

Article

Promoting Energy Efficiency and Emissions Reduction in Urban Areas with Key Performance Indicators and Data Analytics

Angel A. Juan ^{1,*}, Majsja Ammouriova ², Veronika Tsertsvadze ¹, Celia Osorio ¹,
Noelia Fuster ¹ and Yusef Ahsini ¹

¹ Research Center on Production Management and Engineering, Universitat Politècnica de València, 03801 Alcoy, Spain

² Computer Science Department, Universitat Oberta de Catalunya, 08018 Barcelona, Spain

* Correspondence: ajuanp@upv.es

Abstract: With the increasing demand for sustainable urban development, smart cities have emerged as a promising solution for optimizing energy usage, reducing emissions, and enhancing the quality of life for citizens. In this context, the combined use of key performance indicators (KPIs) and data analytics has gained significant attention as a powerful tool for promoting energy efficiency and emissions reduction in urban areas. This paper presents a comprehensive conceptual framework in which a series of KPIs are proposed to serve as essential metrics for guiding, monitoring, and assessing energy efficiency and emissions reduction levels in smart cities. Some of the included KPIs in the analysis are ‘annual energy consumption per person’, ‘reduction in greenhouse gas emissions’, ‘public transport use’, and ‘adoption of renewable energy’. By incorporating these KPIs, city planners and policymakers can gain valuable insights into the effectiveness of sustainability initiatives. Furthermore, the paper explores how the integration of KPIs with data analytics can be used for monitoring and assessing the overall performance of the city in terms of energy efficiency, emissions reduction, and the enhancement of urban living conditions. Visualization tools, such as radar plots, and time series analysis forecasting methods allow data to be processed and patterns to be identified, enabling informed decision-making and efficient resource allocation. Real-life case studies of ongoing smart city projects are presented in the paper, which also provides a KPI comparison among different European cities, as well as models to forecast the evolution of KPIs related to energy usage and emissions reduction in different European cities.

Keywords: urban areas; energy efficiency; emissions reduction; key performance indicators; data analytics



Citation: Juan, A.A.; Ammouriova, M.; Tsertsvadze, V.; Osorio, C.; Fuster, N.; Ahsini, Y. Promoting Energy Efficiency and Emissions Reduction in Urban Areas with Key Performance Indicators and Data Analytics. *Energies* **2023**, *16*, 7195. <https://doi.org/10.3390/en16207195>

Academic Editors: Ahmed F. Zobaa and Andrea Mariscotti

Received: 26 August 2023

Revised: 30 September 2023

Accepted: 19 October 2023

Published: 22 October 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The intersection of rapid urbanization and climate change has sparked a surge of interest in smart cities. These urban environments leverage cutting-edge information and communication technologies, empowering data-driven solutions [1]. By addressing local sustainability challenges, the concept of smart cities strives to facilitate the urban transition. Central to this transition is the strategic and efficient utilization of resources, promoting sustainable development and a reduced ecological footprint. In this context, energy and sustainability emerge as pivotal focal points, as cities endeavor to create resilient environments [2]. To effectively monitor and assess policies aimed at urban transformation, it becomes essential to establish performance indicators that drive energy-saving and zero-emissions initiatives across transportation, mobility, and urban design domains. This research centers on identifying the diverse dimensions of sustainability critical to the development of smart cities. Through well-defined strategies and initiatives, these cities can achieve environmental friendliness, social inclusivity, and economic viability. These interconnected dimensions constitute the foundation for effective policy evaluation in

urban transformation, especially concerning energy efficiency and emissions reduction goals in transportation, mobility, and urban design.

This article presents research conducted within the framework of the UP2030 project, a European initiative focused on defining performance indicators to aid pilot cities in their transition towards achieving climate-neutral objectives (<https://up2030-he.eu/about-project/>, accessed on 26 August 2023). These transitions rely on both social and technological transformations to drive sustainable change. The project adopts the ‘5UP’ methodology, which encompasses update, upskill, upgrade, upscale, and uptake approaches. The UP2030 project involves ten pilot cities. Each pilot city possesses a unique storyline and faces specific challenges that need to be overcome to attain its climate-neutral targets. Accordingly, this paper presents a review of KPIs in such modern urban areas. A comprehensive conceptual framework based on the cities’ storyline is unveiled, proposing KPIs as essential metrics for guiding, monitoring, and assessing energy efficiency and emissions reduction in urban areas. Through the incorporation of these KPIs, city planners and policymakers gain valuable insights into the efficacy of sustainability initiatives. The following study begins with a literature review of KPIs related to urban energy consumption and emissions. Different cities are compared with respect to the selected KPIs in each of the economic, environmental, and social dimensions. This comparison between cities is performed using radar graphs. In addition, the values of the KPIs recorded over time are used to forecast their trend in the future. By applying forecasting models (e.g., the Holt model), energy consumption trends are projected up to 2026. These predictions form the basis for several discussions on the potential impact of proposed strategies.

The rest of the article is arranged as follows: Section 2 reviews how energy efficiency and emissions reduction have been previously addressed in the scientific literature. Based on the previous review, Section 3 proposes a list of KPIs that can be employed in the Economic, Environmental, Social, and Governance dimensions of modern urban areas. Section 4 provides a short overview of the two pilot projects being developed in the cities of Granollers and Milan, while Section 5 describes the methodology employed for selecting the KPIs in each city. Section 6 shows a comparison among different European cities regarding a selected subset of KPIs. The use of statistical tools for forecasting KPI values is illustrated in Section 7. Finally, the main conclusions of this work are presented in Section 8.

2. Related Work on Urban Energy Efficiency and Emissions Reduction

Energy efficiency and emissions reduction constitute relevant dimensions in the establishment of urban areas that align with sustainable development goals. The United Nations sustainable development goals emphasize the significance of sustainable transport and cities (<https://sdgs.un.org/goals>, accessed on 26 August 2023). As urbanization intensifies and the number of vehicles and mass production increase, the urgency to develop cities that cater to current demands while safeguarding resources for future generations becomes essential [3]. Hence, the pursuit of energy-saving and zero-emission policies plays a key role in designing these sustainable cities. These policies must encompass various aspects, including transport, mobility, and urban design, to foster a holistic approach to sustainable development. Smart cities have emerged as a promising solution to address various sustainability challenges. Toli and Murtagh [1] conducted a comprehensive review of smart city definitions, revealing two primary themes. One set of definitions emphasized the integration of humans and infrastructure to create a sustainable city, focusing on sustainability-oriented goals. Alternatively, other definitions underscored the role of information and communication technologies (ICTs) in enhancing the overall quality of life within urban areas. Based on their analysis, the aforementioned authors proposed a definition that views smart cities as an urban transformation concept dedicated to achieving environmental sustainability while simultaneously enhancing the quality of life for citizens. This transformation necessitates the collaboration of multiple stakeholders to establish the essential infrastructure and enable the city’s sustainable evolution. It is in this context that the significance of effective urban planning cannot be overstated, as it forms the foundation

for establishing sustainable urban environments. Urban planners leverage a variety of design elements and tools, including streetscape [4], transportation systems [5], urban design [6], and the integration of ICTs. The combination of these urban elements, coupled with smart approaches, energy-efficient solutions, and sustainable principles, contributes to significant energy savings. Intensive use of ICTs is key for: (i) efficient data collection and processing (including sources such as sensors, smart devices, and databases), which allows for a comprehensive assessment of energy usage and emissions in urban areas [7]; (ii) real-time monitoring of energy efficiency and emissions; (iii) the use of advanced data analytics tools in order to uncover valuable insights and patterns within the data; (iv) the development of predictive models to forecast future trends in energy usage and emissions; and (v) integration with KPIs. Of course, intensive use of ICTs also raises some challenges related to data privacy and security [8], the cost of installing sensors and software development, guaranteeing data quality, interoperability with existing systems, and ethical considerations related to the use of data analytics and surveillance technologies in urban areas [9].

