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Optimal routing for electric vehicle macro-groups in urban areas: Application to the city of Santiago, Chile

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ABSTRACT

With increasing penetration of Electric Vehicles (EVs) and growing interest in Vehicle to Grid (V2G) technology, the route optimization problem for EVs and the interaction with the power grid is becoming a more relevant research topic. We aim to optimize the route selection and charging/discharging patterns to improve the overall economic profits of EVs, considering time-varying energy prices, location of charging infrastructure and traveling schedules for EVs. We propose an optimization-based approach for EV routing where vehicles may recharge on-the-route at public charging infrastructure as well as at privately-owned depots. The objective function considers charging/discharging strategies under both, net billing and net metering tariff schemes. We also study some emerging technological solutions, such as autonomous vehicles, that can introduce more flexibility to the system operations. The proposed approach is evaluated using an origin-destination survey and the real traffic map around Santiago, Chile. Our results show that, while most EVs made minimum-distance home-work trips, it is optimal for some EVs to make additional trips to charge at cheaper nodes or inject at more expensive nodes, resulting in significant profit variations. Additionally, different values of charger availability influence total profit, resulting in profit fluctuations of up to 2 % in our case study.

1. Introduction

The transportation sector is responsible for about 24 % of direct CO_2 emissions from fuel combustion globally [1,2]. Road transportation (including commercial and passenger) accounts for approximately 75 % of transport CO_2 emissions [2]. Even though freight transport operations account for only 10–15 % of vehicle movement in cities, overall transport operations account for up to one-third of traffic-related emissions [3,4]. Hence, from an environmental perspective, electric vehicles (EVs) are the most promising instrument for lowering greenhouse gas (GHG) emissions. However, even though sales have tripled since 2018 [5], EV penetration into the market is still low (especially in emerging markets) and mainly dominated by passenger vehicles and buses. Globally, the electric light commercial vehicle (eLCV) sector has a market share of 2 %, about four times less than passenger cars [5]. The worldwide market shares of electrically-chargeable and hybrid electric delivery vehicles in 2019 were only 1.2 % and 0.2 %, respectively [6].

Governments actively look for reductions in GHG emissions by encouraging the use of EVs. However, the affordability for passengers and companies to shift to EVs is a big obstacle to implementing such technologies. It is an important reason for the low acceptance or resistance to implementing EVs [2,7]. Regarding the consumers' perception of EV costs, the willingness to buy an EV decreases as the price of EVs increases, the charging times enlarge, and the range diminishes [8,9]. Conversely, the perception of the economic benefits (such as lower operating costs) and government incentives strongly impact EV purchase intentions [10].

Accordingly, EV owners continuously seek for new sources of profit to compensate the high cost of EVs. Some authors have explored the profit stream from the management of the Vehicle-to-Grid (V2G) technology showing the availability of EVs to not only act as an energy storage device, but also as a provider of ancillary services for the electric network [11,12]. On the other hand, some emerging and novel technological solutions, such as autonomous vehicles, are taking more and more attention in the EV literature [13–15]. Some experimental results show that collaborative routing and charging/discharging scheduling of electric autonomous vehicles in coupled power-traffic networks are effective to minimize total travel routes and energy purchase [16].

The objective of V2G technology is to cover all the economic costs

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Notation:

Sets

Ω_V Set of all macro-EVs considered in the simulations, each of these represents a different number of actual EVs

Ω_{V^*} Subset of the set of all macro-EVs. This subset contains the autonomous vehicles

Ω_T Set of time periods in the time horizon for the simulations. This set contains 24 elements for our simulations

Ω_N Set of nodes in the electric network supplying energy to the area under study

Binary Variables

$c_{V,T,N}$ Charging variable. It takes a value of "1" when EV "V" is charging at node "N" during time period "T", and "0" otherwise.

$i_{V,T,N}$ Power injection variable. It takes a value of "1" when EV "V" is injecting energy into node "N" using its V2G capability during time period "T", and "0" otherwise.

$m_{V,T}$ Movement variable. It takes a value of "1" if EV "V" is moving during time period "T", and "0" otherwise.

$o_{V,T}$ Disconnection variable. It takes a value of "1" if EV "V" is disconnected from the electric network during time period "T", and "0" otherwise; note that this may happen because the vehicle is moving or simply because it is stopped, but not occupying a charger

$h1_{V,T}$ Home-to-work trip variable. This binary variable takes a value of "1" if EV "V" begins its trip from home to work at time period "T", and "0" otherwise. This variable is used only for the autonomous vehicles model

$h2_{V,T}$ Work-to-home trip variable. This binary variable takes a value of "1" if EV "V" begins its trip from work back to home at time period "T", and "0" otherwise. This variable is used only for the autonomous vehicles model

$x_{V,T,N}$ Vehicle location variable. It takes a value of "1" if EV "V" is located at node "N" at the beginning of time period "T", and "0" otherwise. This will happen both if the vehicle remains in the node for the whole time period and if the vehicle starts a trip from this node on this time period

$d_{V,T,N,NN}$ Trajectory binary variable. It takes a value of "1" if EV "V" moves from node "N" to node "NN" during time "T", and "0" otherwise.

Continuous Variables

$P^c_{V,T,N}$ Charging Energy [kWh]. Amount of energy charged by EV "V", during time period "T" at node "N"

$P^i_{V,T,N}$ Injection Energy [kWh]. Amount of energy injected by EV "V" during time period "T", employing its V2G capability, at node "N"

$P^d_{V,T}$ Consumed Energy [kWh]. Amount of energy consumed by EV "V", due to its movement during time period "T"

$SOC_{V,T}$ State of Charge [kWh]. Amount of energy stored in the battery of EV "V" at the beginning of time period "T"

Parameters

$\overline{P}^c_V$, $\overline{P}^i_V$ These parameters represent the maximum amount of energy [kWh] that an EV can charge or inject during 1 h, respectively

$\underline{P}^c_V$, $\underline{P}^i_V$ Minimum amount of energy [kWh] that an EV can charge or inject during 1 h

α Self-discharge coefficient. This is a parameter that quantifies the amount of energy lost due to self-discharge during 1 h. The amount of energy lost due to self-discharge for the battery in EV "V" during time period "T" will be: $\alpha \bullet SOC_{V,T}$. A value of 0.005 is used in this work, which roughly implies a self-discharge of around 10 % per day

$SOCMAX_V$ Battery capacity [kWh]. Maximum amount of energy that can be stored in the battery associated with macro-EV "V" at any time.

