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Invited Review

Recent advances in integrating demand management and vehicle routing: A methodological review

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ABSTRACT

In logistics and mobility services, new business models such as "attended home delivery", "same-day delivery", and "mobility-on-demand" have been successfully established over the last decade. They have in common that customers order online, while the services are provided offline. To make such online-to-offline services profitable, the efficient operation of a vehicle fleet is an essential prerequisite. Therefore, researchers began to explore approaches for integrating demand management and vehicle routing to support such operations, and a rapidly growing body of literature emerged. However, due to the diversity of existing business models, the analysis and comparison of decision problems and solution concepts are challenging, especially across applications, making the search for appropriate models and algorithms for new problem settings non-trivial.

Therefore, in this survey, we structure this innovative research area and review the existing literature from a methodological perspective. We present a generalized problem definition of integrated demand management and vehicle routing, derive a high-level formulation for the underlying sequential decision process, and present a corresponding mathematical model. We then describe and characterize solution concepts and algorithms from the literature in a structured way. We also present a tabular overview of the literature that connects applications and problem characteristics with solution concepts and allows researchers to quickly step through already studied combinations. Finally, we comment on the state-of-the-art from a cross-application perspective and discuss future research opportunities.

1. Introduction

Over the last decade, many new applications for vehicle routing models and corresponding solution methods have emerged, which have attracted great interest in the research community and in public. Starting points for this development were the introduction of new technologies like drones and delivery robots (Boysen, Fedtke & Schwerdfeger, 2021) and the establishment of new business models such as attended home delivery, same-day delivery, and mobility-on-demand (e.g., Agatz, Campbell, Fleischmann, van Nunen & Savelsbergh, 2013, Voccia, Campbell & Thomas, 2019, and Qin et al., 2020). These business models, often characterized by the term "online-to-offline", allow a service to be booked online that is delivered offline by operating vehicles. Today, with services like Instacart, Amazon PrimeNow, and Uber being commonplace, corresponding business models represent such an essential part of the modern on-demand lifestyle that popular news media like the BBC have covered even the underlying mathematics (Church, 2019).

In this context, demand management has become a popular, often necessary tool. Requests for online-to-offline services arrive over time, and customers have different preferences concerning different fulfillment options. Hence, providers can shape demand, i.e., the set of resulting orders and their characteristics, by offering targeted fulfillment options to specific customers to allow efficient routing operations. A variety of approaches were proposed for this purpose: In the case of attended home delivery (AHD) and field service operations (FSO), the variation of prices or time window availability is often in the focus of demand control (e.g., Strauss, Gülpinar & Zheng, 2021 or Avraham & Raviv, 2021). For same-day delivery (SDD) and mobility-on-demand (MOD) services, accepting or rejecting customer requests may be the approach of choice (e.g., Klapp, Erera & Toriello, 2020 or Fielbaum, Kronmueller & Alonso-Mora, 2021). In general, actively controlling demand entails the following benefits for providers: First, control decisions balance demand in temporal and geographical terms to avoid spilled demand on the one hand and low utilization of fulfillment resources on the

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other hand. This increases the number of orders served by a given fleet and, hence, the overall profit. Second, for time periods or areas where such smoothing does not eliminate capacity shortage, demand control enables allocating available capacity to the most profitable customers (Agatz et al., 2013) and possibly earning additional revenues in the form of delivery fees. Thereby, the average profit per order increases. Third, effective demand control stimulates demand and opens new markets in the form of initially low-demand and, therefore, unprofitable delivery areas (Yang & Strauss, 2017). Fourth, demand control contributes to increasing routing efficiency (Klein, Neugebauer, Ratkovitch & Steinhardt, 2019). By controlling the fulfillment options sold, service providers can "generate" a favorable instance of the resulting routing problem.

In principle, many established approaches from the field of revenue management, like availability control and dynamic pricing, can be used for demand management purposes (see Strauss, Klein & Steinhardt, 2018 and Klein, Koch, Steinhardt & Strauss, 2020 for recent surveys). Unfortunately, the integration of demand management and vehicle routing turns out to be quite complex. More precisely, demand is stochastic and realizes over time, which leads to a sequential decision problem. Providers must decide on fulfillment options for incoming requests without exactly knowing the number of future customers and their preferences. Depending on the orders made, different vehicle routing costs may result, and future revenues may even be displaced, e.g., if an accepted request prevents future orders due to capacity or service constraints. Anticipating these intertemporal effects requires solving vehicle routing problems, which, in general, are NP-hard. Furthermore, to meet customers' expectations, providers must make decisions in real-time (e.g., Poggi, Carrera, Gavaldà, Ayguadé & Torres, 2014).

This complexity led to various new approaches to integrate demand management and vehicle routing, with the center of the respective contributions often depending on the authors' methodological backgrounds (e.g., integer programming or stochastic dynamic programming). However, analyzing the literature shows that the structure of the specific control problems considered is very similar. This observation even holds across application areas. As a consequence, demand management approaches, solution concepts, and algorithms applied in different areas are strongly related. Despite that, the relationships are usually not discussed beyond the areas' borders.

Motivated by these observations, the key contributions of this survey paper are as follows:

(1) To foster a structured comparison of different real-world applications, we present a generalized definition of integrated demand management and vehicle routing problems. To analyze the characteristics of specific decision problems, we identify four components of the underlying sequential decision process: request capture, demand management, order confirmation, and vehicle routing. Using morphological analysis, we characterize each component regarding several dimensions. We summarize this analysis in a comprehensive morphological box and illustrate the results by describing possible realizations for existing applications in AHD, FSO, SDD, and MOD.
(2) As a synthesis of specific modeling approaches existing in the literature, we formulate a high-level mathematical model of the generalized sequential decision problem. As tractable solution concepts for decision problems falling under this generalized formulation, we discuss static deterministic approximations as well as decomposition-based approximations. In particular, we investigate the tasks resulting from decomposition-based approximations, i.e., feasibility check, cost estimation, demand control, and routing control, and present corresponding solution approaches often based on specific auxiliary models.
(3) We present an overview of the literature "at a glance" in two comprehensive tables, linking decision problems and solution concepts to applications. These tables allow researchers to check for suitable approaches without analyzing all possible related fields when they want to apply demand management in their area of interest. Furthermore, they can quickly verify whether certain combinations of specific decision problems and solution concepts have already been examined.
(4) Complementary to the high-level overview of solution concepts, we discuss selected contributions to algorithms used as part of solution approaches for static deterministic approximations and decomposition-based approximations in more detail. For the latter class, we highlight the algorithms that are suitable for addressing several tasks in combination.
(5) Finally, we identify seven different topics around which we discuss the current state of research to deliver cross-application insights, and which represent fruitful starting points for future research.

The scope and the purpose of our work substantially differ from existing surveys. Agatz et al. (2013) focus more on optimizing demand management decisions and less on the associated routing problems. Besides this, they exclusively consider AHD problems. The latter also holds for the survey by Snoeck, Merchán and Winkenbach (2020), who extensively outline possible extensions of AHD-specific problem settings and their implications. Yan, Zhu, Korolko and Woodward (2020) exclusively deal with matching and dynamic pricing in MOD. The recent survey by Soeffker, Ulmer and Mattfeld (2022) considers dynamic vehicle routing in general, with SDD being one of many application areas.

To allow for the necessary focus, we establish the following criteria for selecting the publications for this survey: First, we only include works investigating stochastic and dynamic booking processes. Second, we only consider settings where fulfillment operations must be optimized explicitly by integrating demand management and vehicle routing methods based on profitability or service quality. Hence, we exclude dynamic vehicle routing settings, where providers control service availability purely for ensuring the feasibility of routes and refer the interested reader to surveys by, e.g., Pillac, Gendreau, Guéret and Medaglia (2013), Psaraftis, Wen and Kontovas (2016), and Ulmer, Goodson, Mattfeld and Thomas (2020). Finally, we assume full information and control regarding the resources needed to fulfill services. Consequently, we do not cover problems involving stochastic vehicle availability or platform-based service provision based on two-sided markets, which arise in the context of sharing-based or crowd-sourced fulfillment systems (e.g., Afeche, Liu & Maglaras, 2018, Banerjee, Johari & Riquelme, 2016, and Taylor, 2018). Furthermore, we leave out special cases for readability.

Our survey is structured as follows: In Section 2, we first state the problem of integrating demand management and vehicle routing along a generic process formulation. Subsequently, we discuss the characteristics of this process for several areas of application. We then provide an exact, high-level mathematical model formulation for the resulting sequential decision problem in Section 3. In Section 4, we analyze different solution concepts based on tractable approximations of the exact model from Section 3. Section 4 concludes with a summary of all results up to this point in the form of comprehensive tables of the existing literature. Section 5 comprises a more detailed discussion on solution algorithms and may be skipped by readers only looking for the high-level overview provided in the preceding sections. Section 6 is

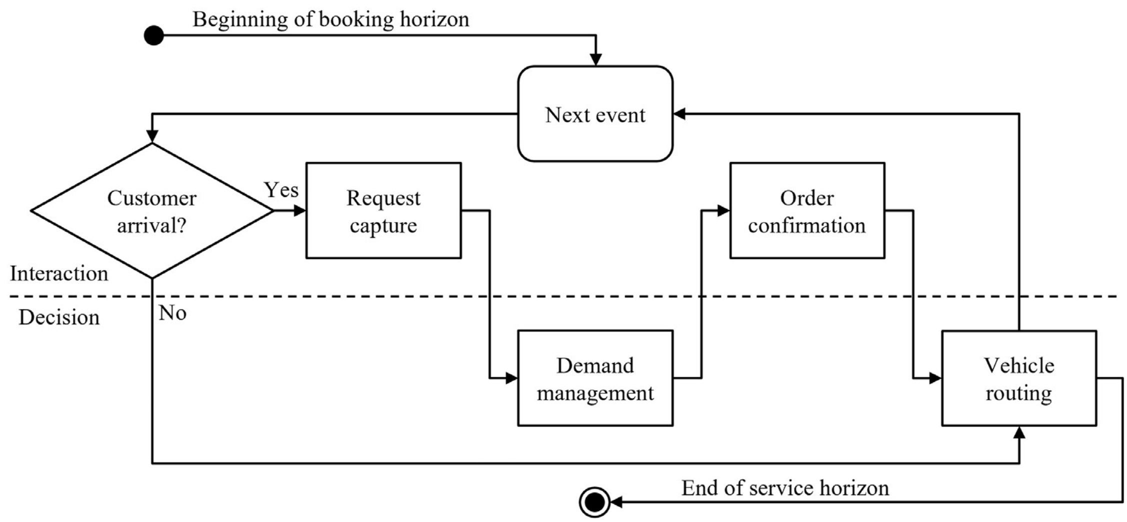

Fig. 1. Components of the sequential decision process.

devoted to key insights and take-aways and includes the discussion of promising research opportunities.

2. Generalized problem definition

This section first investigates a sequential decision process for integrating demand management and vehicle routing from an application-oriented perspective. We identify four essential components that are part of this process and present dimensions that characterize each component as well as possible realizations of each dimension in Section 2.1. Subsequently, we discuss prototypical applications in Section 2.2. The purpose is to show how different realizations of the dimensions relate to real-world implementations.

2.1. Sequential decision process

Providers that offer online-to-offline logistical services regularly face stochastic and dynamic decision problems that arise over time on an operational level. Such problems can be described as sequential decision processes, which cast the overall problem as a sequence of states (Powell, 2019). In each state, the provider must collect and evaluate (stochastic) information concerning customers, logistical resources, i.e., vehicles, and, possibly, the environment (Soeffker et al., 2022). Depending on the information's evaluation, they must also make different types of decisions.

To analyze the problem characteristics, we decompose the resulting decision process into four components for each state. Two of the components include *interactions* with customers, the remaining two deal with the provider's *decisions*. Different types of events may trigger these decisions. Fig. 1 shows the components and their relationships. We explain them in the following and introduce dimensions by which we characterize different realizations of the components as part of a morphological analysis. This technique allows us to systematically describe the entire spectrum of decision problems by reducing the problems to these key dimensions with a set of possible realizations.

Request capture: The arrival of a customer during a sales period, called the booking horizon, triggers this component. The provider can sell different *types of services*: pure transportation (e.g., a ride), transportation in combination with selling goods (e.g., groceries), or transportation in combination with selling ancillaries (e.g., installation). We refer to the latter two as coupled goods and coupled services, respectively. The customer makes a request by specifying parameters of the service wanted, e.g., using a web application or via a call-center. These parameters can be origin and destination, time and mode of transport, and coupled goods or services. The provider must capture these parameters as input for their decisions.

Demand management: This component follows request capturing and must control demand with respect to the provider's *objective*. It tries to exploit that usually several feasible options for service fulfillment exist. Then, it aims at selling the available capacity in a way that maximizes a measure of profit. The profit comprises several components that represent revenues and costs. On the revenue-side, the fees for the logistical service itself and the revenues/profits of coupled goods or services may be relevant. On the cost-side, the unit costs of the coupled goods or services, possible discounts, and the transportation costs must be considered. Depending on the application, also the number of orders, i.e., accepted requests, may serve as an objective. Regardless of the objective function, the provider must ensure that the logistical services sold can be fulfilled subject to operational constraints. The implementation of demand management can be characterized along the following dimensions (Agatz et al., 2013):

- Concerning the *time of decision*, static and dynamic controls can be distinguished. Static controls determine all decisions before the start of the booking horizon based on exogenous information. They do not adjust them depending on endogenous information concerning customers but check for feasibility. As an example, an AHD provider may publish a static price list for their delivery time slots, which is valid for multiple weeks. During each booking process, any customer will be able to place an order at the price of the published delivery fee as long as the provider can feasibly fulfill the order. By contrast, dynamic controls make decisions based on the information becoming available during the booking and service horizon. Beyond the current request's parameters, such information includes existing orders, the vehicles' locations, and loads. In this case, an AHD provider would, e.g., offer individual delivery fees determined at the time of each customer request arrival based on the delivery location and the shopping basket value.
- To influence the customers' choices favorably, the provider can apply two *control types*, namely availability control or price-based control. In availability control, the provider makes decisions on which feasible fulfillment options to of-

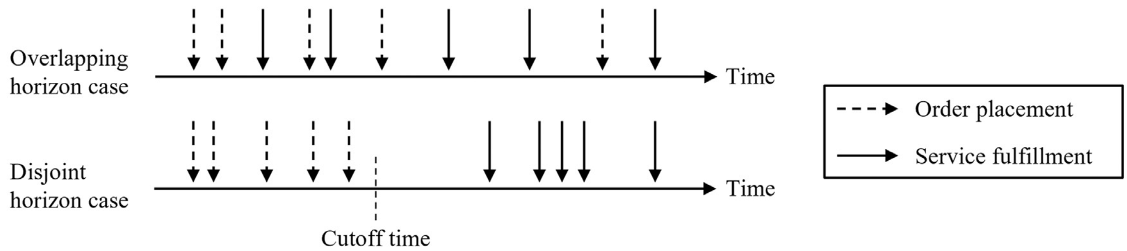

Fig. 2. Booking and service horizon.

fer to the customer, e.g., when prices are fixed. In price-based control, they set fees for the different options. The set of fulfillment options along with their prices form an offer set, from which a customer can choose.

- Finally, the provider can decide on request *processing*, i.e., between real-time processing for single requests or batch processing. In the first case, the provider implements decisions immediately. In the second one, they postpone decisions until, e.g., a specific batch size or state is reached.

Order confirmation: After constructing the offer set, the order confirmation component represents a second interaction with the customers, which consists in presenting offer sets to customers and, potentially, closing a deal. If the provider generally offers only a single *fulfillment option*, customers will either buy or not. If they provide an assortment of multiple options, e.g., different time windows for the transportation, customers will choose an option, which is potentially the no-purchase option, according to some individual preference function, e.g., by maximizing their utilities. If a sale takes place, the corresponding option becomes an order.

