Inferring Passenger Travel Demand to Improve Urban Mobility in Developing Countries Using Cell Phone Data: A Case Study of Senegal

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Inferring Passenger Travel Demand to Improve Urban Mobility in Developing Countries Using Cell Phone Data: A Case Study of Senegal

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***Abstract*—A rise in population, along with urbanization, has been causing an increase in demand for urban transportation services in the sub-Saharan Africa countries. In these countries, mobility of people is mainly ensured by bus services and a large-scale informal public transport service, which is known as paratransit (e.g., car rapides in Senegal, Tro Tros in Ghana, taxis in Uganda and Ethiopia, and Matatus in Kenya). Transport demand estimation is a challenging task, particularly in developing countries, mainly due to its expensive and time-consuming data collection requirements. Without accurate demand estimation, it is difficult for transport operators to provide their services and make other important decisions. In this paper, we present a methodology to estimate passenger demand for public transport services using cell phone data. Significant origins and destinations of inhabitants are extracted and used to build origin–destination matrices that resemble travel demand. Based on the inferred travel demand, we are able to reasonably suggest strategic locations for public transport services such as paratransit and taxi stands, as well as new transit routes. The outcome of this study can be useful for the development of policies that can potentially help fulfill the mobility needs of city inhabitants.**

***Index Terms*—Cell phone data, origin–destination matrix, paratransit, urban mobility, public transport, transit route.**

I. Introduction

The world is experiencing a steady growth in urbanization. In 2010, more than half of the world's population lived in cities [1]. Africa's cities are also growing rapidly. In 2011, the number of people living in Africa exceeded the 1 billion mark and it is expected to increase to 2.4 billion by 2050 [2]. The rise in population is also coupled with urbanization. From 1960 to 2011, urban share of Africa's population rose from 19 percent to 39 percent and by 2040 half of Africa's population will live in cities [2]. This is primarily because cities offer more alternatives for the resolution of social and economic problems compared to rural areas. As more people shift their living to cities they require more houses, shops, schools, health centers, roads, and public transportation. However, most cities have few resources to respond to the magnitude of the change in the urban areas. As a result of the increasing number of urban inhabitants, more travel demand have caused various problems such as, traffic congestion, parking difficulties, traffic accidents, public transport inadequacy, and environmental problems [3].

Besides large-buses, the majority of cities in the Sub-Saharan Africa countries use large-scale informal/flexible transport services, known as paratransit (e.g. car rapides in Senegal, Tro Tros in Ghana, taxis in Ethiopia, and Matatus in Kenya, etc.). The term paratransit conventionally described "those forms of intra-urban passenger transportation which are available to the public, and distinct from conventional transit (scheduled bus and rail) and can operate over the highway and transit system" [4]. In the developed countries paratransit services are available in the form of on-demand responsive transit, dial-a-ride, and dial-a-ride transit schemes, often used by people with limited mobility. In developing countries, paratransit services are available at a larger-scale for the general population, often by unregulated operators within informal sector. However, there are also cases this service is provided by regulated operators within the formal sector. In general, paratransit services in developing countries exhibit the following characteristics: operate without scheduled timetable and are not restricted in terms of the routes or areas in which they may operate; the vehicles are typically small, ranging from 4 seat sedan to midibuses with 17–35 seats; fares are usually set by city government; and the services are provided by private operators [5], [6]. Despite the positive impacts of both the paratransit and large-bus services, there are still unfathomable cases for improving the quality, reliability, accessibility, and coverage of public transport services in developing countries.

Cities in developing countries have faced difficulties in getting a grip on existing and future movements and dynamics of their urban systems, despite the necessity of such information to properly plan their urban public transport systems. The main reason is that most of the developing cities do not have enough budget to collect detailed information necessary for

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the transportation planning. For example, countries in the Sub-Saharan African region have limited data for transport planning, most of the cities do not conduct traffic counting in a regular basis and, except for cities in South Africa, no other city in the sub-Saharan countries has household travel surveys [7].

In recent years, researchers are exploring ways to develop large-scale urban sensing by employing the increasing capabilities found in the cellular networks system. It is easy to approximate the location of cell phone users whenever they make a call or use a short message service. Over the last decade, cell phone penetration rates have increased exponentially. In 2013, there were almost as many cell phone subscriptions as people in the world, and active cell phone cards per 100 inhabitants were 96% globally; 128% in developed countries; and 89% in developing countries [8].

In this study, we explore the use of cell phone data in order to dynamically infer about urban mobility patterns to improve transportation planning. Initially, we focus on extracting dominant home and destination anchors in order to have an idea about travel demand, i.e., the general inward and outward movement of people and vehicles between different locations. Our second attempt is to connect this information to geography of human movement derived from public bus network of a city. This enables us to suggest strategic locations for public transport services such as bus routes, paratransit stands, and pick-up and drop-off locations for taxis, based on actual travel demand.

The rest of this paper is organized as follows: Section II reviews related work on the use of cell phone data for urban mobility analysis. Section III gives a description of the case study area and the different datasets used in our study. Section IV presents the developed methods and results. In Section V, we provide a discussion of results and potential applications, and finally in Section VI, we present a summary of the work developed addressing the main conclusions and pointing out some future research directions of our study.

II. Literature Review

Transport planning traditionally relies on the knowledge of present and future problems that are associated to the urban growth such as how much travel will be generated, where these trips will take place, by which mode and on which routes. One of the major problems associated with public transport planning is estimating and forecasting the demand. Planners need to make a public transport demand forecast for different purposes, such as for extension of existing routes, implementation of new routes, new modes (e.g., Bus Rapid Transit—BRT)/services, scheduling change, prediction of ridership as part of short and long-term plan, and others [9].

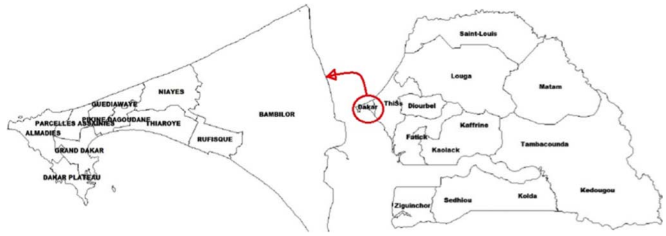
There is a growing trend in using data from new sources to gain better knowledge regarding the urban public transport systems. The city of Dublin, for example, used traditional data and GPS traces of buses to investigate the root causes of traffic congestion in its public transport network. The result helps traffic controllers to visualize the current status of the entire bus network at a glance and quickly observe areas experiencing delay that need detailed analysis [10]. Smart card transactions and automatic vehicle location data are also used to investigate bus passenger travel behavior such as origin and destination estimation [11]; to design personalized travel information systems for individual passengers [12]; and to generate knowledge about future public transport access patterns [13].

On the other hand, cell phone service users produce a huge amount of passive and active mobile positioning data that can collectively inform us about the presence and movement of people in a given area. Over the past few years, various research studies have dealt with the use of passive mobile positioning data, which is automatically stored in the memory files of mobile operators for call activities or movements of handsets in the network. These studies investigate a wide range of issues such as, travel time and speed estimation [14]; road usage patterns assessment [15]; correlation between cell phone traffic and vehicular traffic [16], [17]; traffic status detection [18]; congestion detection [19]; and route classification [20]. Another category of data from cell phone service users are active or application-based data, where a cellphone runs dedicated software that reports its whereabouts to a server outside the cellular network. In this category, a trial experiment has been launched by the Mobile Century project, which deployed GPS equipped Nokia cellphones to gather continuous location and speed profile of vehicles [21]. Other studies by Hongsakham *et al.* [19] and Puntumapon and Pattara-atikom [22] also gathered cell dwell time data through Nokia cellphone loaded with cellular probe software to infer traffic congestion and to differentiate pedestrian and sky train passengers.