The realization of sustainable cities depends upon the seamless integration of renewable energy solutions. In pursuit of this goal, Thellufsen et al. [10] presented a comprehensive approach for transitioning cities to sustainable paradigms. Their approach centered around five key aspects: (i) sustainable biomass utilization; (ii) addressing transportation needs; (iii) sustainable industrial practices; (iv) maximizing the share of variable renewable energy sources; and (v) effectively balancing energy demand and supply. As part of their recommendations, they advocated for the integration of wind and photovoltaic power to enhance renewable energy capacity. Furthermore, the deployment of smart devices, particularly smart grids, assumes a crucial role in the development of smart cities. Smart grids serve as a dynamic platform to integrate diverse energy resources, be it renewable or conventional, in a manner that reduces environmental impact [11]. The establishment of a sustainable city relies on fostering sustainable transportation and mobility, which are essential for facilitating residents' daily movement. Prioritizing public transportation, integrating carsharing and ridesharing solutions [12], investing in electric vehicles' infrastructure, and promoting cycling and walking all contribute to a significant reduction in greenhouse gas emissions. Researchers have been exploring viable alternatives to fossil fuels in vehicles, such as electricity or hydrogen, to enhance sustainability efforts further [13]. By efficiently planning and integrating transportation elements, urban mobility can be significantly improved. Furthermore, waste management assumes a crucial role in sustainable city development, necessitating the adoption of innovative solutions to reduce waste generation. Waste management strategies encompass recycling, energy conversion, incineration, and composting [14]. Embracing a circular economy approach encourages resource re-utilization and recovery, leading to reduced waste generation and minimized reliance on new raw materials. Water resources also merit consideration within the context of circular economy principles [15].

Likewise, ICT forms a critical enabler for data-driven solutions and decision-making processes. The integration of information and communication technologies presents unprecedented opportunities for sustainable transformation. The convergence of the Internet of Things (IoT) and data analytics offers real-time insights that can redefine urban mobility and transportation. The ability to collect and process data on energy utilization, emissions, and mobility patterns empowers decision-makers to implement effective policies, shape behavioral changes, and drive efficient urban transformation. By leveraging the potential of these technologies, cities can optimize energy use and curb emissions, while ensuring seamless and accessible mobility for their inhabitants. Similarly, systems powered by artificial intelligence offer smart management capabilities that empower informed decision-making in various domains, further supporting the sustainable development goals of smart cities. By leveraging ICT, data analytics, and intelligent algorithms, cities can optimize resource allocation, develop less pollutant mobility and transportation systems, enhance energy efficiency, and implement more effective waste management strategies [16].

One of the foundational pillars of urban sustainability is the regulatory framework that guides and supports energy efficiency and emissions reduction projects. Policies and regulations at local, national, and international levels play a critical role. Thus, for instance, Letnik et al. [17] investigates the policies and measures for sustainable urban freight transport in European cities. Their analysis of 129 cities reveals a varied landscape of logistics and mobility planning policies, with an emphasis on softer, cost-effective measures. Similarly, Krause et al. [18] explore options for reducing CO₂ emissions in European road transport by 2050, with a focus on improving vehicle efficiency. The study emphasizes technical feasibility but highlights the need for policies, energy considerations, and fuel properties for a comprehensive analysis. The authors of [19] examine the impact of economic policy uncertainty and clean energy consumption on CO₂ emissions in France from 1987 to 2019, considering urbanization and economic growth. Grafakos et al. [20] focus on the integration of mitigation and adaptation actions in urban climate change plans. These authors examined 147 climate change action plans from European cities and found that most plans show a ‘moderate’ level of integration.

In a different dimension, economic incentives, market mechanisms, and financial instruments are integral components of urban sustainability initiatives. This encompasses an exploration of incentives, subsidies, and market-based approaches that drive investments in clean energy, green technologies, and sustainable urban infrastructure. Hendrickson et al. [21] present a framework for sustainable community development, emphasizing the integration of economic, social, and environmental considerations in municipal policy making. They examine how the economy affects unsustainable development in local areas and propose a typology of market mechanisms to align community development policies with sustainability principles. Bertoldi et al. [22] investigate financing schemes for energy renovations in buildings to advance sustainability goals. They review traditional and emerging financial models, including property tax financing, on-bill financing, energy efficiency mortgages, feed-in tariffs, and crowdfunding, assessing their benefits and challenges.

Smart city initiatives are not solely driven by technological advancements but also by the active engagement of communities and citizens. These include community-based programs, public awareness campaigns, and collaborative decision-making processes. Hence, Cardullo and Kitchin [23] discuss the influence of neoliberal ideals on citizen participation and citizenship within the smart city context. Finally, Camboim et al. [24] explore the essential elements that contribute to making a city smarter, drawing insights from literature, expert interviews, and smart city projects in cities like Amsterdam, Barcelona, Lisbon, and Vienna. The findings suggest that a smart city is characterized by an urban innovation ecosystem where knowledge flows through deliberate interactions among diverse stakeholders, supported by flexible institutions, integrated-participative governance, digital-green infrastructure, and functional urban design.

3. A Classification of KPIs in Transportation, Mobility, and Urban Design

In modern urbanization, the need for addressing pressing challenges—such as greenhouse gas emissions and the interplay between human well-being and the environment—has led to the rise of smart cities. Central to this concept is the recognition that urban transport plays a key role in shaping the trajectory of environmental impact and overall quality of life [25]. A critical aspect is the selection and application of KPIs, which transcend the boundary between smart cities, sustainable mobility, and urban design. KPIs encapsulate a comprehensive perspective, reflecting the intertwined facets of a sustainable city, encompassing elements such as environment, energy, mobility, ICT, citizen well-being, economy, and governance. These metrics offer a global view of a city’s progress toward climate targets and quality of life enhancements. As quantifiable measures of success, KPIs measure the impact of electric mobility, advocate for uniform standards, and guide strategic decisions for more resilient and efficient urban transformations.

Drawing insights from diverse sources [26–37], an exhaustive review has identified a range of KPIs integral to the domain of sustainable cities. These KPIs span across various

categories, offering a structured way to assess progress and challenges. In cases where thematic labeling is absent, a thoughtful categorization based on shared characteristics ensures a cohesive and comprehensive analysis. Thus, Tables 1–4 show these categories in the following dimensions: Economic, Environmental, Social, and Governance. In the Economic dimension, the categories are ICT infrastructure, water and sanitation, waste, electric supply, transport, buildings, and urban planning. Each of these categories includes a number of KPIs dedicated to the Economic dimension. Similarly, the Environmental dimension include air quality, water and sanitation, energy, and environmental quality categories.

Table 1. Selected list of Economic KPIs (the ‘X’ clarify if they belong to ‘Transportation and Mobility’, to ‘Urban Design’, or both).

Category	Indicator	Transportation and Mobility	Urban Design
ICT Infrastructure	Robust protective infrastructure		X
	Flexible infrastructure		X
Water and Sanitation	Effective sanitation		X
	Basic water supply		X
Waste	Municipal waste rate		X
Electricity Supply	Local renewable electricity production		X
	Access to electricity		X
Transport	Diverse and affordable transport networks	X	X
	Effective transport operation and maintenance	X	X
	Dynamic public transport information	X	
	Traffic monitoring	X	
	Intersection control	X	
	Public transport network	X	X
	Public transport network convenience	X	
	Bicycle network	X	X
	Transportation mode share	X	
	Travel time index	X	
	Shared bicycles	X	
	Shared vehicles	X	
	Low-carbon emission passenger vehicles	X	
	Non-polluting vehicles	X	
	Road vehicles	X	
	Smart parking spaces	X	X
Buildings	Public building sustainability		X
	Buildings with high energy efficiency rating		X
Urban Planning	Pedestrian infrastructure	X	X
	Green areas	X	X
	Green area accessibility	X	X
	Appropriate land use and zoning	X	X
	Urban energy sustainability plans		X

Table 2. Selected list of Environmental KPIs (the ‘X’ clarify if they belong to ‘Transportation and Mobility’, to ‘Urban Design’, or both).

Category	Indicator	Transportation and Mobility	Urban Design
Air Quality	Air pollution	X	X
	GHG emissions	X	X
Water and Sanitation	Water consumption		X
	Water pollution		X
Energy	Renewable energy consumption	X	X
	Electricity consumption	X	X
	Fossil fuel	X	X
Environmental Quality	Noise exposure	X	X

Table 3. Selected list of Social KPIs (the ‘X’ clarify if they belong to ‘Transportation and Mobility’, to ‘Urban Design’, or both).

Category	Indicator	Transportation and Mobility	Urban Design
ICT Infrastructure	Robust protective infrastructure		X
	Flexible infrastructure		X
Water and Sanitation	Effective sanitation		X
	Basic water supply		X
Waste	Municipal waste rate		X
Electricity Supply	Local renewable electricity production		X
	Access to electricity		X

Table 4. Selected list of Governance and Propagation KPIs (the ‘X’ clarify if they belong to ‘Transportation and Mobility’, to ‘Urban Design’, or both).