Vehicle routing: The vehicle routing component is executed before or during the period of service fulfillment, called the service horizon. Its task consists in determining feasible and cost-minimizing route plans for the given orders. *Booking and service horizons* can either be disjoint, overlapping, or infinite as illustrated in Fig. 2. In the first case, the provider collects orders until a cutoff time, which lies before the beginning of the service horizon. Here, the provider can postpone definitive vehicle routing decisions until the end of the booking horizon. However, sometimes they may perform tentative route planning as an input for demand management decisions. If the horizons overlap or are infinite, the provider needs to finalize routing decisions before the end of the booking horizon. Here, several events may trigger a decision for a given state. First of all, a new order may have been accepted. Other events include that a vehicle has become idle or must act, e.g., leave the depot, to fulfill operational constraints. Also, it can be reasonable to move a vehicle to another position to be better prepared for future requests. In the latter cases, the vehicle routing component is executed without a customer arrival. Depending on the transportation service sold, the provider must solve different types of *vehicle routing problems* (e.g., Toth & Vigo, 2014). For example, delivery or pickup problems may occur. Also, point-to-point problems may arise. Finally, routing decisions may be subject to different types of *constraints*. These may refer to the fleet size or composition, the vehicles' capacity, or service guarantees like delivery within a specific time window.

The morphological box in Table 1 summarizes the result of the morphological analysis, i.e., it describes the different components based on the dimensions and their potential realizations introduced above. Besides providing a compact summary, it also serves as a tool for further analyses. Specific decision problems, including novel ones, can be derived by selecting a certain realization for each dimension and combining them. In turn, existing decision problems can be classified according to their realizations for each dimension. In the survey at hand, we present the latter type of analysis for prototypical decision problems (Table 2) and decision problems considered in the existing literature (Table 4).

2.2. Applications

This section discusses prototypical applications for which integrating demand management and vehicle routing has already been established or is currently evolving. We deliberately do not explicitly refer to specific companies' existing applications because the underlying business models are adapted fast and refined continuously. However, in all cases, corresponding services exist and can easily be found by simple internet search. In Table 2, we describe the prototypical applications based on the morphological box (Table 1) developed in Section 2.1. Table 4 in Section 4.3 will characterize the related specific problems considered in the existing academic literature.

The most prominent application for AHD is e-groceries (Agatz et al., 2013). Here, transportation is combined with the sales of groceries. Most commonly, the providers try to maximize profit after fulfillment. This profit is determined by the profit per order, which considers the profit of the shopping basket plus the delivery fee, minus the cost of transportation. In the early days of AHD, the usual way to control demand was to define combinations of delivery areas and time windows. For these combinations, the provider computed static prices and the maximal number of customers to be served prior to the booking horizon which led to a form of availability control. Thus, it was possible to provide customers with feedback on fulfillment options after filling their shopping basket in real-time. Until recently, booking and service horizon have usually been disjoint. Customers had to place their orders until the evening before the delivery day. For all orders accepted, the provider must solve a capacitated vehicle routing problem with time windows. Please note that modern approaches do not only set prices dynamically but also offer overlapping time windows of different lengths.

SDD is also used for selling groceries (Archetti & Bertazzi, 2021). New market entrants currently try to establish services that deliver a restricted assortment of food products within very short deadlines. Established players like large grocery and wholesale retailers are experimenting with combining SDD and next-day delivery. However, the concept was initially introduced for courier and express services, the reason why we discuss a corresponding application here (Ghiani, Manni, Quaranta & Triki, 2009). Such services offer pure transportation for, e.g., pharmaceutical drugs or spare parts. Since the provider's capacity is usually fixed on a given day, they maximize the total revenue as a proxy for profit. Depending on the transport's origin and destination and the delivery deadline, the provider dynamically calculates a fee, i.e., sets a price. Again, the provider must process a captured request in real-time. New orders arrive while executing others, i.e., the booking and service horizon overlap. Hence, the provider must deal with a dynamic point-to-point (pickup and delivery) problem with deadlines.

Table 1
Components and dimensions of the sequential decision process.

Process component	Dimension	Realization		
Request capture	Service type	Transportation (TR)	Coupled goods (CG)	Coupled services (CS)
Demand management	Objective Time of decision Control type Processing	Profit (PR) Static Availability (AV) Real-time (RT)	Revenue (RE) Dynamic Price-based (PB) Batch (BA)	Number of orders (NO)
Order confirmation	Fulfillment options	Single (SI)	Multiple (MU)	
Vehicle routing	Booking/service horizon Routing problem Constraints	Disjoint (DJ) Delivery (DE) Fleet	Overlapping (OL) Pick-up (PU) Vehicles	Infinite (IF) Point-to-point (PP) Service guarantees

Table 2
Sample applications.

Process component	Dimension	AHD	SDD	MOD	FSO
Request capture	Service type	Coupled goods	Transportation	Transportation	Coupled services
Demand management	Objective Time Control type Processing	Profit Static Availability Real-time	Revenue Dynamic Price-based Real-time	Number of orders Dynamic Availability Real-time	Number of orders Dynamic Availability Batch
Order confirmation	Fulfillment options	Multiple	Single	Single	Multiple
Vehicle routing	Booking/service horizon Routing problem Constraints	Disjoint Delivery Time windows, vehicle capacity	Overlapping Point-to-point Delivery deadlines	Overlapping Point-to-point Waiting and travel time	Infinite Delivery Time windows, worker skills

An increasingly popular form of public transport is MOD (Hazan, Lang, Wegscheider & Fassenot, 2019). The transportation service is provided using mini-buses and taxis in a shared-ride mode. Public providers may aim at maximizing the number of orders, i.e., rides, performed. Customers can specify the origin and destination and the earliest pick-up or latest arrival time. The fee depends on the origin and destination and is commonly based on published tariffs, such that only the availability is subject to dynamic control. Hence, based on their request and the capacity utilization, customers are either offered a ride or are rejected in real-time. In the first case, a single option is provided which comes with a travel time, a possible waiting time, and the number of passengers on the ride. The customers can then accept the option or reject it. With the switch from call center- to application-based reservation systems, providers have allowed to make reservations on the day of travel leading to overlapping booking and service horizons. Again, a point-to-point (dial-a-ride) transportation problem results whose constraints must consider the vehicles' capacities and ride-specific aspects like waiting and travel times.

FSO represents an emerging application of integrated demand management and vehicle routing (Chen, Thomas & Hewitt, 2016). In a business-to-consumer context, customers receive some furniture, electronics, or home appliances and may require a coupled service like installation for the items delivered. In a business-to-business context, on-site maintenance and repair may represent possible use cases. In the first case, which we consider here, it is common that the customer can select several options from a menu of delivery dates with corresponding time windows, i.e., the provider deliberately restricts the availability of options by availability control. When determining the corresponding offer sets, the provider usually tries to maximize the number of installations. Some days ahead of delivery, the provider informs about which of the customer's options they have chosen for installation. Since lead times for the products can depend heavily on the different products, the problem on hand has no finite horizon. New orders for products with a short lead time can arrive and be ready for installation while waiting for the completion of orders with longer ones. Like for AHD, the provider must solve a capacitated vehicle routing problem with time windows. However, additional constraints like worker skills come into play. Often, corresponding routing problems are identified as technician or field service routing problems.

3. Mathematical model formulation

In this section, we discuss the formalization of the generalized problem definition described in Section 2 by means of mathematical modeling. Since the problem at hand is stochastic and dynamic, an accurate formalization requires a dynamic control model, which is subject of Section 3.1. An integral element of this formalization is also the modeling of the customers' choice behavior, provided that they are given a choice between fulfillment options as part of the order confirmation component. Therefore, we elaborate on these customer choice models separately in Section 3.2.

3.1. Dynamic control model

Mathematically, Markov decision processes (MDPs) provide the foundation for describing most decision problems in demand management and vehicle routing. However, in contrast to, e.g., deterministic vehicle routing, it is not standard in the literature to present a corresponding MDP model, which is an observation already made by Ulmer et al. (2020) for stochastic, dynamic vehicle routing. Reasons may be that the notation is quickly becoming complex and awkward to handle. Moreover, solution approaches are generally approximative and do not rely directly on an exact dynamic control model. Further, the variety of problems leads to rather specific models from a notational point of view (e.g., Al-Kanj, Nascimento & Powell, 2020, Ulmer, Goodson, Mattfeld & Hennig, 2019, Xu et al., 2018, or Yang, Strauss, Currie & Eglese, 2016). Therefore, in the following, we synthesize the models from existing works and provide a generalized, high-level model formulation. We structure the discussion along the model's primary building blocks using the language and notation common for MDPs (e.g., Powell, 2019). For similarly generic models, we refer to Klein et al. (2020), who present formulations from a demand management perspective, and Ulmer et al. (2020), who propose a route-based modeling framework for dynamic routing.

In the model, demand is represented as a set of potential customers $\mathcal{I} = \{1, \ldots, I\}$. Each customer $i \in \mathcal{I}$ comes with a location and has different preferences for the services offered. To serve the customers, the provider has vehicles $h \in \mathcal{H} = \{1, \ldots, H\}$ available. The vehicles may have several restrictions concerning their capacity, which may refer to the maximal feasible load, the maximal travel distance, or the maximal travel time due to working shifts. Based on these assumptions, we describe the building blocks of MDP models. For each possible variant of modeling a certain building block, we provide exemplary references. Please note that the notation chosen makes several deliberate simplifications for the sake of readability. For example, numbers of customers I, in general, are stochastic. Furthermore, we omit indices where possible, and following Al-Kanj et al. (2020), we indicate unambiguous state-dependencies by an index k.

Decision epochs: The booking horizon and the service horizon encompass $k \in \mathcal{K} = \{0, \ldots, K\}$ decision epochs, whose number can be stochastic. Decision epochs represent points in time at which the provider must make a demand management decision, a routing decision, or both. Three types of events can trigger a decision epoch, with the latter two only being relevant for problems with overlapping horizons. The first one is the arrival of a customer request (Ulmer, 2020a). Secondly, routing-related events may require decisions, e.g., if a vehicle becomes available after completing an order (Ulmer, Mattfeld & Köster, 2018). Thirdly, a new decision epoch can be defined to occur after a certain amount of time in which vehicles were idle or orders were not assigned for fulfillment (Chen et al., 2019).

States: Tuples $S_k = (S_k^{cust}, S_k^{veh})$ describe the system's state at the beginning of a decision epoch k and contain all information necessary to make a decision. The vectors S_k^{cust} and S_k^{veh} describe the customers' and vehicles' statuses. For customers, this status may indicate which customers are currently requesting service. Additionally, in case the provider receives orders, information on the orders' parameters (Koch & Klein, 2020) and, for problems with overlapping horizons, the fulfillment status is stored (Chen, Ulmer & Thomas, 2022). For vehicles, the status may refer to the current location (Qiu, Li & Zhao, 2018), the time of arrival at the next customer (Chen et al., 2019) or at the depot (Voccia et al., 2019), or a route plan (Ulmer & Thomas, 2020). Note that information on vehicles is not required for problems with disjoint horizons because final routing is not necessary before the end of the booking horizon.

Decisions: Depending on the state in decision epoch k, the provider must either make a demand management decision and, potentially, a corresponding vehicle routing decision, or a standalone routing decision. When booking horizon and service horizon are disjoint, demand management decisions suffice. The decisions are summarized by variables $x_k = (x_k^{dem}, x_k^{rout})$ that describe the actions taken and are defined as follows:

- **Vehicle routing decisions x_k^{rout}**: If the provider makes a routing decision x_k^{rout} for state S_k, they select a feasible route plan $\phi_k = \{\rho_h : h \in \mathcal{H}\}$, i.e., determine a route ρ_h for each vehicle $h \in \mathcal{H}$ (Ulmer, 2020a). A route plan is called feasible if it does not violate any operational restriction. In this context, the term route plan has a fairly broad meaning, i.e., x_k^{rout} may only state which order to serve next for each vehicle (e.g., Xu et al., 2018). The set of all feasible route plans in state S_k is denoted by Φ_k. In case the booking horizon and service horizon are disjoint, a single routing decision is made at decision epoch $K+1$ (Klein, Mackert, Neugebauer & Steinhardt, 2018), i.e., at the end of the booking horizon.
- **Demand management decisions x_k^{dem}**: A demand management decision x_k^{dem} determines which offer the provider makes for providing a service requested by customer i at decision epoch k. The feasible fulfillment options available are given by $\mathcal{O}_k = \{1, \ldots, O_k\}$. An option $o \in \mathcal{O}_k$ is called feasible if a feasible route plan ϕ_{k+1} exists when the request turns into an order due to the sale of o. When applying availability control, the provider determines an offer set $\Theta_k \subseteq \mathcal{O}_k$ (Avraham & Raviv, 2021). Analogously, when using price-based control, the provider sets prices (service fees) p_{oi} for all options $o \in \mathcal{O}_k$ (Prokhorchuk, Dauwels & Jaillet, 2019).

Transitions: Transitions between states S_k and S_{k+1} may occur for several reasons: If customer i decides (stochastically) to buy an option o, the request becomes an order and S_k^{cust} is updated accordingly. The same holds if customers are served as the provider (partially) executes route plan ϕ_k. In this case, the vehicles' status S_k^{veh} is also updated (Voccia et al., 2019). Mathematically, the transition can be described by a state equation $S_{k+1} = S^M(S_k, x_k, W_{k+1})$. W_{k+1} represents random variables affecting the transition from epoch k to $k+1$. In our case, these include, e.g., the choice of customer i, the preferences and locations of incoming customers (Mackert, 2019), or stochastic travel times (Xu et al., 2018).

Rewards: If the provider sells an option o to a customer i, they obtain a reward $R_k(S_k, x_k) = r_{oi}$. Usually, r_{oi} represents the revenue per order or the profit per order possibly depending on a charged price (service fee) p_{oi} (Strauss et al., 2021). If the objective is to maximize the number of customers served, the reward is set to $r_{oi} = 1$ (Ulmer et al., 2019). Fulfillment costs can be modeled as negative rewards that are incurred once the respective routing decisions become definitive and the route plan is (partly) executed (Klapp, Erera & Toriello, 2018). For disjoint horizon problems, the terminal reward R_{K+1} summarizes all fulfillment cost (Yang et al., 2016).

Policy: A policy $X^\pi(S_k)$ is a rule or function that determines a decision x_k for a state S_k. Here, it refers to vehicle routing and demand management decisions, which are often intertwined. For example, when deciding on an offer set, the provider may have to simultaneously make routing decisions anticipating the possible sale.

Objective function: In general, since the problems are stochastic, the objective consists of maximizing expected rewards (including terminal cost R_{K+1}):

$$J(X^\pi) = \mathbb{E}\left\{\sum_{k=0}^{K} R_k(S_k, X^\pi(S_k)) + \ R_{K+1}\right\}$$

In infinite state problems, we can discount rewards and define the objective as the limit of the expression above, when $K \to \infty$ (Holler et al., 2019).

Value function: To evaluate possible decisions in state S_k, we define the value function $V_k(S_k)$ the provider wants to maximize. It represents the objective function value at the end of the booking and service horizon that can be expected at decision epoch k by the corresponding Bellman equation:

$$V_k(S_k) = \max_{x_k} \mathbb{E}\left\{R_k(S_k, x_k) + V_{k+1}\left(S^M(S_k, x_k, W_{k+1})\right)\ \right\}$$

Thus, $J(X^\pi) = V_0(S_0)$ holds if X^π is an optimal policy. The correct computation of the value function requires optimal demand management decisions for future requests and optimal routing decisions for existing and future orders. Alternatively, it is possible to formulate a Bellman equation based on state-action values (Kullman, Cousineau, Goodson & Mendoza, 2021).

3.2. Customer choice modeling

In case the order confirmation component allows customers to select a fulfillment option from an offer set, any dynamic control model must include a customer choice model. Otherwise, if there is no such interaction during order confirmation, choice modeling can be omitted. More precisely, a choice model predicts a purchase probability $P_o(\Theta_k)$ for each option $o \in \Theta_k$ with respect to the offer set Θ_k and, possibly, prices p_{oi}. For this purpose, parametric, non-parametric, and multi-stage models exist (Strauss et al., 2018 and Berbeglia, Garassino & Vulcano, 2021).

