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Road Network Design in a Developing Country Using Mobile Phone Data: An Application to Senegal

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I. Introduction

For long-term development, transport planners make decisions on whether they should add new roads and/or upgrade the existing ones to meet the demand. The problem regarding making such decisions is named as the Road Network Design (RND) problem, which has vastly been explored in the literature and is regarded as a challenging

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Abstract—This study uses mobile phone data to understand mobility patterns in a country, with limited mobility data, in order to give advice about decisions on how to design the national and regional road network. Our method consists of three parts: (1) filtering mobile phone traces to derive mobility patterns, (2) building an adapted formulation of the gravity-based trip distribution model, which considers telecommunication intensity (i.e., aggregate number of calls and text messages) and travel time as input to forecast the influence of road improvements on country-wide mobility, and (3) optimizing the road network investment based on the adapted trip distribution model by using a local search algorithm. The method was applied to the case study country of Senegal. The mobile phone data was transformed to support informed decisions on road network development in that country given different objectives, namely accessibility and equity. We believe that the methodology is valuable and reproducible to other countries where traditional mobility data is scarce but mobile phone data is available to transport planners.

transport topic [1]. In a developing country, the task of RND is especially urgent because of the following facts:

- fast population growth, which causes the increase of travel demand and is outstripping road development (e.g., in Senegal [2])
- poor and uneven road accessibility over the country, contributing to regional inequalities and limited economic development
- limited budget available for road development.

Therefore, a trade-off has to be made between satisfying more travel demand, increasing accessibility in remote areas, and investing limited resources in an efficient way. Finding this balance can be regarded as a difficult optimization problem.

In order to support the decisions on RND, transport planners first need data to estimate travel demand over the network. Traditionally, those data are collected through mobility surveys, but they are rather difficult to be acquired in developing countries where governments cannot afford to conduct nationwide surveys. Even though mobility survey data are available in most developed countries, this traditional way of collecting data is criticized for being too costly and time-consuming [3]. This is the main reason why most of the existing mobility survey data are infrequently updated, and their sample size is small. In recent years, significant advances have been made in many aspects of transport planning. One of the changes is a growing availability of new mobility-related data sources, which are being explored to complement or even replace the traditional mobility survey data [4], [5].

Among those new data sources, mobile phone data is becoming popular for mobility research and practical planning today mainly because of the high penetration rate of mobile phones even in developing countries (e.g., close to reaching 100% in Senegal [6]). Mobile phone data include all communication activities made by individual users. Transport researchers are mostly interested in location and

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timestamps of mobile phone activities, usually designated as mobile phone traces, since such information can be a proxy for users' movements in space and time [7]. Such traces have been used for many purposes, including estimation of travel demand [8], exploration of urban structures and dynamics [7], [9], [10], detection of road traffic status [11]–[13], and analysis of human activities [14]–[16]. Apart from location and time information, the data of telecommunication, such as caller ID and recipient ID of a call, is sometimes available in some mobile phone data as well. Such telecommunication data can reveal social interaction, complement mobile phone traces, and serve as a good reference for understanding mobility [17]–[19].

Mobile phone traces can only reveal historical travel demand, and this is not adequate for RND. As argued in [20], in many existing studies of RND, travel demand is assumed to be known in advance and fixed. This is a poor assumption since any improvement of the road network would influence travel time and thus change the trip distribution in the region of interest. Therefore, it is necessary to measure the elasticity of trip destinations regarding travel time variations and build a trip distribution forecasting model.

The proposed method in this research consists of three parts: mining mobile phone traces for mobility information, building a gravity-based trip distribution model, and finding optimal configurations for the road network. Our innovation lies in the newly-formed gravity-based trip distribution model, where the population distribution is replaced by telecommunication intensity (i.e., aggregate number of calls and text messages) as an explanatory variable. We believe that the use of this adapted model is not limited to RND problems, but it should also be valuable for other objectives which require estimation or prediction of travel demand in developing countries. Moreover, to the authors' knowledge, few studies have been made on an integral decision-making process which transforms mobile phone data to support informed decisions on RND, to which this research is expected to contribute. In 2014, the 'Data for Development Senegal' challenge (D4D challenge) organized by Orange, a mobile phone network operator, made the data of Orange users in Senegal available for research [21], giving us the opportunities to apply the methodology and solve the practical RND problem for that country.

This paper is organized as follows. In Section 2, we provide a literature review on mobility analysis using mobile phone data and a review on RND problem. In Section 3, we propose the adapted form of the gravity-based trip distribution model and explain how it can be integrated into the RND decision-making process. Following the background information in Section 4, we present a case study of the method applied to Senegal in Section 5. In the final section, conclusions are made, and future research directions are pointed out.

II. Literature Review

A. Mining Mobile Phone Traces for Trip Information

We focus on the method of extracting origin-destination (OD) trip information from mobile phone traces since OD trip matrix in a region is an essential input to RND. In some cases, deriving the use of transport modes from mobile phone traces is also necessary for RND because one is interested in the driving mode. However, this is not necessary for our typical case of application, developing countries, where road transport dominates, and thus we leave it out of the scope of this paper.

OD information can be extracted from mobile phone traces by distinguishing whether a user stopped for a reasonable period from where he/she passed through. The extraction of a stay point depends on two parameters, a time threshold and a distance threshold. A stop is regarded as a sequence of traced positions where the distance between any adjacent positions is less than a distance threshold, and time spent at these positions is greater than a time threshold [22]. Meanwhile, false movements should be detected, which are usually caused by mobile signal jumps between the towers [23].

Through these procedures, an OD matrix of mobile phone users can be estimated, but it should be noted that this matrix is possibly a biased representation of the entire population's behavior, and such biases can be caused by two reasons:

- Since mobile phone data are generated only when users take actions (e.g., making calls), the sampling of each individual's traces might be infrequent, uneven, and biased toward specific locations (e.g., home locations) or times of day (e.g., during the evenings) [24].
- The travel behavior of mobile phone users may not be representative since these users are not uniformly chosen among the population [25].

To solve the first problem, it was suggested to sample highly active mobile phone users because more mobile phone usage can generate more traces, improving the accuracy of trajectory reproduction [26]. Moreover, researchers compared the spatial distribution of mobile phone users' homes (detected through simple facts like most of the people spending their night at their home place) and the spatial distribution of the population given by the census data [27], and they calculated an expansion factor for each zone to upscale the number of trips made by sampled users to the number of trips made by the population [23].

