Developing a Traffic Congestion Model based on Google Traffic Data: A Case Study in Ecuador

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Abstract: Congestion on urban streets has negative impacts on the urban economy, environment, and lifestyle. Congestion, in developing countries, will increase despite knowing its cons. One way to control or reduce congestion is by sharing traffic information through traffic model congestion. This model includes the estimation of the travel time from the desired place of origin-destination. Speed-flow-density parameters help to calculate travel time. These fundamental parameters could be estimated using Floating Car Data from Google. Therefore, the objective of this research is to calibrate equations for the fundamental parameters with traffic state indicators by Google, relating them to ground truth data. Six density-flow equations and six speed-density equations were calibrated using power and linear curve, and some of them were validated. Other cities can use these equations to build their traffic congestion model. With this model, road users can plan the journey and choice the best route or travel in times of low congestion or uptake of public transport, decongesting the city and saving traffic costs related. This comprehensive research extends the knowledge of how Google traffic information can employ in developing cities.

1 INTRODUCTION

Congestion on roads, especially in urban areas, has a large negative social and economic impact on the community as well as on the environment (Bacon et al., 2011). Congestion may cause delay and noise that frustrates motorists and commuters, which also would have health implications. It may also lead to road traffic crashes and the degradation of the road infrastructure (Ackaah, 2019). In developed nations, traffic congestion is taken seriously, applying several measures to reduce it or control it. Unfortunately, most cities in developing countries are experimented and will be doing, hard times with traffic congestions (Yokota, 2004).

In developing economies, the main problem is that congestion keeps on increasing because the number of people owning cars keeps increasing (Ackaah, 2019; Mfenjou, Abba Ari, Abdou, Spies, & Kolyang, 2018). The scenario is complicated when many people live in these cities, intensifying transportation of good and passengers (Jain, Jain, & Jain, 2017). Also, when public transportation does not offer enough quality for drivers to leave their cars at home, or road infrastructure does not encourage drivers to change the mode of transport. Although the problems of vehicular congestion are known, very little has been done, due to the lack of personnel and technology, and especially to financial constraints (Yokota, 2004; Singh, Bansal, & Sofat, 2014).

Congestion can be tackled either by increasing street capacity or through demand management. Increasing capacity is very difficult in urban environments and very expensive that developing countries cannot afford (Baratian-Ghorghi & Zhou, 2015). A more practical means of handling the existing infrastructure to optimize its use has become necessary (Ackaah, 2019). Some demand must be reduced, displaced to other routes, or move to other days if users have access to timely, accurate, and reliable traffic information (Bagloee, Ceder, & Bozic, 2014). This information could influence travel behaviour (Reza & Kermanshah, 2005; Andersson, Hiselius, & Adell, 2018) and could reduce journey time; and traffic congestion along with reduced vehicle emissions and fuel consumption (Hall, 1996). To build a successful

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traffic congestion model is necessary to collect some.

Data collection could be performed using traditional on-road sensors such as inductive loops or road tube counters. These sensors require specialized equipment for their installation in the outdoor. Moreover, maintenance requires that personnel visit the locations and repairs disrupt traffic. Those sensors are limited in terms of their coverage because it is prohibitively expensive to instrument representative road sections in the city. Floating Car Data (FCD) is an alternative data resource, that has high coverage (Altintasi, Tuydes-Yaman, & Tuncay, 2017; van den Haak et al., 2018).

FCD is possible due to the rise in the number of mobile phones (Gunawan & Chandra, 2014) and the increase in Internet use (Jiang, 2019). An indirect measure of the number of mobile phones is the mobile cellular telephone subscriptions (for every 100 people) that employ cellular technology. In 2018, in Ecuador, the subscriptions were 92, while in the whole world was 104.94 (World Bank, 2019b). Other countries that, according to the World Bank (World Bank, 2019a), have similar income had 98 (Serbia), 106 (Tonga), 132 (Argentina), 153 (South Africa), and 180 (Thailand). Internet use was also increased worldwide, and in 2017, around 50% of the population used it via a computer, mobile phone or digital TV (World Bank, 2019b). In the same year, Ecuador had 57%, 73% for Serbia, 41% for Tonga, 74% for Argentina, 56% for South Africa, and 57% for Thailand. Regarding smartphones, in 2017, the percentage of people who use them was 63% in Serbia, 73% in Argentina, 60% in South Africa, and 71% in Thailand (Google, 2018). Considering these values and its growing trend, FCD has a very good opportunity to be used in developing countries.

