Advancing Electric Vehicle Load Estimation for Power Distribution Systems

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***Abstract*—The rapid adoption of electric vehicles (EVs) challenges electric distribution grids due to increased demand and the need for efficient grid management. This paper introduces a methodology to estimate future EV charging loads considering electric, socioeconomic, transport, and household factors. By combining Monte Carlo simulations with regression models, we analyze EVs' spatial distribution and charging demand in Santiago, Chile. Our main methodological contribution is the integration of Monte Carlo simulations, multivariate linear regression, and spatial analysis to provide nuanced estimations of EV charging demand in different substations. This approach accounts for variability and enhances the reliability and usability of our estimations. Incorporating stochastic variables allows the examination of different EV penetration and usage scenarios, offering insights into their distribution network impacts. This method improves demand estimation, which is key for grid management and infrastructure planning. Our flexible methodology can be applied to various urban and energy contexts, facilitating the adaptation of electrical infrastructure for electric mobility.**

I. Introduction

The rise of electric vehicles (EVs) marks a pivotal shift in urban transportation, driven by the urgent need to address environmental and social challenges associated with traditional internal combustion engine (ICE) vehicles. As a cleaner and more energy-efficient alternative, EVs are central to transforming the transportation sector. However, this transition introduces complex challenges, particularly in planning and operating electrical systems to accommodate the increased demand. In Chile, for example, transportation is a major energy consumer, accounting for 34% of total consumption in 2021 and a significant source of greenhouse gas emissions, contributing 33% of the total in 2020 [1]. Electric mobility offers a promising route to reduce emissions, but it also demands careful management of the electrical grid to ensure reliable energy supply and timely investments to avoid congestion.

The integration of electric vehicles significantly impacts electrical demand, underlining the importance of obtaining accurate forecasts of EV-related energy consumption for sizing charging infrastructure and ensuring grid reliability. These forecasts must not only predict expected values but also characterize the uncertainties associated with these predictions to manage risks and variability in energy demand effectively. Understanding EV charging patterns is vital for the strategic use of renewable energy sources, such as solar and wind power, optimizing the utilization of clean energy and further mitigating the carbon footprint of transportation. Effective electrical demand management through smart and coordinated charging strategies and dynamic pricing can enhance grid efficiency and support equitable energy distribution, as pointed out in [2]. However, these approaches require including both the anticipated demand and the range of possible outcomes, emphasizing the need for advanced methodologies in estimating EV-related energy needs with an explicit focus on both the value and its uncertainty.

This study introduces a novel method for estimating future load associated with EV charging in distribution systems to support the sustainable, efficient, and secure integration of electric mobility into the electrical grid. By tackling the challenges of energy demand estimation, this research contributes to the broader goal of achieving sustainable urban mobility and the optimization of electrical systems. This article is structured as follows: Section II discusses the literature regarding the prediction of variables related to the use of EVs. Section III presents the proposed methodology and section IV presents numerical results. Finally, Section V concludes and highlights directions for further research.

II. Prediction of variables related to electromobility

The electrification of transportation through electric vehicles presents both an opportunity and a challenge for modern power systems. While EVs offer a pathway towards sustainable mobility, their widespread adoption necessitates a deeper understanding of their impact on power distribution networks. The existing literature reveals a diverse array of methodologies and findings, reflecting the complexity of this issue.

A. Technical impacts of EV charging in distribution grids

Reference [3] explores the impact of charging plug-in hybrid electric vehicles (PHEVs), considering the mixed usage patterns of ICE and electric vehicles, annual travel distances, and energy consumption. The study assesses the degradation of distribution transformers due to the increased load from EVs. Similarly, research presented in [4], supported by a probabilistic model from [5], investigates the influence of fast charging stations on distribution networks, highlighting concerns such as transformer ageing and voltage levels. Adding to this body of work, [6] conducts a comprehensive study on modeling diverse EV charging units across industrial, commercial, and residential sectors. This research elucidates EV chargers' nonlinear and multi-state load characteristics and their potential impacts on distribution networks, including current and voltage profiles and harmonic distortions. Such detailed analysis aids in anticipating the effects of EV charging on distribution systems and underscores the importance of adapting and enhancing electrical infrastructure to maintain power quality. These studies collectively underscore the multifaceted challenges of integrating EVs into existing power systems, emphasizing the need for comprehensive planning and operational strategies to mitigate potential adverse effects.

