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Original Research Article

Assessing Sustainable Electromobility Futures in a Multi-Model Platform with Power Grid and Urban Planning: A Case Study in Chile

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ABSTRACT

There is a growing shift towards zero-emission transport technologies to mitigate climate change. While electric vehicles are gaining traction, transitioning to electromobility will impact both transportation and energy sectors. Evaluating potential future electromobility scenarios can enable decision-makers to anticipate infrastructure needs, energy demand patterns, and environmental benefits. This paper presents a highly interdisciplinary simulation and assessment framework for evaluating electromobility adoption scenarios in urban centres, integrating five modules: (i) technology adoption, (ii) urban planning, (iii) transport systems, (iv) power distribution, and (v) energy system expansion. While considering grid and urban planning, it assesses the sustainability, performance, and infrastructure requirements of transport electrification through indicators that were determined in a participatory process with public and private collaborators. A case study using data from Temuco and Padre Las Casas in Chile demonstrates the methodology's applicability.

KEYWORDS

Sustainable transportation, Urban model, Electromobility, Multi-agent simulation, Power system model, Policy and decision-making.

INTRODUCTION

To comply with current commitments to decarbonization, electromobility is one of the main alternatives to replacing fossil fuels in the transportation sector [1]. Worldwide, the

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transportation sector represents 19% of the total energy consumption, and 91% of this demand is met by fossil fuels [2]. Furthermore, vehicle emissions contribute significantly to local pollution, resulting in health impacts in urban areas [3], a situation that can worsen with other pollution sources such as biomass burning stoves in winter [4].

Consequently, many countries have set future goals for transport electrification through roadmaps, plans, or strategies (such as Sweden [5], USA [5], Switzerland [6], and Chile [7]). According to the reality of each region, some goals are quite specific in terms of EV and charging infrastructure adoption, while others are more generic; such is the case of Chile. These definitions can be greatly improved by adding input from experts and citizens in assessment tools for decision making, facilitating the simulation and evaluation of potential future scenarios, and allowing more effective participation in the energy planning process.

Still, the transition towards electric mobility is a complex process influenced by a wide range of factors [8], including: i) public policies such as government subsidies, incentives, taxes, and regulations, ii) legal frameworks like safety standards, emissions regulations, licensing requirements, and grid integration, iii) social conditions as consumers habits, routines and preferences, iv) economic considerations [9], particularly the cost of EVs, charging infrastructure investment, the price of electricity, and v) technical constraints, e.g., charging infrastructure availability, grid capacity for charging multiple EVs simultaneously [10], and the need for standardizing charging systems. Capturing this complexity through a single integrated modelling framework is challenging. Therefore, most existing works analyse one or several aspects separately, even though they are interrelated.

For example, previous studies show that the increasing demand for fast EV charging could lead to increased grid congestion and daily peak demand, in highways [11] as well as cities [12]. Studies on the impacts of EV charging highlight the increased operational costs, the reliance on coal-based power, and the need for smart charging strategies to manage peaks [13]. Simultaneously, other electrification trends, such as space heating and cooling, will further strain the grid [14]. Systemic solutions, such as EV charging combined with renewable energy and energy storage, both at village level [15] and country level [16], as well as intelligent processes such as vehicle-to-grid (V2G)[18], offer greater grid flexibility at small scales such as buildings [17] as well as a national level [18]. These solutions are typically designed using power system tools for grid operation simulations (e.g., power flow equilibrium [19]) or transmission expansion tools that optimize grid planning based on new generation and demand forecasts, applicable both in small-scale [20] and large-scale systems [21].

Given the complexity of the problem at hand, comprehensive modelling tools are required to predict and analyse future electrification scenarios. In this regard, multi-agent simulations (MAS) or agent-based modelling (ABM) have become essential frameworks for analysing transport system electrification [22]. ABM dynamically simulates the behaviour of agents, such as citizens, manufacturers, and vehicles, to study mobility transitions [23]. In ABM, EV users can be defined as agents, with EV specifications and sociodemographic attributes (e.g., economic activity, employment status, household size). User decisions —vehicle acquisition, mode choice, travel schedules, routes, and charging behaviour (location, timing, duration)— can be modelled following predefined behaviour rules.

Among existing tools, the Multi-agent Transport Simulation (MATSim) software has been widely used for mobility case studies in cities such as Berlin, Vienna, São Paulo, Santiago, and Singapore [24]. Recent studies have applied MATSim to explore electromobility futures: EV charging locations for Tenerife [25], changes in the metro network in Paris [26], optimal charging infrastructure for Cuenca [27], and the distribution of public chargers in Salt Lake City [28]. Other studies have explored new transportation modes with MATSim: car-sharing fleets considering driver anxiety and weather [29], EV charging impacts on Croatia's hourly energy consumption [30], EV charging station usage and user behaviour in Munich [31], or inductive EV charging [32].

Despite extensive research on the diffusion and operation of EVs, the complexity of the problem leads to many existing gaps [22], including insufficient model validation, the need for joint price- and preference-based scenarios, extending models to diverse regions, and exploring agent interaction topologies (e.g., social networks). In this context, evaluating possible scenarios takes relevance.

The process of evaluating these possible futures (scenarios) is done using a specific approach called design-oriented planning. This approach is part of the larger field of Territorial Planning (planning for a whole area or region). Within this context, design-oriented planning is also known as the exploratory vision of planning because it's used to test different possibilities. Its main focus is on the spatial aspects—meaning how things are physically arranged and organized within that territory [33]. Within this perspective, certain approaches tend to incorporate elements of the so-called "scenario planning". Marien [36], discusses how futures studies in the twenty-first century can use structured scenarios to explore multiple plausible developments grounded in empirical realities and policy challenges. Pettit and Pullar [37] show how spatial modelling scenarios can support land-use planning by linking alternative future pathways to the likelihood of achieving specific policy goals. Therefore, these elements constitute a set of techniques aimed at increasing awareness of possible futures in decision making [34]. In this context, elements of "future studies and futures thinking" [35] are integrated into spatial planning through scenarios. This intertwining of the design of future scenarios with tools of design-oriented planning, such as Geographic Information Systems, simulation models such as MATSim, or decision support instruments, would have the potential to contribute to the development of representations of possible future developments in territorial planning, referred to as "spatial scenario planning" in the literature [36].

Depending on how they are used, scenarios have often been classified as predictive, normative, or exploratory [37]. While predictive scenarios seek to predict the future and normative scenarios aim to project a desirable outcome, exploratory scenarios are intended to encourage discussion about various plausible futures [38]. In this context, exploratory scenarios play an important role in medium- and long-term planning [39], serving as reference points to evaluate the validity and suitability of a given strategy [40]. In this research, the exploration of scenarios through "What if?" questions enables a discussion that broadens the available knowledge for designing strategies for sustainable electromobility planning.

The utility of these prospective representations in spatial planning lies in their ability to assess the effects of different policy instruments and urban and spatial development paths with a single framework, including economic and environmental evaluations [41], [42]. Scenario planning, in turn, emerges as a method that allows the management of uncertainty and supports flexible decision-making [43]. It is of great value for reflection and discussion, allowing anticipation of potential and emerging impacts, while also minimizing unforeseen pressures and negative consequences within urban and transport systems [44]. Future scenarios have demonstrated their ability to integrate complex discussions in areas that are often planned in a disaggregated way [45], such as transport and electricity.

A simulation framework with scenario evaluation can also potentially reduce the inherent uncertainty of planning processes [49] by improving the adaptability of the model and, consequently, of the plans that use it as an input, in line with Prato's [48] proposal to evaluate land-use plans under conditions of uncertainty while considering multiple criteria and associated risks. This adaptability is reflected in the planning and design of strategies suited to different socio-economic contexts, represented by diverse scenarios, as shown by Ariza-Álvarez, Soria-Lara and Aguilera-Benavente [47] when employing scenario building to define adaptive strategies for urban transport and land use. Moreover, these representations create opportunities to discuss possible futures with the various actors present in the territories in a more participatory and collaborative way, consistent with the participatory visioning and collaborative evaluation approaches to transport policies proposed by Soria-Lara and Banister [40], and by Tarriño Ortiz, Soria-Lara and Vassallo [51], as well as with the use of Fuzzy

Cognitive Maps by Van Vliet, Kok and Veldkamp [52] as a joint communication and learning tool.

This paper presents a novel framework for the prospective and multidimensional evaluation of future electromobility scenarios in urban centres, serving as framed exploratory scenarios [37]. Comprehensive multiagent simulations are utilized to assess the scenarios, enabling a collective analysis of energy sustainability, transportation system's performance, charging infrastructure utilization, and its effects on the electrical distribution network and regional power matrix, with high spatial and temporal resolutions. The proposed solution aims to provide pertinent input for decision-making in planning suitable infrastructure to meet the unique requirements of a city. It intends to encourage and facilitate the successful adoption and integration of EVs. A comparison of the proposed framework with existing works is presented in Table 1. While there are some similarities with previous research, none of those works integrates as many aspects as the development described. Most works focus on of present and future EV deployment charging statistics; and while there are previous works focused on the possible impacts of policies on technology adoption, by including more complex diffusion models [46], many others lack the distribution grid impacts and energy system expansion. It is also worth mentioning that none of the reviewed studies report a participatory methodology in their development.

Table 1. Comparison of existing EV planning frameworks

Work	EV adoption	Urban model	Transport model	Power distribution	Energy system expansion	Outputs
[25]	From existing energy projection	Optimal charger allocation on current spaces	Based on MATSim	Not considered	Not considered	Charging and spatial statistics
[27]	No projections	Optimal charger allocation on current spaces	Based on MATSim	Constrains charger allocation	Not considered	Charging and spatial statistics
[28]	No projections	Socioeconomic factors. No projections	Based on MATSim	Not considered	Not considered	Charging statistics
[30]	Varying EV penetration	No projections	Based on MATSim	Not considered	Based on EnergyPLAN	Energy system indicators
[46]	Policy dependent	No projections	Indirect model	Only costs	Not considered	Costs, emissions, sales
[47]	No projections	No projections	Graph model	Hot spot identification	Not considered	Charging sustainability
This work	Based on policy goals	Data-driven approach	Based on MATSim	Based on Pandapower	Based on PLP and FESOP	Economic, social and environmental indicators

This work makes the following contributions to the scientific literature:

- Provides a meaningful interdisciplinary framework that enables the public and private sectors with a novel prospective tool to accelerate electromobility development.
- Performs a participatory process to determine the key performance indicators that the tool will produce for each scenario simulation, ensuring usefulness to different stakeholders.
- Provides a high spatial and temporal resolution simulation platform, making it suitable for diverse urban area assessments.

