g \in VRG, b \in B, d \in D, h \in H \quad (8)$$

$$\sum_{d \in D} \sum_{h \in H} q_{g,b,d,h} \leq GCF_g * \left(P_{g,b} + Y_{g,b}\right) * H * D\ :\ \forall\, g \in DG, b \in B \quad (9)$$

$$q_{g,b,d,h} \leq P_{g,b} + Y_{g,b}\ :\ \forall\, g \in DG, b \in B, d \in D, h \in H \quad (10)$$

$$q_{g,b,d,h-1} - R_{g,b}^{down} * (P_{g,b} + Y_{g,b}) \leq q_{g,b,d,h} \leq q_{g,b,d,h-1} + R_{g,b}^{up} * (P_{g,b} + Y_{g,b})\ :\ \forall\, g \in DG, b \in B, d \in D, h \in \{2..H\} \quad (11)$$

$$q_{g,b,d,24} - R_{g,b}^{down} * (P_{g,b} + Y_{g,b}) \leq q_{g,b,d,h} \leq q_{g,b,d,24} + R_{g,b}^{up} * (P_{g,b} + Y_{g,b})\ :\ \forall\, g \in DG, b \in B, d \in D, h = 1 \quad (12)$$

$$Y_{g,b} \leq P_{g,b}^{max}\ :\quad \forall\, g \in G, b \in B \quad (13)$$

Eq. (8) defines the power output for RES generation, according to their historical hourly capacity factors per bus. Constraints (9) and (10) define the power output for dispatchable generators according to their annual capacity factor and hourly maximum capacities. Eqs. (11) and (12) limit the hourly differences in generation, according to the power units' ramp rates. Constraint (13) limits the capacity to be installed for every technology in each bus, according to their technical maximums.

2.1.6. Reserve requirements and quota constraints

The power reserve constraints and quota constraints are formulated as in (15) - (17) and (14), respectively.

$$\sum_{g \in NCRG} \sum_{b \in B} \sum_{d \in D} \sum_{h \in H} q_{g,b,d,h} \geq REQ * \sum_{b \in B} \sum_{d \in D} \sum_{h \in H}\left(D_{b,d,h} + D_{b,d,h}^{EV} + D_{b,d,h}^{EVT} + D_{b,d,h}^{EVTS}\right) \quad (14)$$

$$r_{g,b,d,h} \leq P_{g,b} + Y_{g,b} - q_{g,b,d,h}\ :\ \forall\, g \in DG, b \in B, d \in D, h \in H \quad (15)$$

$$r_{g,b,d,h} \leq R_{g,b}^{Up} * (P_{g,b} + Y_{g,b})\ :\ \forall\, g \in DG, b \in B, d \in D, h \in H \quad (16)$$

$$\sum_{b \in B} \sum_{g \in DG} r_{g,b,d,h} \geq \left(\sum_{b \in B} \sum_{g \in VRG} RBU * q_{g,b,d,h} + \sum_{b \in B} LBU * \left(D_{b,d,h} + D_{b,d,h}^{EV} + D_{b,d,h}^{EVT} + D_{b,d,h}^{EVTS}\right)\right)\ :\ \forall\ d \in D, h \in H \quad (17)$$

Constraint (14) sets a RES quota. Constraint (15) limits the reserve capacity that a dispatchable generator can provide, in function of its initial and newly installed capacity, and hourly power dispatch. Constraint (16) limits it in terms of the power units' ramp rates. Constraint (17) sets the minimal reserve requirements for the system accounting for a margin of error in demand forecasts, as well as the reserve needed due to variability in RES generation.

2.1.7. Smart charging constraints

The smart EV charging constraints can be formulated as in (18) - (20).

$$\sum_{h\in H} LS^{in}_{b,d,h} = \sum_{h\in H} LS^{out}_{b,d,h} \; : \forall\, b \in B, d \in D \tag{18}$$

$$LS^{out}_{b,d,h} \le D^{EV}_{b,d,h} + D^{EVT}_{b,d,h} \; : \forall\, b \in B, d \in D, h \in H \tag{19}$$

$$\sum_{h\in H} LS^{out}_{b,d,h} \le EVS * \sum_{h\in H}\left(D^{EV}_{b,d,h} + D^{EVT}_{b,d,h}\right) \; : \forall\, b \in B, d \in D \tag{20}$$

Constraint (18) establishes that the total amount of shifted EV load in a power bus and day must be assigned completely to hours of the same day in the same power bus. Constraint (19) ensures that the amount of EV load displaced during an hour cannot be higher than the hourly demand requirements of EVs and electric taxis, which are the vehicles considered for smart charging schemes. Constraint (20) limits the daily load displacements according to the total daily demand in each bus attributed to the share of EVs participating in smart charging schemes.

For the reference scenario (no EVs), EV demand is not considered in the model, therefore $D^{EV}_{b,d,h} = D^{EVT}_{b,d,h} = D^{EVTS}_{b,d,h} = 0 \;\forall\, b \in B, d \in D, h \in H$ in that case. For cases that do not consider smart charging, the variables $LS^{in}_{b,d,h}$ and $LS^{out}_{b,d,h}$ are set to 0 in (2).

2.2. Electric vehicle demand forecast

The level of EV adoption reached by a country depends on a large number of factors [60,61]. Therefore, it is uncertain whether a forecast of EVs will be insufficient or overly optimistic in contrast to the actual adoption level reached. However, this parameter is crucial in order to explain the numerical results of the model used. For this reason, two main levels of EV penetration were considered, so that the actual penetration level achieved could be contained between these levels. These levels are referred to as Low Penetration (LP) and High Penetration (HP). The determination of these scenarios was based on a review of projections for the Chilean electric fleet and a Norton – Bass model [62]. The Bass diffusion model is used to mathematically model how technological innovations will be acquired by a population over time. This considers two groups of buyers: innovators and imitators [63]. Meanwhile the Norton – Bass model includes the possibility for a new generation of the technology appearing, which could present better features or lower prices than previous generations, and have better acceptance [62]. This model is applied in Section 3.2 to forecast both levels of EV penetration in the case studies.

3. Case studies

3.1. Overview of the Chilean power system

The Chilean power system is composed of 3 systems: The National Electric System (SEN), the Electric System of Aysen (SEA) and the Electric System of Magallanes (SEM). The SEN represents 99% of the total electricity consumption and sustains 97% of the population of the country. Chile's electrical system is characterized for having a radial topology, given the country's latitudinal extension. Because of this, there are vastly different weathers according to the region observed, and therefore, RES potentials among regions vary significantly. Chile has a very high solar potential, which is located primarily in the northern zone [64].

Approximately one third of the energy consumption in Chile is attributed to the transport sector, which is responsible for 22% of the total GHG emissions of the country. The energy sector, on the other hand, is responsible for 29% of the total GHG emissions, given the country's historical dependence on fossil fuels for its energy needs [65]. In order to reduce these emission levels, Chile has adopted compromises to reduce its GHG emissions in terms of CO_2 eq per GDP in 30% to year 2030 with respect to the levels seen in 2007 [66]. In order to comply with these goals, the government has set several plans in motion to promote cleaner energy and cleaner transportation. The current legislation sets a goal of 20% of the total power generation to be produced by non-conventional RES (this is, wind, run-of-river hydro below 20MW, biomass, biogas, geothermal, solar and marine RES). Power generation in the Chilean system is still predominantly attributed to fossil fuels, which represent 54% of the generation capacity, and provide 57% of the energy consumed (coal being the most relevant one with almost 40% of the generation). Hydro power counts for 27% of the capacity and generation. The rest is non-conventional RES. Although non-conventional RES represent only 19% of the generation capacity, their potential for growth is tremendous. In the last years, Chile has made important advances in this matter, and is very close to achieving the previously mentioned goal by 2019 [65]. Renewable energy injections have been on the rise, as they went from being approximately 1,000 GWh in 2010 to 11,000 GWh in 2017, a growth of 1,100% in 7 years. Among these technologies, solar power is the predominant one. From having no active projects in the system in 2010, solar power represented 36% of the total RES generation in 2017, becoming the most relevant, and fast-growing non-conventional RES technology in the country [67].