In the context of vehicle routing applications, parametric models rooted in random utility theory dominate. Following this theory, each customer i evaluates the set of offered alternatives with respect to an individual utility function before deciding on either buying one option $o \in \Theta_k$ or leaving the market (e.g., Train, 2009). In general, we assume that the resulting utility for an option $o \in \Theta_k$ has a deterministic and a random part. Customers decide on the alternative that maximizes their utility. If $|\Theta_k| > 1$, customers may substitute across all $o \in \Theta_k$, in case their preferred one is not available (e.g., Kök & Fisher, 2007). In the literature, the existence of such substitution behavior is widely acknowledged (e.g., Ulmer, 2020a, Yan et al., 2020, or Yang et al., 2016). Thus, the resulting purchase decision is stochastic and depends on the characteristics of all options $o \in \Theta_k$ including, if applicable, their prices p_{oi}.

The purpose of choice modeling is to obtain purchase probabilities for each $o \in \Theta_k$, which serve as input parameters for demand control. To this end, the specification of a utility function is necessary for random utility models. The deterministic part is usually expressed as a linear function of a vector of attributes that influence the purchase probabilities. In last-mile logistics, these include the associated time slot (e.g., Yang et al., 2016) and the delivery deadline (Prokhorchuk et al., 2019). Similarly, for passenger transportation, attributes encompass travel time (Qiu et al., 2018 and Atasoy, Ikeda, Song & Ben-Akiva, 2015) as well as origin, destination, and time of day (Al-Kanj et al., 2020). Also, the price p_{oi} represents an attribute if fees are charged.

Different choice models are obtained depending on the assumptions made on the distribution of the random utility part. Thereby, it is crucial to consider that model selection and model specification significantly impact the quality of demand management decisions and the complexity of demand control (Berbeglia et al., 2021). The estimation of the utility function's parameters from historical data is also an optimization problem and can be of varying complexity.

With respect to our domain, authors use the following random utility models:

- **Multinomial logit (MNL) model**: This is the most prominent model. It assumes that the entire customer population can be described by a common utility function. Furthermore, it assumes that the random utility components are independent and identically distributed random variables following a Gumbel distribution. If $O_k = 1$, the MNL reduces to a binary logit model (Al-Kanj et al., 2020). In comparison to other random utility models, the MNL has advantages in terms of computational complexity (Berbeglia et al., 2021). However, it is not sufficiently accurate in many applications, even with a nearly perfect specification: First, it does not capture latent customer preferences. Second, the model suffers from the IIA property (independence from irrelevant alternatives) and therefore only allows for proportional substitution behavior (Train, 2009).
- **Generalized attraction model**: Compared to the MNL model, it captures customer dissatisfaction and thus reduces purchase probabilities for all offered products if the cardinality of an offer set is low (Gallego & Topaloglu, 2019).
- **Finite mixture MNL model**: This model assumes that demand is composed of homogeneous segments whose choice behavior can be described by standard MNL models (Strauss et al., 2018). If the segment affiliations of the arriving customers are unknown, the integration of the model into demand control significantly increases its complexity (Koch & Klein, 2020). The same holds for the parameter estimation problem. Otherwise, the segment-specific MNL models are independent, and there is no increase in complexity (e.g., Lang, Cleophas & Ehmke, 2021b).
- **Nested logit model**: The nested logit (NL) model is appropriate if we can aggregate alternatives into nests in a way such that the IIA holds within each nest but not across nests. Each nest represents a set of substitutes. The model by Wang, Zeng, Ma and Guo (2021) accounts for alternate pick-up and drop-off points customers can choose. Köhler, Ehmke, Campbell and Cleophas (2019) and Strauss et al. (2021) use the NL model to reflect demand interdependencies and non-negligible disproportional substitution behavior due to offering overlapping time windows of different lengths. Because of the higher complexity of demand management decisions, Strauss et al. (2021) approximate the NL model by a standard MNL model.

Lastly, some authors propose parametric models that are specifically designed for pricing control and are not rooted in random utility theory (Campbell & Savelsbergh, 2006; Chen et al., 2019; Haliem, Mani, Aggarwal & Bhargava, 2021; Klein & Steinhardt, 2021; Ulmer, 2020a, and Vinsensius, Wang, Chew & Lee, 2020).

4. Solution concepts

In this section, we discuss solution concepts for dealing with decision problems that fall under the generalized problem definition as presented in Section 2. Due to the problems' complexity, directly solving corresponding dynamic control models (Section 3) to optimality is computationally intractable. As the state space is very large even for small instances, it is not possible to evaluate, e.g., the Bellman equation for each potential state. Moreover, in each state, the determination of demand management decisions and vehicle routing decisions can represent challenging optimization problems of their own.

Instead, the existing literature follows two basic solution concepts, both based on approximations. In Section 4.1, we first describe decomposition-based approximations. Section 4.2 is devoted to static deterministic approximations. In Section 4.3, we merge the results of our analyses of problem characteristics and solution concepts in the form of a tabular overview. Thus, we only provide exemplary references in all the following subsections and refer the reader to Tables 4 and 5 for the extensive classification of all works.

4.1. Decomposition-based approximation

In the academic literature, most authors resort to a decomposition-based approximation. For this purpose, they identify major tasks in the overall decision process to be addressed by the provider. Then, they formalize the tasks and solve corresponding subproblems or combinations of them sequentially. Different types of solution approaches exist: Sometimes, the authors explicitly formulate auxiliary or simplified mathematical models for the problems that are then tackled using a general-purpose solver or some special-purpose algorithm. In other cases, they only describe the problems verbally, propose a conceptual

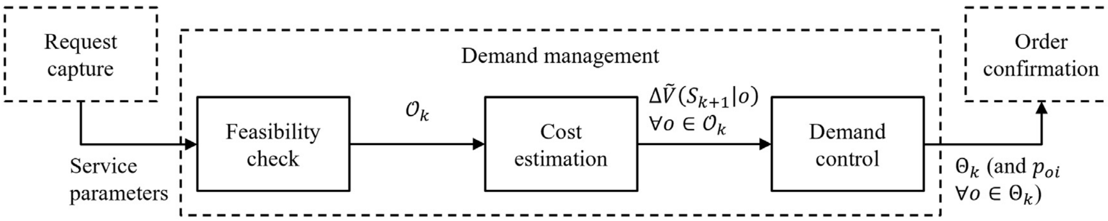

Fig. 3. Tasks of demand management component.

model to, e.g., deal with stochasticity or interdependencies among problems, and again, provide suitable algorithms. We define the tasks in Section 4.1.1 and describe the corresponding solution approaches in Sections 4.1.2–4.1.5. Solution algorithms are subject of Section 5.1.

4.1.1. Task definitions

In Section 2.1, we have identified two components that require the provider to make decisions: demand management and vehicle routing. When analyzing corresponding research papers, it turns out that authors consider up to three different tasks to support demand management decisions x_k^{dem}. Fig. 3 shows the sequence of these tasks and the input data they provide for the succeeding task. Routing control can be viewed as a fourth task associated with the vehicle routing component.

Feasibility check: First, the provider must determine the set $\mathcal{O}_k$ of feasible options with respect to existing orders in state S_k. The exact type of the corresponding vehicle routing problem depends on the application. In case the vehicle routing problem has a feasible solution, this implies that $o \in \mathcal{O}_k$.

Cost estimation: Second, the provider must compute the value difference, i.e., the costs, $\Delta V(S_{k+1}|o) = V_{k+1}(S_{k+1}) - V_{k+1}(S_{k+1}|o)$ for each feasible option $o \in \mathcal{O}_k$ in case the provider sells option o to customer i due to demand management decisions x_k^{dem} compared to not selling it. Hence, the result of the feasibility check is an input for cost estimation. The impact of selling option o is twofold: First, it can lead to the displacement of demand arriving later, in case not enough capacity will be left. Hence, a sale influences future rewards via the *displacement cost* well known from revenue management (Talluri & van Ryzin, 2004a). Second, due to deliveries, it also impacts the costs-side because the usage of some resources causes non-negligible (future) transport costs that are not attributable to requests ex-ante. These costs are captured by the term *marginal delivery cost* or *marginal cost-to-serve* (e.g., Yang & Strauss, 2017). However, due to the "curses of dimensionality" (Powell, 2011), i.e., the large number of possible states and actions, cost values $\Delta V(S_{k+1}|o)$ can usually only be approximated by an estimate $\Delta\tilde{V}(S_{k+1}|o)$.

Demand control: Based on a cost estimate for each feasible option, the provider must make a demand management decision x_k^{dem}:

- When applying availability control, the provider will only offer (accept) an option (a request) $o \in \mathcal{O}_k$ to (by) customer i if $r_{oi} \geq \Delta\tilde{V}(S_{k+1}|o)$. That is, the resulting order is feasible, and the total expected value increases by selling option o. Since the customer preferences for options are heterogenous and stochastic, it may pay off to offer only a restricted offer set $\Theta_k \subseteq \mathcal{O}_k$ to influence choice behavior in a favorable manner.
- When using price-based control, the provider again only offers an option $o \in \mathcal{O}_k$ if $r_{oi} \geq \Delta\tilde{V}(S_{k+1}|o)$ where r_{oi} includes the price p_{oi}. Hence, the $\Delta\tilde{V}(S_{k+1}|o)$ represents a lower bound for the reward r_{oi}, from which a lower bound for the price (service fee or discount) p_{oi} can be derived. Based on this information, the provider can optimize prices to influence demand.

Routing control: The final task results from the vehicle routing component and consists in making routing decisions x_k^{rout}. Again, the feasibility check provides a crucial input to ensure that routing decisions do not violate the operational constraints.

As we show in the following sections, there exist individual solution approaches for each task. Yet, as the tasks build upon each other, the corresponding subproblems are often related. For example, explicit route planning approaches can be applied to feasibility check, cost estimation, and routing control. Therefore, one could argue that solution approaches exist that solve tasks in combination. However, for the sake of clarity, we discuss the approaches for each task individually (Sections 4.1.2–4.1.5). Table 3 provides an overview of the fundamental solution approaches for each task.

4.1.2. Feasibility check

As stated before, the provider can check the feasibility of a potential order as a separate task. In this case, we can distinguish two types of checks:

Route-based check: This type solves some auxiliary model that explicitly considers the constraint satisfaction version of a vehicle routing problem for each fulfillment option o being a candidate for $\mathcal{O}_k$ (e.g., Brailsford, Potts & Smith, 1999 and Berbeglia, Pesant & Rousseau, 2011 or Elting & Ehmke, 2021 in the context of point-to-point transportation). The models are deterministic because the already existing orders and the option o are known for a state S_k. In case a solution exists for the resulting instance, o is included in $\mathcal{O}_k$.

Capacity-based check: These checks determine capacity limits for the number of feasible orders depending on criteria like the location or the time of delivery (e.g., Lang, Cleophas & Ehmke, 2021a) and thereby approximate the constraint satisfaction problem. During the booking horizon, an option o is considered feasible, i.e., included in $\mathcal{O}_k$, if the number of similar orders with respect to the criteria is below the capacity limit. Capacity-based feasibility checks are generally more suitable for disjoint-horizon problems because no routing decisions are required during the booking horizon and, thus, route-based planning is not essential.

4.1.3. Cost estimation

The literature distinguishes between myopic cost estimation and anticipative cost estimation depending on the use of information.

Myopic estimation solely incorporates information about orders that have already been received (Haferkamp & Ehmke, 2022) and does not require any (probabilistic) information about future demand. Therefore, it only aims at marginal cost-to-serve and does not capture a decision's impact on future rewards, i.e., neglects displacement cost. However, the reduced data requirements compared to anticipative estimation can also be a significant advantage in practice if data on future demand are sparse, unreliable, or even not available at all. Usually, myopic estimation relies on a formulation of a static routing problem, so that marginal cost-to-serve

Table 3
Overview of task-specific solution approaches.

Task	Solution approach			
Feasibility check	Route-based (RO)	Capacity-based (CA)		
Cost estimation	Myopic (MY)	Sampling-based (SA)	Deterministic linear program (DL)	Predictive (PR)
Demand control	Accept/reject (AR)	Assortment optimization (AO)	Discrete pricing (DP)	Continuous pricing (CP)
Routing control	Full route plan (FP)	Single route (SR)	Leg-oriented (LO)	

is estimated as the increase in total routing cost caused by adding another order to the respective problem instance.

If information about future demand is available, anticipative estimation is applicable. It addresses two aspects to improve the estimate. First, it can achieve a more accurate estimate of marginal cost-to-serve compared to myopic estimation. For example, this cost may be overestimated in myopic estimates if not considering consolidation opportunities with future orders. Second, anticipation enables an approximation of displacement costs in the first place. Not surprisingly, empirically, many studies demonstrated that anticipative estimation yields better results compared to myopic estimation (Section 6). However, the extent to which this potential can be realized in practice depends on the quality of available data regarding future demand.

Depending on which techniques are used to deal with uncertainty, i.e., characteristics of future requests including the customers' preferences, we distinguish three subclasses of anticipative approaches, namely *sampling-based approaches*, *deterministic linear programming approaches*, and *predictive approaches*. In the following, we characterize these subclasses:

- **Sampling-based**: To obtain a more precise estimation of marginal cost-to-serve, several authors propose the inclusion of sampled future orders into a single (tentative) route plan or a pool of tentative route plans, i.e., a static routing problem. If the corresponding problem allows displacements of sampled orders, its solution also yields an estimate of displacement cost. The idea behind this type of approaches, known as scenario-based planning, is to anticipate how the instance of the routing problem will be structured at the time a potential order is fulfilled. The resulting gain of accuracy is particularly high in the early phase of each booking horizon (Yang et al., 2016). The concept goes back to Bent and van Hentenryck (2004) and Ichoua, Gendreau and Potvin (2006), who apply it to pure dynamic vehicle routing problems. While scenario-based planning considers the future evolution of the decision process from a hindsight perspective, sampling is also possible by dynamically simulating the evolution of the decision process from the current state onward over a limited horizon (Soeffker et al., 2022). This is the principle of rollout approaches, which provide an estimate of both cost components as future decisions are simulated sequentially according to a base policy (e.g., Ulmer, 2020b).
- **Deterministic linear programming**: Originally developed in revenue management (Gallego & Topaloglu, 2019), several publications show that deterministic linear programming techniques are transferable to the field of vehicle routing. They define corresponding auxiliary models, which provide two types of information: On the one hand, the objective function value approximates a certain state value, and hence, the model can be solved twice to calculate a cost estimate $\Delta\tilde{V}(S_{k+1}|o)$ (e.g., Klein et al., 2018). On the other hand, the solution yields information that may also serve directly as an input for demand control. Such models are related to sampling-based approaches in that they also assume expected future demand to be deterministic and include it as an input in aggregated or disaggregated form. The goal is to use this information to predict the expected evolution of the remaining booking and service horizon depending on the demand management and routing decisions. To model customer choice behavior, the inclusion of choice models (Section 3.2) is also possible.
- **Predictive**: A considerable number of authors use predictive models borrowed from the field of statistical learning (Powell, 2019). We can distinguish three types of solution approaches depending on the values to be predicted:
  - The first type approximates the *state value* function $\tilde{V}_{k+1}(S_{k+1}|o)$ for each resulting state S_{k+1} and option o to calculate the cost $\Delta\tilde{V}(S_{k+1}|o)$ as a value difference $\tilde{V}_{k+1}(S_{k+1}) - \tilde{V}_{k+1}(S_{k+1}|o)$ (e.g., Lang et al., 2021a).
  - The second one provides a *direct cost approximation* $\Delta\tilde{V}(S_{k+1}|o)$ (e.g., Qiu et al., 2018).
  - Finally, the third one predicts *state-action values* by Q-learning based on approximating the value of a demand management decision in a particular state. Since maximizing the state-action value in a state S_k directly leads to an optimal solution for demand control, an explicit cost calculation is no longer required (e.g., Chen, Wang, Thomas & Ulmer, 2020).

