Towards a Topological Map-Matching Algorithm for Solid Waste Collection Systems

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Abstract: Global Navigation Satellite Systems (GNSS) such as Global Positioning Systems (GPS) are employed in different Intelligent Transportation Systems (ITS) applications to determine vehicle routes. However, the map-matching problem emerges when GPS measurements are assigned to incorrect road segments on a digital map due to the complexities of the road network and errors from different sources when capturing GPS data. This study presents a Topological Map-Matching Algorithm (TMMA) for determining correct waste collection vehicle routes using GPS measurements in an offline context to help improve solid waste collection services and compute proper performance measures. The TMMA is applied to a real-world case study with ten waste collection routes in the commune of Renca in Santiago, Chile. Overall, results indicate that the accuracy of the algorithm is greater than 90%, and small percentages of false negative cases with unsnapped GPS data points are obtained for most vehicle routes. The sensitivity analysis suggests that larger buffer sizes and higher speed tolerances yield the best solution quality and execution times.

1 INTRODUCTION

In 2016, the estimated generation of urban solid waste worldwide was approximately 2.01 billion tons and was estimated to reach 3.4 billion tons by 2050 (Kaza et al., 2018; Rojas et al., 2018). As population, urbanization, and industrialization increase, authorities must address this accelerated solid waste production rate by implementing adequate solid waste management systems (Khandelwal et al., 2019). However, in most developing countries, unsatisfactory policies, regulatory structures, and inefficient solid waste management negatively impact society, the environment, and the economy. Urban solid waste is usually collected using a manual approach (door-to-door) based on field experience and intuition, generating high operational and transportation costs, low service quality, high traffic congestion, a large amount of greenhouse gas emissions, and high health risk (Blazquez and Vonderohe, 2009; Blazquez and Paredes-Belmar, 2020; Letelier et al., 2022). In addition, municipalities spend between 20% and 50% of their budget on solid waste management, of which 50% to 70% corresponds to waste collection and transportation tasks (Erfani et al., 2017; Blazquez and Paredes-Belmar, 2020; Letelier et al., 2022).

To overcome these issues, in the last decade, there has been an increase in the use of information and communication technologies for solid waste management services as part of smart cities (Ricardo et al., 2018; Vishnu et al., 2021). In particular, the use of Global Positioning Systems (GPS) technology has improved tremendously the solid waste collection process, which is the most expensive within the solid waste value chain (Ghiani et al., 2015; Steyn and Willemse, 2018). Various performance indicators of the solid waste collection process may be computed using GPS measurements such as service time, road traversal time, unloading time, number of stops, fuel consumption, and vehicle emissions, among others, to improve the collection service and planning and minimize operational and transportation costs (Hannan et al., 2015; Akram et al., 2021).

GPS measurements must be associated or snapped to the correct road segment to calculate performance measures accurately. However, due to the complexities of the road network and errors from different

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sources when capturing GPS data, GPS measurements are assigned to incorrect road segments on a digital map, causing the so-called map-matching problem (Blazquez and Vonderohe, 2009; Blazquez et al., 2012; León et al., 2020). Figure 1 illustrates an example of the map-matching problem, in which GPS data points p_1 and p_3 are correctly snapped to the road at locations represented by data points s_1 and s_3, respectively. While data point p_2 is incorrectly snapped to the closest road segment indicated by point s_2. The correct snapping location of the data point p_2 is represented by point c_2. Therefore, there is a need for map-matching algorithms to solve this problem by identifying correct GPS trajectories along the road network.

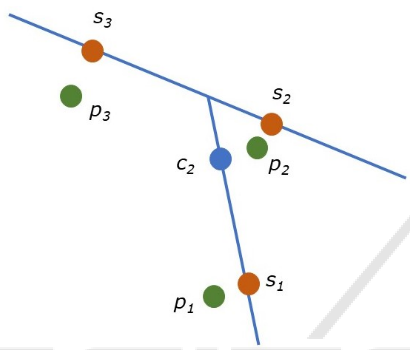

Figure 1: Example of the map-matching problem. Adapted from Blazquez et al. (2022).

