Anticipatory Dynamic Slotting in Attended Home Delivery

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Attended home deliveries are both a symptom and a driver of the world-wide growth in e-commerce. For instance, ordering perishable products such as groceries online requires the recipient to be present during the delivery. For the United Kingdom, Alvarez and Marsal [1] forecast a yearly two-digit increase in e-grocery revenue from 2013 to 2018. Conveniences including a large product range and time savings draw consumers to online providers [2]. To ensure successful deliveries, retailers and customers agree on delivery time windows on order acceptance. While customers expect narrow time windows tailored to their personal schedules, committing to such time windows significantly impacts the retailer's flexibility in order fulfillment. Moreover, as time windows experience varying popularity with customers, a homogeneous utilization of delivery capacities is difficult. Given the high costs of last-mile delivery, retailers endeavor to provide competitive service quality while ensuring a profitable delivery service.

Related research focusses on optimally allocating delivery time windows to order requests while taking both order values and delivery efficiency into account. For instance, a retailer can set delivery fees to incentivize a customer to choose a time window in a way that facilitates efficient routing, considering already accepted and potential future order requests. State-of-the-art literature terms this concept *dynamic pricing* [3]. The complexity of such a multi-faceted optimization problem constitutes a great technical challenge, in particular due to stochastic customer arrivals and time window choices. Existing contributions either rely on simplifying assumptions unsuitable for actual business settings, fall short of realizing the full potential of integrated planning, or propose computationally expensive approaches that do not scale to realistically complex problem instances.

Only recently, Yang and Strauss [4] have presented a dynamic pricing approach that allows an individualized yet immediate time window offer on request arrival and is informed by a comprehensive analysis in advance of the order process. In our study, we extend their idea of offline preparation for the dynamic decision. However, we shift the methodology to target a different problem setting. On the one hand, we apply *dynamic slotting* [3] instead of dynamic pricing. On order request, the retailer withholds time window options they expect to assign more profitably in the future. In contrast to dynamic pricing approaches, we determinedly prevent delivery route deteriorations and skim off valuable demand. Moreover, we extend the potential of dynamic slotting approaches like [5] by anticipating the stochasticity and controllability of future customer choices; that is, we tackle an anticipatory dynamic slotting problem. On the other hand, we consider that delivery time windows may overlap, as motivated by current business practices. In [4], delivery cost approximation and modeling of customer behavior depend on the assumption of non-overlapping time windows.

The *anticipatory dynamic slotting problem* aims to maximize the overall value of accepted order requests for a limited number of delivery vehicles and can be mathematically modeled as a Markov decision process. Let j be an order request with order value r_j, arriving at time t within an order horizon of length T, with $t \leq T$. From all feasible delivery time windows, planners have to find the optimal subset D^* of time windows to offer to request j; that is, they need to control the so-called *offer set*. Given a set of previously committed orders O, the control decision for the individual arrival of order request j affects both immediate and expected future value. Let $V_{t+1}(O)$ be a value function that represents the maximal expected value of the remaining order horizon when arriving in time point $t+1$ with the set of accepted orders O. The planner has to consider the immediate reward r_j of accepting the request versus the expected loss in future value, the opportunity costs $\delta_{t+1,d} = V_{t+1}(O) - V_{t+1}(O \cup o_d)$, when allocating time window d to the order. Considering the requesting customer's probabilities of choosing the respective time windows, $P_j(d, D)$ for $d \epsilon D$, the optimal policy selects the offer set with the highest expected value $\sum_{d \epsilon D} P_j(d, D)(r_j - \delta_{t+1,d})$. This approach reserves time windows with valuable expected demand for valuable order requests. Moreover, it can nudge less valuable customers to choose less popular time windows, thereby enabling an even capacity utilization.