Category	Indicator	Transportation and Mobility	Urban Design
Organization	Effective systems to deter crime		X
Multi-level Governance	Smart city policy		X
Scalability and Replicability	Effective coordination with other government bodies		X
Factors of Success	Diffusion to other locations		X

Notice that the role of KPIs extends beyond transportation and mobility, since they are equally relevant in the sphere of urban design [38,39]. The confluence of human health and the environment has prompted a redesign of urban spaces, advocating for solutions that enhance both individual well-being and broader ecological balance. KPIs act as navigational tools for urban designers, guiding decisions that promote not only sustainable mobility but also holistic urban environments [40–42]. In this context, the selection of KPIs that resonate with the unique objectives and values of each community becomes relevant. By capturing elements such as walking behaviors and health outcomes, KPIs can shape urban areas that foster safe and active lifestyles [43]. In essence, the synergy between smart cities, sustainable mobility, and urban design encapsulates a holistic vision of urban transformation. The harmonious interplay of these domains, guided by KPIs, sets the stage for resilient and efficient cities [44].

4. Case Studies Involving Real-Life Urban Areas

Granollers, a town located in the metropolitan region of Barcelona, is one of the pilot cities within the UP2030 initiative, standing at the forefront of sustainable urban

development (<https://up2030-he.eu/unique-city/granollers>, last accessed on 26 August 2023). As a pioneering participant, Granollers has played a relevant role in the early stages of this project, actively engaging in an ongoing and collaborative partnership aimed at comprehensively understanding the city's unique requirements and priorities. This close and continuous relationship has been instrumental in laying the foundation for a robust and tailored approach to advancing urban sustainability. The pilot study area focuses on the La Bòbila sector, an undeveloped neighborhood located behind the railroad tracks and the passenger and freight station. This sector has faced historical challenges due to the presence of this infrastructure. In this scenario, Granollers is committed to achieving climate neutrality through the Covenant of Mayors and is working on the creation of Low Emission Zones and safe and healthy school environments. In the context of the UP2030 project, Granollers establishes a robust strategy for the reinterpretation and regeneration of the city's neighborhoods. The strategic plan is oriented towards achieving sustainable urban prosperity and an adaptive response to the challenges of climate change. With a human-centered approach, climate neutrality in neighborhoods is prioritized, while a harmonious connection between different zones and neighborhoods of the city is sought through a green axis. The need to overcome infrastructural barriers, especially railways, is identified, proposing solutions for urban permeability to integrate this new sector with the rest of the city. Additionally, the incorporation of newly developed zones dedicated to vital facilities is considered, including sectors such as healthcare, education, sports, and well-being, reinforcing the comprehensive and progressive character of the initiative. At the heart of this cooperative exploration lies the process of distilling the essential KPIs that holistically encapsulate Granollers' sustainable urban objectives. As an example, Table 5 shows the KPIs selected by the project consortium for measuring the Environmental and Energy dimensions.

Table 5. Selected list of Environmental and Energy KPIs.

Category	Indicator
Air Quality	Air pollution
	GHG emissions
Environmental Quality	EMF exposure
	Noise exposure
Energy	Consumption of renewable energy
	Electricity consumption
	Residential thermal energy consumption
	Public building energy consumption
	Adequate affordable energy supply

Another city involved in the UP2030 project is Milan, Italy. In the face of global challenges, Milan has made far-sighted commitments, such as reducing its CO₂ emissions by at least 40% by 2030 and achieving carbon neutrality by 2050 (<https://up2030-he.eu/unique-city/milan>, accessed on 26 August 2023). However, the real challenge lies in translating these commitments to a more tangible scale, reflecting them in regeneration projects that transform the essence of the city. A flagship project in this regard is the Porta Romana Railway Yard and Park, destined to be the 2026 Winter Olympic Park. The Porta Romana area has never been residential but, in the last 10–15 years, the surrounding industrial and artisanal areas have undergone major urban regeneration, with the construction of the Prada Foundation in 2015. The neighborhood lacks public green spaces, making Porta Romana a valuable asset to the community. The challenge is to transform this pilot project into a connection point for the southern suburbs with the central and northern parts of Milan. This space, historically marked by an abandoned railway line that has segmented

the city, is destined to be a symbol of cohesion and regeneration. Milan is moving forward with the vision of aligning these regeneration projects with ambitious goals, such as the decarbonization of buildings, the promotion of resilient communities, the implementation of a circular economy, and the integration of nature-based solutions. In addition to planning, Milan highlights the need for effective measurement and evaluation of KPIs. These KPIs not only monitor the progress and effectiveness of initiatives, but also guide strategic decisions and periodic adjustments when needed. As an example, Table 6 displays the KPIs selected in this city for measuring the Economic and Environmental dimensions.

Table 6. Milan—selection of Economic and Environmental KPIs.

Category	Indicator
Air Quality	Air pollution
	GHG emissions
Buildings	Public building sustainability
	Integrated building management systems in public buildings
	Appropriate codes, standards, and exposure mapping
	Buildings with high energy efficiency rating
Urban Planning	Pedestrian infrastructure
	Green areas
	Green area accessibility
	Urban development and spatial planning
	Appropriate land use and zoning
	Urban energy sustainability plans
Environmental Quality	EMF exposure
	Noise exposure

5. Methodology for Selecting KPIs

This research is developed in the context of the UP2030 Horizon Europe project, which includes very large cities such as Istanbul (Turkey), medium–large cities such as Belfast (UK), Milan (Italy), or Lisbon (Portugal), and small–medium cities such as Granollers (Spain), among others. Notice, however, that while there is a core set of KPIs for all these cities, non-core KPIs are selected for each city based on its characteristics and the specific pilot project it is developing. Thus, in order to track the transitions of the pilot cities in the UP2030, its main goals should be identified. Pilot cities vary in their history, current status, and specific climate-neutral targets. The defined approach in this work consists of three main steps. The first step analyzes the pilots and identifies their main goals. This step is essential to get to know the pilots and their storylines. During the duration of the project, the pilots define their storyline and identify their targets, which trigger the challenges. In the context of the UP2030, three pillars are identified: (i) decarbonization; (ii) resilience; and (iii) a fair transition. According to the analysis of the pilot storylines, the dimensions to be considered in this work were defined as: (i) economic; (ii) environmental; (iii) society and culture; (iv) governance; and (v) propagation. In each dimension, several categories are included. Each category represents an aspect of interest to be monitored. In Figure 1, dimensions are distinguished according to the used shading. In addition, the figure shows the impact of these categories on the project pillars: decarbonization, resilience, and fair transition. The ‘social inclusion’ category impacts the three pillars, while the ‘electric supply’ category is related to decarbonization.

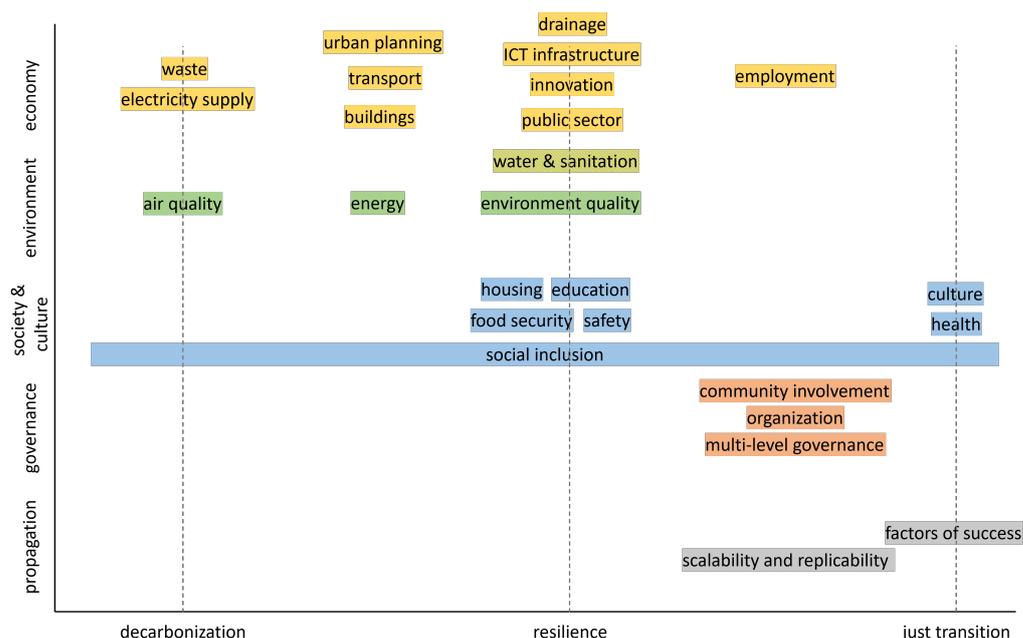


Figure 1. The distribution of categories with respect to the defined dimensions.