$SOCMIN_V$ Battery limit [kWh]. Minimum amount of energy that can be stored in the battery associated with macro-EV "V" at any time, in order to operate the battery without too much aging

NC_N Number of chargers available at node N. This parameter limits the number of vehicles that can be simultaneously charged at any given node. Note that this does not affect neither EVs at home nor EVs at their "work" location

μ Parameter used to modify the number of chargers available at node N

NEV_V Number of actual individual EVs that are included in macro-EV "V"

$DIST_{N,NN}$ istance parameter [km]. This parameter indicates the distance between any pair of nodes in the system

$CONS_V$ Energy consumption parameter [kWh/km]. This parameter indicates the amount of energy per km that the EV needs to drive the distance between any pair of nodes in the system

$P^{DMAX}_{V,T}$ Maximum energy consumption in any movement [kWh]

$\lambda^B_{T,N}$ Buying prices for energy [$/kWh]. Prices at which electric energy can be bought at node "N" during time period "T"

ε Selling price coefficient. Coefficient that relates selling and buying prices for a node and a time period; when it takes a value of "1", both prices are identical. In general, the selling price will be computed as $\varepsilon \bullet \lambda^B_{T,N}$ for some $0 < \varepsilon \leq 1$

$\beta_{V,N}$ Charger type parameter. For each macro-EV and possible location "N", this parameter stores information regarding the type of charging that is allowed for the macro-EV at that specific node

$\mathrm{H}_{V,N}$ Binary value that takes a value of "1" if node "N" is the "home" node for EV "V", and "0" otherwise. (Note that this is not a binary variable)

$\mathrm{W}_{V,N}$ Binary value that takes a value of "1" if node "N" is the "work" node for EV "V", and "0" otherwise.

$\mathrm{A}_{V,N}$ Binary value that takes a value of "1" if node "N" is neither the "home" node nor the "work" node for EV "V", and "0" otherwise.

T_{in} Time of the day at which workers may begin to work. We have used 8 a.m. in our simulations

T_{out} Time of the day at which workers may finish working. We have used 6 p.m. in our simulations

T_{total} Minimum number of hours that workers must remain at their work location. We have used 8 in our simulations

associated with mandatory trips by charging batteries at nodes and times when the price is low and injecting energy surplus from traveling into the grid when the price is high. Thus, it is not only possible to charge the batteries of our vehicle for free, but there is also the possibility that, in addition to traveling, we can earn money by becoming a small electric generator, provided the necessary conditions are met.

Most of the works including V2G focus on showing the additional economic benefits that can be obtained from the use of V2G by EV owners given a certain set of pre-defined routes, not including the analysis of the potential benefits of selecting the appropriate routes and the adequate times for starting and finishing the trips [11,12]. Accordingly, there is a gap of analysis including both V2G and the route and temporal flexibility provided by some technologies such as autonomous vehicles.

Traditional combustion engine domestic vehicles, as well as EVs, typically spend about 95 % of their lifetime parked. These idle periods, combined with battery storage capacity, could make EVs an attractive flexibility solution for the power system. Each EV could effectively become a micro grid-connected storage unit with the potential to provide a broad range of services to the system. At the same time, however, uncontrolled charging could increase peak stress on the grid, necessitating upgrades at the distribution level. Specifically, EV charging can create significant additional electricity demand. This can be met practically and cost-effectively with renewable energy, including solar and wind power fed into the grid. Such developments offer a tantalizing prospect – particularly for cities – to decarbonize the transportation sector while also cutting air and noise pollution, reducing fuel import dependence and adopting new approaches to urban mobility [17].

Chile is a country with a huge potential for renewable energy generation. Accordingly, the Chilean power system is an excellent case study to analyze regarding its interaction with EVs and the use of V2G technology. One important feature of the Chilean electricity market, as noted in Ref. [18], is that Chile has a net billing scheme, instead of a net metering scheme like other countries. Under the Chilean context, the concept of net billing means that the energy injected into the grid is calculated and valued at an injection rate (which is different from the consumption rate), and then the resulting value is subtracted from the cost of energy consumption (calculated as the energy consumption multiplied by the consumption rate). In the same vein, net metering means the energy injected into the grid is directly subtracted from the energy consumption, in kWh [19]. The main retail rate applied to most Chilean residential customers is the BT1 rate, which combines energy and capacity in a single rate, and consequently there is a difference between the rate of the energy injected into the grid and energy consumption. The rationale of this is that the injected energy has less value due to the utilization of distribution infrastructure [20]. Conversely, under a net metering scheme the injected energy is valued at the same rate as energy consumption.

Some authors [21] have shown that a solar PV system under the net billing scheme in the northern part of Chile could be profitable, if the investment cost is lower than 2000 USD/kW. The authors of [22] highlight the fact that PVsystems are more profitable under larger self-consumption rates and that implies an opportunity to push for more incentives to support distributed generation. In this context, and recognizing that the net billing scheme is an important element of the current Chilean electricity market and also that the power distribution sector regulation is under deep review in Chile, it is interesting to study the impact of either keeping this tariff scheme or moving to a net metering tariff scheme.

Regarding vehicle routing problems (VRP), there are a significant literature focusing on logistics operations with EVs [23–28]. These works study the optimal vehicle routing problem, but without considering the V2G technology.

This article presents a day-ahead aggregated scheduling framework in which the primary objective is to maximize the profits of the macro-groups of EV owners (aggregators). The scheduling environment is mobility aware, i.e., the mobility parameters such as source/destination of EV, the chosen route, and time of travel, are of key importance while scheduling a particular EV. In particular, we introduce the EV routing problem with public-private recharging strategy in which vehicles may recharge on-the-route at public charging infrastructure as well as at a privately-owned depot. The objective function is designed to include the penalties that are implemented on the aggregator due to unscheduled EVs, under both net billing and net metering tariff schemes. Furthermore, the development of response indicators to evaluate the reaction of the driver to a particular scheduling, are also presented. These indices contribute to the penalty that may be implemented for lowered satisfaction of the consumer. In this sense, we study the incorporation of some emerging technological solutions, such as autonomous vehicles, that can introduce more flexibility to the system operations and, thus, increase these indices.

