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Towards Sustainable Cities: A KPI-Based Method to Compare Cities' Performance and Encourage the Spread of Electric Cars

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Abstract: European cities have adopted different solutions to address the challenges of charging infrastructure for electric vehicles, depending on their specific characteristics and needs. The widespread adoption of effective solutions could accelerate the transition towards more sustainable urban mobility. However, as cities differ in socio-economic, infrastructural, and environmental aspects, a one-size-fits-all approach may not be suitable. Currently, there is a lack of studies in the literature that identify similarities among cities to support the development of shared strategies for sustainable electric mobility. This paper contributes to filling this gap by proposing a methodology based on Key Performance Indicators (KPIs) to classify and compare cities according to their electric vehicle infrastructure. Using quantitative data from 80 European cities across civil, social, and transport-related factors, as well as electric vehicle charging characteristics, we identified five reference city clusters. A sensitivity analysis, conducted across 30 scenarios, validated the robustness of the KPI framework. This approach provides a tool for policymakers to monitor the evolution of charging infrastructure, supporting data-driven decision-making for sustainable urban mobility. By promoting efficient and adaptable electric vehicle policies, this study aligns with the objectives of the 2030 Agenda for Sustainable Development, particularly in fostering sustainable cities and clean energy adoption.

Keywords: urban sustainable mobility; electric cars; charging infrastructures; KPIs; clusters; robustness; K-Means clustering method

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1. Introduction

In recent years there has been a great effort to increase the use of Electric Vehicles (EVs), particularly cars, with the aim of reducing CO_2 emissions and pollution, especially in urban areas. Factors influencing the demand for electric cars are numerous, such as charging infrastructure/charging power, pricing, policies, incentives, deployment strategies, national commitments, socio-demographic, geographical, psychological and economic factors. These characteristics influence the penetration and success of electric cars in cities located in different geographical areas.

To date, European cities have adopted different solutions to address electric charging infrastructures issues, depending on the specific needs and characteristics of the cities. It would be helpful if the best solutions were transferred to other cities, with the ultimate goal of maximizing the use of electric cars. However, since each city has different characteristics, a good solution applied to one city may not be as successful when applied to another.

2. Literature Review

The literature review related to EV is schematized below.

2.1. Business Models and Economic Considerations

The definition of business models is crucial to ensuring the profitability of EV adoption. Ref. [1] analyzed the factors that directly and indirectly influence the economics of public charging infrastructures, including customer psychology, technical advancements in charging infrastructure and EV batteries, and government policies. Ref. [2] used real cost data from the UK's Rapid Charge Network Project (RCN) to develop a business model that aids future investment and policy decisions. Refs. [3,4] emphasized the need to analyze charging behavior to implement an appropriate business model, while Refs. [5–7] explored infrastructure availability. Ref. [8] provided an extensive analysis of public charging data, including fast-charging infrastructures and limited household data. Ref. [9] examined land-use implications of EV development in European and North American cities. The study highlighted the urgent need to reduce charging infrastructure costs to achieve adequate territorial coverage for widespread EV adoption. However, the research also noted that cheaper energy production may drive urban expansion into low-density areas, with differing effects depending on city characteristics.

Ref. [10] conducted interviews with hardware vendors, software vendors, charging network operators, and other stakeholders, concluding that while hardware costs are decreasing, numerous 'soft costs', such as permit delays and regulatory compliance, still need to be reduced. These costs contribute to higher charging station prices in the USA compared to the EU. Ref. [11] analyzed the economic benefits of various charging modes based on differentiated subsidy policies in three major Chinese cities.

2.2. Charging Infrastructure Planning and Optimization

Ref. [12] developed a social total cost model that includes economic and environmental costs, calculating the total operating cost of charging stations under different distribution conditions. Ref. [13] analyzed strategic plans in two major European cities, assessing their effectiveness, efficiency, and feasibility in establishing public charging networks to encourage EV adoption.

Ref. [14] identified key EV stakeholders—including municipalities, EV users, non-EV users, commercial parties in the EV chain, and grid operators—and examined their objectives and key performance indicators (KPIs) for optimizing public charging infrastructure. In a case study of Beijing, Ref. [15] used a data-driven method with big data from location-based services to measure charging demand indicators. Their findings revealed dynamic relationships between these indicators and public charging station distribution, with variations between weekdays and weekends and different travel distances. A spatial regression model showed the influence of urban structure and service distribution on EV charging behavior.

Ref. [16] proposed an evaluation methodology using eight indicators—such as energy utilization intensity, charger intensity distribution, and carbon intensity—to compare public EV charging infrastructures. Ref. [17], using empirical data from 450,000 km traveled by seven EVs in Germany, developed five KPIs for optimizing EV usage in commercial fleets. Their results indicated that predictable mobility demand improves charging strategies and that a mix of conventional and DC fast charging supports high annual mileage.

Ref. [18] proposed a hybrid method for evaluating city performance using urban indicators and benchmarking, validated through an empirical study. Benchmarking approaches have also been applied in other research, including [19–23].

Using real charging and weather data from three UK counties, Ref. [24] developed a data mining and fuzzy-based model to analyze EV charging demand characteristics across geographical areas and assess potential relative risk levels independent of distribution networks. Ref. [25] applied conditional autoregressive models to estimate how socioeconomic and climatic conditions influence BEV adoption in Norway. Their findings indicate that BEV adoption clusters in urban areas with higher income levels, greater charging station availability, and higher travel demand, while colder areas with a higher proportion of older adults showed lower BEV adoption rates.

2.3. Policy and Planning for EV Market Growth

Cities experience different stages of EV market development, and low adoption rates in early phases can hinder charging infrastructure investments and vice versa. Ref. [26] addressed this "chicken-and-egg dilemma" by proposing planning models that consider charging network layout, investment affordability, and the resulting impact on charging prices. Their work also suggested government subsidy schemes for charging facilities to enhance adoption.

Ref. [27] conducted a spatial analysis for locating public EV charging infrastructure in a high-density city using a contextualized location-allocation model. Their recommendations included expanding charging networks beyond urban cores into suburban areas to meet anticipated demand.

2.4. Barriers to EV Deployment

Ref. [28] investigated the barriers to the deployment of EVs on a global scale. Using a two fixed-effects model and cross-country panel data, Chandra empirically analyzed the impact of a wide range of factors, such as fuel prices, national commitments, and charging infrastructure, on EV demand in certain countries.

2.5. Charging Infrastructure and Spatial Distribution

The spatial heterogeneity of public rapid charging provision for Battery Electric Vehicles (BEVs) is a key factor affecting the spread of electric mobility, as it influences an individual's ability to undertake extended journeys with a BEV. Currently, the development of multiple charging points is limited to large urban areas and strategic road networks. However, Ref. [29] pointed out that the expansion of BEV infrastructure along the global TEN-T transport network is foreseen by current policies. Their study distinguished between 'on-site' and spatial multiplicity in the provision of fast charging.

2.6. Urban Decarbonization Strategies

EV-based mobility is considered a strategy to reduce urban transport externalities. Ref. [30] examined transport users' preferences for adopting EV-based mobility to promote decarbonization in different locations in India. Their research, based on attribution theory, found that place-based decarbonization strategies in Indian cities differ significantly from those in developed cities worldwide. The study highlighted the complex relationships between financial, psychological, and technical attributes, as well as EV infrastructure and familiarity, in shaping positive intentions toward EV adoption for decarbonizing cities.

2.7. Motivation and Contributions

Although much research has been conducted on EV charging infrastructures to promote their use, there is no current study that aims to find similarities and common factors among cities in order to identify homogenous clusters of cities for which common charging solutions for electric cars can be successfully implemented. The contribution of this paper is to provide a method for identifying clusters of cities, calculated from quantitative data on seven different factors, including civil, social and transport, as well as electric cars charging characteristics.

Specifically, the research questions addressed by this paper are as follows:

1. Regarding the use of electric cars, are there common elements that can be identified among different cities?
2. Is it possible to identify certain cities that represent benchmarks in electric car mobility?
3. Is it possible to identify aspects to be improved with the aim of promoting electric car mobility in cities to improve sustainable urban mobility?

This work seeks to answer the above research questions by adopting a clustering approach that groups cities with common elements, using quantitative KPIs related to social, geographical, economic, infrastructural, and transport system aspects. Quantitative indicators and benchmarking with other cities make it possible to assess each city's performance in relation to electric car mobility, revealing the strengths and weaknesses of each city considered by [18]. In addition, establishing a set of KPIs allows for an accurate representation of the phenomenon related to electric car charging infrastructure at different times. This can help to quickly monitor the evolution of the phenomenon over time and help policymakers make appropriate decisions with the ultimate goal of promoting sustainable urban mobility. Benchmarking with different realities, with appropriate normalizations, can also allow any critical issues to be highlighted and any short-sightedness to be monitored over time.

To the best of our knowledge, no other work in the literature to date has addressed this issue. Since the research presented here is the result of a HORIZON 2020 project funded by the European Union, only EU countries were considered.

