IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received October 17, 2020, accepted October 21, 2020, date of publication October 26, 2020, date of current version November 9, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3033518

Urban Traffic Flow Mapping of an Andean Capital: Quito, Ecuador

MARIO SALVADOR GONZÁLEZ-RODRÍGUEZ[1], JEAN-MICHEL CLAIRAND[1], (Member, IEEE), KEVIN SOTO-ESPINOSA[1], JOSUÉ JARAMILLO-FUELANTALA[1], AND GUILLERMO ESCRIVÁ-ESCRIVÁ[2]

[1]Facultad de Ingeniería y Ciencias Aplicadas, Universidad de las Américas, Quito 170122, Ecuador
[2]Institute for Energy Engineering, Universitat Politècnica de València, 46022 Valencia, Spain

Corresponding author: Jean-Michel Clairand (jean.clairand@udla.edu.ec)

This work was supported in part by the Universidad de Las Américas, Quito, Ecuador, under Project SIS.JCG.19.03 and Project SIS.MGR.20.01, and in part by the CYTED Network Ibero-American Thematic Network on ICT Applications for Smart Cities under Grant 518RT0559.

ABSTRACT Several efforts have been devoted to developing sustainable cities to address global environmental challenges and the growth of urban areas. In particular, transportation has various issues such as air pollution, noise, and traffic, which have to be addressed by collecting significant information of the traffic and road conditions of the cities. Automating the data extraction process and street network construction will allow building more useful models to study traffic behavior. This work presents a network modeling approach to identify interest points (extreme and internal) of the city, through a winner-takes-all edge trimming, and mapping the traffic flow between them. Such points can be considered as entries of an Origin-Destination matrix, where such information can be used to model traffic behavior between interest points. The case study of Quito, Ecuador is considered. Besides, to address environmental issues, this paper encourages the replacement of internal combustion taxis with electric vehicles. From the understanding of the vehicle traffic behavior, a pre-feasibility siting of electric taxi (ET) charging stations was carried out. The results will allow performing the sizing of each charging station considering electric power network constraints. This work aims to ensure a sustainable transportation system based on this crucial information.

INDEX TERMS Charging station, driving time and distance, electric vehicle, graph trimming, urban traffic network.

I. INTRODUCTION

Recently, sustainable cities have gained much attention among urban scholars, planners, and policymakers, in different fields of engineering [1], [2]. This includes the development of new strategies for sustainable transportation systems. So far, large cities inhabitants experience issues such as the time spent in traffic, and adverse health effects due to pollution and noise from congested traffic conditions, and pressure from urban population growth [3], [4]. Thus, the main sustainable transportation goal and challenge is to relieve congestion and pollution for urban mobility [5]–[7].

As the population and the automobile use increase considerably, traffic flows and the congestion have become a major problem that every nation in the world is facing. Main roads connect to the city downtown with smaller roads triggering traffic disruption. Drivers are forced to slow down and stop, leading to stopping and going waves and sometimes to the traffic stoppage. The resulting jams are obviously unfavorable to safety and increase costs for both citizens in form of fuel and time and likewise for the general well-being of the city inhabitants [8]. Moreover, in zones of traffic stoppage, pollution grows considerably resulting in health issues for the people living around.

These challenges can be addressed by implementing new transportation policies. Many governments have imposed restrictions on car owners based on the license plate number, which leads to the alleviation of traffic congestion and cleaner air. However, this kind of strategies induces car owners' discomfort and to the purchase of more cars [9], [10]. Hence, new strategies should be proposed [11]. Urban transportation infrastructure is subject to constant changes, and it is necessary to optimize the newly available resources.

The associate editor coordinating the review of this manuscript and approving it for publication was Feng Xia.

In terms of local pollution, electric vehicles (EVs) have gained much attention these last years to mitigate environmental issues [12]. EVs have cradle-to-grave environmental impacts, especially due to the use of lithium batteries, which are heavily toxic in their production phase. Despite this, they do not pollute locally, they are much more efficient than internal combustion vehicles (ICVs). Moreover, although EVs transfer in a certain way the pollution from urban areas to the electricity generation areas, it should be highlighted that EVs can reduce CO_2 emissions with most of the generation mix scenarios. Only with the electricity generated from just coal plants, the well-to-wheel CO_2 emissions of EVs are similar to that of ICVs [13].

However, the purchase cost of EVs is much higher than ICVs, but they are profitable in the long-term, due to lower maintenance and energy costs, and especially if the driven kilometers are high. In the transportation fleet, taxis represent a significant part, which could be appropriate candidates to switch from gasoline to electric.

To ensure access to high-quality transport services in cities requires some strategies and technological improvements, as well as a deeper understanding of travel behavior. Although ETs seem a proper solution to mitigate environmental concerns, several challenges exist for their adoption. Several charging spots have to be installed to support the charging of ETs. For example, in New York, the public charging stations are far from be sufficient to charge the ETs based on their charging requirements [14]. In particular, taxis are driving all day, and not only for small trips, thus, their electricity charging demand is much higher and have to be supplied in quick times due to taxi drivers' schedules [15].

To propose the electrification of taxis, additional needs must be met, such as the location of charging stations, and other relevant strategies for sustainable transportation, such as traffic conditions. Significant efforts have been done in transportation, science to access sensitive and crucial information that helps to manage transportation systems and power consumption efficiently [16].

This paper models the city as a street network interest points (nodes) connected by streets (arcs). Two types of interest points have been identified, on the one had extreme points, which give information on how traversing the cardinal points of Quito city. And on the other hand, internal points of the city which could be used as charging hubs for EVs. The traffic level at and between the interest points is mapped in this work and could be considered as entries of an origin-destination matrix.

The innovative contributions of this paper are highlighted as follows:

- A proper traffic flow network is built of an Andean city based on actual data, with automated geographical network construction and traffic information extraction.
- Identification of interest points (extreme and internal) in the city street network using a winner-takes all edge trimming approach.
- Interest points grouping by geographical proximity and driving time traffic flow mapping between them, as well as, in and out flows.
- This paper is useful as a guideline looking for optimal traffic management, namely building the traffic input for siting of ET stations, or urban policy making.

II. RELATED WORKS

Related work of this paper is divided into two parts. Firstly, an overview of the principal works of urban traffic modeling is described. Then, some works of the location of ET charging stations are presented.

A. URBAN TRAFFIC MODELING

In order to implement appropriate urban traffic policies, i.e. traffic information for deploying ET charging stations, a model of traffic conditions around the city is fundamental [17], [18]. Vehicle traffic modeling has been approached through different methodologies and techniques. Models have in common an underlying structure for the city streets, mainly a grid network, and a traffic flow estimation along with the network. An agent-based model generating trips in a grid-based urban area that mimics realistic travel profiles was carried out in [19]. In [20], the authors deal with an agent-based model of Zurich urban road network, where the traffic density, flow and outflow were estimated according to the Macroscopic Fundamental Diagram. The work of [21] models the equilibrium flow distribution across a road network with EV drivers moving between their origins and destinations, are given with optimal routes and battery recharging plans. The authors in [22], [23] takes into account factors such as driving ranges, real-time traffic conditions, available in-station batteries and real-time sensors information to optimize battery swapping for ETs. Another area of research is modeling the complexity of the city network. For instances in [24], a spatial attraction mechanism, together with matching growth is proposed, to simulate city growth and reveal the hidden spatial scaling relations between different city elements. The authors of [25] proposed a population-weighted efficiency indicator, which tells how efficient the city is and provides a quantitative measurement to guide transportation infrastructure development. Understanding urban traffic is necessary for electric mobility as well as for urban planning, in this sense, many efforts have been developed to understand, predict and visualize traffic behavior in smart cities [26]–[28].

The present paper, models a traffic network structure reducing the street grid into interest points, resulting in a trimming process accompanied by the extraction of the driving distance and time information to model the traffic flow between interest points.

