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Modeling Street-Level Energy and Emissions: The Role of Vehicle Traffic

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Executive Summary

The transportation sector accounts for 25% of global emissions. Europe aims for carbon neutrality by 2050 through new light-duty vehicle technologies and stricter regulations, though these efforts may be insufficient. This work aims to assess a small neighborhood by analyzing over 19,500 routes to calculate an indicator that identifies streets with the highest impacts and to evaluate the individual impacts of various light-duty vehicle technologies and examines how different combinations of technologies, based on traffic distribution, influence overall energy and emissions outcomes. The results highlight how uphill steep roads increase energy use, while downhill sections allow for energy recovery. A Street VSP Impact Factor (SVIF) was developed to identify streets with high energy use and emissions, offering insights into targeted urban planning strategies. The findings suggest that promoting EV adoption and optimizing street infrastructure are key to reducing energy consumption and emissions in cities.

Keywords: Modelling & Simulation, Energy Management, Environmental Impact, Smart Grid Integration and Grid Management.

1 Introduction

Climate change is an urgent issue, with current CO_2 levels reaching around 421 ppm, approximately 50% higher than pre-industrial levels [1]. The transportation sector is a major, responsible for around 25% of global CO_2 emissions [2]. Within this sector, road transport accounts for nearly 75% of emissions, with light-duty vehicles (cars, vans, and small trucks) making up to 45% [2]. In response, Europe is pursuing a pathway to carbon neutrality, aiming for a 55% reduction in emissions by 2030 and climate neutrality by 2050. Central to this strategy is the promotion of new light-duty vehicle (LDV) technologies, including battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and hydrogen fuel cell vehicles (FCEVs). While transitioning to new light-duty vehicle technologies and implementing stringent regulations are crucial steps toward carbon neutrality, they seem to be insufficient. Reducing street-level impacts and optimizing urban infrastructure, through traffic flow improvements, enhanced public transportation, active mobility initiatives such as cycling and walking, and the integration of smart city solutions, can effectively lower transportation emissions while enhancing urban sustainability and livability [3].

To estimate energy consumption and emissions from vehicles at the city level, road transport energy use and emissions indicators are assessed based on the distribution of vehicles technologies across different road categories. Generally, a vehicle perspective methodology is used to define the emission from vehicles at the city level, which can be mainly divided into two approaches: the first involves integrating traffic volumes on road segments with their corresponding emission factors based on dynamic or static databases; the second approach defines the specific energy use and emissions for a given vehicle, then extrapolates the scenario based on traffic count.

Integrating traffic volumes on road segments can be done using a dynamic database built from manual or automated local traffic counting [4], offering high spatial and temporal resolution but requiring significant time and cost. Access to these databases normally is restricted, and the size of the region it covers is very limited [5]. Traffic volume can also be simulated using social media data [6] or telecom data [7] as an alternative to traditional traffic data, but these sources introduce uncertainties due to privacy restrictions, sampling biases, and the need for advanced data processing techniques [5]. Afterward, traffic emissions are estimated using emission factors based on traffic volume, influenced by factors such as fuel consumption, the age and composition of the vehicle fleet, traveling speed, and traffic congestion. These emission factors are often derived from established sources such as the Handbook Emission Factors for Road Transport (HBEFA), which provides detailed emissions data under various driving conditions [8]. Using static database simulators, traffic volume emissions can be estimated for a specific region over a defined period, based on existing emission calculation models such as the Calculation of Air Pollutant Emissions from Road Transport (COPERT) model [9] or the DEMO model [21]. However, these models tend to be very complex and require extensive data inputs.

The second approach regarding the vehicle perspective methodology offers enhanced accuracy by defining energy use and emissions based on vehicle type through predictive models derived from real-world on-road measurements. This allows for more precise results by considering both vehicle characteristics and external conditions. These models may include machine learning techniques [10,11], physics-based and semi-empirical models such as Vehicle Specific Power (VSP) [12,13,14] or energy-based models [15]. By leveraging real-world data, these models predict energy consumption and emissions across various vehicle types with higher precision. This approach facilitates the creation of a vehicle specific database, which can then be extrapolated using dynamic datasets derived from traffic counts, similar to the first approach. While this method yields more accurate predictions, it is more time-consuming and computationally intensive.