The main contributions of this article are summarized as follows.

- Formulation of a routing optimization model that incorporates mobility decisions (in both spatial and temporal dimensions), EV state-of-charge constraints, V2G technology constraints, power limit constraints, and infrastructure constraints related with EV chargers.
- Development of charging cost, charging duration, and EV arrival time at charging stations as performance metrics toward the scheduling of an EV.
- Evaluating the impact of optimal routing (battery consumption and shortest distance) from source to destination for an EV and the consequent scheduling of the EV.
- Evaluating the impact of centralized scheduling under both net billing and net metering tariff schemes while considering routing between source and destination.
- Evaluating the impact of variations of routing and scheduling on the driver response indicators and the satisfaction.

2. Mobility modelling data aggregation and data treatment

Chile's Secretary of Transportation (SECTRA) publishes the newest available data regarding mobility (usually every 10–15 years). This data is obtained by means of an Origin-Destination nation-wide poll (O-D poll) about people's mobility, involving a very high-cost survey (due to its large sample size, which is similar to the sample size used in the national census) registering the origin and the destination of every trip occurring in the studied area. For this reason, this poll is not only the official Chilean transportation information, but also the most frequently used information utilized by many interested businesses or state agencies in order to analyze or study the patters of transportation in the country. This detailed and reliable information provides a map of the real mobility behavior of the drivers in a certain city, clearly identifying where people begin their trips and where they go at different hours of the day.

For our work, we are especially interested in two sets of data that the poll offers, namely, the "distances driven" and the "number of vehicles" information. For the purposes of the poll, the metropolitan area around Santiago de Chile is divided into 45 "*comunas*". For all of these *comunas,* we have information regarding how many vehicles move to any of the other possible *comunas* each day. However, treating each *comuna* individually would imply an extreme computational burden for our mathematical model, so we decided to group these *comunas* into 7 different "macro-areas" or "regions", commonly used for macro-analysis in Santiago de Chile. For each possible pair of macro-areas (A_i, A_j) we then compute how many vehicles have their origin in area A_i and go to area A_j during the day, and also, what is the average distance driven by those vehicles. Note that this value is average distance driven for vehicles that have a "home" in area A_i and a "work" in area A_j, hence this number is not the same as the distance between the two areas (although both numbers are similar). In our work we have labelled these areas as: CEN, NOR, ORI, SOR, SUR, PON and EXT.[1]

Given that we have 7 macro-areas in our model, we have implemented a system featuring $7^2 = 49$ macro-EVs, one for each possible origin-destination combination. Note that we are going to be studying

[1] Note that the names of the areas are abbreviations of their original names in Spanish, and they roughly translate to: Center, North, East, South-East, South, West and South-Western extension, respectively.

only 49 macro-EVs instead of millions of real EVs that could potentially exist in the streets of Santiago in the long term. For each of these macro-EVs, we have three important pieces of information: Area of origin, area of destination, and a number of real EVs that the macro-EV represents. In Table 1, we provide for each macro-EV in our study the total number of EVs that it is representing. The label in each row indicates the region of origin and the label on the column indicates the region of destination.

The numbers in Table 1 correspond to the real number of vehicles moving among macro-areas in Santiago de Chile at the time the last O-D poll was performed. For instance, we consider 1,286,232 vehicles moving daily from a home site at the ORI area to another site at the ORI area where that people work. This is the official Chilean government estimation of the total number of vehicles moving daily from ORI area to ORI area. Since almost no EVs were in Santiago at the time the last O-D poll was done (less than 1 % of all vehicles) and we are interested in analyzing the optimal planning of routes in a high EV density city, we assume all vehicles existing in Chile at the time the last O-D poll was done are EVs in the future scenario analyzed. By assuming that all these numbers in Table 1 are now EVs, we consider the hypothetical situation where the city of Santiago has a very high EV density. Accordingly, the exact number in each cell in Table 1 is not relevant for our analysis, but what is really important is the relative proportion of trips. Thus, assuming that all trips that were really done in Santiago at the time the last O-D poll was done are now done with EVs in a similar proportion, we consider the mobility of people in the city remains quite stable.

Naturally, the critical assumption in our framework is that the macro-EV truly represents the mobility behavior of the people in that group in the future situation of a high EV density city. That is, the routes followed by the macro-EV truly corresponds to the routes followed by most real EVs represented by that macro-EV. This is partially guaranteed by using real data from the last O-D poll performed, which truly represents the mobility of people in Santiago at that time. Although this behavior can change in the future, in a high EV density city, no better data of the mobility of people in Santiago is available.

In Table 2, we present the distance between each pair of areas as we have used it in our problem. Note that the distance covered by a vehicle that has its origin and destination in the same area is not zero, although it is a relatively small number. This is because each area has different "*comunas*"

The relevant parameters describing the EVs used in our simulations are similar to those of the Hyundai EV Ionic, and are presented in Table 3.

We have implemented a market system in which the price paid or obtained for any energy exchange depends on the area and on the time of the day. The prices used in our model correspond to the real average retail electricity price in each macro-area of Santiago de Chile during 2019. For reference, the price of energy in the CEN node is presented in Fig. 1.

3. Problem formulation

In this section we present the detailed formulation of the electric vehicle macro-groups optimization problem that we have implemented. The model is formulated as a mixed-integer linear problem that can be solved using readily available commercial software.

This problem originates from the need to optimally introduce electric mobility and V2G technology, in particular, into a densely populated area; EV routing, charging optimization, and even energy trading must be included in the model in order to adequately simulate a future situation in which EV penetration is much higher than nowadays. Constraints must be implemented regarding EV location and movement, but leaving enough freedom to the optimizer in order to find solutions that optimize total profits. In addition, battery energy, including all charging and discharging operations must be monitored by the optimization, otherwise, unfeasible solutions might emerge from the optimizer.