In the last decades, numerous map-matching algorithms have been proposed in the literature ranging from simple geometric techniques to advanced, complex algorithms such as hidden Markov models, Kalman filter, and fuzzy logic (Blazquez et al., 2018; León et al., 2020). These algorithms have been implemented to solve the map-matching problem in multiple Intelligent Transportation Systems (ITS) applications. For example, as part of an electronic horizon in driver assistance systems, Burgstahler et al. (2016) utilized a map-matching algorithm for mapping vehicle geographical positions onto the digital road map and determining the correct road segment being used. In another study by Klitzke et al. (2019), a map-matching algorithm was used for matching ego vehicle positions to a digital road map as part of the test drives in the validation of autonomous driving systems. Similarly, Kang et al. (2020) employed an iterative closest point-based map-matching algorithm for identifying GPS trajectories on a digital road map in autonomous driving and advanced driver assistance systems. Ricardo et al. (2018) implemented a map-matching algorithm to determine bus lines and bus stops from GPS measurements in Porto, Portugal. A GIS-based map-matching algorithm was employed by Scott et al. (2021) to determine bike share users' route choices along the cycling network within Hamilton, Ontario, Canada, using hub-to-hub GPS trajectories.

Regarding solid waste management applications, most studies employ GPS technology for identifying waste bin levels (Hadria et al., 2018; Anjum et al., 2022) and waste bin locations (Erdinç et al., 2019; Mishra and Kumar Ray, 2020; Moral et al., 2022), monitoring waste collection routes (Steyn and Willemse, 2018), and planning route scheduling (Wilson and Vincent, 2008; Ghiani et al., 2015). However, scarce studies focus on implementing a map-matching algorithm to help improve solid waste collection services and compute correct performance measures by determining the correct route on which vehicles travel. For instance, Ghiani et al. (2015) implemented an automated classification and estimation algorithm for estimating service time at collection points and traversal times along different roads.

This study addresses the map-matching problem by presenting a Topological Map-Matching Algorithm (TMMA) implemented offline for determining correct waste collection vehicle routes using measured data (position, timestamp, and vehicle speed). The proposed TMMA uses parts or all GPS measurements to resolve the map-matching problem. Additionally, computational experiences are reported using real-world GPS data collected by waste collection vehicles in the commune of Renca in Santiago, Chile. A sensitivity analysis is conducted to identify the impact of the algorithm parameters on the solution quality and execution time.

2 TOPOLOGICAL MAP-MATCHING ALGORITHM

Among the map-matching algorithms found in the literature, TMMAs have been preferred in ITS applications since they are simple, efficient, fast, and easy to implement (Hashemi and Karimi, 2014; Gupta and Shanker, 2022). TMMAs employ link connectivity and contiguity to compute the shortest paths and travel time between pairs of GPS measurements. Normally, TMMAs use different algorithmic parameters related to buffer size for finding snapping locations of GPS measurements along road segments, information on traffic flow or congestion, and road features such as speed limit and the number of lanes. In this study, the TMMA utilizes two distinct parameters (buffer size and speed range tolerance), explained below.

