A choice-based dynamic dial-a-ride problem for on-demand transportation

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MATTS
Agenda

• Motivation
• Research objectives
• Description of the on-demand system
• Proposed methodology
  – Choice model
  – Menu/Assortment optimization
  – Choice-based dynamic DARP
  – Solution approach
• Simulation experiments
• Conclusions/Discussions
Motivation

• Advances in information and communication technologies, computational power, data science, vehicle technology …

• Innovative transportation alternatives for both passengers and freight
  – Real-time
  – On-demand
  – Shared
  – Customized
  – Automated
  – Connected
Motivation

If we are now providing customized on-demand solutions, should not we adjust our optimization models (vehicle routing etc.) as well?
Research objectives

• Consider user behavior as realistic as possible when optimizing decisions
  – Trade-off: complexity of behavior and computational efficiency
• A choice-based dynamic dial-a-ride problem (DARP)
  – Choice model
  – Menu/Assortment optimization model
  – Dynamic dial-a-ride problem
Description of the on-demand system

• Requests are initiated through an app
  – with information on arrival time, origin, destination, preferred pickup/delivery time window

• Users are presented an optimized menu of options
  – Service: Taxi – Shared-taxi
  – Time-window: on-time, (may be) earlier, (may be) later
  – Price: three levels (only one is presented to the user)

• Some users may not be presented any alternatives if not profitable or if there are not enough resources.
Definitions for assortment optimization

- The menu is an assortment $s \in S$
- All possible alternatives are given by $a \in A$
- All possible assortments are constructed upfront:
  - $\gamma_{as}$ is 1 if alternative $a$ is in assortment $s$
  - Not offering any alternative is also an assortment
- $\gamma_s$ is the binary decision of the menu/assortment optimization
- For each arriving user, $\sum_{s \in S} \gamma_s = 1$
- This decision is linked to the routing problem
  - Availability of the vehicles, preferred schedule …
Choice model

\[
\begin{align*}
\mathbb{P}_{as} &= y_s \frac{\gamma_{as} e^{\mu V_{as}}}{e^{\mu V_0} + \sum_{\tilde{a} \in A} \gamma_{\tilde{a} s} e^{\mu V_{\tilde{a} s}}} \\
&\forall a \in A, s \in S
\end{align*}
\]

- **\( V_{as} \):** utility function in willingness-to-pay space
  - a function of price, travel time, early and late schedule delay and has an alternative specific constant, all in monetary values
- **\( V_0 \):** utility for the opt-out alternative
  - a simple function of OD distance.
- Value of time for travelers (for in-vehicle, out-of-vehicle time and schedule delay) is distributed randomly in the population.
Choice-based DARP

• Every time a request is received a choice-based DARP is solved:
  – There are a set of existing users, the promised services to them needs to be maintained, i.e., time, price, service
  – The new user will be presented an assortment, so a set of routing options are kept open
Choice-based DARP

- The objective function is the expected profit
- The costs represent the overall marginal cost of an arriving user in terms of
  - Routing cost
  - *Opportunity cost* (based on available seats on the vehicle): provides a simple *forward looking* characteristic, so not completely myopic.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Vehicles</th>
<th>Initial state (existing load)</th>
<th>Offered service</th>
<th>Future state (potential load)</th>
<th>Opportunity cost</th>
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<td>shared-taxi</td>
<td>3</td>
<td>( \hat{c}_{ij} )</td>
</tr>
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</table>
Choice-based DARP

Illustration for the overall marginal cost

• 3 vehicles, 3 users
  – Vehicle 1: user 3, vehicle 2: users 1-2, vehicle 3: idle

• 4\textsuperscript{th} request arrives on node 6
  – Vehicle 1: user 3, vehicle 2: user 2, vehicle 3: users 4-1

(a) before

(b) after
Upon receiving a new user request:
• Generate the set of alternatives
• Generate the set of all possible assortments
• Compute the choice probability for each alternative in each assortment
  – based on the choice model and the preferences of the user
• Solve the choice-based DARP
  – and obtain the menu/assortment to be presented
• Simulate the probabilistic user choice given the optimized menu
• Solve the regular DARP, adding the new user to the set of users to be served with the simulated choice.
Experimental setting