To arrive at an optimal control decision for an arrival in time point t, the respective value of the value function needs to be known for all potential states in $t+1$. However, due to the recursiveness of the value function and the large state space, the value function becomes intractable quickly. Moreover, computing the set of feasible time windows requires to solve a vehicle routing problem with time windows [6]. In [7], we approximately solve this problem by decomposing it. First, we solve the vehicle routing problem on forecasted order requests to define capacities per delivery area and time window. Subsequently, we apply dynamic revenue management controls to allocate time windows per delivery area. While this approach achieves significant revenue increases over a first-come-first-serve acceptance, the static assignment of delivery resources to areas likely impedes the potential of fully integrated planning.

In this study, we dynamically assign delivery resources to order requests, based on feasibility checks with temporary vehicle routes and an approximation of the opportunity costs $\delta_{t+1,d}$. As these opportunity costs reflect the state-dependent value of losing capacity for future requests, we can flexibly react to any situation in the order process and thus cope with the stochasticity in customer arrivals and time window choices. To this end, we propose to utilize an *offline value function approximation* (as introduced in [8]) similar to the dynamic pricing approach of [4]. Before the first order requests arrive, we estimate a linear function that approximates the value function $V_{t+1}(O)$. The approximated value function serves to assess the value of a specific state quickly; hence, it is suitable to inform the offer set selection on arrival of order requests. We determine feasible time windows via a cheapest insertion heuristic as in [6]. This enables the approach to readily cope with overlapping time windows.

Knowing all arriving customers and their preferences allows for treating the anticipatory dynamic slotting problem as a team orienteering problem (TOP) with multiple time windows (see, for instance, [9]). Solution approaches result in the subset of order requests that should be accepted, including time window assignment. Thus, solving the TOP for multiple, simulated samples with complete information makes learning for the probabilistic setting possible. In detail, such an approach provides foresight to the expected acceptable orders per time window and helps us to initialize the value function approximation.

We present a comprehensive performance analysis in regard to profitability of the attended home delivery service. We benchmark our approach with the approaches of [4] and [7] via simulations on realistic instances from a British and a German e-grocer. Our analysis shows that our approach achieves profitable attended home delivery via dynamic slotting and enables to solve realistically sized business problems.

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Bibliography

[1] Alvarez and Marsal, "Home Delivery Fulfilment in UK Grocery. Opportunities and Threads from Market Growth," Alvarez & Marsal Holdings, London, 2014.

[2] Nielsen, "The Future of Grocery. E-Commerce, Digital Technology and Changing Shopping Preferences Around the World," The Nielsen Company, New York, 2015.

[3] N. Agatz, A. M. Campbell, M. Fleischmann, J. Van Nunen and M. W. Savelsbergh, "Revenue Management Opportunities for Internet Retailers," *Journal of Revenue Management and Pricing Management,* vol. 12, no. 2, pp. 128-138, 2013.

[4] X. Yang and A. Strauss, "An Approximate Dynamic Programming Approach to Attended Home Delivery Management," *European Journal of Operations Research,* In Press, 2017.

[5] A. M. Campbell and M. W. Savelsbergh, "Decision Support for Consumer Direct Grocery Initiatives," *Transportation Science,* vol. 39, no. 3, pp. 313-327, 2005.

[6] J. F. Ehmke and A. M. Campbell, "Customer Acceptance Mechanisms for Home Deliveries in Metropolitan Areas," *European Journal of Operational Research,* vol. 233, no. 1, pp. 193-207, 2014.

[7] M. A. Lang, J. F. Ehmke and C. Cleophas, "Multi-criteria Time Window Allocation for Attended Home Deliveries," Available at SSRN: https://ssrn.com/abstract=3000322, 2017.

[8] W. B. Powell, Approximate Dynamic Programming: Solving the Curses of Dimensionality, vol. 703, John Wiley & Sons, 2007.

[9] W. Souffriau, P. Vansteenwegen, G. V. Berghe and D. V. Oudheusden, "The Multiconstraint Team Orienteering Problem with Multiple Time Windows," *Transportation Science,* vol. 47, no. 1, pp. 53-63, 2013.