In terms of cleaner transport alternatives, the government has shown support of EVs usage in public transport, such as public buses and taxis. This is part of the country's National Electromobility Strategy, which states a series of lines of action to promote and push EV technologies forward, such as the development of a national network of public charging infrastructure [3].

Besides Chile's high RES potential, the country possesses large deposits of copper and lithium in the north [8], and has serious pollution problems in the center and south zones, having many of the most polluted cities in South America [68]. Because of these reasons, electromobility has a high potential of being significantly beneficial in ambits such as energy independence, energy efficiency, use of natural resources and reduction of contamination indexes. Given these potential benefits, it is of great importance to foresee the impact that EVs may have in the Chilean power system expansion planning, in order to integrate this technology and make the most of its potential benefits.

3.2. Description of the case studies

The model presented in Section 2 is applied to a simplified version of the Chilean National Electric System (SEN). The Chilean system is adapted as a 45-bus grid (see, Fig.1), each bus with the capability to contain 10 different generation technologies, and joint by 156 transmission lines. Transmission expansion considers 10 candidate lines selected from the Chilean Ministry of Energy's long-term projections for the system [64], based on their potential to facilitate RES penetration and to reduce transmission congestion. Technical information, such as operational costs, existing generation, among others, were obtained from [64] as well.

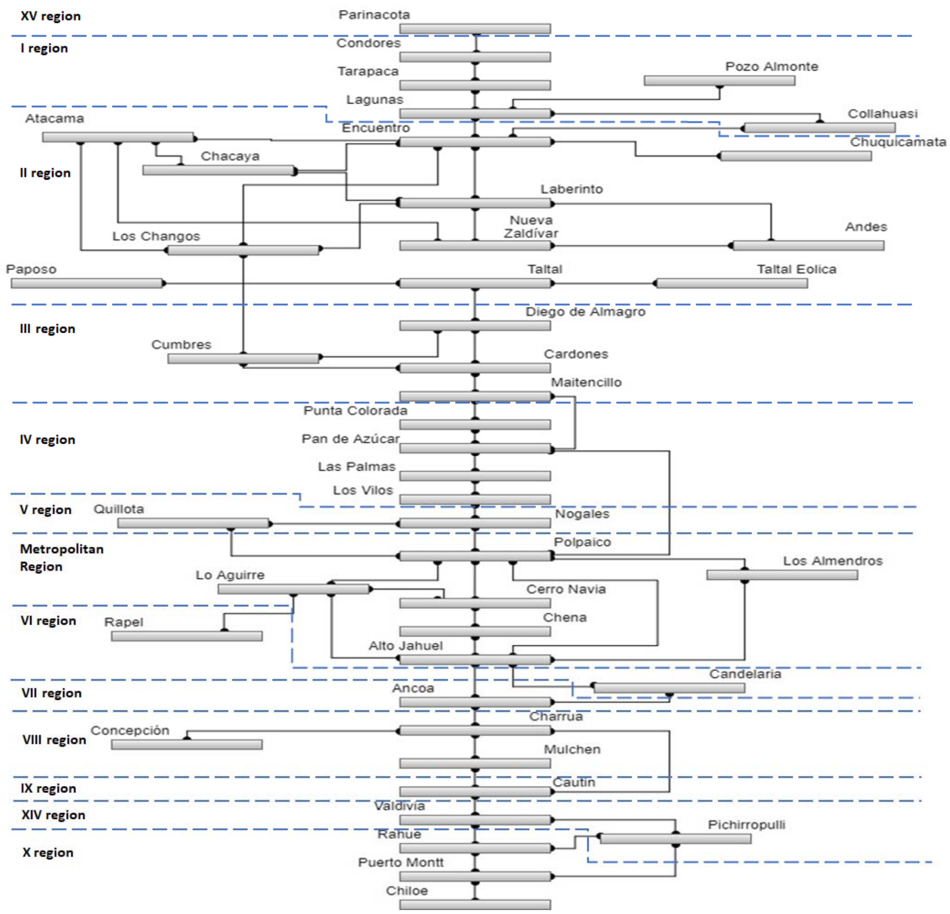


Fig. 1. Diagram of the buses used to represent the Chilean SEN

Capacity factors vary between dispatchable and non-dispatchable generators. For the first group, this factor is reduced only by the time the generator is unable to produce energy due to maintenance or unexpected failures. Because of this, the capacity factor for this type of generators is restricted to an annual value, meanwhile, the maximum hourly generation capacity is equal to the installed capacity of each power plant. Estimating the capacity factor for dispatchable generators based on their historical operation is not possible, since these are not always dispatched by the operator because of their operational costs. That is, estimating the capacity factor in function of their historical operation would imply underestimating the actual annual capacity factor of the technology. Therefore, these capacity factors are obtained from the literature for all dispatchable generation technologies [69], except for hydro dams, which are not considered in [69]. The capacity factor for hydro dams is considered as the value historically used in Chile for system expansion planning [64]. Nuclear generation of electricity is not considered since it is not in the short- nor long-term projections for the current government [64], mostly because of the great potential for generation technologies with lower costs and zero emissions, such as solar and wind. The carbon tax used is 5 US$/t$CO_2$, which is the current CO_2 tax in Chile.

For the case of non-dispatchable generators (i.e., solar, wind, and RoR hydro), their capacity factors were determined from historical data of the generation of these kind of sources during a full year of operation. This is explained in great detail in Section 3.3.

Since this study focuses on generation and transmission expansion, it is assumed that the distribution grid is robust enough as to face the demand requirements of EVs. It is also assumed that there is a sufficient enough availability of charging infrastructure as to charge both in the workplace and in residential areas. Smart charging is assumed possible for users.

Demand requirements for private EVs were obtained from statistical information contained in the Chilean Origin-Destination poll [70]. The average distance traveled by a private vehicle in Santiago is 25 km, which roughly translates into 3.9 kWh, according to the average efficiency of Chile's EV fleet [71]. These values may change in the future, but this is taken as a minimum energy efficiency. Since 40% of the national vehicle fleet is in Santiago and other cities have similar distances, this value is used in all locations. The efficiency of charging infrastructure is assumed to be 90% [21].

The spatial distribution of the vehicle fleet among the buses of the system is obtained from Chile's National Statistics Institute [72], which provides information of the full vehicle fleet by category and its distribution through the country's regions.

It is assumed that the distribution of the vehicle fleet in the country will not change in the future, just as the travel patterns seen today will not vary greatly for the year 2030. Costs or earning for users are not modelled, as it is assumed that there are time-of-use tariffs or some other incentives for users to partake in smart charging schemes, or that the system operator is able to manage EV loads.

The main levels of EV penetration were obtained using projections for the Chilean fleet and a Norton-Bass model that considers new, cheaper cohorts of EVs made available before the year of study. The Low Penetration (LP) scenario considers data of EV purchases in Chile up to 2017 [71], while the High Penetration (HP) scenario considers values obtained by Jensen et al. [60] for the EV fleet of Norway. These are both extreme scenarios and serve the purpose of containing the actual EV deployment in between of them. In consideration of both the projections seen in other studies [73] and the Norton-Bass modelling, the projections for the EV fleet in Chile for year 2030 are presented in Table 1.