Despite the common use of a vehicle perspective methodology, a street perspective methodology can also be employed to estimate vehicle emissions at the city level. Several factors related to street characteristics, such as road grade, surface quality, road length, width and curvature, traffic control measures and maximum speed, have an impact on emissions.

Road gradient directly affects vehicle emissions by increasing fuel consumption and engine load on uphill slopes, leading to higher CO_2 emissions [16]. Research indicates that emissions of CO, HC, and NO_x rise more sharply when transitioning from flat terrain to an uphill gradient than when moving from downhill to flat terrain [17]. Studies using VSP models reveal a parabolic relationship between gradient and VSP, a linear relationship between gradient and fuel consumption, and an inverse parabolic relationship between VSP and fuel consumption [18]. Gradients between 1% and 3% allow fuel savings downhill to offset uphill consumption, whereas gradients of 4%–6% lead to a net increase in fuel use [18]. Road roughness also influences vehicle emissions, as the International Roughness Index (IRI) increases—indicating a rougher or more deteriorated road surface—rolling resistance rises, resulting in higher fuel consumption and emissions[19,20].

Road length, when extended, can improve accessibility, but it often leads to increased vehicular usage, this results in a linear relationship between fuel consumption and city size, and a super linear relationship between CO_2 emissions and total street length [21]. Similarly, widening roads can further amplify fuel consumption and CO_2 emissions due to "induced demand," where added capacity encourages more travel, ultimately offsetting congestion relief and exacerbating overall emissions [22]. Road curvature also plays a crucial role in influencing vehicle fuel consumption and emissions, emphasizing the need to account for the extra energy required to navigate curves [23].

The impact of traffic control measures on fuel consumption and emissions is multifaceted and context dependent. While certain strategies can reduce emissions by optimizing traffic flow, others may inadvertently increase fuel consumption and emissions if not carefully designed and executed [22]. Finally, the maximum speed of a road is determined by various design characteristics and functional considerations. However, it also influences emissions, following a U-shaped pattern. At low speeds (0-50 km/h), stop-and-go driving increases fuel consumption and emissions. Moderate speeds (50-90 km/h) are the most efficient, minimizing emissions through steady driving. At high speeds (above 100-120 km/h), aerodynamic drag increases, leading to higher engine rpm and load, hence raising emissions.

By addressing urban characteristics, it is possible to promote sustainable practices that enhance climate neutrality while improving quality of life. [24]. The aim of this work is to assess a small neighborhood by calculating an indicator that identifies which streets have the most significant impact in terms of energy consumption and emissions due to traffic and their specific characteristics. Additionally, this study will evaluate the individual impact of each light-duty vehicle technology within the neighborhood context and analyze how different combinations of technologies, based on traffic distribution, influence overall energy and emissions outcomes.

2 Methodology

This case study examines a specific area within the Beato neighborhood in Lisbon, consisting of 26 streets, as illustrated in Figure 1. Serving as a representative model, it offers insights that can be applied to other districts in Lisbon and comparable European cities. While primarily residential, the neighborhood also includes a school district, which influences traffic patterns throughout the day. A well-organized bus network ensures efficient connectivity between the neighborhood's central hub and the school zone. Additionally, its limited access points enable effective monitoring of traffic flow in and out of the area.

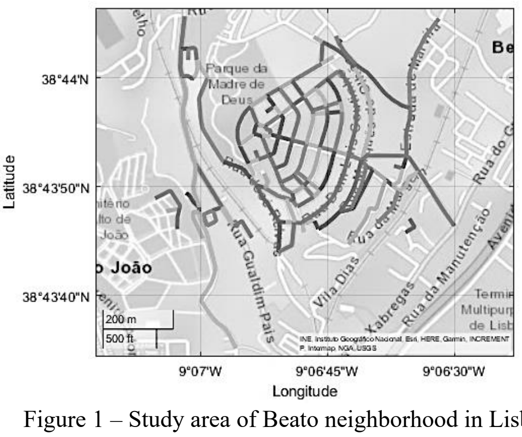

Figure 1 – Study area of Beato neighborhood in Lisbon.

