

Travel efficiency of the Metro Manila public transport network

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Abstract

The sheer number of vehicles traversing roads in Metro Manila frequently leads to road congestion. To avoid heavy traffic, we often hear of plans to encourage the switch to public transport. Here we make an assessment of the travel time disincentive to use mass public transport (PT) compared to more individualized forms, including cabs. We compare the travel distributions of cars and PT in a fully connected journey network inside the National Capital Region (NCR). To model the origins and destinations of this network, the Metropolis-Hastings algorithm was used to weigh samples according to residential and commercial points of interest. Dijkstra's algorithm was used to route cars in street networks, while Pareto-optimal solutions for travel time and transfers were considered for PT. Given free flow in the street network, we found that travel times using PT are about five times longer with riding comprising most of the journey. However, walking and waiting still take a significant amount of time. Route lengths taken over PT were also three times longer than cars. Hence, this large travel time ratio has more to do with inefficiencies in the PT network rather than being a congestion issue. A more thorough analysis can then be performed to reflect efficiencies along high volume thoroughfares.

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1 Introduction

When considering journeys along multi-modal transport such as PT, time alone is not a good measure of travel. There are many other factors to consider, such as the number of transfers, wait times, and walking times [1]. In fact, these factors can be argued to be much more important since public transportation users, locally referred to as commuters, make up the majority of the population. In the Philippines, 88.5% of households do not even own a car [2]. The high volume of vehicles in Metro Manila is the main cause of road congestion [3], and while government policies mostly seek to correct driver behavior, they actually play a very small role [4]. Hence, there must be a shift from a car-centric travel culture to one centered on public transport specially designed for the myriad of users and their daily habits. To simplify our analysis, we consider the simple yet reasonable representation of direct travel: a morning commute of going to work, and a late afternoon/evening commute when going home.

In this paper, we describe the public transportation network in Metro Manila by exploring the symmetries of typical morning and evening commutes. We simulate journeys between 1000 origins and the same number of destinations by calculating Pareto-optimal shortest paths based on two criteria; these being travel times and number of transfers. These origins and destinations were sampled with an exponential decay based on distances from residential and commercial points of interest in the National Capital Region (NCR). We then obtain travel distributions and then assess the symmetry between morning and evening commutes. Lastly, these public transport travel distributions were compared to the travel distributions by use of free flowing cars with no congestion. This was used to assess whether our current public transport system incentivizes shifting away from using cars.

2 Method

The street networks, and residential and commercial POIs used in this study were obtained from OpenStreetMap (OSM) [5]. The General Transit Feed Specification (GTFS) for the NCR was obtained from Sakay.ph from a dataset released for the 2013 Philippine Transit App Challenge. To choose the origins and destinations, we use a weighted random sampling scheme around residential and commercial points of interest (POIs). As opposed to just directly sampling the origins and destinations from OSM-tagged points, our method captures small variations around each point of interest; attenuating the fact that OSM data are not always up-to-date due to its crowdsourced nature. First, we generate a random point and obtain the nearest POI from it. This randomly generated point is then accepted as an origin or destination based on an acceptance probability given by:

$$P_{\text{acceptance}} = \min \left(1, \frac{Q(s^*|s) a(d)}{Q(s|s^*) a^*(d)} \right) = \min \left(1, \frac{a(d)}{a^*(d)} \right) \quad (1)$$

where $a(d)$ is the state probability in the current iteration, with $a^*(d)$ being the previous state probability. This state probability $a(d)$ is given by

$$a(d) = \alpha e^{-d/d_o} \quad (2)$$

where α is a normalization constant that cancels out in Eq. 1, d is the Euclidean distance between the proposed point and its nearest POI, and d_o is a distance constant we set to $d_o = 111$ m. This choice implies that at $d = d_o$, the state probability drops by a factor of 0.37 compared to the exact sampling point of the POI. The generation of random points was constrained to lie in the center of grids with sides 1.11m. Hence, the probability of any one grid being chosen as a proposal point, i.e. the transition kernel, is $Q(s^*|s) = 1/N$, where N is the number of grid cells in the NCR region. This transition kernel from a previous state s^* to a current state s is reversible, and so $Q(s^*|s) = Q(s|s^*)$. When sampling origins and destinations using this scheme, we can use residential or commercial POIs obtained from OSM. We can then model commuter patterns and choose whether they travel from residential to commercial zones, or vice versa. To ensure the ergodicity of this process, we enable the deletion of previously selected points [6]; when a previously accepted point is once again accepted on a later iteration, it is removed from the roster of origins or destinations. Upon generating origins and destinations, we connect them pairwise to create a fully connected network. This results in an unweighted origin-destination (OD) matrix, which considers all journeys with equal importance.

