Charging stations distribution for e-mobility

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***Abstract*—This study addresses the critical need for sustainable urban development by focusing on the strategic distribution of charging stations for electric vehicles (EVs). Leveraging modeling and simulation, the paper extracts and examines behavioral information to guide effective decision-making for problem-solving. The challenge lies in bridging the modeling to reality, considering the scarcity of available data, the distinctive charging dynamics of EVs, and market uncertainties. The current study effectively analyzes the distribution of charging stations in Porto, evaluating factors that influence the electric vehicle charging system through the simulation of various scenarios. These scenarios include unexpected increases in the quantity of EVs and reductions in EVs' range, providing valuable insights for optimizing infrastructure in alignment with urban dynamics.**

***Index Terms*—simulation, electric vehicles, optimization, charging stations, planning, agent-based modeling**

I. Introduction

The pressing need for sustainable urban development has placed significant emphasis on integrating electric mobility within cities. As the integration of electric vehicles (EVs) heavily relies on strategically positioned and well-managed charging stations [1], their optimal distribution becomes imperative for ensuring the seamless accessibility and usability of electric vehicles in urban environments.

To deepen understanding of this challenge, modeling, and simulation play a crucial role in gathering the necessary behavioral information of charging stations and electric vehicles, encompassing not only the current situation but also speculative scenarios that may arise. This information is subsequently utilized to make informed decisions, enabling effective problem-solving strategies.

The challenge lies in the substantial difference between recharging electric vehicles and refueling conventional vehicles. EVs take considerably longer to charge compared to the rapid refueling of traditional vehicles, impacting driver convenience [1]. Moreover, uncertainties in market demand make the installation of charging stations a risk. Therefore, success depends on integrating charging with travel habits and strategically placing stations based on demand to match user expectations and promote wider EV adoption.

The project's primary goals are to analyze the distribution of charging stations in Porto, assess the factors influencing the electric vehicle charging system, simulate different scenarios, and make informed decisions for sustainable urban mobility. This involves examining which variables affect the station distribution and evaluating system efficiency under various conditions. The aim is to provide practical insights for optimizing the EV charging infrastructure in response to urban dynamics.

Our project contributes to sustainable urban development by addressing the strategic distribution of charging stations for electric vehicles in Porto. Using a simulation framework, we provide essential insights for effective decision-making in EV charging infrastructure planning. Our allocation algorithm considers travel distance and real-time occupancy factors, optimizing station placement. Additionally, our project introduces a formula for estimating EV adoption in specific regions, incorporating housing prices and buying power. These contributions advance understanding and provide practical tools for informed decision-making, promoting electric vehicle integration and wider adoption in Porto's urban landscape. The project repository was made publically available.[1]

The paper is organized as follows: Section II provides a concise overview of the related work. Section III encompasses the presentation of our problem formalization, materials, methods, and the selected key performance indicators. Section IV presents the obtained results along with their analysis based on the data employed. The concluding remarks and future work are outlined in Section V.

[1] https://github.com/pmachado01/charging-stations-distribution

II. Related Work

The landscape of charging station infrastructure distribution planning already has numerous research studies addressing the main challenges associated with electric mobility integration. Regarding charging station infrastructure distribution planning, there are two main viewpoints to consider when optimizing them: the electric vehicle owners who are mainly interested in having a fast, efficient, and cheap way to charge their cars using publicly available chargers and the charging stations owners who are interested in maximizing the return on their investments, while also providing a quality service.

The study by Frade et al. [2] addresses the critical issue of optimal charging station placement for electric vehicles in the Avenidas Novas neighborhood of Lisbon, Portugal. The study adopts a methodology based on maximal covering models to optimize demand coverage during both daytime and nighttime periods, catering to residents and workplaces, respectively. Using 2001 census data, the authors estimate the number of EVs in the city and their refueling demand, considering factors such as household characteristics and employment distribution. They also leveraged the census data to divide the region where they applied the model into sections while calculating each section's centroid. They also incorporated the concept of desired distance in the calculation of optimal EV charging station locations. Recognizing the importance of accessibility, the authors introduce the notion of a maximum desirable distance, set at 400 meters, and a maximum acceptable distance, set at 600 meters. These parameters define the gradual coverage area of each charging station, considering the convenience and willingness of users to travel certain distances for refueling. The optimization model determines the locations of charging stations to maximize demand coverage, with varying scenarios exploring different charge-up frequencies and station numbers.

