A multi-tier approach to estimate energy efficiency in urban passenger mobility

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Abstract

**Background:** Recent studies evidence a lack of accurate methods to estimate energy efficiency in urban areas. This is due to the complex nature of obtaining wide range of activity and energy data from a single municipality, especially from developing countries, where data is usually scarce. Under these circumstances, this paper develops a method for estimating the energy efficiency in urban passenger mobility, considering three different levels of detail. The innovative factor is the use of a multi-tier approach to compare and adjust outputs. The method was applied in Sorocaba, Brazil, estimating a baseline of energy efficiency in this city.

**Results:** Results show that energy efficiency varied from 0.67 passenger per kilometer/Mega Joule in 2013 to 0.70 passenger per kilometer/Mega Joule in 2017, which are consistent with the Brazilian passenger transport energy efficiency.

**Conclusions:** The method proved to be an important mechanism for benchmarking purposes and for the decision-making process on transport investments. Moreover, it can be applied in cities from countries with different cultural and economic contexts.

**Keywords:** energy efficiency, energy intensity, transport activity, urban mobility, passenger transport, greenhouse gas emission.

1 Introduction

Global urban population expanded at an accelerated pace over the past century, and it is expected to grow even further in the future. In 1950, 30% of world population lived in urban areas, while currently the share is 54% [1,2]. Prospective scenarios estimate that 68% of the world population will live in urban areas by 2050 [3]. The urbanization process is even more intense in some regions. For instance, about 80% of the European and North American population are considered urban [4,5] In countries such as Brazil and Argentina this proportion reaches 84% and 92%, respectively [3].

As the spatial pattern continuously changes within a city, environmental implications of this phenomenon emerge as a fundamental issue for authorities. Although cities occupy only 2% of the world's land mass, they account for 67% of global primary energy demand [6] (WEC, 2016), and 24% of this is consumed by urban transport [7]. Consequently, cities are responsible for approximately 70% of total global carbon dioxide (CO₂) emission, and most of them are emitted by the transport sector [8].

To overcome these drawbacks, multi-sectorial collaborative efforts are required to improve energy efficiency (EE) in urban transport [9]. The EE improvement can reduce fuel consumption that implies greenhouse gases (GHG) and pollutants emission mitigation.

Nonetheless, studies that assess the effects of private and public initiatives with urban mobility patterns and its consequences on EE are hardly addressed in the literature. A possible explanation is that urban mobility management programs usually encompass a set of interrelated actions, which is difficult to estimate accurately the specific impact of each measure on EE [10].

Recognizing that the development of smart cities requires huge investments [11], it would be appropriate that these interventions enhance EE as much as possible. For that, the initial step required would be to develop a method for estimating the EE in urban transport considering all these aspects.
Along these lines, this paper aims to estimate EE in urban passenger mobility by means of a robust method that considers all transport modes and different levels of detail concerning data availability. The best represents the complex of this issue, we opted to apply the method in a large-sized city from a developing country, where data availability is usually scarce. Hence, we selected Sorocaba, Brazil, to estimate EE in urban transport through the application of the developed method.

Apart this introduction, section 2 summarizes and discusses the main research for estimating EE in urban mobility. Section 3 presents the proposed method and data collection process. In section 4, the results of the conducted experiment are analyzed. Finally, in Section 5, policy implications and further research directions are discussed.

2 Literature Review

In this section, we present the results of the literature review conducted with the purpose to answer the following research question: “What is the most appropriate procedure for measuring EE in urban mobility?” We opted to consider the last ten years in the Web of Science database, since it has the largest catalogue of indexed journals, according to Mongeon and Paul-Hus (2016) [12].

Results from this search evidence a lack of literature on this topic, and thus we decided to complement it with a documentary review based on reports from national and international players. As a result, we identified 14 papers of all identified studies that estimate energy use or CO₂ emissions within city borders. A summary of these studies is presented in Table 1.

The selected studies analyze cities from China (30%), Europe (20%), Brazil (20%), United States (10%) and India (10%). The others (10%) assess a hypothetical situation. Considering the size of these cities, 7% are small (up to 100 thousand inhabitants), 33% are medium-sized (between 100 and 500 thousand inhabitants), 47% are large-sized cities (more than 500 thousand inhabitants) and the remaining 13% are megacities (more than 10 million inhabitants).