B. Socioeconomic influences and spatial distribution

A critical observation from the literature is the insufficient emphasis on socioeconomic factors in modeling EV charging demand and infrastructure development. For instance, [7] quantifies the impact of EV adoption in Santiago, Chile, using variables like energy consumption rates and travel distances but does not extensively account for socioeconomic determinants. Similarly, studies such as [8], focused on the Milan metropolitan area, highlight the need for incorporating average energy consumption and mobility patterns into the sizing of infrastructure, yet often overlook the rich layer of socioeconomic data that could refine these estimates. Furthermore, research proposing a methodology to model fast charging requests [9] provides valuable insights into the charging behavior of light and medium EVs through Monte Carlo simulations, suggesting a nuanced approach that could benefit from integrating socioeconomic and spatial variables. In contrast, studies from Finland [10] and Germany [11] begin to bridge this gap, correlating EV adoption with factors such as income, education, and household characteristics. These findings underscore the significant influence of socioeconomic attributes on EV ownership patterns, affecting the spatial distribution of charging infrastructure needs. The inclusion of socioeconomic influences and spatial distribution considerations in analyses like those in [8] and [9] can enrich our understanding of infrastructure requirements and promote a more nuanced approach to planning for the future of electrified transport spatial distribution of charging infrastructure needs.

C. Geospatial analysis for EV charging

The integration of geographic information system (GIS) and spatio-temporal analysis, as seen in [13], may help in understanding the demand dynamics of EV charging. Utilizing diffusion theory and linear models informed by socioeconomic variables, the authors offer a nuanced view of how EV charging demand clusters within urban areas. Furthermore, the application of statistical models in Philadelphia in [14] to identify the spatial distribution of electric vehicles showcases the importance of demographic data, such as population density and household income, along with urban characteristics like employment density and proximity to the central business district. These factors are instrumental in predicting EV presence and, by extension, charging demand across different urban zones. This approach emphasizes the capability of geospatial analysis to determine where EVs are likely to be adopted and inform the strategic placement of charging infrastructure. Additionally, a study in the United Kingdom [12] leverages demographic and socioeconomic data to predict EV adoption rates and their implications for local power systems, highlighting the potential of geospatial analysis in planning EV infrastructure. Together, these studies underscore the critical role of integrating GIS and socioeconomic insights to plan for the evolving needs of EV charging infrastructure effectively.

D. Summary and research gaps

Despite advancements in modeling the technical and immediate impacts of EV charging on power systems, the literature reveals a notable gap in incorporating socioeconomic and spatial factors into these models. The variability in EV adoption rates across different demographic groups and urban areas suggests that future research should focus on a more holistic approach, combining technical, socioeconomic, and spatial analyses. This integrated perspective is crucial for developing robust, scalable, and equitable strategies for accommodating the rise of electric mobility. In conclusion, the reviewed work underscores the complex interplay between EV adoption, charging behavior, and power system impacts. It highlights the need for innovative approaches that address the technical challenges and consider the socioeconomic and spatial dimensions of electric mobility. Bridging these gaps will be essential for ensuring that the transition to electric vehicles contributes positively to the sustainability, efficiency, and resilience of urban power systems.

III. Proposed Methodology

This section explains the methodology to estimate future electricity demand from EV charging in a specified area, as shown in Fig. 1. We first use a linear regression model to estimate the number of EVs in a spatially distributed fleet, then apply Monte Carlo simulation to calculate energy demand. Thus, the combined models determine the energy demand across different zones. Graph theory then allocates the consumed energy to primary distribution substations based on their capacity. The study area is Santiago, Chile.

A. Electric vehicles energy consumption

Energy consumption for charging the EVs is calculated following [9], including the possibility of slow charging at home. Notice that instead of using a fixed diversity factor, we rely on Monte Carlo simulation to prevent overestimation and properly model the diversity of the EV charging patterns. The Monte Carlo model differentiates between vehicles needing home slow charging and those requiring fast charging due to low-charge alerts while traveling, excluding vehicles leaving the study area. The model uses inputs such as the characteristics of the EV fleet, charging station availability, and driver behaviors.