3.1. Objective function

The objective function of our optimization problem is to obtain the maximum amount of profit for the vehicle aggregator as a whole. Note that we are assuming that all the vehicles in the city work in a coordinated fashion, and hence, the planning obtained will only be optimal in the sense that it is the one allowing for a largest overall profit; some of the vehicles will need to work far from its own optimal plan to allow other EVs to contribute to the system profit. More specifically, the total profit can be computed as the difference between total income and total payments; the income is associated with the money obtained from selling energy to the network using V2G capabilities; the payments are related to the energy bought from the network in order to charge the vehicles. In general, there is a penalty to the selling operations, as the selling price is lower than the buying price at the same node and the same time (implemented through parameter ε). For simulations with $\varepsilon = 1$ both prices are identical and a "net metering" scheme is assumed; for simulations with $\varepsilon < 1$ some sort of "net billing" is assumed. The objective function can be written as:

$$maximize \quad Profit = \sum_{\Omega_V}\sum_{\Omega_T}\left(\varepsilon \bullet \lambda^B_{T,N} \bullet P^i_{V,T,N} - \lambda^B_{T,N} \bullet P^c_{V,T,N}\right) \tag{1}$$

Note that this definition excludes the economic utility obtained from the use of the vehicle; i.e., we are not including the value of the service the vehicle provides to its user by transporting them according to their needs. Hence, for a given car, the computed individual profit may be a negative number, indicating a willingness to pay for using the car in that manner. In other words, a negative profit does not imply that the operation of the car is not sensitive from an economic point of view; rather, it confirms that there are some intangible profits obtained from using the car that we are not including in our modeling.

3.2. EV state equations

The following sets of equations define the relations that must be stated among the different possible states of the EVs; the equations are needed in order to correctly model the behavior of the EVs. Remember from the notation section that the state of a vehicle can be defined using 4 main binary variables: $c_{V,T,N}$ (charging), $i_{V,T,N}$ (injection), $m_{V,T}$ (movement) and $o_{V,T}$ (disconnection). With this in mind, equation (2) states that, at any time, each EV must be in one of three possible situations with respect to the nodes of the network: charging from one of the nodes, or injecting into one of the nodes, or disconnected from the network. Equation (2) also implies that an EV cannot be at two different nodes at the same time.

$$\sum_{\Omega_N}\left(c_{V,T,N} + i_{V,T,N}\right) + o_{V,T} = 1 \quad \forall\, T \in \Omega_T, \forall\, V \in \Omega_V \tag{2}$$

Equation (3), or its equivalent (3b), states that an EV may only be moving if it is disconnected from the electric network.

$$\left(1 - o_{V,T}\right) + m_{V,T} \leq 1 \quad \forall\, T \in \Omega_T, \forall\, V \in \Omega_V \tag{3}$$

$$m_{V,T} \leq o_{V,T} \quad \forall\, T \in \Omega_T, \forall\, V \in \Omega_V \tag{3b}$$

3.3. Power limit equations

We must establish the relationship between the state variables and the power exchange variables. For power charging variables, the power charged by an EV can only be different from zero if the charging binary variable associated with the vehicle is "active"; i.e., it has a value of "1". The amount of power charged is also limited by the previously defined parameter $\beta_{V,N}$, which, in a simplified manner, takes into account the type of charger being used. Similar relations must be written for power injection and power consumption variables. In addition, note that lower limits must also be enforced, to accommodate technical constraints from

Table 1
Number of EVs represented by each macro-EV.

	CEN	NOR	ORI	SOR	SUR	PON	EXT
CEN	56264	40764	103035	43358	44088	41646	2781
NOR	40362	235992	72501	23215	18201	44326	2859
ORI	102867	82888	1286232	121155	59275	49868	1676
SOR	47918	18263	122894	436361	42425	27664	2865
SUR	40572	16135	60950	48415	374625	57151	9035
PON	51800	47747	52299	28862	55075	413179	8752
EXT	2445	3505	3096	2368	10889	10391	102227

Table 2
Distance between each pair of areas. [Km].

	CEN	NOR	ORI	SOR	SUR	PON	EXT
CEN	1,50	12,52	8,56	13,64	10,80	7,13	34,30
NOR	12,44	10,12	14,15	21,94	16,62	12,90	40,10
ORI	8,44	14,38	5,84	12,58	17,33	15,55	39,49
SOR	13,68	21,16	13,37	8,25	10,00	16,33	34,10
SUR	10,49	18,36	16,75	9,76	6,07	11,25	24,12
PON	6,70	12,32	15,25	15,97	10,96	5,30	27,22
EXT	33,00	38,70	35,53	33,00	23,29	26,43	12,38

Table 3
EV parameters.

Feature	Model Parameter	Value
Battery Capacity	$SOCMAX_V$	38.3 kWh
Energy Consumption	$CONS_V$	0.1157 kWh/km
Maximum Power Used	P^{DMAX}	12.77 kW
Maximum Charging Power	$\overline{P}^c$	6.4 kW
Maximum Injecting Power	$\overline{P}^i$	4.4 kW
Minimum Charging Power	$\underline{P}^c$	0.14 kW
Minimum Injecting Power	$\underline{P}^i$	0.1 kW

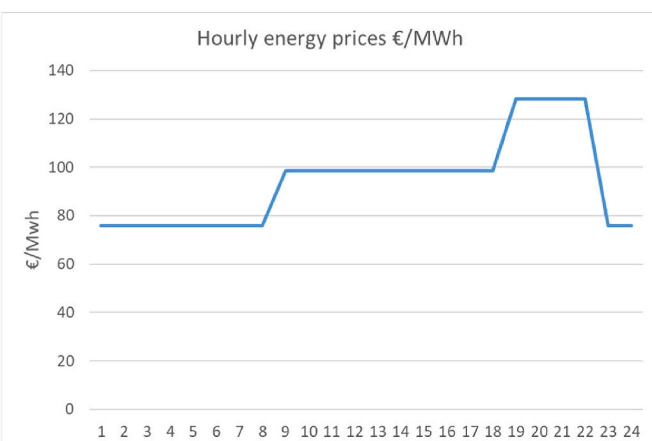

Fig. 1. Hourly energy prices at the "CEN" node.