After identifying the 26 street names, the next step in the methodology involves gathering data from Bing Maps APIs. To initiate the route collection process, a request is sent to the Bing Maps API [25], which requires an origin and a destination as inputs. In this case, one of the 26 streets is used as the origin, with the remaining 25 streets serving as destinations for each request. This process is repeated for every street, ensuring all possible routes are covered. A MATLAB script was developed to extract relevant route data for the study. When a request is sent, the Bing Maps API returns route information in JSON format, including latitude and longitude coordinates, maneuvers, street attributes, and other relevant details. Following the initial request, a subsequent request is sent to the Bing Maps Elevation API [25] to obtain altitude data for the selected route. Additionally, supplementary requests are sent to the OpenStreetMap API [26] along the route to gather detailed information on crosswalks, traffic light locations, stop sign placements, and other key roadway features. Thought data collection, a 26-by-26 matrix is built with an empty diagonal, resulting in a total of 650 possible routes. With all data reunited, it's possible to create driving cycles associated with each route, considering different driving styles and traffic conditions.

The driving styles can be categorized as normal, eco-driving, and aggressive driving, being the main parameters summarized in the Table 1.

Table 1 - Driving Style Characteristics [27].

	Eco	Normal	Aggressive
Target Speed	0.9x Speed limit	1.0x Speed limit	1.2x Speed limit
Anticipatory Driving / Traffic Behavior	Anticipating traffic flow. Avoid unnecessary stops and optimize fuel efficiency	Safe. Reacting to surrounding vehicles without excessive stops or aggressive maneuvers	Reactive. Depending heavily on the vehicle in front, leading to more abrupt stops
Jerk	± 0.4-0.6 m/s^3	± 0.6-0.8 m/s^3	± 1-1.2 m/s^3
Acceleration/ Deacceleration	2.2 m/s^2 -2.8 m/s^2	2.8 m/s^2 -3.4 m/s^2	3.8 m/s^2 -4.8m/s^2

Traffic conditions can be classified as rush hour (RH) or off-rush hour (ORH) and are shaped by key factors such as the unpredictability of stops, the duration of stops, and the characteristics of the road infrastructure. A MATLAB code, adapted from previous work [27], was used to create five driving cycles for each driver's behavior and traffic condition, resulting in 30 driving cycles per route and a total of 19,500 driving cycles generated.

To analyze the generated cycles the Vehicle Specific Power (VSP) methodology is applied to each second of driving [28]. The VSP is calculated according to the equation 1, being this a simplified equation, where *v* corresponds to vehicle speed (m/s), *a* corresponds to vehicle acceleration (m/s^2) and *grade* corresponds to the relationship between altitude and distance traveled (dimensionless).

$$VSP = v \times (1.1 \times a + 9.81 \times grade + 0.132) + 0.000302\, v^3 \tag{1}$$

The calculation of the VSP value is performed every second of the trip and is typically grouped into fourteen mode bins. Using VSP modes allows to analyze vehicle behavior in different bins, by assessing power considering only parameters from vehicle dynamics [29,30], as shown in Table 2.

Table 2 - Vehicle Specific Power Modes Definition.