B. SITING ET CHARGING STATIONS

The siting or placement of charging stations is a crucial task since if it is not done properly, power system problems could occur such as voltage drops and fluctuations, and the

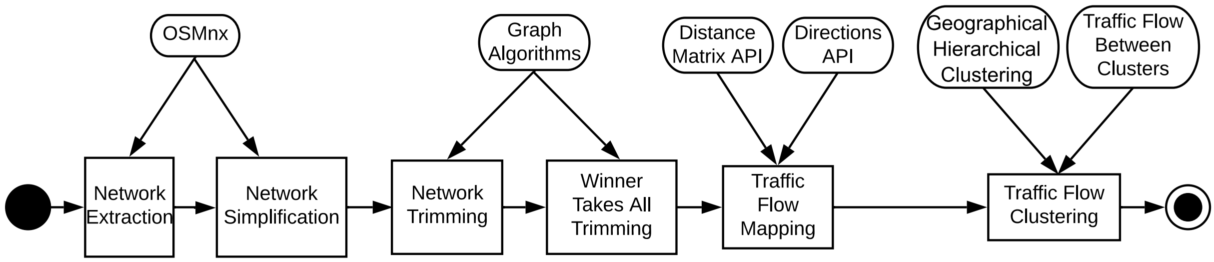


FIGURE 1. **Schematic representation of traffic mapping and clustering process.**

acceptance of drivers. Thus, various works have proposed the siting of ET charging stations [29], [30]. For example, a decision support system for the siting of ET charging stations is studied at [31]. The goal is to maximize the satisfaction of charging demand for ET drivers based on 800 data from Wien on taxi cars. Likewise, the work of [32] provides an optimal location for charging stations using a multi-agent systems simulation framework to simulate the PETs' daily operation in real life such as cruising, picking up passengers, and charging. Pan *et al.* [33] authors discuss the installation of charging stations that take the impact of travelers, taxi drivers, electricity distributors, transport networks, distributors, and electricity users into account. Multi-target optimization is proposed to solve the proposed model. In [34], an optimal planning of charging stations is studied considering distribution systems constraints. However, most of these approaches have not considered spatial-temporal demand coverage approaches. To address this, in [35], an optimization approach was considered for the siting of ET charging stations considering the spatial-temporal demand coverage. The data from Shenzhen, China was used to demonstrate the effectiveness of the approach. The authors of [36] presented the location problem of ET charging stations considering stochastic dynamic itinerary, by minimizing pickup requests and passenger travel times. In [37], the development of the charging demand of ETs is used for the optimal construction planning of ET charging stations. The authors of [38] propose an optimal location of public charging stations using real-world vehicle travel patterns.

Although all these works present optimal location of ET charging stations especially in terms of costs, subject to various constraints, they could be not realistic in terms of transportation logistics, or not applicable to every city. In particular, to stimulate the purchase of EVs for taxi drivers, some facilities in terms of charging have to be performed, thus considering their schedule and traffic conditions.

III. METHODOLOGY: URBAN TRAFFIC FLOW MAPPING AND CLUSTERING

This section describes the process used to map the traffic flow between interest points in the city area of Quito. All the process was automated from extracting the city as a graph to the selection of extreme nodes that traverse the city. First, the network (graph) of the city was extracted. The street network is extracted for a window region of a given area of the city, where a center and a side squared in kilometers are specified. Then a simplification process was carried out to reduce the number of nodes in city graph. The network was also trimmed according the length of the streets (edges) connecting the nodes in the city graph. Once the final nodes, that is, the extreme point of interest in the city area were identified, a fully connected network is built according to the distance between points, and then trimmed according the maximum distance between points, to get a traversal map of points of the city. A winner-takes-all edge trimming approach is carried out to identify the extreme points for the given region, based on the driving distance of the the length of the cumulative streets connecting points. Once, the extreme points are identified, the traffic flow in driving time between them is requested to the Google Distance Matrix API [39]. The extracted data consists of rows containing the "real-time" driving duration and distance values for each pair of extreme points identified as returned by the live traffic from the API.

This strategy is also used to map inner points in the city by reducing the selected window region. The inner points and the ingoing and outgoing traffic for each of them is mapped. The points of minimum traffic flow are identified and are selected as pre-feasibility sites for ET charging stations. A hierarchical clustering analysis based in the Euclidean distance is carried out to identified groups of points, according to their geographical location. The traffic flow is them mapped between groups, to describe the traffic for the extreme points of the city. Finally, the traffic flow between clusters of interest points (extreme and internal) is calculated to illustrate the times for traversing the city of Quito. A schematic representation of the process steps and the main libraries used are depicted in Fig. 1. The detailed process is explained in the next subsections.

A. NETWORK EXTRACTION

The network of the city was extracted according the following steps:

S.1 **Network extraction:** The street network of the city can be extracted with OSMnx [40], which is a tool for collecting data and creation of street networks to analyse them from the perspective of graph theory [41]. Such networks are useful for urban transportation and urban

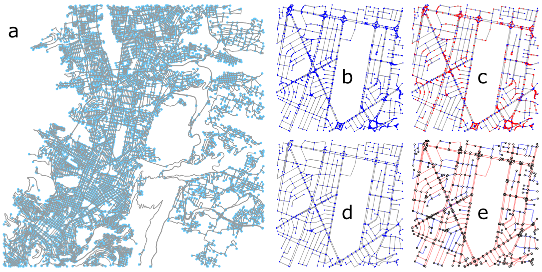


FIGURE 2. (a) Extracted network of the city area of Quito; (b) detail of Quito downtown with all identified nodes; (c) simplification of the network, highlighted nodes in red color will be removed; (d) simplified city network; (e) simplified city network with highlighted main avenues in red.

design studies. The street network can be defined as a graph which is a tuple $G = (V, E)$, where $v_i \in V$; $i = 1, \ldots, n$, is the nodes set belonging to the street network, and $E \subseteq \{\{v_i, v_j\}|(v_i, v_j) \in V^2 \wedge i \neq j\}$, is the set of edges connecting nodes i and j. An edge is a tuple (v_i, v_j), direction is implied in this tuple where the connection goes from v_i to v_j. The nodes in the network are interest points (mainly the corners) of the city and the edges are the streets connecting the corners. The street network is a directed and weighted graph, where the edge weights are the distance between nodes. OSMnx returns the big avenues and highways to be conformed by a series of nodes connected between them. The resulting network is a multigraph, which is a graph in which multiple edges are allowed or needed between nodes. OSMnx also, gives information about the extracted urban network, such as total street length, average street length, number of intersections, to mention a few. See Fig 2 for reference.

S.2 **Network simplification:** OSMnx allows to simplify the network extracted in the step S.1, given that the original network might be too large, which will make it computationally complex to deal with. After the extraction of the network, a simplification process is carried out. OSMnx allows joining all the nodes that are part of a path between intersections, removing them from the network, but adding their weight to a single connection that use intersections as endpoints to keep the correct distance and all additional information between nodes. After the simplification process, a street network is returned with unique connections that are created with the accumulated distance of all nodes corresponding to a simplified path. These final connections are composed of an OSM ID, the "from" and "to" nodes information, and the distance between them. The simplified street network ($G = (V, E)$), can be represented as the weighted adjacency matrix $\mathbf{J}$ and it can be expressed as the element wise product $\mathbf{J} = C \circ \mathbf{D} = J_{ij} = C_{ij} \cdot D_{ij}$ with the connectivity (topology) matrix $\mathbf{C}$ where $C_{ij} = 1$, if a connection between node i and j exists, and $C_{ij} = 0$ otherwise; and the driving distance matrix $\mathbf{D}$ [39], with $D_{ij} = d_{ij}$, where d_{ij} is the distance (weight) from node i to node j. The driving distances are not symmetrical ($D_{ij} \neq D_{ji}$) and self connections are not allowed ($C_{ij} = 0$, for $i = j$). See Fig 2 for reference.

S.3 **Network trimming by edge distance:** Once the simplified street network ($\mathbf{J}$) is obtained (as described in step S.2), the network is trimmed according the distance D_{ij} between nodes. The goal of the trimming process is to extract interest nodes of the network which are extremes points in the city, as well as, the distance between them. The nodes and edges in the network are removed according the following criteria $C_{ij} = 0$ for $D_{ij} < \theta$. This process removes the connection between nodes i and j for which the value of D_{ij} is lower than a given θ value. Here, θ corresponds to a trimming threshold, which can be expressed as the percentile value for which the distance allows to keep a given proportion of the network connections. Unconnected nodes are removed from the trimmed network. The nodes with a lower distance between them are removed from the trimmed network, keeping mainly the edges belonging to main avenues and large streets that interconnect the city, the points interconnected by such streets and avenues are the extreme points to traverse the city. See Fig. 3 for the resulting trimmed network.

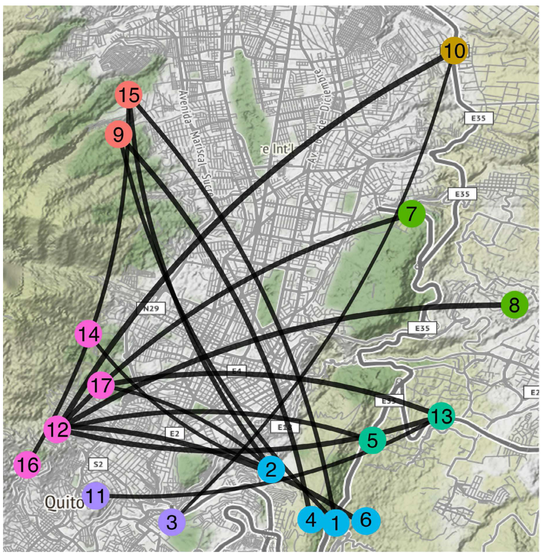


FIGURE 3. Extreme points network for the city area of Quito and corresponding clusters.