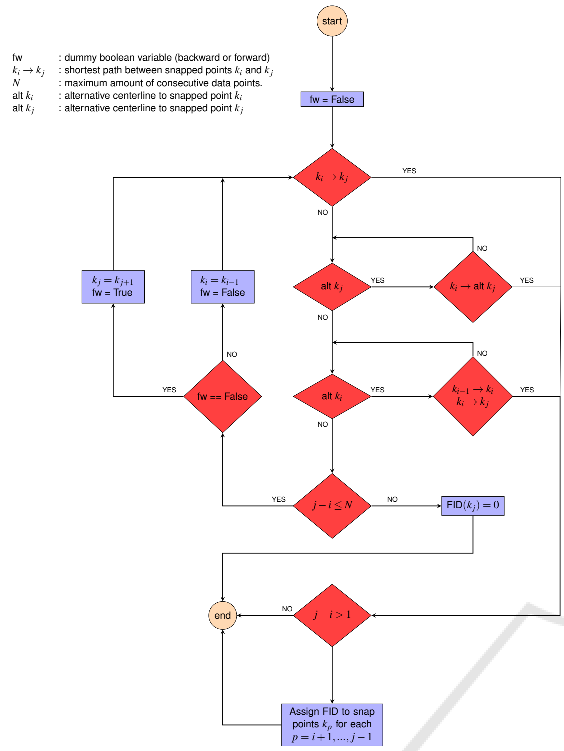

Figure 2: Flow diagram of the TMMA. Adapted from León et al. (2020).

Figure 2 shows the flow diagram of the TMMA used in this study. Once road segment candidates are selected as possible snapping locations within buffers around GPS data points, the TMMA tests pairs of GPS points by snapping them to the closest road segment candidate and computing shortest paths between pairs of snapped GPS points k_i and k_j. Subsequently, travel speeds are calculated using distances of the shortest paths and time differences between timestamps and are compared with the average vehicle speeds recorded with each GPS measurement. Current snapped locations of the GPS points are accepted when the average vehicle speeds are within a speed range tolerance of the travel speeds. On the contrary, current snapped locations of the GPS points are rejected, and other snapping locations (alt k_i and alt k_j) on alternative road segment candidates are tested, shortest paths are recomputed, and speeds are compared again. If there are no feasible routes between snapped locations of GPS points, then the TMMA tests with preceding and succeeding GPS points until the map-matching problem is solved or a predefined number of maximum consecutive GPS points (N) is reached.

Note that those GPS points with no snapping locations on the correct road segment (i.e., false negatives with FID$(k_j) = 0$) are forced to snap to the closest road segment that comprises viable routes between preceding and succeeding GPS points. If GPS points k_p with $p = i+1, ..., j-1$ have no snapping locations on any road segment (false negatives), and if a valid route exists between snapped points k_i and k_j, therefore, these points are snapped to their closest road segments that belong to this viable route and are assigned the FID of the road.

3 CASE STUDY

3.1 Study Area

The capital city of Chile, Santiago, produces approximately 43% of the total waste generated nationwide (Rojas et al., 2018). This study focuses on the commune of Renca, one of the 34 communes that constitute the Great Santiago, with a population of 147,151 inhabitants and an area of 24.0 km^2 (INE, 2017). Renca generates over 70,000 tons of municipal solid waste every year, representing approximately 24.5% more than the total average waste generation of the country. Currently, Renca has a waste collection system comprising a door-to-door collection using a single-compartment compactor truck and two or three crew members per truck responsible for collecting waste from the curbside and throwing it in the rear of the truck for compaction (Blazquez and Paredes-Belmar, 2020).

3.2 Data

This study applied the TMMA to 10 waste collection vehicle routes shown in Figure 3. This figure depicts 350 GPS measurements captured every 30 seconds in the commune of Renca. The vehicle routes include different types of roads (e.g., local and major roads and highways), as shown in Table 1.

Figure 4 presents the basic statistics of the recorded vehicle speeds for each route obtained from the data measurements. This figure shows the fluctuation of vehicle speeds for different types of roads. Overall, lower speeds are observed for vehicle routes along local roads, while higher speeds are perceived along major roads and highways. Note that no differential GPS or other GPS position accuracy improvement methods are available in this study.

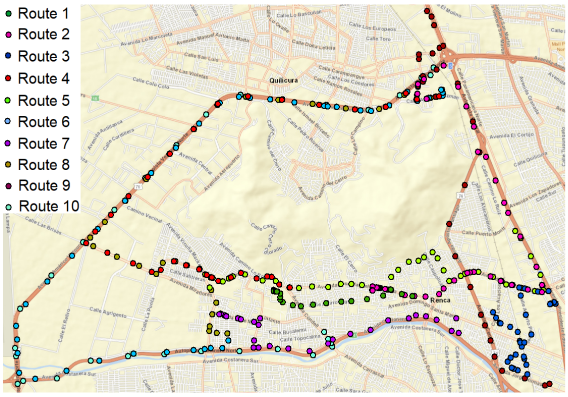

Figure 3: GPS measurements for the waste collection vehicle routes.