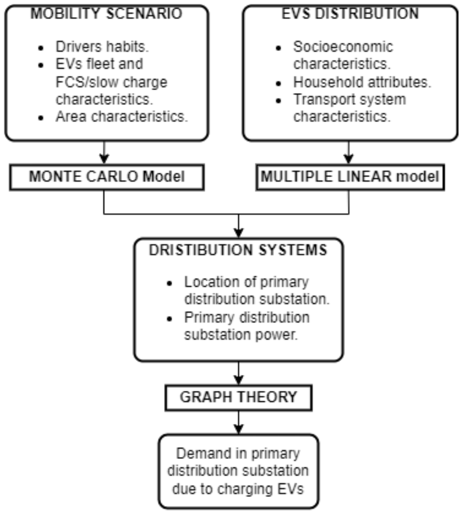

Fig. 1. Model to estimate the future EV load in distribution systems

TABLE I
MOBILITY SCENARIO OF DRIVERS FROM STUDIO AREA.

Parameter cat.	Value			
Vehicles	Type of EV	Percentage [15]	Battery Capacity [kWh] [9]	Efficiency [kWh/km] [9]
	Small	43%	[10 , 20]	0.1 $\pm$ 0.03
	Medium	32%	[20 , 30]	0.15 $\pm$ 0.03
	Large	25%	[30 , 40]	0.2 $\pm$ 0.03
Drivers category [16] [17]	47% Regular driver (68% Full-time , 32% Part-time) 53% Non regular driver			
Parked time [9] [16]		Commuter full-time	Commuter part-time	Non regular driver
	Workdays	μ = 09:00 σ = 00:20	μ = 05:00 σ = 00:15	[1h, 3h] (Uniform distribution)
	Weekends		[1h, 5h] (Uniform distribution)	
Average speed [km/h] [16]			μ = 19.82 , σ = 4.27 (Normal distribution)	
Covered distance [km] [16]			Departure trip	Return trip
		Workdays	μ= 8.8 , σ=2.23 (Normal distribution)	μ=10.2 , σ=2.95 (Normal distribution)
		Weekends	μ= 9.4 , σ=2.4 (Normal distribution)	μ=15.2 , σ=4.43 (Normal distribution)
Initial SoC (at home)		Recharge at home	100%	
		No recharge at home	[30%, 100%] (Uniform distribution)	
SoC threshold [9]		Outward	μ= 25% (Normal distribution)	σ=2.5%
		Return	μ=35% (Normal distribution)	σ=3.5%

The EV fleet is divided into three categories by technical specifications, such as battery capacity and consumption rates, detailed in Table I.

This study develops a detailed mobility scenario for an EV fleet, incorporating fleet characteristics and key factors such as electric vehicle penetration rate (N_{EV}), access to home slow charging, demographic profiles of commuting drivers, and driving habits—categorized into regular or occasional, with regular further divided by employment status (full-time or part-time). It specifies individual EV attributes like battery capacity, consumption rates, initial charge, and departure times per driver profile. The analysis covers both a weekday and a weekend day to reflect driver behavior's impact, examining single outbound and return trips. Variables like travel distances, speeds, parking durations, and charge levels necessitating recharge are randomly assigned using uniform and normal distributions, as outlined in Table I. The approach focuses on vehicles with a one-roundtrip daily pattern.

The State of Charge (SoC) for EVs lacking home slow charging capabilities is modeled to represent a broad spectrum of user behaviors. It is assumed that outward trips predominantly occur during morning peak hours, while return journeys are most common in the afternoon peak periods. The departure times for both regular and irregular travelers are differentiated by weekdays and weekends, applying a normal distribution for each category to reflect average behaviors and variability.

The methodology employed to assess the energy demand for EV charging is visually summarized in the flowchart presented in Fig. 2 (modifying the model recommended in [9]). This approach involves assigning input data randomly to simulate the daily fluctuation in battery SoC for each vehicle from the moment it departs from home until its return. The change in the SoC is determined using Eq. (1).

$$SoC^{i,j}_{arrival} = SoC^{i,j}_{departure} - D_{i,j} \cdot C_{i,j} \cdot \frac{100}{BC_i} \tag{1}$$