Mode	Definition [kW/ton]	Mode	Definition [kW/ton]
1	VSP < -2	8	13 ≤ VSP < 16
2	-2 ≤ VSP < 0	9	16 ≤ VSP < 19
3	0 ≤ VSP < 1	10	19 ≤ VSP < 23
4	1 ≤ VSP < 4	11	23 ≤ VSP < 28
5	4 ≤ VSP < 7	12	28 ≤ VSP < 33
6	7 ≤ VSP < 10	13	33 ≤ VSP < 39
7	10 ≤ VSP < 13	14	VSP ≥ 39

From another perspective, street characteristics directly impact the VSP calculation, so, instead of calculating the VSP for each specific route individually, the goal is to establish an approach to determine VSP at the street level. Based on the 19,500 driving cycles, a mean VSP distribution was established for each street, considering the street directions when applicable. The frequency of street usage was analyzed based on the kilometers traveled on each street across the 19,500 driving cycles. A higher frequency of usage may correlate with the street type and the infrastructure present. The frequency level of each street is entirely dependent on the route design—meaning that if a street is used more often, it likely provides better accessibility.

Leveraging VSP at the street level, along with street usage frequency, enables the calculation of an impact indicator, named Street VSP Impact Factor (SVIF), as shown in Equation 2.

$$SVIF = \%F \times \sum_{i=1}^{14} \%t_i \times \overline{VSP_x} \tag{2}$$

This indicator combines the percentage of time spent in each VSP mode (%) with the average VSP for that mode (W/kg) and the frequency of street usage (%), considering the direction of the street, if applicable. A higher SVIF indicates a street's greater impact on energy consumption and emissions due to frequent use or high-power demand. A lower SVIF suggests less influence, either from low traffic or lower power-demanding conditions. Identifying high SVIF streets helps target areas for traffic management, infrastructure upgrades, and vehicle technology deployment, such as prioritizing electrification in high-impact zones.

While the indicator reflects the impact at the street level, it is also possible to quantify impacts at technology level. For all light-duty vehicles (LDVs), the impact at the technology level can be assessed by applying each vehicle's characteristic VSP profile, which represents energy consumption and, where applicable, emissions based on real driving test data, $\bar{x}_i$ (g/s). Energy consumption (Wh/km) or emissions (g/km), denoted as x, are determined based on the sum of the percentage of time, $\%t_i$, spent in each VSP mode per street, multiplied by the total time, t (s), spent on the street and the energy consumption or emissions in that VSP mode. This sum is then normalized by the total distance, d (km), traveled on that street differentiated by traffic type, as shown in Equation 3.

$$x = \frac{\sum_{i=1}^{14} \bar{x}_i \times \%t_i \times t}{d} \tag{3}$$

The overall impact in terms of energy consumption and emissions (where applicable) is determined by applying the distribution of traffic types and existing technologies to the individual impact of each technology, weighted by the number of vehicles (N), as outlined in Equation 4.

$$\begin{aligned} x_{total} = (\%(BEV + PHEV) \times x_{BEV+PHEV} + \%ICEV_{Petrol} \times x_{ICEV_{Petrol}} \\ + \%ICEV_{Diesel} \times x_{ICEV_{Diesel}} + \%HEV \times x_{HEV}) \times N \end{aligned} \tag{4}$$

3 Results and Discussion

Based on the methodological procedure, the frequency of street use and the SVIF were determined based on traffic type. Each street is represented on the x-axis by a unique number. If the street has two directions, a letter is appended to the number to differentiate them. To compare with the frequency derived from the kilometers traveled on each street across the driving cycles, a real frequency obtained through manual counting during both off-peak and rush hours was used, as illustrated in Figure 2. Additionally, the SVIF indicator was calculated using the real frequency and compared with the SVIF theoretical value, as illustrated in Figure 3.

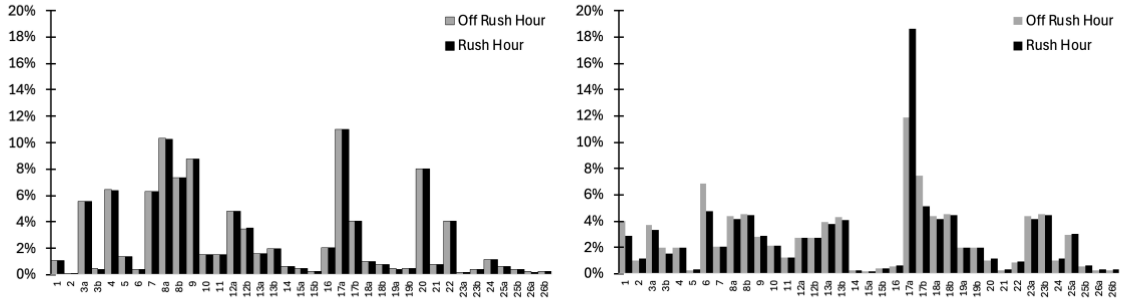

Figure 2 - Street usage frequency (%) as a function of each street, differentiated by traffic type (theoretical vs. real).