There are a number of studies focusing on the use of cellphone data for travel demand estimation. Çolak *et al.* [23] and Alexander *et al.* [24] applied cellphone data to generate trips, which are categorized by time of day and purposes (e.g. home-based-work). Census data are later used to produce the total trip matrices for each case study cities. Toole *et al.* [25] integrated cellphone data with census, surveys, open and crowd-sourced geospatial data to estimate multiple aspects of travel demand that include road network performance and road classification analysis. A new framework was developed by Alexander and Gonzlez [26] to evaluate the demand and congestion impacts of a new transport mode based on different adoption levels, and hourly OD trips computed from cellphone data. Jiang *et al.* [27] used cellphone data to develop an activity-based model in an attempt to generate an overall daily activity patterns.

In order to determine the public transport demand and provide appropriate solutions for a city, it is important to have an understanding of the travel patterns. The origins and destinations of people trips are among the most important of these patterns. Previous studies use cell phone data for origin-destination estimation [28]–[30]. Traditionally, origin-destination surveys require subjects to record data on their travel patterns; where they are moving to and from in the observation period (usually, passenger travel for only one day per route or a whole week); how they are doing so; and why. Within this domain, cell phone data have been used to detect land use patterns, which is important information to estimate the trip-generation property of different areas [31]–[33].

Nonetheless, the majority of the previous studies focused on capturing passenger travel pattern between home and work places. Ahas *et al.* [34] argue that with the rising mobility



(a) Dakar – district level (b) Senegal – region level

Fig. 1. Map of Dakar (a) and Senegal (b).

of individuals, the dominance of home and work anchors has reduced, and people also spend a significant amount of time in other locations. Some researchers investigated the number of places where a person spends a significant amount of time and/or visits frequently [35], [36]. However, these studies lack the ability to link trips between home and top destination locations of transport users. A study by Berlingerio *et al.* [37] uses cell phone data to extract transport demand and apply an optimization technique to identify new transit routes with the main objective of reducing travel and wait times. Our study is also an attempt to extend the effort in how we can explore the potential of cell phone data to extract the travel patterns of people between their home and top destinations. However, time variables (i.e., access, wait, and travel times) are not considered in our analysis for new transit route suggestion. Given the low public transport coverage in Senegal, we give priority to fulfill the requirement of public transport coverage and accessibility. This has been attempted in this study by mining the cell phone data to identify areas of Senegal with high transport demand, but insufficient or no public transport coverage and accessibility. Using the obtained information we suggest strategic locations for public transport services (paratransit and taxi stands, transit routes, and strategic locations for potentially developed high order public transport systems, e.g., BRT).

III. Data and Case Study Area Descriptions

A. *Dakar (Senegal) Description*

Senegal is used as a case study to illustrate the analysis carried out in this study. Senegal is a country located in West Africa and it covers a land area of 196,712 square kilometers. In 2013, Senegal had an estimated population of 13,508,715. Senegal is divided into 14 regions (Fig. 1), which are further divided into 45 departments, and 123 arrondissements (district). Specifically, we carried out detailed analysis on the capital of Senegal, Dakar, and its neighborhood. The Dakar region is divided into four departments (which is an administrative structure without political power), and these departments are further divided into 10 arrondissements with a total population of 3,137,196 [38].

B. *Transit Profile of Dakar*

Transport in Senegal particularly in Dakar was provided by state owned company, *Compagnie senegalaise de transformation et de conditionnement*, which was established in the late 1940s and later transformed to SOTRAC (Societ des Transports en Commun du Cap Vert) in 1971. SOTRAC did not cope with the increasing demand because of its limited fleet size and governments inability to provide sufficient fund to support its operation. This resulted in deterioration of service coverage and quality, which led the company to give up its operation in 1998 [39]. In parallel, the Senegalese government formed a new coordinating body to oversee the urban transport in Dakar, which is the Executive Council of Urban Transport in Dakar (CETUD) in March 1997. Currently, the following public transport services are available in Dakar.

Bus service: bus service is operated by a private public transport company known as Dakar Dem Dikk (DDD), which was established in 2000 to respond to the increasing transport demand in Dakar. DDD started its operation with a total fleet size of 60 buses. In 2004, DDD acquired additional 360 new buses and was able to serve 17 urban routes covering places in and around Dakar [39].

Paratransit service: the development of the paratransit service, which is known by the name Ndiaga Ndiaye and cars rapides, has been started by the inability of large-bus services to satisfy the growing mobility needs of citizens in Dakar. The common paratransit vehicle has a capacity up to 25 passengers (cars rapides). There are also midibuses with capacity up to 35 passengers (Ndiaga Ndiaye). In Dakar, paratransit operates on flexible routes and does not have fixed schedule. However, there are known major stations that can be regarded as origins and destinations for a particular route and commonly perceived intermediate stations. These intermediate stations are not usually marked (no official station stands) but are widely known as regular stops to local users. It is usually possible to hop on/off at any place in between the origin and destination. As a result, the current paratransit based public transportation system does not have much reliability; fares are diverse; and route alignment schemes and timetable do not exist. Paratransit share road space with pedestrians and street traders and queue up in long lines, very often blocking intersections and obstructing traffic flows from other directions as well.

Taxi service: taxi cabs operate 24 hours with capacity of 4 people. Taxi fares are highly variable. A surcharge is added from midnight to 5:00 am. The price is usually subjected to negotiation between the rider and the driver, because taxi meter is either lacking or broken.

In addition, modes of transport in Dakar and its suburbs include walking, cycling or other non-motorized transport modes. There is also a rail service provided by Petit Train de Banlieue, connecting Dakar with larger cities in Senegal.

Being the largest city of the country, Dakar has been facing the classic problem of traffic congestion and fragile public transport system. Recently, some attention has been paid by the government and local authorities to implement strategies for urban mobility improvement such as capacity building of transport actors, renewal of the public transport fleet, rehabilitation of the city train, and improvements of key primary roads. While some progress has been made resolving severe traffic congestion, these strategies did not bring the expected results in terms of improving public transport systems [40]. Clearly there is still room to introduce additional transport demand management measures to improve mobility in Dakar. To implement these measures there is the need to have an

TABLE I
SAMPLE CELL PHONE TRAJECTORIES: BASE STATION LEVEL

User ID	Time stamp	Base station ID
1	18-03-2013 21:30:00	716
1	18-03-2013 21:40:00	718
1	19-03-2013 20:40:00	716

TABLE II
SAMPLE BASE STATION POSITION DATA

Base station ID	Arrondissement ID	Longitude	Latitude
1	2	-17.5251	14.7468
2	2	-17.5244	14.7474
3	2	-17.5226	14.7452

accurate description of the mobility patterns and activities that take place in the city and due to budget limitations of public authorities mobility surveys are poorly available.