All studies consider road mode for calculating the EE. Only Szárz (2011), Saujot and Lefèvre (2016), He et al. (2011) and Menezes et al. (2017) [13–16] also consider rail or non-motorized transport (walking or cycling). Therefore, at this point, it becomes evident the lack of studies that assess EE considering all transport modes.

Regarding the methodological approach, 29% of the studies adopt a top-down approach, 64% a bottom-up approach and 7% adopt both, aiming to adjust the results. Top-down approaches quantify and identify the aggregate energy use and GHG emissions, which is important to comprehend the sectorial use of each type of energy. In turn, bottom-up approaches quantify and identify the disaggregated energy use and GHG emissions, considering a broader variety of data and variables to comprehend and manage each source of energy [17].

The top-down approach is characterized by estimated parameters based on historical relationships, wherein energy demand is determined by means of aggregated data and energy efficiency improvement is exogenous estimated by top-down approach. The bottom-up approach considers technological parameters determined by the expected development in demand and energy end-use technologies, that require a larger and more detailed information [18,19].

To date, there is a limited research body on estimating EE in urban transport considering all transports modes and energy sources, especially using multiple approaches such as bottom-up and top-down. Only Bose and Srinivasachary (1997) [20] adopted both approaches. The bottom-up approach allows analyze the factors that can influence energy use patterns in urban passenger mobility. The top-down approach enables bottom-up results validation. The study firstly estimated the demand for travel based on the analysis of the number of vehicles, distance traveled and vehicle occupancy rate using exogenous data, and then, in order to estimate urban
energy demand using bottom-up approach, the study compiled data of demand and proportion of trips, demand met by roads and railways, modal division, occupation and fuel efficiency.

On the other hand, Hillman and Rawaswami (2010) [21] estimate energy consumption and CO₂ emissions from passenger transport within city boundaries, using a top-down approach based on aggregated data, through the calculation of GHG emissions considering the sum of material and energy flows consumed by the community and emission factors from the Intergovernmental Panel on Climate Change (IPCC) protocols. Jiang et al. (2014) [22] also used only a top-down approach to understand the relationship between energy use from passenger transport and the type of neighborhood structure in urban areas. The use of top-down approach results in a lack of perspective focused on local reality at city level, pointed as a limiting factor by Pissourios (2014) [23].

