Reorganizing Requests in Rural Dial-a-Ride Systems through Needs-Based Scheduling

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Short summary

Providing public transport in demand-sparse rural areas means balancing operational efficiency with equitable service for mobility-deprived users. This paper introduces a Needs-Based Dial-a-Ride Problem (NB-DARP) that integrates behavior models with vehicle routing optimization. Using panel data from rural Japan, we adapt multi-day activity models into a scheduling constraint generation framework to assess user flexibility, and predict availability. Solving the NB-DARP with an Adaptive Large Neighborhood Search (ALNS) metaheuristic, we demonstrate that it outperforms traditional "first come, first served" and ridership-maximizing policies. The proposed framework increases overall service rates and ensures equitable transit access without requiring substantial temporal shifts from users.

Keywords: Activity-Based Modelling, Dial-a-Ride Problem, Rural Mobility, Shared Mobility, Transport Equity and Justice, Vehicle Routing Problem

1 Introduction

Providing public transport in low-density rural areas presents a threefold challenge: balancing service quality, operational efficiency, and profitability. With a growing number of mobility-deprived individuals entirely dependent on public transportation services for their daily mobility needs (Berg & Ihlström, 2019), moving beyond traditional fixed-route services to Demand Responsive Transport (DRT) appears as a solution to avoid high vacancy rates and low profitability (De Jong et al., 2011). However, with limited resources, rural operators face a resource allocation dilemma.

Existing Dial-a-Ride Problem (DARP) literature suggests managing demand with behavior models by guiding initial user choices (Sharif Azadeh et al., 2022) or dropping unlikely requests (Dong et al., 2022). In practice, operators default to a myopic first-come, first-served (FCFS) policy. While this represents impartial equality, it ignores varying user necessities. Alternatively, a ridership-maximizing approach prioritizes aggregated welfare, but risks excluding critical trips. Aiming at social equity, a needs-based approach to resource allocation ensures that limited capacity is prioritized for individuals with critical travel requirements (Lewis et al., 2021). We propose a framework that strategically reschedules flexible trips to unlock capacity for high-priority activities.

To minimize user inconvenience and maximize acceptance, this rescheduling is informed by behavioral constraints, namely need and availability. First, measuring the accumulation of day-to-day travel needs through the use of week-long activity models provides a more conceptually sound framework and captures multi-day behavioral dynamics more accurately than traditional single-day modeling (Haghighi & Miller, 2025). Second, effective rescheduling requires an understanding of user availability. While the logistics literature frequently incorporates availability profiles into vehicle routing (Voigt et al., 2023), these are considered exogenous. To bridge this gap, we adapt time-use pattern recognition models (Hafezi et al., 2019) to construct availability profiles.

Integrating the described scheduling constraint generation model, this paper proposes a needs-based DARP (NB-DARP) to optimize week-long operation schedules. By as-

sessing passenger behavioral constraints, prioritizing high-need requests, and strategically rescheduling flexible trips, we aim to maximize equity and service rates. Comparing NB-DARP against FCFS and efficiency-maximizing policies, we quantify trade-offs between equitable resource allocation, system throughput, and required user flexibility.