The capabilities of the tool for evaluating sustainable electromobility strategies are showcased, with a high-resolution application to a large urban area in Chile (Temuco and Padre Las Casas), and a qualitative comparison with other published works. Insights from indicators and attributes that address the needs of key stakeholders are discussed.

METHODS

The simulation approach consists of five simulation modules. Together, they provide a holistic understanding of the urban-transport-energy nexus. These modules have been designed to address specific components of the complex interplay between urban development, transportation dynamics, technology adoption, and power grid performance, all of which shape the overall energy landscape.

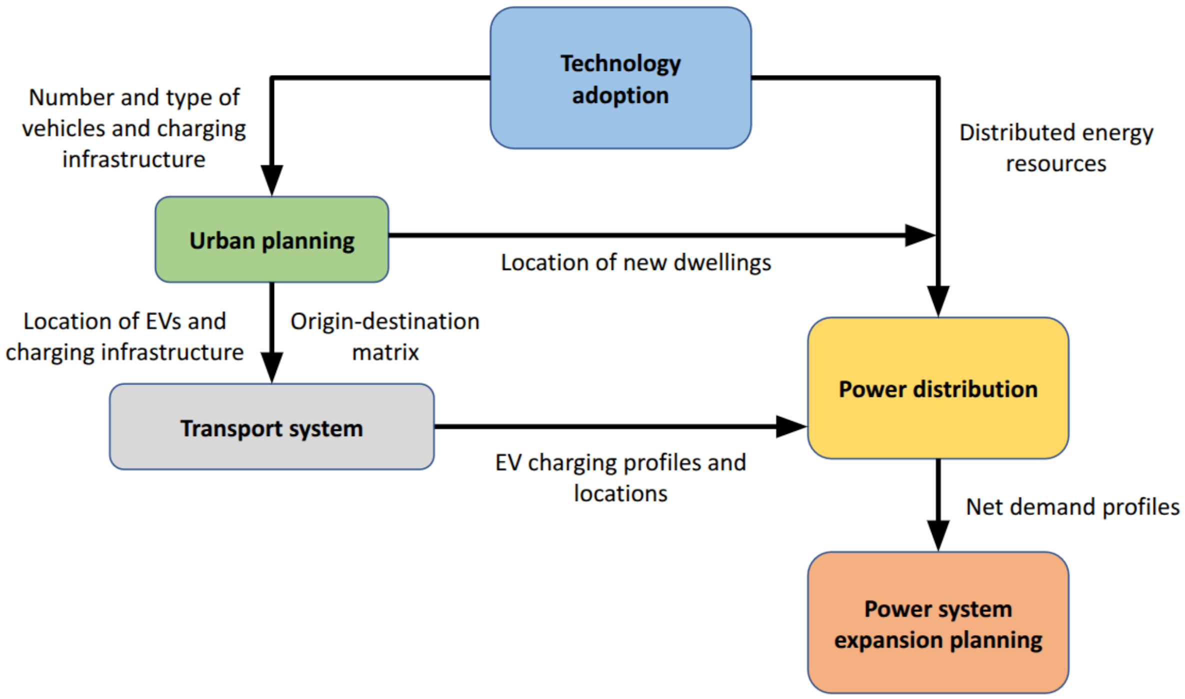

Figure 1. Conceptual architecture of the multi-model platform

The relationship among modules is presented in Figure 1, where each module can be summarized as follows:

- Technology adoption: Estimates the expected technologies for both transport and electrical systems based on specific goals and projections.
- Urban planning: Assesses how the city is expected to expand over time, using urban data-based projections and incorporating factors such as population growth and economic trends.
- Transport system: Simulates the behaviour of individual vehicles in an urban area, combining the use of transport and energy-charging infrastructure.
- Power distribution: Calculates the behaviour of the hosting grid due to the interaction between the base load, EVs, and distributed energy resources.
- Power system expansion planning: Estimates the optimal expansion and operation of the power grid due to the evolution of demand at the national level, also considering technology and fuel cost projections.

All modules are composed of state-of-the-art tools that are already available to the scientific community. The coordinated use of the five modules to provide valuable information about a particular electromobility scenario is the main focus of this work. Details of each module are presented in following subsections, and a list of the main inputs is included in the Appendix.

Participatory process to select scenarios and define evaluation indicators

The number of possible scenarios is too large due to the number of modules and their parameters. Thus, an expert filter was performed through a participatory process to reduce the number of potential adoption scenarios.

The Participatory Roundtables for Sustainable Electromobility (PRSE) were a platform for discussion and knowledge exchange to support the simulation framework development and create relevant prospective electromobility scenarios. These PRSEs gathered diverse perspectives and expertise from relevant actors (industry, academia, and the public sector) to refine the models, validate assumptions, and enhance tool's capabilities. Such a collaborative and participatory approach ensures that the tool is realistic and useful. As a result of these PRSEs, the set of economic, environmental, and social indicators in Table 2 became the main indicators of the results of a simulation run. In this way, each stakeholder will have access to a diverse description of the results of the simulated scenario that can inform their decision-making process.

The PRSEs included 8 sessions with representatives from diverse sectors, including companies, government ministries (Energy, Transport, Environment), transport guilds, academia, and public electric and energy sector institutions, averaging 37 participants per session. These interactive activities focused on indicator selection, in which participants proposed indicators across three dimensions (environmental, social, and economic) and prioritized the most relevant indicators (three per category) by voting for 3-4 option in the Mural online platform. The PSES not only shared project progress but also jointly defined the evaluation scenarios for the integrated tool and validated some of its results.

Table 2. Scenario evaluation indicators defined by the participatory process

Aspects	Indicator	Units
Economic	Individual and national net energy savings	MWh/year
	Projected energy cost (marginal cost)	CLP/kWh
	Savings from fuel imports	USD/year
Environmental	NOx and PM local emissions reduction	Ton NOx/year
	CO2 emissions reduction	Ton CO2e/year
	Residual batteries	Battery quantity/year
Social	Use of charging stations	MWh/year
	Travel and waiting time for EVs	h/km - h/year
	Savings by local emissions reduction (NOx and PM)	USD/year

Technology adoption module

This module integrates historical data and current goals to deliver estimations of EV and distributed energy resources (DERs) deployment. The calculations can be separated into three main components:

- Future number of vehicles: For the case study, existing estimations of the future transportation demand were gathered in units of passenger-kilometers (pkm) from a previous national study [48], detailed by region and urban/interurban sectors. Given the future transportation demand, a linear regression model with historical data of current vehicles in the country from 2014-2021 was fitted and the future number of vehicles per region and vehicle type (light-duty vehicles, light-commercial vehicles, urban buses, taxis, motorcycles, and interurban buses) was estimated. While more sophisticated models exist, the short span of data with considerable presence of EVs, and the odd behaviour of the pandemic years led us to choose a simple linear model. Machine learning approaches could improve these estimations in the future.

- Future number of EVs: To obtain the number of EVs from the total number of vehicles, an adoption curve is used. For the case study, the adoption of EV at the beginning of the study represents the main goals of the National Strategy of Electromobility in Chile [7]. These goals include:
  - 100% electric urban public transportation in 2035,
  - 100% sales of electric light and medium duty vehicles in 2035, and
  - 100% sales of electric interurban buses in 2045.

  An adoption curve for light-duty vehicles was set as a linear increase from 2036 until 2038, followed by a logistic curve. The adoption curve can be modified to represent different goals or to include pessimistic/optimistic scenarios. Then, the number of EVs and the installed capacity of the charging infrastructure based on the number of light-duty EVs were estimated.
- Energy consumption and emissions: The transportation demand data in pkm were also converted to vehicle energy consumption with typical efficiencies for each vehicle type (11.57 km/l for gasoline, 5.3 km/kWh for electric, 18.4 km/l for diesel). These efficiencies were taken as referential values from the national database of energy consumption for popular vehicle models [49]. Future changes of efficiency were not considered in our case study, but could be integrated in future work, as they can impact the future energy consumption by nearly 30% according to sensitivity runs, as included in the Appendix. The calculation is performed in a yearly basis and allows to specify parameters for each vehicle type. Depending on the scenario, the share between existing and EVs allows to transform transportation demand into equivalent energy consumption, and to emissions using national projected emission factors.
- Future DER installations: The statistics of existing net-billing installations from 2015-2024, along with existing goals and potential capacity, are used to project the installed capacity of DERs. All outputs are generated annually and at a regional level, which can then be disaggregated to a city level.

The number and type of both vehicles and charging infrastructure will be used as input in the urban planning module, while the installed capacity of the DERs will be part of the input of the power distribution module.

Urban planning module

Considering that the demographic variables and household distribution in the city are key issues in EV usage across the city, a module was designed to describe current urban attributes and a projection of future tendencies.

This module includes a series of submodules to predict the spatial development of future scenarios for a given urban area. The output includes the number of households segmented by their characteristics, their location in the city, and dwelling types (houses and apartments). Concerning mobility, other outputs of interest are the number of vehicles and charging points for each urban zone. To run the model for a city, the urban area must be characterized in terms of census zones (normally defined as shapes in a Geographical Information System). This module relies on spatial information available from the National Census and the Origin-Destination transportation surveys, and therefore, some specific features could vary for other countries, for which the methodology may need to be slightly adapted.

The submodules are the following:

- Aggregated population: Estimates the total future population for urban areas. It takes as input the National Statistics Institute projections (at urban and rural levels for each municipality, from 2002 to 2035) and extrapolates them to any given year. To extrapolate from 2035 to 2050, a cubic spline was used.