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However, if the travel behavior of the sample is not representative in one zone, it is not reasonable to simply upscale the observed trips to the actual trips by those expansion factors. For example, sampling only the active users would make the observed travel behavior unrepresentative, because researchers found that high frequency of telecommunication is correlated to high mobility [26]. Under this condition, the upscaled number of trips would be overestimated. A more reliable approach is to estimate the OD matrix by referencing the traffic data. Iqbal et al. [28] scaled up the OD matrix which better matches with the observed traffic counts. This method is ideal but practically unfeasible in developing countries because traffic counts data are out-of-date or even unavailable.

There are two ways to further test the validity of the estimated OD matrix. One way is to check if the estimated OD matrix can fit well to a gravity model [27], [29]. No knowledge about the parameter values of the model is a prerequisite, and a better fitness would mean the higher validity, but the weak point is that there are no absolute criteria. The other way is to compare the estimated OD matrix with mobility survey data [27], which is however not always available in developing countries.

B. Road Network Design (RND)

The RND problem is usually formulated as a bi-level problem, where the network designer makes the decisions on how to plan the road network based on the mobility patterns of travelers, and the travelers adapt themselves to the new network by changing their travel behavior to maximize their utilities, forming the new mobility patterns that would influence the network designer's decisions in return [30]. The higher-level problem addresses the question of where new links should be constructed or which existing links should be upgraded. The lower-level problem concerns the estimation of travel demand flows in the network [1].

To solve the lower-level problem, an unconstrained gravity model can be used to predict the distribution of trips influenced by the changes of travel times with the new network. Afterwards, traffic assignment is usually done according to the user-equilibrium principle or the 'all-or-nothing' principle [31]. The latter principle only makes sense in non-congested networks.

Regarding the higher-level problem, the goal is to optimize the network layout according to given objectives. The traditional objectives proposed in the literature usually address efficiency (e.g., to maximize the weighted average accessibility), robustness (e.g., to maximize the weighted reserve capacity of the network), equity (e.g., to minimize the accessibility of the zones with the lowest accessibility levels) [20] and environmental objectives (e.g., to minimize carbon dioxide emissions) [32]. The performance indicators of these objectives can be calculated given the outputs of the lower-level problem, including the matrix of shortest travel times, the OD matrix and traffic volumes. In some studies, the minimization of the total costs of road investments can also be the objective of the network design problem, given some mobility requirements or in complement to other costs (e.g., [30]); however, this is mostly considered as a constraint of the problem [1]. A multi-objective evaluation of solutions can be made by using the well-known weighting method [33]. The weights for the objectives can be determined by decision-makers according to their relative importance, and the overall value of the weighted objectives can be calculated for assessing different solutions.

Historically, the RND problem had two forms of solution: a discrete form dealing with the additions of new links or roadway segments to an existing road network, and a continuous form dealing with the optimal service improvement of existing links [1]. However, an important issue of the real-world road network planning is the multilevel discrete nature of service improvement. As a result, Santos et al. [20] proposed a discrete form dealing with the optimal service improvement of existing and potential new links in the network.

Finding an optimal solution to this problem, regardless of the form adopted, is rather difficult due to its non-linear characteristic and bi-level structure. Heuristic methods are therefore the typical solution approach adopted because they can handle such complexity, preventing exhaustively searching the entire space of possible solutions by trading complete optimality for computational speed [34]. In every iteration, the current solution is compared with the best existing solution obtained in previous iterations. If the current solution is better than the existing best solution, the current solution becomes the best existing solution and a new iteration is performed to generate

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and assess a new solution. Otherwise, after a given number of iterations without any improvements, the optimization is stopped. The process of selecting a next solution can follow different heuristic and meta-heuristic methods including, for example, genetic algorithms [35].

III. Adapting a Gravity-Based Trip Distribution Model

A. Traditional Gravity Model

In a traditional gravity-based trip distribution model, the number of trips between two zones should be proportional to a trip generation indicator (e.g., population size) and inversely proportional to the generalized travel cost between the zones [31]. Improvements to such a model included the use of total trip ends instead of total population. Due to the lack of information regarding trip ends, in many cases, total trip ends can be replaced by the product of population sizes with power parameters to be estimated [29], [36]. Therefore, an improved model can be formulated as the following equation:

$$T_{ij} = K_1 P_i^a P_j^b f(c_{ij}) \tag{1}$$

where T_{ij} is the number of directed trips from zone i to zone j; a and b are the power parameters on population sizes; $f(c_{ij})$ is the cost function; and c_{ij} is the generalized travel cost from zone i to zone j. The generalized travel cost can usually be expressed as a function of the travel time, travel cost and/or distance. The cost functions can be classified into the exponential function or the power function, which are formulated respectively as follows [31]:

$$f(c_{ij}) = \exp(-\beta c_{ij}) \tag{2}$$

$$f(c_{ij}) = c_{ij}^{-n} \tag{3}$$

where β and n are the exponential parameter and the power parameter respectively for the cost function.

One problem is that this kind of gravity model may not always perform well. It was found that if the distance between two zones is larger than 150 kilometers, the number of trips no longer depends on the actual distance [29]. Moreover, the social interaction between two zones is not taken into consideration in this gravity model. For example, two densely populated areas close to each other may generate little travel demand between them in case people in these two areas have different languages, or there are political borders for example. Those drawbacks gave us motivation to formulate a new gravity model utilizing telecommunication data which naturally contains these social interactions.

B. Formulating a New Gravity Model

It was found in a case study in Belgium [37] that the total call duration between two zones was proportional to the product of population of two zones and that an inverse-square law decrease was found between the call duration and the distance, in terms of the following equation:

$$I_{ij} = K_2 P_i P_j / d_{ij}^2 \tag{4}$$

where I_{ij} is the undirected telecommunication intensity (total call duration) between zone i and zone j; and the scaling constant K_2 is the gravity constant for a time span of 6 months of calling activity. It should be noted that this gravity model of telecommunication intensity was fit to the reality in Belgium, where the distance between every two zones is not large.

