Air Pollution Calculation for Location Based Social Networks Multimodal Routing Service

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Abstract. *With the growth of the urban population, the urban mobility infrastructure suffers several types of problems, such as the more significant occurrence of traffic jams, which directly affects the quality of life of the population and the inhabitants who need to use different types of transport, also generating a more extraordinary occurrence of air pollution emitted by vehicles. This work addresses the need to integrate the generation of hybrid multimodal routes through the analysis of geographic data collected from location-based social networks, adding the calculation of greenhouse gas emissions by used vehicles. Further, performs a user experience analysis for the main identified flows of the analyzed urban environment, for users and urban planners analysis. The proposed algorithm proves its efficiency by offering less expensive, healthier trips for the population.*

1. Introduction

The urban environment has changed since the inhabitant's number passed half of the global population living in cities. This phenomenon implies a higher demand for infrastructure in sectors of cities and world capitals, including transportation, housing, water, and energy [Silva et al. 2019]. With the implementation of technology on everyday objects, the Internet of Things (IoT) introduces interactivity and functionality for users and non-users with pervasive computing. These connected elements acquire data from sensors, using statistics formulation and behavior identification data for urban services improvement.

The urban vehicle fleet was directly affected by population growth, implying unhealthy air pollution and lower living quality. For instance, vehicular traffic in an urban environment increases the pollutants emission by combustion engines, bringing major impacts on the health of the inhabitants. In this context, the slow start of sustainable transport, traffic congestion, and poor road infrastructure aggravate the air situation. It has been observed that significant greenhouse gas (GHG) emission has raised, with CO_2 (carbon dioxide) accounting for 75% of global GHG pollution and transport being the primary source of emissions [Zawieska and Pieriegud 2018], which provoke various health issues for urban residents. In addition, many epidemiological and experimental studies suggest that respiratory infections are being associated with high exposure to elements such as NO_2, O_3, particles and products resulting from the combustion of biomass fuels.

In this context, smart city services that aim to reduce the exposure of the population to environments with a high concentration of pollutants are likely to have an impact on the quality of life of its citizens. For instance, users could rely on a service to select less polluted routes for smart mobility of users since air pollution impacts on the inhabitants' health. Approaches to identifying air pollution use active sensors at specific points for collection and subsequent analysis, identifying points of lower air quality. However, regarding the cost of implementation, there is a need to use passive sensing through existing services, such as emission calculations and data from open camera systems [Sobral et al. 2019].

For such services, Location-based social networks (LBSN) are crucial for data leverage about user behavior, with location and temporal information on interactions made on those services. The application and proper treatment of data generated in location-based social networks can improve essential areas of the dynamics of large capital cities, given their more extensive and complex infrastructures [D'Ulizia et al. 2021]. Due to the effective use of current social networks, the data generation is continuous, allowing a more precise analysis of the statistical findings obtained. Applied to urban traffic, the identification of citizen behavior in large cities leads to changes in road structure and a reduction in vehicle traffic.

The best approach for collecting and analyzing data about the phenomena and elements of urban mobility is integrating geographic information systems and methods of visualizing the processed data [Sobral et al. 2019]. Usually collected through different sensors and integrated into the road system or urban vehicles, the data is processed and shown to users and urban planners to alert and improve mobility flow. For data visualization on urban mobility approaches related to air pollution, the population and authorities must consider the impacts caused and the measures to be taken.

This paper proposes integrating a proactive approach to calculate pollution levels for each transport mode used on each proposed route on a routing algorithm, collecting LBSN data to analyze urban flows. First, data processing is performed to make processing specific to the location selected for analysis and filter user behavior on specific parameters, such as limiting trips that occurred at a certain speed in one day. Then, the displacements are grouped to analyze the flow of movement and define preferred routes. For each route, the possible modal is defined, taking into account the price, distance covered in the race and distance covered by the user, the waiting time of the modal, the duration of the race, and the amount of greenhouse gas emissions. Each used route is designed to bring comfort and ecological awareness to urban travel. Evaluation results shows the travel experience of the routes generated in the main flows, serving to analyze the convenience of cost and time for public transport and hired transport services users, such as a 70%-80% reduction in travel costs and a 60%-90% increase in waiting time for routes primarily by public transport modes, among other particular analyzes of the analyzed factors..