Furthermore, Szász (2011), He et al. (2011) and Tartakovsky et al. (2013) [16,24,25] estimate energy use from urban passenger mobility adopting a bottom-up approach, based on detailed data, such as energy consumption studies, using input variables such as average travel distance, average speed, average occupancy per vehicle, final fuel consumption per trip and quantity of trips per mode of transport, but none of them has used local data, which makes difficult clearly describe the use of energy in the urban environment, crucial for planning urban mobility with better energy efficiency. Gerboni et al (2017) [26] provide some preliminary results of integrated modeling between energy use and transport through the bottom-up models.
| Author                  | Activity     | Approach                  | Data base                  | Case study     | Input                                                                 | Output                                 |
|------------------------|--------------|---------------------------|----------------------------|----------------|------------------------------------------------------------------------|-----------------------------------------|
| Szász (2011)           | Passenger    | Bottom-up                 | -                          | Hypothetical   | Energy consumption: distance traveled; consumption coefficient by kilometer and round hour; average speed and average vehicle occupancy | Energy                                   |
| Bose and Srinivasachary (1997) | Passenger | Top-down and Bottom-up | Database (National) | New Delhi (India) | Transport activity by mode; vehicle occupancy; total energy demand by mode of transport and type of energy; energy efficiency by type of vehicle and emission factors | Energy, atmospheric pollutant             |
| Hillman and Rawaswami (2010) | Passenger and freight | Top down | Research (OD), Database (National) | Denver, Portland, Seattle, Minneapolis and Austin (USA) | Regional travel volume per year | Energy, CO₂-e                            |
| He et al. (2011)       | Passenger    | Bottom-up                 | Survey (OD matrix, companies), Database (Municipal) | Jinan (China) | Modal split; travel distance by mode; vehicle occupancy; EE by mode and emission factor | Energy, CO₂-e                            |
| Tartakovsky et al. (2013) | Passenger | Bottom-up                 | Survey (Company)           | Hypothetical   | Fleet; number of passengers; distance and vehicle occupancy           | E, atmospheric pollutant, CO₂ and atmospheric pollutant |
| Giordano et al. (2014) | Passenger    | Top-down,                 | Database (Continental)     | Barcelona (Spain) and Lugano (Switzerland) | Petrol consumption; distance; % of the mileage traveled on urban roads | Energy, CO₂-e                            |
| Aggarwal and Jain (2014) | Passenger   | Bottom-up                 | Survey, Database (State)   | New Delhi (India) | Travel demand; modal split; distance traveled per vehicle; per mode and per fuel and CO₂ emission factor | Energy, CO₂-e                            |
| Jiang et al. (2014)    | Passenger    | Top down                  | Database (National)        | Barcelona (Spain), Amsterdam (Netherlands), London (UK) | Energy consumption; travel frequency; distance per trip; vehicle occupancy; energy intensity factor; consumption coefficient and energy factor by fuel | EE                                      |
| Guimarães and Leal Junior (2016) | Passenger | Bottom-up                 | Research (Company)         | Rio de Janeiro (Brazil) | Total passengers transported; distance and EE                         | Energy, CO₂ and atmospheric pollutant |
| Author            | Activity | Approach | Data base                                                                 | Case study          | Input                                                                 | Output                      |
|-------------------|----------|----------|---------------------------------------------------------------------------|---------------------|----------------------------------------------------------------------|------------------------------|
| Saujot and Lefèvre (2016) [13] | Passenger | Top down | Database (National) and Survey.                                             | Grenoble (France)   | Transport activity by mode; Energy by source and mode and emission factor | Energy, CO₂                  |
| Yang et al. (2017) [30] | Passenger | Bottom-up | Survey, Database (National and Municipal)                                   | Beijing (China)     | Daily displacement data (time; reason) and attributes of each mode (distance; speed; time) | Transport activity, energy and CO₂ |
| Alonso et al. (2017) [31] | Passenger | Bottom-up | Survey (OD matrix), Database (Municipal)                                   | Madrid (Spain)      | Travel distance; speed and travel time; automotive operating costs and vehicle occupancy. | Energy, CO₂ and atmospheric pollutant |
| Menezes et al. (2017) [15] | Passenger and freight | Bottom-up | Database (Municipal, State and Federal)                                    | São Paulo (Brazil)  | Fleet inventory by type of vehicle and fuel; new registered vehicles; vehicle kilometers traveled; age; fuel economy; average number of passengers tonnes transported per mode; fuel prices and taxes; GHG emission factors by type of fuel | Transport activity, energy, CO₂eq |
| Gerboni et al. (2017) [26] | Passenger and freight | Bottom-up | Database (National forecasting or Regional)                               | Unspecified city (Italy) | Mobility demand and Energy by source and mode                        | Energy, CO₂                  |
From the studies presented in Table 1, one can conclude that the decision to adopt a specific approach to meet the needs of each region reflects the level of detail of the model and the sensitivity analysis of the results. Consequently, it is reasonable to argue that the effects on EE due to the implementation of an urban mobility action are perceived differently when using a bottom-up or top-down approach. For this reason, we chose to identify the main inputs considered in the studies evaluated, as presented in Table 2, classifying them according to the approach adopted.

**Table 2. Synthesis of the main input variables of the approaches**

| Input                          | Total | Bottom-up | Top down |
|-------------------------------|-------|-----------|----------|
| Number of passengers transported | 11    | 7         | 4        |
| Modal split (%)               | 8     | 5         | 3        |
| Distance traveled (km)        | 9     | 6         | 3        |
| Types of energy               | 8     | 8         | 0        |
| Category of vehicles          | 7     | 7         | 0        |
| Number of trips per mode      | 6     | 6         | 0        |
| Fuel economy (km/l)           | 5     | 5         | 0        |
| Transport activity (pass-km)  | 5     | 1         | 4        |
| Vehicle occupancy (pass/vehicle) | 5   | 5         | 0        |

Due to the diversity of vehicle and of energy types involved in road transport, an accurate estimation for EE for this mode requires a bottom-up approach with input variables collected locally. However, adopting exclusively a bottom-up approach does not ensure the reliability of the estimates [32]. For that, the adoption of a combined bottom-up and top-down approach is a fundamental step since it allows results adjustments. Nonetheless, assessing the papers presented on Table 1, only Bose and Srinivasachary (1997) [20] use more than one approach, but the adjustment protocol adopted is not clearly described on the paper.