- Population segmentation: Extracts the information for a given urban area in the 2017 National Census and calculates the number of households in each zone, segmented into 12 groups that emerge from the combination of 3 life-cycle stages (independent: no children or senior persons, with children: at least one person younger than 18 years, and senior: with persons older than 65 years and no children), and 4 educational stages of head of household (basic: 8 or less years of formal education, high school: 9 to 12 years, superior incomplete: 12 to 14 years, superior complete: 15 or more years).
- Aggregated dwellings: Extracts the total number of houses and apartments built by zone from the National Census of 2017 and 2002, and with a simple extrapolation, projects the composition (houses/apartments) for future years, including a baseline of existing housing for the 2017 base year. The geo-referenced Building Permits database (2010-2020) is also processed, allowing for the estimation of the number of units built in each zone.
- Dwelling Supply forecasts: A linear projection is used to predict the number of houses and apartments in the city, based on different variables extracted from Census 2002 and 2017. The model considers an aggregated supply of dwellings, based on the number of households estimated for 2035. The number of households is based on projections of total population and household size estimation, based on linear projections (persons by household is shrinking in later years, which is considered in this projection). Afterwards, the future proportion of houses and apartments is estimated based on change rates in the period 2002 and 2017.
- Vehicle disaggregation: Estimates the number of vehicles in each zone, according to an estimated vehicle ownership of the households living in each zone. The rate of vehicle ownership is based on households' characteristics, using a linear predictive model which is calibrated with the Origin-Destination Survey of three different cities in the South of Chile. This model considers a linear combination of three parameters: percentage of houses, percentage of households with children, and percentage of households with superior education (complete and incomplete).
- Charging infrastructure: For private charging, a probability is defined for each zone depending on the number of houses (it is assumed houses will have higher access to off-street parking with the capacity of installing a private EV charger, relative to apartments). For public charging points, the number in each zone is proportional to the distribution of commerce and office built surface for each of the zones (for example, if a zone gathers 5% of commerce and office in the city, the model will assign 5% of EV public charging points to that zone). These land uses were extracted from the National Revenue Service Cadastre of Real Estate properties.
- Origin-Destination matrix: Starting from the initial O-D matrix, considering both the number of trips generated per zone and the current number of households, a trip generation rate is calculated, representing the average number of trips per household within each zone. When new households are projected, the number of trips is estimated using the calculated trip rate. This mechanism allows for the estimation of trips in the event of new households entering the area. For zones that currently have zero trips, this approach considers the rate from similar zones to estimate the trip generation when new households are projected.
- Scenario generator: Combines the results obtained from the spatial attributes sub-module with the attributes per zone (distance to the centre, allowed dwellings, density, and superior education percentage) after modifying the allowed dwellings for certain zones according to a new projection for the target year.
- Scenario simulator: The random forest models utilize the table obtained in the scenario generator sub-module to derive estimates for the new dwellings,

encompassing both houses and apartments. Once the estimation is complete, it undergoes a review and correction process to ensure the results align with the proportions of houses and apartments that were previously estimated.

Transport system module

This module is based on the MATSim tool, an agent-based modelling framework commonly used to simulate travel behaviour and transportation systems [24]. In this model, every agent represents a transport system user who interacts with other agents when moving from an origin to a destination through the existing infrastructure, generally represented by the road network. The agent's interaction allows them to evaluate their travel activities (also called plans) through a performance function, which is then used to model the choice process between these alternatives. In summary, the three steps of the algorithm are [50]:

- Plan execution (mobsim): The plans of all agents are executed simultaneously on the network using a first-in-first-out queue model at every link, which accounts for congestion effects on the road network.
- Plan evaluation (scoring): The executed plan of every agent is evaluated with a performance function.
- Change of plans (replanning): After executing the chosen plans, a predefined share of agents is selected to modify some aspects of a random plan already in their memory (e.g., travel mode or route).

To use MATSim as a simulation framework, it is necessary to build the so-called scenarios, which typically represent complete cities. In general, these scenarios are built on two types of inputs, namely:

- Supply information:
    - Public transport information, comprising buses and train services, their frequencies, routes, stops, and vehicle capacities.
    - Road network, which includes all the streets and intersections of the area of interest, which are represented by links and nodes with capacity factors in vehicles per time unit and vehicles per distance.
- Demand information:
    - Agents' plans, which contain all agent activities with their locations and durations (start and end times), and the respective trips that connect those activities with their mode of travel and route (sequence of links).

In addition to the above-mentioned inputs, the modular architecture of MATSim makes it possible to include other types of information according to the simulation needs. In this case, the functionalities of MATSim were extended using the "*UrbanEV*" contribution to model the use of EVs [31]. To use this library, two additional inputs are necessary:

- Charging infrastructure: Information about the charging network comprising their location, charging power, number of chargers, and type of charger (public, residential, workplace).
- Electric Vehicles: EV technical parameters, such as battery capacity, initial state of charge, energy consumption, maximum charging rate, weight, and vehicle dimensions.

MATSim keeps track of all agents' status through the simulation, such as activities and travel start and end times (hence, information about potential congestion), sequence of links used to travel from an origin to a destination, and location of activities. This is then evaluated by the performance function, which is used to select a potentially different plan already stored in the agent's memory for the next iteration. This level of granularity makes it possible to compute aggregated transport performance indicators such as travel times and travel distances by mode, the share of agents using the different modes, and congestion (e.g., increased travel times in specific network links).

In addition, it is feasible to keep track of specific groups of agents and vehicles, such as EV owners, enabling the possibility to analyse behaviours in those groups of interest while interacting with the corresponding infrastructure. This interaction generates relevant outputs such as charging times and charger occupancy, together with electricity demand profiles per charging point, which are considered inputs for the power distribution module.

While the simulation framework could integrate EV fleets such as cabs, light trucks, and public transport buses, currently in Chile, these types of EV fleets typically charge at dedicated off-route charging terminals rather than on-route. Also, due to their high energy consumption, each charging terminal is operated to comply with local grid restrictions. Therefore, the current version of the simulation framework does not include EV fleets, but they could be included in future versions.

Power distribution module

This module is responsible for evaluating the operational behaviour of the power distribution network of the territory under study. One of the main concerns regarding the adoption of EVs is the large power needed for the charging process. For example, in Chile, an average residential load has a maximum power of 6 kVA [51], which is less than a single EV charger for the slowest type of wall-box charger (7 kW). In that sense, it is expected that power distribution grids will be severely impacted by the adoption of EVs [52].

Additionally, power distribution grids are, by design, three-phase systems that exhibit the best performance when the phases are balanced, namely, the power flowing on each is the same. However, it is expected that a large part of EVs will be connected to a single phase, exacerbating the imbalance between phases.

The most straightforward solution to address these challenges is to install cables with larger capacity. Unfortunately, the cost of this infrastructure update is typically very high and can result in a nontrivial increase in the energy tariff of the final users [53]. Alternatively, since EVs are energy resources equipped with flexible power electronic devices, their charging power is easily and quickly controllable [54].

This feature enables EVs to adapt to the available power capacity in the distribution grid in real time. This means that, for example, when the demand for regular loads is low, the EVs can charge faster. However, EVs can limit their charge when the regular loads increase their power consumption. In fact, EVs could even adapt to the availability of local energy resources, such as solar photovoltaic (PV), or inject power back if needed. Together, these operational conditions in the power distribution grid will have a nonlinear and unpredictable impact on the potential adoption of electromobility in both the private and public sectors.

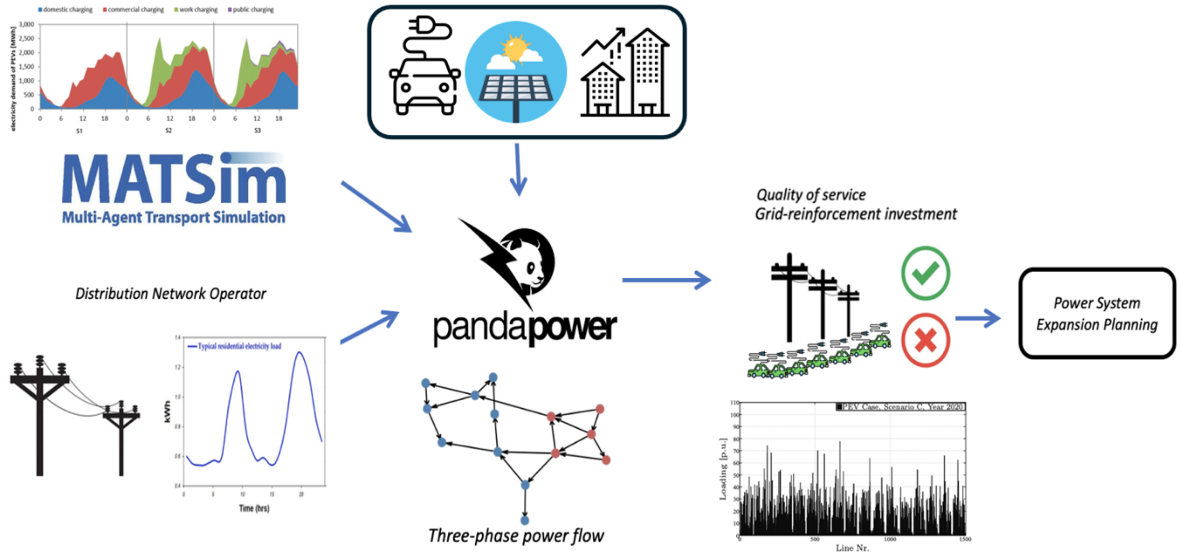

Figure 2. General diagram of the power distribution module

In this context, this module is developed to analyse the impact of different scenarios on the power-balance operation of the power distribution network. The module is conceived to indicate grid stress by evaluating the behaviour of the main electrical variables in a power grid: nodal voltage and line current magnitudes. In the first phase of the simulation tool, this module is based on solving a balanced three-phase power flow problem using *Pandapower*, an open-source power systems tool coded in Python [55]. An extension to a full three-phase system, where unbalances are naturally account for is part of the next steps of this module. The module takes care of preprocessing the input data from different sources and postprocessing the results to deliver meaningful information to other modules.