S.4 **Winner-takes-all distance trimming:** From the extreme points, identified after the trimming performed in step S.3, a fully connected network is built: $C_{ij} = 1, \ \forall \ ij$. Again self connections are excluded and the distance matrix $\mathbf{D}$ is not symmetric. The extreme points fully connected network is then trimmed according to the maximum distance connecting two nodes: $C_{ij} = 1$ for $max[max(D_{ij}, D_{ji}) \ \text{ for } j \in k(i)]$. The only connection that is kept for every node i is the maximum distance connected node in its neighborhood $k(i)$. The maximum distance corresponds to the weight connection between the nodes. All other connections are removed from the neighborhood in a winner-takes-all approach. Following the aforementioned trimming criteria, the network connections are considered to be undirected. The resulting network connects the extreme points and can be used to identified the time to traverse the city. See Fig. 3 for the resulting extreme points network.

B. TRAFFIC FLOW EXTRACTION

Once the network has been extracted, it is necessary to get the information on the traffic flow. The Distance Matrix API [39] is used to get real-time data of the traffic from one point to its connected neighbors. This is a service supplied by Google that provides the travel distance and time based on the recommended driving route between two points. The information is provided by the service in JSON format. To make the requests, the start and end points that are used, corresponds to the origin and destination nodes and every connection present in the final network described in the last subsection III-A. The request can be done, to the Google Distance Matrix API, giving a time interval. Each register, for the traffic flows, records the data with the following structure: *from(latitude, longitude)*, *to(latitude, longitude)*, *mean_time*, *mean_distance*, *time_stamp*. Such data can be used as it is registered, or summarized according a clustering analysis described as follows.

C. SITES CLUSTERING AND TRAFFIC FLOW MAPPING

The identified sites (extreme points) in subsection III-A can be grouped according to their geographical proximity. Near sites will be grouped together, reducing the dimension of the traffic flow network and summarizing driving mean times between cardinal directions of a city. The coordinates information is projected using the World Geodetic System (WGS84), The projected coordinates are then Standardized, as distance based clustering techniques are sensitive to the scale of the variables. A hierarchical clustering is performed using euclidean distance affinity $d_{ij} = \sqrt{\delta_{ij}^X + \delta_{ij}^Y}$ with $\delta_{ij}^X = (X_i - X_j)^2$, $\delta_{ij}^Y = (Y_i - Y_j)^2$; and Ward linkage [42].

The euclidean metric corresponds to the straight-line distance between two points, and is used to build the distance matrix for the clustering technique that uses Ward linkage as a criterion to merge clusters hierarchically.

Ward linkage uses the following objective function recursively to decide if clusters C_i and C_j will merge, $d(C_i \cup C_j, C_k) = \alpha_i d(C_i, C_k) + \alpha_j d(C_j, C_k) + \beta d(C_i, C_j)$, with $\alpha_i = \frac{n_i+n_k}{n_i+n_j+n_k}$, $\alpha_j = \frac{n_j+n_k}{n_i+n_j+n_k}$ and $\beta = \frac{-n_k}{n_i+n_j+n_k}$, for disjoint clusters C_i, C_j, and C_k with sizes n_i, n_j, and n_k respectively. The merge, $C_i \cup C_j$, occurs for the minimum $d(C_i \cup C_j, C_k)$. Once the clusters have been identified, the information from the traffic flow data can be summarised (i.e. averaged) over the clusters inter-connectivity. This is carried out by comparing the origin and destination clusters of the edges and averaging time between the edges connecting nodes belonging to clustered sites.

IV. CASE STUDY: QUITO - ECUADOR

A. TRANSPORTATION SYSTEM INFORMATION

The case study of Quito is particular for different reasons. Quito is the capital of Ecuador, and it is situated in the Andean region at 2,800 altitude meters. Due to high altitude, the combustion in the vehicles is very inefficient, which creates major pollution concerns [43]. Furthermore, Quito has an area of 372.39 km^2, and is 40 km long and 5 km at its widest, most of the important avenues of the city extending from north to south. Since Quito is an Andean city, its relief is uneven, which creates heavy traffic, especially at peak hours. This is the main problem that causes dissatisfaction in citizens due to lost time in traffic, pollution, and noise [44]. Thus, the main duties of majors are to develop solutions to traffic issues. One solution could be to provide proper public transportation, which so far is not proper. Buses and taxis are the main sources of traffic, and thus noise and pollution. To this end, it is crucial to know the traffic conditions of the city and propose guidelines for clean transportation. Proper location of public charging stations for taxis could encourage taxi companies to purchase EVs, so this work gives some insights into the location of public charging stations.

In Quito, like in many cities, taxi services are heavily regulated. In particular, taxi drivers need to validate the regulation process, where they have to satisfy different requirements [45]. Therefore the municipality of Quito determines the number of taxi licenses based on those conditions. Nowadays, there are 12,000 taxi vehicles in the city. The actual major of Quito is promoting the introduction of ETs and electric buses to mitigate pollution issues. For this purpose, 35 ETs have already been purchased by taxi companies. Due to political and social uncertainties, it is not possible to know the number of ETs that will be purchased in the future, so the location of charging stations will be determined by priorities.

B. DATA AND ASSUMPTIONS FOR LOCATIONS OF ET CHARGING STATIONS

This work proposes candidate places for public slow charging stations for ETs. Based on Quito taxi drivers' schedules, it is considered that drivers have to charge their ET at home at night. This will allow providing enough energy for almost all the next day. During daytime, it is expected that public slow charging stations will allow ETs to provide an additional amount of energy in a few hours to avoid range anxiety. This solution is found better than fast charging stations due to the power system and cost constraints.

Based on a previous work that considers the GPS travel patterns of various taxi drivers, it was found that the vehicle is stopped during lunchtime, dinner time, and most of them during all night [46]. Typically, taxi vehicle owners park their cars at home when it is not in use. Considering the shift from gasoline to electric, it is necessary that taxi owners install a residential charging spot. However, taxi drivers drive typically more than 150 km per day, so they can suffer range anxiety, which is the fear that the vehicle has insufficient range to reach the destination. Hence, it is necessary to install public ET charging stations to promote the purchase of ETs.

The different assumptions are considered for the siting of the ET charging stations:

- The taxi drivers start or finish their main trips in the selected interest points, both internal and extreme.
- In zones with significant traffic, charging stations should be installed at the internal points, to avoid more traffic congestion of taxis for finding the charging stations.
- In zones with low traffic, charging stations should be installed in the middle of the nodes (centroids of the internal points clusters).
- Charging stations should be installed close to interest places, e.g: malls, gas stations, parking in commercial or working places [47]. This information could be added to future mappings and could be requested to the google places API.

In zones with high traffic, for the driver's convenience, it is suitable to install charging stations at the beginning of the nodes to avoid losing time in traffic. In zones with low traffic, there is no more the time constraint for the driver's convenience, so to minimize the number of charging stations to install, it could be useful to assume the location in the centroid of the identified nodes.

The process followed for identifying the extreme points in the city of Quito can be replicated for smaller regions of the city in order to identify inner points of interest. Fig. 6 depicts the result of the process for three regions: north with (latitude, longitude) = (−0.115573, −78.487634) and an area of 4 kilometers squared; center (latitude, longitude) = (−0.162812, −78.483310) with an area of 3 kilometers squared; and south (latitude, longitude) = (−0.202488, −78.491241) with an area of 3 kilometers squared.

V. RESULTS AND DISCUSSION

A. TRAFFIC NETWORK FLOW OF QUITO

Fig. 2 shows the network of Quito and the simplification process performed by the OSMnx library. Fig. 2 (a), corresponds to the city area of Quito, including the satellite cities, mainly the valleys of Cumbaya at the east and the Sangolqui at the southeast. The extracted network comes from a region window of size 12 kilometers squared, with a central point in the reference coordinate (latitude = −0.181100, longitude = −78.478611) for the Quito city. The street network is composed of 31273 nodes, and after simplification the street networks contains 9470 nodes, that is 21803 nodes were removed. The simplification process is depicted schematically in panels (b), (c), (d) and (e), for a zoomed portion of the city network. Panel (b) shows all extracted nodes in blue, the network simplification will remove all red nodes depicted in panel (c). The final result corresponds to the city network depicted in panel (d). For comparison, panel (d) shows a diluted street network compared with panel (b), that is the density of blue points (nodes) is lower, due to the removal of intermediate points and the path joining process described in the methodology (see subsection III-A). Finally, panel (d) highlights the important avenues (red) from small streets (blue) in the simplified network.

