Paratransit Routing Considering Dwell Time Uncertainty and Contexts of Requests

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Introduction Paratransit services are indispensable for vulnerable road users, especially for the elderly and the disabled who lack other available mobility options or face lower accessibility to public transit systems. Two operation schemes are available: offline and online. An offline setting requires potential passengers to reserve a ride in advance to secure sufficient time to build vehicle routes by matching requests. Daily operation information is distributed to passengers and drivers. On the other hand, the online setting allows stakeholders to interact in real-time: passengers request service whenever they want and operators assign them to vehicles nearly simultaneously. This makes the online setting would be more responsive to interruptions such as last-minute request cancellations or unexpected vehicle breakdowns.

Uncertainties caused by transit users seem to be more unpredictable as they are uncontrollable by the operators. The best strategy for transit operators can be improving the quality of prediction and preparing for disruptions. Meanwhile, delays during the operation may impact the system more seriously than the cancellation because they force some following requests to be modified, transmitting operational disruption downstream. Thus, a transit delay should get more attention to prevent collateral damage.

There are some recurrent disturbances that would be simpler to predict. For example, loading/unloading delay can be predictable if a rider appears at a meeting point late or uses a support device like a wheelchair. Furthermore, it is reasonable suspicion that there exists a significant relationship between the spatiotemporal characteristics of a location and the amount of potential delay. Traffic conditions can be another factor that intensifies uncertainty but is excluded since vehicles can detour and avoid congested points. In contrast, passengers cannot be abandoned.

Therefore, this study proposes the incorporation of dwell time uncertainty in paratransit operation systems. There has been a vast number of studies investigating this issue, but according to our best knowledge, relating spatiotemporal features of pickup/drop-off points with loading time uncertainties is not a well-visited subject. For example, dwell time is assumed to be constant(e.g. Gupta et al. 2010) or a random variable (e.g. Fu 2002). Garnier, Trepanier, and Morency (2020) conducted linear regression by setting loading time as the dependent variable and other attributes as independent ones. This study, however, plans to use a more complex approach, temporal multimodal multivariate learning (TMML, Park et al. (2022)) and the contextual bandit (CB) (Li, Lu, and Zhou 2017), to estimate the impact of features on loading time.

Problem Definition Consider a paratransit service on a network $G(N,A)$ with vehicles $f \in F$ in its fleet, receiving N_d requests on the day d. When a potential passenger $k \in K_d$ submits personal information along with the request details beforehand, the system adds it to a set of requests B_d accompanied by their features $X_{k,d}$. Dwell time at pickup and drop-off point, $s_{i,k,d}$ and $s_{j,k,d}$, are estimated from distribution modeled by TMML, and considering other factors such as peak hour and distance. After identifying the pickup/drop-off time and location of all passengers, the system builds R_fs, routes for fs, for the day d. The objective of the routing is the optimization of combined performance measures such as total travel time and mile, overall vehicle occupancy, or on-time ratio. The system assigns as many requests to vehicles as possible.

Despite the similarity to the general vehicle routing problem with pickup and delivery and time window, this problem takes into account the variability of dwell time that can deteriorate the system performance. For example, a delay in dwell time in the morning can be propagated to other subsequent requests unless the route is prepared with a buffer to absorb the impact of extended service time. A proposed algorithm should address how to arrange requests to minimize the disruption, making the entire system unreliable.

Methodology Figure 1 illustrates the entire process of the solution. As introduced, the designed approach consists of dwell time estimation by TMML and paratransit vehicle routing using CB. First, TMML uses historical dwell time distribution data collected from requests served to identify potential groups of which requests share similar dwell time distribution. This classification plays an important role in TMML because an observed measure of an element can be used for updating the distribution of others. Afterward, it is possible to estimate the dwell time of a new incoming request and augment it to the feature information, which becomes the input of the request evaluation. Observations on dwell times made during the operation can be updated in the existing database in real time, and the system can distribute update routing if needed. Despite the ability to do so,