The article by Bi et al. [3] introduces a simulation-based heuristic for optimal EV charging station placement in urban settings. Employing agent-based traffic simulation, the study strives to balance network coverage and infrastructure costs, demonstrating its application to Singapore. Utilizing real-world data, including travel surveys and charging event information, enhances the model's relevance. However, notable limitations include the absence of waiting time considerations and the lack of exploration into scenarios with varying charging power. The proposed consolidation algorithm iteratively refines charging station placement, showcasing adaptability to evolving charging demand patterns. The study makes a valuable contribution to the EV infrastructure planning domain but would benefit from addressing waiting times and exploring diverse charging power scenarios for a more comprehensive analysis.

TABLE I
MAPPING TABLE RELATING THE FEATURE TO THE RELATED WORK.

Ref	Features							
	f0	*f1*	*f2*	*f3*	*f4*	*f5*	*f6*	*f7*
Frade et al. [2]					✓		✓	
Bi et al. [3]					✓	✓		✓
Zeb et al. [4]			✓		✓	✓		✓
Wang et al. [5]			✓			✓		

Zeb et al. [4] propose a strategy that involves an optimized combination of different types of charging stations (level 1, level 2, and level 3 chargers) to efficiently manage EV load while minimizing installation cost, losses, and distribution transformer loading. The study incorporates the effects of photovoltaic (PV) generation and models the EV load as a stochastic process. The optimization is performed using particle swarm optimization (PSO), and the proposed approach is validated on the real distribution system of the National University of Sciences and Technology (NUST) in Pakistan. The results indicate that the optimized combination of chargers at judicious locations can significantly reduce costs, daily losses, and distribution transformer congestion compared to scenarios with optimized placement of only level 3 chargers. The paper also discusses the impact of EV charging on power system parameters, such as system losses, transformer utilization, and voltage profiles.

Wang et al. [5] introduced a comprehensive model for an Electric Vehicle charging station empowered by a DC microgrid. The paper's focus on a real-time rule-based algorithm for power management sets it apart. In terms of data, the authors employ a data-driven modeling approach for the EV charging station. The arrival time of EVs, the initial state of charge of EVs, and drivers' choices are introduced as random and non-schedulable variables, capturing the uncertainties of EV charging behavior. Three charging modes (fast, average, slow) with corresponding power demands are considered, adding granularity to the model. The primary output of the model is the real-time power management strategy's performance under various scenarios. The scenarios explored involve power limitation, drivers' choices, disconnection operations, standby mode, shedding, and restoration operations.

1) Mapping Table: We chose 4 relevant features to take into consideration while analyzing the literature, and we found other 4 interesting ones that we decided to apply to our project.

Required Features:

- ***f0*** - uses an alert battery level as the level from which an EV needs to be charged;
- ***f1*** - uses a target battery level, which represents the level until which an EV is going to be charged;
- ***f2*** - analyses the waiting times for a vehicle to charge;
- ***f3*** - applied to the city of Porto.

From the Literature:

- ***f4*** - applied to a concrete location;
- ***f5*** - takes into consideration different charging powers for the stations chargers;
- ***f6*** - does an estimation on the number of EVs to map in the simulation;
- ***f7*** - allows setting the maximum travel distance a vehicle needs to charge itself.