The rest of the paper is described as follows. Section 2 shows the main related works found in the literature referring to the subjects addressed. Section 3 corresponds to the description and integration of the proposed air pollution calculation and multimodal routing service. Section 4 introduces the results obtained from analyzing the main factors that form the trips on the generated routes, forming the user experience obtained. Finally, Section 5 presents the conclusion and proposals for the future work of this paper.

2. Related Works

This section presents the essential concepts about location-based social network sharing usage, urban multimodal routing solutions, and urban mobility pollution analysis. All discussed concepts focused on specific solutions and were categorized into LBSN data usage, direct integration of multimodal routing, mobility flow analysis based on social networks, and air pollution approach.

[Ferreira et al. 2020] investigated how LBSN check-ins could be used for mobility behaviour of tourists study. The authors chose and evaluated Foursquare generated data for behaviour analysis of tourists and city residents, showing their important locations and visiting time. The chosen data treatment and modeling are appropriate for mobility identification. However, data collection in the used case is specific compared to essential mobility elements.

[Rodrigues et al. 2018a] presented a framework called SMAFramework, to integrate heterogeneous urban data sources and find the correlation between them. The work aims to help city planners with urban mobility data and data-driven solutions to facilitate citizen trip experiences around the city. Tool development was made for the framework users to manage, standardize, and integrate the data from different sources for information extraction. The author's approach has important relevance about data leveraging for urban applications, however pollution issues was not raised.

[Rodrigues et al. 2018b] proposed a hybrid multimodal routing solution and an evaluation method for large-scale use and route impact analysis on mobility flow in the use case urban area. Multimodal routes generation includes walking, bus, subways, ferries, other modes, and Hired Private Vehicle (HPV), such as taxis, and application services, like Uber. The authors focus on cost reduction without significant impact on user experience and trip time, not considering the pollution and air quality.

[Kalajdjieski et al. 2020] proposed a prediction air pollution method based on convolutional neural networks (CNNs) using camera images. The authors preferred IoT infrastructure security and traffic light cameras images instead of air pollution sensors, most useful in countries with fewer sensors installed. The evaluation of four architectures that classify images and perform data augmentation for imbalanced datasets, acquiring real-time heat maps, and identifying pollution sources. Although, the approach had significant dependence on public infrastructure, which implies an occasional bottleneck in the system. Simplified and decentralized methods can offer system robustness.

[Zou et al. 2020] introduced a near real-time healthier route planning (HRP) method with an experimental online implementation service for air pollution exposure (APE) minimization in daily travels by the method reliability and feasibility validation. The author's objective was defined as a route planner and minor exposure to pollution without multimodal integration and proper data mining for urban planning analysis and modification.

After analyzing the main issues addressed by the state-of-the-art, it can be highlighted the need to integrate methodologies for data collection and analysis, multimodal routing from urban flows, and the calculation of greenhouse gas emission according to modal used. Table 1 shows the main related works comparison under four categories. Based on the related work, this work proposes the main features of LBSN data usage, multimodal routing, mobility flow analysis integration, providing statistics to be used by users who opt for less polluting modes of transport and by urban transport managers who can optimize values to improve the quality of life.

Table 1. Related Works Features Comparison

Article	LBSN data usage	Multimodal routing	Mobility flow analysis	Air quality measure
[Ferreira et al. 2020]	✓			
[Rodrigues et al. 2018b]	✓	✓	✓	
[Rodrigues et al. 2018a]	✓		✓	
[Kalajdjieski et al. 2020]			✓	✓
[Zou et al. 2020]				✓
Proposed Methodology	✓	✓	✓	✓

3. Air Pollution Calculation Integrated on LBSN Multimodal Routing Service

This section presents the proposed method that was integrated into the existing hybrid multimodal urban routes. The inclusion of the proposed emission approach can generate new results for analyzing emissions in certain areas where the user's location data are collected, calculated and quantified CO_2 emissions from the selected modes that integrate the generation routes. Figure 1 presents the steps in the methodology for generating hybrid multimodal urban routes and the relationship with the approach proposed in this work to calculate the primary greenhouse gas emission.

The steps corresponding to the multimodal urban routing methodology are described throughout this section. The "Record Linkage" step is described in Subsection 3.1, explaining how the data were collected and processed for analysis. The "Clustering" step is described in Subsection 3.2, being necessary for data reduction when identifying the main urban flows in the analyzed environment. The "Routing" and "Visualization of Routes" steps are explained in Subsection 3.4, after identifying flows and building the multimodal possibilities. In conclusion, the "Comparative Analysis of Routes" step is described in Section 4 of this work, demonstrating the metrics resulting from the methodology in addition to determining the amount of CO_2 emitted.