2 Methodology

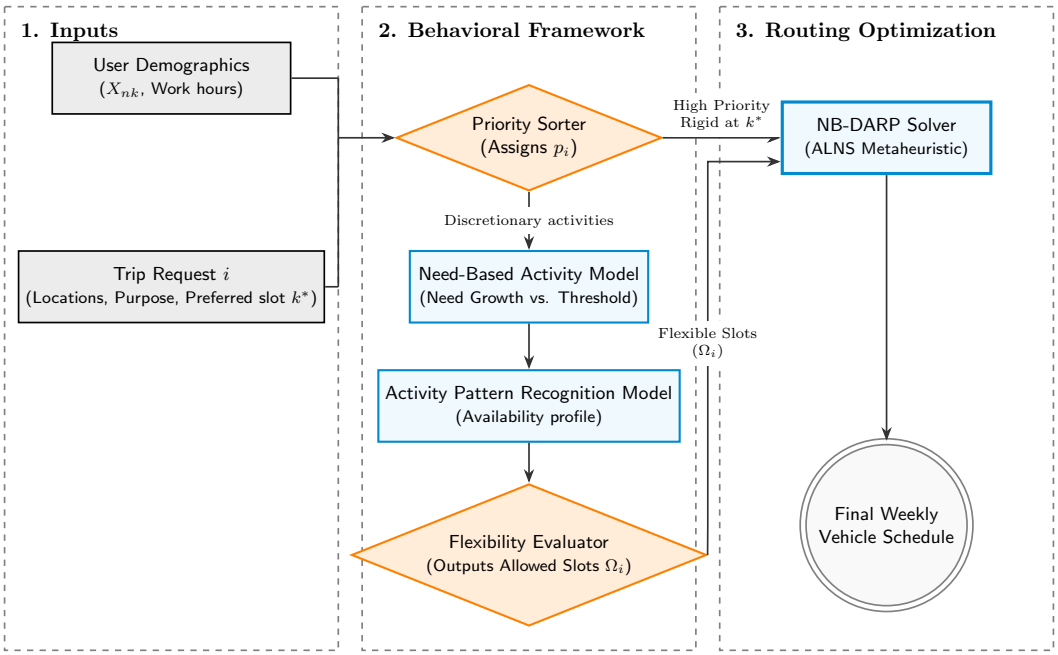


Figure 1: Framework of the Needs-Based Dial-a-Ride Problem (NB-DARP)

We consider a Dial-a-Ride Problem (DARP) in a demand-sparse rural area operated by a single vehicle with a fixed capacity. To maintain service quality while providing users sufficient notice to adjust their schedules, we consider a one-week planning horizon, divided into two three-hour operating slots per day (yielding a total set of slots K, where $|K| = 14$). High service quality is guaranteed by tight pickup time windows of 10 minutes and a maximum ride time of 1.5 times the direct travel time.

Users create accounts prior to use, providing access to demographic data. Requests are accepted until the day before the planning horizon begins. Each request i consists of a pickup stop, a drop-off stop, a requested pickup time, and a trip purpose. Upon collection, requests are prioritized based on trip purpose and assigned a priority score p_i (e.g., medical appointments receive a higher priority than discretionary shopping trips). High-priority requests act as rigid "pegs" in the weekly schedule, while lower-priority requests are granted a set of behaviorally admissible rescheduling slots, Ω_i, determined by an activity-based heuristic.

Activity models for defining of behaviorally admissible slots

Figure 2 illustrates the mechanism used to define the set of behaviorally admissible service slots Ω_i for each request.

To assess user flexibility, we rely on the needs-based activity generation model developed in Arentze & Timmermans (2009) and extended in Nijland et al. (2013). In this model, a multi-day activity pattern agenda is predicted for a given person, under the assumption that individuals make activity-selection decisions on a daily basis and based on the accu-

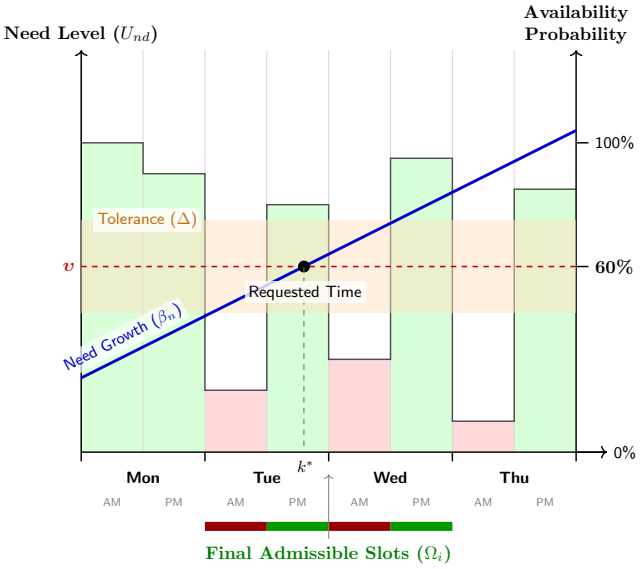


Figure 2: Identification of behaviorally admissible rescheduling slots (Ω_i) based on the intersection of travel need (Δ) and predicted availability $P_{avail,k}$

mulation of travel needs. The utility to conduct an activity of type i on a given day d for an individual n is defined as

$$U_{nd} = (\beta_0 + \sum_k \beta_k X_{1nk})t + \alpha_{nd} + \sum_j \varphi_{ij} I_{ndj} + \varepsilon_{nd} \tag{1}$$

where t is the time since activity i was last conducted before d and ε_{nd} is an error term. The need growth rate $\beta_0 + \sum_k \beta_k X_{1nk}$ depends on socioeconomic attributes X_{1nk}. Each individual's baseline preference for conducting the activity i on day d is expressed by α_{nd}. Interaction with other activities is captured in the last term, with I_{ndj} equal to one if activity j is conducted on the same day and φ_{ij} the increase in utility of activity i when conducted on the same day as activity j.
According to the model, activity i is conducted on the earliest day when utility crosses threshold υ:

$$\upsilon_{nd}^0 = \mu_d^0 + \sum_m \mu_m X_{2dm} \tag{2}$$

The threshold, which is not activity-dependent, depends on each individual's time budget variables X_{2dm}, in our case, their number of daily work hours.
A contribution of our work is that we estimate this model using repeated-choice activity data. Therefore, we are able to capture unobserved inter-individual heterogeneity by including an individual-specific random error component with standard deviation σ_{need} in the need growth rate. The parameters of this behavioral model are estimated via a Bayesian Markov Chain Monte Carlo (MCMC) algorithm utilizing a Random Walk Metropolis-Hastings sampler to address the non-smooth nature of the log-likelihood function and ensure efficient convergence.
We use this model to evaluate the admissibility of alternative service slots k around the user's initially preferred slot k^*. A slot k is considered valid only if the accumulated need, calculated as the product of the user's individualized need growth rate and the temporal delay $|k - k^*|$, remains within a relative tolerance level Δ from the estimated utility threshold: $|U_{nd} - \upsilon_{nd}^0| \leq \upsilon_{nd}^0 \times \Delta$. This temporal bound defines the initial set of feasible rescheduling slots Ω_i.

To refine Ω_i with user availability, we integrate a time-use activity-pattern recognition framework adapted from Hafezi et al. (2019). First, historical daily schedules from the

panel data are clustered using a fuzzy C-means algorithm. We then identify representative time-use profiles for each cluster. Next, a Classification and Regression Tree (CART) is trained to map users' sociodemographic attributes to these profiles. This yields a predicted availability probability $P_{avail,k}$ for any user. This availability profiling is integrated into the NB-DARP in two ways. First, while the needs-based model defines the maximum temporal delay, the availability model prunes the feasible set of slots. If the user's predicted profile indicates engagement in a mandatory or inflexible out-of-home activity during slot k ($P_{avail,k} \leq 60\%$), that slot is removed from the feasible set. Second, the profiles inform the generation of service time windows $[e_i^k, l_i^k]$. If a request is rescheduled to a slot $k \neq k^*$, the original requested time is no longer relevant. Instead, we identify an availability segment within slot k that matches the activity's expected duration and maximizes the probability of user availability, setting the new pickup time at the start of this interval.

Dial-a-Ride Problem

We adapt the classic 3-index formulation from Cordeau (2006). Because we are considering a single vehicle, the third index can be used to represent the operation slots, allowing the rescheduling mechanism to be expressed naturally. The problem's notation is presented in Table 1.

Table 1: Notations

Symbol	**Description**
Sets and Indices	
P	Set of pickup nodes $\{1, \ldots, n\}$.
N	Set of all nodes (pickup, drop-off, and depot).
K	Set of all time slots in the week.
Ω_i	Set of behaviorally admissible slots for request i ($\Omega_i \subseteq K$).
Parameters	
k_i^*	Initially requested time slot for user i ($k_i^* \in \Omega_i$).
$W_{slot}, W_{resc}, W_{uns}$	Objective function weights for opened slots, rescheduled, and unserved requests.
$t_{i,j}$	Travel time from node i to node j .
w_{need}, w_{avail}	Internal weights balancing temporal deviation and availability risk.
γ_i	User-specific travel need accumulation speed.
$P_{avail,k}$	Probability of user availability in slot k.
p_i	Priority score of user i.
Variables	
$x_{i,j}^k$	1 if vehicle travels from i to j in slot k, 0 otherwise.
u_i	1 if request i is unserved, 0 otherwise.
y_k	1 if slot k is opened, 0 otherwise.
α_k	1 if there is a high priority request in slot k, 0 otherwise.

The proposed objective function minimizes a weighted sum of the routing costs, a hybrid user rescheduling penalty, a priority-weighted penalty for unserved requests, and a conditional cost for opening service slots. It is formulated as follows:

$$
\begin{aligned}
\min Z = & \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} t_{i,j} x_{i,j}^{k} \\
& + W_{resc} \sum_{i \in P} \sum_{k \in \Omega_i} \left(w_{need} |k - k_i^*| \gamma_i + w_{avail} (1 - P_{avail,k}) \right) \sum_{j \in N} x_{i,j}^{k} \\
& + W_{uns} \sum_{i \in P} p_i u_i \\
& + W_{slot} \sum_{k \in K} (y_k - \alpha_k)
\end{aligned}
\tag{3}
$$

The first term captures standard routing costs. The second term introduces a hybrid user rescheduling penalty applied when request i is served in slot k. This penalty balances two elements: w_{need} penalizes temporal deviation scaled by the user's specific need-growth rate (γ_i), while w_{avail} penalizes the risk of the user being unavailable ($1 - P_{avail,k}$). The third term penalizes unserved requests proportionally to their priority (p_i). Finally, the fourth term applies a fixed conditional cost for opening service slots, which is waived ($\alpha_k = 1$) if the slot contains a high-priority request. Standard DARP constraints apply, including routing and flow conservation, time-variable consistency and adherence to tight pickup time windows and maximum ride times, and capacity variable consistency with vehicle capacity limits.

