Mobility Studies in Villavicencio: Situation and Prospects Towards a Smart Mobility

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Abstract
Congestion is a contemporary and growing problem in most urban areas around the world, and even middle-sized cities are not exempt from this. In Colombia, this problem is especially accentuated in large cities such as Bogotá, Medellín, and Cali; however, in mid-sized cities such as Villavicencio the situation also tends to worsen and this stresses the need for a better understanding of traffic so that appropriate measures can be taken to minimize its impact. In this city, there is a particular point that attracts congestion near the roundabout called Grama, near Corporación Universitaria del Meta thus affecting the nearby academic community and residents in the area. The objective is to determine the main factors contributing to the increase in traffic and slow mobility throughout the day at the Grama roundabout in Villavicencio, Colombia, through speed measurements. To achieve this, the license plate method was used in order to measure vehicle speeds at the Grama roundabout during peak and off-peak times. As a result, a characterization of traffic speed by vehicle type, namely public transport and private vehicles, during both peak and off-peak times by segments, providing an insight into the main contributing factors to congestion in the area under study.

Keywords
Spatialization, Transport, Travel Time, Modes of Transportation

1. Introduction

Mobility in a city is a basic need of society because moving from one point to another allows individuals to carry out their daily tasks. On the other hand, the dynamics of modern cities are characterized by high rates of mobility of people and goods, a dynamic that is associated with the physical aspects of the community activities and their territorial distribution: the more the city grows, the more the vehicle fleet, the number of people, increases the length of displacement and other aspects that make a permanent diagnosis necessary to generate improvement strategies [1, 2].

Currently, the political agenda on mobility in most cities has promoted numerous mobility projects based on the concept of sustainability that encompasses a set of processes and actions aimed at achieving the rational use of means of transport for individuals and professionals [3].

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Its primary focus is the reduction of traffic congestion, promoting road safety, decreasing air and noise pollution, energy consumption, travel time reduction, and public transport service, among other aspects. Therefore, the sustainable objectives for mobility are mainly focused on improving the quality of life of citizens of current and future generations [4].

The mobility plans in regions such as Latin America and the Caribbean present significant challenges associated with the uncontrolled growth of cities and the constant increase in vehicles fleet, poor mobility culture, corruption, etc [4, 5]. However, efforts are being made by the administration, the university, the state, and society to develop efficient planning processes to optimize scarce resources to cover the demand for human development within the principle of equity. Specifically, maximize the use of the existing infrastructure demanded by the different modes of transport through traffic management processes. Therefore, planning should be a continuous and permanent process of analyzing the current situation and forecasting future scenarios in its development [6].

In Colombia, the city of Villavicencio, located in the east, is a principal commercial point that connects the center with oil and economic zones [7]. Therefore, mobility is a dimension of great concern, considering the challenges of many cities in LATAM and related to its features, such as the roads with bad conditions and the high number of vehicles from different zones of the country. Consequently, it impacts the travel times for displacement, road safety, and other aspects of the community's welfare.

Accordingly, it is crucial to diagnose the mobility dimension in strategic points of the City using data for modeling and understanding the dynamics of mobility in the City [8]. Therefore, this study starts with characterizing vehicular traffic on two Paths of the main Avenue of Villavicencio, Alfonso Lopez. Then, it permitted the estimation of some traffic indicators, such as the vehicular travel time and speeds at crucial moments of the displacements, well known as peak and valley hours.

Finally, an overview of the traffic modeling is presented as a close future perspective to include in the mobility studies in cities such as Villavicencio to reinforce the diagnosis phases in the planning projects. Also, the importance of the data quality is emphasized to understand the context deeply, guiding urban and transport decisions to mobility service improvement in Cities.

2. Methodology

Based on a fieldwork design, the mobility study was developed using the license plate method to analyze the travel time of vehicles on Alfonso Lopez Avenue in Villavicencio, Colombia. The travel speed of each path was determined considering two types of mobility. The off-peak (valley) hours (8:30 a.m – 11:30 a.m and 2:30 p.m – 5:00 p.m) and the peak hour (7:30 a.m – 8:15 a.m, 11:45 a.m – 12:30 p.m and 5:30 p.m. – 6:45 p.m). The fieldwork was designed using counting and verification tools, and prospection work was done in situ with Waze and Google Maps Apps.