Table 1: Road types for each route.

Route	Type of Road
1	Local roads
2	Major roads/Highways
3	Local roads
4	Major roads/Highways
5	Local and major roads
6	Highways
7	Major roads/Highways
8	Major roads/Highways
9	Major roads/Highways
10	Highways

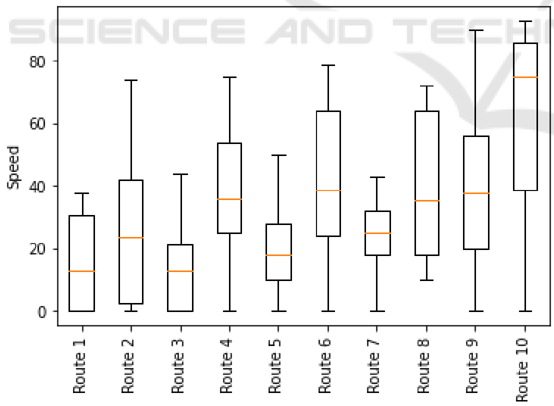

Figure 4: Distribution of vehicle speeds in km/hr for each route.

4 RESULTS

4.1 Performance of the TMMA

The performance of the TMMA is evaluated using the accuracy (i.e., correct snaps of GPS measurements), error (i.e., incorrect snaps of GPS measurements), false negative (FN) cases, and execution times. FN cases correspond to GPS measurements that are not associated with any road segment candidate since the buffer size is too small when these measurements should have snapped to a certain road segment.

The accuracy is computed with Equation (1), where p_c^r is a GPS measurement or data point of a vehicle route r that is snapped to the correct road segment with $c = 1,\ldots,C$, p_n^r is a GPS data point of a vehicle route r with $n = 1,\ldots,N$, C is the total number of correctly snapped GPS data points, and N is the total number of GPS data points.

$$Acc_r = \frac{\sum_c p_c^r}{\sum_n p_n^r} \quad (1)$$

Similarly, Equation (2) is used to calculate the error for each vehicle route, where p_o^r is a GPS data point of a vehicle route r that is snapped to the incorrect road segment with $o = 1,\ldots,O$, and O is the total number of GPS data points snapped to incorrect road segments.

$$Error_r = \frac{\sum_o p_o^r}{\sum_n p_n^r} \quad (2)$$

FN cases (FN_r) are computed with Equation (3) for each vehicle route, where p_f^r is a GPS data point of a vehicle route r that is considered an FN case with $f = 1,\ldots,F$, and F is the total number of GPS data points that are not snapped to any road segment.

$$FN_r = \frac{\sum_f p_f^r}{\sum_n p_n^r} \quad (3)$$

Figure 5 shows the performance results of the TMMA for the analyzed vehicle routes using a base case scenario with a buffer size of 20 meters and a speed range tolerance of 20 km/hr. This figure indicates that the accuracy for most vehicle routes is greater than 90%. Errors arising from the snapping of GPS trajectories to incorrect road segments for Routes 2, 4, and 8 occur mainly along highways because the algorithm assigns GPS data points to viable side roads parallel to the highways. Further research

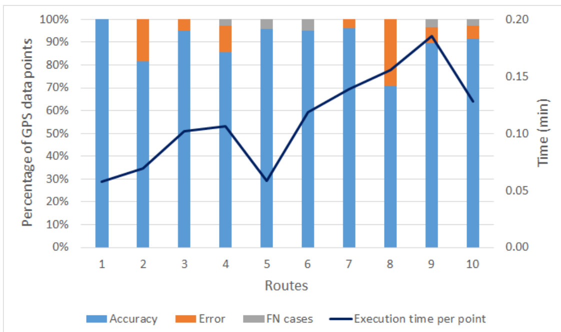

Figure 5: Performance results of the TMMA.

should include the revision of the TMMA for addressing this type of issue, perhaps by also capturing the vehicle heading to accept those road segment candidates with directions (azimuth angle) that are within a predefined heading range tolerance, as in Blazquez et al. (2012), Blazquez et al. (2022) and Chen et al. (2019).