Furthermore, it is important to state that a bottom-up approach requires a larger amount of data (as shown in Table 2), leading to a complex data collection process. As data availability varies among different countries and economic level of development, the use of a bottom-up approach in certain cities may become even more difficult, requiring adaptations from state or national data to represent urban reality, which may compromise the quality of the results. For instance, Bose and Srinivasachary (1997) and Aggarwal and Jain (2014) [20, 28] used national data to estimate energy use from urban transport by a bottom-up approach, while Hillman and Rawaswami (2010), Giordano et al. (2014), Jiang et al. (2014) [21, 22, 27] use exclusively national data in a top-down approach.

As a result from the literature review, we could also verify that the main tools for estimating energy use from urban transport are: Long-range Energy Alternatives Planning system – LEAP [20], ARTEMIS [24], Metropolitan Activity Relocation Simulator – MARS [31], and For Future Inland Transport Systems – ForFITS [15]. Most of these tools consider a bottom-up approach.

In conclusion, when estimating energy use in urban transport, previous researches do not consider altogether: all the city territory; transport modes, energy type, and different approaches considering data availability and results adjustment. Moreover, none of them presents an application. Along these lines, this study incorporates these literature gaps to develop a method for estimating EE in urban transport, applying it in a large-sized city of a developing country, where data availability tends to be scarce.
3 Energy-efficiency model

The developed method models urban passenger mobility for road, rail and water modes. Basically, there are two fundamental approaches: top-down and bottom-up. As shown in Figure 1, it is divided into four phases: (1) Transport system and data collection; (2) Approaches; (3) Top-down; and (4) Bottom-up. The top-down approach is based on aggregated data on energy use and transport activity, while bottom-up approach is a more detailed mechanism for investigating the effects of several variables on EE.

![Figure 1](image.png)

**Figure 1.** Protocol for estimating energy efficiency in urban transport

The bottom-up approach can be developed in two levels according to data availability. Level 2 of the bottom-up approach requires specific data from the city being assessed, and thus it provides estimates of greater certainty. In level 1, data from other municipalities with similar characteristics, from the state or even the country to which the city in question belongs can be adopted. Consequently, the adoption of level 1 is indicated in cases with lack of data or consistency, such as tends to occur in emerging economies.

3.1 Data requirements

Initially, the municipality under study should be described by means of land use, demographic data, transport modes, municipal and inter-municipal fleet, spatial distribution of trips, transport services (itinerary, demand etc.). Due to the lack of statistics on EE in
municipalities and the need to analyze the consistency of the results, we recommend comparing the municipal outputs with those from the state or country (more commonly available). Hence, historical patterns of the outputs must be confronted with aggregate parameters, such as population and Gross Domestic Product (GDP). In Table 3 is lists the minimum data required for implementing each approach and level of detail.

Table 3. Data requirements for each approach

| Inputs                                      | Top-down | Bottom-up |
|---------------------------------------------|----------|-----------|
|                                             |          | L1        | L2        |
| Energy use by source                        | •        | •         | •         |
| Modal split                                 | •        | •         | •         |
| Average trip distance                       | •        | •         | •         |
| Fuel economy¹                               |          |           |           |
| Vehicle stock                               |          |           |           |
| Vehicle kilometer traveled (VKT)¹          |          |           |           |
| Average occupancy¹                           |          |           |           |

3.2 Top-down approach

For rail and water modes, the following inputs are required: energy consumption; total number of passengers transported; and average vehicle kilometer traveled (VKT) by trip within city boundaries. The first step consists in estimating energy use by source. For estimating transport activity (pass-km), it is necessary to obtain the network extension, useful kilometers traveled by line and passengers transported by line, as shown in Equation 1.

\[ TA_{m,i}^{estimated} = \sum_{l} P_{l} . E_{l} . M_{l} \]  

Where,

- \( TA_{m,i} \): transport activity of mode (m), in the year (i) (pass-km);
- \( P_{l} \): passengers transported by line (l) (pass/line-year);
- \( E_{l} \): extension of line (1) (km);
- \( M_{l} \): kilometers traveled per line (i) (%).

Finally, EE for each mode is estimated by the ratio between transport activity and energy use (Equation 2).

\[ EE_{m,i} = \frac{TA_{m,i}^{estimated}}{EU_{m,i}} \]

Where,

- \( TA_{m,i} \): transport activity of mode (m), in the year (i) (pass-km);
- \( EU_{m,i} \): energy use from mode (m), in the year (i) (MJ).