2.1. Study Zone

The Alfonso López Avenue was analyzed in two paths, one going from GRAMA to Carrera 33 with Calle 32 (VORAGINE) and the other one from Carrera 33 with Calle 32 (VORAGINE) to GRAMA. Each path was divided into study segments, thirteen for GRAMMA-VORAGINE and fourteen for VORAGINE-GRAMMA as presented in Table 1.

Table 1
Selected segments by each Path under mobility study

SEGMENT	GRAMMA-VORAGINE	VORAGINE-GRAMMA
1	GRAMA-CALLE 41	CALLE32-CALLE33
2	CALLE 41-CALLE 40	CALLE 33-PALACIOJUSTICIA
3	CALLE 40-CALLE 38	PALACIOJUSTICIA-CALLE 35
4	CALLE 38-CALLE 37B	CALLE 35-CALLE 35A
5	CALLE 37B-CALLE 37A	CALLE 35A-CALLE 36
6	CALLE 37A-CALLE 37	CALLE 36-CALLE 37
7	CALLE 37-CALLE 36	CALLE 37-CALLE 37A
8	CALLE 36-CALLE 35	CALLE 37A-CALLE 37B
9	CALLE 35-RESTAURAN	CALLE 37B-CALLE 37D
10	RESTAURAN-ARQUITECT	CALLE 37D-CALLE 39D
11	ARQUITECTURA-PANTANOVARGAS	CALLE 39D-CALLE 40
12	APANTANOVARGAR-CALLE33B	CALLE 40-CALLE 40A
13	CALLE 33B-CALLE 32	CALLE 40A-CALLE 41
14		CALLE 41-GRAMA

2.2. Plate License Method

The method was used to obtain travel time at two established points. This procedure consists of taking data of the hour of passage, in which the vehicles that travel a segment of the path pass through two or more points of the segments identifying them by their license plate. Then the travel time between the points of the road is calculated knowing the distances that separate them. It only measures travel times; however, It does not measure delays. Therefore, its efficiency depends mainly on the number of vehicles that pass through the considered segment; if the traffic is heavy, an acceptable sample can be obtained to study some aspects of mobility at the location of interest.

2.3. Data Acquisition

A group of practitioners was arranged for fieldwork for the data collection by hand [9]. Two experimenters were located at the corner of the segment under study, called point controls. First, using a format, the last letter of the plate was written with their respective number and the vehicle number. Finally, with the help of the cell phone timer, the exact time the vehicle passed in front of the practitioner was recorded until 40 data were obtained. The data were collected for a peak hour determined by the time of day with a significant number of people and vehicles on the streets; there is greater use of public service. On the other hand, the off-peak or valley hour corresponds to the additional time of the day with fewer people and vehicles circulating the city. Data for peak and valley hours were acquired as follows.

- Valley Hour (Off-Peak) Daytime: Wednesday from 9:10 a.m to 11:35 a.m
- Peak Hour Daytime: Thursday from 7:35 am to 8:12 am, Friday from 7:50 am to 8:11 am, and Tuesday from 7:35 am to 8:15 am
- Valley Hour Night: Wednesday from 3:06 pm to 4:45 pm
- Peak Hour Night: Thursday from 5:32 pm to 6:37 pm and Friday from 5:50 pm to 6:46 pm

2.4. Data Processing

Travel time is determined as the time required to traverse a specific route. For this study, the distance of each segment was taken with an odometer. On the other hand, the travel when the vehicles crossed the zone was obtained with a cellphone stopwatch. As a result, the average speed of each vehicle was estimated with a simple physical relation of variables. However, it is crucial to take into mind some considerations of the variables involved as it is mentioned as follows:

- Travel time: It is the total elapsed time, including stops and waiting, required for a vehicle to travel from one point to another on a specified route under existing traffic conditions.
- Travel speed: It is the average speed in the studied segments. It is obtained by dividing the total distance by the total time elapsed between terminal points (including all delays, i.e., travel time)

The results shown in the following section are the product of the tabulation of the data by the plate method, where the travel times are acquired in each Path of Alfonso López avenue.