The comparison between real and calculated frequency data shows that real frequencies, based on just one day of manual counting, are often higher than the calculated ones during off-rush hours, suggesting more consistent traffic flow. For some streets, like Street 3a, the values align well. However, during rush hours, real frequencies are much higher, likely due to factors like congestion and local events not accounted in the calculation method.

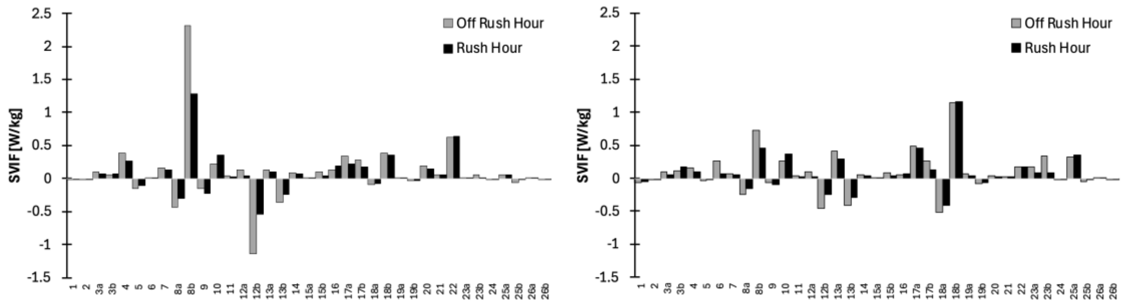

Figure 3- SVIF in function of each street depending on traffic type, using theoretical vs. real frequency.

The SVIF reflects the impact of each street on the neighborhood. In an area with uniform infrastructure and topography, the vehicle frequency play key roles in shaping this impact. Notably, the SVIF calculation maintains a consistent trend, regardless of whether theoretical or real vehicle frequencies are used as input, as the topography profile remains unchanged. While specific values may vary, the overall pattern shows higher impacts during off-rush hours and lower impacts during rush hours. This occurs because vehicles travel at higher speeds during off-rush hours, leading to greater power demands and emissions per second. This suggests that the theoretical SVIF effectively captures the general trend, even if it may underestimate the magnitude of impact in certain traffic conditions.

To quantify the impacts at the technology level, four typical vehicles were considered: one Euro 6 gasoline, one Euro 6 diesel, one Euro 6 HEV, and one EV. Using Equation 3 for all vehicles across all streets, Figure 4 presents the energy consumption during off-rush and on-rush hours, while Figure 5 illustrates CO_2 emissions for the same periods.

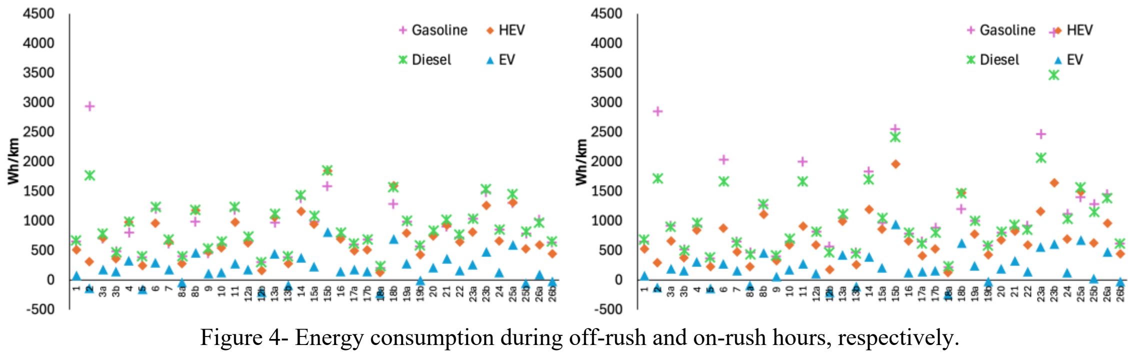

Figure 4- Energy consumption during off-rush and on-rush hours, respectively.