the charging stations.

$$\overline{P}^c_V \bullet c_{V,T,N} \bullet \beta_{V,N} \geq P^c_{V,T,N} \quad \forall T \in \Omega_T, \forall V \in \Omega_V, \forall N \in \Omega_N \tag{4}$$

$$\overline{P}^i_V \bullet i_{V,T,N} \bullet \beta_{V,N} \geq P^i_{V,T,N} \quad \forall T \in \Omega_T, \forall V \in \Omega_V, \forall N \in \Omega_N \tag{5}$$

$$\overline{P}^d_V \bullet m_{V,T} \geq P^d_{V,T} \quad \forall T \in \Omega_T, \forall V \in \Omega_V \tag{6}$$

$$\underline{P}^c_V \bullet c_{V,T,N} \leq P^c_{V,T,N} \quad \forall T \in \Omega_T, \forall V \in \Omega_V, \forall N \in \Omega_N \tag{7}$$

$$\underline{P}^i_V \bullet i_{V,T,N} \leq P^i_{V,T,N} \quad \forall T \in \Omega_T, \forall V \in \Omega_V, \forall N \in \Omega_N \tag{8}$$

3.4. State of charge equations

The state of charge equations represent the energy balance in each EV battery. State of charge at any given moment is related to the state of charge in the previous hour and with the energy exchanges that take place during the hour[2]; also, a self-discharge term is considered in the model.

$$SOC_{V,T+1} = SOC_{V,T} + \sum_{\Omega_N}\left(P^c_{V,T,N} - P^i_{V,T,N}\right) - P^d_{V,T} - \alpha \bullet SOC_{V,T} \quad \forall T \in \Omega_T, T \neq T_{24}, \forall V \in \Omega_V \tag{9}$$

For consistency, we enforce that the battery of each EV finishes each day at least with the same amount of energy as it started; otherwise, EVs could spend their energy during the day without charging, which will make no sense in the long term. This is expressed in equation (10):

$$SOC_{V,T1} \geq SOC_{V,T24} + \sum_{\Omega_N}\left(P^c_{V,T24,N} - P^i_{V,T24,N}\right) - P^d_{V,T24} - \alpha \bullet SOC_{V,T24} \quad \forall V \in \Omega_V, \tag{10}$$

Upper and lower limits must be imposed to the state of charge of each battery, in order to make sure that the battery is always used within its feasible limits; these limits are set through the following equations:

$$SOCMAX_V \geq SOC_{V,T} \quad \forall T \in \Omega_T, \forall V \in \Omega_V \tag{11}$$

$$SOCMIN_V \leq SOC_{V,T} \quad \forall T \in \Omega_T, \forall V \in \Omega_V \tag{12}$$

3.5. Spatial equations

In our model, we must also include a set of equations that model the locational behavior of the vehicle, limiting its options in terms of movement and destinations. Binary variable $x_{V,T,N}$ is crucial for this purpose. Firstly, we must impose that each EV has to be located at one node during each time period; in our model, when an EV is moving during time period "T", we assume its "x" variable is active at the origin node at time period "T" and at its destination node at time period "T+1".

$$\sum_{\Omega_N} x_{V,T,N} = 1 \quad \forall T \in \Omega_T, \forall V \in \Omega_V \tag{13}$$

We also must make sure that charge and injection operations are only performed by vehicles currently at the specific location where the charger is. To this end, we have included equations (14) and (15).

$$x_{V,T,N} \geq c_{V,T,N} \quad \forall N \in \Omega_N, \forall T \in \Omega_T, \forall V \in \Omega_V \tag{14}$$

$$x_{V,T,N} \geq i_{V,T,N} \quad \forall N \in \Omega_N, \forall T \in \Omega_T, \forall V \in \Omega_V \tag{15}$$

[2] Note that in this work all time periods are considered to last for 1 h, and hence power variables (in kW) can be added to obtain a value of energy (in kWh). For the sake of simplicity, we assume this notation; in case different time period durations are used, an additional parameter would be needed.

Additionally, we must enforce the fact that each vehicle finishes the day on the same location where it began, hence, equation (16) is needed.

$$x_{(V,T1,N)} = x_{(V,T24,N)} \quad \forall N \in \Omega_N, \forall V \in \Omega_V \tag{16}$$

However, this equation will become redundant when including equations (24) and (25), which are stricter.

3.6. EV movement equations

The following equations refer to binary variable "d", defined in the notation section. Firstly, we must enforce the fact that for each EV and each time period, there can only be one movement direction.

$$\sum_{N\in\Omega_N}\sum_{NN\in\Omega_N} d_{V,T,N,NN} = 1 \quad \forall T \in \Omega_T, \forall V \in \Omega_V \tag{17}$$

Also note, that, in our model we can account for an EV not moving by assuming it is moving from one node to the same node (this movement will entail no cost or energy loss). Additionally, we must force the relation between the "d" variables and corresponding "x" variables. To that end, we have included the following two equations in our model:

$$x_{V,T,N} \geq d_{V,T,N,NN} \quad \forall N \in \Omega_N, \forall NN \in \Omega_N, \forall T \in \Omega_T, \forall V \in \Omega_V \tag{18}$$

$$x_{V,T+1,NN} \geq d_{V,T,N,NN} \quad \forall N \in \Omega_N, \forall NN \in \Omega_N, \forall T \in \Omega_T, T \neq \mathrm{T}_{24}, \forall V \in \Omega_V \tag{19}$$

Finally, we need to model the relation between the movement variable "m" and variable "d". To that end, we have written the following equation:

$$1 - m_{V,T} = \sum_N d_{V,T,N,N}, \forall T \in \Omega_T, \forall V \in \Omega_V \tag{20}$$

Note the use of the repeated node subindex above. Equation (20) states that, for each time period and for each EV, variable "m" can only be "1" if the summation on the right hand side equals zero. For this summation to equal zero all of its terms must be zero, which, in turn, means that there can be no node "N" that is simultaneously the origin and the destination of a "trip" which is to say, there is no node "N" at which the EV remains between time "T" and time "T+1". In other words, if the EV remains at the same node for 2 consecutive time periods, then its movement binary variable "m" is forced to be zero, and hence the EV is not moving. This can also be understood in an alternate way, whenever an "m" variable is zero, equation (20) forces that the EV must remain at one node.