Any type of prediction can generally be encoded using three types of approximations (Powell, 2011). All of these have in common that values are computed dependent on a set of preselected features representing the state in an aggregated form. Besides the decision epoch k this may include order characteristics as well as route-based features of tentative routes like the vehicles' idle times. The approximations are:

- **Lookup tables**: They store an estimate for all possible resulting combinations of feature values, which is updated each time one of the corresponding states occurs throughout the learning process (e.g., Ulmer et al., 2018).
- **Parametric approximations**: They represent the prediction by an expression of a particular functional form dependent on a set of parameters and the feature values. Most often, a *linear* function, i.e., the weighted sum of all feature values, is chosen (e.g., Yang & Strauss, 2017). However, *piecewise-linear* or *non-linear* specifications are also possible (e.g., Ni, Sun, Wang & Tsang, 2021 and Lebedev, Margellos & Goulart, 2020).
- **Non-parametric approximations**: In contrast to parametric ones, these approximations do not assume that the relationship between the estimate and the feature values is of a particular functional form. Therefore, they can adapt more flexibly to the actual functional relationship, which is likely non-linear. Examples are kernel regression and (deep) neural networks (e.g., Dumouchelle, Frejinger & Lodi, 2021).

4.1.4. Demand control

The demand control task yields the demand management decisions x_k^{dem} that are made in response to an arriving request in stage S_k. For optimizing the demand management decision, potentially based on customer choice behavior, three types of control are proposed in the literature: *accept/reject* control, *assortment optimization,* and *pricing* control.

Accept/reject: If the order confirmation step does not involve any stochastic customer choice decision, demand control boils down to an accept or reject decision for each request. The resulting subproblem can be cast in two ways, both derived from traditional demand management applications (Talluri & van Ryzin, 2004a). First, the provider can subdivide the set of possible requests into subsets according to certain parameters and assign a booking limit to each subset, i.e., an upper bound on the number of orders (Giallombardo, Guerriero & Miglionico, 2020). In this case, a request is accepted if this does not cause the corresponding limit to be exceeded. Second, the cost estimate (Section 4.1.3) can serve as a bid price, i.e., as the minimum profit of a request for it to be accepted. This type of control is also applicable for batched request processing (Ulmer et al., 2018).

Assortment optimization: Under the assumption of substitution behavior and multiple fulfillment options, the demand control task is called an assortment optimization problem (see Gallego & Topaloglu, 2019 for an in-depth introduction). Due to the decision space growing exponentially with O_k, i.e., the number of fulfillment options, it becomes combinatorial. Given $\mathcal{O}_k$ as well as r_{oi}, $\Delta\tilde{V}(S_{k+1}|o)$, and the offer set-dependent purchase probabilities $P_o(\Theta_k)$ for all $o \in \Theta_k$ and $\Theta_k \subseteq \mathcal{O}_k$ provided by the choice model, the objective is to maximize the expected profit after fulfillment:

$$\Theta_k^* = \underset{\Theta_k \subseteq \mathcal{O}_k}{\operatorname{argmax}} \left\{ \sum_{o \in \Theta_k} P_o(\Theta_k) \cdot \left(r_{oi} - \Delta\tilde{V}(S_{k+1}|o) \right) \right\}$$

If necessary, certain structural properties of the offer set can be specified by adding constraints. Additionally, problem structure and problem complexity depend on the choice model (Section 3.2).

Pricing: The basic principle of price-based control is to offer each feasible option $o \in \Theta_k = \mathcal{O}_k$ at some dynamic price p_{oi}, i.e., determine a price vector $\boldsymbol{p}_i = (p_{oi})_{O_k \times 1}$. Thus, rewards $r_{oi}(p_{oi})$ depend on the respective price p_{oi}. In general, pricing optimization requires the same types of input data as assortment optimization, and the problem structure again depends on the choice model defining the purchase probabilities $P_o(p_{oi}, \Theta_k)$. The decision space, i.e., the feasible price vectors, can be similarly vast even if restrictions are imposed. In case the price is only subject to an upper or a lower bound or is entirely unrestricted, a *continuous pricing* problem results, which is modeled as follows (e.g., Yang et al., 2016):

$$\boldsymbol{p}_i^* = \underset{\boldsymbol{p}_i}{\operatorname{argmax}} \left\{ \sum_{o \in \Theta_k} P_o(p_{oi}, \Theta_k) \cdot \left(r_{oi}(p_{oi}) - \Delta\tilde{V}(S_{k+1}|o) \right) \right\}$$

Specifying a set of feasible price points leads to a *discrete pricing* problem, which is a special case of the assortment optimization problem described above. Alternatively, auxiliary models based on quadratic programming (Campbell & Savelsbergh, 2006 and Vinsensius et al., 2020) and predictive models (Chen et al., 2019 and Al-Kanj et al., 2020) are proposed in the academic literature. Finally, note that discounts can also be modeled by allowing $p_{oi} < 0$.

4.1.5. Routing control

Routing control is inherently related to the tasks of the demand management component discussed in 4.1.2–4.1.4. Its goal is to optimize the route plan for serving the set of previously received orders augmented by the newly received one and to potentially make additional routing decisions based on expected demand. In contrast to checking feasibility, the objective is to not only determine a feasible route plan but a cost-minimal one. Depending on the control problem at hand, three types of routing control are possible that differ in what portion of the route plan is determined.

Full route plan: For disjoint horizon problems, routing control is in fact static and deterministic as definitive routing decisions are made after the booking horizon. Therefore, the provider makes a single decision on the *full route plan* under certainty by solving a static vehicle routing problem (Toth & Vigo, 2014). Note that, additionally, tentative route planning is part of some solution approaches for feasibility checking, cost estimation, and demand control of disjoint problems but we do not categorize it as routing control.

Single route: Conversely, for overlapping horizons, some fulfillment planning decisions must be made during the booking horizon and cannot be postponed until its end. Routing control decisions can then be made by repeatedly fixing *complete routes for single vehicles* over time, e.g., when the capacity limit of a vehicle is reached. For this purpose, corresponding routing problems may include tentative decisions for other vehicles. Consequently, most problems consider a tentative route plan beyond the route to be optimized (e.g., Klein & Steinhardt, 2021). This is particularly suitable for deliveries from a central depot as, once a set of orders is loaded onto a vehicle, the route usually cannot be changed any more.

Leg-oriented: Overlapping horizons also allow only fixing a certain part of a route, i.e., the next leg or the next few legs for each vehicle. A leg may correspond to serving an order, moving empty to another location or a charging station, or even idling until the next decision epoch. This type of routing control is often applied to point-to-point transportation problems. In this context, fulfillment planning at each decision epoch only needs to cover a short time span in the case of tight waiting time limits and the absence of pre-bookings (e.g., Kullman et al., 2021). Decisions on relocations and deliberate waiting times of the vehicles, i.e., anticipative routing decisions based on expected demand, can be incorporated, e.g., by means of predictive modeling (e.g., Holler et al., 2019). We refer the interested reader to the works of Berbeglia, Cordeau and Laporte (2010), Soeffker et al. (2022), Ulmer (2017), and Pillac et al. (2013) for an in-depth consideration of these aspects.

4.2. Static deterministic approximation

Integrated demand management and vehicle routing problems can also be cast as static deterministic problems assuming given deterministic customer requests and customer preferences. Only a subset of requests must be accepted as orders. If multiple fulfillment options are defined, it may also be part of the optimization which option should be sold to each customer. Hence, for a fleet of several vehicles, profitable capacitated tour problems or team orienteering problems result (Vansteenwegen & Gunawan, 2019). Therefore, they can be formulated as mixed-integer programs (MIPs). As is the case for dynamic control models, their structure depends on the problem setting. Depending on their use, we distinguish two types of static deterministic approximations for the dynamic control model:

Offline static control: Here, we assume perfect information on incoming customer requests and customer preferences. This assumption reflects an ex-post perspective at the end of the booking horizon. Solution approaches based on offline static control auxiliary models yield static controls, which determine definitive demand management decisions before the start of the booking horizon (e.g., Agatz, Campbell, Fleischmann & Savelsbergh, 2011, Klein et al., 2019, and Mackert, Steinhardt & Klein, 2019). Another motivation for explicitly considering such models results from the fact that their solutions serve as a bound for any policy's performance for the corresponding dynamic problem (e.g., Hosni, Naoum-Sawaya & Artail, 2014).

Online static control: The underlying idea of this approach is to derive both demand management and vehicle routing decisions from a static snapshot of the original dynamic control problem at a specific decision epoch. Consequently, perfect information is only available about existing orders and newly arrived requests. Online static control is applicable for both real-time request processing and batched request processing (e.g., Erdmann, Dandl & Bogenberger, 2021). Expected future orders can, e.g., be integrated by simulating customer arrivals or using aggregated expectations, which results in anticipative auxiliary models. Note that in addition, constraints must ensure all previously made decisions. Exemplary formulations of auxiliary models can be found in Klapp et al. (2020), Voccia et al. (2019), and Wang et al. (2021).

4.3. Tabular overview

This section provides an overview of the literature on modeling and dynamically solving integrated demand management and vehicle routing problems that we consider to be in scope for this survey. To this end, we use the morphological analysis of the problem characteristics from Section 2.1 to classify the individual publications (see Table 1 for the possible realizations of all dimensions). Table 4 comprehensively merges the results of this analysis (Columns 3–10) with the application (Column 2), the selected customer choice model (Column 11), and the basic solution concept of the respective work (Columns 12 and 13). Please note that in addition to the applications considered in Section 2.2, we use the entry "GEN" for publications that consider a generic problem setting and do not specify an application. Also, Column 10 sketches the constraint structure of the respective problem in more detail than given in Table 1. The following entries are possible: single vehicle fleet (SV), heterogeneous fleet (HF), multiple trips per vehicle (MT), maximum route duration (RD), order pickup range (PR), physical vehicle capacity (PC), time windows (TW), delivery deadlines (DD), maximum waiting time (WT), maximum ride time (RT), and battery charging level (CL). Since we focus on dynamic decision making, all publications listed in Table 4 propose dynamic controls, and we omit the dimension "time of decision". Column 11 specifies whether the authors apply a multinomial logit model (ML), a generalized attraction model (GA), a finite mixture MNL model (FM), a nested logit model (NL), or a pricing-specific parametric model (PM). To characterize the solution concept, Column 12 states whether the authors apply a decomposition-based approximation ($\surd$) or a static deterministic one (X). Additionally, Column 13 indicates whether the approach is anticipative ($\surd$) or myopic (X). For the works applying decomposition-based approximation, we summarize the task-specific solution approach that the authors selected in Table 5. We use the classification scheme given in Table 3. In case predictive cost estimation is applied, we additionally state whether it provides a state value estimate (SV), a direct cost estimate (DC), or a state-action value estimate (AV).

5. Solution algorithms

In this section, we provide a more detailed analysis of the specific algorithms used as part of the solution concepts from Section 4. Hence, this section is intended particularly for readers who would like to dive deeper into the literature. We discuss algorithms for both classes of solution concepts in Sections 5.1 and 5.2, respectively.

5.1. Algorithms for decomposition-based approximation

In the following, we discuss algorithms for the tasks individually in Sections 5.1.1–5.1.4. We structure our discussion along the types of solution approaches characterized in Section 4.1. An essential observation is that authors rarely fully decompose the problem, i.e., they often propose a particular algorithm to tackle more than one task. Therefore, at the end of each section, we highlight the algorithms suitable for solving a combination of the current and preceding tasks.

5.1.1. Feasibility check

The complexity of this task ranges from almost trivial (e.g., if the fleet consists of vehicles with a physical capacity of one) to NP-hard for time-window-constrained problems (Savelsbergh, 1985). Consequently, *exact* as well as *heuristic* algorithms are applied. Heuristic algorithms are usually considerably faster compared to exact ones. Thus, as feasibility checks are required simultaneously for all potential options in real-time, the former prevail in the literature. However, they may return false-positive or false-negative results, i.e., incorrectly categorize an option as feasible or infeasible, respectively. The consequence of a false-positive statement and a resulting order of the corresponding option is that the provider cannot serve the respective customer or other customers due to insufficient capacity. This could cause a loss of customer goodwill (e.g., Wang, Wu, Lin & Wang, 2011) or require expensive short-term capacity enhancement measures (e.g., Vinsensius et al., 2020). By way of contrast, false-negative statements might lead to lost sales if a feasible and profitable option is not offered.

Algorithms for route-based checks: Most publications apply route-based feasibility checks, drawing on the extensive set of existing methods for solving classical static vehicle routing problems:

- **Heuristics**: In heuristic algorithms, at least one route plan $\phi \in \Phi_k$ serving all orders accepted so far is maintained or generated online at each decision epoch. If the heuristic finds that augmenting ϕ to a plan ϕ' for an option o is feasible, the check returns a positive result. Most approaches use an insertion heuristic to this end (Solomon, 1987). Insertion heuristics offer high flexibility regarding the extensiveness of the search for a feasible position and are adaptable to many generalizations of the vehicle routing problem (Campbell & Savelsbergh, 2004). For that reason, they are applied to almost any problem setting. The following works present interesting contributions regarding this method: Campbell and Savelsbergh (2005) generate a pool of tentative route plans using a randomized insertion procedure and evaluate all potential insertion positions for a particular fulfillment option. Yang et al. (2016) additionally maintain a tentative route plan from the previous decision epoch. Azi, Gendreau and Potvin (2012) allow splitting routes if there is no feasible insertion position in the original routes of a single route plan, given some maximum route length constraint. Prokhorchuk et al. (2019) check for infeasible and undoubtedly unprofitable options to reduce the computational effort for the downstream tasks.
- **Exact algorithms**: As opposed to heuristics, exact algorithms thoroughly search a static routing problem's solution space. Thus, they do not return false results but at the cost of higher time consumption. In the surveyed literature, authors only consider total enumeration and apply it to less complex problems. For example, they examine problem settings that only involve vehicles with a physical capacity of one (e.g., Chen et al., 2019). Qiu et al. (2018) show that total enumeration is also applicable for vehicle capacities in the lower one-digit range.

Algorithms for capacity-based checks: Since capacity-based feasibility checks approximate route-based auxiliary models, they are heuristic by design. The corresponding algorithms differ in how capacity limits are determined offline. Lebedev et al. (2020), Yang and Strauss (2017), and Strauss et al. (2021) draw on routing approximation techniques by Daganzo (1987). Lang et al. (2021a) ap-

Table 4
General overview.

