UNIVERSIDAD SAN FRANCISCO DE QUITO USFQ

Colegio de Ciencias e Ingeniería

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Paper

Juan Bernardo García Dueñas

Ingeniería Industrial

Trabajo de titulación presentado como requisito
para la obtención del título de
Ingeniería Industrial

Quito, 16 de mayo de 2016

UNIVERSIDAD SAN FRANCISCO DE QUITO USFQ

COLEGIO DE CIENCIAS E INGENIERIA

**HOJA DE CALIFICACIÓN
DE TRABAJO DE TITULACIÓN**

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Juan Bernardo García Dueñas

Calificación:

Nombre del profesor, Título académico Cristina Camacho, MSc.

Firma del profesor ___________________________________

Quito, 16 de mayo de 2016

Derechos de Autor

Firma del estudiante: _______________________________________

Nombres y apellidos: Juan Bernardo García Dueñas

Código: 00107124

Cédula de Identidad: 1714150859

Lugar y fecha: Quito, mayo de 2016

Last-mile delivery optimization using GPS data: a case study

Juan B. García-Dueñas

Universidad San Francisco de Quito

Quito, Pichincha, 170157, Ecuador

Abstract

The development of GPS data analysis and processing is contributing to new solutions in urban logistics, such as route characterization or client detection. The city of Quito, Ecuador, has problems regarding freight transportation. The reduction in magnitude of these problems, through the implementation of a responsible enterprise logistics system, can contribute to a better urban and economic development of this Latin-American capital city. This study proposes and analyses a solution in GPS data manipulation methodologies applied to urban freight distribution. The reliability of traditional routing software methods and truck drivers' empiric knowledge are evaluated by comparing it to mathematical optimization algorithms which consider the city's transportation network, modeled after the Asymmetric Traveling Salesperson Problem (ATSP). Tools used include Python for manipulating data and optimizing, CartoDB for Graphical Information Systems (GIS), and Compass (a logistics application developed by MIT) for generation of route indicators. The results of this study represent a better understanding of solutions to last-mile delivery operations in Quito, and suggest mathematical optimization is a reliable way to develop freight transportation routes.

1. Introduction

A company, which will be referred to as Gorilla Ice, is an international company known for its ice cream. Gorilla Ice outsources its distribution in Ecuador to a local company, referred to as Chilly Trucks. Specifically, Chilly Trucks is in charge of distribution of the international company's products to nanostores, which are small "neighborhood" stores common throughout Latin America. Currently, the use of Chilly Trucks's GPS technology implemented in their trucks is only reactive and control-oriented. However, there is a lot of information that could be used to the company's advantage. This reflects the situation of many local companies; their use of technology is limited compared to its full potential. The company is interested in reducing its operating costs, while providing a better service (fulfillment of delivery times, reduction in variability, etc.).

Quito, Ecuador, has an approximate population of 2.3 million inhabitants over a 4200 [km²] surface area (INEC, 2011). It is not considered a megacity since it contains less than the required population to be defined as one, but it has many characteristics in common with megacities – not to mention that it may become one in the future. Varying criteria for defining a megacity, as stated by Blanco & Fransoo (2013) include a population of over 10 million inhabitants, a high population density over a large area, permanent congestion of traffic, large income disparities, and large organic growth. Quito shares most of these. In addition, according to a projection by the McKinsey Global Institute, by 2025 most large cities and megacities will be in currently developing countries (Dobbs et al., 2011). This calls for research on solutions applied to these types of environments.

In Quito, the number of vehicles rises at a higher rate than the number of its inhabitants in this city (El Telégrafo, 2013), causing major traffic problems. Other causes include inefficient urban planning and insufficient consideration of freight transportation needs by the public sector (Dablanc, 2007 and Blanco, 2015). There is a clear need for solutions in urban freight distribution to nanostores, a particular type of small, usually family-owned store that is prevalent in developing countries. One possible solution is the use of routing technology. A limitation is that companies are not willing to invest in technology unless they observe that it will provide an immediate benefit to them.

Many companies do not adopt routing software since truck drivers have in-depth knowledge of their routes from driving some of them for years. They sometimes know smaller or less transited roads that routing algorithms fail to identify. Questions to consider are as follows: To which extent do truck drivers generate/develop optimal routes? Is it worth it for companies in charge of logistics and distribution to invest in routing technology?

To answer these questions, a comparison was made between three types of routes:

1) The truck driver's *actual* route, referred to as $ActualRoute$
2) A route that would be provided from routing *software*, referred to as $OptimalRoute_{Rectilinear}$, that does not consider restrictions such as one-way streets and turn restrictions
3) A route optimized using *real* distances, referred to as $OptimalRoute_{Real}$, that does take into account the restrictions mentioned above

This study proposes a solution for urban freight transportation, taking advantage of GPS technology that is already implemented in a lot of freight transportation vehicles, but largely unused. The use of GPS data in urban last-mile logistics has been studied increasingly in previous years (Comendador et al., 2012; Pluvinet et al., 2012; Muñoz Silva, 2014). Studies have shown the effectiveness of GPS data analysis methods, but are focused on data analysis or survey methods, as opposed to exploring actual routing solutions with GPS data. In addition, there has been a considerable amount of research on optimization problems applied to urban logistics (Johnson & McGeoch, 1995; Delling et al., 2009; Larson & Odoni, 2007; Rego et al., 2011) but not necessarily considering the application of GPS data. This opens up certain research opportunities on the topic, such as optimization methods for delivery routes, while also considering the environmental impact of the decisions made by freight transportation.