For road transport, it is required the observed energy consumption by source. Usually, such data is available in emission inventories or reports from Energy Agencies. The next step consists in estimating transport activity by mode and transport service. This information is usually available in origin-destination (OD) surveys. Thus, EE for road transport is the ratio between transport activity (pass-km) and energy consumption (MJ).

¹ These inputs are also considered in level 1 approach. However, if they are not available at local level, assumptions from other cities with similar characteristics can be used or even from the state and the country.
3.3 Bottom-up approach

The bottom-up approach requires disaggregate information on vehicle stock. If such information is not available, it should be estimated considering: the number of vehicles sold, a scrappage function, and the average VKT per type of vehicle.

Different approaches can be adopted to estimate the average VKT. Data on bus fleet can be collected directly from local and regional bus companies. For private transport, data can be collected from local interviews, distinguishing commuting, leisure and intercity trips.

To calculate energy use by source, data on fuel economy by model-year is required. Again, for buses, such data can be collected through interviews with local transport operators, while data on private transport can be obtained from manufacturers or reports from sectoral associations.

After estimating the fleet, VKT and fuel economy by model-year, the energy use from urban passenger mobility is estimated by using the Equation 3.

\[ EU_{k,i}^{estimated} = VS_{k,i} \cdot FE_{k,i} \cdot VKT_{k,i} \]  \hspace{1cm} (3)

Where,

\( EU_{k,i} \): energy use from vehicle type (k), in the year (i) (l or m³);
\( VS_{k,i} \): stock of vehicle type (k), in the year (i) (units);
\( FE_{k,i} \): fuel economy of vehicle type (k), in the year (i) (l/km or m³/km);
\( VKT_{k,i} \): VKT of vehicle type (k), in the year (i) (km).

Subsequently, the Equation 4 presents the calculation for estimating the transport activity by model-year. It is required collecting the average vehicle occupancy of buses and private transport.

\[ TA_{k,i}^{estimated} = VS_{k,i} \cdot VKT_{k,i} \cdot AC_{k,i} \]  \hspace{1cm} (4)

Where,

\( TA_{k,i} \): transport activity of vehicle type (k), in the year (i) (pass-km);
\( VS_{k,i} \): stock of vehicle type (k), in the year (i) (units);
\( VKT_{k,i} \): VKT of vehicle type (k), in the year (i) (km);
\( AC_{k,i} \): average occupancy of vehicle type (k), in the year (i) (pass/vehicle).

All energy values are further converted into a common unit (Joules). Then, both energy use and transport activity are compared with the estimates from the top down approach. Eventual differences are adjusted by changing the values of VKT or vehicle occupancy. These modifications should first occur in the parameter with more uncertainties.

It is also important to include active transport. The transport activity from non-motorized trips is the result of multiplying the urban population by the share of pedestrians and cyclists, frequency of trips and average distance by trip. On the other hand, the energy use from non-motorized transport is a result of the product between transport activity (pass-km) and EE (pass-km/MJ). In Brazil, reference values for EE of non-motorized transport are 4.8 pass-km/MJ (for walking) and 8.9 pass-km/MJ (for human-powered bicycle) [33].

To complete, the EE for urban transport is the ratio between transport activity and energy consumption from all transport modes.

4 Energy efficiency in urban mobility

Sorocaba is a city of 644 thousand inhabitants, concentrated in 450 km². It is located 100 km from São Paulo, the richest city in Brazil. Trips in Sorocaba are made exclusively by road. The city's public transport service is offered by two concessionaires, with 261 bus lines,
covering an average length of 11.9 km [34,35]. Besides, it has six kilometers of exclusive bus lanes [36].

In Brazil, the municipalities must elaborate an Urban Mobility Plan to receive investments in urban mobility, as determined in National Urban Mobility Policy - NUMP [37]. Sorocaba was chosen as case study due to the existence of urban mobility plans since 2006.

4.1 Aggregate results

The observed energy consumption is collected from the Municipal Greenhouse Gas Inventory [38] and ANP (2018) [39]. In Brazil, gasoline A is blended with 27% of anhydrous ethanol, while diesel is blended with 10% of biodiesel\(^2\). Figure 2 shows the energy consumption from Sorocaba between 2013 and 2017.

![Figure 2. Observed energy consumption](image)

From the results presented in the Sorocaba OD Survey, conducted in 2013 with 4,000 households, it was possible to identify the modal split and the average daily travel rate per inhabitant.