A general diagram of the internal details of this module is presented in Figure 2. The specific inputs used in the module are the following:

- Base grid parameters, which consider the geographical location of the grid nodes, interconnection among nodes, voltage level, line and transformer parameters, etc., of the existing grid. This data is gathered from the local distribution network operator.
- Historical data of the uncontrollable base load per node (and, ideally, per phase).
- Arrival and departure times of EVs and the locations related to charging activities, as provided by the Transport System module.
- Expected integration of other DERs, such as photovoltaic and/or storage devices, as provided by the Technology Adoption module.
- Expected urban growth of the city, considering the geographical expansion and the dwelling characterization, as provided by the Urban Planning module.

To compute the three-phase balanced power flow solution in various EV adoption scenarios, the module first establishes generation and load profiles for each node within the power grid. Through iterative analysis, the module can analyse: (i) the transferred power (consumed or generated) at each node, accounting for EV charging patterns based on arrival/departure times, the variable output of uncontrollable energy resources such as photovoltaic (PV) generators, and projected electricity demand growth; (ii) the flexibility potential of EVs to modulate their charging rates in response to real-time grid conditions through smart charging or vehicle-to-grid (V2G) capabilities; and (iii) the necessary grid expansion requirements corresponding to urban development, incorporating dynamic updates to network topology. This comprehensive approach enables a precise assessment of grid impacts under different electromobility penetration trajectories while identifying critical infrastructure reinforcement needs.

The electrical magnitudes in this module (nodal voltage and line currents), with which the resulting meaningful information is regarded as (i) the quality of service of the grid, (ii) the needed investment for grid expansion dependent on the urban planning, (iii) the needed investment for keeping the grid operating in acceptable conditions depending on the operating conditions of EVs (e.g., if grid reinforcement is needed), and (iv) the EV-user satisfaction regarding their energy demand (e.g., whether the EV reaches the expected charge before departure).

The power distribution module has the following limitations:

1. It only simulates an electrical network in steady state. Yet, this seems sufficient for being compatible with the other layers of the platform.
2. It relies on data that is not easy to collect from distribution network operators: the location of nodes and lines, and, especially, the electrical parameters needed to run power-flow studies. For this study, geographical information was facilitated by a distribution network operator in Chile, and parameters were computed based on typically used cables and transformers in distribution grids. This introduces approximations to the computation.
3. Measurements are usually not available in all nodes of a grid, so the real power that is drawn or injected in a node are based on assumptions. In this paper, measurements from primary substations were obtained from the same operator. To distribute the power among nodes, the dwelling location and characterization was used.

Power system expansion planning module

The maximum power required to meet the demand for charging EVs could cause grid congestion problems in transmission networks, especially when coinciding with periods of high demand. Furthermore, contrary to the desired outcomes, the production of additional electricity needed to meet the increasing energy demand could be sourced from fossil fuel generators. This module aims to evaluate how different levels of electromobility penetration affect the regional and national electricity grid. The module can determine the optimal expansion of the system that satisfies the new demand for EVs while also evaluating the technical feasibility of supplying the increased energy requirements.

This module is based on Fesop [20] and PLP [56], both open-source software:

- Fesop is an object-oriented Python-based software designed for stochastic power generation, transmission, and storage capacity expansion planning. The mathematical formulation corresponds to the DC power flow with transmission losses, allowing the simulation configuration to be uni-nodal or multi-nodal (in this case, the power balance is given by bus). It simultaneously solves multiple future scenarios, each with an associated probability, to assess the uncertainties in investment decisions during the planning horizon, considering stochastic factors such as renewable energy generation, hydro inflows for reservoirs, load variations, and fuel costs. Additionally, this tool considers ancillary service requirements such as spinning reserves.
- PLP is a tool based on SDDP (Stochastic Dual Dynamic Programming) intended for hydrothermal coordination, developed for long-term operation planning in Chile, and with extensive utilization by the National Electric Coordinator and many companies in the sector. PLP encompasses hydraulic constraints to represent reservoir filtration, irrigation use, inflows from tributaries, and the operation of run-

of-river plants, several of which are unique to the nation. Similar tools exist for other countries or regions that could be used instead to represent a different case study.

The power system expansion planning module requires several categories of input parameters describing the network structure, generation resources, economic data, and uncertainty drivers. Network data includes buses, transmission lines, electrical parameters, existing generation units, and reserve requirements. Hydropower modeling relies on information related to reservoir capacities, inflows, and water release constraints to represent reservoir dynamics. The input dataset also includes a list of candidate expansion projects, comprising both generation and transmission alternatives considered within the planning horizon, as well as economic parameters such as fuel costs for thermal generation technologies.

In addition, configuration parameters define the temporal and stochastic structure of the simulation, including the planning stages, the temporal blocks used to represent intra-period operation, and the number of scenarios considered. Uncertainty is represented through time series of hydrological inflows, renewable generation profiles (e.g., wind and solar), and electricity demand across the defined scenarios. These datasets constitute the input parameters used by the planning module to formulate the scenario-based optimization problem. The power system expansion planning module produces outputs that describe the long-term evolution of the system under the considered scenarios. Specifically, the model reports the evolution of the energy mix by generation technology over the planning horizon, the trajectory of marginal electricity costs across scenarios, and the set of candidate generation and transmission projects selected to satisfy expansion requirements. The spatial resolution corresponds to the network representation defined by the set of buses and transmission lines included in the system model.

The temporal resolution of the operational representation is user-defined and can be configured at hourly, aggregated time-block, or weekly levels. This flexibility allows balancing model fidelity and computational tractability: finer temporal granularity improves the representation of system operation but increases computational cost and simulation time, while coarser aggregation reduces computational requirements. The selected configuration determines the temporal structure used to evaluate expansion decisions across the planning horizon.

The interface between the power distribution module and the power system expansion planning module is defined through the exchange of net electricity demand profiles. The distribution module computes the net demand as the aggregation of base electricity consumption and electromobility charging demand. These profiles are spatially mapped to the corresponding high-voltage buses of the transmission network representation used in Fesop. For each bus, the interface provides time series of net demand that serve as load inputs to the expansion planning model. If required, the demand time series are temporally aggregated to match the temporal resolution adopted in Fesop (e.g., hourly, time blocks, or weekly). Through this interface, the spatial and temporal distribution of EV charging demand captured at the distribution level directly influences the load conditions used to determine optimal generation and transmission expansion decisions in the planning module.

Data chronology

Each module is fed by projections that stem from different datasets. While the transportation module takes as a basis the 2014 Origin-Destination survey, urban planning uses the 2017 Census, and grid analysis uses a January 27, 2023, load profile. This selection obeys solely data availability; if comprehensive, harmonised, and more recent data were available across all domains (mobility, census, and grid), it should be preferred to eliminate possible projection mismatches.

Temuco case study

Temuco and Padre Las Casas form a medium-sized metropolitan area, with 355,410 inhabitants according to the 2017 Census, and is located in southern Chile, within the Araucanía Region, as shown in Figure 3. Temuco functions as the main administrative, economic, and service centre of the region, while Padre Las Casas, situated immediately to the south across the Cautín River, has experienced rapid demographic growth and increasing residential consolidation over recent decades. Together, the two cities exhibit a strong functional integration in terms of labour markets, daily mobility, and access to urban services.

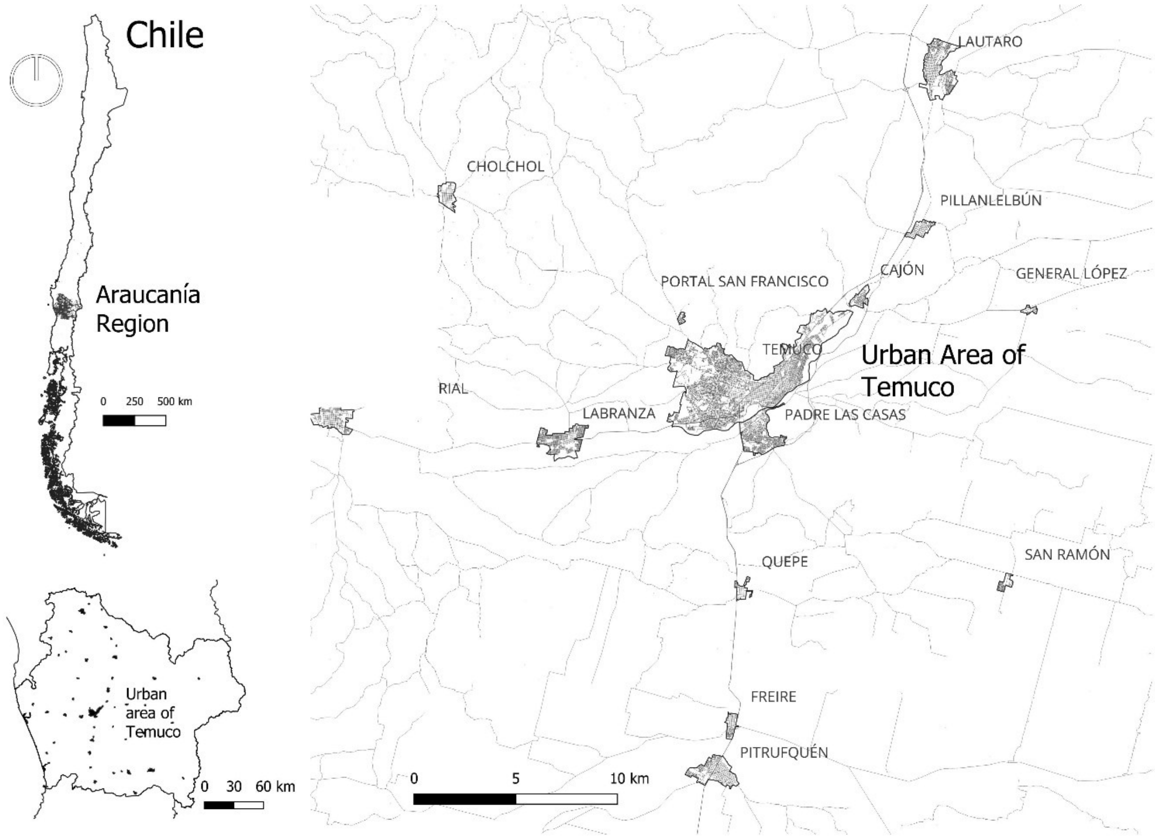

Figure 3. Location of the Temuco-Padre Las Casas urban area within the Araucanía Region and the Chilean territory.