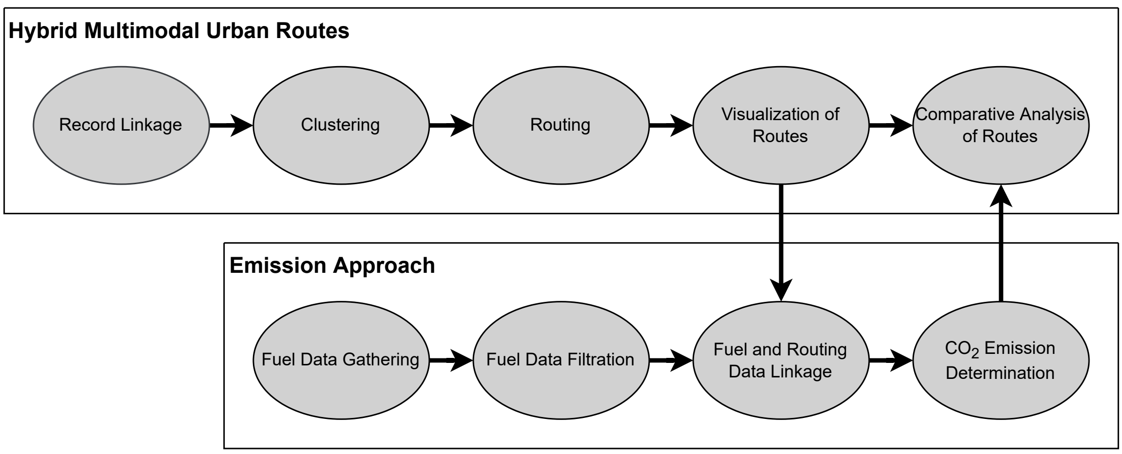


Figure 1. Work flow about emission methodology insertion on Multimodal Service

Subsection 3.3 explains the application of methods for calculating pollutant gas emissions from vehicles in the determined urban environment. This calculation is integrated into the urban routing framework that aims to collect urban data from heterogeneous social networks, normalize and insert them into the analysis of urban flows. We collected user data from the city of São Paulo, such as information about data on fuel and vehicle consumption, however, our proposal can be used anywhere. "Fuel Data Gathering", "Fuel Data Filtration", "Fuel and Routing and Data Linkage" and "CO_2 Emission Determination" steps from Figure 1. are described in Subsection 3.3, specifying the relation between emission approach and hybrid urban routing methodology.

3.1. Data Acquiring and Mining

As the method is used by users and urban planners from different cities with specific characteristics, the choice of geolocation data to be analyzed is arbitrary. The limitation for processed data include records containing the determination of the origin and destination coordinates and the standard definition of the registration time of the coordinates in which only an anonymous user is displaced, thus configuring the valid trip performed.

For the restricted data construction of users needed for the analysis, we used LBSN, since they offer coordinates and time stamps for each user interaction with the service. The two social networks, Foursquare and Twitter, were used as they are two services that provide such necessary elements for the practical analysis of urban mobility [Rodrigues et al. 2019]. When considering that the datasets' coverage area of the records is limited, we opted for using only one sector or city for the full analysis.

We performed datamining with the chosen data to analyze the correct sorting and pattern determination. We used the dataset from [Rodrigues et al. 2018b] that considered the analysis from the city of São Paulo. The raw trip data, acquired from Twitter API, were ordered and filtered by data coincident with a good record of trips made on the same day, with some information regarding the determination of the trip distance, time variation, and the speed between coincident trips.

3.2. Flow Identification

In order to identify the analyzed flow patterns to simplify the mobility analysis and to analyze the relationship with multimodal transport in-depth, the authors [Rodrigues et al. 2017] of the data clustering and analysis methodology used mathematical calculation and visualization and hierarchical clustering programming libraries. The combination of tools and knowledge about the merged data collected from different sources, Rodrigues et al. developed a framework to assist in the analysis of urban mobility.

After exploring the data to identify patterns and recognize trips made by the same users on the same day and with parameter restrictions, the next step is to identify the main flows performed by all trips performed. By identifying the main flows, it is possible to identify the most significant impacts that routes with different modals will have without calculating all the routes obtained in the treatment phase. The grouping of departures and arrivals of each trip identified in the data mining is performed to identify the most relevant zones; then, the flows are classified as trending or secondary.