C. Data Description

Cell phone data: Senegal has a high number of cell phone users. In 2012, the number of active mobile telephone cards per 100 Senegalese inhabitants was 79% [41]. In this study, analyses were performed using mobile communication data made available by SONATEL and Orange within the D4D Challenge. In 2012, SONATEL had share market of 61% in Senegal [41]. The data are based on Call Detail Records (CDRs) of cell phone calls and text exchanges of SONATELs customers, which corresponds to the period from 7th–20th of January 2013. This data is anonymous mobility data for a rolling two weeks at individual level for 300,000 randomly sampled users with the recording location at the granularity of cell tower (Table I).

The original dataset contained more than 9 million unique aliased mobile phone numbers, and further data processing was done at the Orange Labs to retain users that met the following two criteria [42]: (i) users having more than 75% days with interactions per given period; and (ii) users having had an average of less than 1,000 interactions per week. The users with more than 1,000 interactions per week were presumed to be machines or shared phones. We analyzed cellular traffic handled by 1,666 base stations. For commercial and privacy reasons, SONATEL did not provide the actual geographical coordinates of the base stations. New position for each base station is assigned uniformly in its Voronoi cell (the region consisting of all points closer to that antenna than to any other) to make it more difficult to re-identify users [42]. Table II shows a sample data of the new base station positions (latitude, longitude).

Bus data: the bus data were collected from the public transport operator in Dakar (DDD). DDD provides public transport services in two network categories; public and students, which were designed to accommodate the different travel needs of people. These two network categories of users cover urban, suburban, and new circular lines (commuter, and urban) routes. We identified more than 33 routes (66 origin and destination stations) from both the student and public networks. Some of the bus routes share stations, but they serve different intermediate stops. For this reason the final origin-destination pairs are reduced to 24. Table III shows a sample data of the DDD bus network.

TABLE III
SAMPLE BUS STOP DATA

Category	Line no.	Bus station	Latitude	Longitude
Public Network	2a	Daroukhane	14.7827	-17.3723
Public Network	2b	Leclerc	14.6720	-17.4272
Public Network	5a	Terminus Gudiawaye	14.7728	-17.3892
Public Network	5b	Palais de Justice 1	14.6702	-17.443

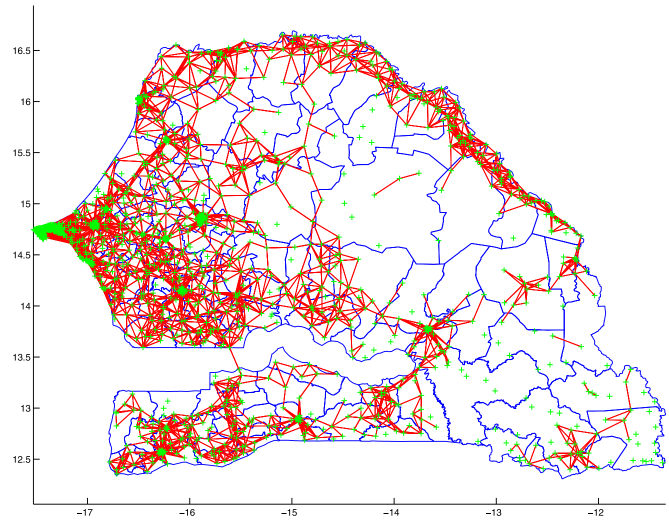


Fig. 2. Travel demand in Senegal, inferred from the cell phone data.

IV. METHODOLOGY AND RESULTS

Our goal was to utilize the large-scale cell phone data to identify passenger travel demand from which a recommendation for strategic locations of potentially useful transit routes and stations can be made. In order to estimate the travel demand, origins and destinations must be identified. Generally, trips are made in both directions. A classic example is the commuting trip where trips are made back and forth between home and workplace. Hence travel demand exists in both locations. Therefore, with our cell phone data we estimated a home-cell tower location for each subject based on the most frequent used cell tower location during the night time (10 PM–7 AM). This home location detection method was first developed by Phithakkitnukoon *et al.* [43] who show its reliability as they compared their result against the actual census data.

For each subject, we further identified the top destinations based on the five most visited cell tower locations, besides the home-cell tower location i.e., the number of connections to each of the cell towers that the subject had used (or visited) was gathered for each subject from which the top five most connected cell tower locations (that are not home cell tower location) are identified as top destinations. Hence, we were able to draw a link from the subject's home-cell tower location to each of the top five visited locations for each subject. Fig. 2 shows these links (in red) on the Senegal map where cell tower locations are represented with green markers. These links establish flows based on cell phone data (cell-based flows) that can be seen as people's travel demand, and it can be observed that the travel demand is relatively high in Dakar region (Fig. 3), which is the most populated region in Senegal, as well as along the coast of Thiès region, which is one of the touristic areas of Senegal.

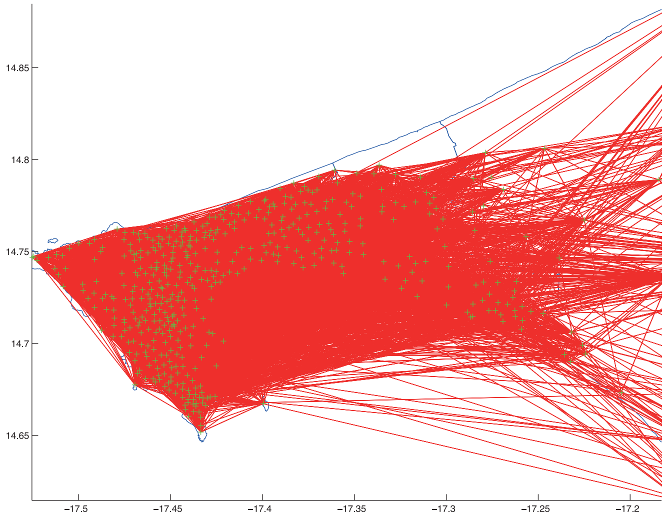


Fig. 3. Travel demand in Dakar, inferred from the cell phone data.

Fig. 4. Bus origin-destination station pairs in Dakar.

Some high demand are also seen along the north and north-eastern boarder regions in Saint-Louis and Matam regions.

In order to make an informed recommendation regarding the public transportation systems, we further examined our result with respect to the existing public transport systems in Senegal. Although the public transportation information of Senegal was limited, we were able to collect some information about the public bus stop locations in Dakar from which we identified 24 origin-destination pairs of existing bus lines (shown in Fig. 4).

Considering the inferred travel demand, each link between two locations was composed of one or more cell-based flows (i.e., one or more people travel between the locations based on cell phone data) thus the flow density corresponds to the level of travel demand in each link (between the two locations). The histogram of flow densities is shown in Fig. 5 with the minimum = 1 flow, maximum = 17,479 flows, average = 60.39 flows, and standard deviation = 250.93 flows. Intuitively, the inferred travel demand varies with the location, and in fact, the travel demand can be influenced by a number of factors, such as land use, road network, socio-demographics, and so on.