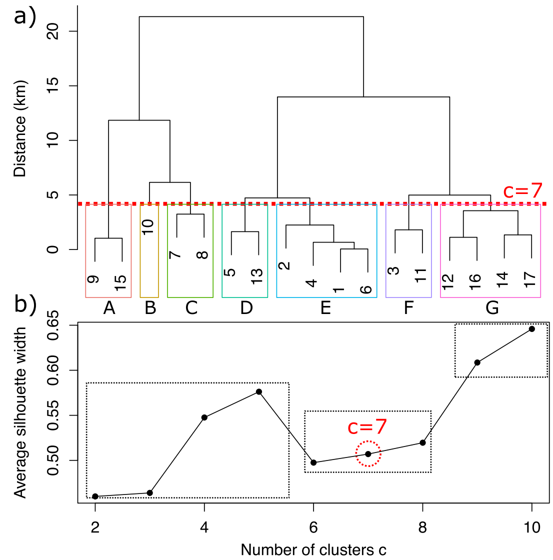


FIGURE 4. (a) Dendrogram of the extreme points with cluster labels; (b) average silhouette width for different number of clusters.

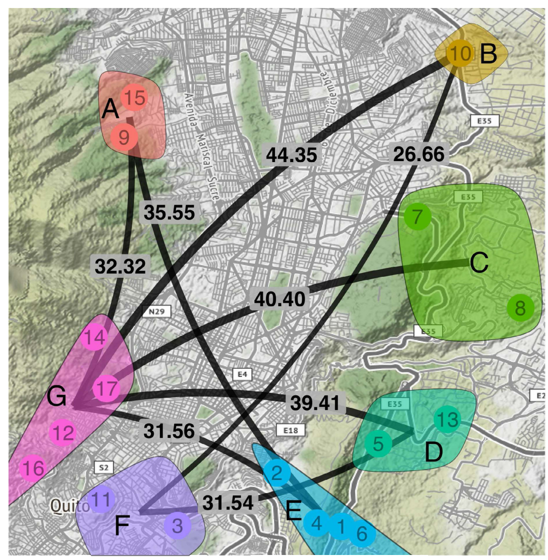
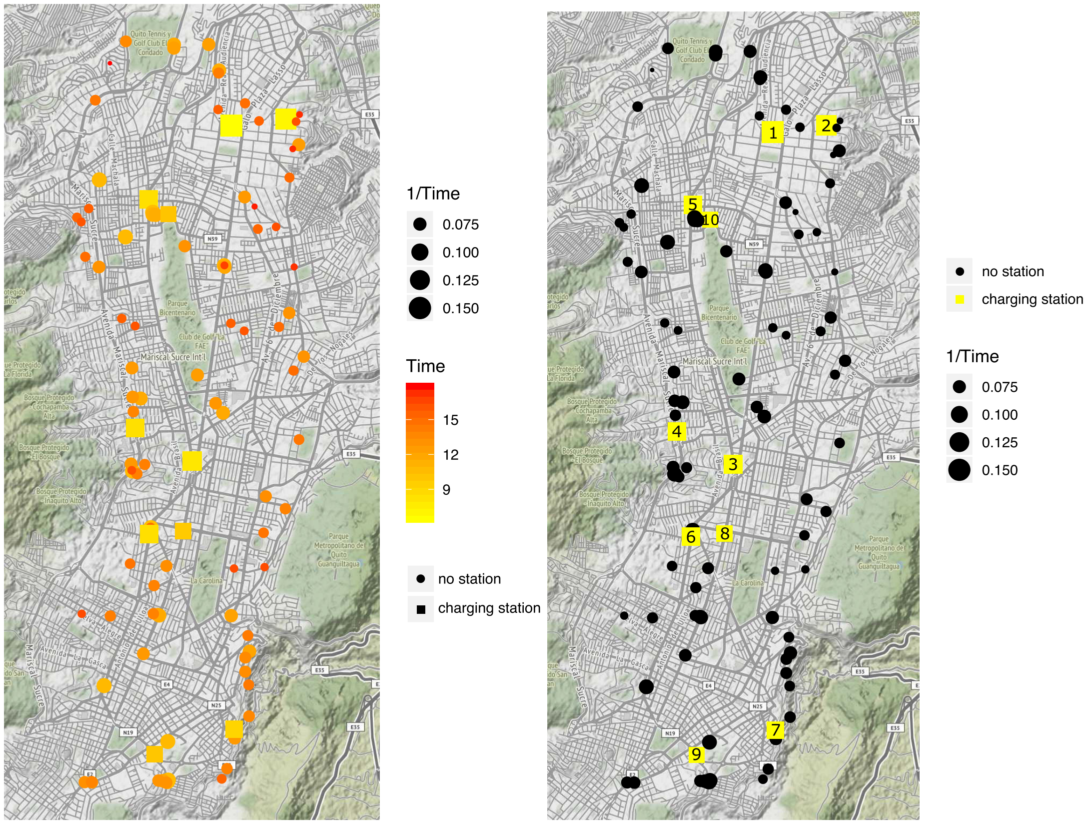


FIGURE 5. Traffic flow between clusters (named from A to G) and mean time between clusters in minutes.

The city of Quito, as the majority of cities, is composed mainly of small streets, which means that the simplification result still implies a large street network. For this reason, a further simplification is necessary. From the street network which is a weighted graph, a trimming threshold θ for the edge (street) distances was used. The value of θ used corresponds to the 97th percentile, that is, only the edges with larger 3% distances were kept in the network. The final



(a) (b)

FIGURE 6. Prefeasibility siting of ET Charging station for points of minimum traffic flow in minutes: (a) Identified points of interest in the network; (b) Ten stations with lower driving time flow and the rest of the nodes.

result of this trimming process is depicted in Fig. 3. The aforementioned trimming process allowed to identified the extreme points in the city, corresponding to the 17 nodes depicted in Fig. 3.

Once, the 17 extreme points have been identified, a fully connected network is built, connecting every node to the other 16 nodes available (no self connections are allowed). The edges weights corresponds to the distance (D_{ij}) between every pair of nodes (i, j). Then an edge trimming is carried out, from the fully connected neighborhood $(k(i))$ of every node i the longest neighbor is identified, that is the neighbor j with a maximum distance from node i: $max[max(D_{ij}, D_{ji}) \text{ for } j \in k(i)]$. This is the only connection that is kept for node i with its corresponding weight. Note that the connections between pairs of nodes are not symmetric, and the maximum between the outgoing D_{ij} and ingoing D_{ij} distance is returned, for all the the neighborhood, in a winner-takes-all fashion. The directions are kept, resulting in a directed network. This is reflected in Fig. 3, where the winner-takes-all trimming process, results in the 16 edges, depicted in the figure. Note that the resulting edges are considered to be undirected, that is ingoing and outgoing time and distances are considered the same, as obtained with the winner takes all approach explained above.

The network in Fig. 3, represents the extreme points in the city area of Quito, and the edges contain information of the mean driving time and mean driving distance necessary to traverse the city of Quito. To obtain the driving distance and time, requests to the Google Distance API were made every 20 minutes, every day, during a week. The average results for the extreme points network in Fig. 3 are shown in Table 1.

It is worth noting that other algorithms can be used to extract the extreme points network, for instance, the maximum spanning tree algorithm. For the case study of the city of Quito the winner-takes-all trimming approach was adopted, given that the resulting network connections were more diverse, between cardinal points. Although a connected extreme points network resulted from the winner-takes-all approach, this was not a necessary condition for the intended analysis, as it is for the resulting maximum spanning tree, and again the more diverse connectivity of the former was preferred.

A hierarchical clustering technique was used to identify clusters of nodes according to the geographical euclidean distance between points. Once the distance matrix is calculated for every pair of points, hierarchical clustering is performed using euclidean distance affinity and Ward linkage.