In the case that the trip OD matrix is almost symmetric (which often occurs when traffic is counted over a whole day), and the generalized travel cost matrix is simply assumed to be symmetric (which is commonly the case in regional and national road network models), then the power parameters on population sizes (i.e., a and b) should almost be equal in equation (1). We can combine (1) with (4) and obtain (5):

$$T_{ij}' = K_3 I_{ij}^m F(c_{ij}) \tag{5}$$

where m is approximately equal to a and b based on the derivation of the equations; T_{ij}' is the number of undirected trips between i and j, approximately equal to $T_{ij} * 2$; $F(c_{ij})$, equal to $f(c_{ij}) d_{ij}^{2m}$, is the new cost function used in the adapted gravity model.

There are two main reasons as to why we expect that using the adapted gravity model can have advantages over using the traditional one. First, the data of telecommunication intensity is more reliable, more precise and more updatable than the population census data. Second, they can reflect the social interaction between zones, which population data cannot.

The adapted gravity-based trip distribution model can be integrated into the RND decision-making process. We can start from estimating OD information using mobile phone data. Next, the adapted gravity model can be estimated, and this is the key to solving the lower-level RND problem.

Since we only focus on the mobility between departments in this case, the national and regional roads in the network are kept and the lower-level roads are removed except several departmental roads that are necessary for inter-departmental connections as well.

IV. Background Information of Case Study

A. Study Area

Senegal, the target country in the case study, is located in West Africa, covering a land area of almost 196,722 square kilometers, and has an estimated population of about 14 million [38]. Senegal ranks 119th on the list of countries of the world by the confirmed GDP estimates in 2014 [39]. It is worth mentioning that the geographic disparities are very pronounced in Senegal, with almost 2 out of 3 residents in rural areas, especially in the south, versus one in four in Dakar [40]. Also, the western part of the country, especially the Dakar region, is more densely populated than the others. Arrondissement, department and region, ordered by size from small to big, are the administrative divisions of Senegal. Among them, department is the basic spatial unit used in this study.

The shape of the existing Senegal road network is simplified and shown in Fig. 1, where the departments in Senegal are labeled with the corresponding number from 1 to 45. The way we simplify the road network is explained as follows. First of all, since we only focus on the mobility between departments in this case, the national and regional roads in the network are kept and the lower-level roads are removed except several departmental roads that are necessary for inter-departmental connections as well. We define department center as the traffic generation centroid, most of which are the capitals. Roads are not extended to the adjacent countries except to the country of Gambia that is an enclave of Senegal. There are two national roads crossing Gambia for the connections between the northern and southern parts of Senegal. It should be noted that there is a river in Gambia crossed by those two national roads, and thus there are two ferry services connecting the separated roads at the Banjul-Barra crossing point (the left one on the map) and the Trans-Gambia crossing point (the right one). Moreover, the newly-constructed highway between Dakar (1) and Diamniadio (4) is a part of the network as well. Note that the section of the Dakar tolled highway between Pikine (3) and Diamniadio was open on August 1st, 2013, and the rest of the sections were open before 2013.

In order to calculate the shortest travel time matrix of this road network, average travel speeds should be known, which are influenced by speed limits, capacity and traffic volume, but knowledge about them is limited given the available information. Thus, the average service speeds on national, regional and departmental roads are simply assumed as 60 km/h, 45 km/h and 30 km/h respectively. The average service speed on the Dakar-Diamniadio tolled highway is assumed to be 80 km/h though in reality this value can even be higher. The reason for making this assumption is to roughly compensate for the effects of the road toll. It is assumed that it takes people around 4.5 hours and 3.5 hours (including travel time, waiting time and effects of ferry tariff) to take the ferry services at the Banjul-Barra crossing point and the Trans-Gambia crossing point respectively. The Dijkstra's Algorithm can be applied to calculate the shortest travel time over the network between every two departments, and the generalized travel cost, equal to shortest travel time in this case, is undirected in this network.

B. Mobile Phone Data

The datasets provided by the D4D challenge are based on the records of phone calls and text exchanges between more than 9 million of Orange's customers in Senegal between January 1st, 2013 and December 31st, 2013. The D4D

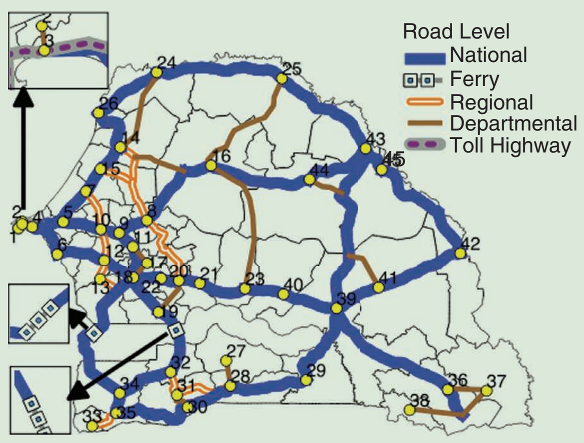

FIG 1 Road network in the study area.

challenge transformed the raw mobile phone data into mobile phone traces and telecommunication data.

Antenna-to-antenna traffic of calls and text messages of more than 9 million users for 1666 antennas on an hourly basis is provided as the telecommunication data. We aggregated the data both spatially and temporally to department-to-department traffic of calls and text messages during each month.

Mobile phone trace data provides one year of coarse-grained mobility data at individual level for about 160,000 randomly sampled users having more than 75% of the days with mobile phone usage in one year. Once users made phone calls or had text messages with others, the arrondissement where they connected to the antenna at that time was recorded, and the scale can be further aggregated to the department. To that extent, their inter-departmental trajectories can be captured over one year. It should be noticed that the users presumed to be machines or shared phone users were excluded from this dataset by the data provider.

V. Applying the Method to the Case Study

A. Extracting Information from Mobile Phone Traces

For a mobile user u, we first aggregated the consecutive traces at the same department as one spatial trace. D_{ur} is the rth spatial trace that the user left. FT_{ur} is the time when the user made the first mobile phone activity at D_{ur}, and LT_{ur} is the time when he/she made the last activity at D_{ur}. The shortest travel time from $D_{u(r-1)}$ to D_{ur} is $t(D_{u(r-1)}, D_{ur})$, and the shortest travel time from D_{ur} to $D_{u(r+1)}$ is $t(D_{ur}, D_{u(r+1)})$. We assumed that u had mobile phone activities at department centers. To filter out the pass-by traces and mobile signal jumps, we applied the rule that the interval $FT_{u(r+1)} - LT_{u(r-1)}$ should be larger than the sum of the assumed least duration of stay at D_{ur}, $t(D_{u(r-1)}, D_{ur})$, and $t(D_{ur}, D_{u(r+1)})$; otherwise, D_{ur} should be removed. In this case, we assumed the least duration of stay at one department to be 2 hours.