A small percentage of FN cases (on average, $< 1.9\%$) is observed in the 10 tested routes of Figure 5. Therefore, the TMMA satisfactorily forces the snap of most GPS points with no associated road segments to the routes between preceding and succeeding GPS points. The remaining FN cases occur for some routes when the vehicles enter the transfer station to unload the collected waste, and there is no road representation in a digital form.

Figure 5 presents the computing time per point for each tested route. The average execution time per GPS point among all routes is approximately 0.12 minutes. This figure suggests that the TMMA needs a higher execution time to solve the map-matching problem for some routes, particularly those with a larger percentage of GPS data points that are snapped to incorrect road segments. On the contrary, routes that reach an accuracy of nearly 100% require smaller times in the execution to solve the problem, such as with Route 1.

4.2 Sensitivity Analysis

This subsection presents the results of the sensitivity analysis of the TMMA for buffers sizes of 10, 20, and 30 meters and speed tolerances of 15, 20, and 25 km/hr. Figures 6-15 depict the variation of the accuracy and the execution times of the TMMA for each route as the buffer size and the speed tolerance fluctuate. Overall, the graphs in these figures show that better results, in terms of accuracy, are obtained with larger buffer sizes ($>$ 20 meters) and higher speed tolerances ($>$ 25 km/hr), independent of the type of roads that comprise each route.

Additionally, the figures indicate that the execution times of the algorithm remain relatively constant as the speed tolerance increases from 15 to 25 km/hr and the buffer size increases from 10 to 30 meters, except for Routes 4 and 8 (Figures 9 and 13, respectively). The latter routes present a higher computing time of the TMMA in a complicated part of the road network for two possible reasons. First, when increasing the speed tolerance, the shortest paths between pairs of incorrect snapped GPS data points are accepted, which are subsequently corrected by the TMMA as preceding and succeeding GPS data points are tested. Second, if the buffer size increases, then a higher number of road segment candidates are selected within each buffer of the GPS data point, and more alternative snapping locations along different road segments for the GPS points are examined.

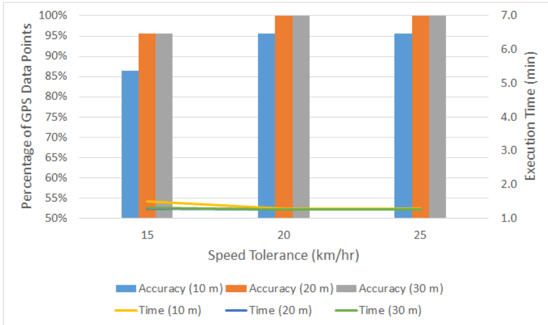

Figure 6: Sensitivity analysis for Route 1.

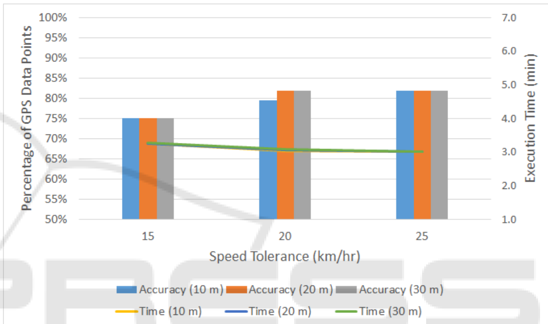

Figure 7: Sensitivity analysis for Route 2.

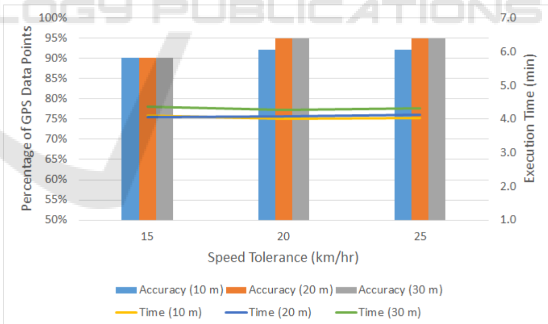

Figure 8: Sensitivity analysis for Route 3.