TABLE 1. Mean time and distance between extreme points in the city of Quito.

from	to	mean time (min)	mean distance (km)	mean speed (km/h)
1	15	34.17	23.36	41.02
2	17	30.54	10.36	20.35
4	9	38.76	24.10	37.31
5	12	36.56	20.89	34.28
6	12	38.96	24.66	37.99
7	12	38.01	24.43	38.56
8	12	42.79	23.65	33.17
9	1	32.93	21.63	39.42
10	12	44.35	26.26	35.53
11	13	31.54	18.74	35.65
12	13	40.46	21.31	31.60
13	17	40.15	16.78	25.07
14	2	28.38	14.12	29.85
15	2	36.36	21.35	35.23
16	15	32.32	18.54	34.41

The corresponding dendrogram for $c = 7$ clusters is depicted in Fig. 4 (a) and the average silhouette width for $c = \{2, \ldots, 10\}$ clusters is shown in the bottom panel. Three regions can be identified in the silhouette plot in Fig. 4 (b); the average silhouette width increases up to $c = 5$ clusters, which is desirable, a second region, for $c = 6$ to $c = 8$, where average silhouette width goes down, and then starts increasing from $c = 9$ and up. One can identified $c = 5$ clusters as optimal, but that would imply joining clusters E-D and clusters F-G. For $c = 7$ a better distribution of clusters is found for the geographical characteristics of the city of Quito. For larger $c = 9$ or $c = 10$ the average silhouette width is larger, but this is expected since each cluster will end up with a lower number of nodes, and average silhouette width will go up to the extreme case in which each cluster will have only one observation (node).

The clustering decisions are justified, given that for small datasets hierarchical clustering works especially well and the computational cost of the agglomerative methods is not an issue when using small data [48].

Finding the optimal number of clusters could be an involved task, in particular for this work, the average silhouette method was used to identify the behavior observed in Fig. 4, and decide the number of clusters. The silhouette measures the similarity of an object with those who belong to its cluster (cohesion) compared to other clusters (separation). The silhouette range ranges from -1 to $+1$, with a high value indicating a good object match to its cluster and poor match to other clusters. One should select the number of clusters that maximizes the average silhouette width [49]. The quantitative average silhouette width was used together with the qualitative visual inspection of the city map, to identify suitable clusters for both the external and internal points of Quito.

The traffic flow in terms of the driving distance and time extracted for the network in Fig. 3 and Table 1 can be summarized for the clusters depicted in Fig. 5. Fig. 5 depicts the seven clusters identified, which are named with letters from A to G, and the flow is expressed as the

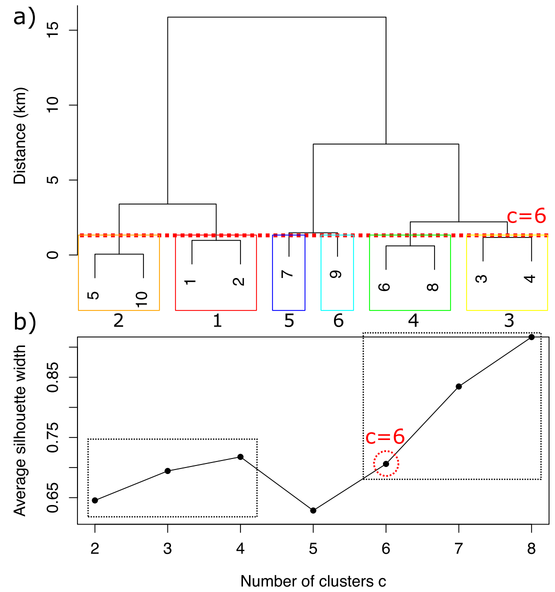
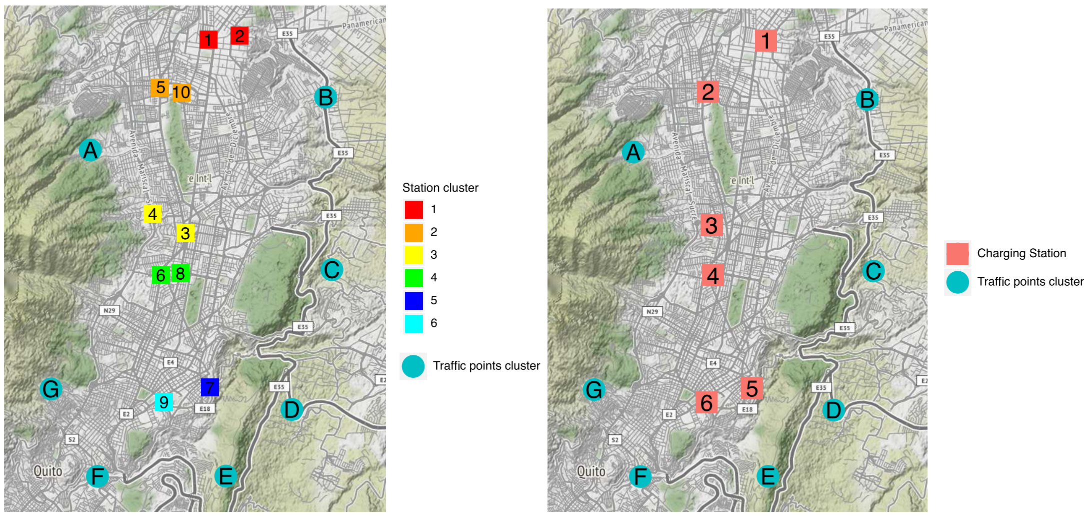


FIGURE 7. (a) Inner points dendrogram with cluster labels; (b) average silhouette width for different number of clusters.

mean driving time between clusters. Table 2 summarizes the meantime, mean distance, and mean speed between clusters. The nodes belonging to a cluster are represented with the same color. For instance, cluster A is represented in red color, and nodes 9 and 15 corresponds to it. Cluster B is composed of only node 10, represented in yellow. Cluster C of nodes 7 and 8 with green colors, and so on. The flow is considered to be symmetrical, that is ingoing and outgoing connections between a pair of clusters are summarized together. the centroids of the clusters (mean values in latitude and longitude), are the origin and final points of the connections. The flow corresponds to the meantime for going from one cluster to another, according to the edges shown in Fig. 3. As an example, the flow (meantime) between cluster C and G is calculated from the edges connecting nodes belonging to cluster C (nodes 7 and 8) with nodes belonging to cluster G (nodes 12, 14, 16, and 17). According to Table 1 (and Fig. 3), two connections exist between clusters C and G, corresponding to edges (7, 12) and (8, 12) with mean times 38.01 and 42.79 respectively. Averaging these values, the flow between clusters C and G is obtained as $\text{mean\_time}(C, G) = \langle 38.01, 42.79 \rangle = 40.40$. This is the mean time between clusters C and G represented in Fig. 5. The flow between clusters provides information on how much time it takes to traverse the city of Quito. For instance, one can appreciate that going from the northwest extreme (cluster A) of the city to the southeast (cluster E) takes around 35.55 minutes on average. Getting to the valley area of Cumbaya (cluster C) from the south part of the city (cluster F) takes 31.54 minutes on average and traversing the city from north to south (B to F) or vice-versa takes 26.66 minutes on average. This last driving time is reduced greatly due to the

TABLE 2. Mean time and distance between clusters in the city of Quito.

from cluster	to cluster	mean time (min)	mean distance (km)	mean speed (km/h)
A	E	35.55	22.61	38.16
A	G	32.32	18.54	34.41
B	F	26.66	23.69	53.32
B	G	44.35	26.26	35.53
C	G	40.40	24.04	35.70
D	F	31.54	18.74	35.65
D	G	39.06	19.66	30.20
E	G	32.62	16.38	30.12



(a)

(b)

FIGURE 8. Prefeasibility siting of ET Charging station by clustering: (a) minimum traffic flow charging points; (b) centroids for each of the six charging stations clusters identified.

existence of the highway Simón Bolívar that connects both extremes of the city.

B. POTENTIAL LOCATIONS OF ET CHARGING STATIONS

Fig. 6 (a) depicts the identified points of interest in the network. Again, driving time and distance information are available. The driving time information is assigned to each node as the aggregate value of the ingoing and outgoing flows (driving time in minutes). The driving time T for each point of interest is depicted on a continuous scale between the minimum 6.45 and maximum value 17.87 in minutes (yellow and red color respectively). The size of the nodes is depicted as the multiplicative inverse of the time $(1/T)$. That is the yellower and bigger the node, the lower the value of the traffic flow (in time) for that node. The ten nodes with lower time values are depicted as squares in Fig. 6 (a). The lower times criteria is used to decide the location of ET charging stations as a first approach. Fig. 6 (b) depicts the ten stations with lower driving time flow in minutes with yellow squares with the rest of the nodes depicted as black circles. The label of the yellow square nodes indicates also its importance, i.e. the node labeled as 1 is the node with the lowest value for the driving time flow. The one labeled with 2 is the second with lower time, and so on. Each of these ten points can be considered to locate an electric charging station.