The motivation for this work stems from the urgent need to support city governments in accelerating the adoption of electric cars. Despite the growing interest in electric mobility, existing studies often focus on individual cities or specific charging strategies, without a broader, data-driven approach to identify patterns and common factors among cities. This research aims to fill this gap by developing a quantitative clustering methodology that allows cities to understand their position within the European electric mobility landscape and identify which successful policies of the most advanced cities can be effectively transferred to their context. By grouping cities with similar characteristics, we provide a practical tool for policymakers to design more tailored and efficient strategies, avoiding the risk of replicating solutions that are not suitable to a city's specific context.

3. Methodology and Data Sources

The methodology adopted in the paper is shown in Figure 1. In Phase 0, starting from all the heterogeneous features of cities (the complete list is provided in Appendix A—Table A1), an analysis of electric cars' features and cities factors was carried out. Therefore, a set of representative Key Performance Indicators (KPIs) was selected (Phase 1) according to the features and factors analysed in Phase 0. These KPIs were selected so to characterize each city in relation to electric car mobility. The selection of these KPIs was an iterative task performed by the 6 partners participating in the European "INCIT-EV" project. By researching the state of the art of similar projects and using the relevant knowledge gained from years of working in EVs-related research, KPIs were selected that best reflect key parameters related to EV implementation. The initial KPIs were subject to some changes during the project, as some of the necessary data were almost impossible to find. As the project knowledge increased, we realized that some KPIs were not representative and therefore some more representative KPIs were included. Although this KPIs selection process may have been influenced by the personal opinion of the project partners, all decisions were made taking into account the opinion of the 6 partners and more than 10 experts and were checked against previous work on the topic, so that the selected KPIs and Vectors were as representative as possible.

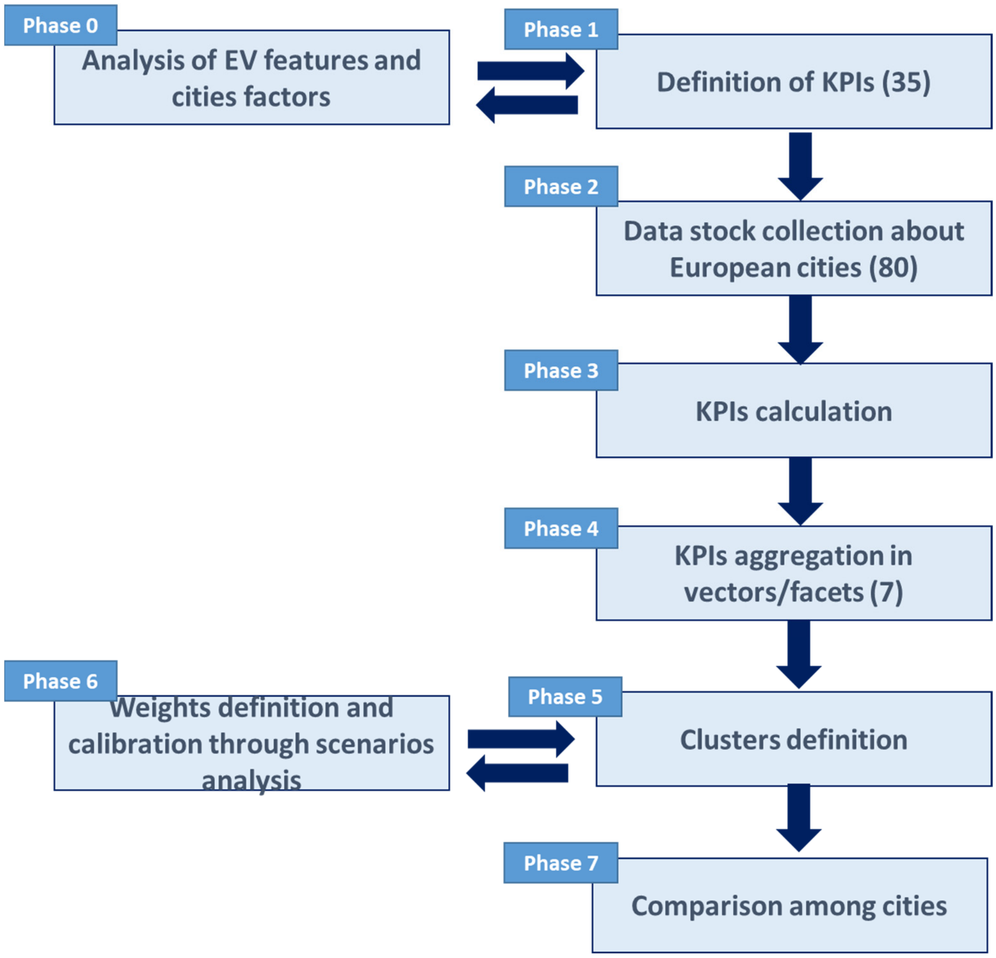

Figure 1. Phases of the adopted methodology.

Once all the KPIs had been defined, all the data required for their calculation were collected (Phase 2) and used to calculate them (Phase 3). Phase 1 led to the identification of 35 KPIs, classified into 7 facets according to the city feature each KPI was measuring. The 7 facets are measured by 7 vectors (Phase 4) that are calculated from the weighted sum of the KPIs belonging to each facet. The selected KPIs were measured for 80 cities located in the following EU Countries: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and UK. The values obtained by computing the 35 KPIs for all 80 European cities were used as input to the k-means quantization technique, that is an unsupervised clustering algorithm that allows grouping objects into k groups based on their characteristics. Thanks to this technique, the cities of the project were grouped into 5 clusters (Phase 5), according to the 7 vectors. Since the definition of the clusters depends on the values of the weights used, a sensibility analysis and further calibration of weights were performed evaluating 30 different scenarios in Phase 6. This phase also made it possible to test the robustness of the solution found. Finally, an in-depth comparison among the clusters was carried out (Phase 7). For this comparison, a representative city for each cluster was selected considering its closeness to the centroids obtained by applying the K-Means clustering technique. Representative cities were then compared according to their values of the 7 facets.

3.1. City Parametrization Methodology

Key Performance Indicators (KPIs) are crucial to assess a process in order to highlight possible criticalities. KPIs are used for strategic and operational improvements in any process or system, supporting decision-based data and their analysis. The parametrization methodology described here proposes a list of KPIs that can parameterize cities in relation to electric car mobility. The KPIs were associated with seven vectors: (1) *Civil and Social*; (2) *Transport*; (3) *Electric vehicles census*; (4) *Electric* car *charging infrastructure*; (5) *Electric car charging services economics*; (6) *Smart Charge/ICT system*; (7) *Environmental impact*.

The objective of the KPIs related to the *Civil and Social* group is to characterize a city from the human point of view, analysing quality of life and a variety of social aspects. The KPIs belonging to this group are: the density of residents, the city's GDP per capita, the unemployment rate, and the average age of the city residents.

The *Transport KPI* group aims to characterize the transport infrastructure of a city. This group includes the urban public and private use vehicles per capita, the urban public and private use cars per capita, public transportation use, and the average daily travel distance (for cars). These indicators can be useful to identify cities with higher private car penetration in order to assess the need for public charging infrastructure.

The third group is the *EV census*, i.e., the number of city electric vehicles by public and private use per vehicle, the number of city electric cars for public and private use per car, and % of electric vehicles in use compared to 2030 estimates. The objective of this group is to characterize the number of electric vehicles in a city.

The fourth group of KPIs, i.e., *EV charging infrastructure*, aims to characterize the EV charging infrastructure of a city. Specifically, the KPIs belonging to this group are: the number of charging stations per inhabitant and per electric vehicle, charging points per electric vehicle, high-power or DC charging points per electric vehicle, AC charging points per electric vehicle, charging stations relative to city area, and the percentage of installed charging stations according to 2030 estimates. These KPIs can be used to identify a city's charging needs in order to increase EV deployment.

Electric car charging services economics KPIs assess the prices of EV charging in a city. The KPIs belonging to this group are: the average price for electricity (residential), the average price for electricity (non-residential), the average price for charging at (semi-)public charging stations, and the time to make the investment profitable.

The sixth group of KPIs is the *Smart Charge/ICT system*. Its objective is to characterize the capabilities of a city infrastructure to provide smart charging services while reducing grid impact and promoting the use of renewable energies. The KPIs within this group are: the wired and wireless communication network coverage, the CPO/EMP control centre for monitoring and control EV charging points, time-based charging, and smart charging aimed at promoting grid stability.

The last group of KPIs is the *Environmental impact of EVs*, and includes the carbon intensity of the country, the percentage of renewables in the country's energy mix, the air quality of the city, and the percentage reduction in CO_2 emissions when driving an EV. Note that temperatures in cities were not considered as a limiting factor to the wide spread of electric mobility by observing that, in northern European countries such as Norway, where the temperature reaches very low values, almost all vehicles currently registered are BEVs (Norway | European Alternative Fuels Observatory).