where $SoC^{i,j}_{departure}$ and $SoC^{i,j}_{arrival}$ are SoC of battery (in %) of i^{th} EV on the j^{th} day at the departure and arrival of the trip (e.g from home to work), $D_{i,j}$ is distance traveled on the specific trip (in km) by the i^{th} EV on the j^{th} day, $C_{i,j}$ is the average consumption of the i^{th} EV on the j^{th} day (in $\frac{kWh}{km}$, and BC_i is the battery capacity of the i^{th} EV (in kWh). Fig. 3 (adapted from [9]) shows the variation in the SoC of an EV making an outward and return trip. The possibility of establishing different SoC threshold $SoC^{i,j}_{limit}$ on each trip allows to adapt where the EV would be charged. Finally, SoC_{FCS} and SoC_{home} are the SoC of the EV when it reaches the Fast Charging Station or home, respectively. If SoC_{EV} goes below SoC_{limit} at the departure or arrival of a trip, a signal of fast charging is activated during the travel. For users with a slow home charging option, fast charging on the trip would no longer be required, as they would slow-charge at home upon arrival. The energy associated with charging electric vehicles is determined as follows:

$$E^{i,j}_{FCS} = (0.8 - \frac{SoC^{i,j}_{FCS}}{100}) \cdot BC_i$$

$$E^{i,j}_{home} = (1.0 - \frac{SoC^{i,j}_{home}}{100}) \cdot BC_i$$

where $E^{i,j}_{FCS}$ is equal to the energy consumed by the i^{th} EV on the j^{th} which has required fast charging. $E^{i,j}_{home}$ is the energy consumed by i^{th} EV on the j^{th} day which had charged at home using slow charging. In fast charging, it is assumed the EV is charged up to 80 % of its capacity to reduce battery degradation. For those charging at home, they reach 100 % of the battery capacity. The power used in fast and slow charging is 50 and 7 kW, respectively [18]. The probability of users forgetting to charge their car at home is 10%. Finally, the percentage of users with the option of slow charging in their homes is set at 70% [19].

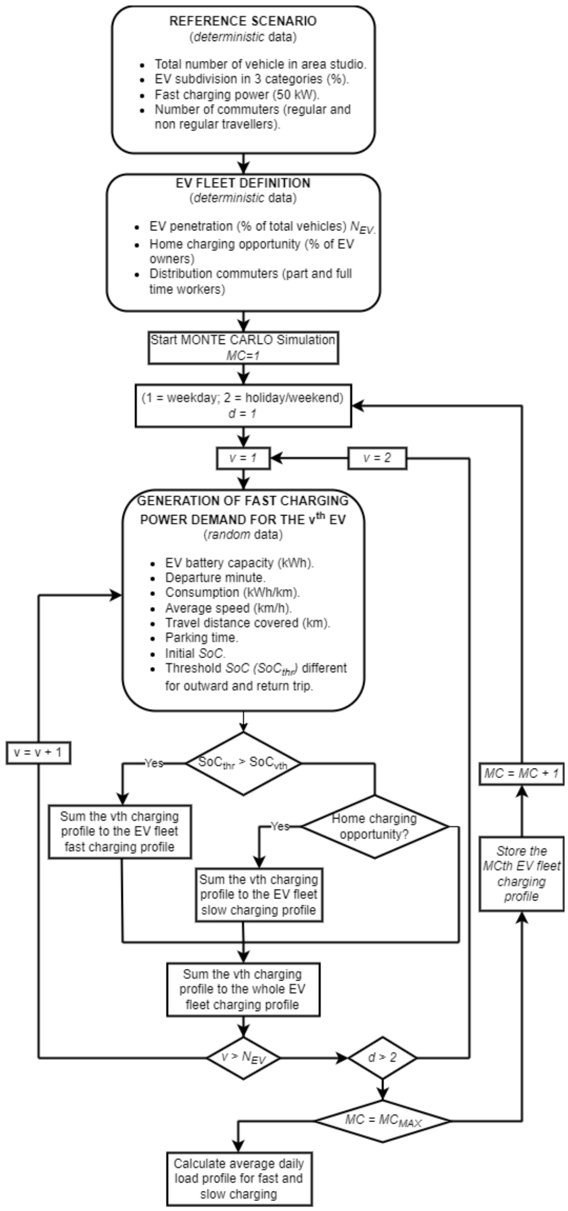

Fig. 2. Diagram of the model to obtain EV charging energy demand.