The technique of determining the main flows analyzed the data collected from Twitter for the analyzed urban region and identified 12 flows of urban mobility, as shown in Figure 2, most of which are concentrated in Jardim Itatinga, Olímpico em São Caetano do Sul, Jardim dos Perdizes, and Aclimação. Only seven flows includes the central four districts and are considered by the author for the user experience analysis [Rodrigues et al. 2019].

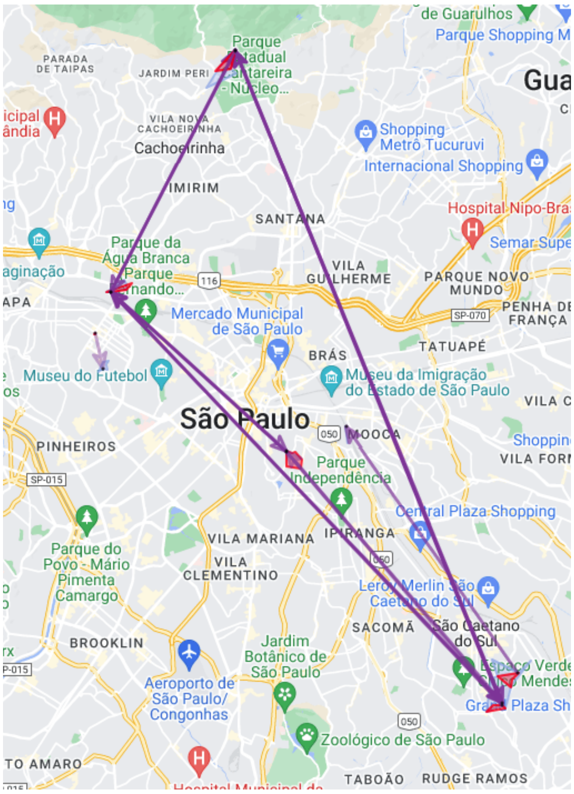


Figure 2. 12 main flows acquired by analysed Twitter Data

3.3. Emission Calculation

Regarding the calculation of emissions per vehicle, we implemented a standardized method of greenhouse gas emissions for all road vehicles and all types of fuel used, applicable to the brazilian urban environment [Álvares Jr. and Linke 2001]. The inventory calculation method proposed by the Intergovernmental Panel on Climate Change (IPCC) defines the emissions of gases harmful to the atmosphere and the health of the population from mobile sources, calculated from the burning of fuel, carbon content, and corresponding CO_2 emissions, determined as a "top-down" approach to performing emission estimations. Therefore, we integrated these calculations into the methodology proposed in this work for the correct proposed values definition.

The greenhouse gas emissions estimation is determined by a "top-down" approach in the form of three main equations. Equation 1 defines the energy consumption (CC) value, measured by tera-joule (TJ); with fuel consumption (CA) value, indicated by liters; a conversion factor of the physical unit of measurement of the amount of fuel to a ton of oil equivalent (tEP), based on the higher calorific value of the fuel (Fconv); the value of the equivalent ton of oil equal to 45.2×10^{-3} TJ (tera-joule), and the upper-to-lower calorific value correction factor (Fcorr).

$$CC = CA \times 45,2 \times 10^{-3} \times Fcorr \tag{1}$$

Algorithm 1 applies the emission calculation to the route determination source code, and consequently for the use of distance values the determination of total CO_2 emitted by each vehicle used in the possible routes. The calculation methodology is implemented through programming and guarantees the independent functionality of the values indicated for different fuels, with the modularity of changing the conversion, correction and emission values for the different types of fuel. Table 2 indicates the values of the conversion factor (Fconv) of the physical unit of fuel quantity measurement and the correction factor (Fcorr) alternates between for solid and liquid fuels (0,9) and gaseous fuels (0,95).

Table 2. Conversion factor values.