Summarizing, KPI groups 1 and 2 are used to define the general characteristics of a city, whereas KPIs from 3 to 7 provide a view of the electric mobility in the city in terms of the number of vehicles, charging infrastructure, or service tariffs, among others, as can be seen in Table 1.

Table 1. Vector definitions.

Vector	Description	Reasons for the Vector Selection/Impact on EV Diffusion
1. *Civil and Social*	Human aspects, including the quality of life and other social aspects.	Higher income and quality of life are usually associated with higher EV penetration.
2. *Transport*	Transport and mobility features, including the use of public transport and total fleet dimension.	Low use of public transport encourages private mobility, including EV.
3. *Electric vehicles census*	Number of electric vehicles by public and private use.	Monitoring the current state of EV diffusion.
4. *Electric* vehicle *charging infrastructure*	EV charging infrastructure, including the number of charging stations by power.	Higher levels of charging infrastructure can support EV implementation.
5. *Electric vehicle charging services economics*	EV charging prices, for residential and not, including fast charging.	Cost comparison for EVs and traditional vehicles.
6. *Smart Charge/ICT system*	Smart charge services and ICT systems, including wired and wireless communications, control and monitoring of EV charging points.	Smarter charging technologies can promote energy optimization and grid stability.
7. *Environmental impact*	Use of renewable energies, air quality in cities.	A direct measure of the GHG emission reduction.

Data needed to calculate the KPIs were collected using a large variety of sources, according to the datasets available at both European and country levels, and carefully evaluating their reliability and reputation. A description of the data gathering process and some of the sources used are provided in Appendix B of this paper. To ensure the accuracy of the data collected, official European or individual country statistical sources were used, such as Eurostat for European data or each country's National Institute of Statistics, such as INE in Spain or CBS in the Netherlands. In cases where data were not readily available, they were searched for on the official web pages of the municipalities. When needed, emails were sent to the municipalities asking for the data or where to find them. The reliability of the data collected was of great importance to the research: if the data were collected but the source was not reliable, they were discarded. If doubts were raised about the reliability of the source, the data were checked against the region's official data that were more easily found; if the data did not match, the source was also discarded. When data were not available, the average of the other cities' values was used. This ensures the estimated data will have the least effect possible on the overall classification of the city.

The KPIs defined in this section were the basis for city parametrization through the vectors. These vectors were used to assess and rank the level of readiness of a city for a large deployment of electric car charging infrastructure. This section describes the methodology used to parametrize the cities investigated here and how KPIs values were calculated.

Once all KPIs were defined and all city data gathered, KPIs can be calculated as explained in Appendix A.

Since each city is different from the others, it is difficult to compare the absolute values of the calculated KPIs. Therefore, all KPIs are normalised, assuming a value between 0 and

100. These values are obtained by referring each KPI to the maximum value assumed by that KPI. Two KPI normalization processes were used:

- *Normalization # 1*: This method is used when the higher the value, the better the result. In this case, the highest value is normalized to 100 and the rest are set proportionally. For example, in the percentage of renewable energies in the energy mix V_1, Equation (1) is used to calculate this normalized KPI:

$$K_1 = \frac{V_1}{Max_v} * 100 \tag{1}$$

where V_c is the value of the city being normalized, and Max_v is the maximum value from all the cities studied.

- *Normalization # 2*: This method is used when the lower the value, the better the result. In this case, the highest value is normalized to 0 and the rest are set proportionally. For example, in the country's carbon intensity V_2, the normalization calculation is given by:

$$K_2 = \frac{(Max_v - V_2)}{Max_v} * 100 \tag{2}$$

Once all KPIs were calculated and normalised, the values of the vectors for each city were calculated. By multiplying each KPI by its assigned weight and then added, the vector value was calculated, as explained in (3) for the case of 3 KPIs included in the V_i vector.

$$V_i = a \cdot K_i^a + b \cdot K_i^b + c \cdot K_i^c \tag{3}$$

where:

- V_i is the *i*-th vector;
- a, b, and c are the weights related to KPIs values K_i^a, K_i^b and K_i^c for each city, respectively, and $a + b + c = 1$; $0 \leq V_i \leq 100$; $0 \leq K_i^a, K_i^b, K_i^c \leq 100$.

Because the number of primary attributes was large, to better visualize and compare the different facets, it was decided to adopt a 2-level hierarchical approach with the 7 facets summarizing the 30 attributes.

The definition of weights was managed by the model designer involving all the partners coming from different countries.

The advantage of defining the weights a priori—as the result of an iterative process—and keeping them constant, allows scenario analyses to be conducted that are not affected by the variation of the weights, and to converge in numerical form the experience and the point of view of the partners, similar to what is done in multi-criteria analyses. In Section 5, a robustness analysis of the most relevant weights is performed.

Table 2 shows the KPIs defined for each vector and their weights.

Table 2. KPIs weight definition.

Vectors	KPIs	KPIs' Weights
1. *Civil and Social*	Habitants density	0.375
	City GDP per capita	0.225
	Unemployment rate	0.2
	City habitants average age	0.2
2. *Transport*	City vehicles for public and private use per inhabitant	0.3
	City cars for public and private use per inhabitant	0.3
	Use of public transport	0.2
	Daily average trip distance (for cars)	0.2

Table 2. *Cont.*

Vectors	KPIs	KPIs' Weights
3. *Electric vehicles census*	City EV for public and private use per inhabitant (*EVs/Habitants*)	0.3333
	City electric cars for public and private use per inhabitant (*City electric cars/Habitants*)	0.3333
	Achieved number of EV related to 2030 estimations	0.3333
4. *Electric vehicle charging services economics*	Average electric energy price (home)	0.2
	Average electric energy price (non-residential)	0.2
	Average price for charging at (semi)public charging station	0.2
	% savings per km	0.2
	% of vehicle overcharge	0.2
5. Electric vehicle charging infrastructure	CS per EV	0.15
	CP per EV	0.225
	High power or DC CPs per EV	0.225
	AC CPs per EV	0.15
	CS vs city surface	0.1
	Achieved CS% related to 2030 estimations	0.15
6. *Smart Charge/ICT system*	Wired and wireless communication network coverage	0.3
	CPO/EMP control centre for monitoring and control of EV charging points	0.1
	Time of use tariff	0.3
	Smart charging aimed at optimising grid stability and renewables use active?	0.3
7. *Environmental impact*	Country carbon intensity	0.25
	% of renewables in the energy mix of the country	0.25
	Air Quality	0.25
	% of CO_2 emission reduction	0.25

3.2. Selected Clustering Methodology

When many cities have to be compared, the graphical analysis process becomes complicated if not impossible. Therefore, all cities analysed were grouped into standard/reference cities, so that each city could be evaluated and compared to these reference cities. The K-Means quantization technique from [31,32] was selected, not only for its simplicity and ease of use, but mainly because it allows the centroids to be identified, i.e., a reference city, for each cluster, and to facilitate their comparison. This method is an unsupervised classification/clustering algorithm that groups objects into k groups, based on their characteristics. The clustering is done by minimizing the sum of the distances between each object and the centroid of its group or cluster. Quadratic or Euclidean distances are usually used. The analysis was performed using the Python Scikit-learn Machine Learning Library (version 1.0.2) [33], where quadratic distance is used.

To avoid undesirable solutions, the methodology was run several times with different random starting centroids. The results that yield the lowest inertia were selected as the best solution. The centroids represent the average and distinctive value of each cluster, i.e., it has the characteristics that best represent each cluster.

Although each city can be described with its vector values, it is with the clustering methodology that the city characteristics are truly shown. The clustering of the 80 cities studied is a good representation of European cities because the cities selected are as spread out and diverse as possible. When comparing the characteristics of each city with other cities, the characteristics of the city are put into perspective, meaning that the city is better characterized.

Despite the effectiveness of K-means in identifying homogeneous clusters of cities, the method presents some limitations. One of the main challenges is its sensitivity to outliers, which can distort the position of the centroids and affect the clustering results. However, this limitation was mitigated through a sensitivity analysis, ensuring the robustness of the final clusters produced. In addition, K-means assumes that the clusters are spherical and evenly distributed, which may not fully capture the complexity of urban mobility patterns. Nevertheless, the selection of representative KPIs and the use of the elbow and silhouette methods allowed us to address the challenge of defining the optimal number of clusters, enhancing the reliability of the analysis.

4. Results

One of the features of the K-Means clustering is that the number of clusters must be previously decided. To support this operation, the elbow [34] and silhouette [35] methods were applied, which led to the identification of 5 clusters of cities as the optimal number. Silhouette method result can be seen on Figure 2.