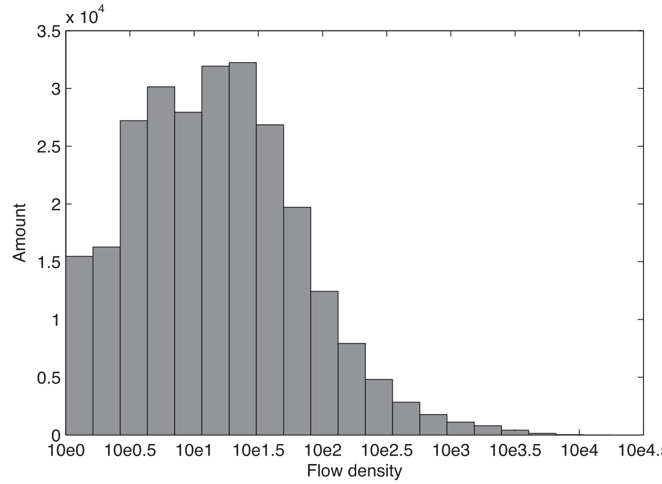


Fig. 5. Histogram of flow densities.

To map the cell-based flows to the public transportation demand, we considered the Dakar bus origin-destination pair links (Fig. 4) as the baseline. Our goal here was to see how much of the inferred travel demand (cell-based flows) assemble the actual bus public transport demand according to the infrastructure that Senegal already has in place. So, we began to re-construct the cell-based flows by continuingly adding cell-based flows from largest flow density to the lowest ones onto the map, and then we observed how cell-based flows assemble the bus routes; we started with a map of 24 bus links (origin-destination pairs) and incrementally overlay the cell-based flows from the largest to the lowest flow links onto the map, and then kept the record of the intersection of both bus and cell-based links. Since the locations of the cell towers and bus stations are not exactly the same, we map-matched these locations by clustering cell towers to nearby bus stations that are within 500 meters. We have examined a range of proximity distances and found that this proximity distance of 500 meters was a proper distance parameter for our analysis here as it avoids overlapping and assigns at least one cell tower to each bus station. As we continued our cell-based flow re-construction process while keeping an eye on the percentage of actual bus routes assembled (i.e., how much it overlaps with bus routes), we found that only the top 22.70% cell-based flows were required to completely assemble the exiting bus routes (100%), as depicted in Fig. 6.

Figs. 7 and 8 show the top 22.70% cell-based flows in Senegal and Dakar region respectively, where the thickness of the flow represents its flow density. Considering these top cell-based flows, that resemble Dakar's bus transportation network, as our inferred public transport demand, it suggests that there is high public transport demand in Dakar and emerging demand in other parts of the country, as well as large noticeable demand between Thiès and Diourbel regions.

The inferred transport demands that we obtained were between cell tower locations and some of them were just meters apart. By taking the same approach with our bus station-based cell tower grouping, we further clustered the cell towers that are within 500-meter vicinity of each other so that it resembles potential public transportation station (i.e., stations are not too close to each other (within a walking distance, for instance)).

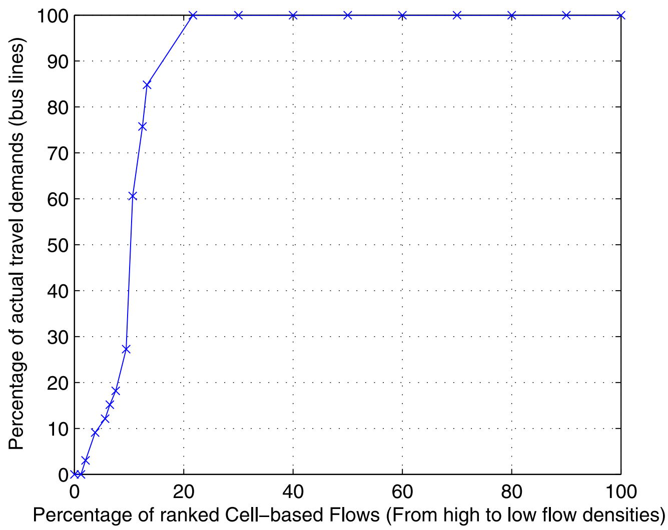


Fig. 6. Percentage of sorted cell-based flows (from high to low) based on flow density versus the percentage of actual bus origin-destination pair links assembled.

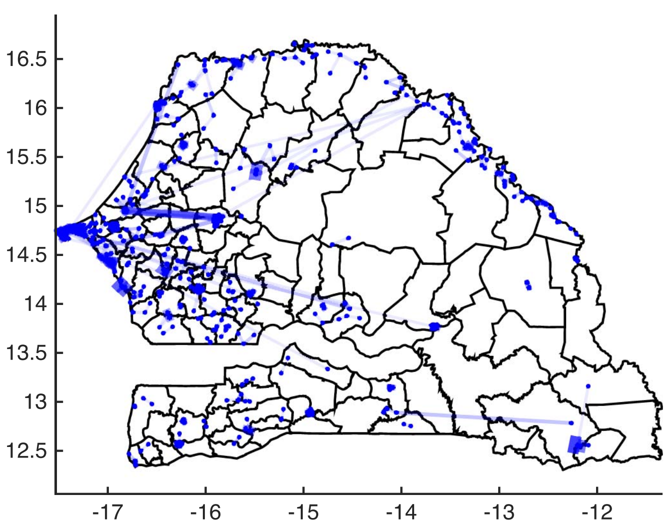


Fig. 7. Top 22.70% cell-based flows in Senegal (i.e., inferred transport demand).

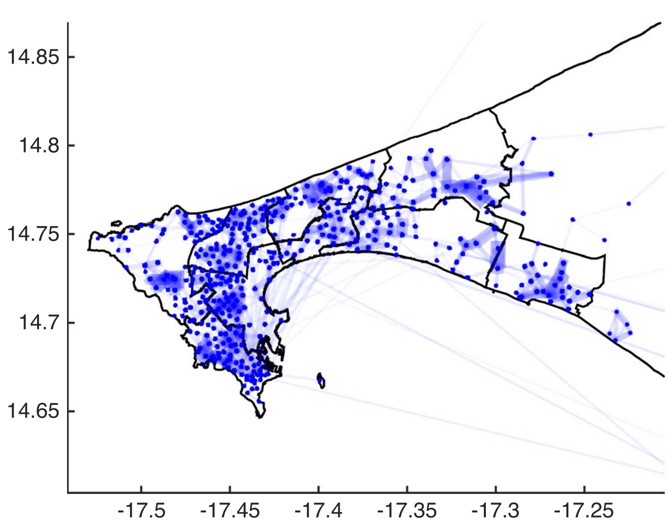


Fig. 8. Top 22.70% cell-based flows in Dakar region (i.e., inferred transport demand).

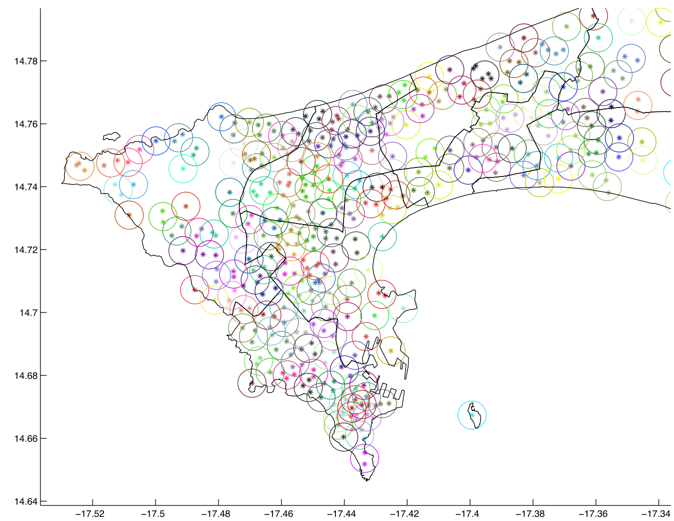


Fig. 9. Clustered cell towers in Dakar.