3.7. Chargers use equations

Firstly, it is important to note that all nodes are not equal for all EVs. In fact, any EV will have one "home" node, one "work" node and 5 "other" nodes. The relation of each EV to each node is represented using parameter $\beta_{V,N}$. This parameter contains information regarding the type of charging that is allowed for the macro-EV at each specific node. If node "N" is the "home" node for macro-EV "V", then the parameter will have a value of "1", implying that there is no limit to how many of the individual EVs are simultaneously charging. For "work" nodes, the value of the parameter will be smaller, but significant (e.g., 0.75 in our simulations). For other nodes, a smaller value is used, meaning that only less than 75 % of the EVs forming the macro-EV are allowed to charge at the same time. A value of "0" would mean that the macro-EV cannot charge at that node at all.

Thus, our model includes several assumptions regarding chargers.

- For vehicles "at home" there is no limitation; i.e., we assume that each EV has a "resting" location from where it can charge or inject energy without any limit in the access to the charging point. Also, there is no limit in the "power" at which it can draw/inject energy at the network, beside the technical limit of the EV, shown in Table 3. In general, this will be true for home owners and it will be reasonably accurate also for the rest of potential vehicles, for example, taxis or commercial fleets that will have a parking associated with enough chargers.
- For vehicles "at work" we assume that EVs have a relatively easy access to chargers, but not all EVs will be allowed to charge at the same time. We use the previously presented parameter $\beta_{V,N}$ to introduce a limitation on the power that can be exchanged by the macro-EV. We fix this value to 0.75 for work nodes; this number can be interpreted in two ways. The first way to see it is that only 75 % of the cars can charge at work at the same time; the second way is to think that all EVs can charge at the same time, but charges are slower and power exchanged is limited to a 75 % of its nominal value. Both interpretations are interchangeable due to the use of a "shared battery" model.
- Finally, for EVs at a "generic" node, we impose stricter limitations. On the one hand, we impose a power exchange limitation by using parameter $\beta_{V,N}$ in a similar way as for EVs "at work", but in this case the value of the parameter is reduced below 0.75. On the other hand, we also impose a limitation in the number of EVs simultaneously charging; this limitation tries to implement the idea that, for a "generic" node, there are limited chargers accessible to the public in general. To implement this second constraint, we need the following (linear) equation.

$$\sum_{V\in\Omega_V} \left(c_{V,T,N} + i_{V,T,N}\right) \bullet \mathrm{A}_{V,N} \bullet \beta_{V,N} \bullet NEV_V \leq \mu \bullet NC_N \quad \forall N \in \Omega_N, \forall T \in \Omega_T \tag{21}$$

Note that as EVs that are at their respective "home" or "work" nodes are excluded from the summation. Also note that the number of chargers available is multiplied by μ, this parameter will have a value of 1 for the base case and will be changed in order to analyze the effect of having more or fewer chargers in the system.

The assumptions made in this section are aligned with the Chilean government plans establishing the firm intention of the Chilean government to reach high EV density cities by 2035 and to build the necessary infrastructure to allow this. Particularly, the Chilean Electromobility National Strategy (published in 2021), the Chilean National Energy Policy (updated in 2022), and the Chilean Decarbonization National Plan (updated in 2023) establish goals of reaching 100 % of the sales of lights and medium-size vehicles being from EVs by 2035 and reaching at least 60 % of the entire vehicle park being from zero-emission vehicles by 2050 (among other electric transport goals). These national policies and plans also establish a charging-infrastructure route map to achieve these goals. Accordingly, we do not include those infrastructure costs in our optimization problem, since that infrastructure is part of the Chilean government plans.

3.8. Energy consumption equations

The amount of energy that an EV needs to use in order to move from one node to a different node is related with both the distance travelled and the energy efficiency of the EV. This relation allows us to write the following equation:

$$\sum_{N\in\Omega_N}\sum_{NN\in\Omega_N} d_{V,T,N,NN} \bullet DIST_{N,NN} \bullet CONS_V = P^d_{V,T} \quad \forall T \in \Omega_T, \forall V \in \Omega_V \tag{22}$$

Also note that this amount of energy cannot exceed a certain amount, as expressed in (23).

$$P^d_{V,T} \leq P^{DMAX}_{V,T} \quad \forall T \in \Omega_T, \forall V \in \Omega_V \tag{23}$$

3.9. EV location equations

In our model, EVs cannot move freely through the road network, but they must comply with certain constraints related to its use by the owners to satisfy certain transportation needs. In particular, all EVs must begin and end the day at their "home" node, as expressed in (24) and (25).

$$x_{(V,T,N)} \geq \mathrm{H}_{V,N} \quad \forall N \in \Omega_N, \forall V \in \Omega_V, \forall T \leq 5 \tag{24}$$

$$x_{(V,T,N)} \geq \mathrm{H}_{V,N} \quad \forall N \in \Omega_N, \forall V \in \Omega_V, \forall T \geq 21 \tag{25}$$

Additionally, the EVs must transport the owner to a specific "work" node every day, and remain there, at least, for a certain amount of time. This is enforced in equation (26).

$$\sum_{T_{in} \leq T \leq T_{out}} \sum_{\Omega_N} x_{V,T,N} \bullet \mathrm{W}_{V,N} \geq T_{total} \quad \forall V \in \Omega_V \tag{26}$$

Equation (26) states that within the time periods comprised between 8 a.m. (T_{in}) and 6 p.m. (T_{out}), each EV must stay "at work" for at least, 8 h (T_{total}). Note that specific check-in and check-out times are not imposed, in order to allow for some margin for optimization, and to promote a staggered use of chargers and roads, avoiding rush hours or at least, discouraging them.