Fuel Types	Fconv values (tEP/m³)
Gasoline	0.771
Anhydrous alcohol	0.520
Hydrated alcohol	0.496
Diesel	0.848
Dry natural gas	0.857

Algorithm 1 Energy consumption algorithm

procedure ENERGY($CA, Fconv, Fcorr$)
    $FconvValue \leftarrow$ ""
    $FcorrValue \leftarrow$ ""
    $FconvList \leftarrow FconvListValues$
    $FcorrList \leftarrow FcorrListValues$
    for $element \in FconvList$ **do**
        if $element[0] == Fconv$ **then**
            $FconvValue \leftarrow element[1]$
    for $element \in FcorrList$ **do**
        if $element[0] == Fcorr$ **then**
            $FcorrValue \leftarrow element[1]$
    $CC \leftarrow (CA * FconvValue * FcorrValue * 45.2 * 10^{(-3)}$
    return CC

After obtaining the energy consumption value, the value is used in the equation to obtain the carbon content (QC) emitted in the burning of a specific fuel used in the locality. The carbon content value, expressed in carbon Giga gram (GgC), is given by multiplying the energy consumption with the carbon emission factor and converting the Giga gram to tons of carbon (10^{-3}), as shown in Equation 2.

$$QC = CC \times Femiss \times 10^{-3} \tag{2}$$

Algorithm 2 calculates the amount of carbon emitted by vehicles. The Table 3 presents the carbon emission factor published by the IPCC [Bolin and Sundararaman 1996] and is integrated into the calculations.

Table 3. Carbon emission factor values.

Fuel Types	Femiss values (tC/TJ)
Gasoline	18.9
Anhydrous alcohol	14.81
Hydrated alcohol	14.81
Diesel	20.2
Dry natural gas	15.3

Algorithm 2 Carbon emission algorithm

procedure CARBON($CC, Femiss$)
    $FemissValue \leftarrow$ ""
    $FemissList \leftarrow FemissListValues$
    for $element \in FemissListValues$ **do**
        if $element[0] == Femiss$ **then**
            $FemissValue \leftarrow element[1]$
    $EC \leftarrow (CC * FemissValue * 10^{(-3)})$
    return EC

Finally, Equation 3 converts the carbon emission value since 44 tons of CO_2 corresponds to 12 tons of carbon. The emission calculation is related to a consumption per vehicle of 8 kilometers per liter in the case of HPV and 2 kilometers per liter for buses. The analyzed equations form the best methodology to obtain greenhouse gas emissions from mobile sources, taking into account the amount of fuel burned, the carbon content, and the corresponding emissions of CO_2.

$$ECO_2 = EC \times 44/12 \tag{3}$$

Algorithm 3 implements the function of converting the amount of carbon emission to CO_2. The proposed method and integration of emission approach calculation into hybrid multimodal urban routes has greater precision because it considers the global annual fuel consumption of the analyzed environment and does not consider the specificity of the vehicle used.

Algorithm 3 CO2 emission algorithm

procedure CO2(EC)
    $ECO2 \leftarrow ((EC * 44/12) * 10^{-6})$
    return $ECO2$

3.4. Routing and Visualization

This section defines the routes performed in identified flows and the different modals alternation between the possibilities of the route to define the metrics that integrate the user experience after determining the main flows based on location data from social networks collected in the city of São Paulo and the establish the calculation of the CO_2 emission of the distance traveled by each vehicle used in the different models.

To compute possibilities of routes with different modals present in the analyzed urban environment, the aid offered by SMAFramework [Rodrigues et al. 2017] in the processing stage is used. In addition, tools from the TomTom Routing API transit and global positioning services are used to identify areas with congestion and their alternatives, integrating them into possible routes. The Google Directions API was used to compute and visualize the routes generated by the multimodal approach.

In the formation stage of multimodal routes, three different means are used: foot, public transport, and the vehicle. In a demonstration of each route formed in each flow acquired, public transport is represented in red, some stretches can be covered on foot in green, and the route in blue indicates the possibility of traveling by Uber [Rodrigues et al. 2019]. The author raises only two types of hybrid routes: “Hybrid 1” is primarily related to public transport, and “Hybrid 2” is primarily represented by Uber. The flows identified by the dataset were identified as long to traverse on foot, so it is only used in conjunction with other modals to construct routes.

Then, after processing the route and distributing it among the different possible modes, an interactive map is defined that displays in a 2D representation the steps determined for each mode that the user will use. The developed algorithm initializes the map generated as an output of the suggested route. Each section of the route has sensitive information such as origin, destination, travel time, an overview polyline - a coded representation of a suggested route of an approximate path to obtain a point sequence that forms a route after being decoded, and mode of transport. Some parts are drawn on the map, and the line’s color defines the mode used.