RESULTS AND DISCUSSION

In this section, the results derived from each model within the framework are presented, focusing on the city of Temuco and Padre Las Casas (Temuco-PLC) as a case study. Although the methodology is general enough to be applied to any region in the world and has been applied to other cities in Chile (Valdivia, Santiago) by the authors, Temuco-PLC represents the most comprehensive and data-rich city application to date. Furthermore, the primary objective of this section is to present the type of results derived from each module, with the Temuco-PLC case serving as an application of the approach in a real-world context.

Technology adoption

The main outputs of this module are related to projections of energy consumption, the number of EVs, and distributed energy resources. The energy consumption resulting from the combination of the transportation projections with the electromobility goals based on the National Strategy is shown in Figure 4a. For comparison, a baseline scenario (segmented line in Figure 4a) is considered, where all future transportation demand is supplied with conventional (less efficient) cars, without an increase in EVs. In this case, the transportation demand projection is given for the entire country. Therefore, the adopted approach first established national-level projections,, which were subsequently disaggregated by region and cities. The orange area in Figure 4a depicts the progressive change towards electricity consumption as EVs are adopted, leading to estimated energy savings in Figure 4b of 81.76 TWh in 2035 and 114.7 TWh in 2050, solely due to the higher efficiency of EVs.

The total transportation demand is also translated to a total number of vehicles, with a portion that corresponds to light-duty vehicles. Given the adoption baseline based on the National Strategy, the total number of light-duty EVs in circulation per year is estimated and shown in **Error! Reference source not found.**c. Assuming a lifetime of an EV with a uniform distribution between 8 and 12 years, a balance to estimate the number of new and discarded cars per year is made. The discarded cars are then used to estimate the expected capacity of residual batteries, which could reach around 10.2 GWh in 2050 (Figure 4d), from 170,016 discarded EVs with a mean battery size of 60 kWh completing their lifetime. The projected fleet of light-duty EVs can also be analysed per region as shown in **Error! Reference source not found.**e. For these, the capacity of the public charging infrastructure (Figure 4f) is determined using international recommendations for fast charging stations of 1 kW per EV [57], which will yield 807 MW in 2035 and 4.6 GW in 2050.

It is worth mentioning that this study focused exclusively on Battery Electric Vehicles (BEVs), since hybrid EVs that require only partial charging may primarily rely on home charging facilities. Therefore, their specific routes and public charging logistics may not require a special study for planning public infrastructure. As these types of vehicles become more common, their additional energy demand, which is consumed at home, should be added to the power grid module to study congestion in future versions of the simulation framework.

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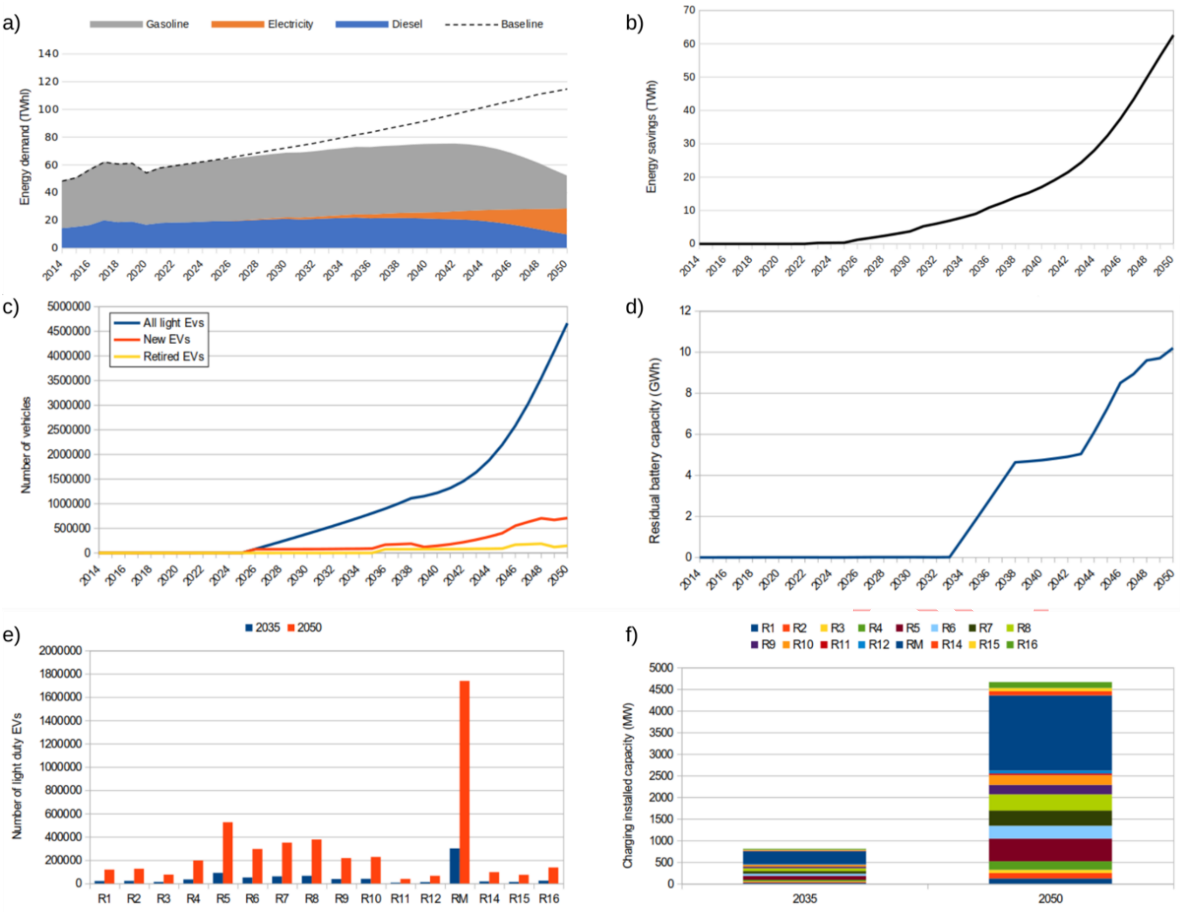

Figure 4. Projections of (a) mobility energy consumption, (b) energy savings, (c) light-duty EV composition: total, new, and discarded EVs, (d) estimated residual battery capacity, and the regional distribution of (e) EVs and (f) charging infrastructure capacity. R1-R16 denote the numbered regions in the country, and RM the metropolitan region

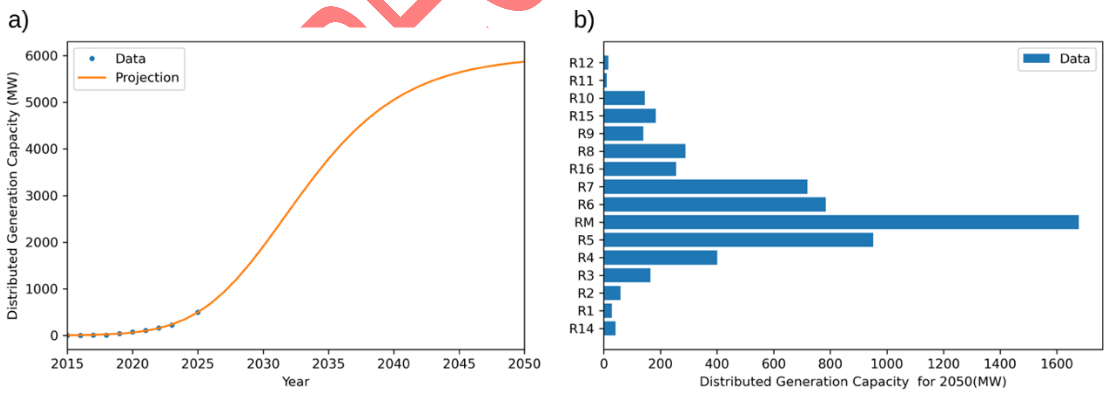

Figure 5. Projected (a) national installed capacity for distributed generation and its (b) distribution per region for 2050. R1-R16 denote the numbered regions in the country, and RM the metropolitan region

Finally, Figure 5 shows the projection for distributed generation, which follows a logistic growth, adjusted to existing installed capacity from 2015-2023, the desired goal of 500 MW in 2025, and reaching the technical potential of 6 GW in 2100 [64].

Urban planning

The urban area selected to model the urban scenarios for Temuco-PLC comprises 246 census zones covering 76,570 ha. This area is defined considering a buffer around the urban area of the municipalities of Temuco and Padre Las Casas. According to the population module, in 2050 the population estimate for the urban area of both municipalities is 363,456 inhabitants, a growth of 12.54 % from the base year of 2017 (when the national census was conducted). The segmentation module of the household indicates the demographic structure of the study area, shown in Table 3. The spatial distribution of the projected growth of houses and apartments is shown in Figure 6.

Table 3. Population proportion by education and life stage

	Basic	Hi-School	Superior incomplete	Superior complete	Total
Senior	11.8 %	7.3 %	2.3 %	2.5 %	23.9 %
w/kids	8.1 %	19.8 %	6.2 %	6.5 %	40.6 %
Independent	6.9 %	14.1 %	7.5 %	7.2 %	35.6 %
Total	26.7 %	41.2 %	15.9 %	16.2 %	100 %

Concerning the aggregated dwellings module, the composition of dwelling types and their changes over time are shown in Table 4.