We applied this filtering algorithm to the mobile phone traces. The number of trips made by the sampled users was estimated between every two departments. We came up with the estimated OD trip matrices of the sampled users in 2013, and we named them as the relative travel demand. We should note that in our case, the travel demand generated from densely populated departments might be overestimated relatively to the demand generated from elsewhere. However, we believe that for the RND purpose, this is acceptable. The alternative would be using the expansion factors, and this would overestimate the travel demand generated from sparsely populated departments, which would therefore lead to investing more on those roads which are actually not busy. In addition, since we do not consider congestion, it is not necessary in this case to calculate the exact number of trips, and it is sufficient to use relative travel demand to represent the network accessibility.

Travelers might use different modes of transportation for moving between departments in Senegal, whilst we only focused on the trips by road transport in this study. Nevertheless, It has been reported by the World Bank [2] that road passenger share in Senegal was above 99%, and road freight share above 95%. Thus, it can be assumed that most of the inter-departmental movements are made by road transport.

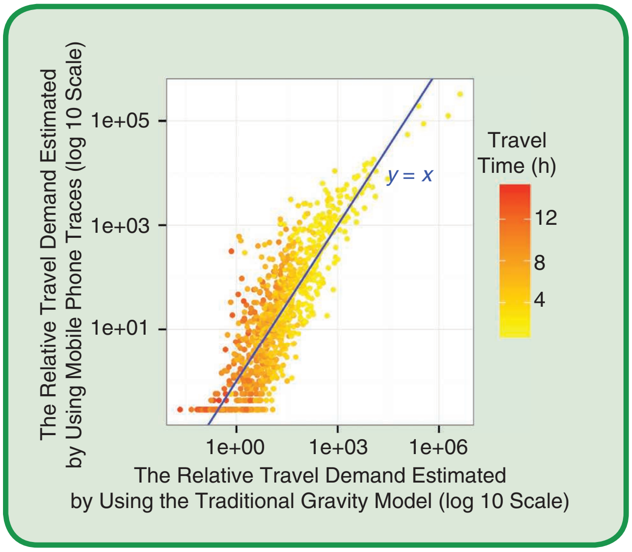

FIG 2 The fitness of the traditional gravity model.

Table I. Estimation result of the traditional gravity model.

Parameter	Estimate	Std. Error	t Value
$\log_{10}(k_1)$	–8.89705	0.34927	–25.47
a	1.07067	0.04305	24.87
b	1.08714	0.04305	25.25
n	2.53015	0.05034	50.26
Adjusted R-Squared	0.7299		

B. Gravity Model Estimation and Validation

First, we used the data before August 1st, 2013 (i.e., training data) to estimate a traditional gravity model. Regarding the cost function, we followed the idea of [29]: fitting both the power law decay and the exponential decay, to find the one that provides a better fit. As a result, the gravity model with the power parameter for cost function fits better. The fitness is shown in Fig. 2, where the y-axis represents the relative travel demand estimated by using mobile phone data, and the x-axis represents the relative travel demand estimated by the gravity model. The estimated values of parameters and the adjusted R-squared are listed in Table I. The functional form of the gravity model with estimated parameters is given as follows:

$$T_{ij} = (1.27e-09) * P_i^{1.07} * P_j^{1.09} * t_{ij}^{-2.53} \quad (6)$$

The estimated value of n (2.53) can reflect the impedance of travel time for trip distribution. The estimated values of a and b are almost equal, as we expected. The estimated value of adjusted R-squared (0.73) indicates that the estimated relative travel demand somehow fits well to the gravity model. It can be observed in Fig. 2 that the longer the travel time between two departments is, the worse the model fits. This is exactly what was observed in [29].

Afterwards, we used the training data to estimate the adapted gravity model. To examine the relationship between the variables, we first plotted in Fig. 3 the monthly average estimated relative travel demand and monthly average telecommunication intensity between every two departments, and indicated the travel times in colors. Note that we used the total number of calls and text messages to indicate the telecommunication intensity in our case, instead of the total duration of calls used by [37]. A power law increase with an exponent close to 1 (indicated by the blue fitting line in Fig. 3) can be observed between the relative travel demand and telecommunication intensity. Moreover, when the travel time between departments is shorter, the ratio of relative travel demand to telecommunication intensity is mostly higher. In summary, the travel demand between two departments is almost proportional to the telecommunication intensity and inversely proportional to the travel time.

The results of fitting the new gravity model with the exponential parameter (which can lead to a better fit compared to the power parameter) to the training data are shown in Fig. 4. In addition, the estimated values of parameters and the adjusted R-squared are listed in Table II. The functional form of the new gravity model with estimated parameters is presented as follows:

$$T_{ij}' = 0.00493 * I_{ij}^{1.001} * \exp(-0.35 * t_{ij}) \quad (7)$$

The estimated value of m (1.001) is slightly different from the values of a and b, unlike what we hypothesized through the derivation in Section III. However, we think that the difference (about 8%) is acceptable because the models were estimated using the real-world data which might include noise. Both Fig. 4 and the adjusted R-squared value indicate that the new formulation of the gravity model fits the data better than the traditional gravity model does.

Furthermore, we compared the performances of two models on the data after August 1st, 2013 (i.e., validation data), as shown in Fig. 5 and Fig. 6. Root Mean Square Error (RMSE) is used as the indicator to test model performance by comparing observed values and predicted values. As calculated, the RMSE of the traditional gravity model is 157,229.3, and the RMSE of the new gravity model is only 5,590.4. The new gravity model can predict the validation data better than the traditional gravity model can.

C. Road Network Design

The approach to RND in this case study takes the following main principles in consideration:

- Planning decisions include adding new links of given levels or upgrading existing links to higher levels.