Furthermore, the data taken for each segment was compared by the practitioners. Finally, the delay times were determined for each registered vehicle to move from the initial point to the final point of the sample. For analysis, the waiting time at traffic lights and the valley and peak hours were considered. The study aimed to acquire data and semi-quantitative traffic behavior analysis by estimating travel and speed time indicators. Therefore, an statistical analysis was not presented for this study.

3. Results

3.1. Experimental Zone Characterization

The characterization of the analysis for the two Paths under study was developed using Google Maps as an informatic tool to collect information related to the distance and relevant conditions of the zone shown in Figure 1. However, the *in situ* recognition was also made to verify the information and optimize the experimental design before fieldwork. Figure 1 (a) shows the GRAMMA-VORAGINE path traveled in a vehicle at pick hour. It comprises the GRAMA avenue and the headquarters of the University of Meta called Pantano de Vargas, with a route on Carrera 33 from the Pantano de Vargas building between the Carrera 33 with Calle 34 to Calle 32 with

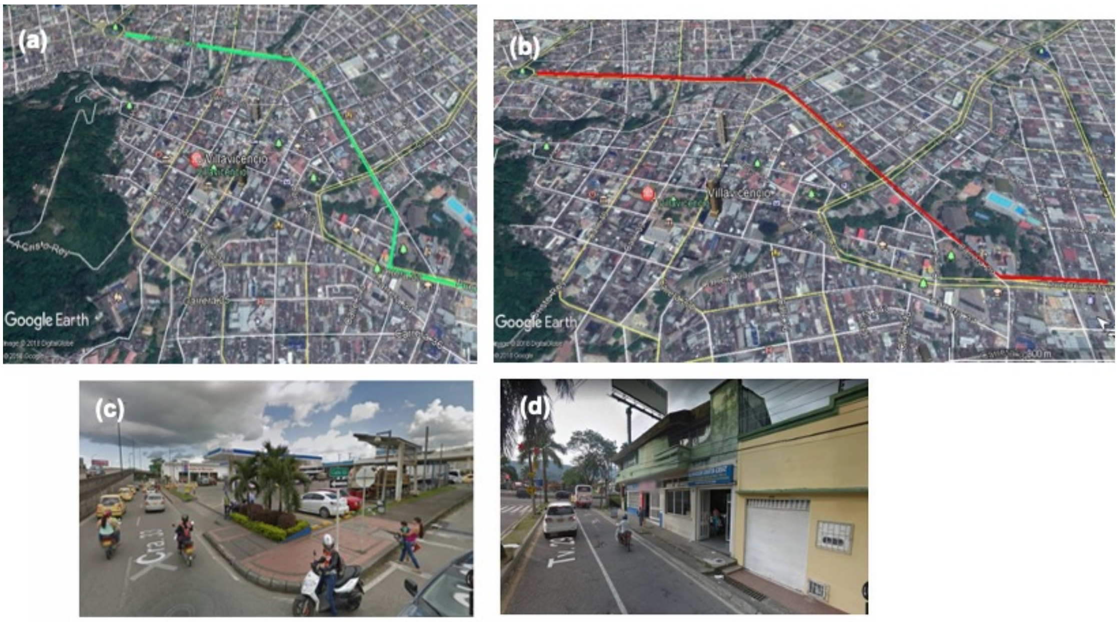

Figure 1: Google Earth App Images for the two Paths. (a) GRAMMA-VORAGINE with a distance of 1643 meters. (b) VORAGINE-GRAMMA with a distance of 1517 m. (c) The thirteenth segment for GRAMMA-VORAGINE (d) The fourteenth segment for VORAGINE-GRAMMA

Carrera 33, which is a sector known as La Vorágine Service Station. The total distance was 1643 m, according to Google Maps App data; *Path Two* called VORAGINE-GRAMMA has presented in Figure 1 (b), and it was traveled between Calle 32 and Carrera 33 to Glorieta de la GRAMA, with a distance of 1517 m. Each path was analyzed by segments, where thirteen segments were selected for GRAMMA-VORAGINE and Fourteen for VORAGINE-GRAMMA, as shown in Table. 1. Figure 1 (c) shows the thirteenth segment analyzed for GRAMMA-VORAGIME, which corresponds to CALLE 33B with CALLE 32, and Figure 1 (d) shows the fourteenth segment at CALLE 41 -GRAMMA for VORAGINE-GRAMMA.