4. Performance Evaluation

This section presents the results obtained by the data analysis methodology from the social networks of the urban reality of São Paulo, generating route possibilities with the use of modals with different distances, making a comparative analysis of the amenities for users relating to several metrics resulting from different routes and average values obtained for each analyzed flow [Rodrigues et al. 2019].

We used the Python software library Matplotlib for generating the graphs and to show the comparative analysis between the flows of evaluated routes. The graphs represent the metrics and inform how the analyzed urban environment deal with the comparison of the seven main flows identified and their possibilities of routes.

After determining the graphs results of the methodology of the multimodal approach, the comparative analysis of the results of the metrics has the addition of the methodology of calculating the CO_2 emission and the generation of results integrated to the approach of the user experience obtained, with the amount of pollution that determined vehicle emitted based on the distance traveled on each generated route.

The generated metrics are represented by the main factors of the linked routes generated among the seven flows were duration of each trip, the distance traveled, the estimated price of each trip with specific modes, waiting time elapsed in each type of route generated, and the distance traveled to foot by each user. When comparing flows and their performances, the distance traveled on foot is integrated into the total distance traveled on the trip, while the average between modes is indicated exclusively in a graph.

4.1. Previous Analysis

The multimodal routing work performed a comparative analysis of the routes generated from the main flows considering the metrics of total distance and traveled on foot, the price charged for each modal used, the estimated travel time, and the waiting time that the user waits for the realization of the trip. Generated bar graphs explain the comparison of the different routes, showing the difference between trips only by public transport, only by Uber, and switching between modes, with “Hybrid 1”, indicating routes with more public transport occurrence, and “Hybrid 2”, indicating routes with more HPV (Uber) occurrence.

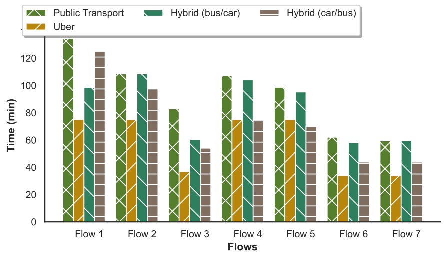
The values obtained by main routes are presented in the Figure 3, comparing the metrics and evidencing the advantages between the different modals chosen for the analysis. Regarding the estimated duration of each trip for each type of route used, the Figure 3a indicates the most prolonged time taken to complete a trip utilizing public transport since they have mandatory stops and take routes that are possibly unnecessary for most users, in contrast to the routes formed only by the use of Uber, with a decrease of 30%-50% of the total duration. Hybrid routes have a negligible decrease compared to traditional types of routes.

Figure 3b presents the distance taken by the different types of routes in the different flows is presented, but the difference is not significant, about 1%-10%, because the construction of the routes is similar concerning the point of origin and destination. The distance taken on foot is also indicated in the graph, being more frequent on routes with public transport due to the need to walk to the boarding point.

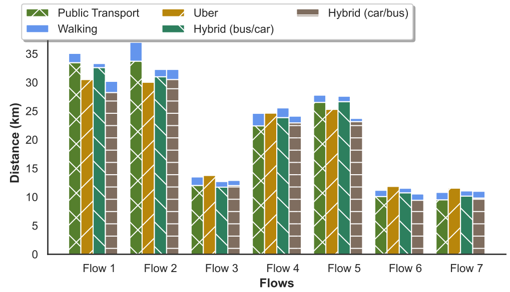
Figure 3c shows the discrepancy between the cost of each type of route used, mainly showing a 70%-80% decrease in spending on public transport and Uber. The hybrid routes have a high cost for using only public transport, but they offer greater convenience, less waiting time, and minor trip duration for users who use the routes.

Figure 3d demonstrates the waiting time for the user at the boarding point for the trip. The wait time is longer on routes with only public transport, compared to routes only performed by Uber, increasing 60%-90%. Alternatively, hybrid routes have a decrease in waiting time obtained on the public transport-only route of around 5%-20%.

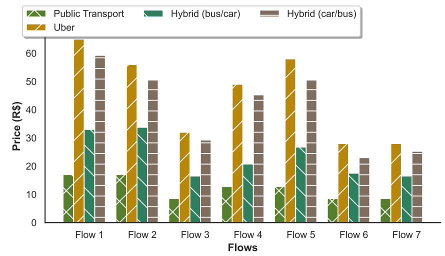
Figure 4 analysis also covers the average impact on the given routes, comparing the multimodal approach with the traditional routes with only public transportation or Uber, made explicit through the graphical representations. Figure 4a shows the average travel time of the analyzed flows shows the relative decrease in the advantage of using the hybrid route type compared to routes taken only by public transport. There is less fluctuation between the duration of routes exclusively performed by Uber due to the consistency of the duration of trips estimated by the application.