To project transport activity, it is also required to estimate the average distance traveled per trip by each type of vehicle for each transport mode. At first, we adopted a Geographic Information System (GIS) to generate a cost matrix for each mode (based on distance), using data from the municipal OD Survey. Nonetheless, the results for buses were not consistent with the data collected directly from the companies. For this reason, we considered the travel time declared by respondents in the OD Survey and the average speed, obtained from URBES (2014) [35], to estimate the average distance per trip by each mode. Figure 3 presents the transport activity by each type of vehicle and transport mode from 2013 to 2017 using the top-down approach.

\(^2\) Although this value varied among the time series assessed, from 5% in 2013 to 10% in 2017.
The average EE in urban transport in Sorocaba using the top-down approach is 0.68 pass-km/MJ. This value is used as a reference to adjust the EE estimated by the bottom-up approach.

4.2 Disaggregate results

Municipal fleet is estimated based on vehicle license statistics, obtained from the National Traffic Department, and the scrappage curves presented in the study of Gonçalves et al. (2019) [40]. Table 4 shows the vehicle stock in 2017 by model-year. This procedure is repeated to estimate the fleet per type of vehicle and energy from 2013 to 2016.

Table 4. Municipal fleet by technology in 2017

| Vehicle       | Technology                  | Stock    | Average age (years) |
|---------------|-----------------------------|----------|---------------------|
| Cars          | Alcohol                     | 1,377    | 15                  |
|               | Natural gas vehicle (NGV)   | 1,352    | 12                  |
|               | Flexible-fueled             | 150,976  | 7                   |
|               | Gasoline                    | 42,084   | 14                  |
|               | Hybrid                      | 172      | 1.4                 |
| Light commercials | Flexible-fueled       | 21,889   | 7                   |
|               | Diesel                      | 6,23     | 7                   |
|               | Gasoline                    | 8,314    | 10                  |
| Motorcycles   | Flexible-fueled             | 13,117   | 5                   |
|               | Gasoline                    | 39,872   | 9                   |
| Micro buses   | Diesel                      | 709      | 6                   |
| Buses         | Diesel                      | 793      | 7                   |

Table 5 presents the annual VKT by vehicle type. For automobiles, results are obtained from Goes et al. (2020) and CETESB (2013) [41,42]. For buses, the annual VKT is obtained from surveys conducted with the main companies that operates in Sorocaba.
Table 5. Annual VKT by technology in 2017 (km)

| Vehicle                  | Technology          | Annual VKT |
|--------------------------|---------------------|------------|
| Cars                     | Alcohol             | 13,595     |
|                          | NGV                 | 13,595     |
|                          | Flexible-fueled     | 15,208     |
|                          | Gasoline            | 14,309     |
|                          | Hybrid              | 15,227     |
| Light commercials        | Flexible-fueled     | 18,255     |
|                          | Diesel              | 24,142     |
|                          | Gasoline            | 14,624     |
| Motorcycles              | Flexible-fueled     | 13,293     |
|                          | Gasoline            | 12,781     |
| Micro buses              | Flexible-fueled     | 61,215     |
|                          | Diesel              | 124,735    |
| Buses                    | Gasoline            | 76,880     |
| Buses (school and chartered) |                   | 42,977     |
| Articulated buses        |                     |            |

4.2.1 Energy use by source

We considered data from the State of São Paulo to estimate the energy use by each type of vehicle [43]. For buses, fuel economy is obtained by interviews with urban bus companies and the main charter companies. Table 6 shows the fuel economy per type of vehicle and energy in 2017.

Table 6. Fuel economy per type of vehicle in 2017 (km/l)³

| Type of vehicle                  | Type of energy | Fuel economy (km/l) |
|----------------------------------|----------------|---------------------|
| Cars                             | Alcohol        | 10.9                |
|                                  | NGV            | 12.0                |
|                                  | Flexible-fueled| 8.3/12.2            |
|                                  | Gasoline       | 11.3                |
|                                  | Hybrid         | 16.5                |
| Light commercials                | Flexible-fueled| 6.2/8.6             |
|                                  | Diesel         | 9.5                 |
|                                  | Gasoline       | 11.3                |
| Motorcycles                      | Flexible-fueled| 29.3/43.2           |
|                                  | Gasoline       | 37.3                |
| Micro buses                      | Diesel         | 4.3                 |
| Buses                            |                | 2.9                 |
| Buses (school and chartered)     |                | 2.6                 |
| Articulated buses                |                | 1.7                 |

It is important to state that, in Brazil, the number of flexible-fuel vehicles (automobiles that can use gasoline and ethanol) is extensive. In this case, it is necessary to consider historical sales of these types of fuel in Sorocaba to estimate their share in the total energy consumed from flexible-fuel vehicles.