Metaheuristic framework

To solve the NB-DARP, we implement an Adaptive Large Neighborhood Search (ALNS) metaheuristic embedded within a Simulated Annealing acceptance framework. ALNS is well-suited for solving routing problems with multi-layered penalty structures. The ALNS algorithm iteratively explores the solution space by applying alternating destroy (removal) and repair (insertion) operators. We employ highly effective operators (Voigt, 2025) and tailor them to our needs-based framework. We use three destroy operators: a standard random removal, a worst-cost removal targeting the most routing-inefficient requests, and a custom "slot emptier" operator designed to consolidate demand by clearing sparsely populated slots. To rebuild the solution, two repair operators are used: a priority-sorted global-best insertion and a regret-2 heuristic, which orders requests based on the cost difference between their optimal and second-best insertion positions. The global-best operator pre-sorts unassigned requests by their priority scores, ensuring that critical trips are inserted into the schedule before lower-priority discretionary activities. Furthermore, as high-priority trips waive the slot-opening cost, the algorithm is encouraged to cluster flexible trips into these anchored windows. The initial solution is built using the global-best insertion heuristic.

3 Results

Needs model estimation results

We estimate the needs-based model of activity generation on trip diary data from a one-month probe person survey conducted in 2023 in the rural town of Tsukechi, Gifu prefecture, Japan. As explanatory variables of activity needs, we include age, gender, household composition and day of the week preference, as shown in Table 2. For the explanatory variables of the threshold, the average number of hours worked on workdays is included, and an interaction term with the trips to the convenience store. The average number of hours worked is expected to increase the threshold and the trips to the convenience store to lower the need to go grocery shopping on the same day.
The results of the parameter estimation are shown in Table 3. For the need-growth rate,

Table 2: Explanatory variables

Variable	**Code**	**Description**
Demographics	Need_Age_Over_40	Binary. Age is over 40.
	Need_Male_Dummy	Binary. Participant is male.
Household	Need_Has_Child	Binary. Presence of a child in the household.
Day of the week	Day_Weekend	Binary. Saturday and Sunday.
Interaction	Interact_Konbini	Binary. Convenience store visit on the same day.
Hours spent at work	Thresh_Avg_Work	Continuous. Average number of hours spent at work. Zero if unemployed.
Heterogeneity	σ_{need}	Standard deviation of the individual-specific random error component.

the baseline rate β_0 is significant (t = 2.48). The sociodemographic parameters are also significant, showing that age and household composition alter shopping need accumulation speed. Having children significantly increases the need growth rate (t = 3.10). Being older than 40 (t = 1.83) and being male (t = -1.95) are also marginally significant, with males showing a slower accumulation of grocery shopping needs. Moreover, the standard deviation of the individual-specific random error component σ_{need} is highly significant (t = 2.94), indicating that substantial unobserved inter-individual heterogeneity exists in our sample.

Table 3: Estimation results

Parameter	Mean	SD	t-ratio	
Need_Base	0.34	0.14	2.48	**
Need_Has_Child	0.42	0.13	3.10	***
Need_Age_Over_40	0.24	0.13	1.83	*
Need_Male_Dummy	-0.25	0.13	-1.95	*
Sigma_Need	0.19	0.06	2.94	***
Day_Weekend	-0.10	0.09	-1.15	
Interact_Konbini	0.42	0.12	3.44	***
Thresh_Base	1.22	0.17	7.35	***
Thresh_Avg_Daily_Work_Hours	0.08	0.05	1.55	
Goodness-of-fit				
Null Model LL	-502.6			
Estimated Model LL	-415.5			
Rho-Square ρ^2	0.17			
Sample size	931 person-days, 282 trips			

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Regarding day preferences and activity interactions, there is no significant preference for conducting shopping activities on the weekend. The interaction parameter for convenience store visits shows a significant positive effect (t=3.44), meaning that there is an increase in utility from conducting grocery shopping trips and konbini trips on the same day. Rather than an expected substitution effect, this suggests that there is an opportunistic nature to konbini trips, which are made more likely by the sole fact of going outside.

For the threshold, the baseline component is highly significant, while the parameter linked to work hours is positive as expected, but not significant at the 95% level (t=1.55), suggesting that the effect of daily work hours on shopping activity generation is less than anticipated. The goodness-of-fit of the model is reflected by a ρ^2 of 0.17. While seemingly low, this indicates a good fit for activity models with a parsimonious set of explanatory variables, aligning with similar findings in the literature (Cho et al., 2023).