2) Gap Analysis: The reviewed literature presents a comprehensive overview of charging station infrastructure distribution planning, primarily emphasizing charging stations' optimization and power consumption. However, notable gaps exist, revealing opportunities for innovation and improvement. The literature predominantly concentrates on charging station placement, network coverage, and infrastructure costs, strongly emphasizing power consumption. However, none of the reviewed studies explicitly addresses the management of electric vehicle (EV) batteries concerning alert and target battery levels. This represents a crucial aspect of EV charging that directly impacts user experience and vehicle maintenance. While studies by Frade et al. [2] and Bi et al. [3] consider specific locations such as Lisbon and Singapore, the works have yet to extend their analysis to Porto. A gap exists in the literature regarding the adaptation of charging station planning models to Porto's unique characteristics and demands, which may differ significantly from other urban environments. By addressing these gaps, our proposed project aims to contribute significantly to the field, offering a more holistic and tailored solution to the challenges posed by electric mobility in Porto.

III. Methodology

A. Problem Formalization

The problem at hand can be articulated through the exploration of three key research inquiries:

- What variables exert influence on the integration and usability of electric vehicles in the urban setting of Porto?
- To what extent does the distribution of charging stations impact the system's overall efficiency, and what measures can enhance this efficiency?
- How do factors like the geographical placement of charging stations, fluctuations in market demand, travel patterns, and overall infrastructure affect the adoption and functionality of electric vehicles, particularly concerning the operation of charging stations?

B. Materials

1) Datasets: To effectively analyze the distribution and utilization of electric vehicle charging points within the city of Porto, these specific data sources were extracted:

- **Census Data from INE**: Census data from the Instituto Nacional de Estatística [6] (INE) provides a statistical sectioning of the city. This data is crucial for understanding the demographic and geographic characteristics of different areas within the city.
- **Electromaps Data**: Electromaps [7] is a platform that provides information about electric vehicle charging stations, including the latitude and longitude coordinates and the number of charging ports of electric vehicle charging points, throughout the city. This data is necessary as it was fused with census data, associating a label that indicates the corresponding statistical section to each station, enabling more precise analysis and planning.

2) Data Estimation: Since no concrete information about the number of electric vehicles in each of Porto's statistical sections, nor for the entirety of Porto city, in 2021 was found, some data estimation was done. For this effect, the number of electric vehicles in Portugal in 2021, from INE [6], was trimmed down multiple times using the purchasing power of Porto Municipality, its population, and the real estate price for each of Porto's divisions (*freguesias*).

The purchasing power of the municipality of Porto in 2021 was 3.343% of Portugal's. In our estimation, we assumed that this ratio was equal to the number of electric vehicles in Portugal in Porto. Then, we calculated the number of electric vehicles per capita in Porto using its 2021 population from INE. Although this result indicates that a citizen of Porto is around 48.1% more likely to own an electric vehicle than the average Portuguese citizen, we estimate that the real ownership rate is higher due to non-accounted factors such as Porto charging infrastructure and the fact that electric vehicles tend to be more usable in urban environments than rural ones.

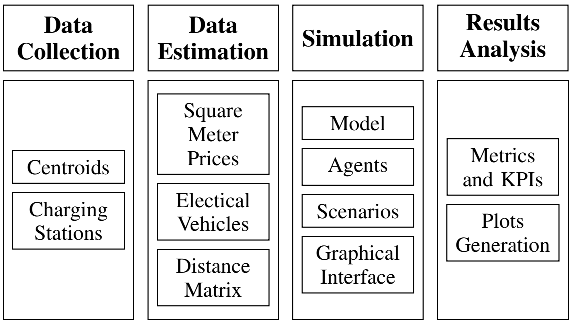

Fig. 1. Diagram of the project pipeline. It follows sequentially and iteratively the steps of data collection, data estimation, simulation, and results analysis.