B. Spatial distribution of the EV fleet inside study area

A regression model determines the spatial distribution of electric vehicles [12] that links EV usage to the study area's socioeconomic, household, and transport variables. This model estimates the EV count for each district using Eq. 2.

$$Y = \alpha + \beta_i \cdot X_i \tag{2}$$

where Y represents the natural logarithm of the ratio of EVs to every thousand combustion vehicles. The term α is the intercept of the linear regression model, and β_i reflects the average impact of incrementing a socioeconomic, household, or transportation characteristic predictor variable (X_i) by one unit. These coefficients are derived from an ordinary least squares regression model, focusing specifically on variables

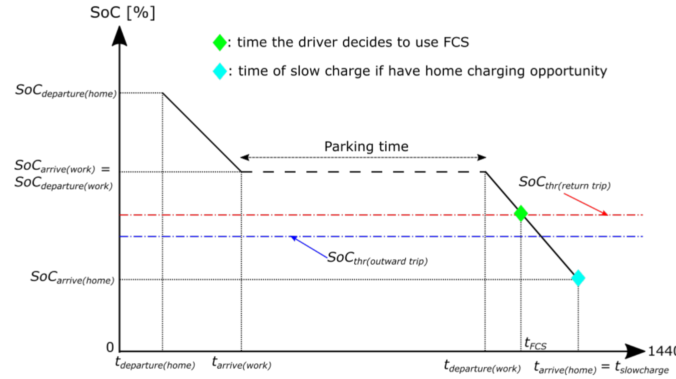

Fig. 3. Calculation of expected fast charge usage, adapted from [9].

strongly correlating with EV adoption. The selection of these coefficients is guided by the methodology outlined in [12], which also informs our estimation of EV acquisition patterns. To ensure that our regression model accurately represents the study area, it is necessary to have access to detailed statistical data. The granularity of this data is broken down by what we refer to as district divisions, as depicted in Figure 4.

Among the socioeconomic variables, the percentage of self-employed workers is chosen as a representative metric for the entire city of Santiago. Average income levels are determined by analyzing the distribution of socioeconomic segments across each district alongside the average income. Regarding household characteristics, the prevalence of semi-detached houses is identified as a consistent variable across the study area, resulting in a uniform value for all districts. In terms of transportation system attributes, given the current low penetration of EVs, the total is computed by aggregating the counts of hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), and battery electric vehicles (BEV). Table II shows the parameters for estimating the acquisition rate of electric vehicles for every district in the study area. Results of this model are used to distribute the energy demand obtained in the Monte Carlo model in each district.

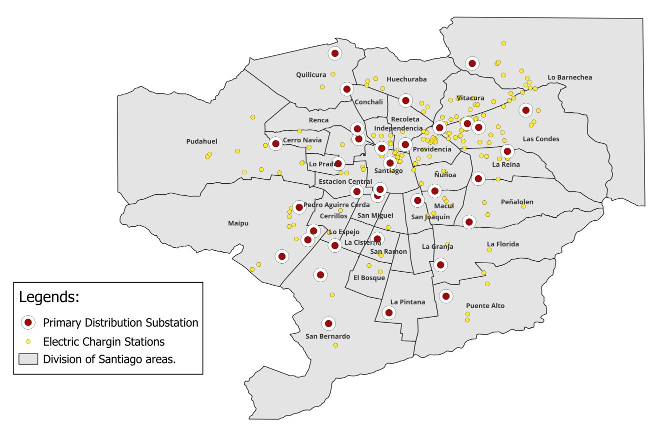

Fig. 4. Primary distribution power station and electric charging station distributed on study area [27] [28].

TABLE II
PARAMETERS USED FOR MULTIPLE LINEAR MODELS IN EACH DISTRICT.

Variable	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
Socioeconomics																	
Median Age (years) [21]	35.7	36	37.3	36	36.6	33.8	35.5	37.7	37.1	36.6	33.3	38.5	39.1	33.4	36.3	37.5	38.3
University Degree (%) [21]	18.7%	8.8%	16.1%	13.6%	23.8%	30.8%	26.6%	27.8%	29.6%	12.7%	7.3%	52.0%	62.4%	49.0%	8.8%	14.3%	33.4%
Self-Employed (%) [22]	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%
Median Income (GBP) [23]	10633	7225	9617	9235	11693	12089	12443	13772	15227	8557	6835	28453	32590	27861	7432	9337	15422
Household																	
Population Density (per ha) [21]	48.2	119.5	114.3	113.4	102.4	22.0	136.3	90.3	51.8	115.5	58.2	39.6	29.8	1.034	119.87	146.7	90.7
Semi-Detached (%) [24]	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%
Mean Residents [21]	3.3	3.4	3.3	3.4	3.0	3.5	2.8	3.0	3.2	3.4	3.6	3.2	2.7	3.8	3.6	3.2	2.9
Transport																	
One Car Household (%) [16]	27%	23%	23%	23%	25%	27%	26%	25%	27%	24%	22%	23%	25%	21%	24%	22%	27%
Car Driver to Work (%) [16]	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%
HEVs per 1000 cars [25]	0.045	0.023	0	0.023	0	0.079	0.057	0.017	0.023	0	0	0.102	0.668	0.108	0	0	0.057
Charge Points [26]	8	4	0	4	0	14	10	3	4	0	0	18	118	19	0	0	10