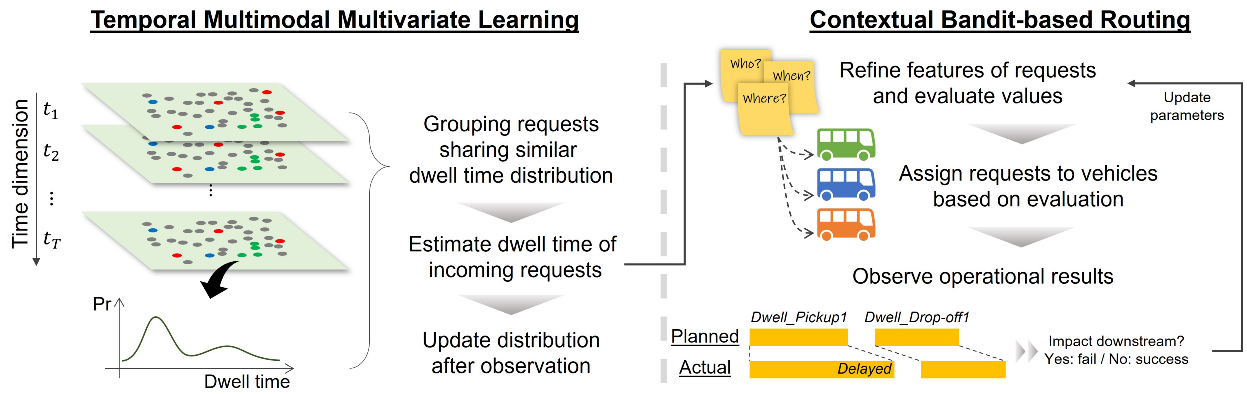

Figure 1 **Solution concept.**

the system will limit the update during the operation only to excessively irregular cases to improve the computational burden. Since the system is in the nearly offline setting, drivers and passengers may not get updates from the system until the daily operation ends.

During the routing, vehicles take turns attaching new requests to build routes. Each request can have its own value that implicitly represents the benefit of routes if merging it. Therefore, a link function, mapping features to the value, should reflect the influence of features in a reasonable way. For example, the usage of a wheelchair will significantly extend the dwell time due to the required operation of a lift, and a binary variable indicating this may have a negative coefficient. When daily routes are complete, vehicles start to travel through them and collect information about dwell time. They are also responsible for observing and archiving the success or failure of routes which can be used for calibrating parameters in the link function. These observations also contribute to the update of dwell time distribution.

Expected Result The solution can yield three main outcomes as shown in Figure 2. First, it can provide a better understanding of dwell time distribution and the relationship with features of request. Some features are specified as crucial factors that impact the dwell time to inform operators of which one should require more attention than others. Second, an optimal request

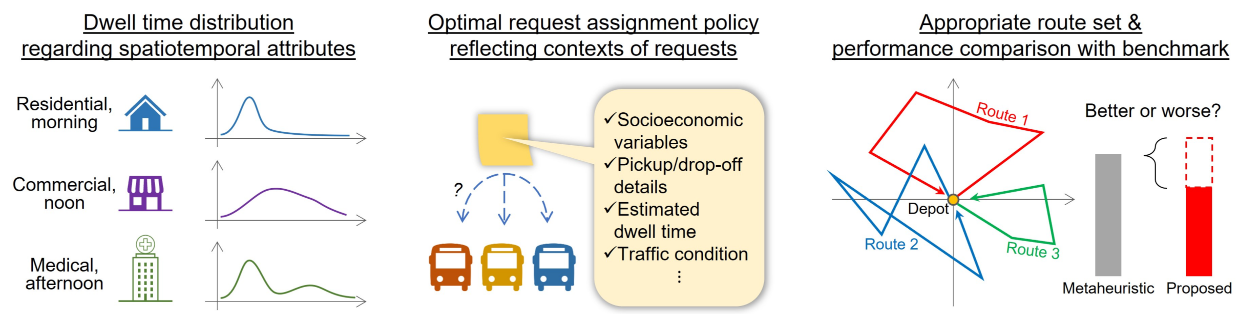

Figure 2 **Format of expected results.**

assignment policy can be proposed as a consequence of considering the contexts of requests. It guides operators to mitigate the unexpected dwell time delay by proactively allocating somewhat doubtful requests to routes that can effectively manage the risk. Lastly, it can generate a satisfactory service route set that meets a predefined constraint set, complying with the initial requests of passengers as much as possible. Moreover, the performance measure can be compared with other route sets generated by more generic approaches such as metaheuristic to verify the influence of dwell time uncertainty.

Conclusion This study concentrates on dwell time uncertainty, one of the disruptions that operators may be able to respond to in advance by analyzing the relationship between their distributions and features of corresponding requests. With the estimated dwell time, a contextual bandit-based vehicle routing is proposed and expected to generate route sets capable of alleviating potential risks of dwell time variation.

The future extension of this work can be a transformation of the system from an offline to an online setting. Although there exists inflexibility in the operation, it is evident that an online system can timely respond to any circumstances occurring in the middle of the operation. Taking advantage of that benefit should be the next goal of the current research.

Acknowledgments

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