The comparison on this research was performed on a sample of routes, modeled after the Traveling Salesperson Problem (TSP). The results show that $OptimalRoute_{Real}$ is more efficient than $ActualRoute$. Additionally, $OptimalRoute_{Rectilinear}$ returns indicators that are not representative of the real-life travel times and/or distances. The results suggest that the optimization procedure applied in this case will provide improved routes with reduced travel distances and times, even when applied to larger problems (i.e.: routes with more stops); while still considering realistic values for distances and times.

2. Literature review

Urban logistics deals with improving distribution systems within city limits, while considering aspects such as sustainability, operations optimization, competitiveness between companies, etc. Last-mile operations are an effective strategy that has been researched, while tailoring solutions to specific needs (Blanco, 2015). It is important to consider that there are important differences in the application of its methodologies in developed countries vs. in developing countries. In the latter's retail scene, megacities (over 10 million inhabitants, a high population density, large area, permanent congestion, income disparities, and large growth) are starting to dominate, as well as the specific type of store associated with it. This type of store, a nanostore, makes up half of the market share of the total retail market. These stores are usually family-owned and family-operated, with 15-40 [m^2] surface area, with an informal credit policy, shortage of cash, etc. (Blanco & Fransoo, 2013). Nanostores are also referred to as traditional channel. In contrast, the modern channel refers to the organized (corporate) retail channel, where professionals carry out organized functions. It is also important to mention that the urban freight system is defective in the sense that it does not account for the needs of goods transportation. (Dablanc, 2007)

It is estimated that by 2025, most megacities will be in currently developing countries. These cities have problems of their own, such as permanent congestion, insufficient urban planning, security problems, varying density and income in neighborhoods, faster growth rates, more informality, a lack of effective technology, lack of information, etc. (Blanco & Fransoo, 2013 and Blanco, 2015). This implies significant differences in supply chain management for these specific cases.

There are close to 50 million nanostores in the developing world. Some characteristics specific to nanostores are a larger number of delivery points, smaller drop sizes, and higher costs of transportation.

Some trucks report more than 100 stops a day (Blanco & Fransoo, 2013). This may benefit the provider and the nanostore owner in some ways, like new logistics opportunities that are not applicable in modern channels of distribution. An example is the option of providing access to credit to storeowners. Nevertheless, designing a logistics system for this type of economy proves a much harder challenge. There have been case studies (Dablanc, 2007; Comendador et al., 2012; Bueno Almeida & Camacho, 2014; Muñoz Silva, 2014; Blanco, 2015) regarding this matter. Examples of effective strategies include regulating pickup times, traffic regulation, research on last-mile operations, integration between transport practitioners and city planning departments, etc. (Dablanc, 2007 and Blanco, 2015)

As the state of the art in urban logistics for developing megacities advances, it is important to adapt solutions to the specific needs of each city. Case studies realized in Ecuador prove the immediate need for solutions, as there has been an increase in demographic and pollution-related indices (Muñoz, 2015 and Sandoval, 2015). It should be mentioned that there is not an active and widely used business-to-consumer online retailer, such as Amazon, in Ecuador as of Q1 2016. It is expected that similar companies will be introduced in the following years. Implications of this include a greater number of trucks driving around the city, those trucks stopping regularly for deliveries, the possible need for infrastructure that facilitates these operations, etc. This calls for an urgent improvement in Ecuador's urban freight system.

Research opportunities have been opened up in certain areas. These include the use of routing problems rather than location problems as modifying the infrastructure of a city is often a more difficult matter. For these applications, Geographical Positioning System (GPS) data is a useful asset that is underestimated and underused in the public and private sector. GPS survey methodologies have been proposed by a number of authors (Comendador et al., 2012; Pluvinet et al., 2012; Muñoz, 2014; Bueno Almeida & Camacho, 2014) and have been proven as effective methods for data collection on freight transportation. By following these methodologies, GPS surveys may provide information on routes, road utilization, covered distances, vehicle speeds, fuel consumption, client localization, etc. which are important indicators while designing optimal routes. A timestamp, as well as latitude and longitude, are basic data that needs to be extracted from raw GPS data. There are methodologies (Bueno Almeida & Camacho, 2014) that have been developed for this, based on criteria that determines if a truck has stopped at a certain location (a delivery point).