Each category includes several KPIs. An aggregated list of KPIs is constructed, including all potential KPIs to be used in the next steps to extract KPIs for each pilot. For each pilot, its profile and KPI list are defined. The profile depicts the categories shown in Figure 1. Firstly, a pilot profile is identified reflecting the pilot storyline. The KPI list is finalized after a discussion with cities to ensure the availability of capacity and data needed to measure the KPIs. These KPIs are classified as core KPIs and pilot-specific KPIs. On the one hand, the core KPIs reflect the project's goals and are common among the pilots. These KPIs are essential to evaluate the aforementioned goals. On the other hand, the pilot-specific KPIs target the monitoring of changes in pilots corresponding to their specific targets. Each city has its specific KPIs and some of these KPIs could be shared with other cities having similar targets. In summary, the selection and classification of KPIs are based on the following criteria: (i) the specific context of the research project, which is focused on urban sustainability, energy optimization, and emissions reduction; (ii) the completion of a literature review to identify established practices and KPI frameworks used in similar research areas and projects; (iii) the project's overarching pillars (decarbonization, resilience, and a fair transition) also served as a guiding framework for classifying KPIs; (iv) city-specific considerations (non-core KPIs were selected for each city based on its specific context, climate-neutral targets, and ongoing pilot projects); (v) the availability of data and capacity in cities to measure and report on specific KPIs (the selected KPIs were finalized after discussions with city representatives to confirm data availability); and (vi) the interconnectedness of KPIs, since some KPIs might impact or might be correlated to others.

6. KPI Measurements in European Urban Centers

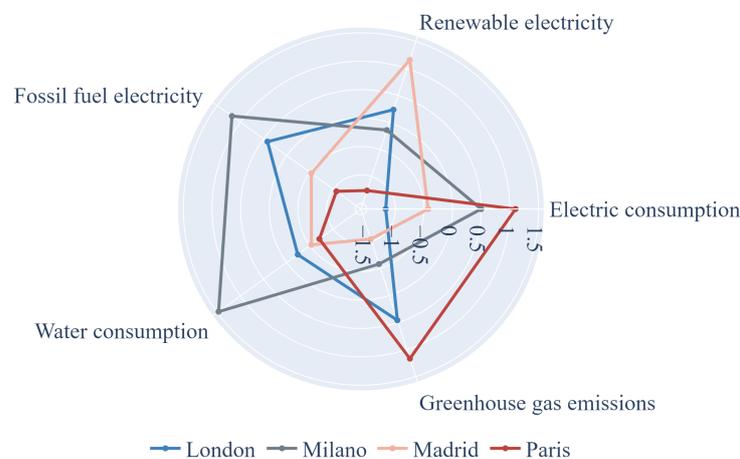
In the preceding sections, an extended framework of KPIs was established to assess social, economic, and environmental aspects within cities. This section presents empirical data reflecting the actual measurements of some of these KPIs across four big European cities: London, Milan, Madrid, and Paris. Table 7 illustrates the values associated with some relevant KPIs (Table A1 in Appendix A shows the public sources from which these values were obtained). These data serve as a foundation for the analysis and comparison of the cities' performance in social well-being, economic growth, and environmental sustainability, offering a holistic assessment of each city's progress.

Table 7. Environmental, Economic, and Social KPI measurements.

KPI	London	Milan	Madrid	Paris
Electric consumption (kWh/hab per year)	3860.05	4992.00	4363.00	5400.00
Percentage of renewable electricity production (country's mix)	39.60	36.00	48.40	25.30
Percentage of fossil fuel electricity production (country's mix)	45.40	59.00	28.60	19.00
Water consumption (l/hab/day)	144.40	234.00	129.00	120.00
Greenhouse gas emissions (tons CO ₂ eq/hab)	7.86	4.08	2.40	10.44
Road vehicles (car/hab)	0.30	0.54	0.56	0.30
Bike line lengths (m/1000 hab)	40.30	162.72	40.33	462.74
Shared bikes (bikes/100,000 hab)	133.00	401.00	232.00	925.00
Municipal waste (kg/hab per year)	779.00	341.00	370.00	489.00
Food insecurity (% of population)	16.00	5.47	11.50	6.30
Fatal accidents (deaths)	75.00	87.00	20.00	100.00
Access to electricity (% of population)	100.00	100.00	100.00	100.00
Social affordable housing (% of houses)	20.70	N/A	2.39	24.20

In order to provide a visual representation that facilitates comparison among the aforementioned cities, three radar plots are provided next. Due to the different units of measurement of the KPIs, the Z-score is computed for each of them, with the exception of the KPI 'Access to electricity', which holds a constant and maximum attainable value across all cities. Figures 2–4 show the environmental, economic, and social KPIs, respectively. The radar plots allow for a concise and comprehensive overview of how each city performs in each KPI as compared with other similar cities in Europe. Thus, for instance, according to this data it can be seen that London seems to perform better in terms of electric consumption (kWh/hab per year) than other European cities, while Madrid seems to excel in the use of renewable electricity production. Similar conclusions can be derived from analyzing the figures in detail.

This segment transitions from the theoretical conception of the KPI indicators into tangible numbers through real-world data from the specified cities. Anchoring the analysis with empirical measurements, accompanied by radar plots, yields a comprehensive understanding of London, Milan, Madrid, and Paris' performance across some of the presented indicators and offers a baseline of comparison for future analysis over the years.

**Figure 2.** Radar plot of Z-scores for Environmental KPIs.

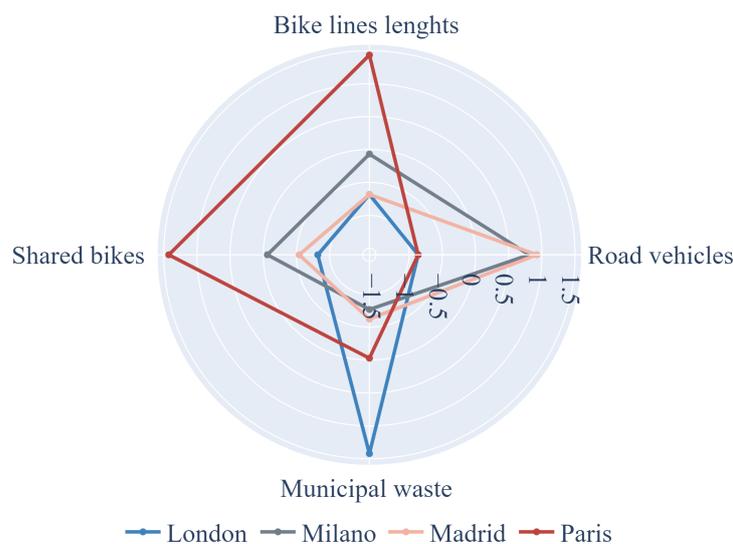


Figure 3. Radar plot of Z-scores for Economic KPIs.

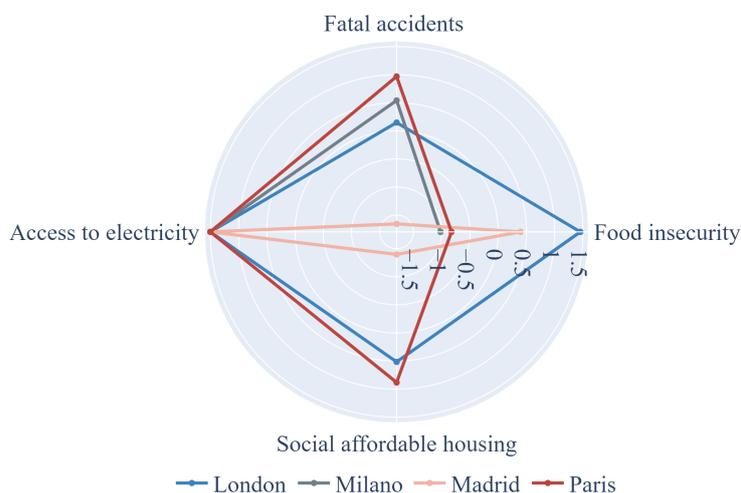


Figure 4. Radar plot of Z-scores for Social KPIs.