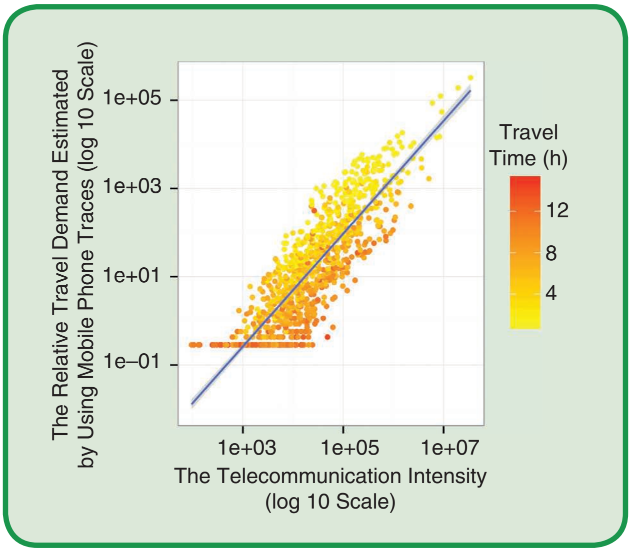

FIG 3 The relationship between relative travel demand, telecommunication intensity and travel time.

Table II. Estimation result of the new gravity model.

Parameter	Estimate	Std. Error	t Value
$\ln(k_3)$	–5.31188	0.25115	–21.15
m	1.00108	0.02041	49.05
θ	0.34970	0.01236	28.3
Adjusted R-Squared	0.8566		

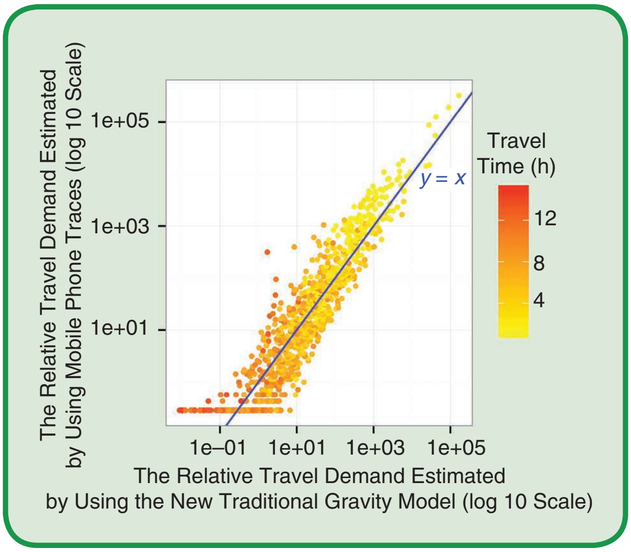

FIG 4 The fitness of the new gravity model.

- Construction costs of adding and upgrading links should not exceed the budget.
- Trip distribution is assumed to be elastic with RND and can be predicted using the gravity model, and the "all-or-nothing" principle is assumed for traffic assignment.
- Both efficiency and equity objectives are considered.

The initial road network is shown in Fig. 7, including five types of roads which are tolled highway, national road, regional road, departmental road and ferry connection. We assumed different levels of average service speed on these different types of road, which can be seen in Table III. Road levels can be improved by raising the corresponding speed levels. Apart from upgrading existing links, adding new links is also considered. In this case if neighboring departments are not connected, a potential straight link was added between them unless there are physical barriers (e.g., mountains). All potential links are shown with dashed lines in Fig. 7. To solve the RND problem, the initial average service speeds of these potential links were assumed to be zero. Highway was considered as the supreme level of all road types. We assumed that the average speed in a highway is 80 km/h, same as the assumed average speed on the tolled highway in Dakar. All road types can be upgraded to highway level. In addition, regional roads can also be upgraded to national roads, and departmental roads can also be upgraded to regional or national roads. Potential links can be added as regional road, national road or highway. Because of long waiting time and limited capacity of ferries, we considered that those ferry services can lead to mobility bottlenecks, which can be eliminated by upgrading the ferry services to bridges, and moreover we assumed that the average service speed on bridges is 60 km/h. The average service speed of each road level and the relative unit costs for road construction and upgrade are shown in Table III. We determined the relative unit costs by referencing [20]. The budget was considered

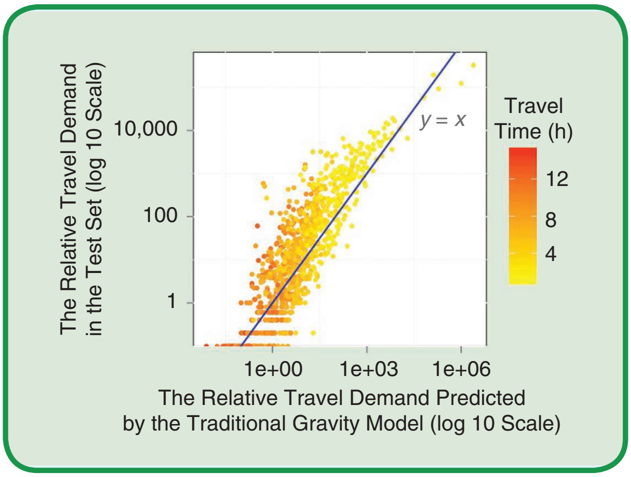

FIG 5 Model performance of the traditional gravity model on the validation data (RMSE: 157,229.3).

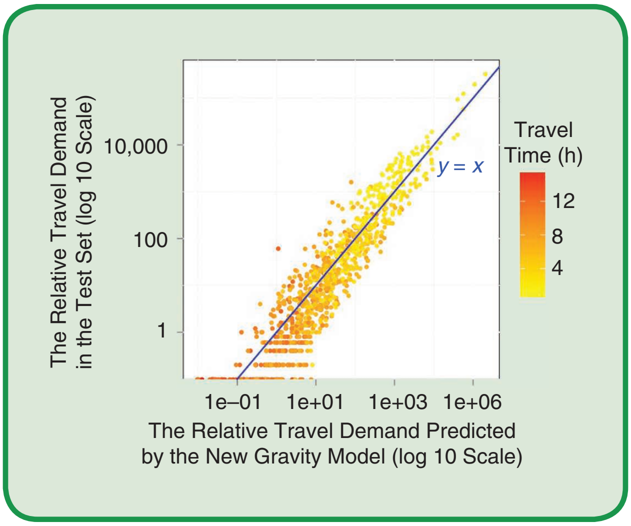

FIG 6 Model performance of the new gravity model on the validation data (RMSE: 5,590.4).