3.2. Average Speed Estimation

The License Plate Method described in Section 2 was used to collect information about travel time in Valley and Peak hours for the two Paths surveyed during two workdays.

Figure 2 presents the average vehicular speed for GRAMMA-VORAGINE in the valley hour for daytime and afternoon-time on Wednesday from 9:10 am to 11:35 am and from 3:06 pm to 4:45 pm. For the day, the average speed was 15.21 km/h, and the afternoon (called night for this case) was 14.05km/h. The segment with the lowest speeds was ARQUITECTURA-PANTANO DE VARGAS, while the one with the highest was CALLE 40 - CALLE 38. On the other hand, it is graphically observed that the average speeds were similar for each segment in GRAMMA-VORAGINE at Valley hour.

Figure 3 shows the average speeds by segments for GRAMMA-VORAGINE at Peak hour on

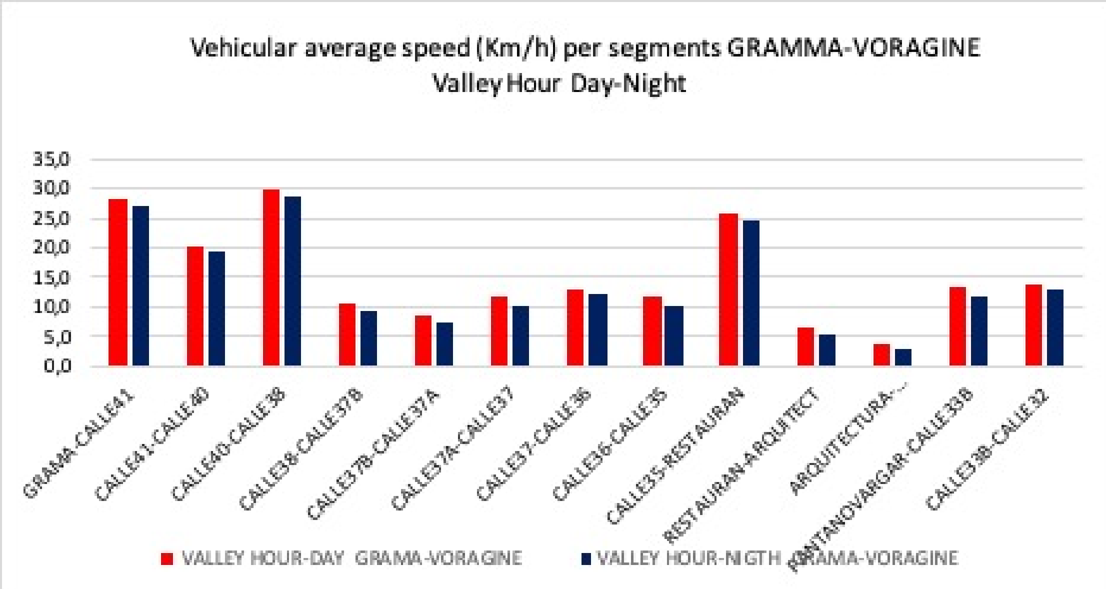

Figure 2: Vehicular Average Speed in each segment for GRAMMA-VORAGINE path at Valley Hour.