Regarding the application of GPS data in logistics, there is more literature on freight transportation that considers inter-city transportation, as opposed to within a city (Greaves & Figliozzi, 2008). This imposes additional restrictions and complications, such as one-way streets, heavy traffic, and time restrictions on certain roads. It is estimated that last-mile operations conform 18-25% of urban traffic for cities such as Quito (Dablanc, 2007). In order to solve the aforementioned traffic problems, Geographical Information Systems (GIS) can be applied to urban logistics in a number of different manners, which include, based on the work of Saunders & Rodrigues da Silva (2009):

- Extraction of data from maps
- Design of logistics networks
- Simulations of modifications on urban areas
- Routing problems

It is worth mentioning the positive impact that these strategies can have on reversing environmental damage caused by pollution. Simulations have shown to reduce energy consumptions by up to 20% (Saunders & Rodrigues da Silva, 2009). Pluvinet et al. (2012) estimate the instantaneous fuel consumption and pollutants emission (CO_2, CO, NOx, and hydrocarbons) in a routing model by using a physical, power-demand approach that considers aspects such as vehicle type, engine, emission technology, etc. (Barth et al., 1996)

3. Methodology

Data from previous work by Bueno & Camacho (2014) was used to compare routes. The routes were optimized by *rectilinear* distances and *real* distances, in order to compare outputs of routing software and real optimal values. This was accomplished by using a two-dimensional projection of the Earth and the Google Maps Distance Matrix API to obtain the respective distances. The Traveling Salesperson Problem (TSP) was used as a model that was resolved by the 2-opt pairwise exchange algorithm. Indicators used to evaluate algorithm performance are the total distance reduction percentage, the proportion of routes which were improved, and the proportion of the routes where *rectilinear* and *real* distances provide the same solution. Details will be given in the following subsections.

3.1. Tools

The list of tools that were employed in the development of this study are described briefly as follows:

- Compass: Application developed by the MIT Megacity Logistics Lab for visualization and analysis of routes. This application features a data extraction function that sorts that raw data from the input database into useful spreadsheets that can be manipulated for convenience.
- Python: This programming language was used for the required data processing and mathematical optimization, on the SPYDER (Scientific PYthon Development EnviRonment) platform.
- CartoDB: Online GIS application used to create visualizations. The required route data was entered to obtain a graphic representation of the routes, which serves as a useful analysis tool.
- MS Excel: Used for data manipulation in spreadsheets.
- Google Distance Matrix API (Application Program Interface): Tool for building software applications that provides travel distances for a matrix of origins and destinations.

3.2. Data

This study uses data from previous work by Bueno & Camacho (2014); a study that proposes a methodology for creating and cleaning a GPS database. Specifically, Bueno & Camacho obtained the raw data from Chilly Trucks, the company in charge of the distribution of Gorilla Ice's products to nanostores. The raw data is a list of georeferenced timesamps (data that includes longitude and latitude coordinates, as well as time and date) from Chilly Trucks's trucks, over a period of 5 months. Bueno & Camacho's methodology consists of processing data to a format that permits manipulation for analysis and visualization. It is worth mentioning the most important parameters that were used for cleaning the data:

- Routes outside of Quito were eliminated: some trucks have inter-city deliveries but were not taken into account for the study. Coordinates were established to eliminate all data outside of the Quito city limits.
- Nighttime data: some trucks are loaded at night, and the GPS is turned on always for security reasons. Therefore, all data before 05h00 and after 20h00 were rejected.
- Parking spots: there are days when a certain truck will have no routes, but will move inside or near the distribution center (DC) of Gorilla Ice and the operations center (OC) of Chilly Trucks. All routes that are fully inside a 30 [m] radius from the OC and the DC were eliminated.
- Long stops: sometimes, the vehicles are at the shop for maintenance or they park at the respective driver's home for long periods of time, as opposed to parking in the OC or DC. If data points are inside a 15 [m] radius for more than 3 [h], they are rejected.
- Speed less than 3 [km/h] for a duration greater than 150 [s]: this is the criteria proposed by Pluvinet (2012) to identify the delivery stops that the driver makes, while excluding stops caused by traffic lights.

- Data was classified into routes under a specific identification, called RouteID, where each route refers to the route covered by a specific truck in a specific date.

The result of this work is a database that includes information for 15 of the company's trucks for the 5 month period. A total of 1344 routes were obtained, of which 950 are appropriate for this study, since 394 routes were discarded (a certain truck's data is corrupted, some trucks exit the city of Quito, etc.). This data was input into the Compass application for visualization. Compass can then process this data and obtain detailed indicators on routes such as number of stops and their locations, total route time and average speed. Finally, the application has a function that allows the downloading of that processed information into organized spreadsheets. This information presents coordinates for the stops that each truck makes in each route for a delivery.

A sample size, n, of 84 routes was determined necessary to obtain a confidence level, $1 - \alpha$, of 95% as well as a margin of error, e, of 6%. Stratified sampling was used so that the optimization algorithm's performance could be evaluated individually among a range of possible types of routes. The routes were sorted into strata, depending on their number of stops. Finally, samples were allocated to each stratum using optimal allocation, where allocation is based on variability and the relative cost of sampling a unit in each stratum (Lohr, 2010). In this case, the cost variable is the relative computing time required to evaluate a route. Table I shows a summary of information regarding the stratified sampling allocation:

Table I: Stratified sampling allocation.

Stratum, h	Number of stops	Stratum size, N_h	Stratum sample size, n_h
1	1 – 25	267	48
2	26 – 50	482	27
3	51 – 75	179	7
4	76 or more	22	2

The objective, as mentioned before, is to compare the actual routes used by truck drivers (referred to as $ActualRoute$) with routes that could be provided by routing software and also with routes that consider real-life distances between stores.