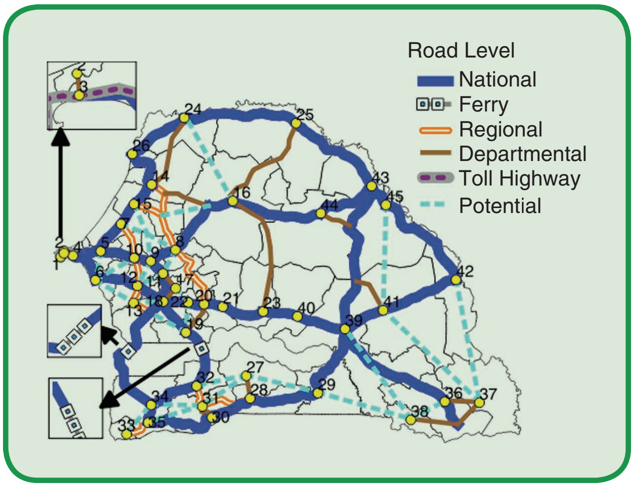

FIG 7 The potential links to be added and the existing links to be improved.

Table III. Design characteristics of different road levels and relative unit costs for road construction and upgrade.

Existing levels	Upgraded Levels: *Regional (45 km/h)*	*National (60 km/h)*	*Highway (80 km/h)*	*Bridge (60 km/h)*
Potential (0 km/h)	1.2	1.6	4	–
Departmental (30 km/h)	0.2	0.6	3	–
Regional (45 km/h)	–	0.4	2.8	–
National (60 km/h)	–	–	2.4	–
Ferry (0–2 km/h)	–	–	–	8

to be 2171 monetary units, which represents 10% of the total budget required to construct all potential links as highways and to upgrade all existing links to the highest level.

> The sensitivity of results to the types of gravity models was examined.

Under the budget constraint, there are still millions of solutions for this RND problem. Each solution represents a distinctive network and the shortest travel times between every two departments may vary for each new solution generated. To compute the fastest paths, we assumed that travelers follow the fastest paths, travelling at the average service speeds consistent with the road levels of the links that are part of their routes. A simple Dijkstra's algorithm was used to compute the fastest paths. Trip distribution was computed assuming that the distribution of telecommunication intensity stays constant and that only travel times have influence.

We assessed the solutions with regard to two objectives, efficiency and equity. To calculate efficiency indicator, we used the maximization of the accessibility of department centers in the country as an indicator. According to [41], accessibility was defined as (proportional to) the spatial interaction between the center and all other centers, and the typical expression used to calculate weighted average accessibility is based on the traditional gravity model. Thus, the performance indicator is dependent on population sizes and the generalized travel costs. The new functional forms used to calculate weighted average accessibility based on the new gravity model were adapted as follows:

$$Z = \sum_{i \in N} \sum_{j \in N \setminus i} T_{ij}' \tag{8}$$

where N is the set of departments; T_{ij}' can be calculated using equation (7).

To calculate the equity indicator, we used the maximization of accessibility for the centers with the lowest accessibility in the country as an indicator [20]. Also, we adapted it to the one based on the new gravity model as follows:

$$E = \sum_{i \in N_{low}} \sum_{j \in N \setminus i} T_{ij}' \tag{9}$$

where, E is the equity indicator; N_{low} is the set of departments with lowest accessibility. In this case, we focus on the 20% of departments with the lowest accessibility.

The optimization model is illustrated as below. In the objective function (10), the weights w_Z and w_E, which can reflect the relative importance, are given to accessibility and equity objectives. The values of the solutions are essentially dependent on the decisions made regarding road levels, which are expressed as y_{lq}, a binary decision variable equal to one if link l in the network is set at road level q and zero otherwise. In our case, the lower-level problem is not an optimization problem anymore since the reacted travel demand can be calculated directly given the decision variable. In the first run, Z_0 and E_0 are set to be the values calculated over the initial network, namely the worst values obtained. Z_B and E_B are the best values obtained for each objective in previous iterations. Constraints (11) and (12) are the expressions of accessibility and equity based on the new gravity model. Constraint (13) is used to guarantee that each link should be set at only one level. The verification of the investment budget is controlled by constraint (14). Expressions of (15) give the domain for each decision variable.

$$\max\ V = \frac{w_z(Z - Z_0)}{Z_B - Z_0} + \frac{w_E(E - E_0)}{E_B - E_0} \tag{10}$$

Subject to:

$$Z = \sum_{i \in N} \sum_{j \in N \setminus i} T_{ij}', \forall i, j \in \boldsymbol{N}(i \neq j) \tag{11}$$

$$E = \sum_{i \in N_{\text{low}}} \sum_{j \in N \setminus i} T_{ij}', \forall i, j \in \boldsymbol{N}(i \neq j) \tag{12}$$

$$\sum_{q \in Q_l} y_{lq} = 1, \forall l \in \boldsymbol{L} \tag{13}$$

$$\sum_{l \in L} \sum_{q \in Q_l} e_{lq} y_{lq} \leq g \tag{14}$$

$$T_{ij} \geq 0, \forall i, j \in \boldsymbol{N}, y_{lq} \in \{0,1\}, l \in \boldsymbol{L}, q \in \boldsymbol{Q} \tag{15}$$

where V is the normalized value of a solution; w_Z and w_E are the weights attached to efficiency and equity objectives; N is the set of departments; L is the set of links; Q is the set of road levels; Q_L is the set of possible road levels for link l since a certain link can only be upgraded or added as certain levels given its current level (See Table III); e_{lq} is the cost of setting link l at road level q; and g is the budget. For this case study, we used the local search algorithm proposed in [42] to solve this optimization problem.

We started from running the model only considering the efficiency objective by setting w_Z to 1 and setting w_E to 0. On an Intel Xeon Quad Core E5-1620 microprocessor running at 3.5 GHz, the application of the algorithm to the problem took about 7 minutes. Given the initial network consisting of 58 nodes and 108 links, this relatively short computational time might be because that the drop search did not influence the solutions very much in this case.