Variable	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH
Socioeconomics																	
Median Age (years) [21]	35.5	39	38.3	35.2	39.7	34.4	33.7	32	37.1	36.6	34.3	33.4	38.2	37.4	37.2	34.5	39.4
University Degree (%) [21]	25.6%	57.4%	14.3%	25.2%	67.2%	19.9%	21.3%	19.9%	20.3%	19.4%	11.7%	17.0%	19.0%	42.7%	10.6%	46.0%	64.7%
Self-Employed (%) [22]	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%	20.2%
Median Income (GBP) [23]	13896	24257	9408	13129	27946	9688	11329	11438	10160	9841	7921	10201	10108	17429	7747	15326	36814
Household																	
Population Density (per ha) [21]	37.9	123.5	115.5	45.1	98.7	11.7	64.4	36.7	93.1	100	61.9	19.7	95.0	112.3	132.1	174.8	30.0
Semi-Detached (%) [24]	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%	31.9%
Mean Residents [21]	3.3	2.5	3.4	3.4	2.2	3.4	3.4	3.5	3.1	3.1	3.4	3.5	3.1	2.7	3.4	2.2	3.0
Transport																	
One Car Household (%) [16]	27%	28%	25%	26%	27%	25%	25%	26%	24%	26%	25%	24%	25%	27%	23%	26%	19%
Car Driver to Work (%) [16]	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%	33.1%
HEVs per 1000 cars [25]	0.108	0.045	0	0	0.209	0.238	0.045	0.034	0.017	0.006	0	0.045	0.011	0.006	0	0.238	0.238
Charge Points [26]	19	8	0	0	37	42	8	6	3	1	0	8	2	1	0	42	42

C. Demand in primary distribution substations

In its *Recovery Post COVID* scenario, the Chilean Ministry of Energy's long-term planning [20] anticipates that 40% of vehicles will be electric by 2050. Our analysis focuses on substations within the study area, specifically primary distribution substations connected to 110 kV as shown in Figure 4. Substation distribution varies, with some districts having multiple substations and others none. We use graph theory to allocate district energy demand proportionally to the installed capacity of local substations or those in neighbouring districts when none are present in a district.

IV. RESULTS

The case study considers a 13% penetration level, corresponding to 617,921 EVs anticipated by 2040. In the initial phase, as shown in Fig. 5, the Monte Carlo model estimates a daily charging load profile for all EVs within the study area. It extracts parameters like capacity in MW and energy demand in megawatt-hours (MWh) based on a day's sample across the entire area. The Monte Carlo approach supports analysis using either median samples or entire samples for risk assessment. Load profiles can be broken down into minute or hourly periods for detailed examination.

Using the regression model, we now estimate EV adoption across districts. The model captures geographical information, enabling the determination of EV spatial distribution within the study area. Fig. 6 shows the rate of EVs per 1,000 ICE vehicles across different districts. Districts with higher EV penetration show a strong positive correlation with variables such as the number of HEVs per 1,000 cars and the availability of charging points. Other variables, like level of education and median income only exhibit a moderate positive correlation.

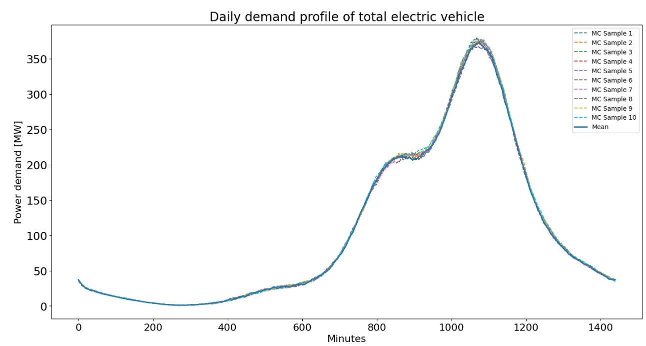

Fig. 5. Daily load profile of electric vehicle fleet for 10 Monte Carlo samples

The energy demand associated to EV charge is spatially distributed considering the rate of EV per district to estimate the impact on primary distribution substations, and the load increase is shown in Fig. 6.Four substations in the eastern districts are the most impacted, which suggests focusing future infrastructure investments there. Moreover, the methodology enables sensitivity analyses and the use of stochastic variables to derive statistical results like median, standard deviation, and percentiles. For instance, Fig. 7 shows how daily energy demand varies in four substations with the percentage of owners with home slow charging ranging from 10% to 90%.