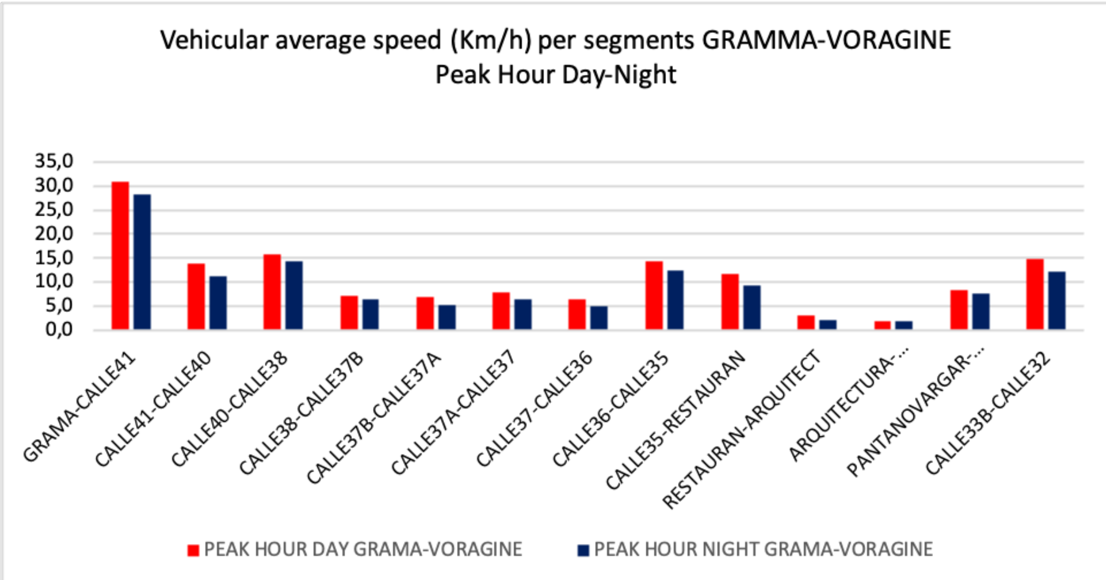

Figure 3: Vehicular Average Speed in each segment for GRAMMA-VORAGINE path at Peak Hour.

Thursday from 7:30 am to 8:06 am, on Friday from 7:46 am to 8:15 am, and Tuesday from 11:46 am to 12:16 pm, with an average speed of 11.02 km/h. They were taken on Thursday from 5:25 pm to 6:35 pm to collect information at night peak hour with; as a result, the average path speed was

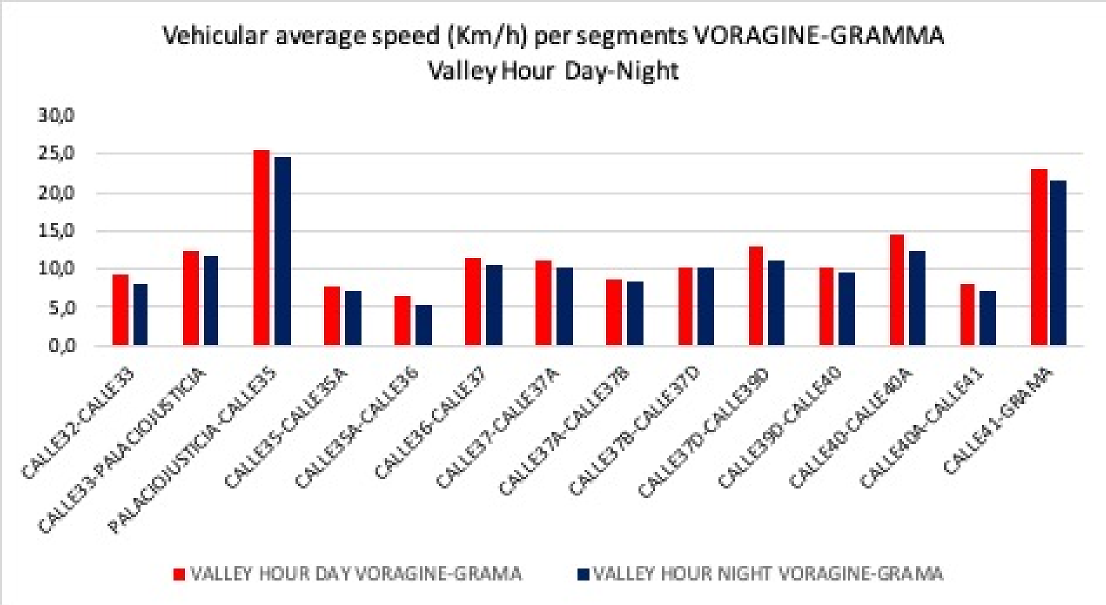

Figure 4: Vehicular Average Speed in each segment for VORAGINE-GRAMMA path at Valley Hour.