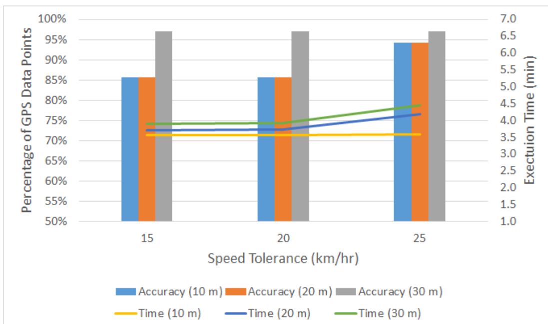

Figure 9: Sensitivity analysis for Route 4.

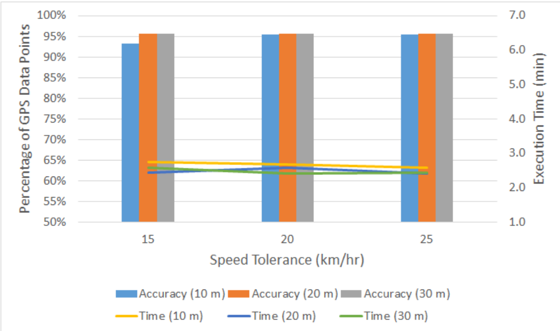

Figure 10: Sensitivity analysis for Route 5.

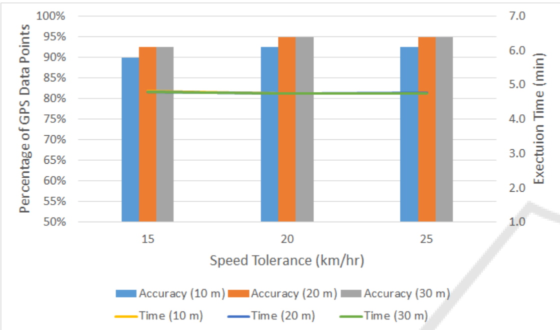

Figure 11: Sensitivity analysis for Route 6.

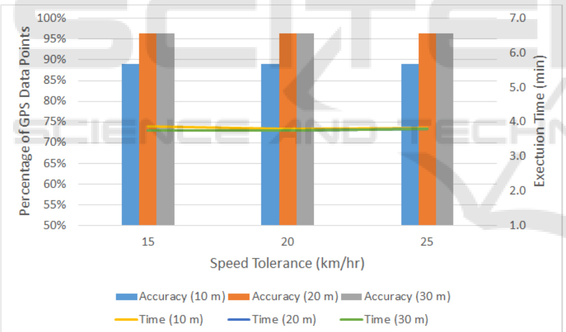

Figure 12: Sensitivity analysis for Route 7.

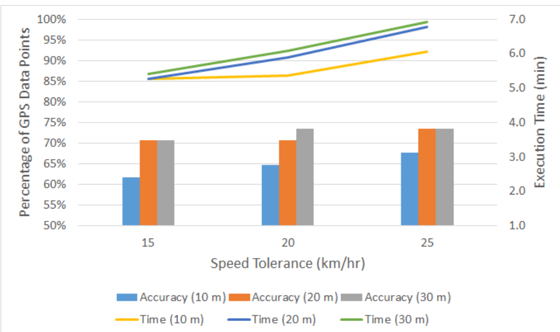

Figure 13: Sensitivity analysis for Route 8.

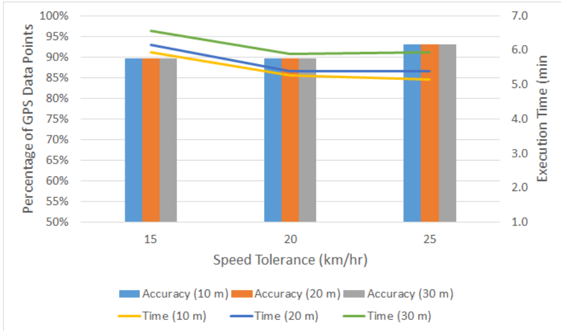

Figure 14: Sensitivity analysis for Route 9.