A distance matrix (which contains the distances between each pair of stores and/or OC and DC) is to be provided in order to solve the optimization model, which is described in detail afterwards. Delling et al. (2009) recommend precomputing a distance matrix before running the actual optimization, as it is a faster procedure. Two different distance matrices must be created in order to calculate each respective type of optimal route:

- Rectilinear distance matrix
- Real distance matrix

Rectilinear distance matrix: routing software usually bases its algorithms (and outputs) on calculations done with *rectilinear* distance (a.k.a. Manhattan distance, taxicab metric, etc.) (Larson & Odoni, 2007). As opposed to Euclidean distance (the straight line as the shortest path between two points), rectilinear distance is the sum of the absolute differences of the Cartesian coordinates between two points. It may be used in applications regarding cities with a grid layout, such as New York City (specifically, Manhattan), but in cities like Quito, where the road network geometry is complicated, this has limited use. As mentioned by Delling et al. (2009), commercial route planning systems might provide suboptimal routes, as their algorithms favor reduced computing time over quality of results. For example, smaller or less transited streets might be overlooked unless they are necessary to reach the target. While optimizing routes, the corresponding output shall be referred to as $OptimalRoute_{Rectilinear}$.

To calculate the rectilinear distances, the Universal Transverse Mercator (UTM) coordinate system of the Earth is used. This is a two dimensional conformal projection of the globe that preserves angles and approximate shapes, although slightly distorting distance and area. Traditional latitude and longitude coordinates are converted to UTM format (via a Python library named "LLUTM_Convertor", developed by Chuck Gantz) in order to compute the required mathematical calculations of distances in meters.

Real distance matrix: to produce accurate and useful results, however, optimal routes have to take into account the local transportation network, which includes restrictions such as one-way streets or turn restrictions. The Google Maps Distance Matrix API was used to access this information. Coordinates for origins and destinations are provided from the Compass output so the API returns the respective *real* distances. While optimizing, this output shall be referred to as $OptimalRoute_{Real}$.

3.3. Methods

To optimize routes, the Traveling Salesperson Problem (TSP) was used as a model. This is a special case of the Vehicle Routing Problem (finding optimal delivery or collection routes from one or several depots to a number of users/stores) in which the goal is to find a least-cost route while visiting each required store (a.k.a. vertex/node) exactly once, with the initial store repeated at the end (Ghiani, 2013 & Weisstein, 2016). For urban settings, however, Ghiani (2013) recommends the Asymmetric Travelling Salesperson Problem (ATSP). Since the cost function (distance is used as the cost parameter in this case, where the result will be referred to as $Total\ Distance$) of traveling from store i to store j is not necessarily the same as traveling from store j to store i, considering the transportation network, this is the case of an ATSP.

A mathematical formulation of the model, obtained from Ghiani (2013), is shown as follows:

Let V' be the set of stores (vertices), and A' be the set of paths between stores (arcs). With each path from store i to store j is associated a cost c_{ij} which represents the distance that needs to be covered while traveling between the stores. Note that c_{ij} is not necessarily equal to c_{ji}, due to the asymmetric aspect of the model.

Finally, let $x_{ij}, (i,j) \in A'$, be a binary decision variable equal to 1 if the arc (i,j) is part of the solution; 0 otherwise. Then,

$$Minimize \sum_{(i,j)\in A'} c_{ij}\, x_{ij} \tag{1}$$

Subject to:

$$\sum_{i\in V'\setminus\{j\}} x_{ij} = 1, \;\; j \in V' \tag{2}$$

$$\sum_{j\in V'\setminus\{i\}} x_{ij} = 1, \;\; i \in V' \tag{3}$$

$$\sum_{i\in S}\sum_{j\notin S} x_{ij} \geq 1, \;\; S \subset V', \;\; |S| \geq 2 \tag{4}$$

$$x_{ij} \in \{0,1\}, \;\; (i,j) \in A' \tag{5}$$

Where equation (1) is the cost objective function that will be minimized. Constraint (2) states that only one path enters each store $j \in V'$ and, similarly, constraint (3) states that only one path exits each store $i \in V'$. Constraint (4) guarantees that the tour has at least one path coming out from each proper and a non-empty subset S of stores in V'.

To compute a solution, a number of different methods exist. These include algorithms for obtaining an exact solution, such as a brute force search (explores all possible permutations), and heuristic algorithms. The latter may produce a suboptimal solution, but is preferred due to the large computing power required by exact methods.

In Python, a brute force search was tried as an initial approach, in which a list (or array, vector, etc.) of all permutations of the routes was created to calculate their cost one by one. This proved ineffective for routes which contained more than 10 stores, as the time required to produce the list would increase dramatically which each store added, considering the number of permutations is $n!$ for n stores.