Table 4. Dwelling typology overview in Temuco

Year	Area	Houses	Apartments	Total
2002	Rural	3,338 (99.97 %)	1 (0.03 %)	3,339
2002	Urban	65,910 (90.97 %)	6,543 (9.03 %)	72,453
2017	Rural	17,135 (100 %)	0 (0 %)	17,135
2017	Urban	97,461 (85.82 %)	16,098 (14.18 %)	113,559

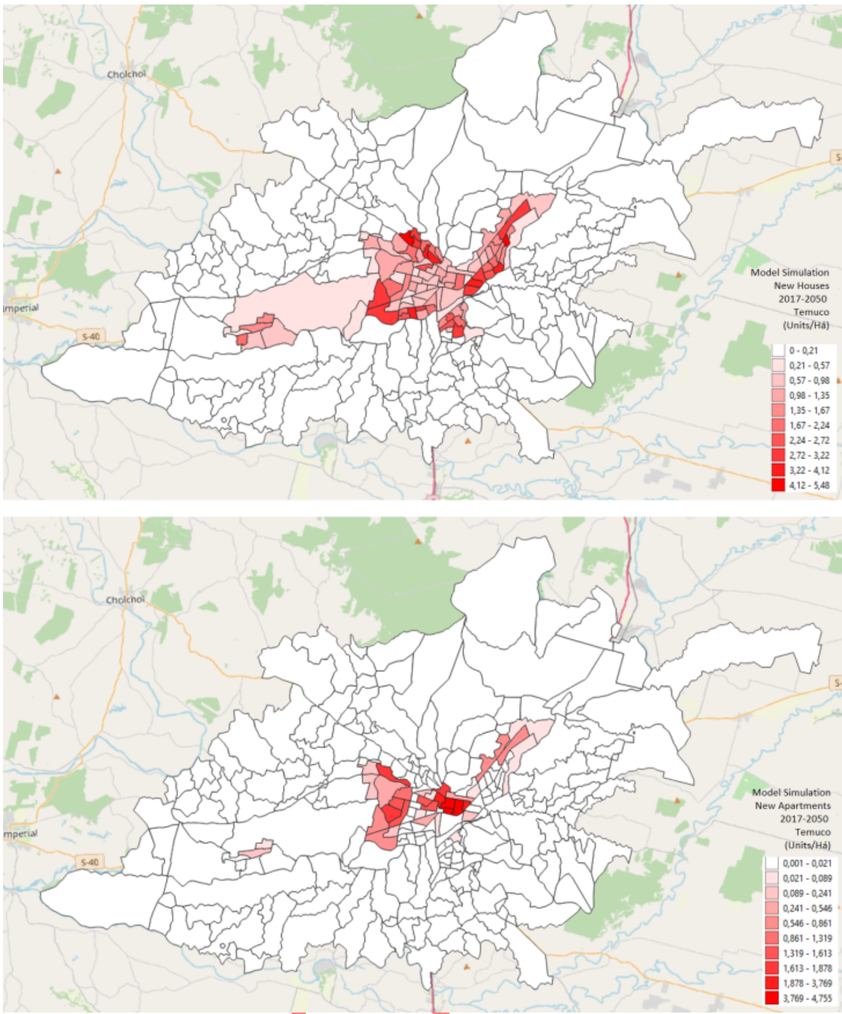

Figure 6. Heat maps of houses (upper panel) and apartment (lower panel) growth per census zones in the study area for Temuco

Figure 6 shows an example of two output variables from the Urban Planning Module. The upper map shows the localization of new houses, mostly in the expansion areas of the city, reproducing the tendency of single unit dwellings to locate in less central areas but with more available plot space. The lower map shows the location of new apartments, which, in opposition to houses, seek for proximity to urban amenities in denser areas.

Transport system

This section presents the MATSim-based transport simulation outputs used as input for the estimation of charging demand and electrical load at public charging points. Within the scope of this study, the transport module is used as a means to characterize the charging events induced by EV operation rather than as a standalone transport analysis. This allows the identification of the temporal and spatial occurrence of charging demand and supports the evaluation of charger utilization and the resulting electrical impact on the charging infrastructure. To test the module, the transport and charging demand are simulated considering all private vehicles represented in the Temuco travel survey, from 2014 [65]. For these initial simulations, the EV fleet and the charging network (private and public) are estimated using the technology adoption and urban planning modules. Different cases can be simulated to evaluate a range of scenarios, such as different levels of access to residential chargers, different starting states of charge, etc. For this particular scenario, it was assumed that the fleet of private vehicles starts their daily schedule with a state of charge based on access to a private charger (50% for EV users without private chargers and 80% for those with private chargers). Figure 7 shows the results of a MATSim simulation for a weekday, covering the period from 00:00 to 23:59, for the current configuration of Padre Las Casas. Here, the temporal variation in the number of vehicles is a consequence of the corresponding charging infrastructure, causing EV users to charge during the day as they move across the city.

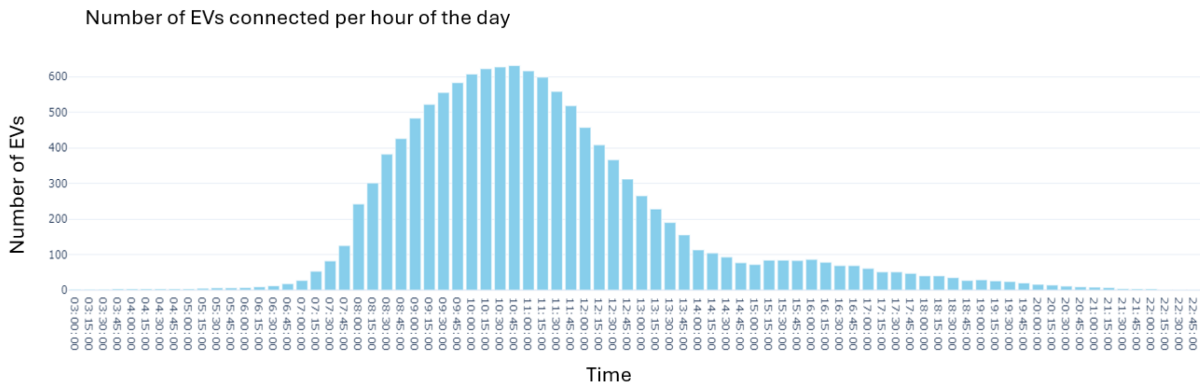

Figure 7. Number of EVs connected to the PLC grid per hour of the day

The previous results show how the simulation considers the effect of having access to a residential charger. When agents do not have a charger at home, they decide to charge the minimum amount of energy needed on a public charger to complete their daily travel demands, reducing the impact on their daily schedule. On the other hand, when agents have access to residential chargers, they charge their vehicles as soon as they arrive home and continue charging the vehicle until the battery is fully charged (or until the end of the simulation). These charging profiles are integrated as inputs into the power distribution module.

Power distribution

For simplicity, results on a reduced area of Temuco are presented for this module. In particular, the analysis is focused on Padre Las Casas' network. Figure 8 presents the power distribution network geographically.

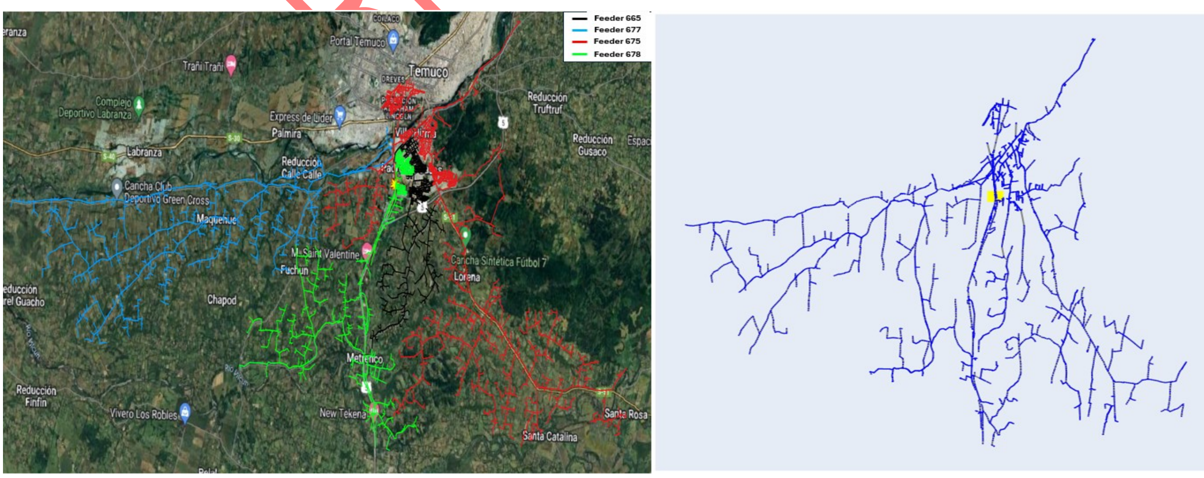

Figure 8. Geographical view of the distribution grid in Padre Las Casas (left panel), with the distribution network of Padre Las Casas defined in Pandapower (right panel)

Padre Las Casas distribution grid is characterized by four medium-voltage feeders that are connected through a transformer to the high-voltage transmission network. Additionally, for this particular case, the load data is available only at the feeder head. However, to obtain significant results for validating this module, these consumptions were disaggregated among the dwellings present in the PLC network, which was defined in Pandapower as shown in the right panel of Figure 8, considering an average consumption value for each, with the loads connected according to the locations provided by the urban planning module.

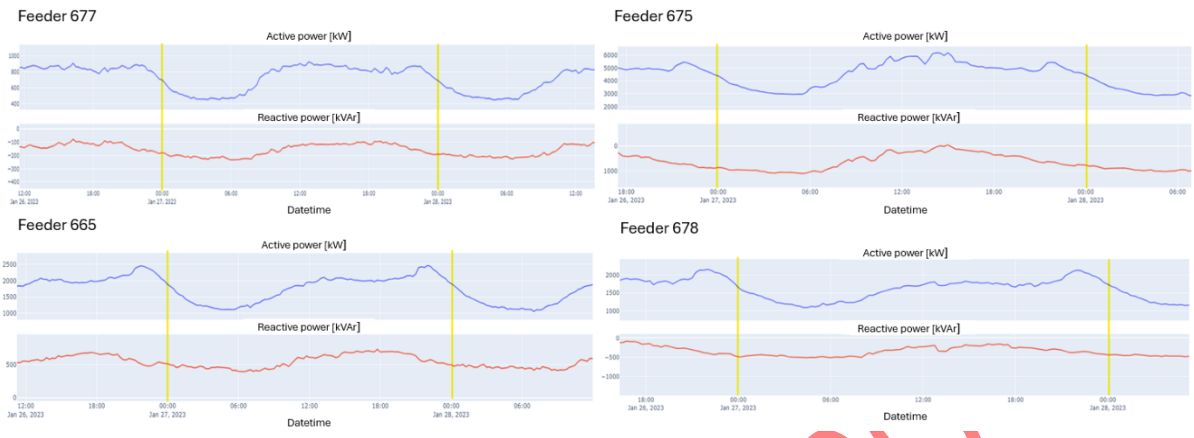

Figure 9. Demand curve for the four PLC feeders for January 27, 2023

Using data collected from the local distribution network operator, CGE, a daily load profile for the four feeders is presented in Figure 9 for January 27, 2023. To evaluate network performance in different scenarios, four cases are proposed.