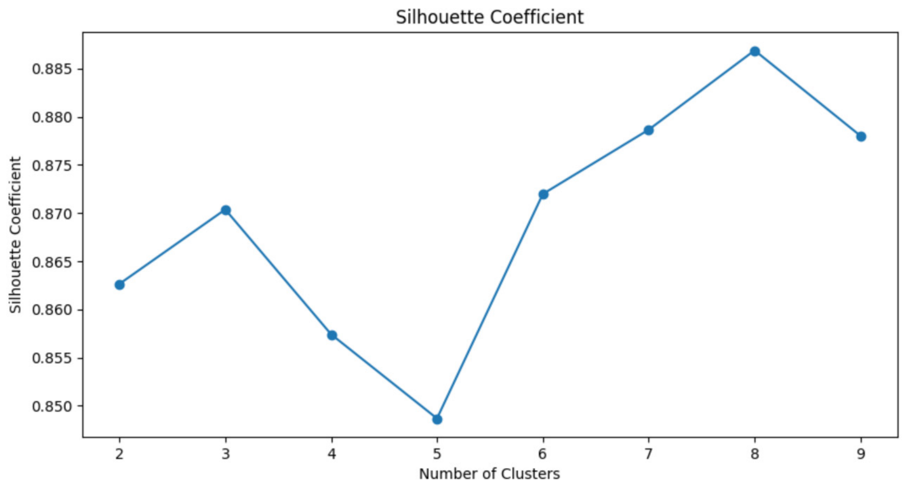

Figure 2. Silhouette method result.

In fact, when selecting 4 clusters, cities with distinct characteristics were grouped into the same cluster, whereas with 6 clusters some clusters were found to be too similar to each other.

Table 3 shows the values obtained for the 5 centroids/reference cities selected by the K-Means methodology, in relation to the 7 vectors considered. For each vector, the highest and lowest values are highlighted in yellow and green, respectively. In the last column, a label indicates the most indicative features for the corresponding reference city.

Reference City 3 is labeled as *"High EV fleet and good charging infrastructure quality"* due to its EV census value of 75.72, which is by far the highest among clusters, and an EV charging infrastructure score of 55.98, the highest among all clusters. Similarly, Reference City 1 is labeled as *"Low EV fleet and high environmental impact"*, with an EV census of 8.73, which is the lowest of all clusters, and an environmental impact score of 24.27, also the lowest value. Finally, Reference City 4, labeled as *"Low EV fleet but good charging infrastructure quality"*, shows a low EV census of 13.24 the second lowest, while presenting a charging infrastructure score of 48.5, the second highest, indicating a strong infrastructure despite limited EV adoption.

Table 3. Features of the Reference Cities.

City	No. of Cities Included	Civil and Social	Transport	EV Census	EV Charging Infrastructure	EV Charging Services Economics	Smart Charge/ICT System	Environmental Impact of the EV	Label
Reference City 1	18	47.25	51.46	8.73	18.98	58.15	100	24.27	Low EV fleet and high environmental impact
Reference City 2	24	45.75	50.83	16.6	20.91	57.31	94.75	58.61	Balanced case with low environmental impact
Reference City 3	4	46.94	32.94	75.72	55.98	53.78	70	38.41	High EV fleet and good charging infrastructure quality
Reference City 4	8	50.06	42.44	13.24	48.5	46.49	100	44.60	Low EV fleet but good charging infrastructure quality
Reference City 5	26	53.76	37.18	23.81	17.59	40.38	98.85	47.77	Balanced case with high charging prices and higher EV fleet

Yellow color indicates the highest value for a certain column; green color indicated the lowest value for a certain column.

The classification of cities into five reference clusters allows the EU to tailor policies to enhance the adoption of electric vehicles that can be synthesized as follows. For Reference City, 1 financial incentives are needed for electric vehicles purchase and grid decarbonization. For Reference City 2, investment in public charging infrastructure and tax benefits for fleet operators can accelerate EV penetration. Reference City 3 would benefit from supporting Vehicle-to-Grid (V2G) services and smart charging technologies. For Reference City 4, awareness campaigns and subsidies for individuals to purchase electric vehicles are key. Finally, for Reference City 5, the promotion of dynamic pricing and cheaper power generation would help reduce charging costs and further support the adoption of electric vehicles.

In Figures 3 and 4, spider graphs of the reference cities obtained by applying the K-Means methodology are provided.

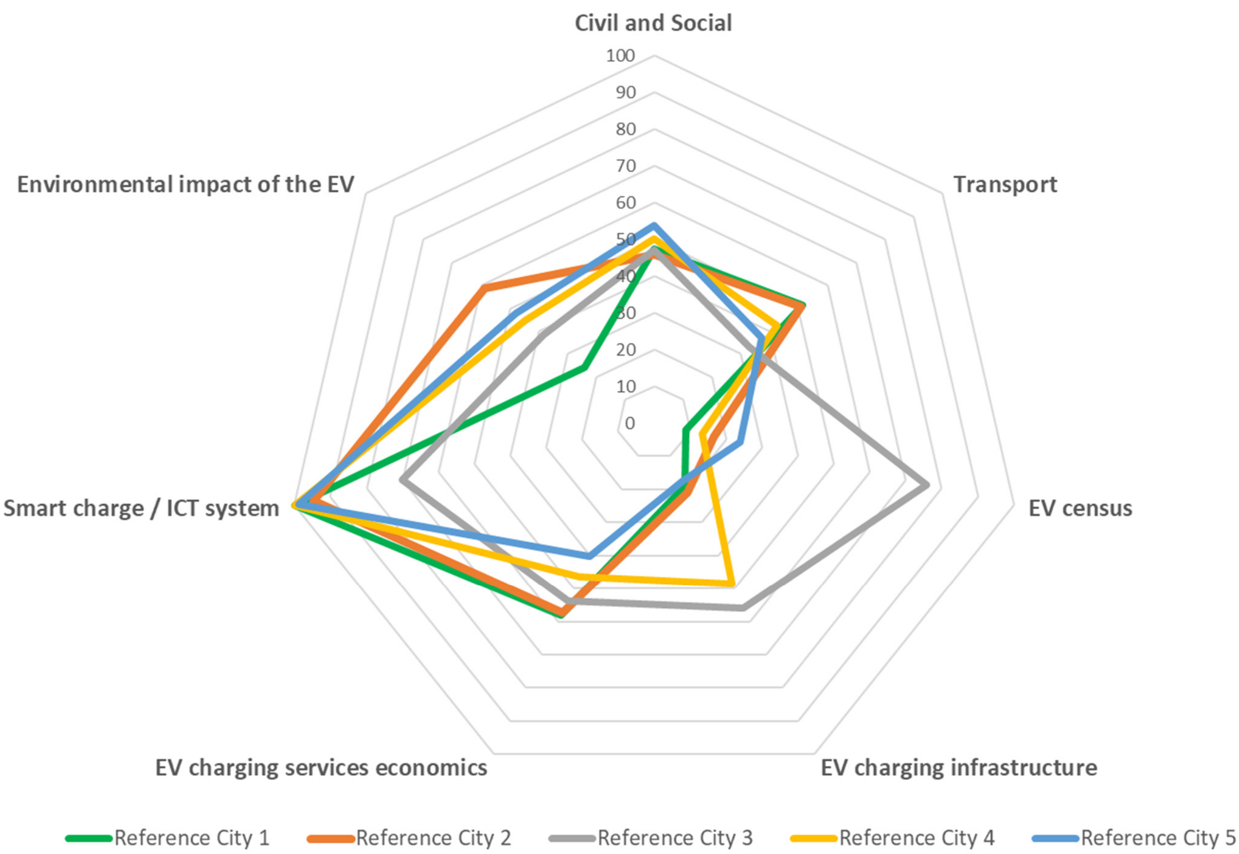

Figure 3. Reference Cities/centroids.

Figure 4. *Cont.*

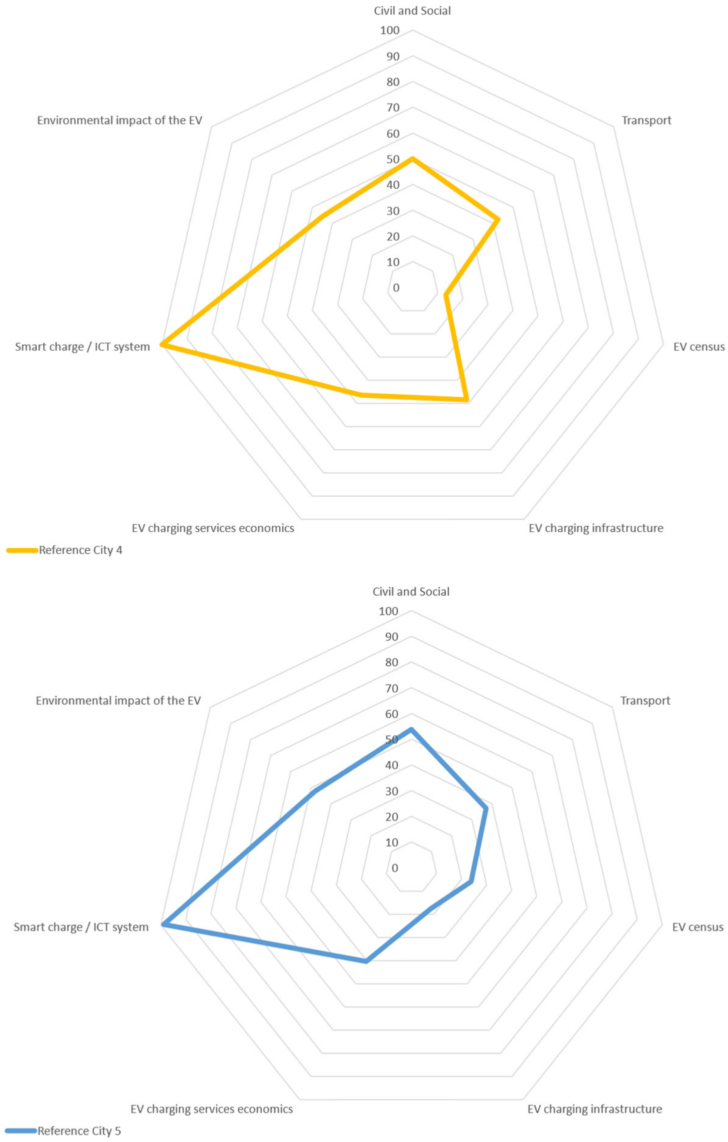

Figure 4. Comparisons among Reference Cities/centroids.