FCD collects real-time traffic data by locating the vehicle via mobile phones or GPS over the road network (Altintasi et al., 2017). This data is then processed, to calculate travel time or average speeds in every road segment. This information is sharing to users through an online map or mobile phone applications. For example, Google's application combines location data taken from participants' GPS-equipped mobile phones with a traditional sensor (Google, 2009). Car location is map-matched, and speed and direction of travel are sent anonymously to a central processing centre. Their aggregated results are shown overlaying road maps with congestion information through four colour codes. Traffic information provided by Google is 85% accurate for cars and 71% for motorbikes (Ahmed, Mehdi, Ngoduy, & Abbas, 2019). This traffic congestion information is valuable by road users and road system managers.

Road users can plan the journey and choice the route, while road system managers view travel time as an essential network performance indicator (Rose, 2006). Travel time is calculated using the segment length, the number of intersections in the route, traffic flow, speed, and traffic density. The last three ones are the fundamental parameters in traffic engineering (Garber & Hoel, 2014). This information helps to identify different traffic states (congested, free-flow, etc.) and events (i.e., entering or exiting from a queue/bottleneck, shockwave propagation, etc.) (Altintasi et al., 2017). Despite the importance of these fundamental relationships, some cities in developing nations have not invested in getting them. One option for those cities is to use Google traffic information to calculate speed-flow-density parameters. Google shares aggregate data, after applying some "noise" (Knoop, Van Erp, Leclercq, & Hoogendoorn, 2018), and only shares that information with few institutions in the world (university, institutes or transportation centre's) in their program Better Cities (Eland, 2015). These institutions belong to developed countries, so it is difficult to obtain this numerical information for cities in developing nations.

However, Google codes the numerical information using four colours and gives it for free through its platforms (web and mobile app). This colour-coded traffic (live and typical) is available in several cities worldwide. Google traffic information is a result of shared data from more than 2 billion monthly active users (Matney, 2017). By default, the user shares their location data by Google's location service and sent to the Google database for further processing. It may be stored on the device until it has an Internet connection. For traffic, users' information is classified based on speed. It is worth mentioning that the user can turn it off this option to avoid sharing his/her location data. In spite of the growth of smartphone use, Internet access, and the number of Google active users, it is not known if the colour-coded traffic indicator is accurate in developing countries.

The aim of this research is to calibrate equations for the colour-coded traffic indicators provided by Google using ground truth data. Data were collected in urban streets from a medium city (Loja-Ecuador). As a result, several equations were calibrated y validated. In order to show this research, the rest of this paper is structured as follows. Section 2 gives an overview of the materials and methods. It describes the sample size, data collection variables, and procedure, data processing. Also, it analyses the relationship between speed data and the colour-coded condition. Section 3 shows the model calibration process and validation. Lastly, the final part presents the principal conclusions.

2 MATERIALS AND METHODS

2.1 Sample Size

Loja, a medium city from Ecuador, was selected for this study. Ecuador is a developing country located in South America. Loja has about 215,000 inhabitants (INEC, 2010) and around 50,000 registered vehicles (INEC, 2014). In its urban area, collection data process included two stages: the calibration and validation. For calibration it collected data in 16 urban streets, while, for validation it collected in 3 urban streets from the same city (see figure 1). Streets from both data collection had two lanes and one direction of traffic circulation, and less than 5% of the longitudinal slope. Also, streets had a speed limit of 50 km/h.

2.2 Data Collection Variables

Two groups of variables were collected: Google traffic information and ground truth data. First, from Google applications (web or mobile app), the colour-coded was recorded. Four colours are available: green = no traffic delay, orange = medium amount of traffic, red = traffic delays and darker red = the slower speed of traffic on the road (Google, 2019). Also, it was collected when the street was closure and when the application did not show any colour. In the ground truth data were collected the traffic flow and vehicles speeds.