Time-use activity pattern recognition and CART results

Applying the time-use framework to the panel data yielded four distinct activity profiles. The clustering algorithm partitioned the weekday schedules as illustrated in Figure 3:

- **Profile 1 (Worker, 44.0%):** Characterized by continuous out-of-home work durations, and leaving work around 4:00 PM.
- **Profile 2 (Home-centric / Retiree, 19%):** Characterized by spending nearly the entire day at home with few out-of-home activities, yielding a substantial window of temporal availability.
- **Profile 3 (Worker with long hours, 26%):** Characterized by continuous out-of-home work durations, and leaving work later than profile 1, with availability limited to early morning or evening.
- **Profile 4 (Part-time / Mixed Schedule, 11%):** Characterized by fragmented or shorter out-of-home work durations, often combined with other discretionary activities throughout the day.

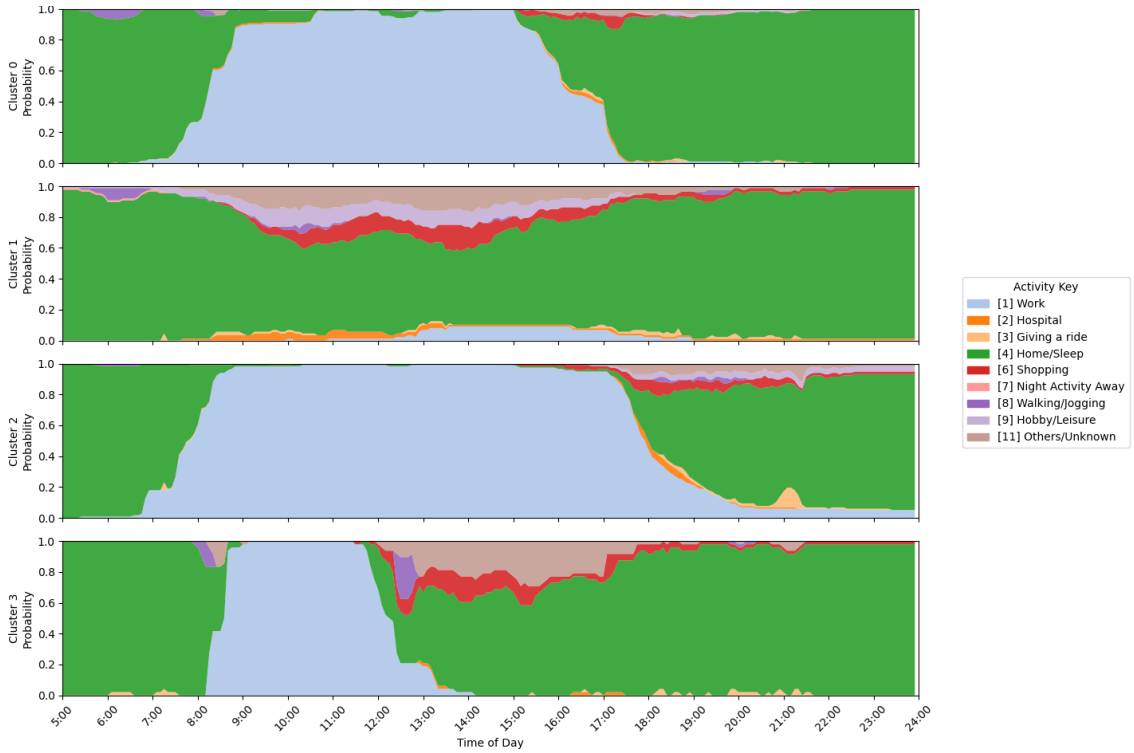


Figure 3: Activity patterns identified with C-means

To predict these four profiles for synthetic requests, we trained a CART classifier using the survey participants' sociodemographic and temporal data. The resulting decision tree achieved a predictive accuracy of 77%. Feature importance analysis revealed that *Occupation* was the dominant predictor (accounting for 19.5% of the variance), followed by *Gender* (14.6%), *Household size* (12.6%), and the *Presence of children in the household* (12.4%).

NB-DARP performance

To simulate realistic transport demand, synthetic service requests are generated using the observed activity diaries. Out-of-home activities are mapped to the nearest network stops, with departure times aligned with operational windows. The set of behaviorally admissible slots for each request is determined based on the user's sociodemographic attributes. Priority scores are assigned to activities: medical appointments are designated as high priority ($p_i = 5$) and shopping as low priority ($p_i = 1$). We generate different demand instances from 30 to 110 requests per week distributed across shopping trips (70%), and hospital trips (30%). Table 4 shows that as flexibility is increased, the number of flexible users rises significantly, while the average number of viable slots remains stable at approximately four. Increasing flexibility provides the algorithm a bigger candidate pool for rescheduling, but does not necessarily enable extreme shifts.