7. Time Series Analysis on KPIs

Having the ability to collect historical data that assess the evolution of the city's performance for some KPIs allows anticipating potential trends in future values based on the current urban policies in place. An effective approach for this task involves the application of time series models, which utilize sequential KPI measurements to forecast future values. Time series models are based on well-known statistical techniques designed for the analysis and prediction of data points that evolve over time. These models consider the temporal sequence of data, aiming to identify underlying patterns, trends, and seasonal variations. A good introduction to time series analysis can be found in Montgomery et al. [45]. Among these models, Holt's double exponential smoothing (DES) is used when there is a trend but not seasonality in the data [46]. This method expands upon simple exponential smoothing by introducing a trend component alongside the basic level component. This augmentation facilitates the capture of linear trends within the data. The approach incorporates two smoothing parameters, one for the level and another for the trend. By iteratively updating both the level and trend, this technique generates smoothed values that effectively combine information about the trend and the basic level. The technique involves Equations (1) and (2), where y_t is the observed value at

time t , L_t represents the smoothed level at time t , T_t represents the trend at time t , α is the smoothing parameter for the level, and β is the smoothing parameter for the trend:

$$L_t = \alpha y_t + (1 - \alpha)(L_{t-1} + T_{t-1}) \quad (1)$$

$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1} \quad (2)$$

The prediction for time t is denoted by the smoothed value S_t , which is calculated as $S_t = L_t + T_t$.

Using historical measurements of electric consumption for the cities of London (<https://data.london.gov.uk>, accessed on 26 August 2023), Amsterdam (<https://opendata.cbs.nl>, accessed on 26 August 2023), Helsinki (<https://hri.fi>, accessed on 26 August 2023), Vienna (<https://digitales.wien.gv.at>, accessed on August 26 2023), Madrid (www.comunidad.madrid, accessed on 26 August 2023), and Cologne (www.govdata.de, accessed on 26 August 2023), a Holt's model is trained to forecast the future values until 2026. To obtain the coefficients α and β , cross-validation is used and the level and trend are estimated from the data using Python's library Statsmodels [47]. Figures 5–10 show the predicted electric consumption in these cities. These predictions are based on data published between 2020 and 2022, depending on the rate at which each city updates its publicly available data.

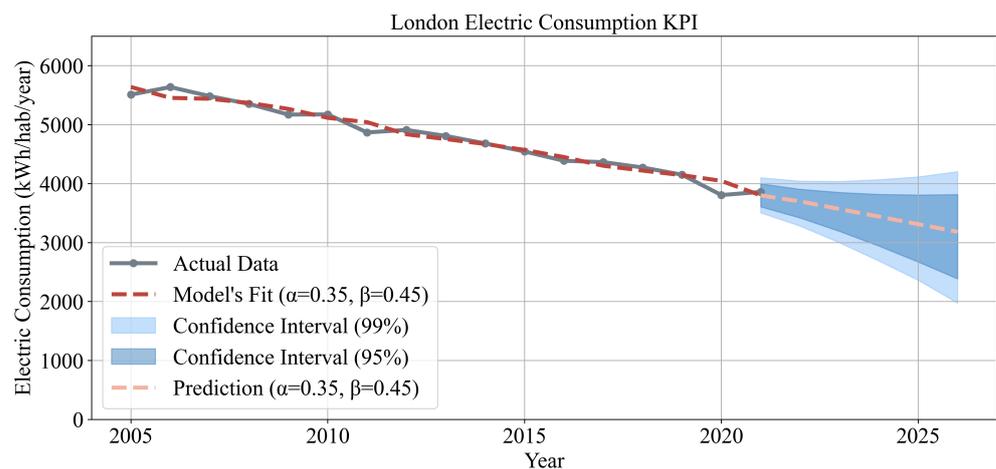


Figure 5. London's forecasted electric consumption.

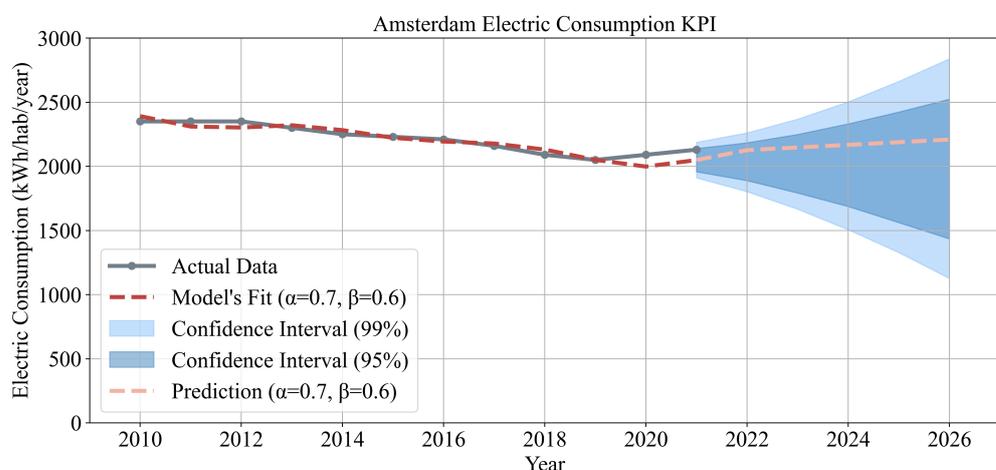


Figure 6. Amsterdam's forecasted electric consumption.

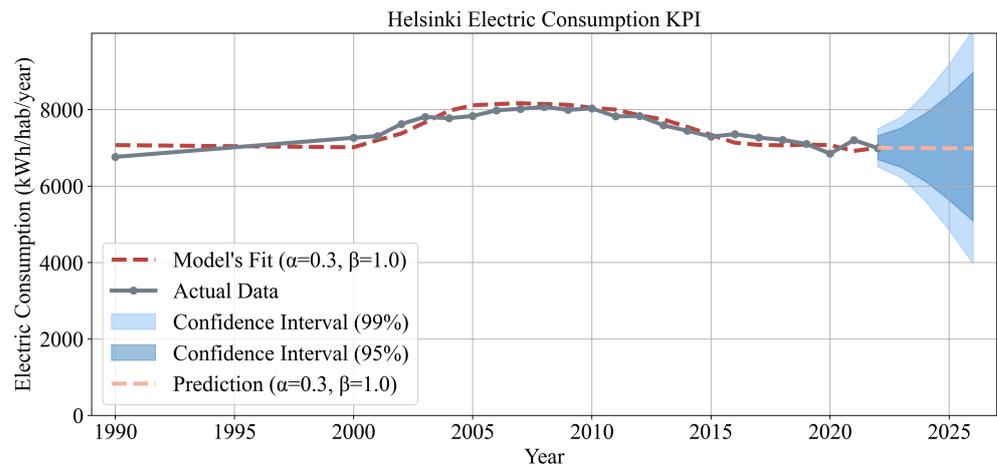


Figure 7. Helsinki’s forecasted electric consumption.

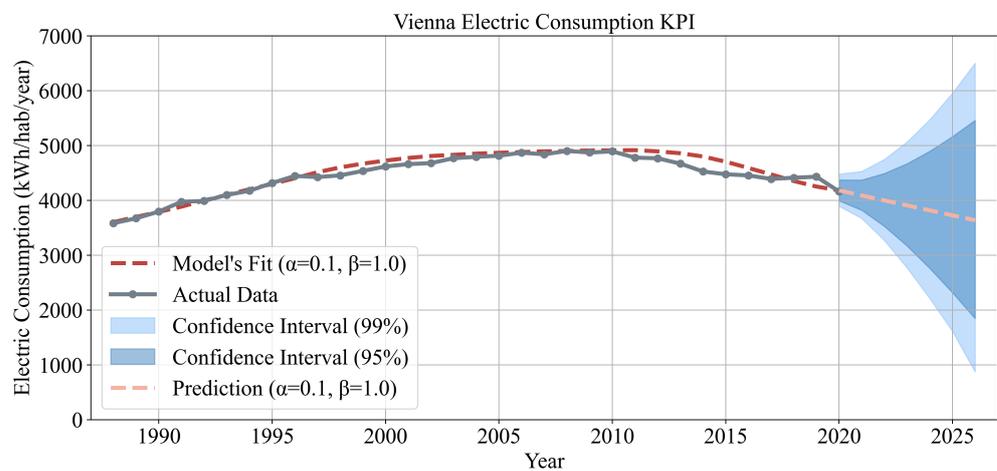


Figure 8. Vienna’s forecasted electric consumption.