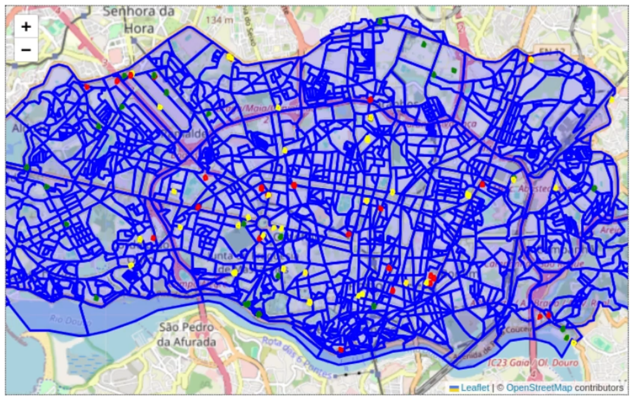

Fig. 2. Graphical representation of the simulation execution.

From the datasets mentioned previously, no statistical sections' wealth-related information was found, so, for this purpose, we decided to use the price per area (square meter price) for the real estate of the municipality's divisions (*freguesias*). These values were extracted from the real estate website *idealista* [8] and are compared to the value related to the entirety of Porto's city. Then, considering that the number of EVs in each municipality division is related linearly to the ratio of real estate price, the number of EVs for each division is obtained. Lastly, these vehicles are distributed according to their population throughout their statistical sections.

To speed up the simulation process and avoid unnecessary calculations during the simulation, the distance matrix between each statistical section centroid was calculated beforehand. Since this value corresponds to the Euclidean distance between locations, a factor of 1.25 was applied in order to better translate the behavior of a car in traffic on a non-straight path.

3) Tools: To establish a dynamic experimental setting, a blend of tools, environments, and programming languages was employed for data collection and simulation purposes:

- ***Python*** functioned as the primary programming language, chosen for its versatility and readability, streamlining both model implementation and data analysis.
- ***MESA*** [2], a Python package, formed the foundation for the simulation code. This package facilitated the development of an agent-based simulation with high-level structures. Additionally, an extension named ***Mesa-Geo*** [3] was integrated to provide geographical representation for agents, enhancing simulation visualization.
- Lastly, ***QGIS*** [4] served as the open-source geographic information system, enabling data collection from INE.

In the project's initial phase, the simulation was planned to run on the SUMO [5] software. However, as the project's requirements and objectives did not necessitate such a detailed-level simulator, the decision was made to switch to utilizing MESA.

C. Methods

1) Pipeline: The methodology employed in this study adheres to a **sequential** and **iterative** approach, as illustrated in Figure 1. It comprises four distinct phases:

1) **Data Collection:** In this initial stage, the requisite datasets highlighted in Section III-B1 are gathered and processed into pertinent data structures for subsequent steps and simulation.
2) **Data Estimation:** This phase involves performing calculations and information retrieval to estimate the data detailed in Section III-B2. The obtained data is then processed into a suitable data structure.
3) **Simulation:** Responsible for real-time simulation execution with graphical visualization (see Figure 2) based on specified input variables from the configuration file. Throughout the simulation, output variables are logged for use in the final phase.
4) **Results Analysis:** Serving as the concluding phase, this step employs data processing scripts to extract metrics and key performance indicators along with the respective graphical visualization.

[2] https://mesa.readthedocs.io/en/stable/
[3] https://github.com/projectmesa/mesa-geo
[4] https://www.qgis.org/en/site/
[5] https://eclipse.dev/sumo/

2) Logical Model: Since this study does not necessitate replicating the intricate details of car movement and travel, we have opted for an **agent-based** simulation, condensing the agent's actions into active high-level actions, that serves both **descriptive** and **speculative** purposes. The choice to be descriptive ensures a comprehensive understanding of the system, while the speculative nature of the simulation allows for exploring potential scenarios, anticipating system behaviors, and gaining insights into how the introduced agent-based model responds to various conditions and inputs. The agents designed for this purpose encompass:

- **Centroid:** This agent functions more as an auxiliary entity, storing information about charging stations and geographical data for accurate display.
- **Charging Station:** Responsible for managing cars that are either charging or waiting in the queue, this agent also includes attributes such as the corresponding centroid, the number of charging ports, and data structures related to currently charging or waiting cars.
- **Electric Vehicle:** EVs stand out as the most intricate type of agent. They possess complex attributes such as battery level, battery capacity, target battery level when charging, battery level that triggers an alert to find a charging station, and the distance they are willing to travel to find an unoccupied charging station. Additionally, they exhibit complex behaviors, including charging the battery, moving to expend energy, and locating and traveling to the optimal charging station. Finally, this agent can exist in one of the five states represented in Figure 3:
  - **Wander:** This is the default behavior of an EV when its energy level has not reached the alert battery level. If the battery level is below the specified threshold, it uses the station allocation algorithm, described in Section III-C4, to find the optimal charging station. Otherwise, it uses a uniform probability function to determine whether or not it should spend a certain amount of energy that is equivalent to traveling a predefined (input) distance.
  - **Inactive:** If the EV runs out of battery during the wandering state, it transitions to an "Inactive" state, where it simply stands still and does nothing. This behavior is only reachable from the "Wander" state, as waiting in the queue at a charging station to charge does not consume energy, and the station-finding algorithm accounts for the current battery level of the vehicle.
  - **To Station:** When the vehicle identifies the need to charge during the wandering state and finds a feasible destination, it transitions to the "To Station" state, actively traveling towards the optimal charging station.
  - **To Origin:** After completing the charging process, the EV transitions to the "To Origin" state, where it travels back to its origin centroid.
  - **In Station:** This state encompasses both charging and waiting in the queue at the charging station. The EV enters this state when it arrives at the charging station and is ready to either charge or wait in line.

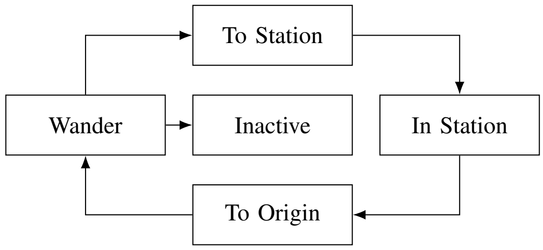

Fig. 3. State diagram of the "Vehicle" agent. The "Inactive" state can only reached when the agent is in the "Wander" state.

3) Simulation Variables: The simulation is influenced by exogenous variables categorized into two types – controllable and uncontrollable. The set of controllable variables consists of:

- **Initial Battery Level Distribution (%):** This variable manages the initial battery level of vehicles based on a uniform distribution probability function. The sampled value ranges from 0 to 1, indicating the battery level relative to the full capacity of the vehicle.
- **Battery Capacity Distribution (km):** This variable determines the maximum energy capacity of the vehicle using a uniform distribution probability function. The unit is in kilometers, representing the distance a vehicle can travel until it runs out of energy when its battery is full.
- **Target Battery Level (%):** During charging, this represents the energy rate at which the charging process should stop, simulating scenarios where vehicles are not charged to full capacity. The value ranges from 0 to 1 and is relative to the vehicle's battery capacity.
- **Alert Battery Level (%):** This variable indicates the relative energy level at which the vehicle should

start searching for a charging station to recharge, ranging from 0 to 1.

- **Station Charging Power (km/h):** This variable determines the speed at which electric vehicles charge at a station, indicating the amount of energy, in kilometers, restored in a given time unit.
- **Vehicle Wander Probability (%):** When a vehicle agent is in the "Wander" state, it can either move to spend some energy or stay still. This variable determines the probability of the vehicle choosing to move around.
- **Vehicle Moving Speed Distribution (km/h):** This variable determines the moving speed of a vehicle using a uniform distribution probability function. It is used to infer the velocity at which an electric vehicle will travel when in the state of wandering or traveling.
- **Desirable Travel Distance Distribution (km):** This variable uses a uniform distribution probability function to determine the distance a vehicle is willing to travel to reach a charging station with at least one free charger. This variable is utilized in the charging station allocation algorithm described in the following section.