2.3 Data Collection Procedure

Data were recorded from 5 January 2019 to 18 January 2019 in the 19 selected streets. Colour-coded was collected manually during the daytime (06h00 to 22h00). It was selected this time range due to the typical traffic information in Google for this city is between those hours. This range also avoids the noise that occurs in low flows that are in the night (Knoop et al., 2018). Traffic flow and vehicle speeds were collected manually in situ in the middle of the street.

Figure 1: Map of the downtown of Loja city (Ecuador) with the studied streets.

Traffic flow was estimated with the collected vehicles in a time interval (mostly 10 minutes). The vehicle speed was estimated from two marks on the pavement (usually 2 meters) and with the time that the vehicle spent passing that marks. All data collection was performed under good weather conditions.

2.4 Data Processing

Speeds of every vehicle were estimated using the ground truth data. It calculated the average speed and traffic flow every 10 minutes. It selected this period time due the Google typical traffic information is given in that range. Density was estimated using calculated speed and flow. The colour-coded was related to those parameters, and their results are shown in a section later.

2.5 Speed Analysis

Google only presents traffic conditions as colour-coded. Exactly it cannot be said what parameters considered in their calculation or what are their thresholds. Speed behaviour patterns were explored using several boxplots, plotting the ground truth speed and the colour-coded traffic indicator, as can be seen in figure 2.

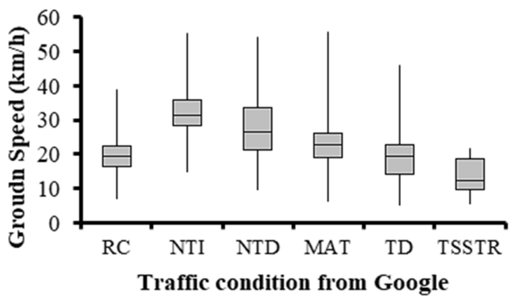

Figure 2: Boxplots of average ground truth speed clustered by several traffic indicators from Google. RC: road closure, NTI: no traffic information, NTD: no traffic delay, MAT: medium amount of traffic, TD: traffic delays, TSSTR: the slower speed of traffic on the road.

Google does not provide any colour when it does not have enough information, or the street is closure; however, in-situ vehicles were circulating in those indicators. So, boxplots also included the indicator of no traffic information and road closure sign. This leaves doubts about the reliability of Google traffic information in this city. However, another study found that Google data can be used for analysing traffic management scenarios and for informing and signalling users on the road, after comparing in-situ speed and Google information in The Netherlands (van den Haak et al., 2018).

Consequently, figure 2 shows that the speed decreases from "no traffic delay" (green colour) to "the slower speed of traffic" (darker red). However, boxplots have a wide range of speeds and the same speed is found in another boxplot. For example, 40 km/h is found in green colour (no traffic delay), orange colour (medium amount of traffic), and red colour (traffic delays). This particularity makes it difficult to calibrate equations, as there are no unique data for each condition. Thus, it analysed the speed-flow-density relationships with the colour-coded indicators. Then, in the next section, its results are shown.

A cluster analysis was performed to get a better understand of Google traffic indicators. Ground truth speed and colour-coded conditions were used in this analysis employing statistical Software R (R Core Team, 2013). Google offers four colours, so in the first analysis was assumed four clusters (>83.5% of similarity) with average linkage and Euclidean distance. It shows its results in table 1.

Table 1: Cluster analysis results between ground truth speeds and colour-coded traffic indicators.

Four clusters analysis				
Cluster	Number of obs.	Similarity (%)	Average speed (km/h)	Speed thresholds (km/h)*
1	158	83.5	44.33	>38
2	330	87.5	31.06	26-38
3	929	89.1	20.70	16-26
4	189	89.8	11.38	<16
Six clusters analysis				
1	21	91.9	51.65	>47
2	137	90.8	43.21	39-47
3	100	93.9	35.37	32-39
4	230	92.4	29.19	25-32
5	929	89.1	20.70	16-25
6	189	89.8	11.38	<16
*Adding or resting half of the average speed difference among clusters.				