The ten possible ET charging stations identified in Fig. 6 can be grouped together using hierarchical clustering according to their geolocation, in the same manner, as the traffic flow clusters were identified previously.

The corresponding dendrogram for $c = 6$ clusters is depicted in Fig. 7 (a) and the average silhouette width for $c = \{2, \ldots, 8\}$ clusters is shown in the bottom panel. Two regions can be identified in the silhouette plot Fig. 7 (b), the average silhouette width increases up to $c = 4$ clusters, with a break point for $c = 5$ where the average width is minimum, and starts to increase for larger values of c, where a second region, can be identified for $c = 6$ to $c = 8$, One can identified $c = 4$ clusters as optimal, just before the aforementioned break-point in $c = 5$, but $c = 6$ yields a better distribution of the clusters found for the inner points.

The six identified clusters are geographically depicted in Fig. 8 (a) which shows the ten charging points (with minimum traffic flow) and their corresponding cluster. Fig. 8 (b) depicts the centroids for each of the six ET charging station clusters identified. The centroids of the extreme points traffic flow clusters are depicted, as blue pastel circles, in both

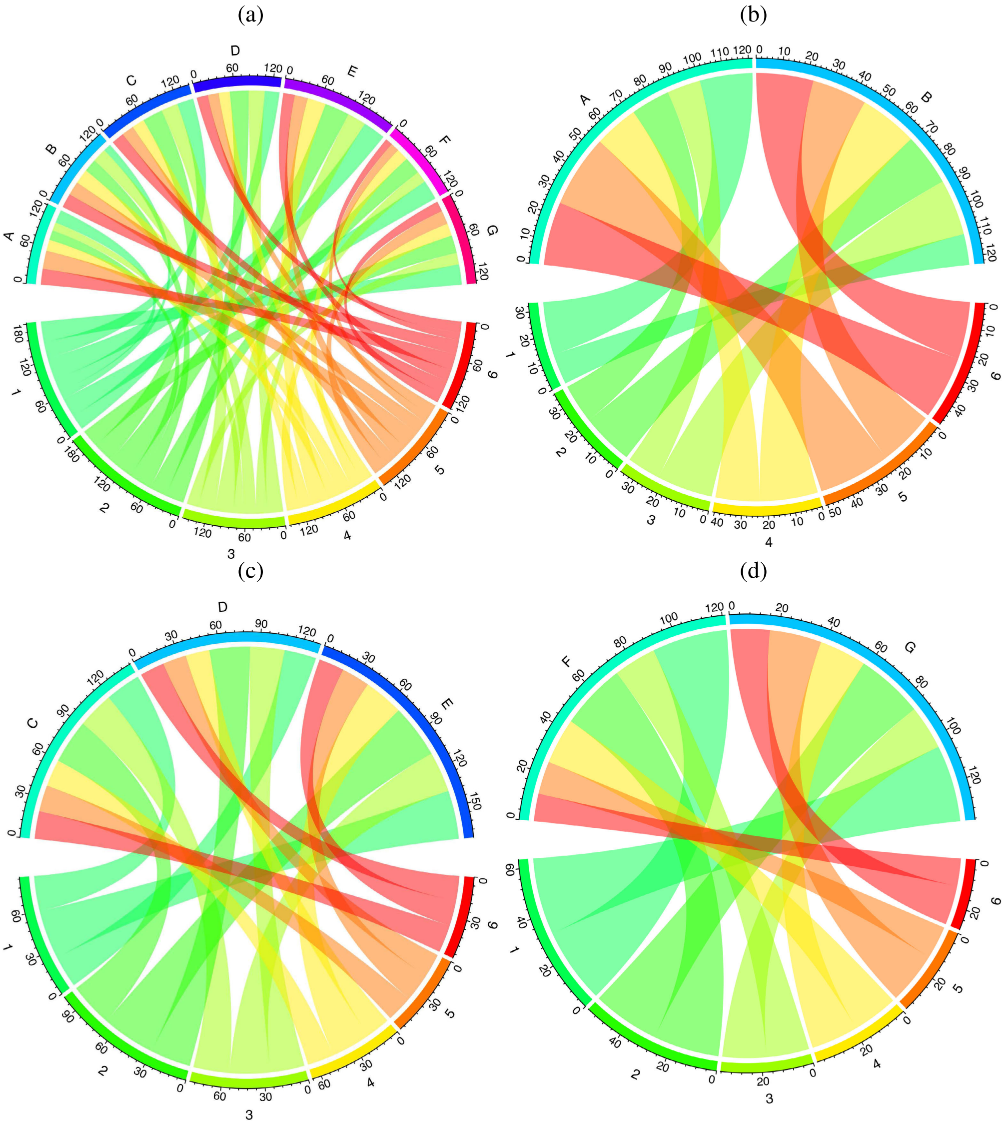


FIGURE 9. Chord diagram depicting traffic flow profiles between interest points (extreme) clusters and charging station (internal) clusters: (a) all stations (1-6) and interest points clusters (A-G); (b) all stations and northern clusters (A, B); (c) all charging stations and valley regions (C, D, E); (d) all stations and southern clusters (F, G).

panels for reference. As follows, the meantime flow between charging points and extreme points of interest in the city is analyzed.

Fig. 9 depicts the traffic flow in mean the time between points for possible charging stations named from 1 to 6, and extreme points in the city named from A to G. Table 3 summarizes the interest points with minimum flow time selected as potential stations.

The traffic between regions is represented as segments in a chord diagram, such segments are proportional to the traffic flow in each identified point, both, internal (1 to 6), and extreme (A to G) points. A chord diagram is typically used to display the inter-relationships between the nodes or block of nodes of a network (from an adjacency matrix). The blocks (node subsets) are arranged radially around a circle and the relationships are drawn as arcs that connect the blocks. The block importance is reflected as the segment size, and the importance of the relationships as the width of the arcs. Arcs widths correspond to the time in minutes between interest points (internal 1 to 6 and extreme A to G)

TABLE 3. Interest points with minimum flow time selected as prefeasibility stations.

node	mean time (min)	cluster
1	6.44	1
2	7.03	1
3	7.94	2
4	8.41	2
5	8.43	3
6	8.48	3
7	9.07	4
8	9.75	4
9	10.01	5
10	10.11	6

and segment sizes are depicted with commutative traffic times.

Fig. 9 (a) shows the flow between all charging and extreme points clusters. The circle sectors for charging points 1 and 2 are the largest, that is, moving from and to charging points 1 and 2 and all extreme points clusters take the largest times given that they are located in the north extreme, inside, the city of Quito. Also, it can be observed, as expected, that flow is minimum in the neighborhood and larger for long-distance points. Occurs the contrary for station 6, moving from and to charging point 6, takes the lower time given that such a place is rapidly accessed from almost every longest point (B, C, D, E) through the Simón Bolívar highway. The circle sector size indicates the flow size incoming or outgoing from that station, and can be used as a reference for the station sizing.

Note that these locations are located in various areas of coverage, which allows serving with taxi service all the main zones of the city. Moreover, they are situated close to interesting places that allow drivers to find quickly passengers.

Although this information provided is crucial for providing the most proper places to install charging stations, it is crucial also to study the number of charging spots that have to be installed in each station, considering the grid constraints (e.g.: the size of the feeder in each location, cost of investment). Moreover, several scenarios depending on the possible penetration of ETs should be considered to quantify if the investment is profitable.

C. DISCUSSION

The present work discusses a case study for the modeling of a traffic network for the city of Quito. For the city street network extraction, OSMnx proved to be a valuable tool, when compared with commonly used methods of dealing with urban information, which are based on Geographic Information Systems [50], [51]. Combined with the traffic information extraction using the Google API, the two inputs for building a traffic model, the street network, and the traffic information, are readily available to start the computational analysis of the model.

The main drawback observed, regarding the model scalability, is related to the extraction of traffic information using the Google API, which could be expensive. For the networks presented in this work, which are relatively small, with an upper limit N nodes and $K = N \times (N - 1)$ total connections; that is, $N = 17$ and $N = 91$ for the internal and external connections, the request cost was of 300 credits (USD dollars) a week, for 20 minutes interval requests. The OSMnx simplified network was of the order of $N = 9470$, $K = 21137$, which is four orders of magnitude larger than the used network. Scaling the model to the number of nodes OSMnx allows to extract could be not permissible economy wise.

For this work the extracted data, was processed in an offline way, but an application can be carried out extending the presented work, to process the requested data online fashion, to deal with ''real-time'' traffic information and events along with the city network.