The uncontrollable input variables consist of real-world and historical data:

- **Centroids of Porto:** This variable is a data structure containing real-world data from the INE about the statistical sections of the city of Porto, as detailed in Section III-B1.
- **Charging Stations of Porto:** This variable is also a data structure containing real-world data from the Electromaps API about the city of Porto, as described in Section III-B1.
- **Electical Vehicles Distribution**: This variable extends the data structure with the centroids of Porto, associating, for each region, the number of electrical vehicles, as explained in Section III-B2.

For the endogenous variables, the simulation outputs the following variables:

- **Number of Dead Cars:** This variable represents the chronological instances of cars running out of energy, possibly due to being unable to reach a charging station. It serves as an indicator of poor station distribution.
- **Time Spent Waiting for Charger (min):** This variable represents the duration distribution, in minutes, that vehicles spend waiting for an available charging station.
- **Time Spent Charging (min):** This variable indicates the average time, in minutes, that vehicles spend actively charging at a station.
- **Charging Station Usage (%):** This variable represents the percentage of used chargers over time, providing insight into their overall utilization.
- **Traveled Distance to Reach Charging Station (km):** This variable signifies the average distance, in kilometers, that vehicles travel to reach a charging station, reflecting the accessibility of charging infrastructure.
- **Number of Cars in Charging Station Waiting Line:** This variable denotes the count of cars queuing or waiting in line at a charging station over time, indicating potential congestion or demand imbalances.

These endogenous variables collectively provide a comprehensive overview of the simulation's outcomes and can be crucial for assessing the efficiency and effectiveness of the electric vehicle charging system under various scenarios.

4) Station Allocation Algorithm: When the battery level falls below the alert threshold, the vehicle must locate the most suitable charging station, considering both travel distance and waiting time. In practice, the real-time occupancy status of charging stations can be easily accessed through online services such as *Google Maps* [6]. This information empowers drivers to make informed decisions about where to charge their vehicles. To emulate this behavior, the algorithm assumes that drivers have access to the usage data of charging stations, even though the number of vehicles in the waiting queue is unknown.

The station allocation algorithm, presented in Algorithm 1, takes as input a matrix D, where $D_{i,j}$ represents the distance between centroids with indices i and j, a set U, where $U_{i,j}$ contains the current usage rate of a station with index j in centroid i, a set S, where S_i contains the number of charging stations in centroid i, the current centroid index c, the current battery level b, and the desirable travel distance t of the vehicle.

The algorithm iterates through the centroids, filtering those within reachable distance based on the current battery level. Its priority is identifying a charging station within the desired travel distance that is not at full capacity. If such a station is unavailable, the algorithm defaults to selecting the closest centroid, randomly choosing one of the stations in that centroid. The algorithm returns both the indexes of the optimal centroid and charging station. If no station is available, -1 is returned for both

[6]https://www.google.com/maps

Algorithm 1: Station allocation pseudo-algorithm

```
Data: D, U, S, c ≥ 0, b > 0, t > 0
Result: optimal_centroid, optimal_station
optimal_centroid ← −1;
optimal_station ← −1;
optimal_distance ← t;
closest_centroid ← −1;
closest_distance ← +∞;
for i ← 0; i < |S|; i = i + 1 do
    if D_{c,i} ≤ b then
        if D_{c,i} < closest_distance then
            closest_centroid ← i;
            closest_distance ← D_{c,i};
        end
        if D_{c,i} < optimal_distance then
            for j ← 0; j < S_i; j = j + 1 do
                if U_{i,j} < 100% then
                    optimal_centroid ← i;
                    optimal_station ← j;
                    optimal_distance ← D_{c,i};
                    break
                end
            end
        end
    end
end
if optimal_centroid = −1 and closest_centroid ≠ −1 then
    optimal_centroid ← closest_centroid;
    optimal_station ← random(0, S_closest_centroid);
end
return optimal_centroid, optimal_station
```

output variables.