Furthermore, results estimated from the bottom-up approach are adjusted in comparison to values obtained in the top-down approach. This step is conducted by adjusting the VKT of the different types of vehicles and the share of fuel consumed from the flexible fuel vehicles. In addition, results are adjusted with the transport activity estimated through both approaches.

³ CETESB (2017) [43].
Figure 4 illustrates the baseline of energy use by source after the required adjustments, as well as the values of fuel consumption obtained by the National Oil Agency (ANP) adopted in the top-down approach. Hence, we can verify that adjusted energy use patterns per type of energy are very similar to those in the top-down approach.

Especially for diesel, energy use data was directly gathered from Sorocaba urban bus companies, while the ANP values estimated by top-down approach represents diesel used by all types of vehicles in the city, such as vehicles used in Urban Freight Transportation; long distance Freight Transportation; and Intercity or Interstate passenger transportation.

**Figure 4.** Comparison of energy use patterns by type of source and approach

### 4.2.2 Transport activity

For estimating transport activity, average vehicle load/occupancy for valley and peak period is determined for each type of vehicle. In the case of urban buses, this value was estimated based on visual surveys conducted during the experiment. For chartered buses, we conducted an interview with the three main companies of Sorocaba, which represent 84% of the city's fleet. The average occupancy of light vehicles was estimated based on data from the OD survey. Table 7 summarizes the estimated occupancy rates.
Table 7. Occupancy rate per type of vehicle (pass./ vehicle)

| Type of vehicle               | Average occupancy⁴ |
|-------------------------------|---------------------|
| Car                           | 1.3                 |
| Light commercial              | 1.0                 |
| Motorcycle                    | 1.0                 |
| Micro bus                     | 14.5                |
| Basic city bus                | 32.6                |
| Special and standard buses    | 44.9                |
| Articulated bus               | 41.8                |

After estimating the fleet, VKT and the average occupancy by vehicle, we could estimate transport activity by transport mode. Nonetheless, when comparing this value with that estimated using the top-down approach, adjustments in the average vehicle occupancy of light vehicles were required. In this case, differences between both approaches ranges from -0.5% to 2%. For heavy vehicles, this adjustment was not necessary since operational data was collected directly with transport operators.

4.2.3 Energy Efficiency

Table 8 presents the estimated EE for each type of vehicle, as well as the energy intensity of urban transport in Sorocaba. These values are also illustrated in Figure 5.

Table 8. EE and intensity by mode

| Mode                          | 2013  | 2014  | 2015  | 2016  | 2017  |
|-------------------------------|-------|-------|-------|-------|-------|
| On foot                       | 4.81  | 4.81  | 4.81  | 4.81  | 4.81  |
| Bicycles                      | 8.93  | 8.93  | 8.93  | 8.93  | 8.93  |
| Motorcycles                   | 1.41  | 1.37  | 1.28  | 1.36  | 1.45  |
| Cars                          | 0.43  | 0.48  | 0.42  | 0.42  | 0.44  |
| Buses                         | 2.32  | 2.32  | 2.63  | 2.68  | 2.89  |
| Bus (suburban and municipal)  | 2.31  | 2.39  | 2.35  | 2.42  | 2.54  |
| EE [pass-km/MJ]               | 0.67  | 0.72  | 0.65  | 0.66  | 0.70  |
| Energy intensity [kJ/pass-km] | 1,499 | 1,398 | 1,544 | 1,51  | 1,429 |

EE in Sorocaba ranges from 0.67 (2013) to 0.70 (2017) pass-km/MJ and there is no trend over time in EE enhancement. According to Gonçalves and D'Agosto (2017) [44], EE of road passenger transport in Brazil, considering urban and regional transport, varied from 0.93 to 0.97 p-km/MJ between 2000 and 2017. As noted, EE in Sorocaba lies outside this interval. It is important to stress that national values also consider long-distance road transport and different modes, such as rail and water transport, which have higher EE levels than urban road transport. In this perspective, 44.3% of the national passenger transport activity is performed by buses in urban areas and 2.8% by buses in long-distance operations.