9.45 km/h. The segment with the lowest speeds was ARQUITECTURA-PANTANO DE VARGAS, while the one with the highest was GLORIETA LA GRAMMA-CALLE41. Additionally, it is appreciated graphically that the speeds are similar for each segment for GRAMMA-VORAGINE at peak hours.

Figure 4 exhibits the average vehicular speeds for VORAGINE-GRAMMA at valley hour, from Calle 32 and Glorieta de la Grama on Wednesday from 8:30 am to 10:58 am, with an average speed of 12.26 km/ h. The late valley hour was also taken on Wednesday from 2:45 pm to 4:49 pm with an average speed of 11.27 km/h. The segment with the lowest speeds was CALLE 35A – CALLE 36, while the one with the highest speeds was PALACIO DE JUSTICIA – CALLE 35. Furthermore, it is possible to observe a similar situation to path one, where the speeds are near for all segments.

Figure 5 presents the average speed for VORAGINE-GRAMMA at peak hour, from Calle 32 to Glorieta de la Grama, during the daytime on Thursday from 7:35 am to 8:12 am, on Friday from 7:50 am to 8:11 am, and Tuesday from 7:35 am to 8:15 am, with an average speed of 10.36 km/h. For the night peak hour, the data was taken on Thursday from 5:32 pm to 6:37 pm and Friday from 5:50 pm to 6:46 pm, with an average speed of 9.16 km/h. The segment with the lowest speeds was CALLE 35A – CALLE 36, while the one with the highest speeds was PALACIO DE JUSTICIA – CALLE 35. The results exhibit similar behavior to Path one; it is graphically observed that the speeds are also near for each segment.

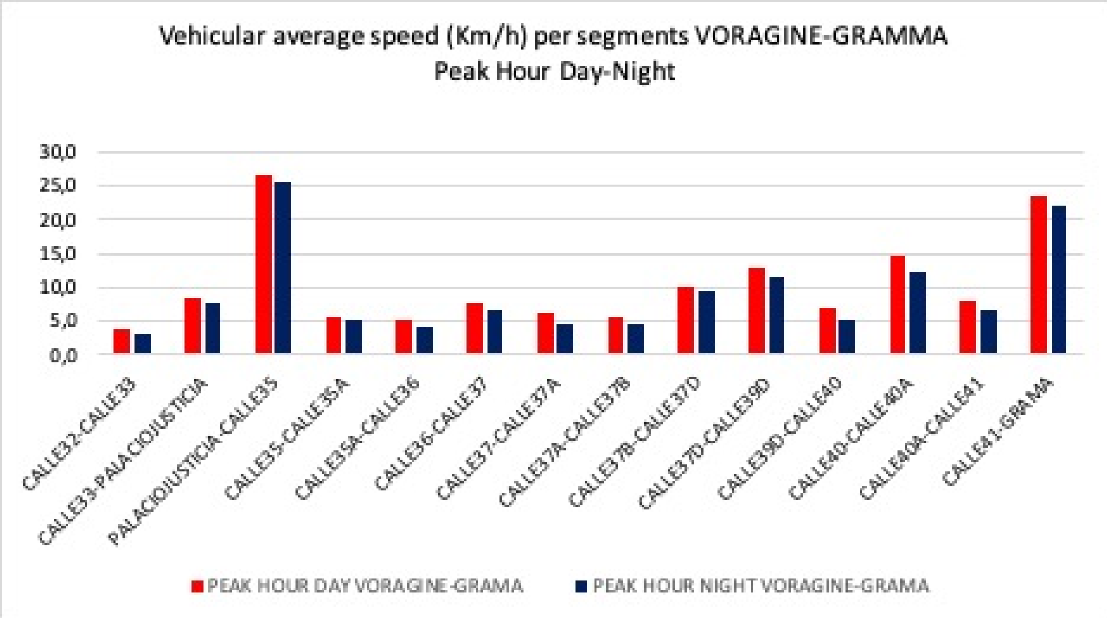

Figure 5: Vehicular Average Speed in each segment for VORAGINE-GRAMMA path at Peak Hour.