V. CONCLUSIONS

The proposed methodology provides a comprehensive framework for predicting energy and power demand for charging EVs by integrating a multifactorial perspective, including electric, socioeconomic, transport, and household variables. This approach enhances EV consumption estimation accuracy,

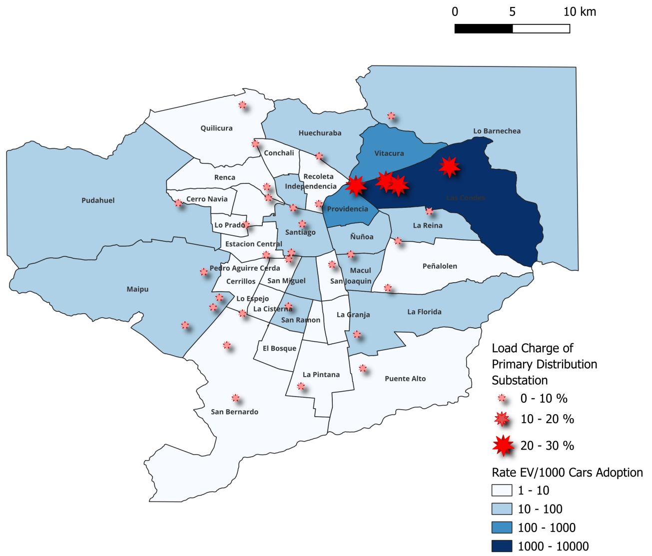

Fig. 6. Increase of load charge (%) in primary distribution substations and adoption of EVs in different districts of Santiago

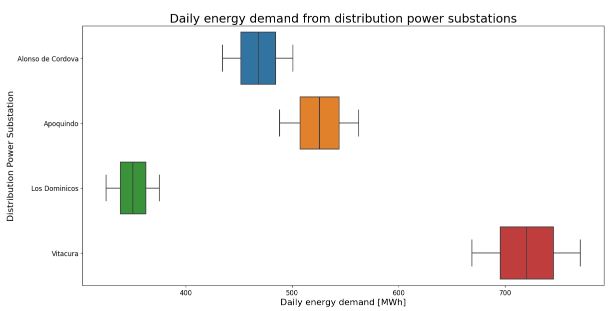

Fig. 7. Boxplot of energy demand from power substations at sensibility of owner percentage with home slow charging

improving power system infrastructure planning and resource management. Our results suggest we can refine the methodology's effectiveness by incorporating variable inputs, such as dynamic mobility scenarios and diverse EV distributions. Adjusting for biases and updating input parameters to reflect real-time data and regional characteristics will further sharpen the accuracy of predictions. Moreover, tailoring the regression model to reflect better the cultural and residential specifics of the study area will minimize errors in EV acquisition. Furthermore, improving the quality of regression models and adjusting model parameters to district-specific variables could enhance model accuracy. This methodology's versatility allows it to be applied across various regions and electric distribution systems, provided the requisite data is available. Spatial and temporal diversity are considered using stochastic variables in Monte Carlo simulation, but future work could explore new methods for incorporating diversity into the simulation. Finally, incorporating stochastic variables enables the exploration of diverse mobility and EV penetration scenarios, enriching the analysis of the impact on distribution networks.

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REFERENCES

[1] Comisión Nacional de Energía. Anuario Estadístico de Energía, **2022**.

[2] T. L. Acker and R. Castro, Power System Impacts of Electric Vehicle Charging Strategies, *Electricity*, vol. 3, pp. 297-324, Jul. 2022,

[3] C. Roe and A. P. Meliopoulos and J. Meisel and T. Overbye. Power System Level Impacts of Plug-In Hybrid Electric Vehicles Using Simulation Data. *2008 IEEE Energy 2030 Conf.* **2008**.