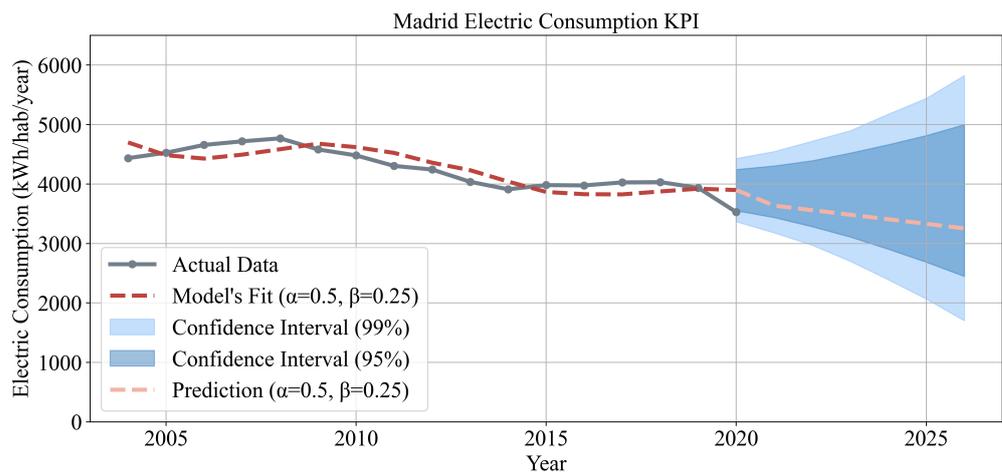


Figure 9. Madrid’s forecasted electric consumption.

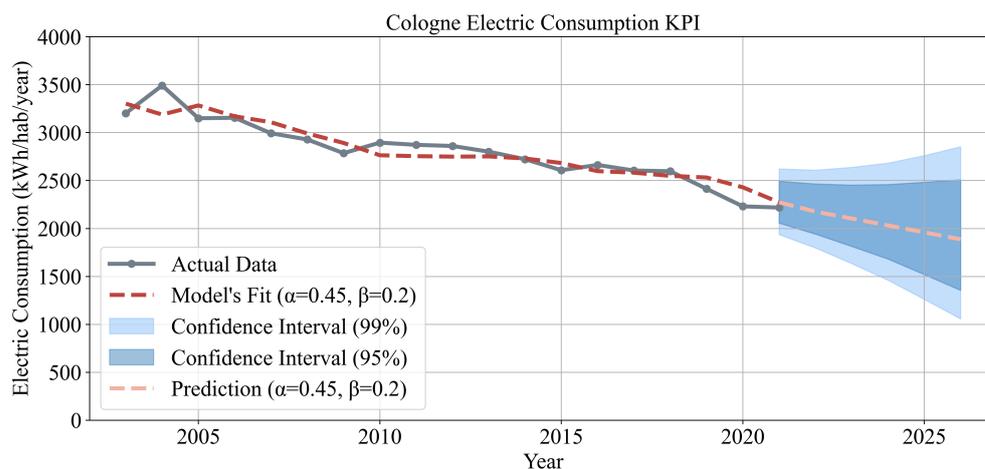


Figure 10. Cologne’s forecasted electric consumption.

The errors observed in the models vary from one city to another. Notice that the values of the root mean square error during the validation phase are not large compared to the magnitude of the actual values, specifically: 64.85 for London, 35.19 for Amsterdam, 209.28 for Helsinki, 177.94 for Vienna, 287.44 for Madrid, and 160.16 for Cologne. This suggests that the errors fall within an acceptable range, instilling confidence in the conclusions drawn from the predictions.

Examining the recent trends in electric consumption across cities such as London, Vienna, Madrid, and Cologne reveals a consistent and ongoing decline. This downward trajectory is expected to persist at least until 2026, with an expected decrease of 16.23%, 13.02%, 16.52%, and 16.95%, respectively. In contrast, Amsterdam is poised for an increase in energy consumption over the forthcoming years of approximately 7.79%. Unless novel approaches are introduced to disrupt the pattern, Helsinki’s electric consumption is projected to remain relatively stable, with an expected variation of -0.25% , akin to its past levels. Furthermore, based on the latest measurements, Amsterdam and Cologne stand out as the cities with the lowest energy consumption per capita, both recording levels below 2250 kWh/hab per year. In comparison, Madrid, Vienna, and London exhibit similar energy usage patterns, with values hovering around 4000 kWh/hab per year. Meanwhile, Helsinki distinguishes itself within this comparison with a notably higher figure of 7000 kWh/hab per year.

In order to double check the forecasted values obtained with Holt’s method, an ARIMA model [48] has also been employed to forecast the electric consumption per capita of each city by the year 2026. In particular, the automatic ARIMA capabilities implemented in R and Python libraries have been employed. These capabilities take care of adjusting the parameters of the corresponding ARIMA model [49]. Table 8 provides a comparison between the forecasts generated by the two approaches. Notice that both models yield comparable predictions for all cities, except for Madrid, which exhibits a deviation of 10.99% between the models, probably due to the fact that COVID-19 had a significant effect on the electric consumption per capita in this city and, while Holt’s method was adjusted to consider this factor, the ARIMA model was not adjusted.

Notice that, while more advanced ARIMA forecasting models could also have been used in this study, the choice of using exponential smoothing is based on the following reasons: (i) exponential smoothing is a relatively simple and intuitive method, making it accessible to a broader audience, including policymakers and city planners who may not have in-depth expertise in time series forecasting; (ii) exponential smoothing methods are computationally efficient, making them suitable for handling large datasets (if needed) and real-time forecasting requirements; (iii) estimating the parameters of exponential smoothing models is relatively straightforward and does not require advanced statistical techniques. While ARIMA is a powerful time series forecasting method, these models can be complex

to build and less intuitive for policymakers and stakeholders. In addition, ARIMA models often require a larger amount of historical data to estimate model parameters accurately. For some KPIs, cities may have limited historical data available, making ARIMA less practical.

Table 8. Holt’s DES vs. ARIMA predictions on electric consumption per capita—year 2026.

	Holt’s DES	Auto-ARIMA	% Variation
London	3184.11	3245.40	+1.92
Amsterdam	2208.76	2293.69	+3.84
Helsinki	6987.11	7061.52	+1.06
Vienna	3637.31	3626.80	−0.29
Madrid	3254.61	2896.63	−10.99
Cologne	1887.74	1888.31	+0.03

8. Conclusions

This paper has explored energy optimization and emissions reduction in urban areas within the context of a European research project. The focus has been on addressing transportation, mobility, and urban-design challenges in the pursuit of smarter and more sustainable cities. Smart cities represent a promising solution to the complex issues posed by urbanization and climate change, aiming to optimize energy usage, reduce emissions, and improve the overall quality of life for their citizens.

One of the key contributions of this work has been the development of a comprehensive framework that integrates KPIs and analytical tools. This framework offers powerful tools to promote energy efficiency and emissions reduction in urban environments. It provides city planners and policymakers with a systematic approach to monitoring urban performance and enhance living conditions. The conceptual framework presented in this paper outlines a structured methodology for achieving these goals: (i) selection of relevant KPIs, which involves selecting KPIs that align with the specific objectives of smart city initiatives related to energy efficiency, emissions reduction, and quality of life enhancements; (ii) data collection and monitoring, which involves implementing sensors and IoT technologies for the collection and monitoring of relevant data; (iii) data analysis, which is performed to process and analyze the collected data, including identifying trends, patterns, and anomalies; (iv) benchmarking and comparison against predefined reference values or benchmarks from similar cities allows for performance evaluation; (v) visualization of KPI data using various tools such as radar plots, charts, and dashboards for better insights; (vi) time series analysis and predictive modeling to forecast future trends of selected KPIs, enabling proactive decision-making; (vii) regular reporting on the city’s performance based on KPIs, which helps track progress and identify areas for improvement; and (viii) an iterative improvement approach, which ensures continuous optimization of energy efficiency, emissions reduction, and urban living conditions.

The analysis has already yielded valuable results. For example, radar plots have been employed to visualize and compare KPI measurements for several European cities, which has allowed commenting on their relative performance. Additionally, time series analysis has been utilized to forecast future trends in KPIs related to energy consumption in these cities, providing insights into their trajectories. The results from these experiments have demonstrated the effectiveness of the approach in assessing and predicting energy-related KPIs. Notably, the findings indicate ongoing trends toward reduced energy consumption in cities like London, Vienna, Madrid, and Cologne, with Amsterdam showing a contrasting trend of increased consumption. These insights are valuable for city planners and policymakers as they seek to optimize energy usage and emissions reduction. All in all, the work illustrates how the integration of KPIs with various analytical techniques can empower city planners and policymakers to drive sustainable development in urban areas. The availability of updated KPI data for monitoring and predictive purposes is particularly critical for cities aspiring to

become smarter and more sustainable. Still, the following limitations of this study can be highlighted: (i) it relies on the availability and quality of data, which has been shown to be limited for specific KPIs in some cases; (ii) it primarily focuses on individual KPIs, potentially not capturing the full complexity of urban systems with interdependencies among various factors; and (iii) its scope is limited to a specific time period and geographical context, while urban environments are dynamic, and factors influencing energy consumption, emissions, and other KPIs can change over time.