Table 4: Demand instances

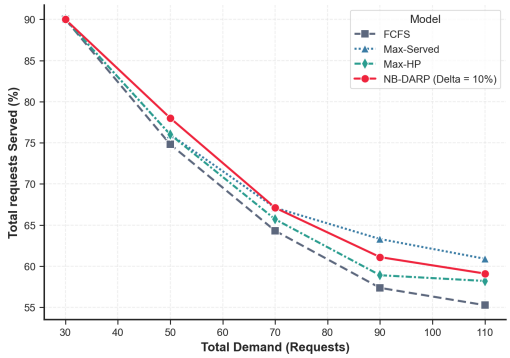
Demand	**High need requests**	**Flexible users at $\Delta = 10\%$**	**Average admissible slots at $\Delta = 10\%$**	**Flexible users at $\Delta = 50\%$**	**Average admissible slots at $\Delta = 50\%$**
30	9	1	5	14	4.0
50	15	1	5	23	3.7
70	21	2	4.5	34	4.0
90	27	4	5	45	4.2
110	33	5	5.2	56	4.11

Comparison with other capacity allocation strategies

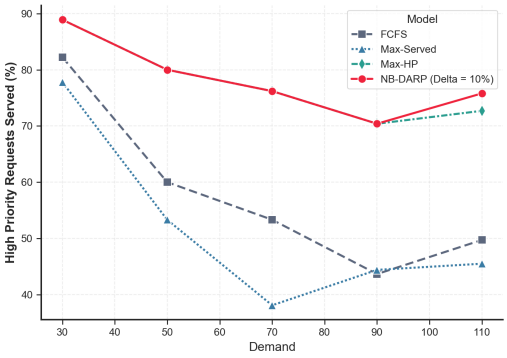
We compare the proposed NB-DARP to three other operational policies constrained by static time windows. The first is First Come First Served (FCFS). To evaluate the FCFS baseline, we average the outcomes across five random permutations of the request set. The second operational policy, *Max-Served*, is to serve the maximum number of users, regardless of their flexibility or priority level. The third policy, *Max-HP*, is similar but prioritizes high-need requests with a penalty cost for unserved requests proportional to the priority score. Those three policies are compared to the NB-DARP with $\Delta = 10\%$. For the NB-DARP, the weights are set as $W_{slot} = 1500$, $W_{uns} = 100$, $W_{resc} = 100$.

The experimental results demonstrate that the baselines encounter a structural capacity limit as demand increases. As shown in Figure 4a, while all models satisfy 90% of demand at $N = 30$, performance diverges significantly as demand rises. The higher exclusion of high-priority users under the Max-Served baseline reveals that these requests impose a higher operational burden than standard requests. The Max-Served and the Max-HP baselines establish upper-bounds for the service rate for all users and high-priority users, respectively. Our proposed NB-DARP matches those limits at demand levels 30, 50 and 70. At higher demand levels (90 and 110), although total system throughput is slightly lower than that of the Max-Served baseline, the high-priority service rate aligns with and even exceeds that of the Max-HP baseline. The NB-DARP uses temporal flexibility as an operational buffer to satisfy high-priority demand without sacrificing system-wide throughput. By shifting flexible, lower-priority requests into adjacent slots where their availability is verified, the algorithm re-allocates fleet capacity to high-priority requests.

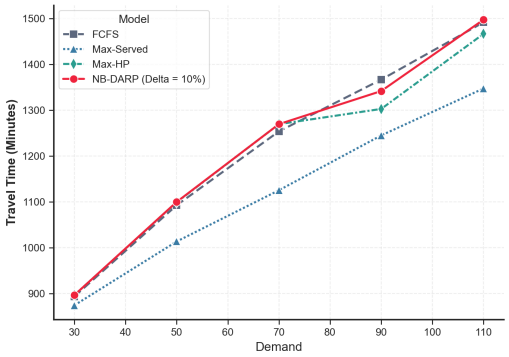
The improved service rates of the NB-DARP are accompanied by higher operational performance. At peak demand, the NB-DARP achieves a fleet efficiency of 60%, compared to 53% for the Max-Served model, which has a higher idle time. Despite the increase in total travel time required to serve more passengers, the travel time per served request remains stable and similar to the value under the myopic FCFS baseline. The algorithm is leveraging the expanded solution space to identify geographically cohesive clusters that are unavailable under static scheduling.