5) Simulation Scenarios: In this work, 3 simulation scenarios were run and analyzed. The differences between these scenarios are in the exogenous variables, such as the EV price and autonomy range.

Scenario A is the work's baseline, and it is the descriptive model of the 2021 Porto's electric vehicles and charging stations behavior. In Table II, the input variables and their default values for the baseline model are presented.

The other scenarios consist of two speculative models. The first one, *Scenario B*, considers a scenario in which the government gave an incentive that lowered the EVs average price by $5,000€$. This decrease causes a growth in the number of EVs available since these variables have an inverse proportionality relationship. The second one, *Scenario C*, simulates a decrease in the battery capacity distribution of 40%, which may happen due to a considerable decrease in temperature in Winter.

TABLE II
MODEL'S INPUT VARIABLES AND RESPECTIVE DEFAULT VALUES.

Input Variable	*Default Value*
EV Average Price	$35,000€$
Initial Battery Level Distribution	$[50\%, 100\%]$
Battery Capacity Distribution	[250Km, 500Km]
Target Battery Level	$[85\%, 100\%]$
Alert Battery Level	$[15\%, 30\%]$
Station Charging Power	250Km/h
Vehicle Wander Probability	40%
Vehicle Moving Speed Distribution	[25Km/h, 120Km/h]
Desirable Travel Distance Distribution	[5Km, 15Km]

TABLE III
EXPECTED VALUES PER INDICATOR

Indicator	*Expected Value*
#1	75%
#2	60
#3	5 *km*
#4	20 *min*

D. Key Performance Indicators

Key Performance Indicators are specific calculated metrics that serve as a comprehensive measure of performance for a system. They encompass a set of various metrics and are instrumental in offering a precise assessment of the system's current state and its historical progression.

After analyzing the system carefully, the following indicators were identified:

- ***#1*** Average Charging Station Workload *(percentage of the time they are used)*
- ***#2*** Number of Charging Stations *(/100K population)*
- ***#3*** Average Travel Distance
- ***#4*** Average Travel Time Waiting for a Charger

The necessity to have expected values for each key performance indicator relies on the fact that they are needed to serve as a basis for each of the decision criteria that the system will have. In the table III below are presented the expected values for each of the indicators.

1) Decision Criteria: Decision criteria are predetermined standards or guidelines used to evaluate the system's performance. They define the specific benchmarks or thresholds that need to be met to make informed decisions. Decision criteria are often related to Key

TABLE IV
INDICATORS PER DECISION BASED ON SPECIFIC CONDITIONS

Indicator	Decision	*Condition*
#1	Increase the number of chargers per station OR Create new stations	$> 80\%$
#2	Increase the number of charging stations	< 30
#2	Decrease the number of charging stations	> 60
#3	Redistribute the stations in a better way OR Create new stations	$> 7Km$
#4	Increase charging power OR Increase the number of chargers per station	$> 30min$

Performance Indicators, as *KPIs* are the metrics that are used to measure and evaluate performance against these criteria. In other words, decision criteria provide the context for interpreting *KPIs* and determining whether the system or process is meeting the desired objectives or not.

In the table IV below is shown a list of possible decisions for each indicator based on a certain condition. The decision follows as: "If the measured value for the indicator is *less/greater* than x we should apply the *decision*".

IV. RESULTS & DISCUSSION

For each of the 3 scenarios mentioned in Section III-C5, several metrics were retrieved for a time span of 2 and a half days. Such metrics were related to the usage of the charging stations, travel distance to the charging stations, and time spent waiting for the charging ports. Their values were then compared to their respective key performance indicator to not only evaluate the performance of the displacement of charging stations throughout the city but also to understand the behavior that the speculative scenarios had on it. These collected metrics can be observed in Table V.