VI. CONCLUSION

In the past few years, growing attention has been devoted to sustainable transportation. Hence, this paper proposed a method for modeling a street network between interest points identified through a winner-takes-all trimming process. Once, the interest points of the network are identified, the flow between points and the ingoing and outgoing flows are modeled from data acquired from the driving distance and driving time returned by the Google Distance API.

This information is used to analyze the traffic in different regions of the city of Quito, and to identify potential location sites for ET charging stations around the city. Both, interest points of the city and traffic stations spots are grouped according to their geographical proximity using a hierarchical clustering approach. The traffic flow between extreme points of the city and charging stations were characterized, giving information that might be used for station sizing.

In future studies, a network complexity analysis and metric description, of the street/traffic network, warrants further investigation. Also, a model based on the information of traffic of Quito, for the optimization of the sizing of the charging stations of ETs will be studied, considering various constraints such as grid conditions, taxi drivers schedules, and traffic conditions.

ACKNOWLEDGMENT

The authors would like to thank P. Guerra-Terán from the Universidad de las Américas, Ecuador, and I. Cedeño from BYD E-Motors Ecuador, for the fruitful discussion.

REFERENCES

[1] S. E. Bibri and J. Krogstie, ''Smart sustainable cities of the future: An extensive interdisciplinary literature review,'' *Sustain. Cities Soc.*, vol. 31, pp. 183–212, May 2017.

[2] D. Caparros-Midwood, S. Barr, and R. Dawson, ''Optimised spatial planning to meet long term urban sustainability objectives,'' *Comput., Environ. Urban Syst.*, vol. 54, pp. 154–164, Nov. 2015.

[3] C.-C. Lu, S. Yan, and Y.-W. Huang, ''Optimal scheduling of a taxi fleet with mixed electric and gasoline vehicles to service advance reservations,'' *Transp. Res. C, Emerg. Technol.*, vol. 93, pp. 479–500, Aug. 2018.

[4] S. Gurram, A. L. Stuart, and A. R. Pinjari, ''Agent-based modeling to estimate exposures to urban air pollution from transportation: Exposure disparities and impacts of high-resolution data,'' *Comput., Environ. Urban Syst.*, vol. 75, pp. 22–34, May 2019.

[5] J. Beaudoin, Y. H. Farzin, and C.-Y.-C. Lin Lawell, ''Public transit investment and sustainable transportation: A review of studies of transit's impact on traffic congestion and air quality,'' *Res. Transp. Econ.*, vol. 52, pp. 15–22, Oct. 2015.

[6] Y. Xu, S. Jiang, R. Li, J. Zhang, J. Zhao, S. Abbar, and M. C. González, ''Unraveling environmental justice in ambient PM2.5 exposure in beijing: A big data approach,'' *Comput., Environ. Urban Syst.*, vol. 75, pp. 12–21, May 2019.

[7] Y. Lou, W. M. Jayantha, L. Shen, Z. Liu, and T. Shu, ''The application of low-carbon city (LCC) indicators—A comparison between academia and practice,'' *Sustain. Cities Soc.*, vol. 51, Nov. 2019, Art. no. 101677.

[8] C. Backfrieder, G. Ostermayer, and C. F. Mecklenbrauker, ''Increased traffic flow through node-based bottleneck prediction and V2X communication,'' *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 2, pp. 349–363, Feb. 2017.

[9] J. Zhang, F.-Y. Wang, K. Wang, W.-H. Lin, X. Xu, and C. Chen, "Data-driven intelligent transportation systems: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 4, pp. 1624–1639, Dec. 2011.

[10] N. Valenzuela-Levi, "Why do more unequal countries spend more on private vehicles? Evidence and implications for the future of cities," *Sustain. Cities Soc.*, vol. 43, pp. 384–394, Nov. 2018.

[11] M. Kii, R. Moeckel, and J.-C. Thill, "Land use, transport, and environment interactions: WCTR 2016 contributions and future research directions," *Comput., Environ. Urban Syst.*, vol. 77, Sep. 2019, Art. no. 101335.

[12] M. Mahmoudi, Y. Song, H. J. Miller, and X. Zhou, "Accessibility with time and resource constraints: Computing hyper-prisms for sustainable transportation planning," *Comput., Environ. Urban Syst.*, vol. 73, pp. 171–183, Jan. 2019.

[13] W. Shen, W. Han, D. Chock, Q. Chai, and A. Zhang, "Well-to-wheels life-cycle analysis of alternative fuels and vehicle technologies in China," *Energy Policy*, vol. 49, pp. 296–307, Oct. 2012.

[14] L. Hu, J. Dong, Z. Lin, and J. Yang, "Analyzing battery electric vehicle feasibility from taxi travel patterns: The case study of New York City, USA," *Transp. Res. C, Emerg. Technol.*, vol. 87, pp. 91–104, Feb. 2018.

[15] J.-M. Clairand, P. Guerra-Terán, X. Serrano-Guerrero, M. González-Rodríguez, and G. Escrivá-Escrivá, "Electric vehicles for public transportation in power systems: A review of methodologies," *Energies*, vol. 12, no. 16, p. 3114, Aug. 2019.

[16] S. Mehar, S. Zeadally, G. Remy, and S. M. Senouci, "Sustainable transportation management system for a fleet of electric vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 3, pp. 1401–1414, Jun. 2015.

[17] E. Cascetta, F. Russo, F. A. Viola, and A. Vitetta, "A model of route perception in urban road networks," *Transp. Res. B, Methodol.*, vol. 36, no. 7, pp. 577–592, Aug. 2002.

[18] X. Qian, T. Lei, J. Xue, Z. Lei, and S. V. Ukkusuri, "Impact of transportation network companies on urban congestion: Evidence from large-scale trajectory data," *Sustain. Cities Soc.*, vol. 55, Apr. 2020, Art. no. 102053.

[19] D. J. Fagnant and K. M. Kockelman, "The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios," *Transp. Res. C, Emerg. Technol.*, vol. 40, pp. 1–13, Mar. 2014.

[20] N. Zheng, R. A. Waraich, K. W. Axhausen, and N. Geroliminis, "A dynamic cordon pricing scheme combining the macroscopic fundamental diagram and an agent-based traffic model," *Transp. Res. A, Policy Pract.*, vol. 46, no. 8, pp. 1291–1303, Oct. 2012.

[21] Z. Chen, F. He, and Y. Yin, "Optimal deployment of charging lanes for electric vehicles in transportation networks," *Transp. Res. B, Methodol.*, vol. 91, pp. 344–365, Sep. 2016.

[22] P. You, S. H. Low, Z. Yang, Y. Zhang, and L. Fu, "Real-time recommendation algorithm of battery swapping stations for electric taxis," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Jul. 2016, pp. 1–5.

[23] Y. Wang, W. Ding, L. Huang, Z. Wei, H. Liu, and J. A. Stankovic, "Toward urban electric taxi systems in smart cities: The battery swapping challenge," *IEEE Trans. Veh. Technol.*, vol. 67, no. 3, pp. 1946–1960, Mar. 2018.

[24] R. Li, L. Dong, J. Zhang, X. Wang, W.-X. Wang, Z. Di, and H. E. Stanley, "Simple spatial scaling rules behind complex cities," *Nature Commun.*, vol. 8, no. 1, pp. 1–7, Dec. 2017.

[25] L. Dong, R. Li, J. Zhang, and Z. Di, "Population-weighted efficiency in transportation networks," *Sci. Rep.*, vol. 6, no. 1, pp. 1–10, Sep. 2016.

[26] S. Liu, J. Pu, Q. Luo, H. Qu, L. M. Ni, and R. Krishnan, "VAIT: A visual analytics system for metropolitan transportation," *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 4, pp. 1586–1596, Dec. 2013.

[27] I. Kalamaras, A. Zamichos, A. Salamanis, A. Drosou, D. D. Kehagias, G. Margaritis, S. Papadopoulos, and D. Tzovaras, "An interactive visual analytics platform for smart intelligent transportation systems management," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 2, pp. 487–496, Feb. 2018.

[28] M. González, D. Dominguez, and Á. Sánchez, "Learning sequences of sparse correlated patterns using small-world attractor neural networks: An application to traffic videos," *Neurocomputing*, vol. 74, nos. 14–15, pp. 2361–2367, Jul. 2011.

[29] M. Bilal and M. Rizwan, "Electric vehicles in a smart grid: A comprehensive survey on optimal location of charging station," *IET Smart Grid*, vol. 3, no. 3, pp. 267–279, Jun. 2020.