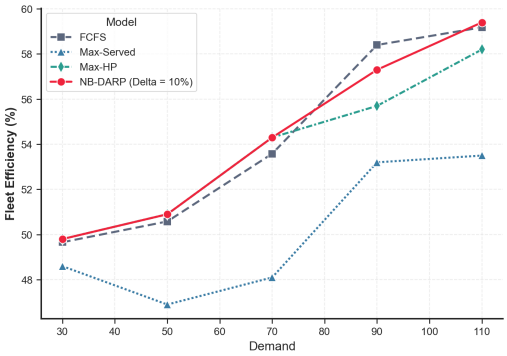
(a) Service rate across policies and demand levels



(b) Service rate of high priority requests



(c) Travel time across policies and demand levels

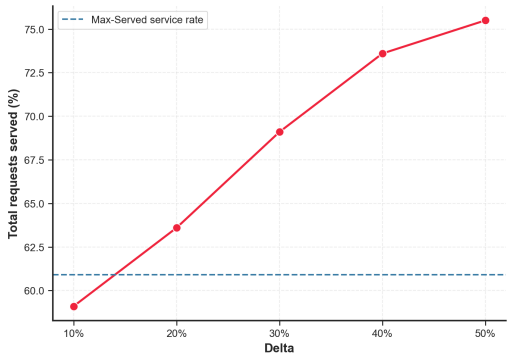


(d) Efficiency (Service time utilization rate) across policies and demand levels

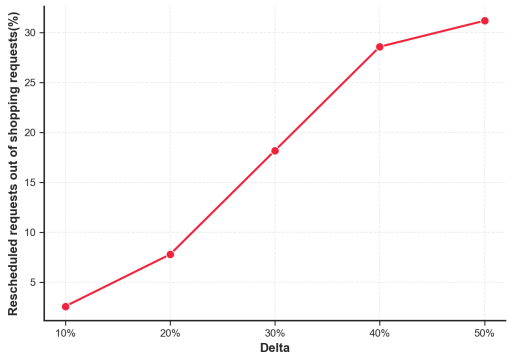
Figure 4: Comparison metrics across FCFS, Max-Served, Max-HP, and NB-DARP

Sensitivity analysis of flexibility level (Δ)

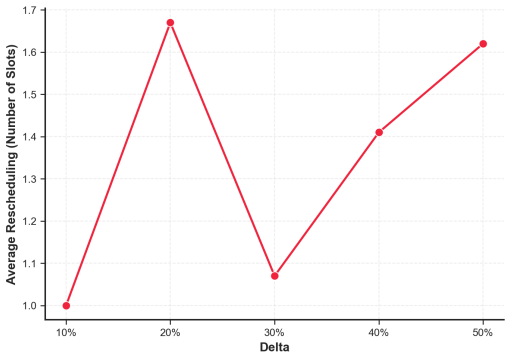
Figure 5 illustrates the system's sensitivity to Δ at demand level $N = 110$, which accounts for the assumed user's needs-based flexibility. Results show that even minor flexibility allows for significant improvements in the service rate. At all flexibility levels, the NB-DARP model matches the high-priority service rate of the Max-HP baseline. As for the upper bound set by the Max-Served baseline for the overall throughput illustrated in Figure 5a, it is exceeded from the flexibility level $\Delta = 20\%$. The increase in service rate is directly correlated with the increase in rescheduled requests, as illustrated by the synchronized upwards trajectories in Figures 5a and 5b. However, average rescheduling per user remains below 1.7 slots, and the proportion of rescheduled users amongst standard users remains below 35%. Additionally, the relationship between flexibility and individual inconvenience is non-monotonic, as illustrated by 5c. It appears the algorithm does not rely on extreme shifts for a few individuals, but it distributes minor and efficient shifts across a broader flexible population.



(a) Service rate across flexibility levels



(b) Percentage of rescheduled requests across flexibility levels



(c) Average slot delay across flexibility levels

Figure 5: Results of the sensitivity analysis of Δ

Equity

We assess the equity of each model using the Theil index. The Theil index allows for the quantification of horizontal (T_W) and vertical (T_B) equity (Alex Karner et al., 2024). Under a needs-based allocation of capacity, higher values for the between-group component (T_B) validate the model's capacity to differentiate users based on need. The Theil index

is applied to disutility, which is defined as:

$$x_i = \begin{cases} 1.0 & \text{if served in preferred slot} \\ 1.0 + \Delta s_i & \text{if rescheduled by } \Delta s_i \text{ slots} \\ 20.0 & \text{if unserved} \end{cases} \tag{4}$$

This function sets a baseline utility for optimal service, linearly scales penalties for temporal shifts, and imposes a severe penalty (20.0) to reflect the critical mobility loss of an unserved request. The resulting equity metrics for the high-priority group (medical trips) and the standard group (shopping trips) are summarized in Table 5.