Authors	Application	Service type	Objective	Control type	Processing	Fulfillment options	Booking/service horizon	Routing problem	Constraints	Choice model	Decomposition	Anticipation
Al-Kanj et al. (2020)	MOD	TR	PR	PB	BA	SI	OL	PP	PC, CL, PR	ML	√	√
Alonso-Mora et al. (2017)	MOD	TR	NO	AV	BA	SI	OL	PP	PC, WT, RT	–	X	√
Angelelli et al. (2021)	GEN	TR	PR	AV	RT	SI	DJ	PU	SV	–	√	√
Archetti et al. (2021)	GEN	TR	PR	AV	RT	SI	OL	DE	PC, HF, TW, MT	–	√	X
Atasoy et al. (2015)	MOD	TR	PR	AV	RT	MU	OL	PP	PC, HF, WT, RT	ML	√	X
Avraham and Raviv (2021)	FSO	CS	NO	AV	RT	MU	IF	DE	TW	ML	√	√
Azi et al. (2012)	SDD	TR	PR	AV	RT	SI	OL	DE	TW, MT, RD	–	√	√
Bertsimas et al. (2019)	MOD	TR	PR	AV	BA	SI	OL	PP	PC, TW	–	X	X
Campbell and Savelsbergh (2005)	AHD	CG	PR	AV	RT	MU	DJ	DE	PC, TW	–	√	√
Campbell and Savelsbergh (2006)	AHD	CG	PR	PB	RT	MU	DJ	DE	PC, TW	PM	√	X
Chen et al. (2019)	MOD	TR	RE	PB	RT	SI	OL	PP	PC, PR	PM	√	√
Chen et al. (2020)	SDD	TR	NO	AV	RT	SI	OL	DE	DD, MT	–	√	√
Chen et al. (2022)	SDD	TR	NO	AV	RT	SI	OL	DE	PC, HF, DD, MT	–	√	√
Côté et al. (2021)	SDD	TR	PR	AV	BA	SI	OL	DE	TW, MT	–	X	√
Dayarian et al. (2020)	SDD	TR	NO	AV	BA	SI	OL	DE	SV, PC, HF, DD	–	X	X
Dumouchelle et al. (2021)	GEN	TR	PR	AV	RT	SI	DJ	PU	PC	–	√	√
Erdmann et al. (2021)	MOD	TR	PR	AV	RT, BA	SI	OL	PP	PC, TW, WT	–	X	X
Fielbaum et al. (2021)	MOD	TR	PR	AV	BA	SI	OL	PP	PC, WT, RT	–	X	√
Giallombardo et al. (2020)	GEN	TR	PR	AV	RT	SI	DJ	PU	PC	–	√	√
Haferkamp and Ehmke (2022)	MOD	TR	NO	AV	RT	SI	OL	PP	WT, RT	–	X	√
Haliem et al. (2021)	MOD	TR	PR	PB	BA	SI	OL	PP	PC	PM	√	√
Holler et al. (2019)	MOD	TR	RE	AV	BA	SI	OL	PP	PC, PR, WT	–	√	√
Hosni et al. (2014)	MOD	TR	PR	AV	RT	SI	OL	PP	PC, HF, WT, RT	–	√	X
Jahanshahi et al. (2022)	SDD	TR	NO	AV	RT	SI	OL	PP	PC, DD	–	√	√
Klapp et al. (2018)	SDD	TR	PR	AV	BA	SI	OL	DE	SV, MT, RD	–	X	√
Klapp et al. (2020)	SDD	TR	PR	AV	RT	SI	OL	DE	SV, MT, RD	–	X	√
Klein et al. (2018)	AHD	CG	PR	PB	RT	MU	DJ	DE	PC, TW	ML	√	√
Klein and Steinhardt (2021)	SDD	CG	PR	PB	RT	MU	OL	DE	DD, MT	PM	√	√
Koch and Klein (2020))	AHD	CG	PR	PB	RT	MU	DJ	DE	TW	FL	√	√
Köhler et al. (2019)	AHD	CG	NO	PB	RT	MU	DJ	DE	TW	NL	√	X
Köhler et al. (2020)	AHD	CG	NO	AV	RT	MU	DJ	DE	TW	–	√	X
Kullman et al. (2021)	MOD	TR	PR	AV	RT	SI	OL	PP	PC, WT, CL	–	√	√
La Rocca and Cordeau (2019)	MOD	TR	RE	AV	BA	SI	IF	PP	PC, WT, CL	–	X	X
Lang et al. (2021a)	AHD	CG	RE	AV	RT	MU	DJ	DE	TW	FL	√	√
Lang et al. (2021b)	AHD	CG	RE	AV	RT	MU	DJ	DE	TW	FL	√	√
Lebedev et al. (2020)	AHD	CG	PR	PB	RT	MU	DJ	DE	TW	ML	√	√
Lebedev et al. (2022)	AHD	CG	PR	PB	RT	MU	DJ	DE	TW	ML	√	√
Lotfi and Abdelghany (2022)	MOD	TR	PR	AV	BA	MU	OL	PP	PC, TW	–	√	X
Mackert (2019)	AHD	CG	PR	AV	RT	MU	DJ	DE	PC, TW	GA	√	√
Ni et al. (2021)	MOD	TR	PR	PB	BA	MU	OL	PP	CL	PM	√	√
Prokhorchuk et al. (2019)	SDD	TR	RE	PB	RT	MU	OL	DE	DD, MT	ML	√	√
Qiu et al. (2018)	MOD	TR	PR	PB	RT	MU	OL	PP	PC, HF, RT, PR	ML	√	√
Strauss et al. (2021)	AHD	CG	PR	PB	RT	MU	DJ	DE	PC, TW	NL	√	√
Ulmer (2020a)	SDD	CG	RE	PB	RT	MU	OL	DE	DD, MT	PM	√	√
Ulmer (2020b)	FSO	CS	NO	AV	BA	SI	OL, IF	DE	SV	–	√	√
Ulmer et al. (2018)	GEN	TR	NO	AV	BA	SI	OL	PU	SV	–	√	√
Ulmer et al. (2019)	GEN	TR	NO	AV	BA	SI	OL	PU	SV	–	√	√
Ulmer and Thomas (2020)	GEN	TR	RE	AV	RT	SI	DJ	DE	SV, PC	–	√	√
Vinsensius et al. (2020)	AHD	CG	PR	PB	RT	MU	DJ	DE	PC, HF, RD, MT, TW	PM	√	√
Voccia et al. (2019)	SDD	TR	NO	AV	BA	SI	OL	DE	TW, MT	–	X	√
Wang et al. (2021)	MOD	TR	PR	PB	BA	MU	OL	PP	PC, TW	NL	X	X
Xu et al. (2018)	MOD	TR	RE	AV	BA	SI	OL	PP	PC	–	√	√
Yang and Strauss (2017)	AHD	CG	PR	PB	RT	MU	DJ	DE	PC, TW	ML	√	√
Yang et al. (2016)	AHD	CG	PR	PB	RT	MU	DJ	DE	PC, TW	ML	√	√
Zhang et al. (2022)	GEN	TR	NO	AV	RT	SI	OL	DE	MT	–	√	√

Table 5
Overview of decomposition-based approaches.

Authors	Feasibility check	Cost estimation	Demand control	Routing control
Al-Kanj et al. (2020)	RO	PR, SV	DP	LO
Angelelli et al. (2021)	RO	SA	AR	FP
Archetti et al. (2021)	RO	MY	AR	SR
Atasoy et al. (2015)	RO	MY	AO	SR
Avraham and Raviv (2021)	RO	PR, DC	AO	FP
Azi et al. (2012)	RO	SA	AR	SR
Campbell and Savelsbergh (2005)	RO	SA	AR	FP
Campbell and Savelsbergh (2006)	RO	MY	DP	FP
Chen et al. (2019)	RO	PR, SV	DP	LO
Chen et al. (2020)	RO	PR, AV	AR	SR
Chen et al. (2022)	RO	PR, AV	AR	SR
Dumouchelle et al. (2021)	CA	PR, AV	AR	FP
Giallombardo et al. (2020)	CA	DL	AR	FP
Haliem et al. (2021)	RO	MY	CP	LO
Holler et al. (2019)	RO	PR, AV	AR	LO
Hosni et al. (2014)	RO	MY	AR	LO
Jahanshahi et al. (2022)	RO	PR, AV	AR	LO
Klein et al. (2018)	RO	DL	CP	FP
Klein and Steinhardt (2021)	RO	SA	DP	SR
Koch and Klein (2020)	RO	PR, SV	DP	FP
Köhler et al. (2019)	RO	MY	DP	FP
Köhler et al. (2020)	RO	MY	AO	FP
Kullman et al. (2021)	RO	PR, AV	AR	LO
Lang et al. (2021a)	CA	PR, SV	AO	FP
Lang et al. (2021b)	CA	PR, SV	AO	FP
Lebedev et al. (2020)	CA	PR, SV	CP	FP
Lebedev et al. (2022)	CA	PR, SV	CP	FP
Lotfi and Abdelghany (2022)	RO	MY	AR	SR
Mackert (2019)	RO	DL	AO	FP
Ni et al. (2021)	RO	PR, SV	CP	LO
Prokhorchuk et al. (2019)	RO	PR, SV	CP	SR
Qiu et al. (2018)	RO	PR, DC	CP	LO
Strauss et al. (2021)	CA	DL	DP	FP
Ulmer (2020a)	RO	PR, SV	CP	SR
Ulmer (2020b)	RO	SA, PR, SV	AR	LO
Ulmer et al. (2018)	RO	PR, SV	AR	LO
Ulmer et al. (2019)	RO	SA, PR, SV	AR	LO
Ulmer and Thomas (2020)	RO	PR, SV	AR	FP
Vinsensius et al. (2020)	CA	PR, SV	DP	FP
Xu et al. (2018)	RO	PR, SV	AR	LO
Yang and Strauss (2017)	CA	PR, SV	CP	FP
Yang et al. (2016)	RO	SA	CP	FP
Zhang et al. (2022)	RO	DL	AR	SR

ply the iterated local search algorithm by Souffriau, Vansteenwegen, Vanden Berghe and Van Oudheusden (2013) to solve sampled instances of the offline static control problem (Section 4.2). Lang et al. (2021b) also solve an offline problem with forecasted orders but assume that the provider must serve all orders.

5.1.2. Cost estimation

As outlined in Section 4.1.3, any cost estimation is approximate due the task's high complexity. This section discusses the algorithms presented in the literature, which again may yield cost estimates of varying quality.

Algorithms for myopic estimation: Applying myopic estimation yields an estimate of *tentative marginal cost-to-serve*, i.e., the increase in total delivery cost caused by additionally serving a potential order o. The term *tentative* expresses that they only refer to the orders accepted so far. For this estimate to be exact, routing costs of the optimal route plans ϕ'^* and ϕ^* with and without the potential order need to be determined, which is often very time-consuming. Therefore, only Hosni et al. (2014) apply a standard mixed-integer programming solver (MIP solver) to search for the minimum-cost update, however, separately for each vehicle and thus heuristically. The other algorithms rely on insertion heuristics.

Campbell and Savelsbergh (2006) approximate the tentative marginal cost-to-serve by the insertion cost of a potential order concerning a pool of tentative route plans. Atasoy et al. (2015) develop a similar procedure that differentiates between different vehicle types but is based only on a single current route plan. Köhler et al. (2019) and Köhler, Ehmke and Campbell (2020) observe that the insertion cost decreases depending on the routing flexibility for a given set of orders. Hence, they use measures for the routing flexibility as a cost estimate.

It is important to note that even exact tentative marginal cost-to-serve are an approximation of the true marginal cost-to-serve. The latter can be computed at the end of the booking horizon, being the cost difference between optimal route plans with and without the potential order. In the following, we denote this true hindsight cost as *ex-post marginal cost-to-serve*. This distinction is required because a tentative route plan can structurally differ from the final route plan to a large extent (Yang et al., 2016).

Hence, we have a chain of three potential sources of inaccuracy for myopic estimation: First, heuristic algorithms only approximate the exact tentative marginal cost-to-serve. Second, even the exact tentative marginal cost-to-serve only approximate the ex-post marginal cost-to-serve. Third, as explained in Section 4.1.1, the ex-post marginal cost-to-serve is just one cost component and must be complemented by the exact displacement cost to obtain a perfectly accurate cost estimate. Within the class of myopic approaches, an algorithmic improvement can just tackle the first source of inaccuracy as the other two are of a structural nature.

It is only through anticipation that a *refinement of the marginal cost-to-serve estimate* beyond the exact tentative value and toward the ex-post value and the *estimation of displacement cost* becomes possible. However, not all approaches take advantage of both opportunities, as explained in the following.

Algorithms for sampling-based estimation: Solution algorithms for sampling-based cost estimation are related to those for myopic estimation in that they are also essentially routing heuristics. However, the inclusion of sampled orders necessitates adaptions.

Azi et al. (2012) calculate the average insertion cost of a potential order into a pool of route plans, each initialized with sampled orders. They permanently insert new orders into the sampled route plans and reoptimize them using an adaptive large neighborhood search heuristic. Yang et al. (2016) compute a weighted combination of the average insertion cost regarding two pools of route plans: One contains route plans of all received orders. The other consists of historic final route plans and, hence, entirely contains sampled orders. The tentative insertion cost is expected to gain accuracy throughout the booking horizon, so its weight is gradually increased. Displacement of sampled customers is not possible in either approach.

In contrast, the following three algorithms also estimate displacement cost. Campbell and Savelsbergh (2005) construct a single route plan from scratch using a profit-based insertion heuristic for each potential order. In the first phase, they insert all existing orders. In the second one, they include the potential order together with a set of sampled ones. Thereby, they adjust the sampled orders' revenues by the probabilities of their arrival. The resulting objective function values of the solution with and without the potential order are used to determine a cost estimate, including displacement cost. Angelelli, Archetti, Filippi and Vindigni (2021) follow the same ideas but draw on a different routing heuristic (Chao, Golden & Wasil, 1996). Klein and Steinhardt (2021) propose a method to refine cost estimates derived from scenario-sampling through the explicit integration of future demand control decisions and the resulting customer choice behavior. Ulmer (2020b) presents a rollout algorithm. It uses a pre-trained state value approximation and an insertion heuristic to simulate demand control and routing control, respectively.

Algorithms for deterministic linear programming: Deterministic linear programming models are usually solved through MIP solvers. To achieve tractable formulations, authors propose several techniques. Such formulations require an approximation of final routing cost based on known and expected orders. Since expected orders depend on future demand management decisions and, potentially, on customer choice behavior, they must also include these aspects.

Klein et al. (2018) solve a model leaning on the choice-based deterministic linear program (e.g., Liu & van Ryzin, 2008). For estimating routing cost, they combine insertion-based tentative route planning with a seed-based routing approximation developed by Fisher and Jaikumar (1981). To account for expected demand management and the resulting purchase decisions, they define a set of potential price lists and pre-compute choice probabilities. Mackert (2019) uses the same routing approach to adapt the sales-based deterministic linear program by Gallego, Ratliff and Shebalov (2015), which endogenizes a choice model in the form of linearized constraints. The same is true for the formulation used by Strauss et al. (2021). However, they apply the approximation developed by Daganzo (1987) to estimate the final routing cost. Zhang, Luo, Florio and Van Woensel (2022) solve a multiple-knapsack problem approximating both future demand management and routing decisions. Giallombardo et al. (2020) geographically aggregate requests to allow for explicit route planning. If the request arrival rate is prohibitively high for real-time decisions, Klein et al. (2018) and Giallombardo et al. (2020) propose solving their auxiliary model at larger time intervals and re-using current cost estimates until an update is available.

Algorithms for predictive estimation: For predictive approaches, algorithms solve the estimation problem of the statistical model, i.e., they train the model based on historical or simulated booking data (e.g., Powell, 2019). This training involves several steps, such as feature value calculation, model updates, and exploration. For each of these steps, a wide range of methods from the field of statistical learning can be applied in various combinations to the control problem considered in this survey. Therefore, we refrain from discussing the individual methods and their composition in detail and only give an overview of the most important contributions.

- **State value approximations**: Lang et al. (2021b) apply a backward dynamic programming algorithm to compute a lookup table. Ulmer et al. (2018) and Al-Kanj et al. (2020) propose dynamically refining the partitioning of lookup tables during the offline learning process. Ulmer et al. (2019) amend this approach by an online rollout component. The parametric models by Prokhorchuk et al. (2019) and Koch and Klein (2020)) entail features derived from route plans. Like sampling-based approaches, the latter include sampled orders into the route plan, which they gradually remove during the booking horizon. Both works use linear regression for policy updates. Koch and Klein (2020) find that side constraints incorporating the value function's structural properties improve the learning performance. The algorithms of Yang and Strauss (2017) and Vinsensius et al. (2020) do not require any tentative route planning. Both update the parameters using a stochastic gradient step immediately after each value observation but differ in the way of calculating the final delivery cost: Yang and Strauss (2017) use a routing approximation by Daganzo (1987), Vinsensius et al. (2020) construct each final route plan with a minimum-regret insertion heuristic (Pisinger & Ropke, 2007). For non-linear statistical models, Lebedev et al. (2020) and Lebedev, Margellos and Goulart (2022) show that policy updates are not prohibitively complex. The same is true for non-parametric statistical models, i.e., neural networks, for which special policy update methods exist depending on the model specification (Chen et al., 2019 and Lang et al., 2021a).
- **Direct cost approximations**: To directly learn a non-linear cost function, Avraham and Raviv (2021) conduct an iterative local search within a gradient descend framework and use simulation to evaluate a parameter set's quality. Qiu et al. (2018) employ a covariance matrix adaption evolution strategy, i.e., a numerical optimization method, to learn the parameters of a linear function.
- **State-action value approximations**: Instead of a value function or a cost function, Q-learning is based on learning a state-action value function. Combining Q-learning with a deep neural network representation of the state-action value function is called Deep Q-learning. It is, e.g., applied in the following two works: Chen et al. (2020) train the network such that it learns a policy which balances acceptance rates over sub-areas. Kullman et al. (2021) estimate a separate Q-value for each vehicle and mimic centralized control during training by a reward-sharing mechanism. Holler et al. (2019) propose a proximal policy optimization method that also relies on a neural network representation of the policy. Jahanshahi et al. (2022) train a Double Deep Q-Network with prioritized experience replay. Finally, Dumouchelle et al. (2021) train a neural network combining Monte Carlo tree search with the SARSA algorithm.