- Scenario 1: Includes only residential loads with the base demand for the year 2023.
- Scenario 2: Consider residential loads based on the projected demand for 2050, assuming an annual increase of 3.32% in the electricity demand.
- Scenario 3: Incorporate residential loads for 2050 alongside the integration of EVs.
- Scenario 4: Account for residential loads for 2050, EVs, and distributed generation.

Power flow analysis is performed over 24 hours using data from January 27, which spans from 00:00 to 23:45, with a 15-minute sampling interval, resulting in iterations for each time step. The voltage ranges for acceptable operation between the busbars or nodes of the grid are set at ±5 % of their values per unit.

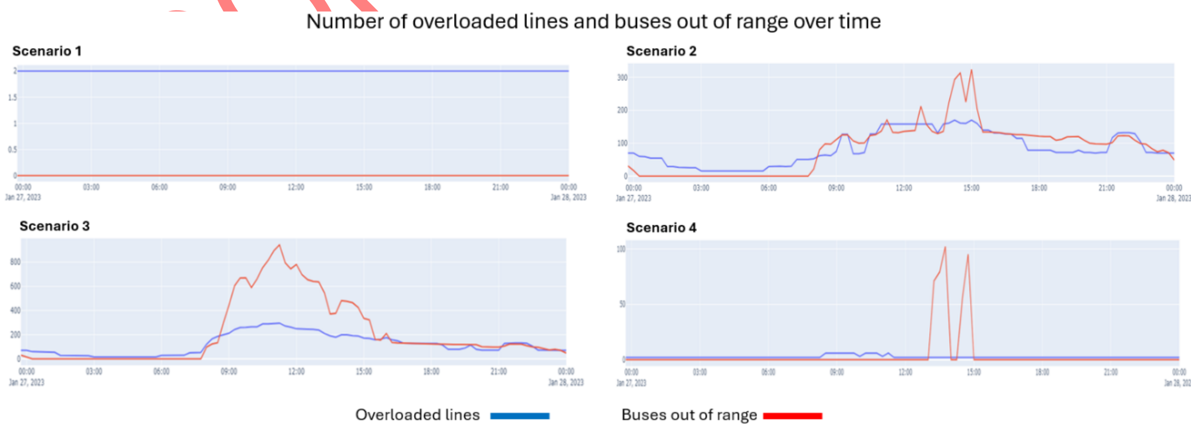

Figure 10. Number of overloaded lines and out-of-range busbars for the four scenarios

With this data, the daily operational conditions of the grid are computed. Figure 10 illustrates the variation in the number of overloaded lines (based on maximum current capacity) and busbars operating outside the acceptable range. In Scenario 1, the grid operates almost stably, with issues observed in only two distribution lines, while all busbars remain within the specified range. In Scenario 2, there is a significant increase in both overloaded lines and out-of-range busbars due to higher demand. When EVs are incorporated into Scenario 3, these problems are exacerbated, resulting in over 800 out-of-range busbars and approximately 300 overloaded lines. Finally, in Scenario 4, the addition of DERs drastically reduces the number of issues, bringing the grid performance closer to that of Scenario 1. Despite this improvement, some problems persist briefly around noon, probably due to insufficient distributed generation to meet peak demand, requiring intervention from the utility to cover the remaining load. These findings suggest that full reinforcement of problematic lines is unnecessary, as effective resource management could mitigate these issues and avoid additional expenses.

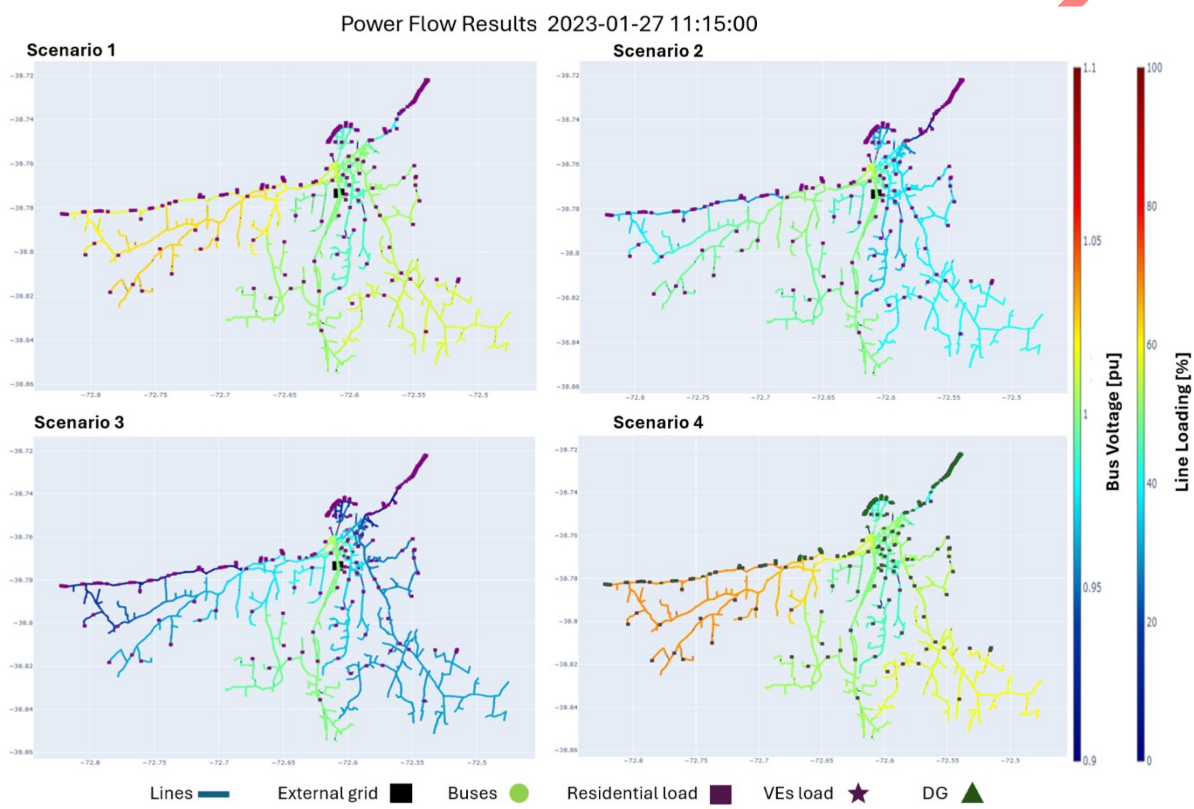

Figure 11. Heat map with power flow results at 11:15 h for the four scenarios

In Figure 11, a heat map shows the power flow results for the iteration at 11:15 h, one of the most congested periods for the network. In Scenarios 1 and 4, the voltages measured in the busbars remain close to 1 p.u., indicating a stable operating condition. In contrast, in Scenarios 2 and 3, the increased demand leads to a significant decline in voltage levels across the network, with some busbars dropping to values near 0.9 p.u.

Table 5. Summary of line replacement for the four scenarios

Scenario	Replaced lines	Replaced line length (km)
1	2	0.093
2	171	7.556
3	304	13.074
4	6	0.204

Finally, the reinforcement of the distribution lines for each scenario is summarized in Table 5. The lines selected here correspond to those that were overloaded according to the power

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flow results. That is, whenever a single power-flow solution (thus associated to a single timestep) presents a current value above the line capacity, this will mean the line is overloaded and needs to be replaced. The cost of replacement of a line was considered as 300,000 USD/km[†].

Power system expansion planning

This module analyses the optimal expansion of the electric grid considering several generation technologies, transmission facilities, and a 20-year demand forecast. The tests explore the expansion planning of the National Electric System under various stochastic scenarios, capturing uncertainties in renewable resource variability and projected demand growth. The results of this module allow the identification of the system's structural needs and guide the strategic investments required to maintain reliability throughout the planning horizon.

The grid model includes 26 bus bars and nearly 900 generation units, which include thermal, hydro, and renewable power plants (solar and wind). The planning horizon spans 2021 to 2050. This allows the model to capture the progressive effects of technological transitions, the evolution of operational constraints, and decarbonization policies. Figure 12 presents the results of the integrated expansion and operation analysis performed with PLP and Fesop under three stochastic scenarios.

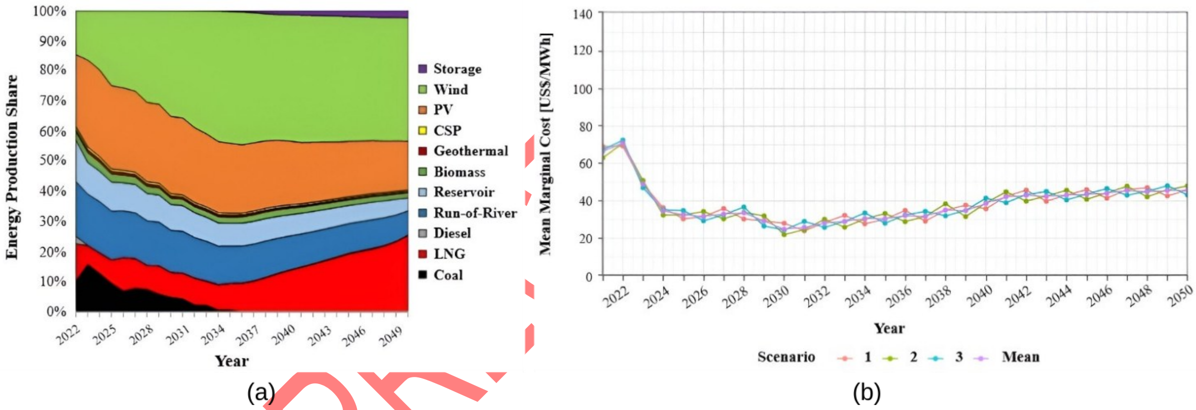

Figure 12. Projected energy production share (left) and mean marginal costs (right) for the expansion planning of the National Electric System, considering three stochastic scenarios

Figure 12a illustrates the energy production mix evolution by technology over a predefined observation period. The results show that meeting growing electricity demand and compensating for capacity reductions due to decarbonization will require a balanced expansion of wind and photovoltaic plants. However, the high variability and limited dispatchability of these technologies significantly elevate system reserve requirements. Consequently, the model indicates a continued need for flexible natural gas generation to provide firm capacity and ensure system reliability during periods of low renewable output.

