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Towards Assessing Accessibility Resulting from Integrating Demand-Responsive and Conventional Public Transport with Travel Time Uncertainty

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1. INTRODUCTION

Transportation networks provide people with the means to reach opportunities (i.e., accessibility), e.g., schools and workplaces [1, 2]. Conventional Public Transportation (CPT), e.g., fixed-route buses and trains, is most effective in densely populated areas, where it offers extensive and affordable coverage [3]. In low-density areas (e.g., suburbs), CPT provides insufficient accessibility, as few opportunities can be reached within reasonable travel times. Operators limit frequency and coverage to prevent high costs per passenger [4], leaving such areas car-dependent, with private vehicles often the only viable mode [5]. Demand Responsive Transportation (DRT) offers a flexible alternative, as routes and schedules adapt to users' requests. With growing interest in integrating DRT with CPT, it is essential to evaluate its impact on accessibility, particularly when DRT operates as stop-to-stop service, both as a feeder and as a standalone mode. Yet, rigorous methods to assess accessibility under these conditions remain lacking. To address this gap, we propose a method that accounts for travel time uncertainty in DRT, rather than relying on deterministic or oversimplified assumptions.

2. METHODOLOGY

A. Accessibility

We use an isochrone-based measure to quantify how many additional opportunities individuals can access within a given time threshold due to the introduction of DRT. Accessibility is computed by calculating the shortest travel time from each location to all others using available transport modes (DRT, CPT, walking), and counting the opportunities reachable within the threshold. The study area is divided into hexagons, with centroids $\mathcal{C} \subseteq \mathbb{R}^2$ used as trip origins and destinations. The accessibility measure is expressed as:

$$A_u(t) = \sum_{v \in \mathcal{C}} O_v \cdot \mathbf{1}_{T_{uv}(t) \leq \tau} \quad (1)$$

where $A_u(t)$ is the accessibility of hexagon u at time $t \in [00:00, 24:00]$, O_v is the opportunities in hexagon v , $T_{uv}(t)$ is the shortest travel time from u to v , departing at time t , τ is the travel time threshold, and $\mathbf{1}_{T_{uv}(t) \leq \tau}$ is an indicator function that equals 1 if $T_{uv}(t) \leq \tau$, and 0 otherwise.

B. Travel time prediction

$T_{uv}(t)$ is a random variable because it depends on factors such as detours imposed by other passengers, which may change from day to day. Therefore, $A_u(t)$ is also a random variable. The distribution of $T_{uv}(t)$ can be estimated using ML models trained on observed trips.

Let $\hat{A}_u(t)$ and $\hat{T}_{uv}(t)$ be the estimated travel time and accessibility. Via such models we extrapolate $T_{uv}(t)$ for (u, v) pairs with no observed trips; ML models exploit spatial similarity to do so. To account for uncertainty, we do not rely on a single deterministic value of $\hat{T}_{uv}(t)$; instead, we encode percentiles of its distribution. In this study, we

consider only the 95th percentile (P95). Given a pair (u, v) and departure time t , the ML model is a function $f(u, v, t) = [\hat{\mu}_{uv}(t), \hat{\sigma}_{uv}(t)]$, the estimated mean and standard deviation of $T_{uv}(t)$. We compare three ML models: Linear Regression (LR), Random Forest Regressor (RFR), and Bayesian Neural Network (BNN). We tried three probability distributions—Normal, Gamma, and Lognormal—to compute percentiles and assessed point prediction accuracy and uncertainty quantification. We used Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for accuracy, and Negative Log-Likelihood (NLL) for probabilistic estimate quality. The best-performing model was selected for the rest of the study.

C. Unified modeling of demand responsive Transportation with conventional public transportation

Accessibility is typically calculated using a graph structure, where shortest paths can be computed and travel times to opportunities are the time of those paths. To account for the dynamics of transport networks, the time dimension is incorporated into this graph, resulting in a Time-Expanded Graph (TEG) [6]. In a TEG, nodes are defined as *stoptimes* (u, t_{arr}, t_{dep}) , representing arrival and departure of a vehicle at location $u \in \mathbb{R}^2$ at times $t_{arr}, t_{dep} \in \mathbb{R}$, respectively. For CPT lines with scheduled trips, it is feasible to use a TEG to compute accessibility, since *stoptimes* are scheduled in advance. Each CPT trip is represented by a sequence of *stoptimes* connected by edges. However, no scheduled *stoptimes* exist in DRT and such a graph cannot be computed. To address this, we adopt an approach similar to [7], augmenting the CPT TEG with "virtual lines". These represent potential DRT trips not necessarily observed in the past. While [7] model DRT solely as a feeder service—connecting areas to selected CPT stops—our approach generalizes this by also supporting complete DRT origin-to-destination journeys, without requiring transfer to CPT. We enrich the CPT TEG \mathcal{G} with virtual DRT lines to enable centroid-to-centroid multimodal journeys (Figure 1). Virtual lines can start or end in CPT stops or in "DRT barycenters" in each hexagon. A DRT barycenter is the barycenter of pick-up or drop-off locations in the historical dataset (B1–B4 in Figure 1). For hexagons without observed pick-up or drop-off, we do not add virtual lines, restricting DRT modeling to areas with observed demand. The virtual lines enable five types of multimodal trips between origin u and destination v , as shown in Figure 1. All walking connections between centroids, barycenters, and CPT stops are handled by CityChrone [8]. We consider that all trips start and end with walking, reflecting the fact that users need always to walk a short distance to reach CPT or DRT services, or to arrive at the destination centroid. We also model line changes between services (e.g., CPT–CPT or CPT–DRT) via walking links, also managed by CityChrone.