Combination with other tasks: All algorithms for myopic cost estimation simultaneously provide a cost estimate and a statement on the feasibility for each potential order.

Yang et al. (2016) and Klein and Steinhardt (2021) simultaneously check feasibility when applying their routing heuristics to determine sampling-based cost estimates. Since some predictive cost estimation algorithms require tentative route planning to calculate feature values, such as the free time budget, combining them with a route-based feasibility check (e.g., Ulmer et al., 2018) is natural.

Integrated capacity-based feasibility checks are, on the one hand, possible via the routing approximations used as part of the deterministic linear programming approach by Strauss et al. (2021) as well as the predictive approaches by Lebedev et al. (2020), Yang and Strauss (2017), and Lang et al. (2021a). On the other hand, the cost estimate can incorporate the likelihood that a potential order leads to an infeasible route plan. If the likelihood is high, the aim is to set the value of the cost estimate sufficiently high to prevent offering the respective fulfillment option. Vinsensius et al. (2020) and Dumouchelle et al. (2021) propose such algorithms.

5.1.3. Demand control

In this section, we examine algorithms for the demand control task. The complexity of this task depends on both the type of solution approach, according to which we structure the following discussion, and the choice model providing purchase probabilities.

Algorithms for accept/reject control: Accept/reject decisions based on both booking limits and bid prices require minimal computational effort. For booking limits, it is sufficient to check whether a potential order causes the respective limit to be exceeded (Giallombardo et al., 2020). Controlling demand based on bid prices requires checking whether a potential order's profit is larger than or at least equal to the cost estimate. If not, the request is rejected (Hosni et al., 2014). However, some algorithms allow such requests to be reconsidered in subsequent decision epochs until they expire (Holler et al., 2019). Maximizing state-action values (Kullman et al., 2021) or solving a matching problem via the Kuhn-Munkres algorithm (Xu et al., 2018) are also suitable for accept/reject control.

Algorithms for assortment optimization: Under the assumption of an MNL choice model, an optimal offer set exists among the nested-by-revenue ones (Talluri & van Ryzin, 2004b). Lang et al. (2021a) and Lang et al. (2021b) take advantage of this property, which does no longer hold in case of side constraints. The application considered by Atasoy et al. (2015) requires such constraints to guarantee that at most one option of different classes of fulfillment options is offered. However, the total unimodularity of this constraint allows formulating the problem as a linear program (see Davis, Gallego & Topaloglu, 2013 and Bechler, Steinhardt & Mackert, 2021 for an overview of such linearization techniques). Similarly, Mackert (2019) uses a linearized formulation of the assortment optimization problem arising under the assumption of a generalized attraction choice model. For problem settings where $|\Theta_k|$ is low, Avraham and Raviv (2021) find that total enumeration is an efficient method to solve assortment optimization problems given that all options with $r_{oi} < \Delta\tilde{V}(S_{k+1}|o)$ can be excluded.

Algorithms for pricing: Discrete pricing problems can be modeled as assortment optimization problems, such that algorithms described in the previous paragraph are applicable. Like Atasoy et al. (2015), Strauss et al. (2021) solve an MNL-based pricing problem with unimodular constraints using a MIP solver. The constraints guarantee that less convenient options are priced lower than more convenient ones. Koch and Klein (2020) tackle the discrete pricing problem under a finite-mixture MNL model through a greedy construction heuristic.

Yang et al. (2016) are the first to describe the continuous pricing problem resulting from applying the MNL model in the context of demand management for a vehicle routing application. Drawing on Dong, Kouvelis and Tian (2009), they show that the problem is non-linear but concave, so they can apply any numerical optimization method.

While all pricing policies discussed so far involve discrete choice models, the literature describes some other variants. Campbell and Savelsbergh (2006) propose a two-step algorithm. First, they perform a rule-based selection of feasible options to be offered at a discount. By solving the piecewise linear approximation of a quadratic program, they determine the value of all discounts. Vinsensius et al. (2020) apply a similar algorithm and solve the resulting quadratic program directly in closed form. Ulmer (2020a) proposes a rule-based policy that makes offers at a static base price or a price equal to the cost estimate if the latter exceeds the base price. Haliem et al. (2021) use a similar method. Köhler et al. (2019) present another rule-based algorithm analogous to the assortment optimization method by Köhler et al. (2020). Al-Kanj et al. (2020) and Chen et al. (2019) show that machine learning methods are also suitable for solving pricing problems heuristically.

Combination with other tasks: As booking limits generally reflect the available logistical capacity, their use for the demand control task involves a capacity-based feasibility check. Concerning the other demand control approaches, existing works exclusively tackle demand control separate from other tasks.

5.1.4. Routing control

Algorithms for determining vehicle routing decisions for control problems with integrated demand management have much in common with pure vehicle routing algorithms (Soeffker et al., 2022). Due to the constraint structure depending on operational restrictions, they are also highly specific to the problem setting of individual applications. As we generally focus on demand management, we only provide a high-level overview.

Algorithms for full route plan approaches: In problem settings with disjoint booking and service horizons, a static vehicle routing problem arises after the cutoff time. Thus, any route planning heuristic suitable for the respective model can be applied.

Algorithms for single route approaches: In the case of overlapping horizons, routing control may rely on fixing complete routes. Here, it is possible to extend the feasibility check to not only search for a feasible update for tentative route planning but a cost-minimal one. Azi et al. (2012) were the first to propose such an algorithm. They insert every new order into a valid route plan containing all received orders and reoptimize it by adaptive large neighborhood search upon each insertion. Archetti, Guerriero and Macrina (2021) periodically perform a local search, Lotfi and Abdelghany (2022) apply a greedy heuristic. Atasoy et al. (2015) consider a problem setting where each vehicle can be used for different transportation modes. Thus, they divide each route into blocks within which the mode remains the same. If possible, they insert new orders into an existing block. Otherwise, they create a new block solving a shortest path problem.

Algorithms for leg-oriented approaches: Alternatively, the provider can decide on the next legs of vehicles. The methods by Ulmer et al. (2018) and Ulmer et al. (2019) require a decision whether to wait at the current location or to proceed toward the next location according to the updated route plan at each decision epoch. For applications with point-to-point transportation, standalone algorithms can determine empty relocations as shown by Chen et al. (2019), who use a random walk process. In contrast, Ni et al. (2021) apply a MIP solver to determine all routing decisions including relocations.

Combination with other tasks: For the routing control task, there are many combination opportunities with preceding tasks. Many algorithms for feasibility check and cost estimation already yield route plans as a “side-product.” Hence, these plans can be used directly (e.g., Klein & Steinhardt, 2021) or optimized further by the heuristics described above. Xu et al. (2018) and Qiu et al. (2018) show that algorithms for demand control can also yield routing decisions. Decisions on relocations can also be made in conjunction with demand control. State(-action) value-based accept/reject methods offer one way to integrate these tasks (Al-Kanj et al., 2020; Holler et al., 2019; Jahanshahi et al., 2022, and Kullman et al., 2021). Haliem et al. (2021) estimate dedicated state-action values for relocations, which also serve as an input for pricing decisions.

5.2. Algorithms for static deterministic approximation

In contrast to solution concepts based on decomposition, which are often inspired by traditional demand management applications, this class of concepts rather originate from pure dynamic vehicle routing (Berbeglia et al., 2010) and, hence, are only suitable in case of overlapping horizons. In each decision epoch, solving an auxiliary online static control model (Section 4.2) simultaneously provides a demand control and routing control decision. This results in another important characteristic compared to decomposition-based approximations: the lack of an explicit cost estimate. However, the notion of myopic and anticipative decision making is transferable since online static control models may also include information on future demand. In the literature, static deterministic approximation is only applied, with one exception, for accept/reject control. Therefore, the complexity of the periodic optimization problem is mainly determined by the vehicle routing component and the use of anticipation. Consequently, we consider algorithms for myopic and anticipative approaches separately in Sections 5.2.1 and 5.2.2.

5.2.1. Algorithms for myopic approaches

La Rocca and Cordeau (2019) present the only exact solution algorithm within the class of myopic approaches. They apply a MIP solver to a linear assignment problem with dummy vehicles, which leads to a set of new orders with vehicle assignments. The route plan is then complemented with charging and relocation decisions for unassigned vehicles by separate rule-based policies dependent on the current system state.

Other authors rely on heuristics: Erdmann et al. (2021) propose a greedy matching heuristic to determine order-vehicle assignments. Bertsimas, Jaillet and Martin (2019) solve an auxiliary network flow model using a MIP solver. They use the solution from the previous decision epoch as a warm start and a backbone algorithm for preprocessing to reduce the computational effort.

The auxiliary bi-level programming model used by Wang et al. (2021) is very complex as it incorporates choice-based pricing control and thus needs to be solved by a specialized heuristic search algorithm. Dayarian, Savelsbergh and Clarke (2020) use a two-stage heuristic that first creates a potentially infeasible route plan serving all received orders and potential orders using a large neighborhood search with a worst-removal destroy operator. Second, potential orders are removed following a greedy scheme until reaching feasibility.

5.2.2. Algorithms for anticipative approaches

Some works solving anticipative auxiliary models also consider problems that allow a thorough search of the solution space. For vehicle capacities in the lower one-digit range, Alonso-Mora, Wallar and Rus (2017) show that total enumeration is applicable. They construct a shareability graph, first proposed by Santi et al. (2014), to identify the set of all feasible routes and solve a matching problem to determine which of these to assign to vehicles. To allow for anticipation and relocations, a set of sampled requests with reduced rejection penalty costs is added to the batch of newly arrived ones. Fielbaum et al. (2021) propose two extensions for this algorithm: First, they modify arc costs according to the expected demand at the vehicle’s destination. Second, they refine the sampling procedure for future orders through an online method for estimating demand distributions for sampling that does not require historical data. Klapp et al. (2018) and Klapp et al. (2020) consider single-vehicle, multi-trip problems for which the application of a MIP solver is also practical. Both works develop policies based on a-priori plans, which are computed by solving the offline static control problem based on expected customer arrivals associated with rejection penalties. The a-priori plan is then updated at each decision epoch by solving the online static control problem or a simplified version of it. Following the authors mentioned above, Klapp et al. (2020) state that it is beneficial to warm-start the solver with data from the previous decision epoch. However, they also present a metaheuristic tailored to the problem’s structure to reduce computation time further.

This leads us to more complex static control problems where metaheuristics are, in fact, the only practical solution approach. Haferkamp and Ehmke (2022) apply a large neighborhood search with three classical removal operators and regret-insertion. Voccia et al. (2019) generate scenarios by sampling future requests and solve a relaxation of the online static control problem for each scenario instance by a variable neighborhood search. They then apply a consensus function (Bent & van Hentenryck, 2004) to the set of resulting scenario plans. This function identifies which part of each idle vehicle’s route can accommodate new orders in each scenario plan, selects the best plan, and with it the subset of requests to accept. The chosen plan is then repaired for feasibility by removing potential orders. Also based on scenario-sampling, Côté, de Queiroz, Gallesi and Iori (2021) first evaluate whether it is beneficial to delay the start of all planned routes. If not, they first ensure that each request is either planned to be served by a vehicle departing in the current decision epoch, a later decision epoch, or is rejected consistently in all scenarios before applying the consensus function. For route planning, they use an adaptive large neighborhood search.

6. Conclusion and research opportunities

In this survey, we reviewed the methodological advances regarding the integration of demand management and vehicle routing. This research area, whose origins can be situated around the mid-2000s, encompasses a wide range of applications. Therefore, we first developed a generalized definition and a high-level mathematical model of the underlying sequential decision process, and then used this as a basis for analyzing and classifying the literature concerning the decision problems, solution concepts, and algorithms presented.

Based on this analysis, we can now discuss important insights and challenges from a cross-application perspective. In particular, we draw conclusions regarding the current state of research and, simultaneously, point toward future research opportunities. We structure the elaboration along the following seven topics:

Generic model formulations: Establishing some form of a common modeling language is undoubtedly beneficial to describe problem settings in a standardized and concise manner and to be able to relate these settings to each other on a formal level. To this end, it seems most natural to formalize the various settings in terms of corresponding Markov decision processes to fully capture the dynamic and stochastic nature of the underlying control problems. Since many existing works already include such models, we advocate that these become a standard for future publications and introduced a generic, high-level formulation representing a possible starting point for modeling specific control problems in any area of application. One example in this context is the model by Yang et al. (2016) for dynamic pricing in AHD, on which several authors have based their models afterward. A particular challenge arises because vehicle routing dynamics and the reactions of customers to demand management must be modeled. Klein et al. (2020) discuss examples of modeling integrations of demand management techniques and operational decision making from different fields of applications. An important step to improve the presentation of relevant control problems toward a more generic description is to establish and use common terminology that this review aims to contribute to.

Generic solution frameworks: Just like standardized modeling, a uniform description of solution concepts enables methodological transfers within and between the application-specific literature streams and thus a faster progress of research overall. We aimed to contribute toward such a unification by explicitly distinguishing decomposition-based approximations and static deterministic ones as well as the associated solution approaches (Section 4). We encourage authors of future works on decomposition-based approximation to be explicit about how they address each task, how they orchestrate their complete solution method, and how it could possibly be adapted to other problem settings. It is also promising to align solution approaches and model formulation more closely. Substantial efforts in this direction already exist in related fields, e.g., by Ulmer et al. (2020) introducing a route-based Markov decision process for dynamic vehicle routing problems.

Advancement of solution approaches: We also see opportunities for future research at the methodological level. For the feasibility check, machine learning methods suitable for solving binary classification problems could be a valuable extension of the existing body of methods for capacity-based checks. Recent work by Dumouchelle et al. (2021) and van der Hagen, Agatz, Spliet, Visser and Kok (2022) shows that this is a promising research avenue. The same observation accounts for constraint programming techniques for route-based feasibility checks. Recent advances in approximate dynamic programming could improve cost estimates (Ulmer et al., 2019). To derive more accurate features from route plans, the inclusion of sampled orders could be further investigated (Koch & Klein, 2020). The application of more accurate choice models, whose major drawback is that they cause an increase in complexity of the demand control task, could be facilitated by developing tailored assortment planning and pricing heuristics. Sampling methods that rely on online demand data could enable anticipation in the absence of a reliable source of historical data (Fielbaum et al., 2021).

Performance assessment: Due to the abovementioned heterogeneity of the problem settings and dependencies on instance characteristics, comparing the performance of complete solution approaches on a general level is difficult. However, there seems to be a universally valid insight repeatedly reported in different areas of application: Anticipative approaches consistently dominate myopic ones, particularly in problem instances characterized by a medium scarcity of fulfillment capacity (e.g., Azi et al., 2012 and Voccia et al., 2019). Especially the anticipation of displacement effects is found to have a significant impact by several authors (e.g., Klein et al., 2018) comparing their approaches with the method by Yang et al. (2016), which uses anticipation only to refine the estimate of marginal cost-to-serve. Another interesting finding is that anticipation reduces the systematic discrimination against customers based on their location (e.g., Prokhorchuk et al., 2019), an issue that Soeffker, Ulmer and Mattfeld (2017) raised first. We believe that researchers should put more emphasis on identifying the components of the overall solution procedure to which a certain increase in performance can be attributed. To a certain extent, this is examined, e.g., in the study by Haferkamp and Ehmke (2022). Regarding the performance, authors should also evaluate the robustness of anticipative approaches in case that the parameters used in choice models and demand distributions differ from the real-world (Srour, Agatz & Oppen, 2018). To allow a generalized empirical validation of these performance insights, Lang et al. (2021a) identify the development of a benchmarking tool as an essential task for future research. First promising steps in this direction are being taken (Bertsimas et al., 2019 and Lang & Cleophas, 2020).