An alternative cluster analysis was added to the table 1, considering six clusters (>89.1% of similarity) in analogy to the six levels of service (LOS) from the Highway Capacity Manual for urban streets (TRB, 2010) (see table 2). Also, it used the average linkage and Euclidean distance as parameters for the analysis.

In table 2, clusters from 1 (green = no traffic delay) to 4 or 6 (darker red=the slower speed of traffic on the road). Speed thresholds are calculated adding or resting half or the speed difference among the clusters. For example, the speed difference between cluster 4 and 5 is 8.49 km/h, so half of this is 4.25 km/h, and then lower thresholds will be $29.19-4.25 = 24.9 \approx 25$ km/h. The upper threshold will be calculated using 3 and 4 cluster speeds. According to table 2, streets in this study should be classified as class III or IV, because their speed limit is 50 km/h. According to the four cluster analysis from table 1, the four average speeds do not fit in III or IV class. If the speed thresholds from Table 3 are rearranged, data could fit in class III, for example, A and B (green), C and D (orange), E (red), F (darker red). However, with six clusters, almost every value matches with the thresholds of urban street class III. In this way, Google could offer traffic information in terms of the level of service. Also, it would solve the problem that it found one speed on several levels or colour codes, so it can be used in the practice.

3 RESULTS

Although some traffic indicators from Google have a trend with speed, and it has some relationship with the level of service, there is not clear how this can be used to build a traffic congestion mode from Google.

Table 2: Level of service (LOS) of urban streets.

Urban street class	I	II	III	IV
Speed* (km/h)	90-70	70-55	55-50	55-40
FFS** (km/h)	80	65	50	45
LOS	Average travel speed (km/h)			
A	> 72	> 59	> 50	> 41
B	> 56-72	> 46-59	> 39-50	> 32-41
C	> 40-56	> 33-46	> 28-39	> 23-32
D	> 32-40	> 26-33	> 22-28	> 18-23
E	> 26-32	> 21-26	> 17-22	> 14-18
F	≤ 26	≤ 21	≤ 17	≤ 14
* Range of free-flow speed, ** Typical FFS.				

Therefore, other analyses were conducted to calibrate equations from speed-density-flow variables. After calibrated them, a validation process was performed to evaluate the quality of the developed equations. Those equations will help to build the traffic congestion model.

3.1 Calibration of Equations

Figure 3 plotted density and flow data clustering by Google traffic indicators. Also, a power trend line was also plotted in that figure; in order to compare R-squared with other trend lines. The power curve was chosen due to its consistency when density is zero flow is also zero. Table 3 shows the power curve equations.

The regular shape of the curve of density-flow relationship is an inverted U. In these cases, the data only covers the first part of the curve. When the flow gets higher, also, density gets higher until an inflection point, where the flow starts decreasing when density continues growing. The trends in figure 3 are not close to the inflection point. It is interesting that data slope is getting flattered when is more congested (NDT, MAT, TD, and TSSTR). This trend is consistent with the theory of fundamental diagrams because when it is more congested, adding more vehicles will increase the density more slowly than traffic without delay. NDT, MAT and TD have similar flow data until the density of 20 veh/km. It is also interesting that the highest density in every figure (NDT, MAT, TD, and TSSTR) increases approximately from 20 in 20: green colour is up to 40 veh/km, orange colour is up to 60 veh/km, red colour is up to 80 veh/km and darker red is up to 100 veh/km. The curves in RC and NTI have similar shape than the others even when there is no traffic information or it has the road closure sign.

Secondly, figure 4 plotted density and speed data clustering using the same Google traffic indicators. Furthermore, a linear trend line was plotted according to the fundamental diagram theory. Table 3 also shows these linear equations. The data trends from figure 4 are consistent with the fundamental diagram. Most conditions (NTI, NTD, MAT, TD, and TSSTR) have higher R-squared with exponential or power trend line. However, there is a straight line used in the flow-density relationship, so it selected that regression. The trend line in each indicator has a different slope than the others, similar in figure 3.