Table 5: Theil index of user disutility at $N = 110$

Model	Δ	**Total** (T)	**Between** (T_B)	**Within** (T_W)	**HP Disut.**	**Std Disut.**
FCFS		0.57	0.00	0.57	10.56	9.04
Max-Served		0.65	0.02	0.62	11.36	7.17
Max-HP		0.61	0.02	0.59	6.18	10.13
NB-DARP	0.10	0.62	0.03	0.59	5.61	10.16
NB-DARP	0.30	0.72	0.00	0.72	6.18	7.36

As a myopic policy, the FCFS baseline results in a near-zero vertical inequality, but a high disutility to high-priority users exceeding that of the standard population. The Max-Served baseline and the Max-HP baseline both have a higher vertical inequality, as they disproportionately burden high-priority users (11.36 vs 7.17) and standard users (10.13 vs 6.18), respectively. As it reschedules users with flexibility level $\Delta = 10\%$, the proposed NB-DARP favors high-priority users, dropping the disutility for them at lower levels than the Max-HP baseline. At higher flexibility ($\Delta = 30$), vertical inequality drops to almost zero, while horizontal inequality rises, specifically from the difference in disutility between the unfavored group of standard users who are flexible and rescheduled, and those whose behavioral constraints do not allow rescheduling.

4 Conclusion

Using panel data from rural Japan, we demonstrated that strategic rescheduling of Dial-a-Ride requests can be enabled by integrating behavioral constraints into vehicle routing. Simulation results show that the NB-DARP outperforms traditional FCFS and capacity-maximizing policies by protecting high-priority trips without sacrificing system-wide throughput. Crucially, our analysis reveals that major temporal shifts are not required to achieve optimal, equitable schedules. Operators can leverage this finding by offering targeted incentives to encourage minor scheduling flexibility among users, ultimately fostering a more just and efficient rural mobility system.

Acknowledgements

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References

Alex Karner, Rafael H. M. Pereira, & Steven Farber. (2024, January). Advances and pitfalls in measuring transportation equity. *Transportation*. doi: 10.1007/s11116-023-10460-7

Arentze, T. A., & Timmermans, H. J. (2009, February). A need-based model of multi-day, multi-person activity generation. *Transportation Research Part B: Methodological*, *43*(2), 251–265. doi: 10.1016/j.trb.2008.05.007

Berg, J., & Ihlström, J. (2019, February). The importance of public transport for mobility and everyday activities among rural residents. *Social Sciences*, *8*(2). doi: 10.3390/socsci8020058

Cho, W., Chung, J.-H., & Kim, J. (2023, June). Need-based approach for modeling multiday activity participation patterns and identifying the impact of activity/travel conditions. *Transportation Research Part A: Policy and Practice*, *172*, 103665. doi: 10.1016/j.tra.2023.103665

Cordeau, J.-F. (2006, June). A branch-and-cut algorithm for the dial-a-ride problem. *Operations Research*, *54*(3), 573–586. doi: 10.1287/opre.1060.0283

De Jong, W., Vogels, J., Van Wijk, K., & Cazemier, O. (2011, November). The key factors for providing successful public transport in low-density areas in the netherlands. *Research in Transportation Business & Management*, *2*, 65–73. doi: 10.1016/j.rtbm.2011.07.002

Dong, X., Chow, J. Y., Waller, S. T., & Rey, D. (2022, February). A chance-constrained dial-a-ride problem with utility-maximising demand and multiple pricing structures. *Transportation Research Part E: Logistics and Transportation Review*, *158*, 102601. doi: 10.1016/j.tre.2021.102601

Hafezi, M. H., Liu, L., & Millward, H. (2019, August). A time-use activity-pattern recognition model for activity-based travel demand modeling. *Transportation*, *46*(4), 1369–1394. doi: 10.1007/s11116-017-9840-9

Haghighi, M., & Miller, E. J. (2025, January). Week-long activity-based modelling: a review of the existing models and datasets and a comprehensive conceptual framework. *Transport Reviews*, *45*(1), 119–148. doi: 10.1080/01441647.2024.2416652

Lewis, E. O., MacKenzie, D., & Kaminsky, J. (2021, March). Exploring equity: How equity norms have been applied implicitly and explicitly in transportation research and practice. *Transportation Research Interdisciplinary Perspectives*, *9*, 100332. doi: 10.1016/j.trip.2021.100332

Nijland, L., Arentze, T., & Timmermans, H. (2013, February). Representing and estimating interactions between activities in a need-based model of activity generation. *Transportation*, *40*(2), 413–430. doi: 10.1007/s11116-012-9423-8

Sharif Azadeh, S., Atasoy, B., Ben-Akiva, M. E., Bierlaire, M., & Maknoon, M. (2022, July). Choice-driven dial-a-ride problem for demand responsive mobility service. *Transportation Research Part B: Methodological*, *161*, 128–149. doi: 10.1016/j.trb.2022.04.008

Voigt, S. (2025, April). A review and ranking of operators in adaptive large neighborhood search for vehicle routing problems. *European Journal of Operational Research*, *322*(2), 357–375. doi: 10.1016/j.ejor.2024.05.033

Voigt, S., Frank, M., Fontaine, P., & Kuhn, H. (2023, March). The vehicle routing problem with availability profiles. *Transportation Science*, *57*(2), 531–551. doi: 10.1287/trsc.2022.1182