50 user requests, 6 OD pairs
2 vehicles with 5 seats

Scenarios:
• Frequency of user arrival (0-20 min vs 20-60 min)
• Advance booking (0-30 min vs 30-90 min)
• Opportunity cost (same as vs half of the routing cost)

Others on the parameters of the choice model, e.g., attractiveness of opt-out (less attractive, similar, more attractive)
Experimental results (1)

Under loose/advanced booking

- Frequent arrival: higher profit per use, more users can share service, less users served in total
- High opportunity cost: more sharing, more users served

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<tbody>
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Experimental results (2)

Under frequent arrival

- Advance/loose booking: higher profit, more users served
- High opportunity cost: more sharing, more users served

<table>
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<th>Loose booking High opp. cost</th>
<th>Tight booking High opp. cost</th>
<th>Loose booking Low opp. cost</th>
<th>Tight booking Low opp. cost</th>
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<td>51.67</td>
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<td>Avg users on-board</td>
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</table>
Conclusions/Discussions

• Proof-of-concept for choice-based routing models in the context of on-demand solutions
• Importance of forward-looking in decision making

Ongoing and future work
• Improving computational efficiency: real-time in realistic scenarios
  – Tightening the formulation, eliminating dominated assortments etc.
• Enhancing the forward-looking aspect, prediction of travel times and demand
• Enhanced choice models with higher level of heterogeneity
• Maximizing consumer surplus together with profit
• Linking offered alternatives to the pricing mechanism
  – e.g., advance booking and/or larger time windows to better prices etc.
• Learning the behavior / continuously updating the preferences
Thank you!
Appendix
Model formulation (1)

\[
\begin{align*}
\text{maximize} & \quad \sum_{s \in S} w_s \\
\text{subject to:} & \quad w_s \leq \sum_{a \in A} \gamma_{as} \mathbb{P}_{as}(f_{as} y_s - \delta_a) + M(1 - y_s) - \left( \sum_{a \in A} \gamma_{as} \mathbb{P}_{as} \right) \left( \sum_{k \in K} \Delta^k \right) (s \in S), \\
& \quad w_s \leq My_s \quad (s \in S), \\
& \quad \sigma^k = \sum_{i \in N} \sum_{j \in N} (\bar{c}^k_{ij} + c_{ij} x^k_{ij}) - \bar{C}^k \quad (k \in K), \\
& \quad \Delta^k = \sigma^k \sum_{j \in N} (1 - x^k_{nj}) \quad (k \in K), \\
& \quad \delta_a = \sum_{k \in K} \sigma^k z^k_a \quad (a \in A), \\
& \quad z^k_a \leq \sum_{j \in N} x^k_{nj} \quad (k \in K, a \in A), \\
& \quad \sum_{j \in N} x^k_{nj} \leq \sum_{a \in A} z^k_a \quad (k \in K), \\
& \quad \sum_{k \in K} z^k_a = \sum_{s \in S} \gamma_{as} y_s \quad (a \in A), \\
& \quad \sum_{s \in S} y_s = 1,
\end{align*}
\]
Model formulation (2)

Vehicle routing part of the constraints:

\[
\begin{align*}
\sum_{k \in K} \sum_{j \in N} x_{ij}^k &= 1 \quad (i \in P \setminus \{n\}), \\
\sum_{j \in N} x_{ij}^k - \sum_{j \in N} x_{n+i,j}^k &= 0 \quad (i \in P, k \in K), \\
\sum_{j \in N} x_{0j}^k &= 1 \quad (k \in K), \\
\sum_{j \in N} x_{ij}^k - \sum_{j \in N} x_{ij}^k &= 0 \quad (i \in P \cup D, k \in K), \\
\sum_{i \in N} x_{i,2n+1}^k &= 1 \quad (k \in K), \\
B_j^k &\geq (B_i^k + d_i + t_{ij}) x_{ij}^k \quad (i, j \in N, k \in K), \\
L_i^k &= B_{n+1}^k - (B_i^k + d_i) \quad (i \in P, k \in K), \\
t_{i,n+1} &\leq L_i^k \leq L_i^{Max} \quad (i \in P, k \in K) \\
e_i &\leq B_i^k \leq l_i \quad (i \in N \setminus \{n, 2n\}, k \in K), \\
e_{ia} - M(1 - z_a^k) &\leq B_i^k \leq l_{ia} + M(1 - z_a^k) \quad (i \in \{n, 2n\}, k \in K, a \in A),
\end{align*}
\]
Model formulation (3)