Table 1
EV fleet projections

EV type	Low penetration	High penetration
Electric private vehicles	150,000	500,000
Electric taxis	28,000	53,000
Electric buses	360	3,550

According to these projections, five case studies are explored:

- Case 1: no EVs; a referential scenario with no consideration for EVs demand requirements.
- Case 2: low EV penetration (**LP**); a scenario with a low penetration of EVs and upon-arrival charging demand requirements.
- Case 3: low EV penetration with smart charging (**LPS**); the same penetration level with smart charging available.
- Case 4: high EV penetration (**HP**)
- Case 5: high EV penetration with smart charging (**HPS**)

For the cases with smart charging available, it is arbitrarily assumed that half of the EV fleet can participate in these schemes.

The hourly distribution of EV loads is derived from statistical data of daily arrival times of vehicles for trips. This information is available by category for private vehicles, taxis, and public buses. Fig. 2 shows this information for the case of private vehicles. According to the hourly share of end of trips, the daily demand requirements will be allocated to these hours in a proportionate distribution. The same process is applied to both electric taxis and electric buses. It is assumed that EVs will charge once they arrive at their destinations (i.e., upon-arrival charging). This may not be entirely accurate for public transportation, but it represents a good approximation.

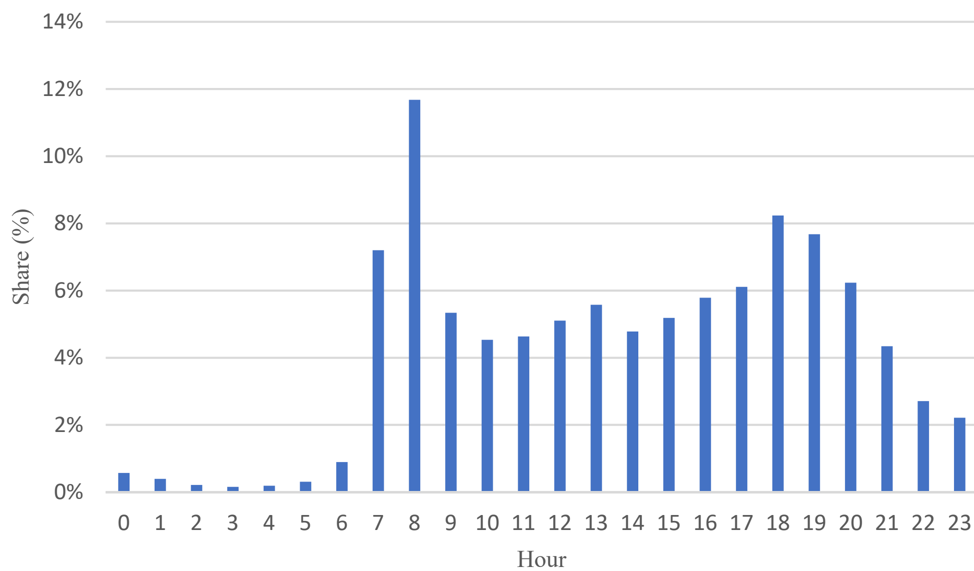


Fig. 2. Pattern of arrival time for a private vehicle trip

It is assumed that it is possible for EVs to charge their daily load requirements during a time window of 1 hour, as well as that charging infrastructure will be available in 2030 to a level where at least 50% of the fleet will have access to a point at work and at home. Current electric taxis in Chile are mostly BYD's model e6, while electric buses are BYD's model K9. Through the datasheets of these models, and the daily average distance by each public means of transport, their daily load requirements were determined [73,74]. Given the buses' high energy consumption and their operation, they were not considered as viable for smart charging schemes. Even if they had the means to charge at a higher power, their average daily consumption is too close to their battery capacity, meaning roughly half of the buses will need to charge in order to finish their daily routes. Since these routes are assigned by a private operator (Red), it is assumed they will prioritize passenger demand instead of price of electricity when charging. Electric taxis and private EVs have requirements that can be fulfilled within an hour and are well below their battery capacities, therefore these are considered to be able to postpone their charge as needed for the smart charging schemes.

The allocation of EV demand for each city is related to the distribution of the current vehicle fleet among regions and cities, and their proximity to the power system buses. It is assumed that the EV fleet will have a similar distribution by 2030.

3.3. Representative days

In order to accurately capture the operational hourly dynamics of power systems (such as demand variations and capacity factors of RES generation) throughout a year, the model considers an hourly time resolution. Since many of these factors also follow a seasonal pattern, several days are required to represent these variations correctly. This level of detail can dramatically increase the computational complexity of the problem. As a solution to this, representative days in terms of the mentioned factors are utilized. This seeks to reduce the complexity and solving time of the problem, while maintaining an appropriate representation of the operational hourly dynamics of the system. The optimal number of representative days is not trivial, and some studies have found that using around six days offers the best trade-off between resolution speed of the problem and representativity of the data [75].

For the determination of the representative days, the k-means clustering algorithm was used, and the amount of clusters used were evaluated with the “elbow method” and the Silhouette and Calinski-Harabasz criteria, as these are among the most frequently utilized in literature [76]. The input data utilized for this were the historical hourly generation of solar PV, wind, and run-of-river hydro generation technologies for the year 2016 [77], along with the forecasted hourly demand per bus for the year 2030 [64]. The clustering method was used with a variable number of clusters, and in agreement with the current literature, six days provided good metric results (as using more clusters would not improve the representativity of the information significantly and would only add to the complexity of the problem). The same number of days to represent the Chilean national electric system was also used in [49]. The resulting clusters are presented in Table 2.

Table 2
Description of clusters of representative days

Cluster	Centroid	Number of days	Assigned weight	Assigned name
1	Nov. 11	111	0.304	Summer workweek
2	May 5	86	0.236	Autumn
3	Jun. 11	45	0.123	Winter workweek
4	Aug. 12	54	0.148	Spring
5	Oct. 9	38	0.104	Summer weekend
6	May 1	31	0.085	Winter weekend

The hourly data of representative days are obtained by taking hourly average of all days within a cluster, as suggested in [75], as this keeps all the information and yearly demand level. Since the cluster centroid would be smoothed out, and the day most similar to it would be unusually smooth, when averaging the days in each cluster, the standard deviation was kept via scaling as to represent the average of all standard deviations for each variable in each cluster. Therefore, for demand, each hour for each bus was obtained as the average of all demands of that hour/bus in each cluster. The same process was done for wind and run-of-river hydro capacity factors. As for solar PV generation, since its capacity factor tends to vary between 0 and 1 in a daily cycle, the average of all days in each cluster was used. Weekends break the continuity of the temporal resolution, but for this case, tests were run in order to confirm that ramping constraints were not active during the transition from one day to another, therefore, the results were not significantly affected.

Seasons also affect the consumption of EVs, as drivers use air conditioning/heating. To include this, EV demand was scaled according to seasonal factors of 1.2 for winter and 1.1 for summer [16], while spring and autumn demands were left unchanged.

4. Results and sensitivity analyses

This section presents the results of the case studies described before. The results for the sensitivity analyses are presented as well.

4.1. Main case studies

Using the co-optimization model presented in Section 2, the five case studies described in Section 3.2 were tested. The results were obtained in terms of costs, emissions, investments, and load curves after applying smart charging, in the cases where it was relevant.