Models from table 3 are applicable in the showed range. Equations 8 and 9 have similar parameters, so only one equation can be calibrated. However, in this investigation, the models have been left in their original version, to see the traffic indicators separately. In general, R-squared from density-flow equations is bigger than density-speed models.

3.2 Validation of Calibrated Equations

A validation process was performed to evaluate the quality of the calibrated models from table 3. For this validation, it was collected data from three streets in the same city. These streets had similar characteristics to the ones in the calibration process. Collecting data and data processing was the same than in the calibration process.

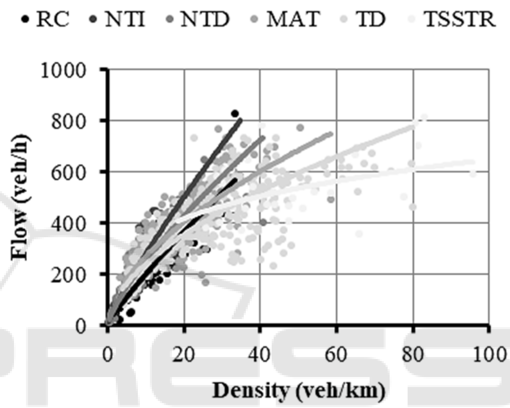

Figure 3: Density and flow data clustered by several traffic indicators from Google. RC: road closure, NTI: no traffic information, NTD: no traffic delay, MAT: medium amount of traffic, TD: traffic delays, TSSTR: the slower speed of traffic on the road.

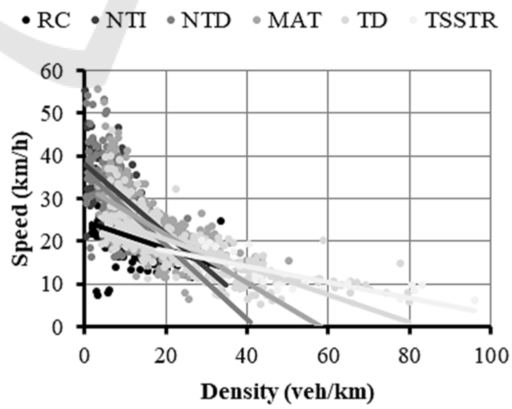

Figure 4: Density and speed data clustered by several traffic conditions from Google. RC: road closure, NTI: no traffic information, NTD: no traffic delay, MAT: medium amount of traffic, TD: traffic delays, TSSTR: the slower speed of traffic on the road.

Table 3: Calibrated equations for density/flow and speed/density for several Google traffic indicators.

Traffic indicator	Colour-coded	Calibrated equation	R^2	#
RC	None	$q = 27{,}25k^{0.87}$	0,83	(1)
NTI	None	$q = 39{,}46k^{0.85}$	0,94	(2)
NTD	Green	$q = 42{,}80k^{0.77}$	0,88	(3)
MAT	Orange	$q = 70{,}65k^{0.58}$	0,64	(4)
TD	Red	$q = 65{,}36k^{0.57}$	0,71	(5)
TSSTR	Darker red	$q = 184{,}14k^{0.27}$	0,29	(6)
RC	None	$s = -0{,}33k + 24{,}77$	0,20	(7)
NTI	None	$s = -0.82k + 38{,}20$	0,45	(8)
NTD	Green	$s = -0{,}87k + 36{,}36$	0,41	(9)
MAT	Orange	$s = -0{,}57k + 32{,}91$	0,42	(10)
TD	Red	$s = -0{,}33k + 26{,}98$	0,57	(11)
TSSTR	Darker red	$s = -0{,}19k + 21{,}71$	0,65	(12)
q = traffic flow (veh/h), k = traffic density (veh/km), s = average speed (km/h), RC: road closure, NTI: no traffic information, NTD: no traffic delay, MAT: medium amount of traffic, TD: traffic delays, TSSTR: the slower speed of traffic on the road.				