Load of the vehicles, opportunity cost:

\[
\begin{align*}
Q_{ij}^k & \geq (Q_i^k + q_{ij})x_{ij}^k \quad (i \in N, j \in N \setminus \{n, 2n\}, k \in K), \\
Q_i^k + QO^k + O^k + QO'^k & \leq M(1 - x_{in}^k) + Q_i^k \quad (i \in N, k \in K), \\
Q_i^k - QO^k - O^k - QO'^k & \leq M(1 - x_{i,2n}^k) + Q_{2n}^k \quad (i \in N, k \in K), \\
z_a^k & \leq O^k + O'^k \quad (a \in AT, k \in K), \\
z_a^k & \leq O^k + O'^k \quad (a \in AST, k \in K), \\
O^k + O'^k & \leq \sum_{a \in AT} z_a^k \quad (k \in K), \\
O^k + O'^k & \leq \sum_{a \in AST} z_a^k \quad (k \in K), \\
O^k + O'^k + O'^k & \leq 1 \quad (k \in K), \\
\hat{c}_{ij}^k & \geq \frac{Q_i^k}{Q} \hat{c}_{ij} - M(1 - x_{ij}^k) \quad (i, j \in N, k \in K),
\end{align*}
\]
Model formulation (4)

Definition of variables:

\[ x_{ij}^k \in \{0, 1\} \quad (i, j \in N, k \in K), \]
\[ B_i^k \in \mathbb{R}^+ \quad (i \in N, k \in K), \]
\[ L_i^k \in \mathbb{R}^+ \quad (i \in P, k \in K), \]
\[ Q_{vi}^k \in [0, Q] \quad (i \in N, k \in K), \]
\[ c_{ij}^k \in \mathbb{R}^+ \quad (i, j \in N, k \in K), \]
\[ w_s \in \mathbb{R}^+ \quad (s \in S), \]
\[ y_s \in \{0, 1\} \quad (s \in S), \]
\[ z_a^k \in \{0, 1\} \quad (a \in A, k \in K), \]
\[ O^k, O''^k, O''''^k \in \{0, 1\} \quad (k \in K), \]
\[ \sigma^k, \Delta^k, \tilde{C}^k \in \mathbb{R} \quad (k \in K), \]
\[ \delta_a \in \mathbb{R} \quad (a \in A). \]
Experimental results

• Attractiveness of the opt-out alternative
  – More profit when it is lower as expected

<table>
<thead>
<tr>
<th></th>
<th>Less attractive opt-out</th>
<th>Similar opt-out</th>
<th>More attractive opt-out</th>
</tr>
</thead>
<tbody>
<tr>
<td>Served users</td>
<td>37.25</td>
<td>39.00</td>
<td>24.60</td>
</tr>
<tr>
<td>Profit per user</td>
<td>10.76</td>
<td>10.70</td>
<td>7.88</td>
</tr>
<tr>
<td>Shared-Taxi %</td>
<td>57.53</td>
<td>51.67</td>
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</tr>
<tr>
<td>Avg users on-board</td>
<td>1.59</td>
<td>1.39</td>
<td>1.00</td>
</tr>
<tr>
<td>Max users on-board</td>
<td>5.00</td>
<td>4.50</td>
<td>1.00</td>
</tr>
</tbody>
</table>
Experiments - insights

• Computational burden
  – Is worst when users arrive frequently and they book in advance