The costs in all five cases are presented in Table 3. Transmission investments were the same for all cases, since EV demand amounted to a 0.85% (LP) and to a 2.35% (HP) of the total demand of the rest of the system (thus, its impact in expansion planning is limited). Four new transmission lines are built. Two lines are in regions I and II (and they are built mainly to allow a greater integration of solar power, bringing power from the buses in the north to the rest of the system). Another line is built to increase the transmission capacity of the Metropolitan Region, which is the country's capital and holds a large part of the demand. And another line is built in the southern region, in response to the increase in demand of another relevant city in the country, Concepción. Given these results, the considered levels of EV demand will not make any significant change to transmission investment, as these lines are built mainly for other reasons. CO_2 emissions follow a similar pattern than that of total costs: both cases having smart charging schemes reduce emissions. This is because smart charging allows making a better use of the solar capacity of the system. In the same way, generation investments are slightly higher in smart charging scenarios, which in turn result in lower operational costs, making these investments an optimal long-term decision.

Table 3
Total costs for each scenario (million US$)

	No EVs	LP	LPS	HP	HPS
Generation investments	627	645	649	676	683
Transmission investments	12	12	12	12	12
Operational costs	1,637	1,655	1,647	1,687	1,673
Carbon taxes	118	119	118	122	120
Non – supplied energy	0	0	0	0	0
Total	2,394	2,430	2,426	2,496	2,487

The load curves (when applying smart charging) were obtained by multiplying the national loads seen in every representative day and their respective weights. For illustrative purposes, three curves are presented in Fig. 3. These curves are the average load of the system without considering EV demand, the average load of the system plus upon-arrival charging EV load and, finally, the average load of the system plus smart EV load. Fig. 3 presents these curves for Case 5: HPS (since Case 3: LPS yields to similar, but less prominent results). Using smart charging, the load peak is reduced and displaced from its original time position to the mid of the day (hours 12 to 17, when solar power is at its maximum potential) and early morning (hours 2 to 5, when demand is the lowest). This is because the cases analyzed consider charging at work as a possibility for all EVs applying smart charging. Part of the shifted demand is also sent to early morning hours, where demand is at its lowest level, because this allows to take advantage of some marginal generation units in the system that were already producing and can increase their output at certain hours without modifying the marginal cost of the system.

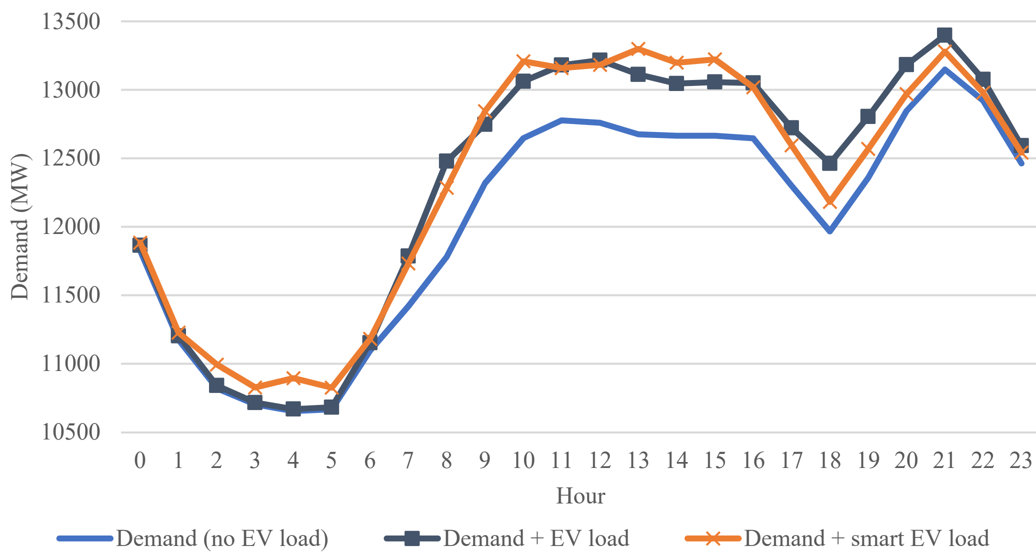


Fig. 3. Average load curves in the HPS scenario

In terms of new power capacity installed, the results are presented in Fig. 4. The main new generation technology installed is solar power, with an amount that is at least tenfold that of any other generation technology installed in any scenario. In both LP and HP scenarios, the use of smart charging allows for a larger capacity of solar power installed, being HPS the case with the highest capacity of solar power installed, followed by the LPS scenario. This complementarity between smart charging and solar power investments is explained by the shifts observed in the load curves presented in Fig. 3. It is also interesting that wind power capacity remains the same among all scenarios, since this generation technology is less reliable (i.e., more variable) than solar, making it more difficult to be integrated into the system.

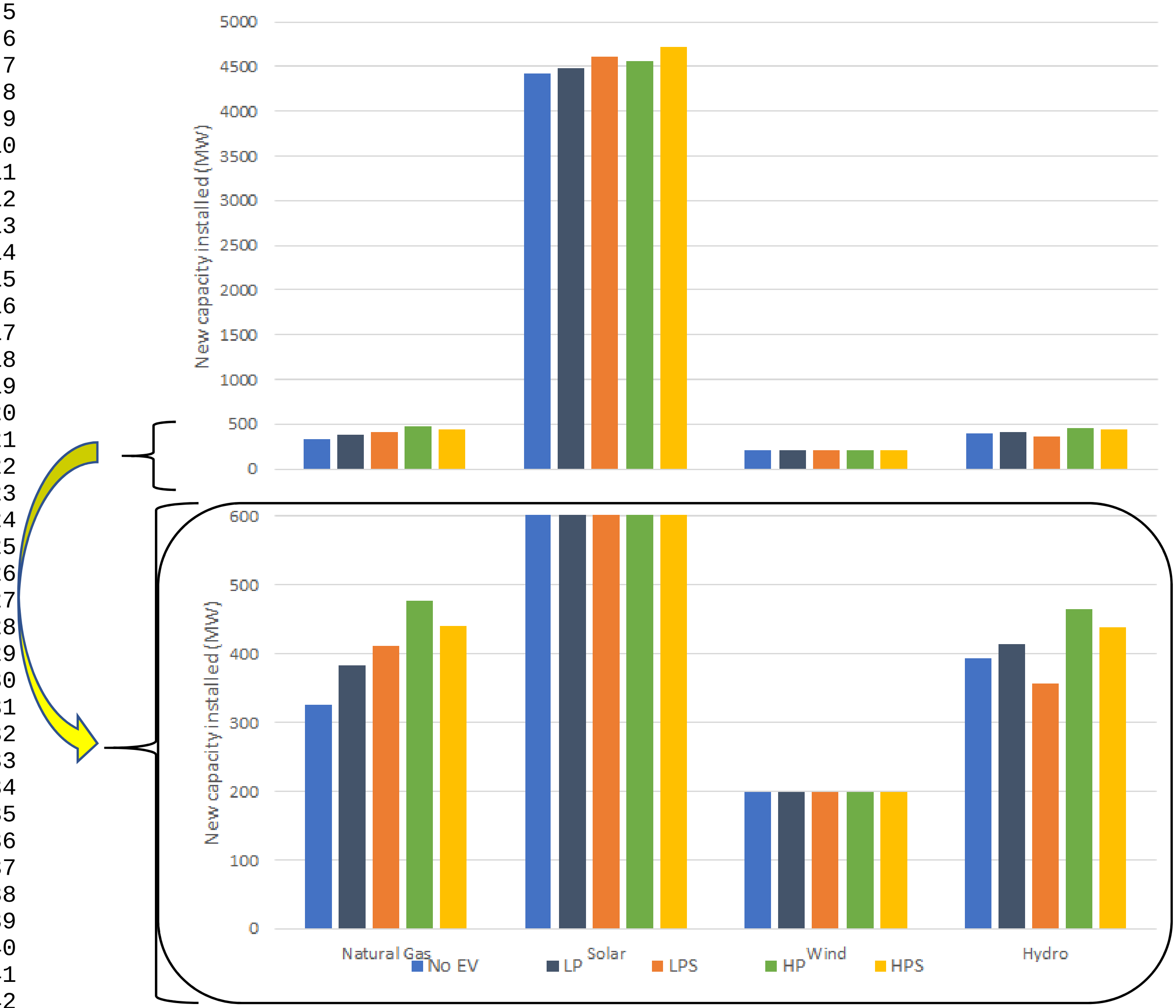


Fig. 4. New power capacity installed, in MW, in each scenario, with the lower image being a zoomed-in version of the upper one.