Upon generating origins and destinations that reflect NCR commuters, we use the RAPTOR (Round-Based Public Transport Routing) [7] algorithm by way of the R library “r5r” [8–10]. RAPTOR calculates Pareto-optimal shortest paths in public transport networks yielding travel time and number of transfers. Since we use GTFS data, some baseline competing traffic level, i.e. congestion, is already embedded into the travel schedule. Further changes to congestion levels are not taken into account. On the other hand, routing cars in street networks employed a Multilevel Dijkstra algorithm [11] using the Open Source Routing Machine (OSRM). Since car routing is graph based, incorporating time dependent edge weights such as congestion levels increase computational complexity to overwhelming levels. Hence, we can only route cars by assuming free flow, with edge weights representing static street lengths. Other routing engines, such as those used by Google Maps, incorporate user information to add congestion modifiers to free flow routing results. However, we do not have access to these kinds of data. Travel characteristics, such as travel time, are very sensitive to the set departure time due to how public transport changes during the day. This is described by the modified temporal unit problem (MTUP) [12]. To mitigate this, we calculated travel times at different departure times over a ten-minute window, doing five Monte Carlo draws for each minute. This results in 50 total measurements for each departure time — taking the median along this time window yields us an appropriate estimate of a certain journey.

3 Results and Discussion

We compare travel time performance using the ratio (r_t) of travel time using PT to travel time using a car. We note that GTFS feeds for PT were recorded with congestion, while car routing assumes free flow. In Fig. 1, we show these travel distributions for residential to commercial points in the NCR, and vice versa, respectively. The resulting distributions do not change significantly based on the departure time, and so we chose to show results only when commuters depart at 7a.m.; invoking this temporal symmetry to say that the results are the same for other hours of the day. However, there exists a spatial asymmetry on time (Fig. 1a) and route length distributions. While the morning and evening commute average travel time are roughly the same (at above 5), the residential to commercial experience is significantly more varied, with a rare few even getting close to or better than 1, while some would exceed a factor of 10. The number of transfers remains the same (Fig. 1b).

We find that the mean travel time by public transport is about 5 to 6 times longer than by car (Fig. 1a). The ideal behavior of equal performance for cars and PT is also highlighted. There is a huge deterrent for travelers to use public transport as traveling by car would be significantly less time consuming. However, due to the lack of congestion when routing cars, this result may be skewed in their favor. In Fig. 1b, we find that the total number of trips taken in a single journey borders mostly around 3 to 4 transfers. We found that when increasing the frequency of vehicle units on PT routes, total commute times decrease marginally while journeys that take 4 trips increase noticeably. This is caused by Pareto-optimal commutes generally requiring more transfers than before.

We also investigate the contributions of walking, waiting, and riding in total commute times on Fig. 1c. We find that a majority of commute times are contributed by actual ride times and not by walking and