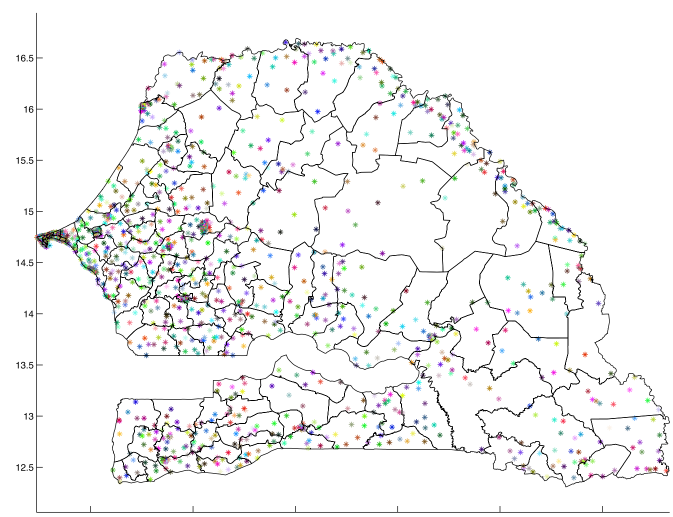


Fig. 10. Clustered cell towers in Senegal.

Figs. 9 and 10 show the clustered cell towers in Dakar region and Senegal, respectively.

With the clustered cell towers that resemble potential public transport stations, we plotted the top 22.70% cell-based flows that resemble public transport demand between potential stations, as illustrated in Fig. 11 (Dakar region) and Fig. 12 (Senegal). The already existing bus routes were excluded in these plots (Figs. 12 and 13) because we wanted to observe the travel demand for the locations that lack public transit services.

Based on our obtained results, a sensible recommendation regarding the development of future transit routes that meet the actual needs of people can be made. Suggesting a development of new transit routes for all referred transport demand (shown Fig. 12) may not be realistic, as it may require a huge government budget. Our more possible recommendation is to suggest the potential transit routes that are highly needed, i.e., top inferred routes quantitatively, for example, (1) top transit routes that have flow densities great than the average density, or (2) top transit routes with flow densities greater than half of the average density (as shown in Figs. 13 and 14, respectively).

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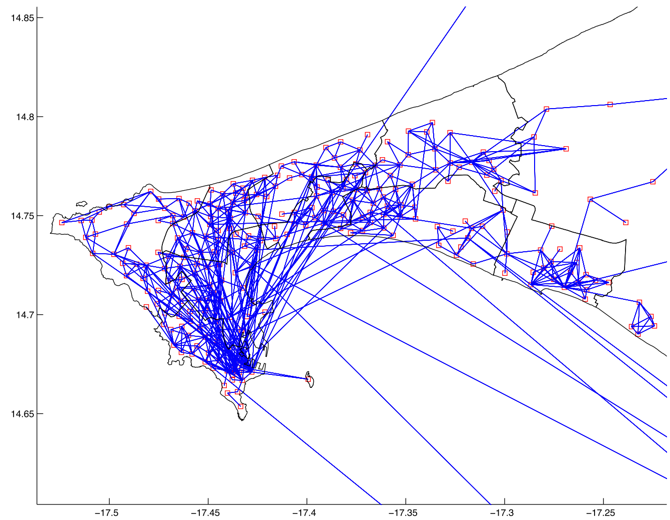


Fig. 11. Top cell-based flows across clustered cell towers in Dakar.

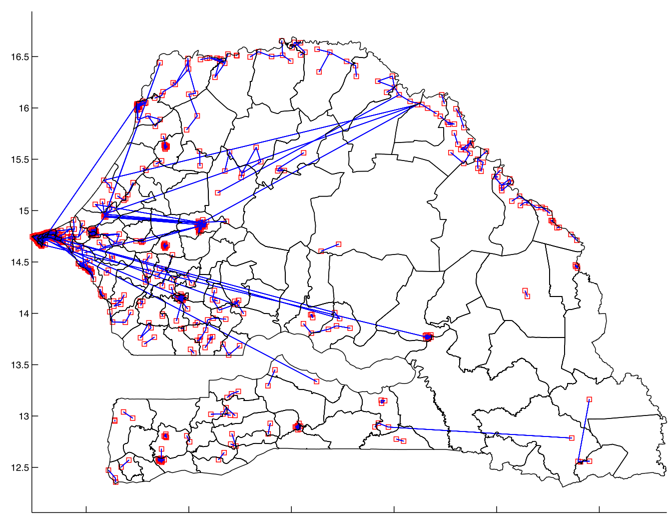


Fig. 12. Top cell-based flows across clustered cell towers in Senegal.

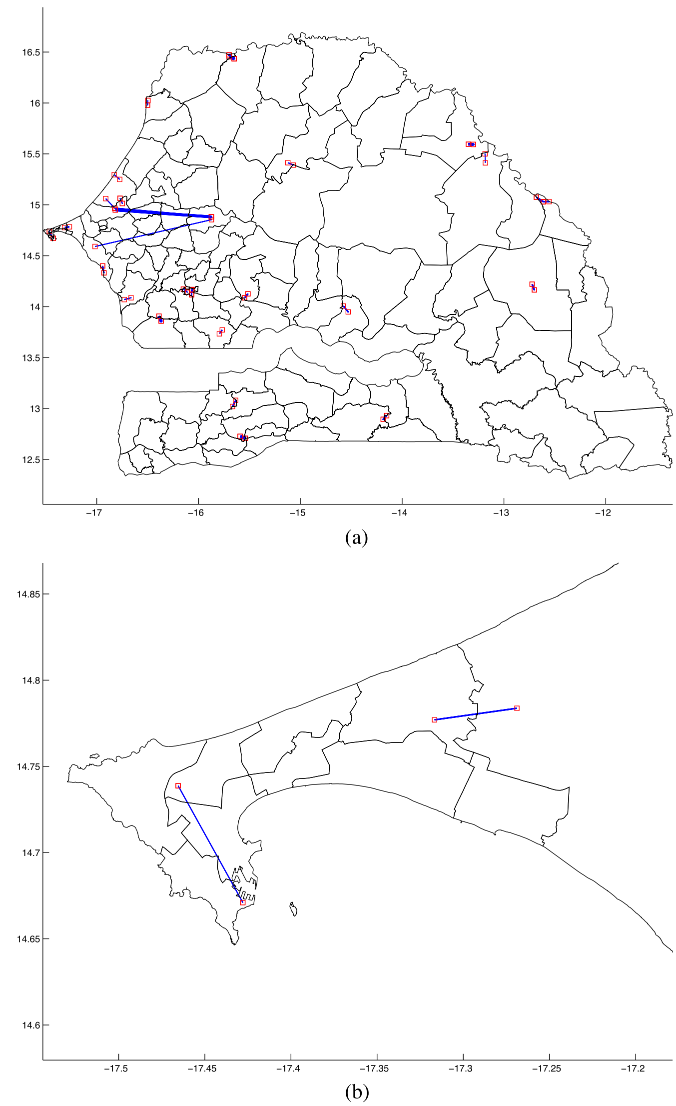


Fig. 13. Suggested 47 potential transit routes (top inferred routes with flow density greater than the average). (a) Senegal. (b) Dakar.