The new network of the best solution to the single efficiency objective is shown in Fig. 8, highlighting all the links that are upgraded in this solution. The upgraded links mainly radiate from the Dakar region, to reach Dagana (24), Mbacke (8) and Bignona (34), which are all in the western part of the country. The line extended to Bignona passes through Gambia, where the Trans-Gambia ferry service is included, and thus a bridge is suggested to be built to replace that ferry service. The connection between Tivaouane (7) and Bambey (10) and the connection between Fatick (12) and Foundiougne (13) are found as the most important regional roads for the accessibility in the country; therefore, they are suggested to be upgraded to national roads. Moreover, a link is suggested to be added between Thies (5) and Mbour (6). It is not surprising to find that all the links suggested to be upgraded are in the western part of Senegal, where the departments are more densely populated and there is higher travel demand. In this planning solution, the value of efficiency indicator Z increases by 6.55% from the value of the initial network.

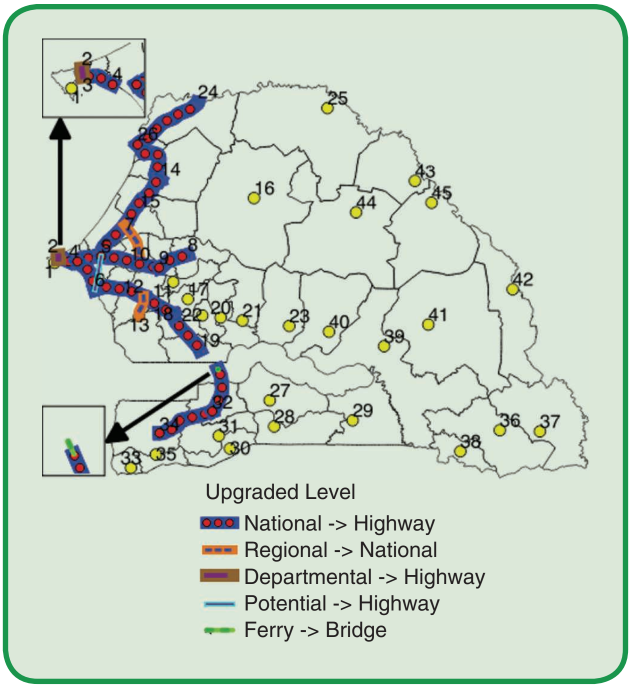

FIG 8 All upgraded links of the optimal solution to the single efficiency objective based on the new gravity model.

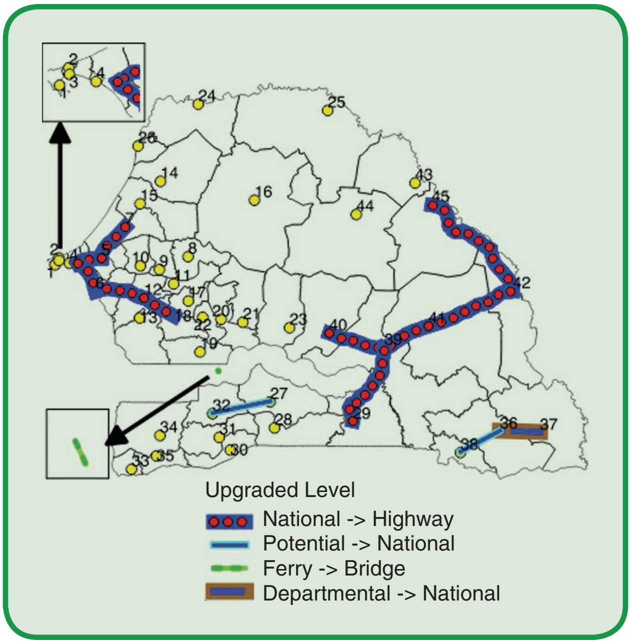

FIG 9 All upgraded links of the optimal solution to both efficiency and equity objectives based on the new gravity model.

As introduced in Section 3.1, the geographical disparities are pronounced in Senegal. The Dakar region developed much more than the south-eastern regions of the country. Considering efficiency as the only objective for RND would lead to increasing gaps between rich and poor departments' welfare. For sustainable development, we took the equity issue into account to plan the road network in Senegal as well.

To make a trade-off between the objectives, the different weights can be varied. In this case, we gave equal weights (0.5) to the efficiency and equity objectives. This change does not influence the computational time much, and the obtained best solution is depicted in Fig. 9. As expected, this planning solution includes the improvement of roads both in the western and eastern part of Senegal. The Trans-Gambia ferry service is suggested again to be replaced by a bridge. From the values of assessment indicators of the current network, the value of equity indicator E increases by 18.34%, and the value of efficiency indicator Z increases by 3.54% from the ones of the initial network.

To test the sensitivity of the solutions to a budget reduction, the budget level is considered as 50% of the initial budget for the single efficiency objective, and for the objective of 50% efficiency and 50% equity. Under budget constraints of 1086 monetary units, the best solution for the single efficiency objective and for both efficiency and equity objectives are depicted respectively at the left side and the right side of Fig. 10. In Table IV, the sensitivity of the assessment indicators to the budget limits are presented for different objectives respectively. It can be observed that the increase of the efficiency indicator slows down with the increase of budget, while there is still much room for improvement on the equity of the road network in Senegal.

Finally, the sensitivity of results to the types of gravity models was examined. We also used the traditional gravity model to optimize the road network for the single efficiency objective, and the solution is shown in Fig. 11. Comparing Fig. 8 and Fig. 11, we found that the upgraded links of both solutions mainly radiate from the Dakar region. However, in the solution by using the new gravity model, the radiation of the upgraded links is suggested to reach farther regions, while in the solution by using the traditional gravity model, the upgraded links are more concentrated near the Dakar region. Moreover, there is no road development suggested in the southwestern part of the country except the link between Ziguinchor (35) and Bignona (45), and the bridge is not suggested to replace the ferry service. This difference can be explained by the observed fact that the traditional gravity model underestimates long-distance travel demand (See Section 5.2).

We believe that the method presented in this work can be applied not only to the country of Senegal but also to other countries, mostly those that are still developing, because traditional mobility data is limited, whereas mobile phone data is potentially obtainable given the large number of mobile phone users.

VI. Conclusions and Recommendations for Future Work

In this paper, we presented a 3-step approach to transforming mobile phone data to support informed decisions on RND in developing countries without the availability of traditional mobility data. The method was applied to the case study of Senegal.