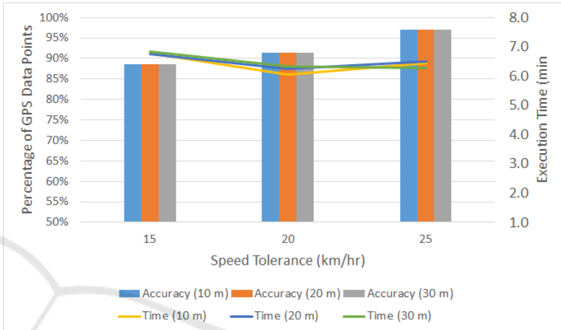

Figure 15: Sensitivity analysis for Route 10.

Table 2 presents the percentage of FN cases for different speed tolerance and buffer size parameter values. This table indicates that road segment candidates are assigned to GPS data points as the buffer size increases, and thus, the percentage of FN cases diminishes. Routes 1, 2, 3, and 7 are not listed since these routes have no FN cases as the parameter values vary. The percentage of FN cases for most routes does not fluctuate as the speed tolerance increases.

5 CONCLUSIONS

This study employs a TMMA for determining correct waste collection routes to improve solid waste collection services and compute appropriate performance measures (e.g., service time, road traversal time, unloading time, number of stops, fuel consumption, vehicle emissions, etc.). The TMMA was tested with ten vehicle routes in the commune of Renca in Santiago, Chile. Results of the TMMA are presented for a base case and sensitivity analysis of different parameter models. Overall, for the base case, more than 90% of the GPS data points are snapped to correct road segments for most routes, a small percentage of FN cases exist for most routes, and the average execution time per GPS point is approximately 0.12 minutes.

Table 2: FN cases for different tested buffer sizes.

Speed Tolerance	Buffer Size		
	10m	20m	30m
Route 4			
15 km/hr	0.0%	0.0%	0.0%
20 km/hr	0.0%	2.9%	2.9%
25 km/hr	0.0%	0.0%	0.0%
Route 5			
15 km/hr	4.3%	4.3%	4.3%
20 km/hr	4.3%	4.3%	4.3%
25 km/hr	4.3%	4.3%	4.3%
Route 6			
15 km/hr	7.5%	5.0%	5.0%
20 km/hr	7.5%	5.0%	5.0%
25 km/hr	7.5%	5.0%	5.0%
Route 8			
15 km/hr	8.8%	2.9%	2.9%
20 km/hr	2.9%	0.0%	0.0%
25 km/hr	0.0%	0.0%	0.0%
Route 9			
15 km/hr	2.9%	2.9%	2.9%
20 km/hr	2.9%	2.9%	2.9%
25 km/hr	2.9%	2.9%	2.9%
Route 10			
15 km/hr	0.0%	0.0%	0.0%
20 km/hr	2.9%	0.0%	0.0%
25 km/hr	0.0%	0.0%	0.0%

The sensitivity analysis suggests a tendency to yield improved solution quality with larger buffer sizes and higher speed tolerances. The execution time of the TMMA remains approximately constant as the parameters are varied, except for a couple of routes, in which GPS measurements are captured along parallel roads (e.g., highways and side roads). Thus, the TMMA should be revised in future research to address map-matching problems that arise when there are equally viable paths between pairs of GPS points. In addition, further research should test the TMMA with different sampling frequencies and vehicle routes from other communes or cities to identify the appropriate algorithm parameters for each tested data sets. Finally, future research should compare the results of this study with a proper benchmark.

GPS technology aids in determining correct vehicle routes to increase the effectiveness of waste collection systems, which are imperative for reducing negative impacts on the environment and society. Thus, municipal authorities must make informed decisions to address the current accelerated solid waste production rate, particularly in urban areas. A real-time TMMA may be required to monitor and surveil a fleet of waste collection vehicles.

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