Other key contributions of this research work are described next: (i) the paper introduces the application of time series analysis, particularly exponential smoothing and ARIMA models, to forecast KPIs related to urban sustainability, focusing on electric consumption per capita; (ii) the paper discusses how the use of relatively simple and computationally efficient time series models makes the forecasting methodology accessible to a wide audience, including policymakers and city planners; (iii) the paper offers city-specific insights by applying time series forecasting to multiple European cities, such as London, Amsterdam, Helsinki, Vienna, Madrid, and Cologne; and (iv) the paper conducts a validation of the forecasting models, comparing the results of exponential smoothing with those of ARIMA models.

In addition to the presented results, this work has laid the foundation for future research in several directions: (i) further investigation into urban planning and design strategies that prioritize energy efficiency and sustainability, such as building orientation, green spaces, and sustainable transportation networks; (ii) development of multi-objective optimization techniques that balance energy efficiency with social equity, economic viability, and environmental preservation in urban development; (iii) exploration of dynamic mobility management systems that adapt to real-time traffic conditions and weather patterns to optimize transportation routes and reduce energy consumption; (iv) use of IoT technologies to gather real-time data for energy optimization and implement automated energy-saving measures.

Author Contributions: Conceptualization, A.A.J. and M.A.; methodology, C.O., Y.A. and V.T.; investigation, V.T., C.O., Y.A. and N.F.; writing—original draft preparation, all authors; writing—review and editing, A.A.J. and M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This work has been partially funded by the European Commission (UP2030, HORIZON-MISS-2021-CIT-02-01-101096405), and the Spanish Ministry of Science and Innovation (PID2022-138860NB-I00 and RED2022-134703-T).

Data Availability Statement: See links in the main text.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Sources of Data for Cities

Table A1 displays the sources from which data utilized in Table 7 was collected. Notice that most of these sources are public repositories, while others refer to scientific publications.

Table A1. Sources for KPI values (all links have been accessed on 26 August 2023).

KPI	London	Milan	Madrid	Paris
Electric consumption (kWh/hab per year)	www.london.gov.uk	http://dati.comune.milano.it	www.fenercom.com	www.apur.org
Percentage of renewable electricity production (country's mix)	https://docs.publishing.service.gov.uk	www.trade.gov	www.ree.es	www.trade.gov
Percentage of fossil fuel electricity production (country's mix)	https://docs.publishing.service.gov.uk	www.iea.org	www.ree.es	www.iea.org
Water consumption (l/hab/day)	www.london.gov.uk	Vanham and Bidoglio [50]	www.ine.es	www.eaudeparis.fr
Greenhouse gas emissions (tons CO ₂ eq/hab)	https://data.london.gov.uk	https://partecipazione.comune.milano.it	www.madrid.es	www.paris.fr
Road vehicles (car/hab)	https://tfl.gov.uk	www.istat.it	www.madrid.es	www.apur.org
Bike line lengths (m/1000 hab)	www.london.gov.uk	https://easymilano.com	www.telemadrid.es	www.paris.fr
Shared bikes (bikes/100,000 hab)	https://tfl.gov.uk	https://bikemi.com	https://www.bicimad.com	www.velib-metropole.fr
Municipal waste (kg/hab per year)	www.london.gov.uk	www.municipalwasteurope.eu	https://datos.madrid.es	www.municipalwasteurope.eu
Food insecurity (% of population)	https://data.london.gov.uk	www.foodpolicymilano.org	www.invisiblesdetetuan.org	www.santepubliquefrance.fr
Fatal accidents (deaths)	https://tfl.gov.uk	www.polis.lombardia.it	www.madrid.es	www.lejdd.fr
Access to electricity (% of population)	https://data.worldbank.org	https://data.worldbank.org	https://data.worldbank.org	https://data.worldbank.org
Social affordable housing (% of houses)	https://trustforlondon.org.uk	No data has been found	https://datos.madrid.es	www.apur.org

References

1. Toli, A.M.; Murtagh, N. The concept of sustainability in smart city definitions. *Front. Built Environ.* **2020**, *6*, 77. [\[CrossRef\]](#)
2. Clement, J.; Ruysschaert, B.; Crutzen, N. Smart city strategies—A driver for the localization of the sustainable development goals? *Ecol. Econ.* **2023**, *213*, 107941. [\[CrossRef\]](#)
3. Trindade, E.P.; Hinnig, M.P.F.; da Costa, E.M.; Marques, J.S.; Bastos, R.C.; Yigitcanlar, T. Sustainable development of smart cities: A systematic review of the literature. *J. Open Innov. Technol. Mark. Complex.* **2017**, *3*, 1–14. [\[CrossRef\]](#)
4. Rehan, R.M. Sustainable streetscape as an effective tool in sustainable urban design. *Hbr J.* **2013**, *9*, 173–186. [\[CrossRef\]](#)
5. Stojanovski, T. Urban design and public transportation—public spaces, visual proximity and Transit-Oriented Development (TOD). *J. Urban Des.* **2020**, *25*, 134–154. [\[CrossRef\]](#)
6. Quan, S.J.; Li, C. Urban form and building energy use: A systematic review of measures, mechanisms, and methodologies. *Renew. Sustain. Energy Rev.* **2021**, *139*, 110662. [\[CrossRef\]](#)
7. Balogun, A.L.; Marks, D.; Sharma, R.; Shekhar, H.; Balmes, C.; Maheng, D.; Arshad, A.; Salehi, P. Assessing the potentials of digitalization as a tool for climate change adaptation and sustainable development in urban centres. *Sustain. Cities Soc.* **2020**, *53*, 101888. [\[CrossRef\]](#)
8. Al-Turjman, F.; Zahmatkesh, H.; Shahroze, R. An overview of security and privacy in smart cities' IoT communications. *Trans. Emerg. Telecommun. Technol.* **2022**, *33*, e3677. [\[CrossRef\]](#)
9. Chang, V. An ethical framework for big data and smart cities. *Technol. Forecast. Soc. Change* **2021**, *165*, 120559. [\[CrossRef\]](#)
10. Thellufsen, J.Z.; Lund, H.; Sorknaes, P.; Østergaard, P.; Chang, M.; Drysdale, D.; Nielsen, S.; Djørup, S.; Sperling, K. Smart energy cities in a 100% renewable energy context. *Renew. Sustain. Energy Rev.* **2020**, *129*, 109922. [\[CrossRef\]](#)
11. Farmanbar, M.; Parham, K.; Arild, Ø.; Rong, C. A widespread review of smart grids towards smart cities. *Energies* **2019**, *12*, 4484. [\[CrossRef\]](#)
12. Martins, L.d.C.; de la Torre, R.; Corlu, C.G.; Juan, A.A.; Masmoudi, M.A. Optimizing ride-sharing operations in smart sustainable cities: Challenges and the need for agile algorithms. *Comput. Ind. Eng.* **2021**, *153*, 107080. [\[CrossRef\]](#)
13. Almouhanna, A.; Quintero-Araujo, C.L.; Panadero, J.; Juan, A.A.; Khosravi, B.; Ouelhadj, D. The location routing problem using electric vehicles with constrained distance. *Comput. Oper. Res.* **2020**, *115*, 104864. [\[CrossRef\]](#)
14. Nanda, S.; Berruti, F. Municipal solid waste management and landfilling technologies: A review. *Environ. Chem. Lett.* **2021**, *19*, 1433–1456. [\[CrossRef\]](#)
15. Bak, J. Circular Water Management in Smart Cities. In *Water in Circular Economy*; Smol, M., Prasad, M.N.V., Stefanakis, A., Eds.; Springer: Cham, Switzerland, 2023; pp. 31–40.
16. Corlu, C.G.; de la Torre, R.; Serrano-Hernandez, A.; Juan, A.A.; Faulin, J. Optimizing energy consumption in transportation: Literature review, insights, and research opportunities. *Energies* **2020**, *13*, 1115. [\[CrossRef\]](#)
17. Letnik, T.; Marksel, M.; Luppino, G.; Bardi, A.; Božičnik, S. Review of policies and measures for sustainable and energy efficient urban transport. *Energy* **2018**, *163*, 245–257. [\[CrossRef\]](#)
18. Krause, J.; Thiel, C.; Tsokolis, D.; Samaras, Z.; Rota, C.; Ward, A.; Prenninger, P.; Coosemans, T.; Neugebauer, S.; Verhoeve, W. EU road vehicle energy consumption and CO₂ emissions by 2050—Expert-based scenarios. *Energy Policy* **2020**, *138*, 111224. [\[CrossRef\]](#)
19. Xue, C.; Shahbaz, M.; Ahmed, Z.; Ahmad, M.; Sinha, A. Clean energy consumption, economic growth, and environmental sustainability: What is the role of economic policy uncertainty? *Renew. Energy* **2022**, *184*, 899–907. [\[CrossRef\]](#)
20. Grafakos, S.; Viero, G.; Reckien, D.; Trigg, K.; Viguie, V.; Sudmant, A.; Graves, C.; Foley, A.; Heidrich, O.; Mirailles, J.; et al. Integration of mitigation and adaptation in urban climate change action plans in Europe: A systematic assessment. *Renew. Sustain. Energy Rev.* **2020**, *121*, 109623. [\[CrossRef\]](#)
21. Hendrickson, D.J.; Lindberg, C.; Connelly, S.; Roseland, M. Pushing the envelope: Market mechanisms for sustainable community development. *J. Urban. Int. Res. Placemaking Urban Sustain.* **2011**, *4*, 153–173. [\[CrossRef\]](#)
22. Bertoldi, P.; Economidou, M.; Palermo, V.; Boza-Kiss, B.; Todeschi, V. How to finance energy renovation of residential buildings: Review of current and emerging financing instruments in the EU. *Wiley Interdiscip. Rev. Energy Environ.* **2021**, *10*, e384. [\[CrossRef\]](#)
23. Cardullo, P.; Kitchin, R. Smart urbanism and smart citizenship: The neoliberal logic of 'citizen-focused' smart cities in Europe. *Environ. Plan. C Politics Space* **2019**, *37*, 813–830. [\[CrossRef\]](#)
24. Camboim, G.F.; Zawislak, P.A.; Pufal, N.A. Driving elements to make cities smarter: Evidences from European projects. *Technol. Forecast. Soc. Chang.* **2019**, *142*, 154–167. [\[CrossRef\]](#)
25. Winkler, L.; Pearce, D.; Nelson, J.; Babacan, O. The effect of sustainable mobility transition policies on cumulative urban transport emissions and energy demand. *Nat. Commun.* **2023**, *14*, 2357. [\[CrossRef\]](#) [\[PubMed\]](#)
26. Danielis, R.; Scorrano, M.; Giansoldati, M. Decarbonising transport in Europe: Trends, goals, policies and passenger car scenarios. *Res. Transp. Econ.* **2022**, *91*, 101068. [\[CrossRef\]](#)
27. Kaparias, I.; Bell, M.; Tomassini, M. Key performance indicators for traffic management and intelligent transport systems. *ISIS Conduits Consort* **2011**, *14*, 19–68.
28. Angelakoglou, K.; Kourtzanidis, K.; Giourka, P.; Apostolopoulos, V.; Nikolopoulos, N.; Kantorovitch, J. From a comprehensive pool to a project-specific list of key performance indicators for monitoring the positive energy transition of smart cities—An experience-based approach. *Smart Cities* **2020**, *3*, 705–735. [\[CrossRef\]](#)