A. Baseline

As it is possible to see in Figure 4, the baseline scenario, which consisted of a descriptive model of the 2021 Porto's electric vehicles and charging stations behavior, started with a sudden peak in charging stations'

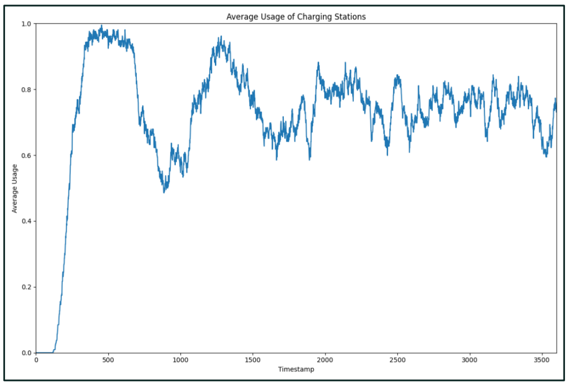

Fig. 4. Average usage of charging stations in the baseline scenario.

workload. This demand for electric vehicle autonomy later stabilized into the 60 to 80% range. As for the metrics collected, besides the *Average Time Waiting for Charger* metric of 36.24 minutes, all the values are in conformity with the key performance indicators previously defined.

B. Government Incentive

Scenario B evaluated the agents' behavior in the case of a reduction in the price of electric vehicles of $5,000$€. This led to an increase in the number of electric vehicles in the model of 17.1%, 261 units.

This expected growth led to an undesirable average charging stations' workload of 83% ($> 80\%$) and also a 261% increase in average waiting time compared to the baseline.

By installing an extra charger in each of the charging stations, both of these issues are solved since the values return to be in conformity with the key performance indicators. This solution scenario is referenced as *Scenario B'* in Table V. Given the extremely positive results retrieved for this scenario, a cheaper solution becomes evident: the placement of a new charger in key charging stations. This way, the possible inefficient use of resources caused by this solution would be addressed.

C. Decrease in Vehicles Autonomy

In Scenario C, a decrease in vehicle autonomy by 40% was simulated. This shrinks of the EV's batteries naturally resulted in a surge of trips to charging stations, but even though it may have increased the average waiting times by 25% (8 min) It only led to a small growth in the average workload (2.7%).

One way to address these long waiting queues is to change the charging ports for more capable ones. The new ports chosen for this solution are 28%) more

TABLE V
METRICS COLLECTED FROM THE SCENARIOS SIMULATED.

Scenario	Avg. Station Workload (%)	Avg. Travel Distance (Km)	Avg. Time Waiting for Charger (min)
Baseline	71.70	3.35	36.24
Scenario B	83.20	5.91	94.90
Scenario B'	56.62	1.75	10.20
Scenario C	73.65	4.70	44.02
Scenario C'	59.45	2.92	19.48

powerful, resulting in an increase in the charging speed of more than 70Km of autonomy for each hour. Although this new acquisition would be expensive [9], with values ranging from $12,500$$ to $52,000$$ depending on the charging power, 24Kw and 62.5Kw [7]. This solution scenario, depicted as *Scenario C'* in Table V, yields average waiting times in conformity with the key performance results, decrease of (55.7%), and also improves both the average workload (19.3%) and average travel distance (37.9%).

V. Conclusion and Future Work

In conclusion, this simulation project aimed to evaluate the satisfaction of the needs of EVs in a city by analyzing the charging infrastructure. Despite the challenges faced in sourcing accurate data on the number of EVs, which forced us to make non-ideal estimations, the developed model demonstrated its effectiveness in simulating the diverse scenarios presented. The decisions made to address the non-reasonable key performance indicators retrieved from the speculative models successfully enhanced the system, as evidenced by the positive impact it had on them. Notably, the project achieved all planned objectives, highlighting the success of the undertaken efforts.

Future work should focus on improving data accuracy by gathering information from more sources, reducing the need for estimations. Additionally, integrating human routines into the simulation, accounting for in-house charging, and enhancing graphical representation will contribute to a more comprehensive and user-friendly model. These refinements will further advance the understanding of electric vehicle charging infrastructure and support the development of efficient urban mobility systems.

[7]Far more powerful charging ports exist, but no price was found for them.

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