In Sorocaba, only 26% of the transport activity is performed by buses. Moreover, 58.3% of Sorocaba’s transport activity is performed by individual road mode in comparison to 45% of the national values. Therefore, Sorocaba’s transport matrix is more dependable on less energy efficient modes than the national one, corroborating thus to the lower EE levels estimated in the method. Beyond that, motorization rate in Sorocaba is higher than the national value: 0.72 vehicles per inhabitant [45] compared to 0.23 vehicles per inhabitant [46], which contributes to lower the estimated EE.

⁴ Source: Authors, based on DENATRAN (2018) and CETESB (2017) [43,48].
It is also possible to note that EE for automobiles varies from 0.42 to 0.48 pass-km/MJ. These values are in accordance with the standards identified in the literature for light vehicles, which varies from 0.33 to 0.59 pass-km/MJ [33,47]. In addition, estimations over time for EE of automobiles are the ones that most resemble the estimations for EE in the Sorocaba urban passenger mobility system. This is due to the fact that automobiles represent 86% of total energy consumed by the transport sector and approximately 54% of the total transport activity in the city.

Finally, it is important to highlight that non-motorized transport contributes to the growth of 4% in EE of urban transport. More specifically, variations range from 4.5% (in 2013) to 4.3% (in 2017). Therefore, we reinforce the necessity to consider non-motorized transport when estimating EE in urban transport.

5 Conclusions and policy implications

Results from literature review suggest the adoption of a bottom-up approach combined with a top-down approach is the most suitable solution to assess EE in urban mobility. In fact, the adoption of a bottom-up approach using local and disaggregated data is fundamental specially when considering road transport, due to its diversity in energy use and vehicles types. Besides, the level of disaggregation of this approach allows measuring, evaluating and reporting the results through the application of actions that intend to improve EE in urban transport.

Nonetheless, data adjustment is a fundamental step to ensure accuracy and reliability and it is not possible to adjust results by adopting exclusively a bottom-up approach. Thus, we recommend adopting a bottom-up approach, using preferably a local database, simultaneously with a top-down approach that considers information from other official data sources from State or National level, and then adjusting eventual divergences. Along these lines, the model developed to estimate EE in urban passenger mobility considering simultaneously: all the city territory; transport modes; energy types; and different approaches, considering data availability.

Moreover, the model also addresses the data collection, which should be carefully followed to guarantee that only transport within city borders are considered for estimating EE.

The method to estimate EE in urban transport were applied in a large-size city, Sorocaba, Brazil. Usually, in developing countries, as Brazil, there is a lack of data and statistics on urban transport. Hence, the model was successfully applied even with the difficulties faced on the data collection process (e.g. fleet, transport activity, VKT and occupancy rate). These
impedances reinforce the importance of measuring data and statistics on urban transport. Beyond that, the case study indicated that the method allows adaptations in case of lack of data, going from a higher level of disaggregation (bottom-up level 2) to a less detailed approach (top-down).

Results from this case study confirm the consistency and applicability of the model, since they are within the range identified in the national and international literature. They also ensure that the model can be applied to any type of city, in the presence of consistent information on the total Energy use by source of energy, modal split and average trip distance.

Therefore, EE can be used as an indicator to assist the government decision making on investments in Brazilian municipalities to implement actions to reach a higher level of EE in their mobility.

Furthermore, the application of such method to cities with different characteristics and backgrounds could be the subject of research for future studies. This would enable developing benchmarking studies to determine the best actions on urban mobility management regarding their influence on EE and even the elaboration of a city ranking based on EE. Besides, it can also be applied as the basis for the development of an EE standard and certification program for cities. Such program would recognize participant cities that achieve a minimum level of performance, and specific targets would be set for different levels of ambition.

**Ethics approval and consent to participate**

Not applicable.

**Consent for publication**

Not applicable.

**Availability of data and materials**

The main datasets on which the results of the manuscript based are presented in the main paper.

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**Author Contributions**

Renata Bandeira, Tássia Assis, Isabela Almeida, Rodrigo Freitas carried conceptualization and literature review; Daniel Gonçalves and Renata Bandeira carried out the methodology and analyzed the data; George Goes and Mariane Costa wrote the text. They wrote the paper under the guidance of Márcio D’Agosto, who revised the paper.

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