It can be noted that some of the vectors which related to the facets such as "Environmental impact of the EV" or "EV census" show a wide range of values, while others related to "Smart Charge/ICT System" or "Civil and Social" take values which are very close to each other. This does not mean that all cities perform similarly in the "Civil and Social" aspects, but that it is in other vectors where differences between the cities are more pronounced and most affect the obtained results.

It can also be highlighted that some vectors are characterized by a higher range of values, such as "EV census" or "Environmental impact", whereas others present more similar values, such as "Civil and Social" or "Transport".

When compared with the other clusters, Reference city 1 shows a lower value in *Environmental Impact* and *EV Census and Infrastructure* but a higher value in *Charging Service Economics*. This indicates that Reference City 1 represents cities from countries that are usually characterized by high energy generation rates deriving from fossils fuels. This makes electricity prices lower while generating a high negative impact on the environment. These cities also have a lower level of electric mobility, including charging infrastructures.

Reference City 3 has the highest values in vectors related to electric mobility, such as *EV census* and *EV Charging Infrastructure*, and represent European cities with higher penetration of EVs and more developed charging infrastructures. The cities belonging to Reference City 3 represent a sort of *best practice* for other cities to develop charging infrastructure and increase EVs penetration.

Reference city 4 presents a high value in *Electric car charging infrastructure* with respect to the low value of *EV census*. This does not mean that the city is more developed than the average in terms of infrastructure, but that the number of charging stations per electric car is much higher than the average. This may be due to the fact that city public bodies and companies are promoting electric mobility by developing charging infrastructures. However, at the time of observation, inhabitants do not adopt as many electric cars as other cities with a similar level of development in charging infrastructure; this may be due to economic, social, or other reasons.

Figure 5 provides a comparison between the two most similar (left graph) and most different (right graph) reference cities.

Figure 5. Most similar (**top** graph) and most different (**bottom** graph) reference cities.

As shown in Figure 5 top side, Reference city 2 and Reference city 5 are the most similar, as all seven facet values are very close to each other for these two reference cities. These types of cities represent the majority of European cities considered in this study (50 cities out of 80). Some small differences between these two reference cities are related to *Transport* and *EV charging services economics*.

On the other hand, Reference city 1 and Reference city 3 show the most distant values in terms of *EV census* and *Electric car charging infrastructure*, but identical behaviour considering *Civil and Social* as well as *EV charging services economics* (Figure 5 bottom side).

Location of the cities and correspondce to the specific reference city is presented on Figure 6. Most Eastern European cities and some Greek cities fall within Reference city 1. This makes sense as these are countries with high carbon-intensive energy generation, which gives them a low value in the environmental impact vector. Energy is also cheaper in these areas than in the rest of Europe, which gives them a high value in the electric car charging services economic vector. Only Dutch cities are included in Reference City 3, as the Netherlands is far ahead of the rest of the EU countries in adopting electric vehicles. Most European cities fall into Reference Cities 2 or 5, as these are the more balanced reference cities and, therefore, the ones that best represent an average European city. Some Eastern European cities and Lisbon fall under Reference city 4, where the country government or city municipality has made efforts to develop charging infrastructure, but few citizens have adopted electric vehicles.

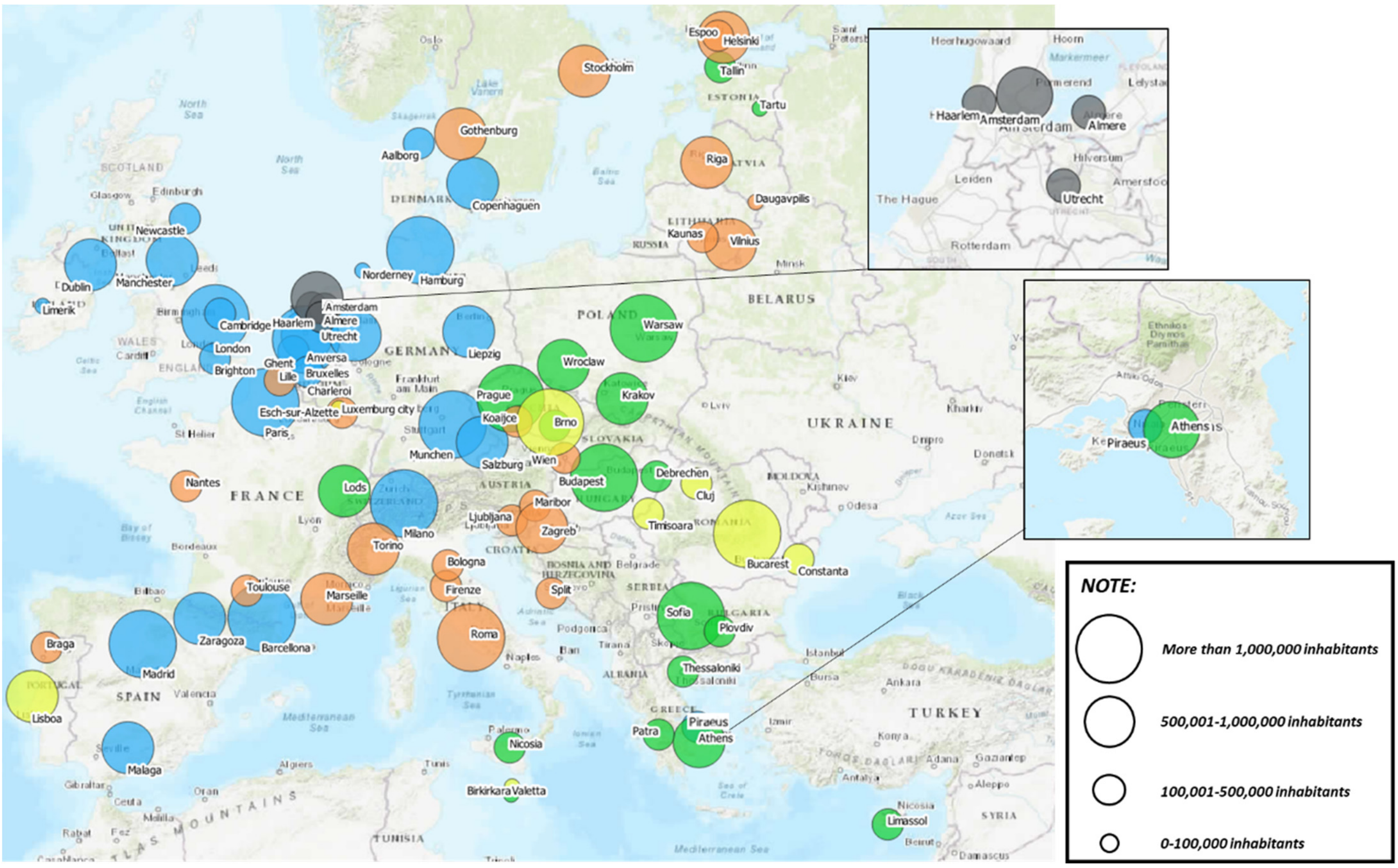

Figure 6. Location of the cities. Colours correspond to the specific reference city (green: Reference City #1; orange: Reference City #2; grey: Reference City #3; yellow: Reference City #4; blue: Reference City #5).

It should be noted that, to compare cities, civil and social attributes have also been included, such as the density of residents, the city's GDP per capita, the unemployment rate, and the average age of the city residents. All of these attributes are merged in the facet "1-civil and social", whereas the attributes related to electric charging services, such as the number of charging stations per inhabitant and per electric vehicle, charging points per electric vehicle, high-power or DC charging points per electric vehicle, and AC charging points per electric vehicle, are merged in the facet "4-Electric vehicle charging infrastructure".

5. Robustness of the Solution

The previously mentioned results were obtained using a defined set of weights. The selection of these weights was decided by all members who participated in the project. The value of each weight was decided in relation to its importance of the KPIs in the same vector. This means that the values of the weights chosen are affected by a certain level of subjectivity. Therefore, a sensitivity analysis was performed to assess the robustness of the obtained solution, i.e., how much the solution changes as the values of the weights change.