3. RESULTS

A. Study area and data

We evaluate our methodology on three French regions and present results for Orléans Métropole. We use a large real world historical DRT

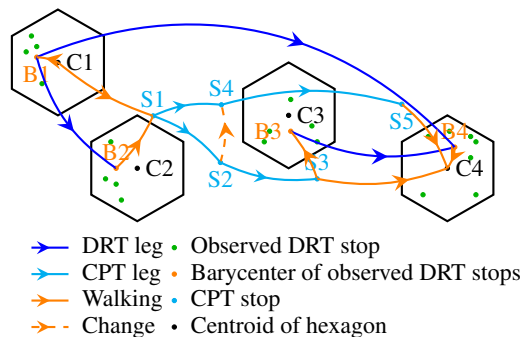


Fig. 1. Illustration of DRT integration with CPT

trip dataset (over 1 million trips, 2018–2024), collected by vehicles operated by [9]. Additionally, we incorporate publicly available datasets, including the 2025 CPT GTFS, street networks from OpenStreetMap (OSM) and locations of opportunities extracted from OSM.

B. Prediction of travel time distributions

Table 1 presents the evaluation scores for both point prediction accuracy (using MAE and RMSE) and probabilistic performance (using NLL under three distributions: Lognormal, Normal, and Gamma). RFR achieves the best point prediction accuracy overall, with the lowest MAE and RMSE in most cases. In Lille, for instance, RFR yields an MAE of 3.80 min and RMSE of 4.43 min, slightly outperforming BNN. BNN, however, records the lowest RMSE in Lille (3.96), and shows competitive MAE in other regions as well. The differences in MAE and RMSE between RFR and BNN are small and may be negligible in practice. For uncertainty quantification, BNN significantly outperforms both RFR and LR. Under the Normal assumption, BNN obtains the lowest NLL across all territories (e.g., 0.71 in Lille).

Given BNN’s competitive point prediction performance and its clear advantage in uncertainty estimation, we select it as the final model for estimating travel time percentiles used to enrich the CPT TEG with virtual lines.

Table 1. Performance comparison of travel time distribution prediction models across three territories

Territory	Model	MAE (min)	RMSE (min)	NLL		
				Lognorm.	Normal	Gamma
Lille M.	LR	4.41	5.95	39.21	32.49	7.29
	RFR	3.80	4.43	117.82	142.46	7.49
	BNN	3.99	3.96	7.24	0.71	7.16
Orléans M.	LR	3.31	4.58	38.96	32.71	6.82
	RFR	2.75	3.87	108.50	125.57	6.80
	BNN	2.87	3.97	6.68	0.65	6.69
Yvelines	LR	3.29	4.31	51.88	45.45	6.86
	RFR	2.77	3.85	174.76	192.02	6.94
	BNN	2.71	3.98	6.66	0.50	6.68

C. Accessibility evaluation

The accessibility of each hexagon was calculated on the weekday of April 25, 2024, using a maximum travel time threshold of 30 minutes. As explained in the methodology, this was done by simulating a trip from that hexagon to every other hexagon in the region, departing at 7:00 a.m. The travel time threshold was based on the average travel time from peripheral areas to the center of Orleans, making it an appropriate cutoff for evaluating regional accessibility.

Figures 2 demonstrate the impact of integrating DRT with CPT. In the figures, the CPT-only map (left) reveal substantial areas with low accessibility scores (light blue) in peripheral regions. The combined CPT+DRT map (center) show markedly improved accessibility scores across almost the entire territory, with some areas reaching dark blue (high accessibility scores > 200). The relative improvement maps (right) quantify these enhancements with percentage differences calculated as $(\text{CPT+DRT} - \text{CPT}) / \text{CPT} \times 100$. The green hexagons, represent areas newly made accessible by DRT that were previously unserved by public Transportation (No access to CPT within a considered maximum walk time of 15 Minutes).

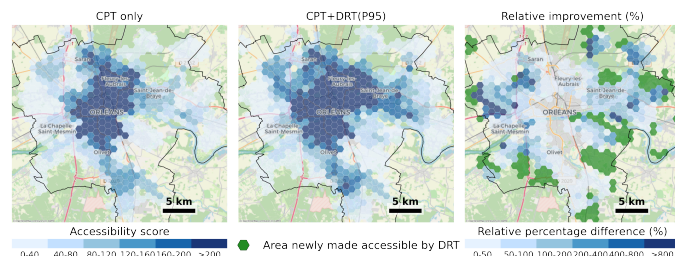


Fig. 2. Accessibility scores and relative percentage improvement between CPT only and P95 (CPT+DRT) scenarios

4. CONCLUSION

In this study, we first investigated the impact of DRT on accessibility using the proposed method. We also examined how travel time variability in DRT affects accessibility by using probabilistic machine learning models across three French territories. Our results demonstrate that the BNN with a Normal distribution provides the best overall performance, effectively balancing point prediction accuracy and the ability to model travel time uncertainty. However, our study has several limitations that suggest directions for future research. We assumed unrestricted availability of DRT vehicles, without considering fleet size constraints, vehicle capacity, or operational costs.

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