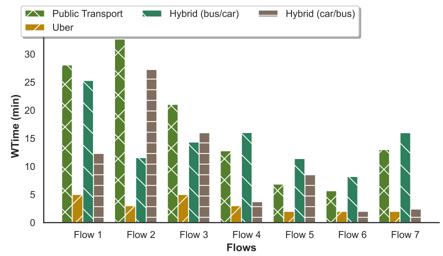
(a) Estimate trip duration.



(b) Travel Distance for each flow.



(c) Estimate price.



(d) Waiting time per flow.

Figure 3. Comparative graphics between obtained metrics.

In Figure 4b, the same evidence observed in Figure 3b is indicated. The average distance taken of the three types of routes is similar in terms of length, despite the reduced occurrence of fluctuation in the routes performed by Uber because it has greater constancy compared to the public transport.

Figure 4c presents the average price among the types of routes analyzed indicates the difference between public transport and Uber use, increasing by about 75%. The hybrid modal alternative appears to increase about 50% of the cost for users who need to financial save for use.

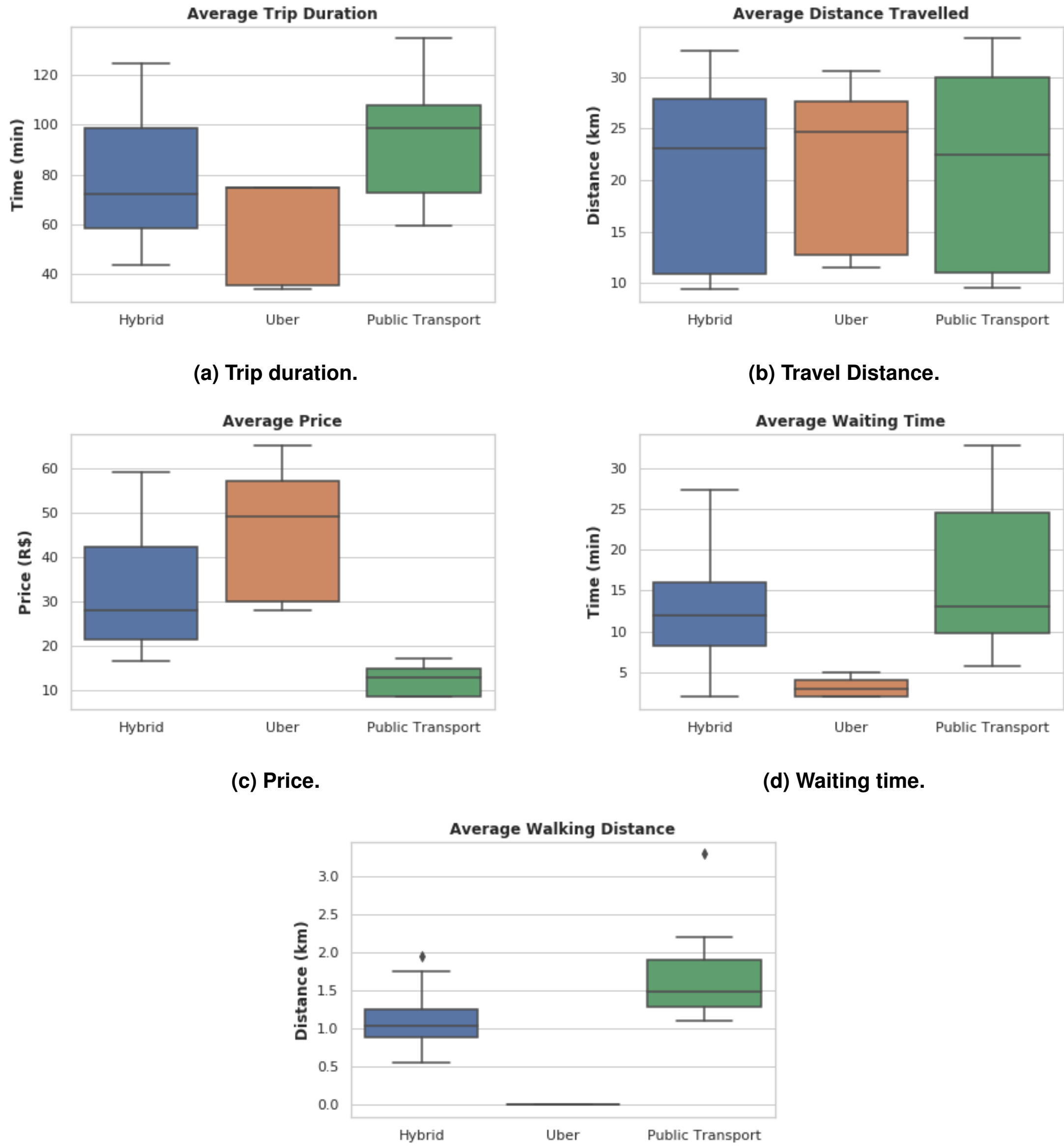
Figure 4d demonstrates the disparity in the waiting time for the trip between the types of routes is shown, with more excellent value for public transport compared to routes taken by Uber, with an increase of 75%-90%. The hybrid type offers a viable alternative by balancing the waiting time between the two types of traditional routes, as seen in the price occurrence (Figure 3d).