3.3. Speed of Type of Vehicle

The estimation of the average speed by type of vehicle, namely Bus, taxi, and private car, is presented in Figure 6 for the two paths under study, daytime and night and valley-peak hour. Figure 6(a) Shows the average speed for GRAMMA-VORAGINE in the valley and peak daytime hours. It is easily observed that the Bus shows the lowest speeds, and all vehicles transit slower at peak hours than at valley hours. The same situation is present for the night, as shown in Figure 6(b), where the average speed for GRAMMA-VORAGINE at the valley and peak hours is illustrated. It is also possible to observe that there is no substantial difference between daytime and night for average speed per type of vehicle.

On the other hand, Figure 6(c) shows the average speed for the path two VORAGINE-GRAMMA at the valley and peak hours during the daytime, and Figure 6(d) for the valley and peak hours at night. It is also observed that the bus is the slowest of the vehicles. Likewise, it could be inferred that circulation is more complicated at night, and there are no crucial changes between daytime and night for average speed per type of vehicle.

4. Related work

Contemporary urban planning strategies are varied in their efforts to design efficient and balanced transportation systems [10, 11]. In particular, simulation-based approaches offer the ability to proactively and quickly diagnose traffic safety problems and to evaluate appropriate initiatives [12]. Many of these consist of *microscopic traffic flow modeling*, *i.e.*, models for the

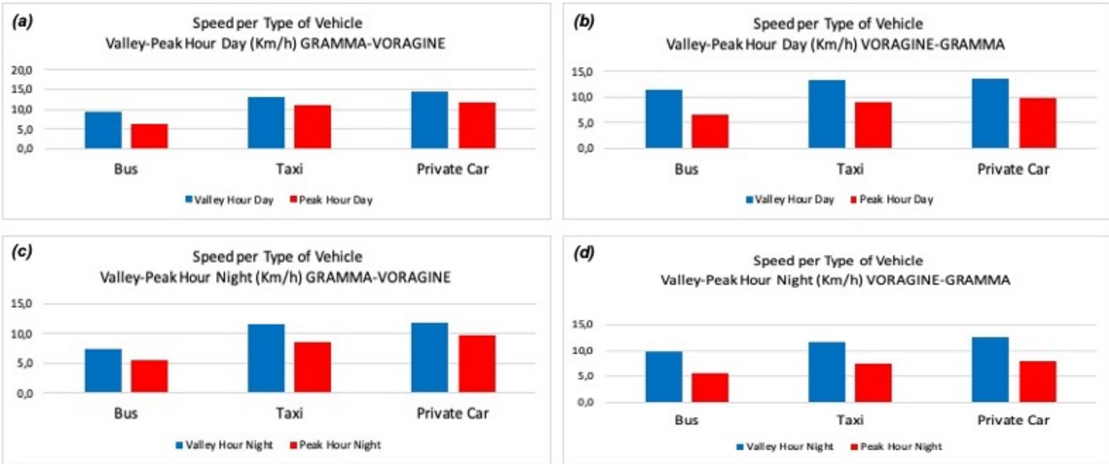

Figure 6: Average Speed by Type of Vehicle. (a) Vehicular average speed in GRAMMA-VORAGINE path for a valley-peak hour at daytime. (b) Vehicular average speed in VORAGINE-GRAMMA path for a valley-peak hour at daytime. (c) Vehicular average speed in GRAMMA-VORAGINE path for a valley-peak hour at night. (d) Vehicular average speed in VORAGINE-GRAMMA path for a valley-peak hour at night.