A heuristics pairwise exchange method, known as 2-opt, was finally used to optimize the routes, as this is the most famous and practiced method due to the accuracy of its results, simplicity and relative computing power required (Croes, 1958 and Johnson & McGeoch, 1995). This local search algorithm is an iterative method commonly used to solve TSP. In each iteration of this method, the best possible 2-opt move is applied. The objective, as explained by Burtscher (2014) is to "find the best *pair* of edges $(i,\ i+1)$ and $(j,\ j+1)$ such that replacing them with $(i,\ j)$ and $(i+1,\ j+1)$ minimizes tour length". Figure 1 is a visual model of the exchanges produced by 2-opt:

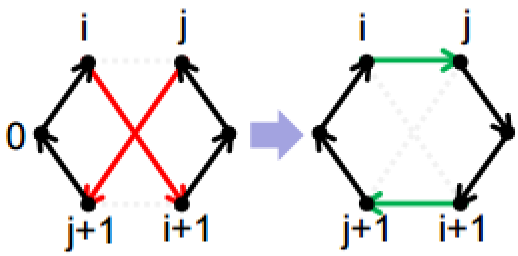

Figure 1: Illustration of the 2-opt pairwise exchange method. Source: Burtscher, 2014.

There is a way to solve an ATSP model which involves expanding the distance matrix (Jonker & Volgenant, 1983), but it would seem inefficient with relation to computing time and power, considering the scale of the problem. Instead, a high-speed 2-opt TSP solver for large problem sizes, proposed by Burtscher (2014), was adapted for this specific case. Traditional algorithms evaluate the whole route's length on each iteration. Burtscher's method, on the other hand, is based on evaluating solely the *change* in length from a 2-opt switch. This greatly reduces the level of complication of the required programming, as well as the computation time. It is designed for a Symmetric TSP (STSP), but was adapted to solve an ATSP.

The heuristic was initialized with the existing $ActualRoute$, which is represented by the ordinal sequence (1, 2, 3, 4, …, n, 1), where each number corresponds to each store. Finding a local minimum based on $ActualRoute$ would prove an effective solution, since 2-opt works well when switching routes that overlap each other, as these switches tend to reduce distances greatly. The result would be an improvement on the $ActualRoute$.

To analyze each individual route in the sample, an indicator, $Total\ Distance$, was computed for the three different types of routes ($ActualRoute$, $OptimalRoute_{Rectilinear}$ and $OptimalRoute_{Real}$) so as to compare their efficiency. This value was calculated with the TSP model's cost function. These indicators serve to compute global indicators for each stratum (described below), and consecutively for the whole sample.

Global indicators used to compare the efficiency of the algorithm are:

- The average distance reduction of the routes, expressed as a percentage.
- The total percentage of routes that were improved– where the *actual* route was improved by using *real* distances.

- The percentage of routes where using *real* distances returned a different store sequence than when using *rectilinear* distances.

4. Results

Table II: %decrease and proportion results per strata.

Stratum, h	Number of stops	Stratum size, N_h	Stratum sample size, n_h	Average actual distance [m]	Average optimized distance [m]	Average distance reduction [$\%decrease$]	Percentage of improved routes [%]	Percentage of routes with different sequences – *real* vs. *rectilinear* distances (%)
1	1 – 25	267	48	38574	37587	3.80	91.76	95.51
2	26 – 50	482	27	54647	52600	4.44	100.00	100.00
3	51 – 75	179	7	94428	91690	3.15	100.00	100.00
4	76 or more	22	2	93132	90744	2.65	100.00	100.00

Table II shows the optimization results for each of the strata. The percentage of distance that can be reduced is significantly larger in shorter routes (1-50 stops) than in longer routes (51 or more stops). The results also show that the algorithm improved 100% of the routes in strata 2, 3, and 4 (26 or more stops), and 91.76% of the routes in stratum 1 (1-25 stops). In addition, in 100% of the routes in strata 2, 3, and 4 (26 or more stops), and in 95.51% of routes in stratum 1 (1-25 stops), the use of *real* distances provided a different solution than the use of *rectilinear* distances.

Table III: Overall %decrease results.

$\%decrease$	$Variance(\%decrease)$	$Std.Error(\%decrease)$
3.974	2.3271E-05	0.004824

Additionally, a confidence interval of 95% certainty was obtained:

$$\%3.028 \leq \%decrease \leq \%4.919$$

As can be seen in Table III, $OptimalRoute_{Real}$ is a more effective route than $ActualRoute$, since there is an average decrease in distance of 3.974% in the routes after applying the algorithm.

Table IV: Overall proportion of routes with a different sequence of stores.

	$Proportion$ [%]	$Variance(Proportion)$	$Std.Error(Proportion)$
Real vs. Actual	97.684%	0.10423E-04	0.010209119
Real vs. Rectilinear	98.737%	5.9171E-05	0.007692272

In Table IV are results regarding comparisons between types of routes. As shown in the above results, improvement was possible in a large percentage (97.684%) of routes. Also, an even larger proportion (98.737%) of routes obtain a different sequence when optimizing using *rectilinear* distances vs. *real* distances. The routes which were not optimized, or where the *real* and *rectilinear* distances produced the same results, belong exclusively to stratum 1 (1-25 stops).

A comparison between the $ActualRoute$ and the new $OptimalRoute_{Real}$ for a sample route is shown in Figure 2. It can be observed that the $OptimalRoute_{Real}$ follows a much simpler path.