[4] K. Yunus and H. Z. De La Parra and M. Reza. Distribution grid impact of Plug-In Electric Vehicles charging at fast charging stations using stochastic charging model. *Proc. of the 2011 14th European Conference on Power Electronics and Applications* **2011**,

[5] K. J. Yunus. Plug-in Electric Vehicle Charging Impacts on Power Systems. *Goteborg: Chalmers University of Technology*, **2010**.

[6] E. Tibaduiza-Rincón, J. López-Lezama, and N. Muñoz-Galeano, Prospective Analysis of Massive Integration of Electric Vehicle Chargers and Their Impact on Power Quality in Distribution Networks, *World Electric Vehicle Journal*, vol. 14, no. 12, pp. 324, Nov. 2023,

[7] M. Riveros and G. Paredes and L. Vargas. Impact of electric vehicles on the reconfiguration requirements of a distribution network: The Santiago city case. *2012 Sixth IEEE/PES Transmission and Distribution: Latin America Conference and Exposition* **2012**,

[8] G. Mauri and A. Valsecchi. Fast charging stations for electric vehicle: The impact on the mv distribution grids of the Milan metropolitan area. *2012 IEEE Int. Energy Conf. and Exhibition* **2012**,

[9] G. Celli and G. G. Soma and F. Pilo and F. Lacu and S. Mocci and N. Natale. Aggregated electric vehicles load profiles with fast charging stations. *2012 2014 Power Systems Computation Conference* **2014**, 1–7.

[10] J. Saarenpää and M. Kolehmainen and H. Niska. Geodemographic analysis and estimation of early plug-in hybrid electric vehicle adoption. *Applied Energy 107* **2013**, 456–464.

[11] P. Plötz and U. Schneider and J. Globisch and Elisabeth Dütschke. Who will buy electric vehicles? Identifying early adopters in Germany. *Transportation Research Part A: Policy and Practice 67* **2014**,

[12] C. Morton, J. Anable, G. Yeboah, C. Cottrill. The spatial pattern of demand in the early market for electric vehicles: Evidence from the United Kingdom. *Journal of Transport Geography 72* **2018**, 119–130.

[13] F. Heymann and C. Pereira and V. Miranda and F. J. Soares. Spatial load forecasting of electric vehicle charging using GIS and diffusion theory. *2017 IEEE PES Innovative Smart Grid Technologies Conf. Europe* **2017**,

[14] D. Chen, Y. Wang, and K. Kockelman. Where are the electric vehicles? A spatial model for vehicle-choice count data. *Journal of Transport Geography* 43. **2015**,

[15] ANAC, Asociación Nacional Automotriz de Chile. Mercado Automotor, **Sept. 2017**. [Link]

[16] Universidad Alberto Hurtado, Observatorio Social. Encuesta Origen Destino Santiago 2012. **2014** [Link]

[17] Instituto Nacional de Estadísticas, Gobierno de Chile. Encuesta Suplementaria de Ingresos 2017. **Jul. 2018**

[18] S. Rivera and S. Kouro and S. M. Goetz and R. Lizana and E. Romero-Cadaval. Electric Vehicle Charging Infrastructure: From Grid to Battery. *Jun vol. 15 IEEE Industrial Electronics Magazine* **2021**, 37–51.

[19] Superintendencia de Electricidad y Combustible. Infraestructura de recarga de vehículos Eléctricos. [Link]

[20] Ministerio de Energía, Gobierno de Chile. Proceso de Planificación Energética de Largo Plazo. **Jun. 2021**

[21] Instituto Nacional de Estadísticas, Resultados del Censo, **2017**. [Link]

[22] Centro de Micro Datos, Universidad de Chile. Encuesta de Ocupación y Desocupación en el Gran Santiago, **Sept. 2018**. [Link]

[23] Adimark. "Mapa socioeconómico de Chile. Nivel socioeconómico de los hogares del país basado en datos del Censo". **2012**

[24] Ministerio de Vivienda y Urbanismo, Gobierno de Chile. Déficit Habitacional CASEN, **Jun. 2017**. [Link]

[25] Instituto Nacional de Estadísticas, Gobierno de Chile. Permisos de vehículos de Circulación **Jun. 2019**. [Link]

[26] Infraestructura de Datos Espaciales, Ministerio de Energía de Chile. Visor de Capas, **Jun. 2024**. [Link]

[27] Comisión Nacional de Energía, Gobierno de Chile. Geo Portal. [Link]

[28] Coordinador Eléctrico Nacional. Plataforma de Infotécnica. [Link]