study of vehicle traffic dynamics where single vehicle-driver units are simulated with their relevant properties, such as position and speed, being represented as if these units were single points [13, 14]. The advantages of microscopic modeling include the assessment of the future design, the analysis of several aspects of transport infrastructure, *etc.* Monitoring systems, such as those using aerial footage, can be used to automatically detect vehicle trajectories and subsequently assess the effectiveness of public policy measures to regulate these [15]. Examples of this include the use of microscopic traffic modeling in combination with data obtained from this type of footage in order to quantify the effect of traffic-calming approaches, *e.g.*, speed cushions, with recent results showing that these measures are effective in reducing the influx of vehicles on roads [16]. Real-time traffic data captured by these monitoring systems have also been used in the development and continuous update of machine learning models for the prediction of driver behavior. Examples of this include the use of these monitoring data for the continuous update of the hyperparameters of deep learning prediction models allowing the digital twin modeling of real-time traffic [17]. However, in spite of these and other significant advances, the current literature reportedly presents a void in the use of this type of modeling for the evaluation of traffic safety in environments that are commonly observed in emergent countries [12].

Other approaches focus on *macroscopic traffic modeling*, rather than microscopic modeling, with the difference between the two is that the latter considers the interaction between individual vehicles whereas the former considers the aggregate behavior of traffic flow [18, 19]. This macroscopic modeling paradigm is especially used when studying vehicle behavior at junctions, which reportedly constitute the most critical point on the road network [20]. *Automated planning* platforms using the macroscopic paradigm have been proposed for the implementation of efficient urban traffic control measures in various metropolitan areas. Domain-dependent model update approaches have been proposed using learning techniques that monitor traffic junctions and automatically generate actions that match the dynamics of the junction, thus allowing automated planning platforms to quickly adapt to changing city traffic behavior, generating better planning domains that require less model engineering work [21]. Similar models in both paradigms have been used in the study of junctions controlled by traffic lights resulting in methods for the better understanding and improvement of traffic at these critical points of the road [20]. Examples of macroscopic modeling include the work of [22], where traffic flow modeling is used in order to determine whether a roundabout in Hlohovec, Slovakia, has sufficient spatial capacity for managing the traffic load of the town. Similarly, [23] use flow modeling in order to assess the impact of buses on the traffic indicators in Melbourne, Australia, showing that the congestion created by this type of public transportation is greatly outweighed by their reduction of traffic in the city.

Many other contemporary models also focus on *traffic conflicts*, defined as situations involving two or more drivers where at least one of these is forced to take evasive action in order to prevent an accident with the others, *e.g.*, where one driver has to swerve abruptly in order to avoid a collision [24, 25, 26]. [27] propose a methodology for the assessment of human driver behavior in urban scenarios where automated vehicles also use the roads, thus interacting with their traditional, human-driven counterparts, and where traffic conflicts might arise.

Many research initiatives on traffic modeling require the acquisition of transit data, *e.g.*, a number of vehicles moving through a street or intersection within a time window and the speed of each, a process that traditionally, and still frequently, is carried out mostly by manual surveys, such as in the research conducted by [22], [23] and [27]. This, by itself, poses challenges related to the reliability of the data and the associated costs of the manual process which in recent years have increasingly been addressed through the growing use of computer vision techniques, as these become more sophisticated, for the automated acquisition of traffic data [28, 29, 30, 31, 32]. Additional challenges are introduced when studying the traffic of bicycles, for instance, given that these are able to use routes other than the regular roads, including cycle paths and passageways for pedestrians [33]. [34] propose a model for the study of bicycle behavior in Warsaw, Poland, showing that, during rush hours, cyclists generally choose to use main roads.

5. Conclusions

The results presented in this article evidence the feasibility of the proposed approach, namely the license plate method, for the characterization of vehicle speed in the area under study, which is a focal point in the city of Villavicencio and an attractor of traffic. This characterization, discriminated by vehicle type, namely public transport vehicles and private ones, is expected to contribute to the further understanding of the underlying causes of congestion at this point of the city, especially how this varies by vehicle type between peak and valley (off-peak) times. Future work contemplates the extension of the proposed approach and its validation in other areas of Villavicencio and larger urban areas in the country.

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