As the number of possible combinations of values of the weights is very high, the weights were distributed so that, for each vector, only one KPI assumes a much higher value than the others. For the *Civil and Social* vector, the selected weights can be seen in Table 4.

Table 4. Weights of the scenarios for the civil and social vector.

Scenarios	Weights			
	Habitants' Density	**City GDP per Capita**	**Unemployment Rate**	**City Habitants Average Age**
Original	0.375	0.225	0.2	0.2
Scenario 1	0.7	0.1	0.1	0.1
Scenario 2	0.1	0.7	0.1	0.1
Scenario 3	0.1	0.1	0.7	0.1
Scenario 4	0.1	0.1	0.1	0.7

The same procedure was applied to all vectors, obtaining 30 different scenarios.

For the 30 scenarios the new values for the vectors were calculated. The new obtained values were compared with the original ones and the root-mean-square deviation (RMSE) was calculated for each one of them. This process helped to identify which combination of weights produced the most and least changes in the values of each vector.

This change in the values of the reference cities means that some cities may change their cluster. These changes in clusters are more important than the value of the reference city itself. References cities are an easy way to compare European cities to each other. It is more important that cities with similar characteristics are grouped into the same cluster than the value of its centroid. For this reason, the new cluster each city transferred to was compared with the original one. If most of the cities remained in the same cluster, we concluded that the initial solution obtained was very representative and robust, since the changes in the weights do not affect the final solution.

From the 30 scenarios, only 16 were used to calculate the new reference cities, as shown in Table 5.

This was done to reduce the process of calculating new reference cities. From the 30 scenarios, those with the most and least changes in each vector from the original version were selected. These scenarios were those with the highest and lowest RMSE values of each of the seven vectors, resulting in 14 scenarios. The other two scenarios selected were a combination of all seven scenarios with the highest RMSE and the seven scenarios with the lowest RMSE.

Table 5. Features of the scenarios for sensitivity analysis.

# of Scenarios	***Feature***
7	Highest RMSE value (one from each vector)
7	Lowest RMSE value (one from each vector)
1	Combination of the 7 highest RMSE scenarios
1	Combination of the 7 lowest RMSE scenarios
all	Fewer than 21 changes between clusters
6	More than 10 changes between clusters
4	Fewer than 5 changes between clusters

It is also important to mention that Clusters 2 and 5, both balanced cases, were characterized by the highest number of city changes, especially between them, since they are the two most similar clusters (Figure 5). On the other hand, Cluster 3, labelled "High EV fleet and good charging infrastructure quality", did not change in any of the 16 scenarios. Cluster 4, labelled "Low EV fleet but good charging infrastructure quality", has the fewer changes. This means that clusters with more defined characteristics have the least change, while similar clusters have the most change.

Considering that these results were obtained by giving extreme values to the weights, we can conclude that, with all the data collected and all the KPIs calculated, the city's parametrization process is robust enough that a significant change in the values of the weights does not produce a significant change in the results obtained.

The analysis shown here on the importance of weight values in the final solution can also be extrapolated to other changes in the data selected or the way they were used and grouped, for example the number of KPIs selected or how are group in different vectors. Although the handling of some data might seem subjective, all of the simulations were conducted to reduce noise in the final solution as much as possible. As explained above, missing data were filled in with the normalized mean value of the KPI, as this reduced the noise introduced in the K-Means clustering process. A simple normalization process was chosen as it was good enough for the clustering methodology. Although a more advanced normalization process could have been used, the result of the sensibility analysis shows that a change in the normalization process or in the missing data-filling strategy would not have resulted in a significant change in the final solution.

6. Discussion

The acceptance and consequent deployment of EVs are often related to a lack of knowledge of the technologies, the level of deployment of charging infrastructures, and incentives to reduce the purchase price of vehicles and to keep charging operations easy for users.

Electric vehicle technology has evolved in a short time. The technical characteristics of EVs, compared with the vehicles available a few years ago, are completely different. However, not all users and drivers are aware of these advances in the technologies adopted in newer EVs. Therefore, awareness campaigns and technical articles published in specialized magazines aimed at users can mitigate this critical point. Any promotional activity can be better tailored to the specific characteristics of users to be effective. With this in mind, the classification of identified cities can be used to design the campaigns appropriately, leveraging the specific key elements that characterize the clustered cities. For example, one option for promoting electric mobility among the population is to involve young people and implement specific educational projects in collaboration with schools.

To ensure the accessibility of public charging points that can be used during parking on the street, some actions are required. The knowledge of similarities among cities can help to transfer best practice policies to cities classified in the same reference cluster. A wide range of charging stations has been made available in recent years, which should meet the diverse needs of electric vehicle drivers.

Finally, incentive policies are not sufficient for the overall development of electric mobility, especially in cities at the beginning of the transition process, but complementary policies are needed to disincentivize the use of non-sustainable alternatives, following a push and pull approach. Thus, on the one hand, there is a need to make the purchase of electric vehicles an attractive option for users, for example, by providing incentives for the purchase of electric cars and home charging, reducing ownership taxes, and offering free charging. On the other hand, some measures that limit the use of polluting vehicles, such as introducing congestion and pollution charges, and banning access to restricted traffic zones, can complement the actions. In any case, knowledge of the typical characteristics of cities can support the choice of the most appropriate set of actions to be planned and monitored during the transition phase.

7. Conclusions

The worrying increase in greenhouse gas emissions and pollutants generated by the transport sector makes it necessary to find more sustainable transport solutions. The use of electric cars certainly represents a promising solution to achieve high-quality climate-friendly mobility in cities.

This paper presents a methodology to select, calculate, and analyze a set of KPIs related to electric mobility, considering seven different facets, with the final goal of comparing cities' performance in terms of electric car use and possibly sharing best practices to encourage their uptake. The methodological approach was applied to a set of eighty cities located in Europe. Five clusters of reference cities were identified by applying the K-means methodology: each European city considered refers to one of these five reference cities. A sensitivity analysis was also performed to evaluate the robustness of the KPI framework proposed.

The results obtained represent a picture of the situation of electric car charging infrastructures for the year 2023 in 80 European cities. The results show that only 12 out of 80 cities can boast a good quality of electric car charging infrastructure. Of these 12 cities, only 4 also have a large electric car fleet and they are all located in the Netherlands, whereas the remaining 8 cities have a small electric car fleet and are primarily located in Eastern Europe.

Building a picture of the phenomenon under study for a specific city is crucial since it can help policymakers in the decision-making process. Also, having defined how to take this picture helps in taking other pictures of the same phenomenon in later periods with the same criteria. The focus of the paper is in fact on comparing cities with their past and not on comparing cities from different countries. Having a set of KPIs with which to trigger pictures at different times can help monitor the phenomenon quickly.

The results of the research conducted can be applied to any city to analyse the differences with other cities and why the cities most prepared for the integration of electric cars are a step ahead of the others. The paper provides some policy indications for both the analyzed cities and those not considered. Regarding the analyzed cities, the results obtained indicate their current status in terms of EV mobility, thus providing indications for future investments or directions. Dutch cities can certainly be considered as a main reference. Regarding the cities that were not included in this study, the paper presents a new methodological approach for benchmarking with electric car needs and expectations.

City governments seeking to improve the integration of electric cars in their cities can use this research as a source of information on which cities have good policies and are good to follow. In fact, the comparison with different cases can provide a better understanding of the state of a city in relation to electric car mobility and highlight any underlying problems, thus helping decision-makers make appropriate decisions to design more targeted policies and plans for cities with the goal of fostering electric car deployment.

KPIs can be easily computed for other cities considering the simple formulas used. This will allow direct comparison with the reference cities identified in this study. In addition, a list of the data sources used to calculate the KPIs is provided and included in the references, helping cities efficiently gather the information needed to perform the analysis. Using this approach, cities can identify the target cluster to which they belong, understand what factors limit the adoption of electric vehicles, and support adequate policy decisions.

This approach not only makes the methodology replicable but also allows cities to track their progress over time and measure the impact of new policies or infrastructure developments.

The main limitation of this study lies in the fact that the data used to generate KPIs were collected in a specific year.

Future research will be dedicated to monitoring the evolution of the selected cities over time to check if cities can improve their current status regarding electric car mobility, and if the most virtuous cluster can include more cities than we have currently observed. New updated data related to the same reference cities will then be collected to check the evolution of the cities over time. A further research idea could be to check if the identified clusters are also be valid for a wider set of cities, not considered at this stage of the research.

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Abbreviations

KPI	Key Performance Indicator
EV	Electric Vehicle
CO_2	Carbon Dioxide
GDP	Gross Domestic Product
DC and AC charging	Direct Current and Alternating Current charging

RMSE	Root Mean Square Error
INE	National Institute of Statistics of Spain
CBS	National Institute of Statistics of the Netherlands
UK	United Kingdom
EU	European Union
GHG	Greenhouse Gases
ICT	Information and Communication Technology
CPO	Charge Point Operator
EMP	E-Mobility Provider

Appendix A. KPIs' Formulas Summary

The calculations made for each KPI are explained in detail for all the cases in Table A1 and a data repository is shownin Appendix B. Some KPIs are easily calculable ratios, such as $N_{EV}^{p} = \frac{N_{EV}}{P}$, where N_{EV}^{p} is the number of electric vehicles in a city per capita, for public and private use; N_{EV} is the number of electric vehicles in a city, for public and private use; P is the population of a city.