Under rush conditions, gasoline and diesel vehicles consume more energy, while EVs remain relatively stable, likely due to their high efficiency. HEVs improve efficiency on rush hours as only fuel consumption is considered. While congestion negatively impacts all powertrains, EVs consistently remain the most energy efficient. Streets with high energy demand in both rush and off-rush hours are linked to steep inclines, whereas downhill sections allow a reduction in overall technology consumption, particularly for EVs, where they primarily regenerate energy.

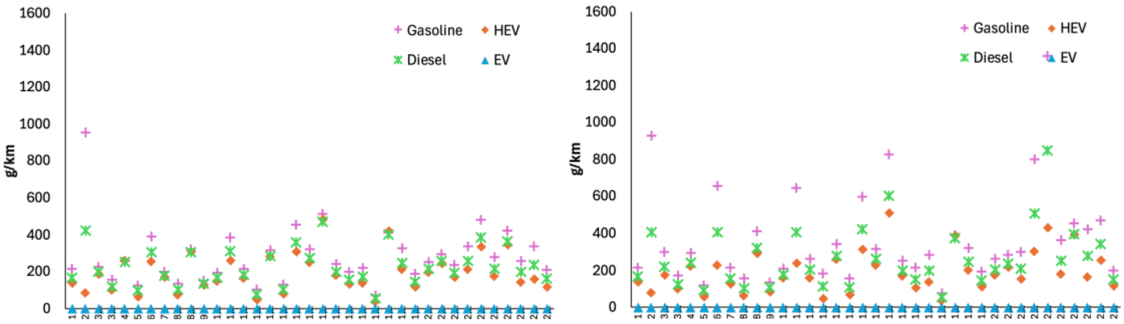

Figure 5- CO_2 emission during off-rush and on-rush hours, respectively.

Based on Figure 5, gasoline and diesel vehicles emit significant CO_2, with gasoline showing slightly higher emissions than diesel, particularly during rush conditions. HEVs produce lower emissions overall but experience an increase in congestion, likely due to greater reliance on the internal combustion engine. EVs remain the cleanest option, generating zero emissions in all conditions, as predicted. As with energy consumption, traffic congestion raises CO_2 emissions for gasoline and diesel vehicles, while HEVs see a smaller increase, and EVs remain unaffected.

Based on Equation 4, the distribution of the Portuguese fleet—39.85% gasoline vehicles, 1.45% HEVs, 57.06% diesel vehicles, and 1.63% EVs and PHEVs [31] —along with the actual frequency of vehicle usage, are used to assess the overall impact on energy consumption and emissions during both on and off rush hours, as illustrated on Figure 6.

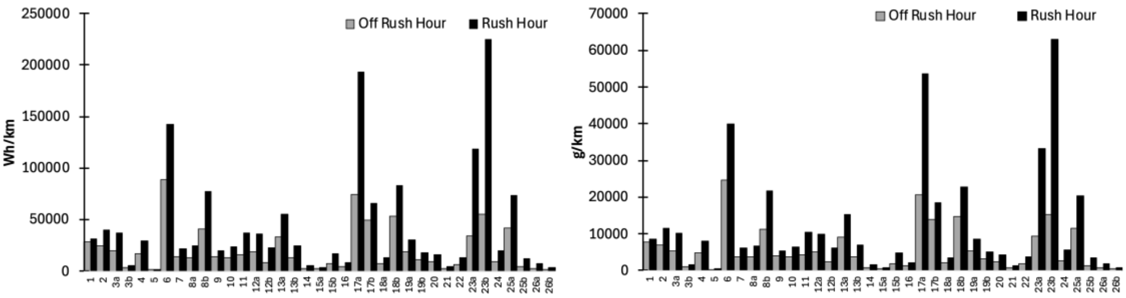

Figure 6- Overall Energy Consumption and CO_2 Emissions for Off Rush and On Rush hours.