Figure 12b, in turn, shows the evolution of the system's marginal cost across the three scenarios considered, along with their average value. A reduction in the marginal cost is observed during the initial years, which can be attributed to the increase in renewable generation and the retirement of higher-cost thermal units. However, starting in 2038, an upward trend becomes evident, driven by the greater reserve requirements needed to manage

† This value has been suggested by the distribution system operator that shared the grid data.

the variability of renewable sources. These reserves are primarily supplied by thermal units, as previously illustrated in Figure 12a.

Together, these findings highlight the importance of integrating renewable deployment with adequate flexible resources and transmission expansion to support a secure and cost-efficient energy transition.

CONCLUSIONS

The presented integrated simulation framework offers a multitude of opportunities and benefits in assessing sustainable electromobility scenarios. By quantifying the potential impacts of the adoption of EVs in urban electric grids and the national energy system, stakeholders can gain insight into the intricate relationships between various sectors. This understanding can facilitate informed decision-making and policy formulation, enabling the identification of optimal pathways to reduce carbon emissions.

Integrating diverse modules within a single platform presents inherent challenges. The synergistic interplay of technology adoption, urban planning, transport systems, power distribution, and expansion of the power system requires meticulous calibration and coordination. Ensuring the accuracy and reliability of these interconnected models requires rigorous validation procedures and the harmonization of assumptions.

This work established several promising avenues for future research. The simulation platform could serve as a pivotal tool for the design of public policy on electromobility, facilitating evidence-based decision-making and the evaluation of policy effectiveness. The wide effects of commonly proposed policy interventions, such as subsidies to EVs, could be analysed from an energy requirement and land use perspective using a single integrated tool. Furthermore, the platform can bridge the gap between energy plans and regional territorial planning, paving the way for more cohesive and integrated urban development strategies. Exploring links between climate change adaptation/mitigation plans, transportation planning, and land use management presents an exciting avenue for comprehensively addressing sustainability challenges. In addition, investigating the intricate connections between land use, transportation, and energy systems can provide valuable insight into the holistic planning required for sustainable urban environments. These emerging research directions have the potential to inform interdisciplinary policies that transcend traditional boundaries.

The work in case study preparation and analysis highlights the crucial need for access to rich, harmonised, and meticulously curated data. This is particularly evident in urban transportation modelling, where comprehensive origin-destination surveys are indispensable. However, these surveys are infrequent due to their lengthy and intricate processes; for example, in Chile, they are typically administered only once a decade. These challenges underscore the paramount importance of exploring alternative data sources, such as data from mobile networks for transportation, which offers continuous and real-time insights.

The accuracy of energy models is often hampered by the availability and quality of data from the electrical system, particularly topological information. This is crucial for short-term operations and long-term strategic planning, including the modelling of energy grids for electromobility analysis. Maintaining up-to-date topological data is an ongoing hurdle. Overcoming these data limitations is critical for reliable energy forecasting and planning, preventing misleading or detrimental model outputs. Investing in advanced data collection, rigorous validation, and standardized data formats is essential for robust and insightful analysis of energy systems and electromobility scenarios. Future work should aim to integrate optimization across all stages, in order to provide decision-makers a powerful tool for planning purposes.

The integration of these diverse data sources requires strong collaborations with private companies (electric utilities, mobile companies, etc.) and energy and transportation policy makers. Establishing these relationships is crucial for accessing proprietary data, ensuring data interoperability, and aligning modelling efforts with policy objectives. This collaborative approach is essential for accurately modelling EV scenarios, understanding their impact on both transportation networks and energy grids, and informing effective policy decisions for sustainable electromobility.

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NOMENCLATURE

Abbreviations

ABM	Agent-Based Model
DER	Distributed Energy Resource
EV	Electric Vehicle
MAS	Multi-Agent Simulation
O-D	Origin-Destination
pkm	Passenger Kilometer
p.u.	Per Unit
PLC	Padre Las Casas
PRSE	Participatory Roundtables for Sustainable Electromobility
PV	Photovoltaic
R1-R16	Numbered administrative Regions in Chile
RF	Random Forest
RM	Metropolitan Region
SDDP	Stochastic Dual Dynamic Programming
V2G	Vehicle to Grid

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APPENDIX

Description of the inputs of the simulation modules

- The main inputs of each module are:Technology adoption: Transportation demand projection time series, historical number of vehicles per type, region and year, EV goals (percentage of total vehicles per year), vehicle efficiency per type, lifetime of new EVs in years, expected capacity of future residual batteries, capacity of public charging infrastructure (installed charging capacity per EV or number of chargers per EV), distributed generation goals (installed capacity per year). EV and DER projection curves can be modified.
- Urban planning: Total number of households in study area for each year (2017 to 2050), vehicle ownership rate, geometry of Census Zones in study area, and for each census zone: number of households, number of houses and apartments, proportion of households with children, and proportion of households with Higher Education.
- Transport System: The transport network requires inputs from OpenStreetMap (OSM): each paved road link was defined by its length, free-flow speed, number of lanes, and capacity, according to the corresponding road attributes. The agent population was constructed from the origin–destination surveys (EOD) available for each city. Based on these data, MATSim agents were assigned daily activity plans including activity type (e.g., home, work, shopping), activity location, start time, end time, duration, transport mode, and route, allowing the simulated demand to reflect the observed mobility patterns of each urban area. The electric mobility module was parameterized using charging infrastructure and electric vehicle attributes. Charging infrastructure included charger location, charger type (residential, workplace, and public), charging power, and number of chargers. Residential charging was represented using standard home chargers, while public charging considered 22 kW chargers and higher-power public chargers where applicable. In addition, multiple scenarios were evaluated by varying the initial state of charge (SoC) of electric vehicles. Specifically, three initial SoC conditions were considered (50%, 30%, and 20%), and in each case, the assigned value was randomly distributed across all EV agents. These scenarios were used to analyse public charger utilization, road congestion, and impacts on the electricity network.
- Power distribution: grid topology (electrical infrastructure and how they are connected, including electrical parameters), base load measurements (base scenario when no EVs

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are available), base load yearly-growth-rate, expected power injection from renewable resources, EV characteristics (charging power, battery size), EV arrivals and departures, and the type of households or buildings in the area under study as per their geographical location.

- Power system expansion planning: network structure (buses, transmission lines, existing generation units, and reserve requirements), generation resources (reservoir capacities, inflows, and water release constraints), candidate expansion projects (both generation and transmission alternatives considered within the planning horizon), economic data (fuel costs for thermal generation technologies), configuration parameters for simulation (planning stages, temporal blocks, and number of scenarios considered), and uncertainty drivers (hydrological inflows, renewable generation profiles, and electricity demand across the defined scenarios).

Sensitivity of predicted energy consumption

A sensitivity analysis was performed by increasing the energy efficiency of new light-duty vehicles based on the current minimum energy efficiency standards in Chile [58], set progressively as kilometers per equivalent litre of gasoline of 18,8 km/l by 2026, 22,8 km/l by 2029, and 28,9 km/l beyond 2030. These values correspond to an optimistic case in which the standard is set for the entire vehicle park of light-duty gasoline and diesel cars. For EVs, we took a linear increase from 5 to 7 km/kWh between 2025 and 2035 instead, as EVs already reach higher values than these minimum equivalent efficiencies. With these settings, the differences between constant and increasing efficiencies are shown in Figure 13, where the energy consumption decreases significantly during the transition, leading to a total reduction of nearly 34% in 2035 and 28% in 2050 compared to the constant efficiency case. Therefore, adjusting the energy efficiency to realistic future values can be an influential factor for energy planning and emission estimates.

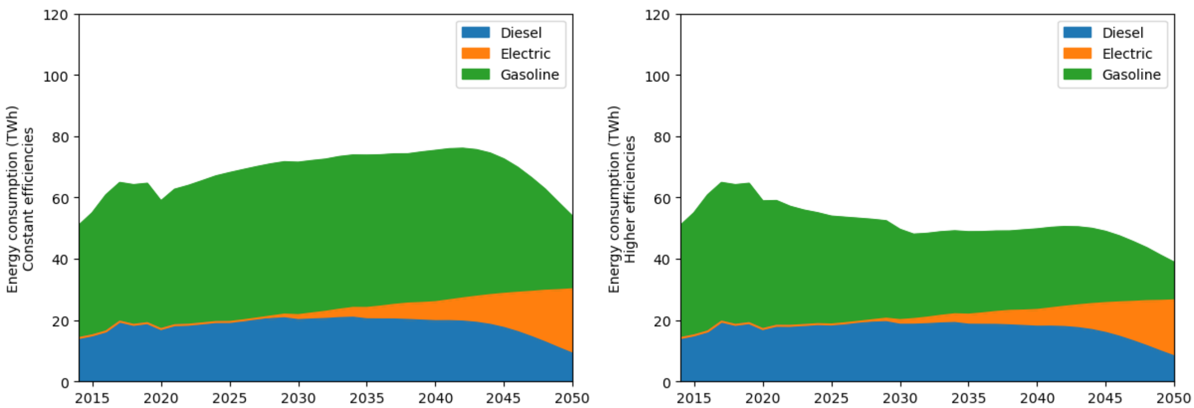

Figure 13. Sensitivity analysis of energy consumption by comparing constant vehicle efficiencies (left) to increasing vehicle energy efficiencies according to minimum standards (right).