The suggested top inferred transit routes in option 1 include a total of 47 potential routes, while there are 234 suggested routes among the top inferred routes of option 2.

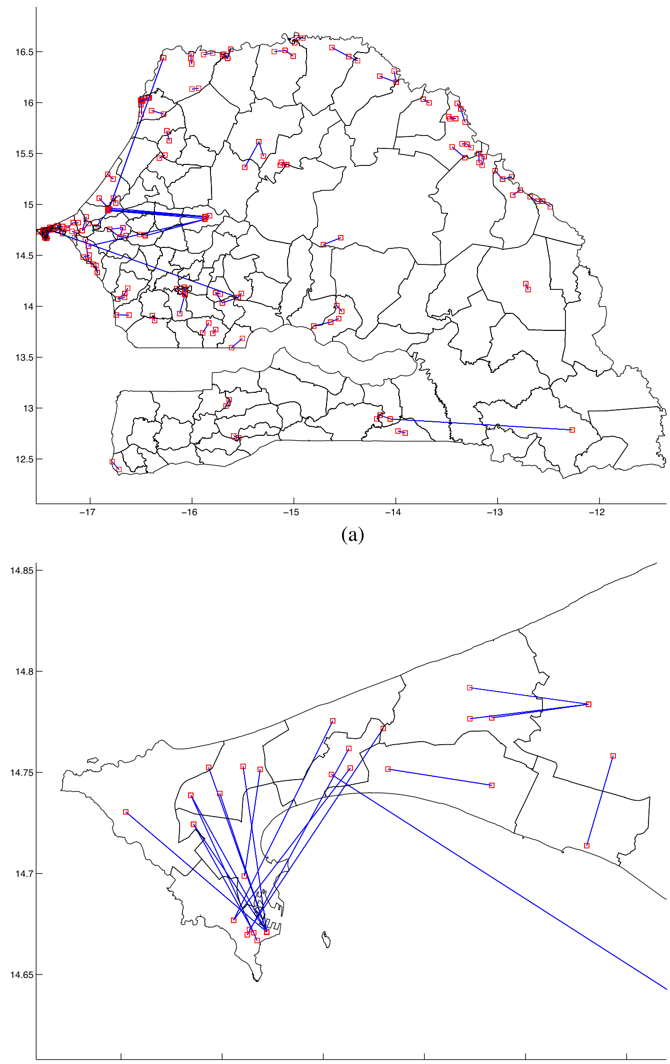
The above conditions with respect to the use of the average density are arbitrary. We were only choosing these conditions as examples to demonstrate the potential use of our inferred transport demand results to facilitate decision making concerning new transport route planning and development.

V. Validation

There are many factors that play whether we estimate the travel demand using cellphone data: the user must be active; the user must be a customer of SONATEL, which supplies the data; and calling plans, which can influence the number of samples obtained at each hour or day, and so on. Because of this, validation of our results against ground truth data is challenging. Adding to this challenge is the fact that transport planners in Senegal do not have comprehensive travel surveys.

Nevertheless, we attempted to validate our results with census data [38]. To estimate the travel demand, the origin and destination locations of trips must be identified. Therefore, using cell phone data we estimated a home-cell tower location for each subject based on the most frequent used cell tower location during the nighttime. We accumulated number of subjects whose home-cell towers are located within each of the 14 different administered regions of Senegal and compared our result against the actual census data. Fig. 15 shows a scatterplot of inferred residential regional population of the cell phone users vs. the actual regional population density obtained from the census data. The figure shows that the two estimates are closely related, with a correlation coefficient, $R = 0.85202$. We believe that this result validates our approach.

In our analysis, we did not show if the existing public transport provides enough capacity for the expected ridership. Our attempt to analyze the capacity of transit routes was not successful because of unavailability of sufficient data. For instance, the buses do not follow the actual timetables of DDD



(a)

(b)

Fig. 14. Suggested 234 potential transit routes (top inferred routes with flow density greater than the average/2). (a) Senegal. (b) Dakar.

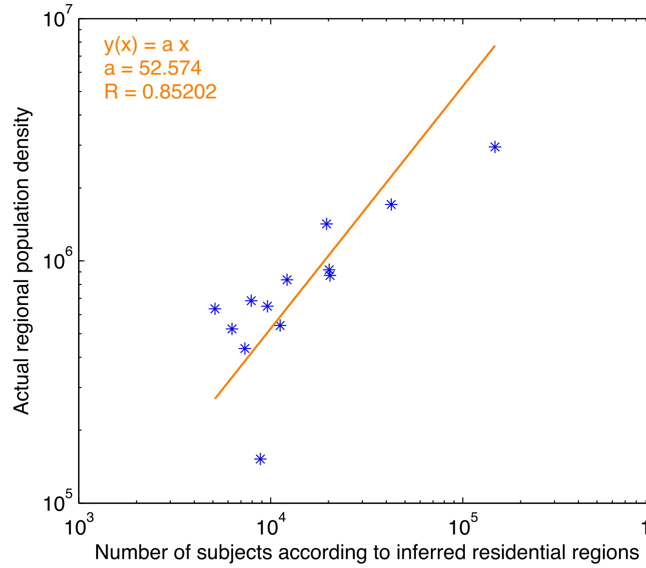


Fig. 15. Comparison between the inferred residential regional population of the cell phone users and the actual regional population density obtained from the census data.

that makes it difficult to obtain the number of bus vehicles using a given route for a specific time of the day [44]; and the information regarding the number of paratransit vehicles passing a given route is not available. These information are crucial to compute the capacity of a given transit route in terms of passengers per hour that could be carried along a given route. The general notion is that Senegalese people have limited transport options to satisfy their mobility requirements and studies show that many neighborhoods are noticeably underserved by the public transportation system. For example: in Senegal, 45% of the urban transport needs are supported by walking, cycling or other non-motorized transport systems [45]; and regardless of Dakar's more than 3 million inhabitants, there is low provision of transportation, only 25% of people's daily trips are covered by motorized modes [46], and a qualitative survey made in Dakar also revealed shortage in the supply side of the transportation system [47].

Our attempt to get local experts opinion regarding the practicality of our results is partially successful. We were not able to receive a comprehensive travel survey to validate the estimated travel demands. However, we received information regarding the road network of Senegal and which part of Dakar has the highest traffic. For example, there is a heavy traffic flows on Dakar's east-west corridors, especially during rush hours. The Senegalese government responds by increasing the supply of road space by building more roads such as the construction of a highway in Dakar, which was opened to traffic in two phases: the Patte d'Oie-to-Pikine section was opened first in 2011, followed by the Pikine-to-Diamniadio section on August 1st, 2013 [48]. The high travel demand along this route was also clearly identified in our analysis.