Figure 4e displays the average distance traveled in the walking form is separated from the total trip distance to explain the disproportion of traditional routes and the feasibility of using a hybrid route to reduce the distance necessary for a user to go to the boarding point for the trip start.

4.2. Emission Analysis

Figure 5 represents the obtained results involving the emission calculation of the seven flows acquired through the distance traveled calculated by the vehicles used in those routes, being converted to the amount of fuel consumed and integrated into the calculation. The comparative analysis of the route formations between the main flows indicates the pollution generated by different approaches.

A higher emission is evidenced by the types of routes performed by public



(a) Trip duration. **(b) Travel Distance.**

(c) Price. **(d) Waiting time.**

(e) Walking Distance.

Figure 4. Average performance of routes metrics, considering flows 1 to 7.

transport due to high fuel consumption, with about an 85% increase compared to the use of Uber and a more significant adjustment of emissions in the routes of hybrid use of the modals. However, it is necessary to point out the greater passenger transport capacity of public transport, justifying the high emission by this modal.

Figure 6 shows the average of the emission calculation values applied in the seven main routes, indicating the highest concentration of pollution among the other types of generated routes. A more significant occurrence of pollution by public transport is observed, but it is necessary to consider the number of people transported per trip compared to an HPV, with a maximum capacity of four people transported.

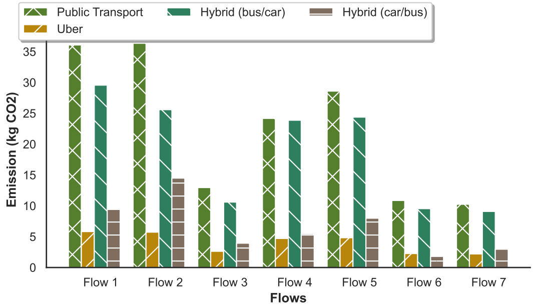


Figure 5. CO_2 emission in defined routes.

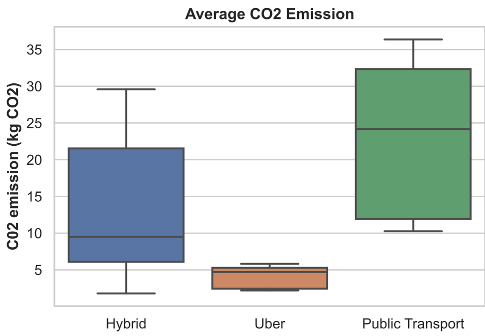


Figure 6. Average CO_2 emission in defined routes.

5. Conclusion

This work presents a novel approach to multimodal urban pollution-aware routing needs by using location-based social network collected data, offering less expensive, healthier trips for the population and data collection about carbon emissions for mobility planners to consider when turning urban scenarios dynamic and sustainable.

After acquiring and submitting the geo-located data from social networks, the mobility flows are identified with separated multimodal used on routes, where each chosen modal carbon dioxide emission calculated on those routes, and evaluating them on certain metrics, such as waiting time, walking distance, and price estimation. The proposed algorithm proves its efficiency and can be used by users of route applications, city authorities, and for environmental studies on urban mobility, therefore developing a better and productive life quality for smart cities.

As future works, a more efficient data acquiring method can be applied for a large set of geo-located data in less populated urban areas with pollution active sensing coverage in order of reliable emission sensing and mobility analysis.

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