Although the new solar power capacity is very high, the historical generation portfolio still presents an important amount of fossil fuels. This can be seen clearly when looking at the per-technology energy generation (Table 4). Solar amounts to almost 20% of the energy generated. The highest shares for RES generation are the ones present in the LPS and HPS cases, just like the cases with the highest solar power installed. This result suggests the conclusion that a higher EV fleet participating in smart charging schemes allows for a better integration of solar power into the system. Since HP and LP scenarios present different demand levels, the differences in shares of RES between cases with and without smart charging are more notorious.[2]

[2] It is important to mention that this conclusion applies to regions with a high potential for solar power, such as it is the case for Chile.

Table 4

Energy generation per technology in each scenario (GWh)

Technology	No EVs	LP	LPS	HP	HPS
Coal	17,927.0	18,027.3	17,917.7	18,219.4	17,963.7
Natural gas	20,282.9	20,743.7	20,756.4	21,538.0	21,301.9
Oil	0.6	1.1	0.6	1.7	0.6
Total thermal	38,210.5	38,772.0	38,674.7	39,759.2	39,266.3
(%)	(36.5%)	(36.4%)	(36.3%)	(36.8%)	(36.3%)
Hydro	29,517.9	29,665.5	29,354.5	30,025.6	29,990.4
Hydro – RoR	12,293.8	12,293.8	12,293.8	12,293.8	12,293.8
Wind	3,629.8	3,629.8	3,629.8	3,629.8	3,629.8
Solar	20,579.3	20,767.0	21,163.1	21,011.9	21,517.4
Biomass	968.2	966.7	977.4	962.9	983.5
Geothermal	395.3	394.4	395.9	393.2	395.3
Total renewable	66,417.0	67,717.2	67,814.5	68,317.2	68,810.1
(%)	(63.5%)	(63.6%)	(63.7%)	(63.2%)	(63.7%)
Total	104,627.5	106,489.2	106,489.2	108,076.4	108,076.4

The decision to displace part of the load into the daytime might be counterintuitive, as demand is at its lowest level during the early morning, but marginal costs justify this approach in economic terms. The curves in Fig. 5 present the marginal costs averaged per bus and per day for Case 5 (HPS), considering the demand in each bus and weight of each day. These curves are the average for all days, average for both summer days, and average for both winter days, respectively. Given the high amount of solar power present in the system, operational costs during the day are very low. As it is expected, summer days present the lowest marginal costs, and in every case, these are lower during the day. In Northern Chile, the local marginal price falls during the day in most power buses. In the south of Chile, on the contrary, there are more buses that present prices that remain constant during the whole day, because hydro power is more common. These differences are accentuated according to the season and are crucial when determining whether a bus will be benefited from smart charging schemes or not. Thus, shifting load during the summer may be more beneficial than doing it during the winter, where in some buses there may be no net benefit at all.

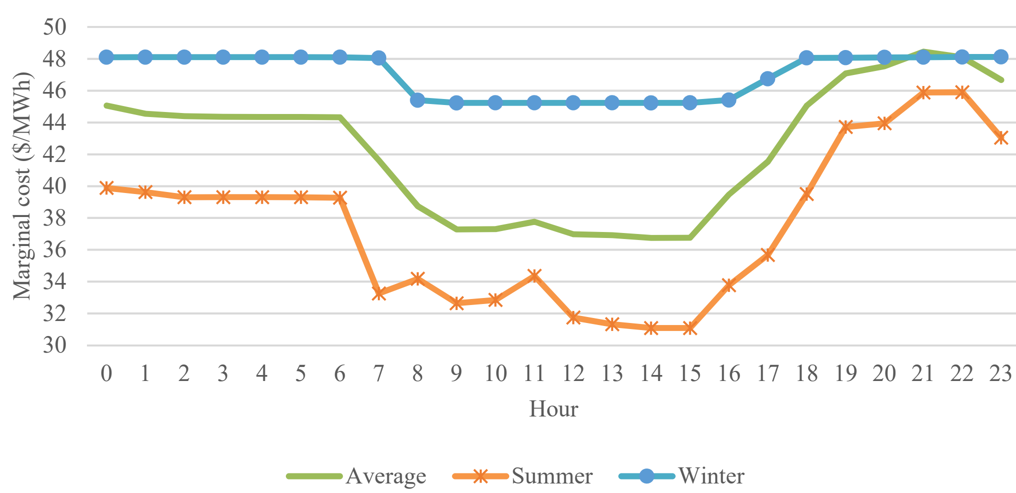
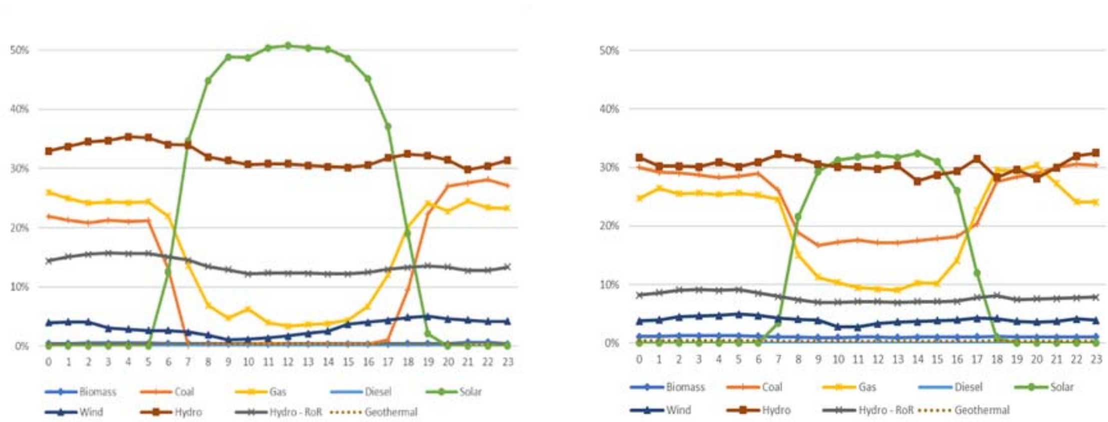


Fig. 5. Average marginal costs for the HPS scenario

As to further convey the relevance of seasonal patterns for different kinds of generation technologies, and their participation in the energy generation, Fig. 6 presents the share of energy injected per generation technology for the summer workweek days and the winter workweek days.



(A) Summer (B) Winter

Fig. 6. Energy generation share in the HPS scenario

Even during winter, where solar generation presents its lowest capacity factors, it still manages to be the highest generating technology during some hours of the day. This explains why it is convenient to displace some EV loads into mid-of-the-day hours. As mentioned earlier, for an actual implementation of these schemes, it is convenient to look at each bus separately, during each of the used representative days, in order to determine whether or not the marginal costs make it beneficial or not to have EVs participating in smart charging schemes in each bus.