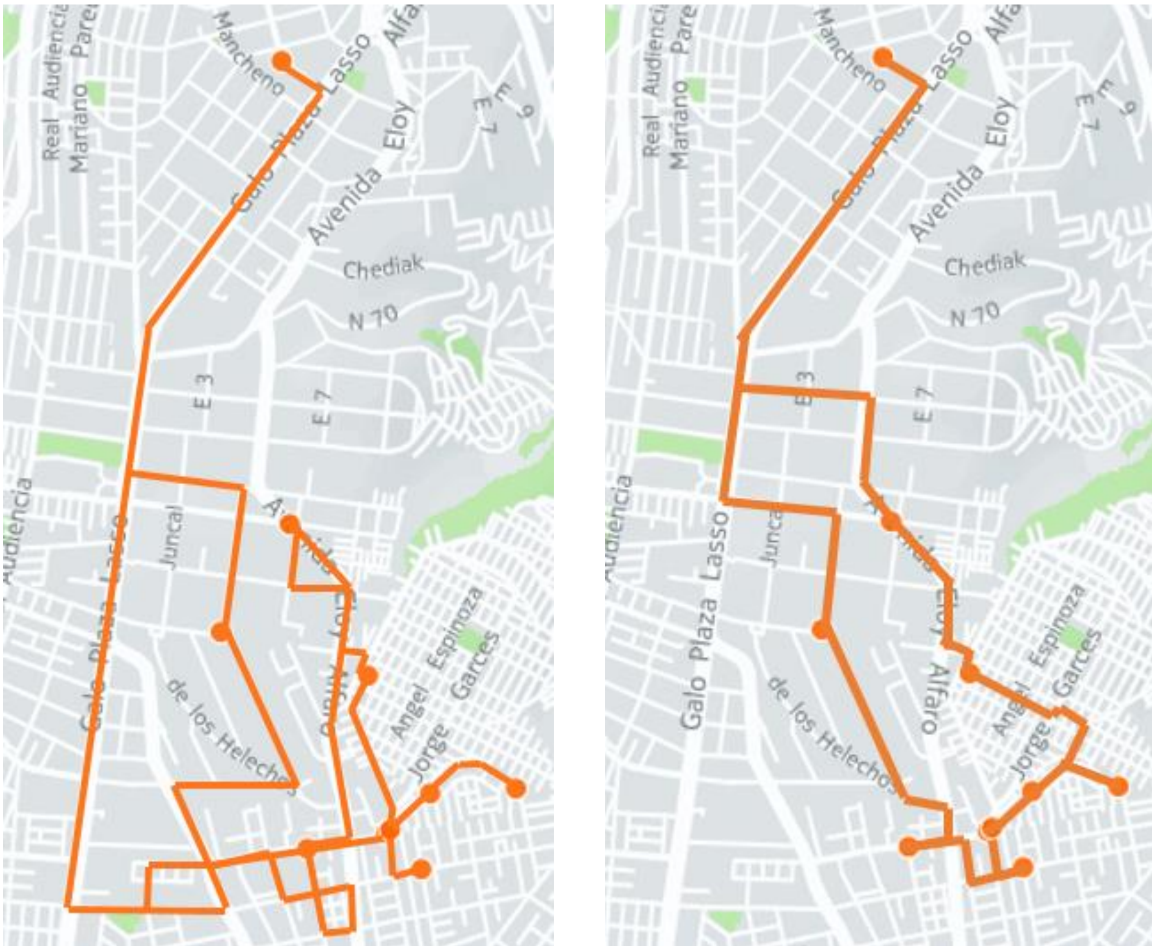

Figure 2: A comparison between (Left) $ActualRoute$ and (Right) $OptimalRoute_{Real}$ for RouteID 18D.

5. Discussion

Apart from the fact that there is an average reduction in distance for all routes when applying the algorithm, the non-optimality of the $ActualRoutes$ can be confirmed by observing the sample $ActualRoute$ on Compass, as is shown in Figure 2. The 2-opt algorithm works well when switching roads that overlap each other. This is an appropriate explanation for the considerable reduction in distance while optimizing the routes, since the $ActualRoute$ overlaps itself on multiple occasions. This suggests the algorithm works as expected. It has proven effective at optimizing delivery routes in a theoretical setting.

On the other hand, since there is such a low proportion of routes where $OptimalRoute_{Real}$ and $OptimalRoute_{Rectilinear}$ obtain the same sequence of stores as the optimal path, there is additional evidence that supports the fact that the rectilinear-distance-based algorithms are not as effective as algorithms that use real distances.

Stratified sampling was used as a tool that allowed analysis on different types of routes, according to their number of stops. Findings include the fact that as routes get moderately longer (more than 51 stops), there is a smaller margin for distance reduction through mathematical optimization. This information with regard to $\%reduction$ of distances can be extrapolated for operations planning and control. Also, it is worth noting that the algorithm improved all routes with more than 25 stops, and most routes with less than 25 stops.

In Appendix A, samples of routes from Compass are provided, which show how they may very well be less than optimal; this can be observed in the number of overlapping roads, as well as the excessive amount of turns the driver makes to account for one-way streets.