We were encouraged to carry out further analysis to see if the travel patterns estimated by the cellphone data are coherent with the urban movements on the main road network of Senegal. About 90% of movements of people and goods in Senegal are made via roads [49]. The current road network in Senegal can be classified into five levels: national roads, regional roads, department roads, urban way and classified tracks. National roads provide connections between several administrative regions and with neighboring states. Regional roads provide connections between different departments of the same region. The remaining roads provide connections within the departments [49]. To pursue our investigation, we aggregated individual trips that are made between different districts of Senegal (there are 123 districts). Fig. 16(a) provides a qualitative understanding of the travel patterns of people between districts of Senegal, which was inferred through cellphone data. The aggregate flows of people are shown using color differentiation in four groups. The red color stands for high flow (above the 75th percentile); the yellow color stands for flows between the 50th and the 75th percentiles; the green color stands for flows between the 25th and the 50th percentiles; and the blue color stands for low flow (below the 25th percentile). Red markers show the centroids of the districts. There is a high concentration of movements

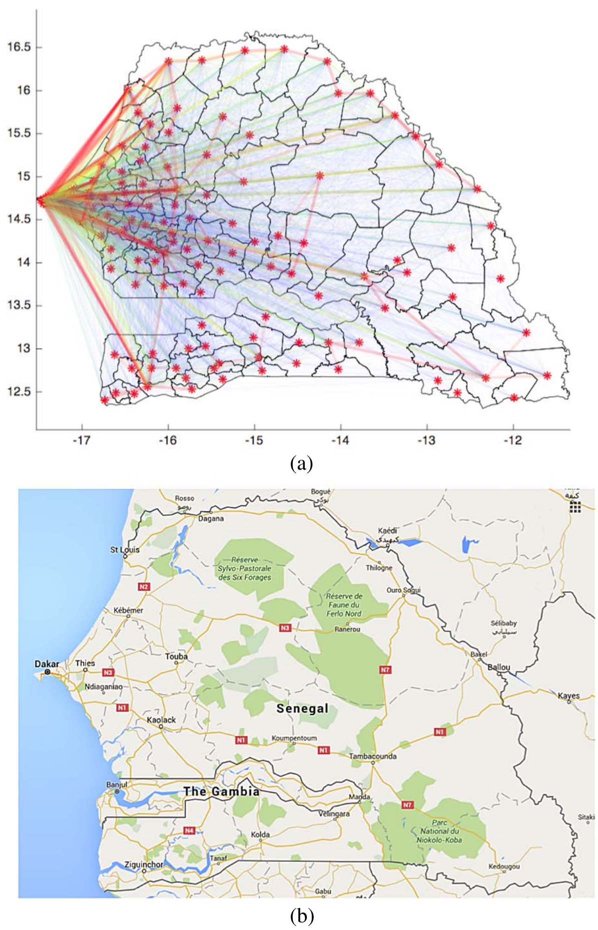


Fig. 16. Map of Senegal: (a) Mobility of people between districts inferred from the cell phone data and (b) Road Network (Source: Google Maps).

within districts in Dakar, Thies, Saint- Louis and Matam. The urban movement along the national road N2 from Dakar to Bakel, which is in the northeast coast (with main hubs along the route: St-Louis, Richard Toll, Ndioum, and Orossogui), is clearly identified by our result. This result allows us to see how the travel patterns of people estimated through cellphone data assimilate the urban movements on the main road network of Senegal shown in Fig. 16(b). The underlying assumption is that the pattern and amount of cellphone traffic movement is related with the intensity of urban movements in the existing road network and understanding this relationship will help in managing urban dynamics.

VI. Discussion of Potential Applications

In the last decade, the transport sector in the Sub-Saharan Africa countries has been recognized by the African planners and policy makers, economic analysts, and international donors as one of the key components for growth, poverty alleviation and sustainable human development. Most of the previous efforts were directed towards interregional, interurban and rural transport sectors. Recently, given the fact that the urban share of Sub-Saharan African population has grown substantially and is expected to continue in the future, the concern for the Sub-Saharan Africa transport policy program is shifting towards improving urban mobility and accessibility [50], [51]. Joining this effort, our study aims to improve the urban mobility system in the Sub-Saharan countries. To demonstrate our methods, we used Senegal as a case study country. We showed an application of passive mobile positioning data to detect the spatial distribution and temporal evolution of movements of Senegalese citizens. Our analyses open up new possibilities to gain insights into how cell phone data can be applied for urban and transportation planning. The results could be used in a wide range of applications and domains. As shown in this study, results can be used to quantify the flows of people and vehicles, and measure the mobility needs of citizens (transport demand). Specifically, this study makes the following contributions.

A. *Improving the Current Practice of Urban Public Transport Bus Service*

In Dakar, the mobility of people is ensured in part by the large-bus services and by the paratransit service, which is the main mobility actor in Dakar. Regardless of these services, some neighborhoods of Dakar do not have sufficient public transportation, which were clearly identified and visualized in our analysis (Figs. 13 and 14). We propose two alternatives for transport authorities regarding the development of potential public bus routes to accommodate the mobility needs of the underserved neighborhoods in Dakar: (i) introducing new public bus routes; and (ii) improving existing public bus routes. These alternatives can be prioritized based on availability of budget and characteristics of transport demand on a given route.

In Fig. 17, we identified new transit route suggestions such as A-C, B-D, and B-H. The suggested routes are connecting locations A and B, with locations C and D. Locations A and B are the heart of Dakar, commonly known as Plateau (also referred as downtown), which has a high concentration of office buildings, public administrations, shopping and hotels. Locations C and D belong to a neighborhood named Grand Yoff, which is one of the most populous neighborhoods in Dakar. While these locations are covered with proper urban public transport system, our analysis indicated the necessity of additional route, where there is sufficient transport demand to support the introduction of new bus routes. In the case of new bus route B-H, even though DDDs bus routes 8 and E12 are already serving the Lopold Sdar Senghor International Airport, the addition of new route can be justified by limiting the number of intermediate stops to connect the downtown area with the Airport with shorter travel time.

Fig. 17 also shows transit route recommendations (B-F and E-G) to link the downtown area (neighborhoods of Plateau, Medina, Gueule Tapee Fass-Colobane, and Fann-Point E-Amitie) with Pracelles Assainies, which is one of the most populous neighborhoods in Dakar. From our analysis, we were able to detect relatively high flow density between the two destinations to support the addition of these new routes. The new routes can be introduced with a small number of intermediate stops or express versions of the existing routes provided by DDD such as bus routes 1, 17, 23, and E4. Introducing a new route on existing corridor can be advantageous because of

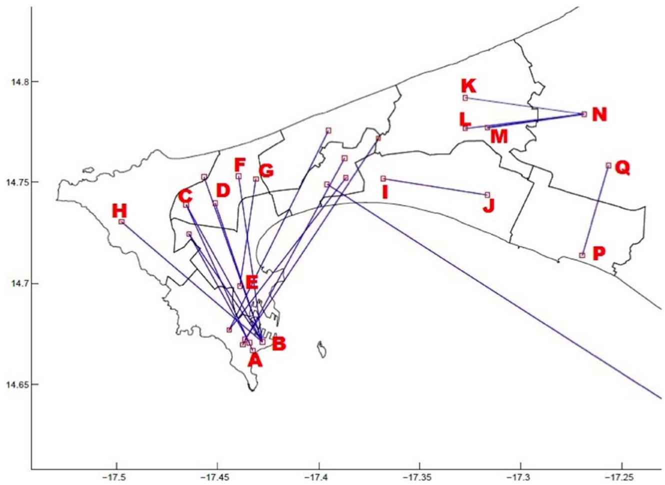


Fig. 17. Some transit route recommendations.

the existing infrastructure such as terminals, which make the implementation of new routes easier.