In some of the simulations presented in this work, a subset of the EVs is assumed to be composed of autonomous vehicles. For this subset of EVs, an alternative to equations (24)–(26) must be implemented in order to run the simulations according to the appropriate dynamics of these vehicles. Autonomous EVs do not need to remain at the "work" node when the owner is not using them, and also do not need to spend the night hours at "home"; these EVs only need to transport the user from "home" to "work" and backwards at specified moments. In our model, these constraints have been implemented as follows:

$$\sum_{\Omega_N} x_{V,T,N} \bullet H_{V,N} \geq h1_{V,T} \quad \forall V \in \Omega_{V^*}, \forall T \in \Omega_T \tag{27}$$

$$\sum_{\Omega_N} x_{V,T,N} \bullet W_{V,N} \geq h2_{V,T} \quad \forall V \in \Omega_{V^*}, \forall T \in \Omega_T \tag{28}$$

$$\sum_{\Omega_N} (x_{V,T+1,N} + x_{V,T+2,N}) \bullet W_{V,N} \geq h1_{V,T} \ \ \forall V \in \Omega_{V^*}, \forall T \in \Omega_T \tag{29}$$

$$\sum_{\Omega_N} (x_{V,T+1,N} + x_{V,T+2,N}) \bullet H_{V,N} \geq h2_{V,T} \ \ \forall V \in \Omega_{V^*}, \forall T \in \Omega_T \tag{30}$$

Note that equation (27) above states that vehicle "V" must be in its "home" node when binary variable $h1_{V,T}$ equals "1", this is needed to make sure that the trip from home to work can take place; similarly (28) states that vehicle "V" must be in its "work" node when binary variable $h2_{V,T}$ equals "1", this is needed to make sure that the trip from work to home can take place. Equation (29) states that vehicle "V", that was at "home" at the period indicated by binary variable $h1_{V,T}$ must be at "work" either on the next period or after two time periods. Similarly, (30) imposes limits on the return trip. Additionally, a set of constraints must be imposed to limit the time periods at which both trips can take place:

$$\sum_{T<(T_{in}-M)} h1_{V,T} = 0 \quad \forall V \in \Omega_{V^*} \tag{31}$$

$$\sum_{(T_{in}-M) \leq T \leq (T_{in}+M)} h1_{V,T} = 1 \quad \forall V \in \Omega_{V^*} \tag{32}$$

$$\sum_{(T_{in}+M)<T} h1_{V,T} = 0 \quad \forall V \in \Omega_{V^*} \tag{33}$$

$$\sum_{T<(T_{out}-M)} h2_{V,T} = 0 \quad \forall V \in \Omega_{V^*} \tag{34}$$

$$\sum_{(T_{out}-M) \leq T \leq (T_{out}+M)} h2_{V,T} = 1 \quad \forall V \in \Omega_{V^*} \tag{35}$$

$$\sum_{(T_{out}+M)<T} h2_{V,T} = 0 \quad \forall V \in \Omega_{V^*} \tag{36}$$

Note that, in the above equations, parameter "M" is used. This parameter provides a margin for the EVs regarding at what time they can begin their daily trips from home to work and from work to home.

3.10. Full models

As previously detailed, two models are considered in this work. The first model is for conventional EVs and it comprises equations (1)–(15) and (17))-(26). The alternative model, considering some autonomous EVs, contains equations (1)–(15) and (17))-(23) for all EVs, as well as equations (24)–(26) for regular EVs and (27)–(36) for autonomous EVs.

4. Case studies

In this section all case studies analyzed are presented in an orderly manner. In the first subsection (4.1), the base case is presented and its results are shown and discussed. In subsequent sections (4.2–4.5), additional simulations are presented, comparing the results with those obtained in the base case. The main results obtained from all the simulations are summarized in Table 4.

4.1. Base case (A1)

The first case study is a case in which we implement the model exactly as described in the previous sections. The number of macro-EVs is 49, and the time horizon includes 24 1-h time periods, thus simulating one full day. Each macro-EV has an origin node assigned and must spend some hours at a destination ("work") node during the day; then, it must end the day at the origin node. In this case study we have implemented a value of $\mu = 1$ and a value of $\varepsilon = 0.85$, this means that we use the base number of chargers and that we assume a net billing framework for energy exchange with the network. Also, a value of the self-discharge parameter $\rho = 0.005$ which is equivalent to 0.5 % per hour is used for this and all the simulations presented in this paper. In terms of time schedule for the EVs, we have imposed constraints stating that all vehicles must spend at least 8 h at work, and these hours must be in the interval between 8:00 a.m. and 6:00 p.m.

For this simulation, a total profit of 1.9946 M€ is obtained. The most profitable of the 49 macro-EVs is "ORI-ORI" and has a profit of 0.62 M€. Note that this EV accounts for nearly one third of the total profit in the system. Also, note that this is the macro-EV comprising the most individual EVs and that its home and work nodes are the same, so a small amount of energy is needed for movement. The least profitable one is "EXT-NOR", and has a profit of −0.0002 M€. We can also compute the "per EV" profit, and the results range from a maximum of 0.655 € for the EVs of "SURO-SUR" to a minimum of −0.052 € for the EVs in the "EXT-NOR" macro-EV.

The results obtained from the simulation include the optimal values for all the variables, which are a total of 321,196 variables (of which 274,743 are binary variables). As it is impossible to show the results for all these variables, only an illustrative set of values of the variables is illustrated next.

Regarding EV movement, most EVs only drive the minimum possible number of kilometers, just doing the home-work and the work-home trips; however, for some EVs, it is profitable to make more trips. In particular, 10 EVs take 3 trips and 2 EVs take 4 trips during the day. Both EVs making four trips stop at node "PON" on their way to "work" and, then, they stop there again when going back "home". These are the "CEN-EXT" and the "NOR-EXT" EVs; these EVs use their stops at that intermediate "PON" area to charge their batteries because energy at the "PON" node is cheaper than at the rest of the nodes. In the case of the 10 EVs that make 3 trips each day, all these EVs make one extra trip, either

Table 4
Results for all the simulations performed.