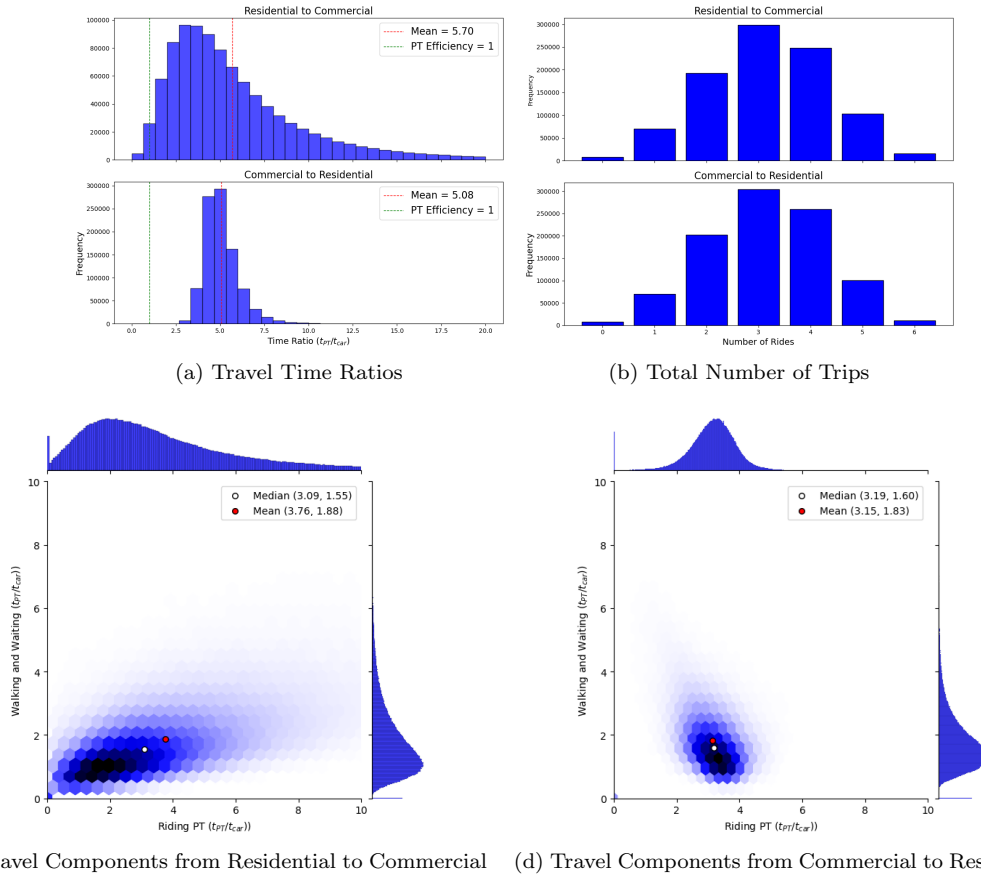


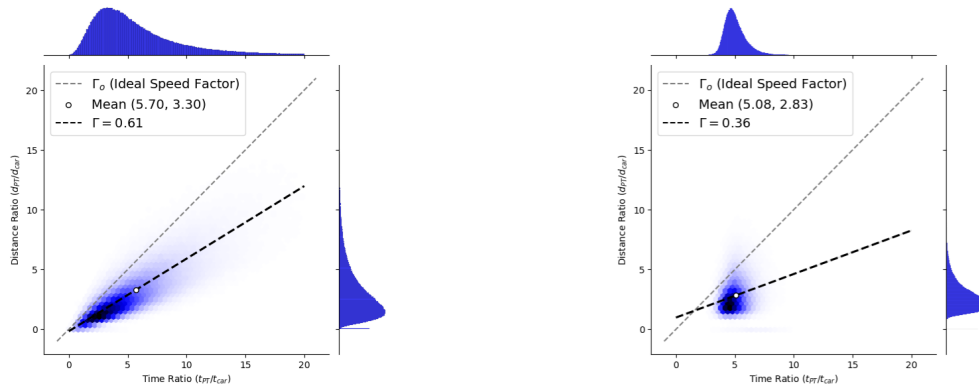
Figure 1: (a) The reversing of origins and destinations affect travel distributions - but averages are not significantly changed, however (b) the number of trips taken for each journey is invariant of travel direction. The components of commute time for morning (c) and evening (d) commutes with riding being dominant, but walking and waiting still taking significant times. We see different distributions based on travel direction, but the same mean behavior. These distributions were obtained assuming a fully connected network between origins and destinations.

waiting. However, the time it takes to walk between stops and wait for PUVs is still 1.45 times longer than completing the whole journey by taking a car without congestion. The riding component on the other hand is about 3.25 times longer than this benchmark. Such a large factor leads to the question of what causes the disparity, which we split into two: a) the PT routes themselves are longer; and b) loading/unloading mixed with congestion during baseline data collection. Using OSRM, we determine the corresponding route distance in Fig. 2. We observe that PT routes are about 3 times longer than routes taken by cars. This suggests that the disparity in PT travel times is mainly due to route assignment inefficiencies rather than traffic congestion reflected in the originally collected GTFS data.

4 Conclusion

In this paper, we chose to construct a fully connected synthetic network between all possible OD pairs. While this may not reflect real-world commuter patterns, our methods can be extended to a different OD matrix. Still, our work provides insight into the performance of PT on uniformly distributed journeys. The experience of a commuter with PT in the NCR is still inferior to that of a car in free flow. Hence, our current systems fail to encourage a shift from a car-centric economy to a more sustainable one. We find that an average commute takes about 5 times longer than a car in free-flow, taking about 3 to 4 trips. Most commute times are spent riding PT vehicles, although significant amounts are also spent on walking and waiting. We find that these results are invariant under temporal alternation, but the direction of journeys alters travel distributions.

To confirm whether these large travel time ratios are due to the baseline competing traffic level already embedded in PT routing, we also obtain route lengths ratios as they are unaffected by congestion. By comparing the lengths of routes taken by PT and cars, we see that PT routes are about 3 times longer themselves. This implies that although large travel time ratios are in part caused by neglecting congestion for car travel, the PT routes themselves are inefficient i.e. routes taken are indirect. Our work can be expanded to generating origins and destinations for multi-segment travel (e.g., a person who takes children



(a) Travel Distributions from Residential to Commercial (b) Travel Distributions from Commercial to Residential

Figure 2: (The distribution of route length and travel time ratios for typical journeys for (a) residential to commercial, and (b) vice versa. These points represent 97% of all OD's generated, with these typical journeys being defined as those with time ratios below 20. Three percent of our generated OD's are inaccessible to PT. The speed factor Γ represents the disparity between route lengths and travel times, with Γ_o representing similar PT and car travel behaviors.

to school before going to work, or buys from the market on the way back), which accounts for a large majority of actual travel. Hand-in-hand with infrastructure improvements (e.g. better sidewalks) among others, the Land Transportation Franchising and Regulatory Board (LTFRB) must then weigh these results if the goal is to convince people to use (or continue using) public transportation in the NCR.

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