Limitations include the fact that only the 2-opt algorithm was used. In a larger study, different optimization methodologies could be tried, perhaps even considering their specific computation requirements. Some of the most effective methods that have been proposed in the literature for solving TSP are 3-opt, genetic algorithms, and Christofides' algorithm (Johnson & McGeoch, 1995; Sharma et al., 2005; Larson & Odoni, 2007). Some of these are probabilistic methods, which implies that the solutions might change with each "run" of the algorithm. Similarly, a different initialization method could be applied. There are constructive heuristics, such as the greedy algorithm (a.k.a. NN – Nearest Neighbor algorithm), which could provide a different basis over which to run improvement algorithms on.

Also, there is no account in the model for traffic data. This is a particularly challenging topic, considering the traffic in Quito is a largely influencing factor on travel times. A more complicated model would include this for the calculation of travel times and for the routing itself. The Google Distance Matrix API, in addition to the distances provided beforehand, can provide historical traffic information that could be used for this purpose, but this would require standardized starting times for each route. Furthermore, this would require confirmation from truck driver surveys. Also worth mentioning is that the same Distance Matrix API can provide current traffic information, an interesting feature to consider if a real-time routing technology is to be developed in the future for commercial freight in Quito.

There was no opportunity to conduct truck driver surveys. These should be used to confirm the results of the optimization models, or to obtain extra input to help refine them. Allen & Browne (2008) state that driver surveys may be used to gather data about the overall route pattern, loading/parking locations, lunch stops, cash deposits, and more. Since the drivers have covered the same routes for many years, they can possibly have information that validates or rejects the optimal routes proposed by the models. In UPS, a system is used where a computer algorithm improves existing routes but the truck drivers are challenged to improve them even further (Zax, 2013). This "hybrid" system, built on trust and empowerment of the driver, has proven useful; the optimized results become another input that the driver uses together with his/her intuition in order to generate the best possible routes.

If the decision is to not conduct truck driver surveys, however, then direct field testing of the optimal routes should provide accurate enough results, although with the added cost of experimentation by the drivers. Additionally, information regarding the stores (coordinates, opening times, type of store, etc.) may be obtained to validate the models.

Another important limitation is that environmental impact was not included in the analysis, other than considering through the fact that shorter distances and travel times usually consume less fuel and pollute less (Saunders & Rodrigues da Silva, 2009). In a more comprehensive model, instantaneous fuel consumption and pollutants emission may be estimated in a routing model by using a physical approach based on the power demand required, according to vehicle type, engine, level of wear, speeds, accelerations, mass, etc. (Barth et al., 1996; Pluvinet et al., 2012).

Also, it should be taken into consideration the idea of creating a model with a more complex cost function. This can be useful as a final evaluation for a company like Chilly Trucks to decide if it is economically feasible and convenient to adopt this solution. The value that could be optimized is the cost itself of traveling that route. In addition to distance; time and fuel consumption should be added as constraints to the model. The total cost of traveling the route would be calculated for the $ActualRoutes$, as well as for the optimized ones. Time can be calculated with traffic data, as mentioned above. In order to calculate fuel consumption, however, another approach can be used: if a vehicle's engine computer is integrated into the database, efficiency tracking is available, which considers stops and starts, hills or operating at high speeds for extended periods of time (Pluvinet et al., 2012). This can also be used to forecast vehicle maintenance, for example.

6. Conclusion and recommendations

An analysis on the reliability of rectilinear-distance-based routing algorithms and truck drivers' experimentally-created routes was performed. The results suggest that accessing the road network data and calculating real travel distances before optimizing is an efficient way to address routing problems in cities such as Quito, which contain major traffic problems, as well as a complicated road geometry. While truck drivers may have developed and know their routes very well, vehicle routing through mathematical optimization may prove to be more effective, which in turn could benefit the logistics company with reduced costs and better service provided to customers (more deliveries arriving on time, for example). Alternatively, mathematically optimized routes can serve as a tool for drivers to improve their routes intuitively. Further research opportunities include a detailed analysis on environmental impact of vehicle routing (these results should be included in future routing models) and the development of an algorithm that optimizes the cost of routes by taking into account historical traffic data and fuel consumption.

7. Acknowledgments

The author acknowledges the guidance, supervision and contributions of Daniel Merchán (MIT), with respect to methodology and algorithms, and Carlos Suárez (USFQ), with respect to methodology and revision of the paper.

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Appendix A - Sample routes from Compass