First, the OD matrices of trips made by sampled users were estimated from mobile phone traces. We discussed whether the expansion factors, applied in many existing studies, should be used to upscale sampled users to population in this case, and we decided not to use them because (1) they would lead to new biases that would potentially cause more serious problem on RND; and (2) relative travel demand is enough for supporting decisions on RND in our case. Since no other ground truth data is available, we used the derived OD matrices of sampled users, as the best available mobility information, to tentatively serve as a relative proxy for travel demand distribution in the country of application, though we were aware that the travel demand generated from the densely populated areas might be relatively overestimated in this way.

Second, we defined an adapted form of gravity model, which was built based on telecommunication distribution instead of population distribution, and it empirically fit the data better than the traditional gravity model did. We recommended that in order to fully prove the outperformance of the new gravity model, the relative travel demand and the gravity models should better be validated with the complementary use of traffic data if the latter is available in future research. However, we have to state that the current approach is the best that is possible with the information available on the ground. In fact, the use of this newly-formed model is not only limited to RND. In a more general sense, this model could also be used to, for example, estimate the impact of closing/opening one road in terms of flow redistribution, or as input in a mode share estimation or market analysis for a new interurban transit system.

Third, we built a decision-making system for RND based on the adapted gravity models, and we produced some solutions for the Senegal network under different scenarios. We explained that decision-makers should be careful with the interpretation of the results we presented in this case, because the possible overestimation of travel demand generated from densely populated departments would lead the gravity models to over-predict the travel demand there and thus lead the system to weigh more importance of developing roads there. In real applications, based on the actual planning strategies, the decision-makers can input their own data, including average travel speed, weights of objectives, available budget, unit cost of road infrastructure, and validated mobility data, and they can obtain the results in an efficient way.

We believe that the method presented in this work can be applied not only to the country of Senegal but also to other countries, mostly those that are still developing, because traditional mobility data is limited whereas mobile phone data is potentially obtainable given the large number of mobile phone users.

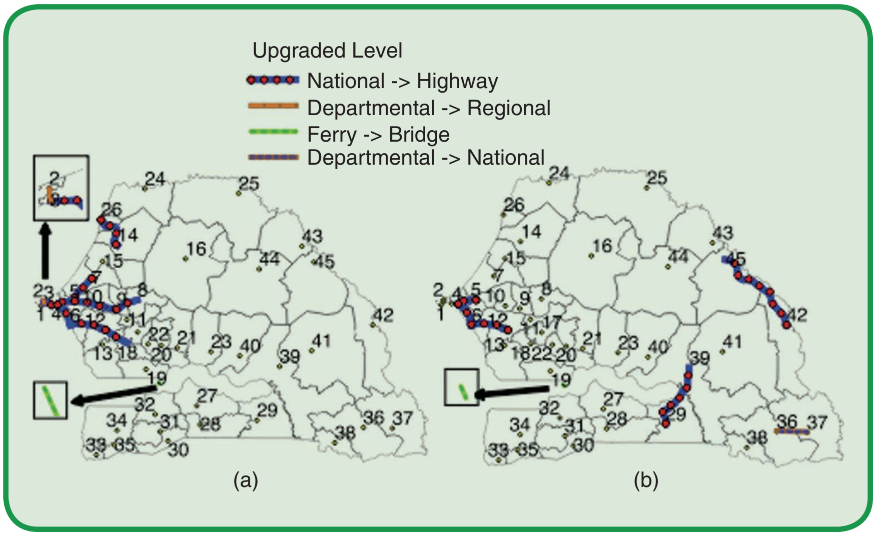

FIG 10 All upgraded links of the optimal solutions given ½ budget.

Solution	Indicator	Budget 50%	Budget Full
For the single efficiency objective	*Z* (efficiency)	4.64%	6.55%
For both efficiency and equity objectives	*Z* (efficiency)	2.16%	3.54%
	E (equity)	8.99%	18.34%

Table IV. The increase of assessment indicator values under different scenarios.

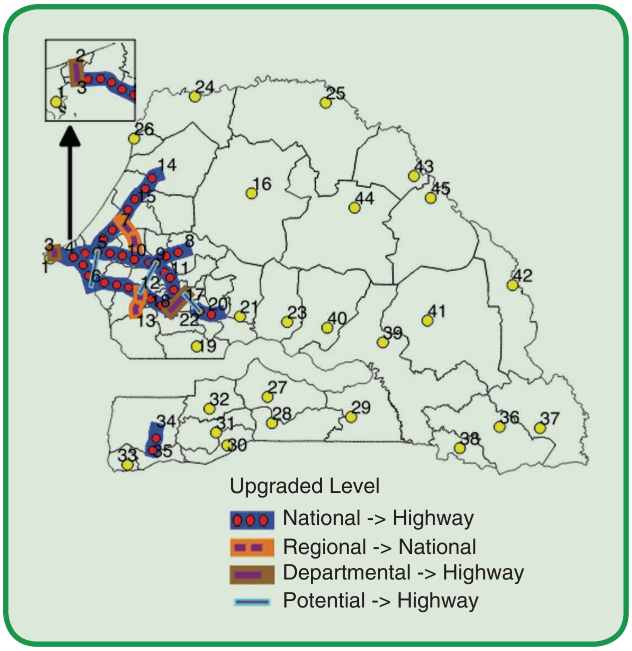

FIG 11 All upgraded links of the optimal solution to the single efficiency objective based on the traditional gravity model.

Nevertheless, this work can still be improved in respect to a couple of features. First, to improve the optimization model, more detailed road network data (e.g., road capacity, speed limit and the corresponding level of service) can be collected. Current travel times can be estimated even using mobile phone data [43]. To that extent, instead of the simple assumption of 'all-or-nothing', the effect of congestion, which is especially relevant in high-demand areas, can be taken into consideration when travel demand can be assigned to different routes. Efforts can also be made to incorporate the mode choice model into RND if a multimodal transport network is considered. Second, there is a new trend that more and more people use mobile applications instead of the traditional call and SMS functions to contact with each other even in a developing country. Therefore, the internet connection data or the data recorded in those mobile applications might have better qualities than the traditional mobile phone data to help transport planners understand telecommunication and mobility patterns.

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About the Authors

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