29. Sdoukopoulos, A.; Pitsiava-Latinopoulou, M. Assessing urban mobility sustainability through a system of indicators: The case of Greek cities. *WIT Trans. Ecol. Environ.* **2017**, *226*, 617–631.
30. World Business Council for Sustainable Development. SMP2.0 Sustainable Mobility Indicators. 2015. Available online: <https://www.wbcsd.org/contentwbc/download/1081/13863/1> (accessed on 26 August 2023).
31. López Chao, A.; Casares Gallego, A.; Lopez-Chao, V.; Alvarellos, A. Indicators framework for sustainable urban design. *Atmosphere* **2020**, *11*, 1143. [[CrossRef](#)]
32. Genta, C.; Lombardi, P.; Mari, V.; Moghadam, S.T. Key Performance Indicators for Sustainable Urban Development: Case Study Approach. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *296*, 012009. [[CrossRef](#)]
33. Da Silva, J. *City Resilience Index: Understanding and Measuring City Resilience*; Rockefeller Foundation (Arup International Development): New York, NY, USA, 2013.
34. Azcona, K.U.; Agorreta, L.F.; Trinidad, F.J.D.; Perez, F.R.; Gómez, J.V. Smart Zero Carbon City Readiness Level: Sistema de indicadores para el diagnóstico de las ciudades en su camino hacia la descarbonización y su aplicación en País Vasco. *DYNA* **2018**, *93*, 332–338.
35. Lien, S.K.; Sørnes, K.; Walnum, H.T.; Hauge, Å.L.; Lindberg, K.B. Selection of key performance indicators (KPIs) in the transition towards low-carbon urban communities. In Proceedings of the ECEEE Summer Study Proceedings, Presqu'île de Giens, France, 3–8 June 2019; pp. 907–915.
36. World Benchmarking Alliance. Just Transition Methodology. 2021. Available online: <https://assets.worldbenchmarkingalliance.org/app/uploads/2021/07/Just-Transition-Methodology.pdf> (accessed on 26 August 2023).
37. United for Smart Sustainable Cities. *Collection Methodology for Key Performance Indicators for Smart Sustainable Cities*; U4SSC: Geneva, Switzerland, 2017.
38. Natanian, J.; Auer, T. Beyond nearly zero energy urban design: A holistic microclimatic energy and environmental quality evaluation workflow. *Sustain. Cities Soc.* **2020**, *56*, 102094. [[CrossRef](#)]
39. Yang, L.; van Dam, K.H.; Zhang, L. Developing goals and indicators for the design of sustainable and integrated transport infrastructure and urban spaces. *Sustainability* **2020**, *12*, 9677. [[CrossRef](#)]
40. Garau, C.; Pavan, V.M. Evaluating urban quality: Indicators and assessment tools for smart sustainable cities. *Sustainability* **2018**, *10*, 575. [[CrossRef](#)]
41. Caragliu, A.; Del Bo, C.; Nijkamp, P. Smart cities in Europe. *J. Urban Technol.* **2011**, *18*, 65–82. [[CrossRef](#)]
42. Jackson, L.E. The relationship of urban design to human health and condition. *Landsc. Urban Plan.* **2003**, *64*, 191–200. [[CrossRef](#)]
43. Hooper, P.; Knuiman, M.; Foster, S.; Giles-Corti, B. The building blocks of a 'Liveable Neighbourhood': Identifying the key performance indicators for walking of an operational planning policy in Perth, Western Australia. *Health Place* **2015**, *36*, 173–183. [[CrossRef](#)] [[PubMed](#)]
44. Beneicke, J.; Juan, A.A.; Xhafa, F.; Lopez-Lopez, D.; Freixes, A. Empowering citizens' cognition and decision making in smart sustainable cities. *IEEE Consum. Electron. Mag.* **2019**, *9*, 102–108. [[CrossRef](#)]
45. Montgomery, D.C.; Jennings, C.L.; Kulahci, M. *Introduction to Time Series Analysis and Forecasting*; John Wiley & Sons: Hoboken, NJ, USA, 2015.
46. Woodward, W.A.; Sadler, B.P.; Robertson, S. *Time Series for Data Science: Analysis and Forecasting*; CRC Press: Boca Raton, FL, USA, 2022.
47. Persson, I.; Khojasteh, J. Python packages for exploratory factor analysis. *Struct. Equ. Model. A Multidiscip. J.* **2021**, *28*, 983–988. [[CrossRef](#)]
48. Bisgaard, S.; Kulahci, M. *Time Series Analysis and Forecasting by Example*; John Wiley & Sons: Hoboken, NJ, USA, 2011.
49. Tran, N.; Reed, D.A. Automatic ARIMA time series modeling for adaptive I/O prefetching. *IEEE Trans. Parallel Distrib. Syst.* **2004**, *15*, 362–377. [[CrossRef](#)]
50. Vanham, D.; Bidoglio, G. The water footprint of Milan. *Water Sci. Technol.* **2014**, *69*, 789–795. [[CrossRef](#)] [[PubMed](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.