Some other KPIs need a more complex calculation, such as $d = \frac{p_{EV} - f_{EV}}{p_{ST}^{km} - p_{EV}^{km}}$, where d is the distance to make the EV investment profitable (expressed in kilometres), p_{EV} and f_{EV} are the buying price of an electric and a traditional ICE vehicle, respectively. p_{ST}^{km} and p_{EV}^{km} are the average price per km respectively for electric and ICE vehicle.

Finally, some KPIs do not need any calculation, such as *"Unemployment rate"*, since the KPI is represented by a single parameter.

Table A1 provides all the formulas of the KPIs, the units of each KPI, the data needed for its calculation, and a brief description of each KPI.

Table A1. Vectors-KPIs Summary Table.

Vector	KPI Identifier	KPI Name	Used Parameters per KPI	Formula	Units	Description
Civil and Social	C&S_KPI_01	Habitants density	City population and area	city population/city area	Habitants/km2	This KPI provides information about the city habitants density and can be related to parking availability at home for example
Civil and Social	C&S_KPI_02	City GDP per capita	City GDP per capita	-	€/habitant	This KPI provides information about the differences in the cost of living and inflation rates on a city and can be related to the amount of EV in the city
Civil and Social	C&S_KPI_03	Unemployment rate	Unemployment rate	-	%	This KPI provides information about the unemployed percentage of city inhabitants and can be related to the amount of EV in the city
Civil and Social	C&S_KPI_04	City habitants average age	City habitants average age	-	years	This KPI provides information about the average age of city inhabitants and can be related to the predisposition to change and acquire a new technology such as an electric vehicle
Transport	T_KPI_01	City vehicles for public and private use per inhabitant	Total amount of vehicles (car, bus, truck, ...) in the city and total population	city vehicles/city population	Vehicles/Habitants	This KPI provides information about the city vehicles amount and the potential for EV
Transport	T_KPI_02	City cars for public and private use per inhabitant	Total amount of cars in the city and total population	city cars/city population	City cars/Habitants	This KPI provides information about the city cars amount and the potential for EV

Table A1. *Cont.*

Vector	KPI Identifier	KPI Name	Used Parameters per KPI	Formula	Units	Description
Transport	T_KPI_03	Use of public transport	Total amount of cars in the city and total population	Average daily trips in public transport	Trips/day	This KPI provides information about the use of public transport in the city and can be related to the expansion possibilities of EVs
Transport	T_KPI_04	Daily average trip distance (for cars)	Daily average trip distance (for cars)	Daily average trip distance (for cars)	km/day&car	This KPI provides information about the use of cars in the city and can be related to the expansion possibilities of EVs
EV census	EVC_KPI_01	City EV for public and private use per inhabitant	Total amount of EV (car, bus, truck, . . .) in the city and total population	city EV/city population	EVs/Habitants	This KPI provides information about the city EV amount and the potential for EV
EV census	EVC_KPI_02	City electric cars for public and private use per inhabitant	Total amount of electric cars in the city and total population	city electric cars/city population	City electric cars/Habitants	This KPI provides information about the city electric cars amount and the potential for EV
EV census	Proposed	Achieved EV % related to 2030 estimations	Total EV in 2020 Expected total EV in 2030	(Total EV in the whole country in 2020/Expected total EV in 2030)*100	%	This KPI provides information about how close the city is in 2020 to reach the expected levels in EV in 2030.
EV charging infrastructure	EVCI_KPI_01	CS per inhabitant	Total amount of EV CSs the city and total population	EV CSs/city population	CSs/Habitant	This KPI provides information about the amount of charging stations related to the city population
EV charging infrastructure	EVCI_KPI_02	CS per EV	Total amount of EV CSs the city and total EV amount	EV CSs/EV amount	CSs/EV	This KPI provides information about the amount of charging stations related to the city EV amount
EV charging infrastructure	EVCI_KPI_03	CP per inhabitant	Total amount of EV CPs the city and total population	EV CPs/city population	CPs/Habitant	This KPI provides information about the amount of charging points related to the city population
EV charging infrastructure	EVCI_KPI_04	CP per EV	Total amount of EV CPs the city and total EV amount	EV CPs/EV amount	CPs/EV	This KPI provides information about the amount of charging points related to the city EV amount
EV charging infrastructure	EVCI_KPI_05	High power or DC CPs per VE	Total amount of EV high power DC CP and total EV amount	DC CPs/EV	CPs/EV	This KPI provides information about the amount of fast charging points related to the city EV amount
EV charging infrastructure	EVCI_KPI_06	AC CPs per VE	Total amount of EV AC charging points and EV amount	AC CPs/EV	CPs/EV	This KPI provides information about the amount of AC charging points related to the city EV amount
EV charging infrastructure	EVCI_KPI_07	CS vs city surface	Total amount of EV CSs in the city and city surface	EV CSs/city area	CSs/km2	This KPI provides information about the distance to be travelled to find a CS
EV charging infrastructure	Proposed	Achieved CS% related to 2030 estimations	Number of CS in the whole country in 2020 Expected number of CS in the whole country in 2030	(Number of CS in the whole country in 2020/Expected number of CS in the whole country in 2030)*100	%	This KPI provides information about how close the city is in 2020 to reach the expected number of CS in 2030.
EV charging services economics	EVCSE_KPI_01	Average electric energy price (home)	Average electric energy price (home)	Average electric energy price (home)	€/kWh	This KPI provides information about the energy costs for home use
EV charging services economics	EVCSE_KPI_02	Average electric energy price (non-residential)	Average electric energy price (non-residential)	Average electric energy price (non-residential)	€/kWh	This KPI provides information about the energy costs for non-residential use
EV charging services economics	EVCSE_KPI_03	Average price for charging at (semi)public charging station	Average price for charging at (semi)public charging station	Average price for charging at (semi)public charging station	€/kWh	This KPI provides information about the average charging cost an EV driver has to face in the city
EV charging services economics	EVCSE_KPI_04	% savings per km	Average price per fuel (kwh or fuel) and average fuel consumption per 100kms	(Av price per km fuel vehicle/Av price per km EV)-1	%	This KPI provides information about the average savings per km driving an EV
EV charging services economics	EVCSE_KPI_05	% of electric vehicle overcharge	Average priece per EV and fuel vehicle	(EV price/Fuel Vehicle price)-1	%	This KPI provides information about the average overcharge when buying an EV

Table A1. *Cont.*

Vector	KPI Identifier	KPI Name	Used Parameters per KPI	Formula	Units	Description
EV charging services economics	Proposed	Distance to make the investment profitable (kms)	Average saving per km driving an EV and Average overcharge per EV	(EV price-Fuel Vehicle price)/(Av price per km fuel vehicle-Av price per km EV)	kms	This KPI provides information about the average distance in kms an EV has to drive to make the investment profitable
Smart charge/ICT system	SCIS_KPI_01	Wired and wireless communication network coverage	Wired and wireless communication network coverage	% Wired and wireless communication network coverage area	%	This KPI provides information about the area (%) of the city covered by wireless and/or wired communications networks, needed for remote management of CS
Smart charge/ICT system	SCIS_KPI_02	CPO/EMP control centre for monitoring and control of EV charging points	Wired and wireless communication network coverage	% Wired and wireless communication network coverage area	0 or 1	This KPI provides information about the possibilities of remote management/monitoring of EV CP in the city
Smart charge/ICT system	SCIS_KPI_03	Time of use tariff	-	-	0 or 1	This KPI provides information about the existence of time of use tariffs in the city. ToU tariff can enable, night charge through lower prices and reducing EV charge grid impact through indirect demand management of the charger.
Smart charge/ICT system	SCIS_KPI_04	Smart charging aimed at optimising grid stability and renewables use active?	-	-	0 or 1	This KPI provides information about the existence of regulations that promote the use of distributed RES in CS (or other consumption points). The integration of RES in CS is a good method to reduce EV charge grid impact
Environmental impact of the EV	EIEV_KPI_01	Country carbon intensity	For every city characterised, Country carbon intensity	Country carbon intensity	tCO2-eq/MWh or gCO2-eq/kWh	This KPI provides information about the grid impact of the energy provided to EVs
Environmental impact of the EV	EIEV_KPI_02	% of renewables in the energy mix of the country	For every city characterised, % of renewables in the energy mix of the country	% of renewables in the energy mix of the country	%-eq/kWh	This KPI provides information about the grid impact of the energy provided to EVs
Environmental impact of the EV	EIEV_KPI_03	Air Quality	City emissions of PM2,5; PM10; O3; NO2 and SO2	For each pollutant a number from 0 to 5 will be asigned depending on the quantity emitted, being 0 extremely poor air quality and 5 good air quality. The lowest number from all pollutants will be asigned as KPI.	From 0 to 5	This KPI provides information about the air quality in the city.
Environmental impact of the EV	Proposed	% of CO2 Emission Reduction	Fuel Vehicle CO2 Emissions per km and EV CO2 Emissions per km	(Fuel Vehicle CO2 Emissions/EV CO2 Emissions)-1	%	This KPI provides information about the % of reduccion in the CO2 emissions by driving an EV taking into consideration the carbon intensity of the country in the electricity generation.