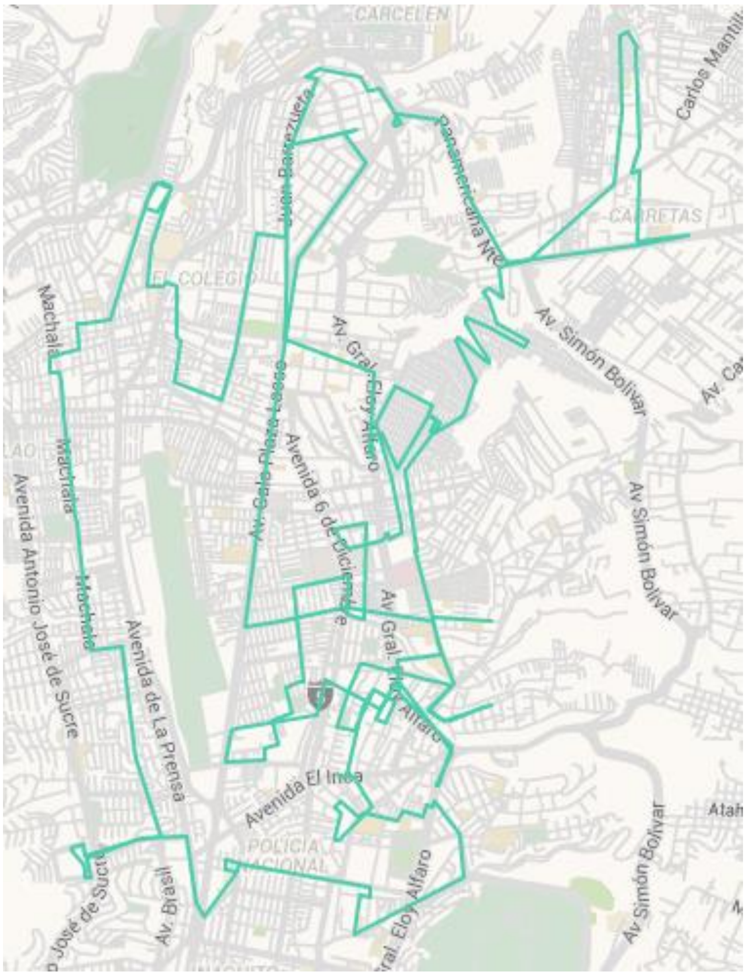

Figure A1: RouteID 19F.

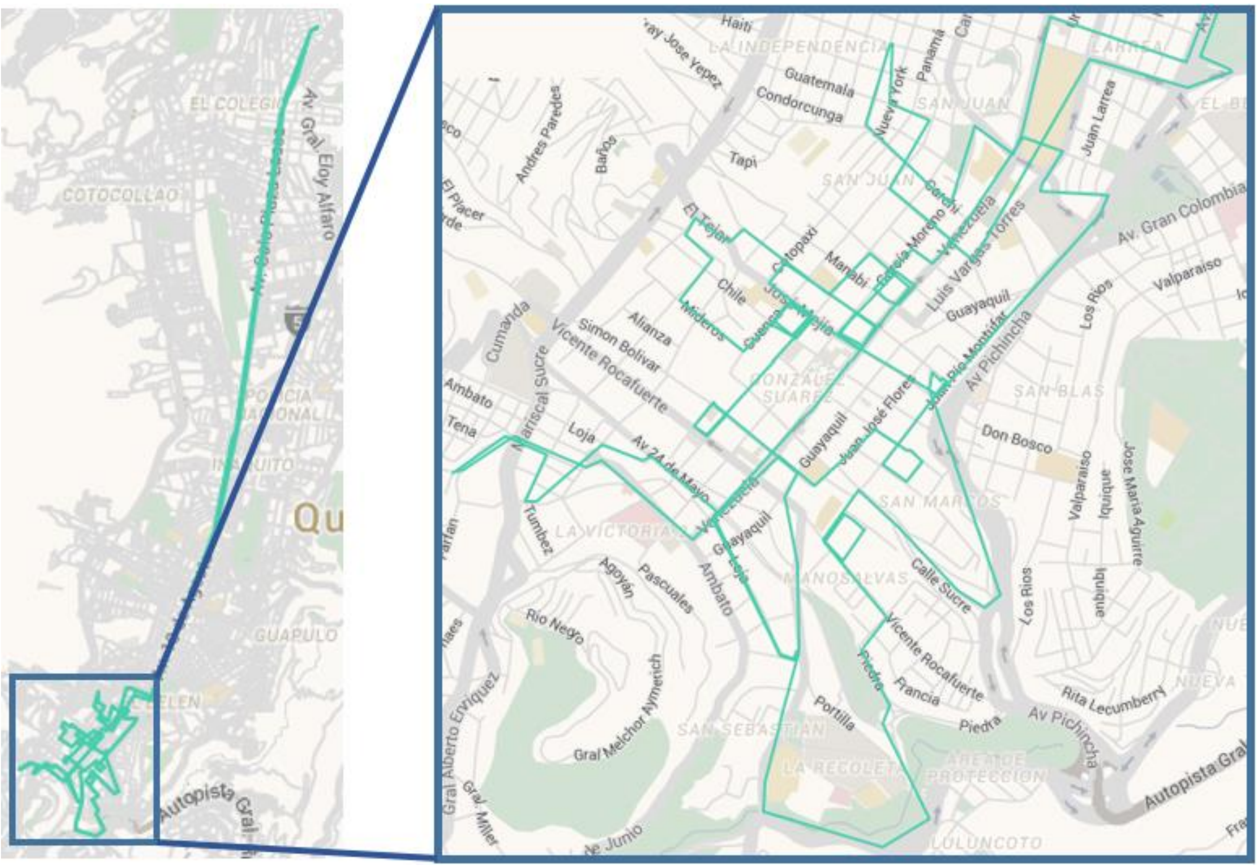

Figure A2: RouteID 1BB.