[30] A. Y. S. Lam, Y.-W. Leung, and X. Chu, "Electric vehicle charging station placement: Formulation, complexity, and solutions," *IEEE Trans. Smart Grid*, vol. 5, no. 6, pp. 2846–2856, Nov. 2014.

[31] J. Asamer, M. Reinthaler, M. Ruthmair, M. Straub, and J. Puchinger, "Optimizing charging station locations for urban taxi providers," *Transp. Res. A, Policy Pract.*, vol. 85, pp. 233–246, Mar. 2016.

[32] C. Jiang, Z. Jing, T. Ji, and Q. Wu, "Optimal location of PEVCSs using MAS and ER approach," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 20, pp. 4377–4387, Nov. 2018.

[33] A. Pan, T. Zhao, H. Yu, and Y. Zhang, "Deploying public charging stations for electric taxis: A charging demand simulation embedded approach," *IEEE Access*, vol. 7, pp. 17412–17424, 2019.

[34] Z. Liu, F. Wen, and G. Ledwich, "Optimal planning of electric-vehicle charging stations in distribution systems," *IEEE Trans. Power Del.*, vol. 28, no. 1, pp. 102–110, Jan. 2013.

[35] W. Tu, Q. Li, Z. Fang, S.-L. Shaw, B. Zhou, and X. Chang, "Optimizing the locations of electric taxi charging stations: A spatial–temporal demand coverage approach," *Transp. Res. C, Emerg. Technol.*, vol. 65, pp. 172–189, Apr. 2016.

[36] J. Jung, J. Y. J. Chow, R. Jayakrishnan, and J. Y. Park, "Stochastic dynamic itinerary interception refueling location problem with queue delay for electric taxi charging stations," *Transp. Res. C, Emerg. Technol.*, vol. 40, pp. 123–142, Mar. 2014.

[37] X. Meng, W. Zhang, Y. Bao, Y. Yan, R. Yuan, Z. Chen, and J. Li, "Sequential construction planning of electric taxi charging stations considering the development of charging demand," *J. Cleaner Prod.*, vol. 259, Jun. 2020, Art. no. 120794.

[38] N. Shahraki, H. Cai, M. Turkay, and M. Xu, "Optimal locations of electric public charging stations using real world vehicle travel patterns," *Transp. Res. D, Transp. Environ.*, vol. 41, pp. 165–176, Dec. 2015.

[39] Google LLC. *Google Maps Platform*. Accessed: Oct. 1, 2020. [Online]. Available: https://cloud.google.com/maps-platform

[40] G. Boeing, "OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks," *Comput., Environ. Urban Syst.*, vol. 65, pp. 126–139, Sep. 2017.

[41] L. R. Foulds, *Graph Theory Applications*. New York, NY, USA: Springer, 2012.

[42] J. H. Ward, "Hierarchical grouping to optimize an objective function," *J. Amer. Stat. Assoc.*, vol. 58, no. 301, pp. 236–244, Mar. 1963.

[43] J. Kleine Deters, R. Zalakeviciute, M. Gonzalez, and Y. Rybarczyk, "Modeling PM2.5 urban pollution using machine learning and selected meteorological parameters," *J. Electr. Comput. Eng.*, vol. 2017, pp. 1–14, 2017.

[44] L. Bravo-Moncayo, I. Pavón-García, J. Lucio-Naranjo, and R. Mosquera, "Contingent valuation of road traffic noise: A case study in the urban area of quito, ecuador," *Case Stud. Transp. Policy*, vol. 5, no. 4, pp. 722–730, Dec. 2017.

[45] El. Comercio. (2020). *En Marzo del 2020 Concluirá el Proceso de Regularización de Taxis en Quito*. [Online]. Available: https://www.elcomercio.com/actualidad/quito-taxis-regularizacion-amt-ordenanza.html

[46] F. Sarmiento-Delgado, J.-M. Clairand, P. Guerra-Teran, and G. Escriva-Escriva, "Electric vehicle charging load prediction for private cars and taxis based on vehicle usage data," in *Proc. IEEE CHILEAN Conf. Electr., Electron. Eng., Inf. Commun. Technol. (CHILECON)*, Nov. 2019, pp. 1–6.

[47] EcuadorTV. *Quito tendrá 10 Electrolineras en Estacionamientos*. Accessed: Oct. 1, 2020. [Online]. Available: https://www.ecuadortv.ec/noticias/actualidad/electrolinera-quito

[48] O. Akman, T. Comar, D. Hrozencik, and J. Gonzales, "Data clustering and self-organizing maps in biology," in *Algebraic and Combinatorial Computational Biology*. Amsterdam, The Netherlands: Elsevier, 2019, pp. 351–374.

[49] B. Mirkin, "Choosing the number of clusters," *Wiley Interdiscipl. Rev., Data Mining Knowl. Discovery*, vol. 1, no. 3, pp. 252–260, May/Jun. 2011.

[50] A. Comber, C. Brunsdon, and E. Green, "Using a GIS-based network analysis to determine urban greenspace accessibility for different ethnic and religious groups," *Landscape Urban Planning*, vol. 86, no. 1, pp. 103–114, May 2008.

[51] H. Gong, C. Chen, E. Bialostozky, and C. T. Lawson, "A GPS/GIS method for travel mode detection in new york city," *Comput., Environ. Urban Syst.*, vol. 36, no. 2, pp. 131–139, Mar. 2012.

MARIO SALVADOR GONZÁLEZ-RODRÍGUEZ was born in León, Nicaragua, in 1981. He received the B.Sc. degree in industrial engineering from the Universidad Nacional de Ingeniería, Managua, Nicaragua, in 2004, and the M.Sc. and Ph.D. degrees in computer science from the Autonomous University of Madrid (UAM), in 2008 and 2012, respectively. He is specialized in the area of artificial intelligence, complex systems, and information processing using neural networks. He was a Visiting Professor with the Universidad de Los Andes, Bogota, Colombia, in 2017. He has been an Associate Professor with the Universidad de las Américas, Quito, Ecuador, since 2016. His research interests include the modeling of attractor networks for pattern retrieval, data analytics, artificial intelligence, and smart transportation systems.

JEAN-MICHEL CLAIRAND (Member, IEEE) was born in Quito, Ecuador, in 1990. He received the M.Sc. degree from the Ecole Nationale Supérieure de l'Electronique et Ses Applications (ENSEA), Cergy-Pontoise, France, in 2014, and the Ph.D. degree in industrial production engineering from the Universitat Politècnica de València, Spain, in 2018. He worked with Empresa Eléctrica Quito, in 2014. He was an International Visiting Graduate Student with the Department of Electrical and Computer Engineering, University of Waterloo, Canada, from 2017 to 2018. He was/has been a Lecturer with the Universidad de las Américas, Quito, from 2014 to 2017, and an Assistant Professor since 2018. He was a Visiting Researcher with the Department of Agro-Environmental Sciences, Università degli Studi di Bari Aldo Moro, Italy, in 2019. His research interests include electric vehicles, smart grid optimization, energy efficiency, and microgrids.

KEVIN SOTO-ESPINOSA was born in Santo Domingo de los Tsáchilas, Ecuador, in 1996. He received the engineering degree in computer systems from the Universidad de Las Américas (UDLA), in 2020. He is currently working as a Frontend Developer with Mindsoft, Quito, Ecuador. His research interests include software development and artificial intelligence.

JOSUÉ JARAMILLO-FUELANTALA was born in Quito, Ecuador, in 1997. He received the engineering degree in computer systems from the Universidad de Las Américas (UDLA), in 2020. He has participated in numerous national and international computer-related tournaments, obtaining the first places in several of them. He is currently the Lead Development Engineer with Mindsoft, Quito. His research interests include software development and artificial intelligence.

GUILLERMO ESCRIVÁ-ESCRIVÁ was born in Gandía, Spain, in 1975. He received the Ph.D. degree in industrial engineering from the Universitat Politècnica de València (UPV), Spain, in 2009. He has been a Professor with the Department of Electrical Engineering, UPV, since 2005. From 2000 to 2005, he worked in a large construction company as a facilities engineer. During his time as a University Professor, he has collaborated in various national and European projects. He has collaborated with entities from Spain and from countries, such as the United States, Holland, and Ecuador in different research projects. Among his publications are several teaching books, more than 20 articles in high impact research journals, and communications in international congresses. He is one of the collaborators of the Laboratory of Distributed Energy Resources, UPV (Labder) and was one of the developers of the Derd Energy Management System that has controlled the power demand of the Vera Campus at UPV for more than eight years. He presents high technical training in research and applied studies and has great interest in the transfer of knowledge from the university to industry and vice versa. His research interests include energy efficiency, renewable energies, and quality problems in power systems.