We also make route suggestions to provide a connection between the district of Niayes and Bambilor (K-N, L-N, and M-N) as well as improving public transport links between the district of Rufisque and Bambilor (P-Q). Because of their short distances, the new routes can be introduced as extension of an existing bus route. For example, DDD's existing bus line 11, which terminates at terminus Lat Dior or bus line 16, which terminates at terminus Malika would extend to accommodate the new routes K-N, L-N, and M-N. On the other hand, existing bus line 15, which terminates at terminus da Bargny can be extended to accommodate new route P-Q.

B. Improving the Current Practice of Urban Paratransit Service

In most cases, the paratransit system complements or works in parallel with the bus service that has failed to expand to meet the increasing travel demand due to population growth. The paratransit system in Dakar is intended to contribute for mobility to the general public, despite the fact that it is criticized for its inefficiency to anticipate potential users at different locations of the city. This often makes the system unreliable and users face huge difficulty to rely on the service to plan their trip [52]. To address this problem, paratransit operators can use the suggested routes to redirect their service offerings to the identified locations where their services are mostly needed. In addition, the use of small vehicles gives the paratransit system advantage to serve areas with low travel demand and increasingly dispersed trip-generating activities, which were identified through our analysis.

C. Providing Indicators for Potential High Order Public Transport Development

Contemporary Senegalese cities are dealing with quick changes in population growth and urbanization that alter travel requirements constantly. Responsible authorities are searching ways to improve the quality, reliability, and coverage of public transport systems. One possible option is public transport improvement by strengthening operation of existing paratransit and large-bus services, and the other potential alternative is a hybrid system comprised of both paratransit and a high order public transport system [53]. There are a number of city authorities in developing countries taking this initiative and proposed BRT system [54]. In the case of Dakar, CETUD appointed SAFEGE/SCE to carry out the engineering studies for a pilot dedicated-lane BRT system [55]. One of the major problems associated to this kind of expansion are estimating and forecasting public transport demand through conventional methods that require massive data collection work such as expensive travel surveys, demographic and land use characteristics [56]. In this regard transport planners can use our analysis framework to understand the mobility patterns of people and the recommended transit routes can be also part of the potentially developed high order transport system.

D. Cost-Effective Transport Planning Approach

The first tasks involved in public transport planning such as travel demand estimation through traditional transportation models require massive data collection effort. In addition, the period required for model estimation and demand forecasting process may take years, during which time the dynamics of urban activities, transportation systems, as well as policies of interest may change, often requiring new data collection and modeling effort [57]. Our study takes advantage of presence of large amount of cell phone data in Senegal to demonstrate how transport planners can sense the movement of people more regularly, with reduced cost, and in a large scale, especially in circumstances where relevant data are unavailable or poorly supplied. This can potentially inspire transport planners in developing countries to shift from the costly and time consuming traditional transportation planning, to a more data-driven planning process, where citizens themselves are part of the sensing infrastructure.

VII. Conclusion and Future Work

In developing countries, planners are facing great difficulties in capturing the existing and future mobility trends due to the limited budget they can access for transport data collection purposes. Currently, data from alternative sources are becoming available and can be used to sense the movement of people in cities more regularly, with reduced cost and in a large scale. It becomes particularly useful and essential in cases where relevant data are not available, or poorly supplied. Cellular network is ubiquitous in today's cities and the high cell phone penetration rate in the developing countries provides planners ways to opportunistically sense the presence and movement of people at fine-grained resolution. We argue that despite the low development state of the transportation planning practice in the developing countries, they may benefit from what is now about a decade of research on using cell phone data, to achieve a more efficient public transport system without having to go through the expensive structure that developed countries have set up for this purpose.

In this study, we developed methodologies to extract the mobility patterns of people using their cell phone usage as a proxy. Our results enable transport planners (public transport operators) to analyze their public transport offerings, and efficiently plan new transit routes or extend existing routes to fulfill the mobility needs of users by maximizing the bus route coverage and accessibility. In order to demonstrate our methodologies we used Senegal as a case study country.

This study brings important benefits to a vast group of stakeholders. For example, by using the extracted mobility patterns, it will be possible for public transport operators to understand better about the transport demand and manage their service offerings accordingly. With better information on the mobility patterns of people, city authorities have more opportunities to resolve social and economic problems, and can make informed decisions in terms of future sustainable urban infrastructure planning to better serve citizens. Above all, this study will contribute to the sustainable urban mobility system in terms of using cost-effective cell phone data, and improving coverage, accessibility and efficiency of the public transport systems. Despite the significance of our analysis, we should emphasize some important limitations of the study. Regardless of SONATEL's share market of 61% in Senegal, in principle, our analysis is only applicable to subscribers of SONATEL. In order to associate the extracted movements and flows to all inhabitants of Senegal, we need to assume that our sample is representative of the current distribution of people in the country. Other reasons that can affect the outcomes of our analysis include: number of mobile devices (and Subscriber Identity Module (SIM) cards) each person carries; and calling plans, which can influence the number of samples obtained at each hour or day. Nonetheless, a recent study in Kenya shows that mobility estimates based on cell phone data are robust to the substantial biases in phone ownership across different user groups [57].

The transit route suggestions were based on the travel patterns of people. In addition to the travel pattern information, what is equally important in the planning of new routes/extension of routes is if the new route provides shorter travel time or higher ridership, and also if the out of vehicle times such as access, waiting, and transfer are minimized. Our study did not consider the later information and we limited the scope of our analysis on providing recommendations of convenient linkages between users' origin and destination in highly needed areas. However, one has to bear in mind that bus routes intended to minimize travel time may not satisfy the requirements of maximum coverage and accessibility.

We allocated all the transport demand to the available public transport systems. This is due to the fact that public transport systems share above 85% of the trips among the motorized transport modes within the urban areas of Senegal [45]. Our method is by no means equivalent to the traditional multi-stage travel demand forecasting method, which includes analysis of trip generation, trip distribution, modal choice and trip assignment. The aim of our study is to provide transport planners, especially in the developing countries, with an option that can be considered in the absence of comprehensive transport data to produce estimates of ridership and plan their transportation systems.

Our route recommendation is mainly based on flows between origin and destination (terminus locations). Future studies have to consider availability of important trip generators along the transit route to decide intermediate stops. We were not able to obtain full information regarding the urban transit network of Dakar. We validated our results based on transit network data obtained from DDD such as bus routes, network type, and origin and destination bus stop locations. As part of our future work, we will improve our methodologies by incorporating additional relevant information such as existing transit route capacity, bus ridership data, and more information regarding the paratransit services as they become available. In addition, we only focused on obtaining the mobility patterns of people between their home and top five destination locations without accounting for intermediate activities carried out by a person. However, we recognize the importance of integrating intermediate activities of each subject that our analysis lacks for the time being. We plan to address this task in the future when more data are available from the study region.

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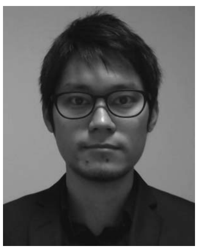

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