Appendix B. Data References and Gathering Process

The data gathering process conducted for the project was of high importance due to the amount and reliability of data needed. In this Appendix, the work followed for the gathering process is explained. All of the references used are shown in the data repository referenced in Appendix A.

The optimal data were the data for the city. This was not always possible, and sometimes data from the Metropolitan Area, Region, County/Municipality or Country were the only ones available. If this was the case, the data were filled using the same ratio as the data in the region.

For example: If Madrid city has 3,266,126 inhabitants and the Community of Madrid has 6,661,949, and the only electric vehicle data we can find are 18,000 in the whole Community, we will maintain the same ratio and calculate the EV in Madrid city:

$$EVs\ in\ the\ city\ of\ Madrid = \frac{EV\ census\ * City\ population}{Metropolitan\ area\ population} = \frac{18,000 * 3,266,126}{6,661,949} = 8825$$

Sometimes data for the city/region can only be found in percentages. For example, the % of EV in the city/region or the % of cars referred to the total of vehicles. With these data, it is also possible to calculate the data needed.

Use help from official organizations: Sometimes some data are particularly difficult to find. In those cases, e-mails to the official City Hall, or the official statistics institute of the country were sent. The transport ministry or similar organizations in the country were also be very helpful.

Some references used for the data can be found here.

Appendix B.1. Civil and Social Data

- Data for City Population. These data were used as a reference if city limits were not clear to identify them. Data from this source were not used, but instead we used data from the most reliable source and the nearest year we were able to find.

  https://worldpopulationreview.com/ (accessed on January 2022)

- Population (region Eurostat)

  https://ec.europa.eu/eurostat/databrowser/view/tgs00096/default/table?lang=en (accessed on January 2022)

  - For example: Berlin and Brussels have almost the same population in both references as the regions consist of almost the whole city exclusively. But for other cities, such as Zaragoza, the city population is 675,000 while the region, Aragón, has 1,330,300 habitants, and 973 km^2 for Zaragoza while the whole region is 47,720 km^2. As only city data are selected for the task, use the most reliable and similar data to the first reference, as they give data for the city and not the region.
  - These examples show that in some cases data must be taken from the region, and in others from the city. In the case of Zaragoza/Aragon, it is necessary to look for specific data for Zaragoza (population and/or surface area) since the EUROSTAT population data are limited to the region.
  - In the case of Berlin or Brussels, it is correct to take the region to calculate the KPIs and use the data available in EUROSTAT.

- For City Area (km^2) it was not possible to find a data source with city area data for all the selected cities. City population data from the reference before were used as a guide to find city area if city limits were uncertain.
- Eurostat data for GDP, Unemployment and Average Age are provided by region (if city data can be found please use those, if not, use region data from EUROSTAT).

  - GDP per capita (country)

  https://ec.europa.eu/eurostat/databrowser/view/sdg_08_10/default/map?lang=en (accessed on January 2022)

  - GDP (region)

https://ec.europa.eu/eurostat/databrowser/view/nama_10r_3gdp/default/map?lang=en (accessed on January 2022)

- ○ GDP per capita (region 2019)

https://ec.europa.eu/eurostat/web/products-eurostat-news/-/ddn-20210303-1 (accessed on January 2022)

- ○ Unemployment (region)

https://ec.europa.eu/eurostat/databrowser/view/tgs00010/default/map?lang=en (accessed on January 2022)

- ○ Data for City habitant's average age

https://ec.europa.eu/eurostat/statistics-explained/index.php?title=City_statistics_%E2%80%93_demography (accessed on January 2022)
https://ugeo.urbistat.com/AdminStat/en (accessed on January 2022)

Appendix B.2. Transport and EV Census

NOTE

As there is not a general source with data for all the cities some useful references have been selected. Data from these references should be used to check for consistency as it is not segregated by city. It was the task of each partner to look for data as reliable as possible and check in these references for consistency and reliability.

https://infogram.com/1pd21nkxzz7vnxcmv9z7xjv5llfk75zdzjg (accessed on January 2022)
https://stats.oecd.org/Index.aspx?anddatasetcode=ITF_PASSENGER_TRANSPORT (accessed on January 2022)
https://ec.europa.eu/transport/facts-fundings/statistics/pocketbook-2020_en (accessed on January 2022)
https://www.oica.net/category/sales-statistics/ (accessed on January 2022)
https://www.acea.auto/nav/?content=passenger-car-registrations (accessed on January 2022)
https://www.ev-volumes.com/datacenter/ (accessed on January 2022)
https://theicct.org/sites/default/files/publications/ICCT_EU_Pocketbook_2020_Web_Dec2020.pdf (accessed on January 2022)
https://read.oecd-ilibrary.org/transport/itf-transport-outlook-2017_9789282108000-en#page1 (accessed on January 2022)
https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Manufacturing/gx-2020-global-automotive-consumer-study-europe.pdf (accessed on January 2022)
https://www.connaissancedesenergies.org/sites/default/files/pdf-actualites/Global_EV_Outlook_2020.pdf (accessed on January 2022)
https://www.statista.com/ (accessed on January 2022)
https://www.eea.europa.eu/publications/electric-vehicles-in-europe (accessed on January 2022)
https://www.emta.com/?lang=en (accessed on January 2022)
https://en.wikipedia.org/wiki/List_of_countries_by_vehicles_per_capita (accessed on January 2022)
https://www.eea.europa.eu/data-and-maps/indicators/proportion-of-vehicle-fleet-meeting-5/assessment (accessed on January 2022)

- Average daily passengers transported in public transport: These data were one of the hardest to find. A lot of times the data were found in the annual total in the region. With those data and population in the region/city, it is possible to find the data needed, as done before with the EV in Madrid example.

Appendix B.3. Electric Vehicles Charging Infrastructure

- Four reference links are provided for this vector. If more reliable data were found in other sources, they were used, and these references were only used in the case of no reliable data being found. Depending on the city, the best data could be found on different pages. We used the higher data for the amount of city charging stations. Some references only show charging stations, not charging points, or how these are (fast charging in DC or slow charging in AC). If this happened, we used the same ratio shown on the other webpage.
    - For example: If some page had 100 Charging Stations (CS) and 250 Charging Points (CP), we might see 300 CS on other pages but no data for CP available. The data used will be 300 CS and 300 CS*250 CP/100 CS to maintain the ratio and make the CP data as reliable and consistent as possible.

    https://www.eafo.eu/
    https://www.electromaps.com/ (accessed on January 2022)
    https://es.chargemap.com/ (accessed on January 2022)
    https://www.plugshare.com/ (accessed on January 2022)

Appendix B.4. EV Charging Services Economics

- Average electric energy price (home) (€/kWh)

https://ec.europa.eu/eurostat/databrowser/view/nrg_pc_204/default/table?lang=en (accessed on January 2022)

- Average electric energy price (non-residential) (€/kWh)

https://ec.europa.eu/eurostat/databrowser/view/nrg_pc_205/default/table?lang=en (accessed on January 2022)

Data initially without taxes in the last two links, in the project the data were used with taxes, so the option was added in both of the links provided.

Appendix B.5. Smart Charge ICT System

- % Wired and wireless communication network coverage area. This represents the % of the city area that is covered by at least one communication network (wired or wireless). If the whole city is covered, the data should be 100%.

    https://www.gsma.com/coverage/ (accessed on January 2022)

- CPO/EMP control centre for monitoring and control of EV charging points; time of use tariff and smart charging aimed at optimizing grid stability and renewables use active vectors will consist of "1" if there is at least one Monitoring Control Centre, Time Tariff or Smart Charging regulations that meets the proposed conditions. That is, if there is not one control centre for monitoring and control EV charging points "0" is selected, if there is at least one control centre "1" is selected.

Appendix B.6. Environmental Impact of the EV

- Country carbon intensity: These data referred to the electricity generation only. Data of the whole country were selected.

    https://www.eea.europa.eu/data-and-maps
    https://www.iea.org/ (accessed on January 2022)

- % Of renewables in the energy mix of the country. Data from the whole country.

    https://www.iea.org/ (accessed on January 2022)

- Air Quality: If one city had more than one measurement for the average, we used the higher value of them all. If the data were segregated daily, we used the average data for the last year available.

https://www.eea.europa.eu/themes/air/country-fact-sheets/2020-country-fact-sheets (accessed on January 2022)
https://aqicn.org/data-platform/register/ (accessed on January 2022)
https://www.iqair.com/world-air-quality (accessed on January 2022)

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