Suitability of demand control policies: Whether providers should prefer availability control or price-based control policies cannot be answered equally clearly, which is why no approach has become dominant in the literature either. Several authors argue that persuasive control strategies, i.e., those using incentives, are superior to coercive ones restricting service availability because they are more likely to be endorsed by customers. Consequently, availability control and especially policies that might reject customers without offering alternative fulfillment options are seen critically (e.g., Asdemir, Jacob & Krishnan, 2009). As Lee and Savelsbergh (2015) point out, the resulting dissatisfaction in MOD settings is amplified by the fact that rejected customers might have to switch to an alternative means of transportation at short notice. Offering a set of fulfillment options instead of only a single one bears the potential to reduce the rate of these provider-side rejections substantially. On the other hand, charging dynamic prices for a logistical service is an inherent competitive disadvantage (Lang et al., 2021b). It may even be restricted or forbidden due to regulation (Bruck, Cordeau & Iori, 2018). Other types of incentives can use discounts or vouchers (Agatz, Fleischmann & Van Nunen, 2008) or highlight the environmental benefits of specific fulfillment options (Agatz, Fan & Stam, 2021a) to alleviate these issues.

Advancement of choice modeling and fulfillment options: In both availability control and price-based control, the path toward more customer-friendly controls leads to the growing importance of choice modeling and the design of fulfillment options. As illustrated in Section 3.2, accurately modeling customer choice behavior is widely recognized as a success factor for demand management in general. The results of Mackert et al. (2019) show that this is also the case for vehicle routing applications. In future research, instead of passively fitting choice models, choice behavior could be actively explored, especially if the available historical data are sparse or biased due to suboptimal demand management in the past (Bondoux, Nguyen, Fiig & Acuna-Agost, 2020). Furthermore, the integration of more advanced choice models like the exponomial (Alptekinoğlu & Semple, 2016) or the Markov chain model (Feldman & Topaloglu, 2017) is a promising topic for future research. Likewise, the development of suitable types of fulfillment options should depend on the application examined. Although this is a strategic planning task (Talluri & van Ryzin, 2004a), it often has methodological implications. We believe the potential for future research in this regard exists in all application areas. For instance, Strauss et al. (2021) apply the concept of flexible products in AHD. Atasoy et al. (2015) propose an MOD system that allows customers to choose the mode of transport. Avraham and Raviv (2021) suggest offering arriving customers time slots of several consecutive working days simultaneously.

Transfer into practice: More research also seems necessary, in our view, to address problems that arise when transferring existing methods into practice. These include concurrency issues (Avraham & Raviv, 2021) as well as the management of disruptions and failed fulfillments, which can be investigated, for example, by taking stochastic travel times into account (Prokhorchuk et al., 2019). Another issue lies in the scalability of solution approaches concerning large instances, as they usually occur in practice (Bertsimas et al., 2019).

With the survey at hand, we hope to promote the transfer of the large body of existing approaches to novel problem settings or even new applications. Interestingly, all three themes that Agatz, Hewitt and Thomas (2021b) identify as characteristics of impactful research in the field of transportation are present in the surveyed research area: multi-objective optimization, stochastic optimization, and the integration of stakeholder behavior. Therefore, we believe active demand management to be a key enabler of new, sustainable business models for smart mobility and transportation applications.

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References

Afeche, P., Liu, Z., & Maglaras, C. (2018). *Ride-hailing networks with strategic drivers: The impact of platform control capabilities on performance. working paper*. University of Toronto. https://doi.org/10.2139/ssrn.3120544.

Agatz, N. A. H., Campbell, A. M., Fleischmann, M., van Nunen, J., & Savelsbergh, M. W. P. (2013). Revenue management opportunities for internet retailers. *Journal of Revenue and Pricing Management, 12*(2), 128–138. https://doi.org/10.1057/rpm.2012.51.

Agatz, N. A. H., Campbell, A., Fleischmann, M., & Savelsbergh, M. W. P. (2011). Time slot management in attended home delivery. *Transportation Science, 45*(3), 435–449. https://doi.org/10.1287/trsc.1100.0346.

Agatz, N. A. H., Fan, Y., & Stam, D. (2021a). The impact of green labels on time slot choice and operational sustainability. *Production and Operations Management, 30*(7), 2285–2303. https://doi.org/10.1111/poms.13368.

Agatz, N. A. H., Fleischmann, M., & Van Nunen, J. A. (2008). E-fulfillment and multi-channel distribution – A review. *European Journal of Operational Research, 187*(2), 339–356. https://doi.org/10.1016/j.ejor.2007.04.024.

Agatz, N. A. H., Hewitt, M., & Thomas, B. W. (2021b). Make no little plans": Impactful research to solve the next generation of transportation problems. *Networks, 77*(2), 269–286. https://doi.org/10.1002/net.22002.

Al-Kanj, L., Nascimento, J., & Powell, W. B. (2020). Approximate dynamic programming for planning a ride-hailing system using autonomous fleets of electric vehicles. *European Journal of Operational Research, 284*(3), 1088–1106. https://doi.org/10.1016/j.ejor.2020.01.033.

Alonso-Mora, J., Wallar, A., & Rus, D. (2017). Predictive routing for autonomous mobility-on-demand systems with ride-sharing. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 3583–3590). https://doi.org/10.1109/IROS.2017.8206203.

Alptekinoğlu, A., & Semple, J. H. (2016). The exponomial choice model: A new alternative for assortment and price optimization. *Operations Research, 64*(1), 79–93. https://doi.org/10.1287/opre.2015.1459.

Angelelli, E., Archetti, C., Filippi, C., & Vindigni, M. (2021). A dynamic and probabilistic orienteering problem. *Computers & Operations Research, 136*, Article 105454. https://doi.org/10.1016/j.cor.2021.105454.

Archetti, C., & Bertazzi, L. (2021). Recent challenges in routing and inventory routing: E-commerce and last-mile delivery. *Networks, 77*(2), 255–268. https://doi.org/10.1002/net.21995.

Archetti, C., Guerriero, F., & Macrina, G. (2021). The online vehicle routing problem with occasional drivers. *Computers & Operations Research, 127*, Article 105144. https://doi.org/10.1016/j.cor.2020.105144.

Asdemir, K., Jacob, V. S., & Krishnan, R. (2009). Dynamic pricing of multiple home delivery options. *European Journal of Operational Research, 196*(1), 246–257. https://doi.org/10.1016/j.ejor.2008.03.005.

Atasoy, B., Ikeda, T., Song, X., & Ben-Akiva, M.E. (2015). The concept and impact analysis of a flexible mobility on demand system. *Transportation Research Part C: Emerging Technologies,* 56, 373–392. doi: 10.1016/j.trc.2015.04.009.

Avraham, E., & Raviv, T. (2021). The steady-state mobile personnel booking problem. *Transportation Research Part B: Methodological, 154*, 266–288. https://doi.org/10.1016/j.trb.2021.10.008.

Azi, N., Gendreau, M., & Potvin, J.-Y. (2012). A dynamic vehicle routing problem with multiple delivery routes. *Annals of Operations Research, 199*(1), 103–112. https://doi.org/10.1007/s10479-011-0991-3.

Banerjee, S., Johari, R., & Riquelme, C. (2016). Dynamic pricing in ridesharing platforms. *ACM SIGecom Exchanges, 15*(1), 65–70. https://doi.org/10.1145/2994501.2994505.

Bechler, G., Steinhardt, C., & Mackert, J. (2021). On the linear integration of attraction choice models in business optimization problems. *SN Operations Research Forum, 2*(1), 1–13. https://doi.org/10.1007/s43069-021-00056-1.

Bent, R. W., & van Hentenryck, P. (2004). Scenario-based planning for partially dynamic vehicle routing with stochastic customers. *Operations Research, 52*(6), 977–987. https://doi.org/10.1287/opre.1040.0124.

Berbeglia, G., Cordeau, J. F., & Laporte, G. (2010). Dynamic pickup and delivery problems. *European Journal of Operational Research, 202*(1), 8–15. https://doi.org/10.1016/j.ejor.2009.04.024.

Berbeglia, G., Garassino, A., & Vulcano, G. (2021). A comparative empirical study of discrete choice models in retail operations. *Management Science, online first*. https://doi.org/10.1287/mnsc.2021.4069.

Berbeglia, G., Pesant, G., & Rousseau, L.-M. (2011). Checking the feasibility of dial-a-ride instances using constraint programming. *Transportation Science, 45*(3), 399–412. https://doi.org/10.1287/trsc.1100.0336.

Bertsimas, D., Jaillet, P., & Martin, S. (2019). Online vehicle routing: The edge of optimization in large-scale applications. *Operations Research, 67*(1), 143–162. https://doi.org/10.1287/opre.2018.1763.

Bondoux, N., Nguyen, A. Q., Fiig, T., & Acuna-Agost, R. (2020). Reinforcement learning applied to airline revenue management. *Journal of Revenue and Pricing Management, 19*(5), 1–17. https://doi.org/10.1057/s41272-020-00228-4.

Boysen, N., Fedtke, S., & Schwerdfeger, S. (2021). Last-mile delivery concepts: A survey from an operational research perspective. *OR Spectrum, 43*(1), 1–58. https://doi.org/10.1007/s00291-020-00607-8.

Brailsford, S. C., Potts, C. N., & Smith, B. M. (1999). Constraint satisfaction problems: Algorithms and applications. *European Journal of Operational Research, 119*(3), 557–581. https://doi.org/10.1016/S0377-2217(98)00364-6.

Bruck, B. P., Cordeau, J.-F., & Iori, M. (2018). A practical time slot management and routing problem for attended home services. *Omega, 81*, 208–219. https://doi.org/10.1016/j.omega.2017.11.003.

Campbell, A. M., & Savelsbergh, M. W. P. (2004). Efficient insertion heuristics for vehicle routing and scheduling problems. *Transportation Science, 38*(3), 369–378. https://doi.org/10.1287/trsc.1030.0046.

Campbell, A. M., & Savelsbergh, M. W. P. (2005). Decision support for consumer direct grocery initiatives. *Transportation Science, 39*(3), 313–327. https://doi.org/10.1287/trsc.1040.0105.

Campbell, A. M., & Savelsbergh, M. W. P. (2006). Incentive schemes for attended home delivery services. *Transportation Science, 40*(3), 327–341. https://doi.org/10.1287/trsc.1050.0136.

Chao, I. M., Golden, B. L., & Wasil, E. A. (1996). A fast and effective heuristic for the orienteering problem. *European Journal of Operational Research, 88*(3), 475–489. https://doi.org/10.1016/0377-2217(95)00035-6.

Chen, H., Jiao, Y., Qin, Z., Tang, X., Li, H., An, B., et al., (2019). InBEDE: Integrating contextual bandit with TD learning for joint pricing and dispatch of ride-hailing platforms. In *2019 IEEE International Conference on Data Mining (ICDM)* (pp. 61–70). https://doi.org/10.1109/ICDM.2019.00016.

Chen, X., Thomas, B. W., & Hewitt, M. (2016). The technician routing problem with experience-based service times. *Omega, 61*, 49–61. https://doi.org/10.1016/j.omega.2015.07.006.

Chen, X., Ulmer, M. W., & Thomas, B. W. (2022). Deep Q-learning for same-day delivery with vehicles and drones. *European Journal of Operational Research, 298*(3), 939–952. https://doi.org/10.1016/j.ejor.2021.06.021.

Chen, X., Wang, T., Thomas, B. W., & Ulmer, M. W. (2020). *Same-day delivery with fairness. working paper*. University of Iowa.

Church, G. (2019). The maths problem that could bring the world to a halt. *BBC*. Retrieved from https://www.bbc.com/future/article/20190606-the-maths-problem-that-modern-life-depends-on . Last accessed: 21/03/2022.

Côté, J. F., de Queiroz, T. A., Gallesi, F., & Iori, M. (2021). *Dynamic optimization algorithms for same-day delivery problems. working paper*. Université Laval.

Daganzo, C. F. (1987). Modeling distribution problems with time windows: Part I. *Transportation Science, 21*(3), 171–179. https://doi.org/10.1287/trsc.21.3.171.

Davis, J., Gallego, G., & Topaloglu, H. (2013). *Assortment planning under the multinomial logit model with totally unimodular constraint structures. working paper*. Cornell University.

Dayarian, I., Savelsbergh, M. W. P., & Clarke, J.-P. (2020). Same-day delivery with drone resupply. *Transportation Science, 54*(1), 229–249. https://doi.org/10.1287/trsc.2019.0944.

Dong, L., Kouvelis, P., & Tian, Z. (2009). Dynamic pricing and inventory control of substitute products. *Manufacturing & Service Operations Management, 11*(2), 317–339. https://doi.org/10.1287/msom.1080.0221.

Dumouchelle, J., Frejinger, E., & Lodi, A. (2021). Can machine learning help in solving cargo capacity management booking control problems? *Working paper*. Polytechnique Montréal.

Elting, S., & Ehmke, J. F. (2021). Potential of shared taxi services in rural areas – A case study. *Transportation Research Procedia, 52*, 661–668. https://doi.org/10.1016/j.trpro.2021.01.079.

Erdmann, M., Dandl, F., & Bogenberger, K. (2021). Combining immediate customer responses and car–passenger reassignments in on-demand mobility services. *Transportation Research Part C: Emerging Technologies, 126*, Article 103104. https://doi.org/10.1016/j.trc.2021.103104.

Feldman, J. B., & Topaloglu, H. (2017). Revenue management under the Markov chain choice model. *Operations Research, 65*(5), 1322–1342. https://doi.org/10.1287/opre.2017.1628.

Fielbaum, A., Kronmueller, M., & Alonso-Mora, J. (2021). Anticipatory routing methods for an on-demand ridepooling mobility system. *Transportation*, 1–42. https://doi.org/10.1007/s11116-021-10232-1.

Fisher, M. L., & Jaikumar, R. (1981). A generalized assignment heuristic for vehicle routing. *Networks, 11*(2), 109–124. https://doi.org/10.1002/net.3230110205.

Gallego, G., Ratliff, R., & Shebalov, S. (2015). A general attraction model and sales-based linear program for network revenue management under customer choice. *Operations Research, 63*(1), 212–232. https://doi.org/10.1287/opre.2014.1328.

Gallego, G., & Topaloglu, H. (2019). *Revenue management and pricing analytics*. New York, NY: Springer. https://doi.org/10.1007/978-1-4939-9606-3.

Ghiani, G., Manni, E., Quaranta, A., & Triki, C. (2009). Anticipatory algorithms for same-day courier dispatching. *Transportation Research Part E: Logistics and Transportation Review, 45*(1), 96–106. https://doi.org/10.1016/j.tre.2008.08.003.

Giallombardo, G., Guerriero, F., & Miglionico, G. (2020). *Profit maximization via capacity control for distribution logistics problems. working paper*. University of Calabria.

Haferkamp, J., & Ehmke, J. F. (2022). Effectiveness of demand and fulfillment control in dynamic fleet management of ride-sharing systems. *Networks, 79*(3), 314–337. https://doi.org/10.1002/net.22062.

Haliem, M., Mani, G., Aggarwal, V., & Bhargava, B. (2021). A distributed model-free ride-sharing approach for joint matching, pricing, and dispatching using deep reinforcement learning. *IEEE Transactions on Intelligent Transportation Systems, 22*(12), 7931–7942. https://doi.org/10.1109/TITS.2021.3096537.

Hazan, J., Lang, N., Wegscheider, A., & Fassenot, B. (2019). *On-demand transit can unlock urban mobility*. Boston Consulting Group Retrieved from https://www.bcg.com/de-de/publications/2019/on-demand-transit-can-unlock-urban-mobility Last accessed: 21/03/2022.