The prediction errors were calculated to validate the previous calibrated speed models. Those errors were: mean absolute error (MAE) and mean absolute percentage error (MAPE) (see table 4). An analysis of variance (ANOVA) was carried out to validate the models, determining whether the difference between predicted values (equations) and collected data from validation means are statistically significant. Those values should not differ in a 95% level of confidence. It shows in table 4 the predicted errors and ANOVA results.

Table 4: Calibrated equations for density/flow and speed/density for several Google traffic indicators.

#	MAE*	MAPE (%)	ANOVA	
			95% CI	P value
(1)	-	-	-	-
(2)	-	-	-	-
(3)	2.05	21.17	(8.67; 13.34)	0.138
(4)	4.19	27.01	(14.65; 18.39)	0.057
(5)	7.19	31.68	(21.56; 24.85)	0.050
(6)	-	-	-	-
(7)	-	-	-	-
(8)	-	-	-	-
(9)	5.61	27.68	(20.69; 24.01)	0.051
(10)	4.57	22.41	(20.18; 23.05)	0.011
(11)	2.92	17.11	(18.07; 19.83)	0.409
(12)	-	-	-	-
- Not enough data to validate models, MAE = mean absolute error, MAPE = mean absolute percentage error, 95% CI= confidence interval, * In equations 3-5 MAE is in veh/h and in equations 9-11 is in km/h.				

Table 4 does not have prediction errors or ANOVA analysis for equations 1, 2, 6-8 and 12; because the collected data from the validation process were not enough to do it. The highest density error was 7.19 veh/h, while the highest speed error was 5.61 km/h. Predicted error was away 31.68% and 27.68% from the calibrated values. Despite these high values, the p-value exceeds from the assumed level of significance (α=0.05) in almost all equations. This means that the average predicted values do not differ from the collected validation ones; in consequence, those models are valid. However, caution is suggested in equations 5 and 9, because they are close to that level of significance.

4 CONCLUSIONS

The aim of this article was to calibrate equations for the colour-coded traffic indicators provided by Google using ground truth data. After analysing the results, it presents the following conclusions:

Colour-coded from Google have a reasonable trend with the ground truth speeds. However, their data dispersion makes it difficult to calibrate equations. Therefore, a new analysis was conducted with variables from fundamental diagrams (speed-flow-density) and the colour-code traffic indicators. In the density-flow analysis, data were consistent with the theory of traffic engineering and equations were calibrated using the power curve. Data were also consistent in the density-speed analysis, and calibrated some linear models. The density-speed models have lower R-squared values than the density-flow models, so it recommended taking caution when using. Those models were validated using prediction errors and ANOVA analysis.

After the cluster analysis of average speed ground truth and traffic indicators from Google, their relationships are unclear. The HCM has 6 LOS, and Google offers 4 levels (four colours). However, if it is divided the speed data into six levels, Google could offer the information in terms of the level of service, considering the average speed thresholds approximately fits in the urban street LOS. An advantage of this arrangement is that a speed range will belong to a particular LOS and therefore to a single colour. In contrast, in Google traffic information, the same speed range belongs to several colour-coded indicators. This information will be helpful for cities that want to build a low-cost traffic congestion model.

This study has a number of limitations. First, it performed collection data in just one city, which probably will not have the same urban environments than in others. Also, the urban streets have a speed limit of 50 km/h, have two lanes, one direction, and are flat. Additionally, this study starts from the assumption that the data in the middle of the tangent belong to the whole street, while other elements should consider when approaching or exiting from the intersection. Furthermore, the calibrated equations are valid in a specific range, so they should not use out of those ranges.

Despite these limitations, the present study helps to understand the use of Google traffic indicators in urban streets, offering useful information for urban planners and street designers. It showed the relationship between LOS and the average speed ground truth. It showed that when Google does not provide colour or in a road closure sign, real traffic was circulating through those streets. Also, based on the growth of smartphone use, Internet access, and the number of Google active users, the calibrated equations can be used by other cities to create their traffic model. This methodology could employ in other places or help to develop ITS.

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