4.2. Sensitivity analyses

Considering the previous results, different parameters of the model were modified in order to provide a deeper insight into their influence on the obtained results. This also allows to better understand how to ensure a better integration of RES into the generation grid, supported by the flexibility provided by EVs smart charging.

4.2.1. CO_2 tax modification

The CO_2 tax applied to all main case studies is 5 US\$/tCO_2. In this sensitivity test, the tax was modified to 0 US\$/tCO_2 and to 50 US\$/tCO_2, according to suggested amounts in [78]. For the scenario with no CO_2 tax, the number of transmission lines built remains the same, implying that, for these low amounts, the CO_2 tax does not play an important role in determining the optimal transmission expansion. Solar power installed is reduced, but still close to 80% of the new generation capacity installed, which means that even without taxes, its low capital price and operational costs are enough incentive to make it a highly competitive generation technology for the Chilean system.

Meanwhile, when implementing a CO_2 tax of 50 US\$/tCO_2, the number of transmission lines built goes from 4 to 6 when not using smart charging; and goes back to 5 when smart charging schemes are allowed. This means that, with a higher flexibility, it is possible to postpone some transmission investments. The specific line that gets delayed would increase the transmission capacity of a bus with high wind generation capacity potential, which gets built in the scenario without smart charging. Whereas, in the smart charging case, this wind farm is not built, as demand can be better allocated to adjust to the existing generation. Using a high carbon tax also implies more investments in gas generation technologies, as their emissions are lower than those of coal generation and are used as a mean to displace them. An interesting aspect is that, with this high carbon tax, the amount of wind power installed is larger when not considering EV demand than in the scenario that considers it along with smart charging. This can be explained by the high solar potential that Chile has, as it is possible to use this technology which, despite its variability in intensity, focuses on a clearly defined time window. Besides, as mentioned earlier, some of the wind power to be installed would require the construction of an extra line, while the transmission investments required for solar power were already part of the optimal planning in previous scenarios.

Without a CO_2 tax, the shifted EV demand goes mostly to early morning hours, with a small amount allocated to afternoon hours (Fig. 7). Therefore, the CO_2 tax, applied to systems with a high solar share of generation and the possibility to displace loads, is crucial in determining the optimal hours for load shifting.

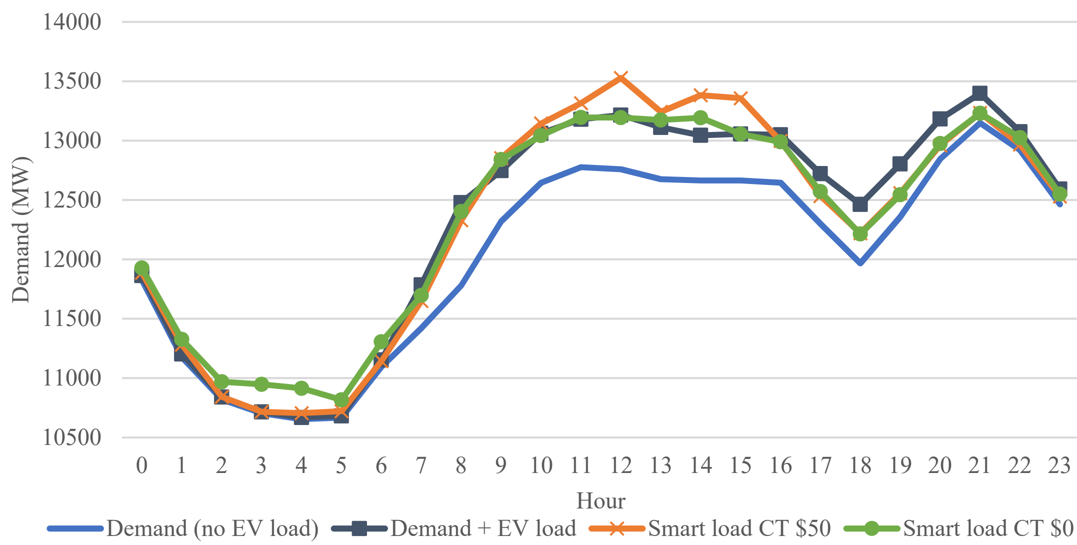


Fig. 7. Load curves in the HPS scenario with different CO_2 taxes

4.2.2. 100% electric vehicle fleet

This sensitivity test considers that all the vehicle fleet is electric. This is, for 2030, there are five million private vehicles/station wagons, 100,000 electric taxis, and 8,000 electric buses in the Chilean system. Smart charging was considered for this scenario. This scenario is beyond projections for Chile, and it is not expected to be a reality in 2030, but it is interesting as a study of how it might impact the system.

In the scenario without smart charging, five lines are installed, meanwhile, with smart charging, there are 4 new lines installed (the same than in the main case studies). This means, in the same way than the previous sensitivity test, smart charging can help delaying transmission investments. The extra line to be constructed was the same one discussed in the previous test. EV demand in this scenario reaches 11,967 GWh, which equals 11.33% of the original power demand (that did not consider EVs). Given the significant increase in demand, the amount of solar power installed now increases, especially when smart charging is available. In this particular case, for the same level of demand, over 400 MW extra of solar power are installed when smart charging is available. Solar capacity installed without smart charging is 5,401 MW and it goes up to 5,822 MW when allowing smart charging.

Given the trip patterns discussed earlier, this high increase in the EV fleet would make for a new peak of consumption at 8:00 AM if smart charging were not available (Fig. 8). Smart charging distributes this peak among the hours of high solar activity, and it also allocates some of it to the early morning hours, as seen in other cases. The load is taken from the new peak in the morning and from the late afternoon hours, when solar generation decreases. This would suggest that, when having a significant EV fleet, the time of charging will be of critical importance. Even when not focusing on the current load peak, EV demand could displace this peak, with a big enough fleet. This could go as far as having the peak load displaced to morning hours, as seen in other studies such as [29]. It is important to mention that this considers the possibility to supply part of this demand in the workplace. If this were not the case, this peak-load shifting effect would increase even further, as it would be most likely that EVs are charged at the time of arrival at home.

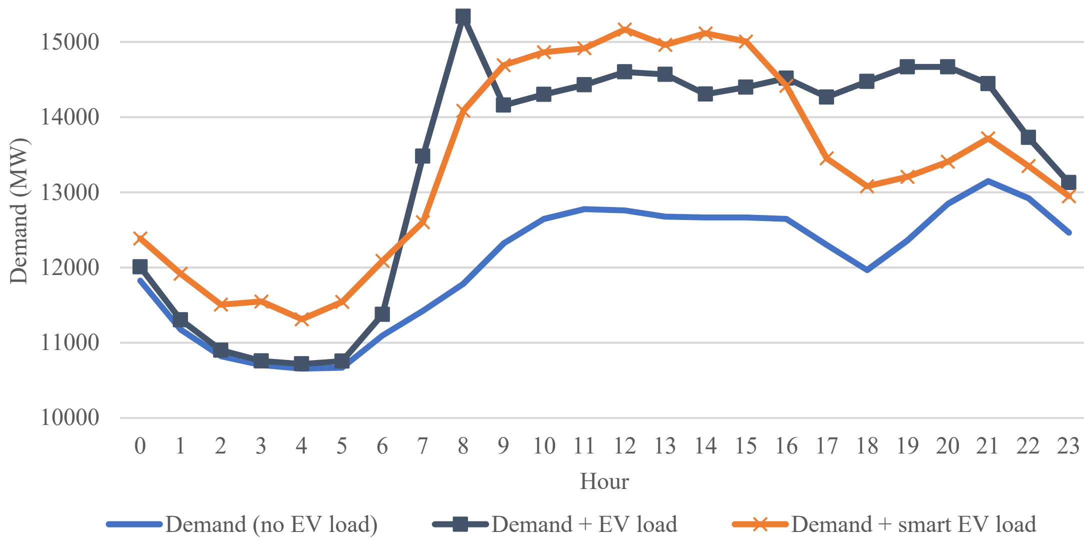


Fig. 8. Load curves for a 100% EV fleet

4.2.3. Restricted amount of new solar power

In consideration of the observed high amount of solar power installed, and its relevance in determining the optimal hour for EV charging, this sensitivity test restricts the new solar power installed. This allows to see the dependency of the results with the new solar power. The new limit is set at 2GW of additional capacity available to be installed, roughly half of the capacity optimally installed in the main case studies. This restriction is applied to Cases 1 and 5 (i.e., no EVs and HPS cases).