The analysis of the energy consumption data shows that energy usage during off rush hours is generally lower than during on rush hours, which is expected due to lighter traffic. However, certain streets, such as Street 6, Street 17a, and Street 23b, have exceptionally high energy consumption during rush hours, mainly due to heavy traffic, and in the case of Street 17a, also due to a steeper incline. On the other hand, streets like Street 5 and Street 15a exhibit low energy consumption, attributed to low traffic flow and negative road grade, which reduce vehicle energy demand. In terms of CO_2 emissions, the data follows the same trend as energy consumption, with higher values during rush hours. Comparing the energy consumption and SVIF using the real frequency, it was found that the during the off rush hours there is moderate to strong correlation between the energy consumption and SVIF ($r = 0.607$) with a p-value < 0.001, indicating a statistically significant relationship. On the other hand, during on rush hours, the correlation between energy consumption and SVIF was moderate ($r = 0.385$) with a p-value ≈ 0.019, also statistically significant but weaker than in the off rush hour scenario. Given the weaker and less consistent correlation, it can be inferred that the SVIF is less capable of adapting to on-rush-hour scenarios compared to off-rush-hour periods. This may be due to the fact that the indicator is not influenced by the total time spent. During on-rush hours, even though power demand might be lower, vehicles tend to spend significantly more time in traffic. As a result, overall energy consumption and CO_2 emissions increase, which is not fully captured by the SVIF during on rush hours. Nonetheless, the SVIF indicator is able to detect roads more prone to generate higher energy use and emissions in an automated way, only by known the street coordinates.

4 Conclusion

The aim of this work was to address street level energy use and emissions, whether due to their intrinsic characteristics, by their usage frequency or a combination of both. Street topography significantly impacts energy use and emissions. Uphill steep roads increase energy consumption, while downhill sections allow for energy recovery, especially for EVs.

When comparing vehicle technologies, EVs are the most energy-efficient and produce the least emissions, particularly in urban areas. HEVs show improved efficiency during rush hours, while gasoline and diesel vehicles have higher energy use and emissions. Promoting EVs in urban areas, particularly the ones with higher energy demand or higher traffic frequency is crucial for reducing emissions, with HEVs being a secondary option.

The Street VSP Impact Factor (SVIF) identifies streets with high energy use and emissions, especially during off rush hours. These streets require targeted interventions to optimize energy use and reduce emissions. Real traffic data showed slight differences from theoretical models, but SVIF still captured the general trends accurately. Combining real-time data with theoretical models enhances the accuracy of emissions and energy predictions.

This approach not only supports identifying potential modifications at the neighborhood level but also supports the formulation of more effective policies, ensuring that urban planning is both adaptable and responsive to local needs. Focusing on streets with high SVIF is key for infrastructure improvements and emissions reductions. Also, policy measures that encourage EV adoption and the development of energy-efficient infrastructure are critical to achieving lower energy consumption and emissions in urban areas.

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Presenter Biography

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Luís Sousa received the PhD in 2003 in Mechanical Engineering from Instituto Superior Técnico (IST), Portugal. He is Assistant Professor at IST, and integrated researcher at LAETA. Main research topics include vehicle design, statics and dynamics of structures. He is involved in some national and international projects on simulation, mechanical design and optimization.

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Gonçalo Duarte received the Ph.D. in Mechanical Engineering (2013) from Instituto Superior Técnico, Portugal. He is currently Lecturer at Instituto Superior de Engenharia de Lisboa and Assistant Researcher at IN+ Center for Innovation, Technology and Policy Research. His main research topics address the real-world, on-road energy and environmental impacts of vehicle propulsion technologies, with particular focus on current and future vehicle certification standards and proceedings.