Simulation code	μ multiplier for the number of chargers	ε relative price for energy sold via V2G	Alternative Chargers Distribution	Autonomous Vehicles	Slack Hours	Total Profit (in M€)	Total Number of Chargers Used	Computation time (in minutes)	Computation error (in %. by default: 0,1 %)
A1	1	0.85	No	No		1.9940	387	17	
B1	1	1.50	No	No		17.4361	0	214	0.41
B2	1	1.10	No	No		7.2370	202	180	0.38
B3	1	1.00	No	No		4.7780	237	141	
B4	1	0.90	No	No		2.8920	387	19	
Base-case	*1*	*0.85*	*No*	*No*		*1.9940*	*387*	*17*	
B5	1	0.80	No	No		1.1579	389	2	
B6	1	0.75	No	No		0.5400	368	1	
B7	1	0.50	No	No		−0.9230	36	47	
B8	1	0.00	No	No		−0.9239	36	267	
C1	200	0.85	No	No		2.0250	1765	2	
C2	40	0.85	No	No		2.0200	1761	15	
C3	20	0.85	No	No		2.0200	1761	7	
C4	10	0.85	No	No		2.0250	1761	11	
C5	2	0.85	No	No		2.0120	714	21	
Base-case	*1*	*0.85*	*No*	*No*		*1.9940*	*387*	*17*	
C6	1	0.85	No	No		1.9890	215	1	
C7	0	0.85	No	No		1.9857	32	1	
C8	0	0.85	No	No		1.9843	0	1	
D1	20	0.85	Yes	No		2.0250	1763	4	
D2	1	0.85	Yes	No		2.0050	602	26	
D3	0	0.85	Yes	No		1.9860	44	2	
D4	1	1.00	Yes	No		4.7860	353	720	0.11
E1	1	0.85	No	Yes	0	1.9850	395	48	
E2	1	0.85	No	Yes	1	1.9900	406	248	
E3	1	0.85	No	Yes	2	2.0005	395	549	
E4	1	0.85	No	Yes	3	2.0090	1440	395	0.36

when going to work or when coming back home, and these extra trips take them to one of three possible nodes: "ORI", "SUR" or "PON". On the one hand, the EVs that take an extra trip to node "PON" all go there to charge, because it is a cheap node. On the other hand, the EVs that go to "ORI" or "SUR" go there to inject via V2G because these are expensive nodes.

4.2. Set B of case-studies. Sensitivity analysis on the value of $\boldsymbol{\varepsilon}$

In this set of cases, 8 different values are tried for parameter ε, and its effect is discussed. Note that for high values of ε more chargers are used and a better profit can be obtained. This result is as expected, given that high values of ε mean that energy injected into the network via V2G is sold at a better price. However, for very high values of ε, around 1, fewer chargers are used, probably due to the fact that at that price, a profit can be made basically at every node, note that profit is bigger in this case. Also note that for small values of ε the income generated is smaller than the operating costs and hence a negative profit is obtained.

4.3. Set C of case-studies. Sensitivity analysis on the value of $\boldsymbol{\mu}$

The value of parameter μ reflects the number of publicly available chargers in the system: when μ is 1, the simulation runs with the base number of chargers at each node; for different values of the parameter, the number of chargers is multiplied by μ. We have used 8 alternative values of μ to run different simulations. Note that for values of μ at 10 or over, the profit is basically constant, this means that the number of chargers is enough and no additional profit can be obtained by installing more chargers. On the other hand, for values less than 1, the total profit decreases to a minimum of 1.9843 M€, which is obtained for $\mu = 0$. A conclusion can be obtained regarding the true impact of publicly available chargers: the difference in profit among the two extreme cases is around 0.04 M€. Remember that home and work chargers are not affected by this parameter.

4.4. Set D of case-studies. Implementation of an alternative charger distribution

For the next set of case studies, we have run simulations with an alternative charger distribution. The new distribution uses the same number of total chargers as in the base case, but distributed differently throughout the system as follows: considering the results for the base case, move all the chargers that were never used to the locations were some chargers were in use, thus placing all the chargers in places where users really need them. With this new distribution, 4 different cases are run for different values of ε and μ, as shown in Table 4. The relevant comparisons for these case studies are case D1 vs case C3; D2 vs A1; D3 vs C7 and D4 vs B3. Note that, in all the cases, a small increase in profit is obtained, confirming the intuition that a better placement of chargers can improve the economic results.

4.5. Set E of case-studies. Autonomous vehicles

The last set of case-studies implements a model including some autonomous vehicles as described in the previous sections. Note that this is the only set of case-studies to feature Autonomous Vehicles. In general, these cases can provide greater profits when the margin of operation (M) is large. In particular, for a value of M = 3, profits can rise from 1.994 M€ to 2.009 M€. Also note that the computational burden of these cases is clearly greater than for the previous cases, basically due to the fact that the autonomous EVs have much more freedom of operation, as constraints forcing them to stay at "home" or "work" are not imposed. For this case study our problem is run considering that all the EVs that have the "CEN" node as their "home" are fully autonomous as described in the previous sections. Note, from Table 4, that one of the cases was simulated for 12 h on a standard computer and was not able to reach the desired 0.1 % error according to CPLEX (the solution obtained had an error of 0.355 % after 12 h). Additional computations, not presented in this work, suggest that for a case in which all EVs are autonomous, computation times were increased much more and no acceptable margin of error could be obtained in a reasonable computation time.

5. Conclusions

This paper has presented an optimization approach for charging/discharging and routing EVs. Our formulation integrates spatial and temporal mobility decisions, EV constraints, and infrastructure constraints. Metrics such as charging cost, duration, and EV arrival time were introduced, facilitating the evaluation of scheduling strategies' efficiency. Profitability of each macro-EV and even each individual EV can be assessed. Most EVs primarily made minimum-distance trips, while some made additional trips to charge at cheaper nodes, or inject at more expensive nodes, resulting in significant profit variations. Alternative charger distributions have been compared. Examination of centralized scheduling under various tariff schemes provided insights into economic implications and can help with regulatory decisions. Notably, different values of charger availability influenced total profit, resulting in profit fluctuations of up to 2 % in our model.

CRediT authorship contribution statement

Sebastián de la Torre: Writing – review & editing, Writing – original draft, Supervision, Software, Funding acquisition, Conceptualization. **José Aguado:** Writing – review & editing, Methodology, Conceptualization. **Enzo Sauma:** Writing – review & editing, Software, Formal analysis, Data curation, Conceptualization. **Alejandro Lozano-Martos:** Software, Conceptualization.

Declaration of competing interest

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Data availability

Data will be made available on request.

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