As it would be expected, the maximum available amount of solar power capacity is installed in this case, along with a small increase in hydro and gas generation technologies. The total capacity installed is far less than the obtained in the main case studies, which means that the high construction of solar capacity was due to its lower costs, beyond being able to cope with existing demand levels. When considering Case 1 (no EVs), one of the lines in the north of Chile is not built, and this results in some instances of non-supplied energy, but not enough as to justify the construction of the line. As an alternative, there is now a small amount of diesel installed, in order to supply energy for certain hours when transmission lines are saturated. On the other hand, when considering Case 5 (HPS), the line in the northern region is built again, since demand increases and the investment becomes justified. There is no new diesel installed and no instances of non-supplied energy in this case.

When using smart charging schemes, the shifted load goes uniquely to early morning hours (Fig. 9). Even though the solar capacity installed is significant, it is not enough as to make mid-of-the-day hours charging optimal. This means that the optimal charging hours for EVs depend critically on the amount of solar power capacity available in the case of the Chilean system. In this scenario, the load is shifted, even from hours with full solar generation. It is important to mention that these load curves are obtained from the weighted average of the national demand over all representative days. Therefore, some buses, in some seasons, may still benefit from mid-of-the-day hours charging. In conclusion, as mentioned in other studies, the optimal charging hour depends critically on the generation portfolio, and for Chile, if the solar potential was not highly exploited, the second-best alternative would be to charge in early morning hours.

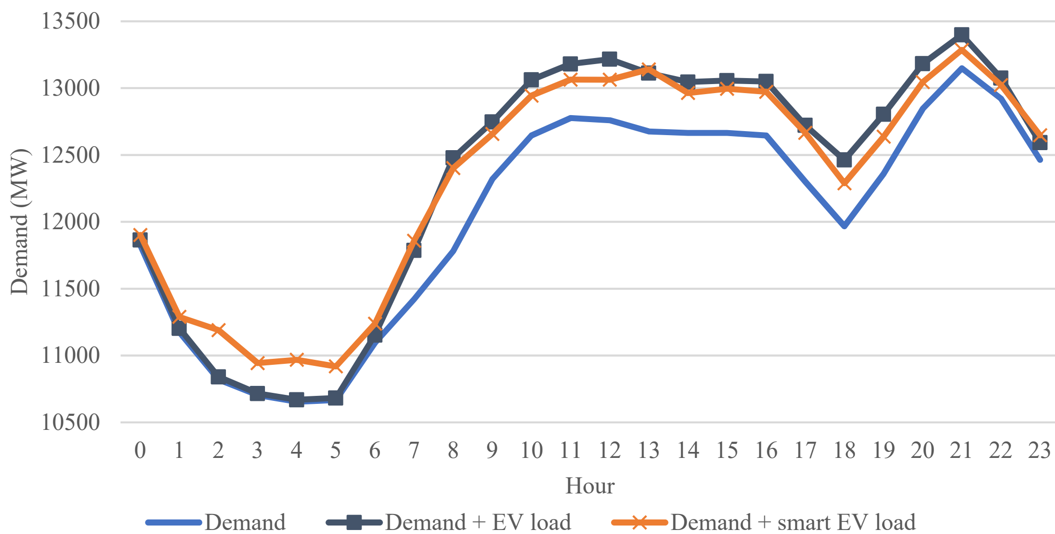


Fig. 9. Load curves in the case of restricted new solar capacity to install

4.2.4. Simple Vehicle-to-Grid (V2G) experiment

As mentioned earlier, this work does not focus on V2G given the need for further exploration in terms of its efficiency, along with there being a great number of barriers/alternatives to it as is discussed in [43]. Nonetheless, this sensitivity test modifies some model constraints in order to simulate a scenario where EVs could discharge their batteries, injecting energy into the power system. No extra costs, such as an incentive for participation, are considered, and the only additional cost comes in the way of the efficiency assumed for EV discharge. Obviously, this is an oversimplification, since generally V2G schemes must consider a cost of implementation as an incentive for the users (because of the consequences that these schemes may have in the battery's life expectancy), besides aspects of convenience and availability of the EV. Another cost to be considered is the financial cost of an aggregator, an entity in charge of implementing control mechanisms to optimize and canalize the load requirements and battery capacities of each EV participating, in order to provide a large amount of capacity [40-42]. As mentioned earlier, discharge efficiencies are highly important as well, and have a history of being overestimated [44]. In this particular exercise, discharge efficiency was assumed to be 90%, as some other theoretical studies have used. With this, the roundtrip efficiency is 81% for V2G schemes. This analysis is applied to the HP scenario.

Equations (2), (19) and (20) of the model presented in Section 2 are modified. For the case of (2), this is modified to include the efficiency when discharging an EV into the grid (η_d) as it is shown in equation (21). Equations (19) and (20) now consider the whole capacity of the EV battery, which is implemented as C_i times their daily demands, with i being the type of EV. This information for private vehicles and taxis was taken from current models in the EV fleet [71,79]. Equations (22) and (23) are derived from (19), and now must be stated separately, as they correspond to hourly charging and discharging into the grid. This means EVs cannot charge (nor discharge) more than their battery capacities. Equation (24) derives from (20), and states that the daily V2G participation of EVs must leave enough charge as to allow them to carry out their daily trips. This equation does not need to be stated again, as daily charge/discharge is bound by equation (18).

$$\sum_{g\in G} q_{g,b,d,h} + \sum_{l\in L_b^+} ef_{l,d,h} - \sum_{l\in L_b^-} ef_{l,d,h} + \sum_{c\in C_b^+} cf_{c,d,h} - \sum_{c\in C_b^-} cf_{c,d,h} + \eta_d * LS_{b,d,h}^{out} = D_{b,d,h} + D_{b,d,h}^{EV} + D_{b,d,h}^{EVT} + D_{b,d,h}^{EVTS} - NonS_{b,d,h} + LS_{b,d,h}^{in} \ : \ \forall\, d \in D, h \in H, b \in B \tag{21}$$

$$LS_{b,d,h}^{out} \leq C_{EV} * D_{b,d,h}^{EV} + C_{EVT} * D_{b,d,h}^{EVT} \ : \ \forall\, b \in B, d \in D, h \in H \tag{22}$$

$$LS_{b,d,h}^{in} \leq C_{EV} * D_{b,d,h}^{EV} + C_{EVT} * D_{b,d,h}^{EVT} \ : \ \forall\, b \in B, d \in D, h \in H \tag{23}$$

$$\sum_{h\in H} LS_{b,d,h}^{out} \leq EVS * \sum_{h\in H}\left((C_{EV} - 1) * D_{b,d,h}^{EV} + (C_{EVT} - 1) * D_{b,d,h}^{EVT}\right) \ : \ \forall\, b \in B, d \in D \tag{24}$$