Holler, J., Vuorio, R., Qin, Z., Tang, X., Jiao, Y., Jin, T., et al., (2019). Deep reinforcement learning for multi-driver vehicle dispatching and repositioning problem. In *2019 IEEE International Conference on Data Mining (ICDM)* (pp. 1090–1095). https://doi.org/10.1109/ICDM.2019.00129.

Hosni, H., Naoum-Sawaya, J., & Artail, H. (2014). The shared-taxi problem: Formulation and solution methods. *Transportation Research Part B: Methodological, 70*, 303–318. https://doi.org/10.1016/j.trb.2014.09.011.

Ichoua, S., Gendreau, M., & Potvin, J.-Y. (2006). Exploiting knowledge about future demands for real-time vehicle dispatching. *Transportation Science, 40*(2), 211–225. https://doi.org/10.1287/trsc.1050.0114.

Jahanshahi, H., Bozanta, A., Cevik, M., Kavuk, E.M., .Tosun, A., Sonuc, S.B. e.t al. (2022). A deep reinforcement learning approach for the meal delivery problem. *Knowledge-Based Systems,* 243, 108489. doi: 10.1016/j.knosys.2022.108489.

Klapp, M. A., Erera, A. L., & Toriello, A. (2018). The dynamic dispatch waves problem for same-day delivery. *European Journal of Operational Research, 271*(2), 519–534. https://doi.org/10.1016/j.ejor.2018.05.032.

Klapp, M. A., Erera, A. L., & Toriello, A. (2020). Request acceptance in same-day delivery. *Transportation Research Part E: Logistics and Transportation Review, 143*, Article 102083. https://doi.org/10.1016/j.tre.2020.102083.

Klein, R., Koch, S., Steinhardt, C., & Strauss, A. K. (2020). A review of revenue management: Recent generalizations and advances in industry applications. *European Journal of Operational Research, 284*(2), 397–412. https://doi.org/10.1016/j.ejor.2019.06.034.

Klein, R., Mackert, J., Neugebauer, M., & Steinhardt, C. (2018). A model-based approximation of opportunity cost for dynamic pricing in attended home delivery. *OR Spectrum, 40*(4), 969–996. https://doi.org/10.1007/s00291-017-0501-3.

Klein, R., Neugebauer, M., Ratkovitch, D., & Steinhardt, C. (2019). Differentiated time slot pricing under routing considerations in attended home delivery. *Transportation Science, 53*(1), 236–255. https://doi.org/10.1287/trsc.2017.0738.

Klein, V., & Steinhardt, C. (2021). *Dynamic demand management and online tour planning for same-day delivery. working paper*. Bundeswehr University Munich.

Koch, S., & Klein, R. (2020). Route-based approximate dynamic programming for dynamic pricing in attended home delivery. *European Journal of Operational Research, 287*(2), 633–652. https://doi.org/10.1016/j.ejor.2020.04.002.

Köhler, C., Ehmke, J. F., & Campbell, A. M. (2020). Flexible time window management for attended home deliveries. *Omega, 91*, Article 102023. https://doi.org/10.1016/j.omega.2019.01.001.

Köhler, C., Ehmke, J. F., Campbell, A. M., & Cleophas, C. (2019). *Flexible dynamic time window pricing for attended home deliveries. working paper*. University of Magdeburg. https://doi.org/10.24352/UB.OVGU-2019-087.

Kök, A. G., & Fisher, M. L. (2007). Demand estimation and assortment optimization under substitution: Methodology and application. *Operations Research, 55*(6), 1001–1021. https://doi.org/10.1287/opre.1070.0409.

Kullman, N., Cousineau, M., Goodson, J. C., & Mendoza, J. (2021). Dynamic ride-hailing with electric vehicles. *Transportation Science, online first*. https://doi.org/10.1287/trsc.2021.1042.

La Rocca, C. R, & Cordeau, J.-F. (2019). Heuristics for electric taxi fleet management at Teo Taxi. *Information Systems and Operational Research, 57*(4), 642–666. https://doi.org/10.1080/03155986.2019.1607808.

Lang, M. A. K., & Cleophas, C. (2020). Establishing an extendable benchmarking framework for E-fulfillment. In *Proceedings of the 53rd Hawaii International Conference on System Sciences* (pp. 1589–1598). https://doi.org/10.24251/HICSS.2020.195.

Lang, M. A. K., Cleophas, C., & Ehmke, J. F. (2021a). Anticipative dynamic slotting for attended home deliveries. *Operations Research Forum, 2*(4), 1–39. https://doi.org/10.1007/s43069-021-00086-9.

Lang, M. A. K., Cleophas, C., & Ehmke, J. F. (2021b). Multi-criteria decision making in dynamic slotting for attended home deliveries. *Omega, 102*, Article 102305. https://doi.org/10.1016/j.omega.2020.102305.

Lebedev, D., Margellos, K., & Goulart, P. (2020). *Approximate dynamic programming for delivery time slot pricing: A sensitivity analysis. working paper*. University of Oxford.

Lebedev, D., Margellos, K., & Goulart, P. (2022). Convexity and feedback in approximate dynamic programming for delivery time slot pricing. *IEEE Transactions on Control Systems Technology, 30*(2), 893–900. https://doi.org/10.1109/TCST.2021.3093648.

Lee, A., & Savelsbergh, M. W. P. (2015). Dynamic ridesharing: Is there a role for dedicated drivers? *Transportation Research Part B: Methodological, 81*(2), 483–497. https://doi.org/10.1016/j.trb.2015.02.013.

Liu, Q., & van Ryzin, G. (2008). On the choice-based linear programming model for network revenue management. *Manufacturing & Service Operations Management, 10*(2), 288–310. https://doi.org/10.1287/msom.1070.0169.

Lotfi, S., & Abdelghany, K. (2022). Ride matching and vehicle routing for on-demand mobility services. *Journal of Heuristics, online first*. https://doi.org/10.1007/s10732-022-09491-7.

Mackert, J. (2019). Choice-based dynamic time slot management in attended home delivery. *Computers & Industrial Engineering, 129*, 333–345. https://doi.org/10.1016/j.cie.2019.01.048.

Mackert, J., Steinhardt, C., & Klein, R. (2019). Integrating customer choice in differentiated slotting for last-mile logistics. *Logistics Research, 12*(1), 5. https://doi.org/10.23773/2019_5.

Ni, L., Sun, B., Wang, S., & Tsang, D. H. (2021). Dynamic pricing mechanism design for electric mobility-on-demand systems. *IEEE Transactions on Intelligent Transportation Systems, online first*. https://doi.org/10.1109/TITS.2021.3103199.

Pillac, V., Gendreau, M., Guéret, C., & Medaglia, A. L. (2013). A review of dynamic vehicle routing problems. *European Journal of Operational Research, 225*(1), 1–11. https://doi.org/10.1016/j.ejor.2012.08.015.

Pisinger, D., & Ropke, S. (2007). A general heuristic for vehicle routing problems. *Computers & Operations Research, 34*(8), 2403–2435. https://doi.org/10.1016/j.cor.2005.09.012.

Poggi, N., Carrera, D., Gavaldà, R., Ayguadé, E., & Torres, J. (2014). A methodology for the evaluation of high response time on E-commerce users and sales. *Information Systems Frontiers, 16*(5), 867–885. https://doi.org/10.1007/s10796-012-9387-4.

Powell, W. B. (2011). *Approximate dynamic programming: Solving the curses of dimensionality* (2nd ed.). Hoboken, NJ: John Wiley & Sons. https://doi.org/10.1002/9781118029176.

Powell, W. B. (2019). A unified framework for stochastic optimization. *European Journal of Operational Research, 275*(3), 795–821. https://doi.org/10.1016/j.ejor.2018.07.014.

Prokhorchuk, A., Dauwels, J., & Jaillet, P. (2019). *Stochastic dynamic pricing for same–day delivery routing. working paper*. Nanyang Technological University.

Psaraftis, H. N., Wen, M., & Kontovas, C. A. (2016). Dynamic vehicle routing problems: Three decades and counting. *Networks, 67*(1), 3–31. https://doi.org/10.1002/net.21628.

Qin, Z., Tang, X., Jiao, Y., Zhang, F., Xu, Z., Zhu, H., et al., (2020). Ride-hailing order dispatching at DiDi via reinforcement learning. *INFORMS Journal on Applied Analytics, 50*(5), 272–286. https://doi.org/10.1287/inte.2020.1047.

Qiu, H., Li, R., & Zhao, J. (2018). *Dynamic pricing in shared mobility on demand service. working paper*. Massachusetts Institute of Technology.

Santi, P., Resta, G., Szell, M., Sobolevsky, S., Strogatz, S. H., & Ratti, C. (2014). Quantifying the benefits of vehicle pooling with shareability networks. *Proceedings of the National Academy of Sciences of the United States of America, 111*(37), 13290–13294. https://doi.org/10.1073/pnas.1403657111.

Savelsbergh, M. W. P. (1985). Local search in routing problems with time windows. *Annals of Operations Research, 4*, 285–305. https://doi.org/10.1007/BF02022044.

Snoeck, A., Merchán, D., & Winkenbach, M. (2020). Revenue management in last-mile delivery: State-of-the-art and future research directions. *Transportation Research Procedia,* 46, 109–116. doi: 10.1016/j.trpro.2020.03.170.

Soeffker, N., Ulmer, M. W., & Mattfeld, D. C. (2017). On fairness aspects of customer acceptance mechanisms in dynamic vehicle routing. In *Proceedings of Logistikmanagement* (pp. 17–24).

Soeffker, N., Ulmer, M. W., & Mattfeld, D. C. (2022). Stochastic dynamic vehicle routing in the light of prescriptive analytics: A review. *European Journal of Operational Research, 298*(3), 801–820. https://doi.org/10.1016/j.ejor.2021.07.014.

Solomon, M. M. (1987). Algorithms for the vehicle routing and scheduling problems with time window constraints. *Operations Research, 35*(2), 254–265. https://doi.org/10.1287/opre.35.2.254.

Souffriau, W., Vansteenwegen, P., Vanden Berghe, G., & Van Oudheusden, D. (2013). The multiconstraint team orienteering problem with multiple time windows. *Transportation Science, 47*(1), 53–63. https://doi.org/10.1287/trsc.1110.0377.

Srour, F. J., Agatz, N., & Oppen, J. (2018). Strategies for handling temporal uncertainty in pickup and delivery problems with time windows. *Transportation Science, 52*(1), 3–19. https://doi.org/10.1287/trsc.2015.0658.

Strauss, A. K., Gülpinar, N., & Zheng, Y. (2021). Dynamic pricing of flexible time slots for attended home delivery. *European Journal of Operational Research, 294*(3), 1022–1041. https://doi.org/10.1016/j.ejor.2020.03.007.

Strauss, A. K., Klein, R., & Steinhardt, C. (2018). A review of choice-based revenue management: Theory and methods. *European Journal of Operational Research, 271*(2), 375–387. https://doi.org/10.1016/j.ejor.2018.01.011.

Talluri, K. T., & van Ryzin, G. (2004a). *The theory and practice of revenue management*. Boston, MA: Springer. https://doi.org/10.1007/b139000.

Talluri, K. T., & van Ryzin, G. (2004b). Revenue management under a general discrete choice model of consumer behavior. *Management Science, 50*(1), 15–33. https://doi.org/10.1287/mnsc.1030.0147.

Taylor, T. A. (2018). On-demand service platforms. *Manufacturing & Service Operations Management, 20*(4), 704–720. https://doi.org/10.1287/msom.2017.0678.

Toth, P., & Vigo, D. (2014). (Eds.).Vehicle routing: Problems, methods, and applications. Philadelphia, PA: Society for Industrial and Applied Mathematics. doi: 10.1137/1.9781611973594.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511805271.

Ulmer, M. W. (2017). *Approximate dynamic programming for dynamic vehicle routing*. Cham: Springer. https://doi.org/10.1007/978-3-319-55511-9.

Ulmer, M. W. (2020a). Dynamic pricing and routing for same-day delivery. *Transportation Science, 54*(4), 1016–1033. https://doi.org/10.1287/trsc.2019.0958.

Ulmer, M. W. (2020b). Horizontal combinations of online and offline approximate dynamic programming for stochastic dynamic vehicle routing. *Central European Journal of Operations Research, 28*(1), 279–308. https://doi.org/10.1007/s10100-018-0588-x.

Ulmer, M. W., Goodson, J. C., Mattfeld, D. C., & Hennig, M. (2019). Offline-online approximate dynamic programming for dynamic vehicle routing with stochastic requests. *Transportation Science, 53*(1), 185–202. https://doi.org/10.1287/trsc.2017.0767.

Ulmer, M. W., Goodson, J. C., Mattfeld, D. C., & Thomas, B. W. (2020). On modeling stochastic dynamic vehicle routing problems. *EURO Journal on Transportation and Logistics, 9*(2), Article 100008. https://doi.org/10.1016/j.ejtl.2020.100008.

Ulmer, M. W., Mattfeld, D. C., & Köster, F. (2018). Budgeting time for dynamic vehicle routing with stochastic customer requests. *Transportation Science, 52*(1), 20–37. https://doi.org/10.1287/trsc.2016.0719.

Ulmer, M. W., & Thomas, B. W. (2020). Meso-parametric value function approximation for dynamic customer acceptances in delivery routing. *European Journal of Operational Research, 285*(1), 183–195. https://doi.org/10.1016/j.ejor.2019.04.029.

van der Hagen, L., Agatz, N., Spliet, R., Visser, T. R., & Kok, A. L. (2022). *Machine learning-based feasibility checks for dynamic time slot management. working paper*. Erasmus University Rotterdam. https://doi.org/10.2139/ssrn.4011237.

Vansteenwegen, P., & Gunawan, A. (2019). *Orienteering problems: Models and algorithms for vehicle routing problems with profits*. Cham: Springer. https://doi.org/10.1007/978-3-030-29746-6.

Vinsensius, A., Wang, Y., Chew, E. K., & Lee, L. H. (2020). Dynamic incentive mechanism for delivery slot management in e-commerce attended home delivery. *Transportation Science, 54*(3), 567–587. https://doi.org/10.1287/trsc.2019.0953.

Voccia, S. A., Campbell, A. M., & Thomas, B. W. (2019). The same-day delivery problem for online purchases. *Transportation Science, 53*(1), 167–184. https://doi.org/10.1287/trsc.2016.0732.

Wang, L., Zeng, L., Ma, W., & Guo, Y. (2021). Integrating passenger incentives to optimize routing for demand-responsive customized bus systems. *IEEE access : practical innovations, open solutions, 9*, 21507–21521. https://doi.org/10.1109/ACCESS.2021.3055855.

Wang, Y.-S., Wu, S.-C., Lin, H.-H., & Wang, Y.-Y. (2011). The relationship of service failure severity, service recovery justice and perceived switching costs with customer loyalty in the context of e-tailing. *International Journal of Information Management, 31*(4), 350–359. https://doi.org/10.1016/j.ijinfomgt.2010.09.001.

Xu, Z., Li, Z., Guan, Q., Zhang, D., Li, Q., Nan, J., et al., (2018). Large-scale order dispatch in on-demand ride-hailing platforms: A learning and planning approach. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (pp. 905–913). https://doi.org/10.1145/3219819.3219824.

Yan, C., Zhu, H., Korolko, N., & Woodward, D. (2020). Dynamic pricing and matching in ride-hailing platforms. *Naval Research Logistics, 67*(8), 705–724. https://doi.org/10.1002/nav.21872.

Yang, X., & Strauss, A. K. (2017). An approximate dynamic programming approach to attended home delivery management. *European Journal of Operational Research, 263*(3), 935–945. https://doi.org/10.1016/j.ejor.2017.06.034.

Yang, X., Strauss, A. K., Currie, C. S. M., & Eglese, R. (2016). Choice-based demand management and vehicle routing in e-fulfillment. *Transportation Science, 50*(2), 473–488. https://doi.org/10.1287/trsc.2014.0549.

Zhang, J., Luo, K., Florio, A. M., & Van Woensel, T. (2022). *Solving large-scale dynamic vehicle routing problems with stochastic requests. working paper*. Eindhoven University of Technology.