The results in terms of installed new power are relatively similar, although solar capacity installed grows more because V2G provides a larger degree of flexibility to the power system. Hydro generation grows as well, meanwhile gas generation technologies suffer a reduction in its installed capacity. This can be explained since EVs participating in V2G schemes are able to offer some of the regulation ancillary services that gas used to provide. In terms of costs, the V2G exercise leads to slightly lower costs than the regular HPS scenario studied. Nonetheless, it must be kept in mind that this exercise ignored some costs associated with the implementation of V2G schemes, besides not using an empirical value for EVs discharge efficiency. In terms of transmission expansion, the line in the north of Chile is not built. For the case of buses with a high solar capacity already installed, the possibility to use EV batteries as storage allowed the model to postpone transmission investments. Roughly speaking, the operational behavior of the EV charge/discharge consisted on loading the batteries during the daytime (9:00 – 18:00) and discharging them afterwards, in order to reduce the peak load (Fig. 10). As a result, V2G moves the peak load to mid-of-the-day hours.

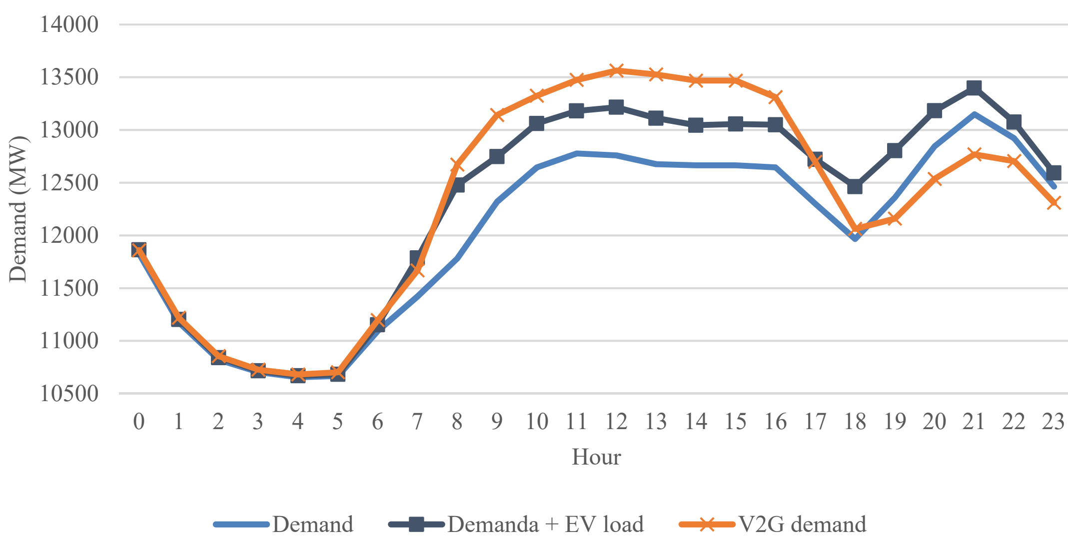


Fig. 10. Load curves for V2G applied to the HPS scenario

In addition, another run of the model was performed with a lower efficiency, such as those proposed by [44], and in this case the costs for the V2G scenario were superior than those for the HPS scenario, making smart charging more cost effective. With all of this in consideration, it cannot be concluded that V2G schemes are convenient to implement for an EV fleet of this size, under the current conditions.

5. Discussion

This work presented a planning model that co-optimizes power transmission and generation expansion, considering different levels of EV uptake both in public and private sectors. The hourly operation of the system was incorporated into the long-term planning analysis by using representative days obtained through clustering techniques, which include historic RES generation and demand patterns. Initial EV demand patterns were generated using real data from Chile's National Statistical Institute [70,72]. Smart charging schemes for EVs were available in some of the cases, which allowed them to optimize their time-of-day charging schedules. The results suggest that, since 2030 is not too far from now, EV demand will not reach significant proportions in comparison with previous demand levels, and, thus, the charging pattern is the most important aspect, since it could affect peak hours. In the HP scenario, EV demand corresponded to approximately 3% of the power system demand. Because of this, transmission expansion was similar for the 5 main study cases. Sensitivity tests did produce modifications in the transmission installed. Specifically, transmission expansion is strongly related with the level of solar power that is installed in the system.

As for the optimal charging schedule for the EV fleet in the Chilean system, this depends on many factors, as the sensitivity tests revealed. The price of CO_2 taxes, and the level of solar generation capacity reached, are some of the main indicators that policy makers should have into consideration. If the solar generation level is not high enough, the EV load will be displaced to nighttime, when demand is low. For the case of Chile, this work suggests that day charging (when solar power is at its peak) will increase, considering the huge solar power potential of Chile.

In particular, the results suggest that the use of smart charging allows for an additional increase in the solar power installed. With this additional solar power in the Chilean grid, the nationwide solar power generation increases an extra 2.4% and fossil fuel-based generation decreases an additional 2.5% only due to the implementation of smart charging. This complementarity between smart charging and solar power investments is explained by the load shifts observed from peak load hours to both mid-of-the-day and early-morning hours when smart charging is allowed and there is a large penetration of solar power. These results are beneficial for Chile's National Electric Coordinator ("*Coordinador Eléctrico Nacional*"), the entity in charge not only of the correct operation of Chile's electric system, but also of proposing its expansion planning. This power system operator and planner can use these insights to foresee the value of smart charging, and, for instance, the convenience of using a time-of-use type tariff in order to push EV charging to daytime hours, given that an adequate penetration of solar power has been reached.

Solar PV generation is the predominant technology installed, and its participation grew higher in cases with larger amounts of EVs in the system, and even more when smart charging schemes were allowed. Although CSP technologies were not considered in this work, their production is based on the solar resource as well, so it may be expected that the reached level of generation will be split between PV and CSP technologies. An interesting aspect is that the results for this system are somehow beneficial for solar energy, meanwhile in other studies, such as [24], it is wind power the technology that grows the most. This indicates that, in view of the existing generation grid, and the potential for expansion for each technology in the modelled system, results may differ. Nonetheless, the benefits for the system due to the flexibility provided by smart charging schemes remain and are augmented as the EV fleet grows.

6. Conclusions

The main conclusion of this work is that the use of smart charging may significantly alter the power system expansion plan. In the particular case of Chile, smart charging allows for an additional increase in the solar power installed, increasing solar power generation (in more than 2.4% only due to the implementation of smart charging). However, for different power systems, smart charging may encourage different generation technologies to be installed. In any case, the conclusion that smart charging may significantly alter the power system expansion plan is still valid.

Although the presented case studies resulted in relatively small differences in total demand levels and total costs, a clear trend was detected when incorporating EVs into the system. Moreover, these benefits could become more relevant when working with stochastic capacity factors for RES, since flexibility becomes a real benefit for the system at the real operation time.

As future work, some interesting topics would be to delve deeper into modelling with different kinds of EVs in the system, with different charging patterns, battery capacities and availability. The inclusion of CSP technologies would also be beneficial for a system such as the Chilean one, given the flexibility they could provide. For this specific system as well, it would be commendable to perform a similar study, but with a further away objective year, as to allow the EV uptake to reach significant, and more influential levels of impact in the expansion planning decision making. Additionally, as mentioned earlier, a similar model with stochastic RES variables could provide a better insight into the benefits associated with an increased flexibility.

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