

Chapter 2

Rich Vehicle Routing: Environment

In this chapter, we first recall the development in the field of vehicle routing problems (VRPs). We then describe the characteristics of rich vehicle routing problems (RVRPs) in Sect. 2.2 focusing on uncertainty and replanning aspects. We briefly describe logistics management (LM) in Sect. 2.3 and embed (rich) vehicle routing in context of LM's hierarchical planning in Sect. 2.4. We describe the environment rich vehicle routing is conducted in, the recent developments, and emerging challenges in Sect. 2.5. In Sects. 2.5.1–2.5.3, we identify travel times, service times, customer demands, and requests as the four main drivers of uncertainty. We further identify time windows, working hours, and capacities as the major constraints and costs and reliability as the major objectives for RVRPs induced by the practical applications.

Uncertainty results in the requirement for replanning. Further, a consideration of possible future events in current planning is desired. Therefore, we describe the technologies enabling replanning and stepwise planning as well as predictions of uncertain future events in Sects. 2.5.4 and 2.5.5. Since the majority of routing applications is road-based and uncertainty and the requirement for replanning occur especially in conurbations, we focus on road-based routing in urban areas.

2.1 Vehicle Routing

Vehicle routing reflects the quantitative scientific field for servicing customers by a fleet of vehicles. Vehicle routing problems have a long tradition. As first VRP the classical traveling salesperson problem (TSP) can be seen. In the TSP, a salesperson visits a set of customers. The objective is to determine a *tour* visiting every customer with minimal overall travel costs. As the TSP, the vast majority of VRPs are considered static and deterministic meaning that all information is known a-priori. These VRPs are usually modeled via mixed integer programs (MIPs) based on a mathematical graph. These graphs consist of a set of vertexes and a set of connecting edges. The vertexes represent customers or depots. The edges represent the paths between

customers and depots. Edges usually contain costs. These costs depict the travel times or distances between customers. For VRPs, a solution generally is defined by the assignment of customers to vehicles and the sequence of the assigned customers for every vehicle, i.e., the classical idea of “routing”.

Solutions for static and deterministic VRPs are derived with methods of combinatorial optimization. Optimal solutions are achieved by means of branch and bound (Land and Doig 1960), branch and cut algorithms (Nemhauser and Wolsey 1988), or dynamic programming (Christofides et al. 1981). The derivation of solutions for VRPs is generally of non-polynomial complexity (Garey and Johnson 1979), i.e., a small increase in the instance’s size results in a significant increase in the solution space. Optimal solutions can only be obtained for instances of small size. For larger instances, solutions are derived by a “good guess” of how an optimal solution may look like. These approaches are called *heuristics*. A classical heuristic for the sequencing of customers per vehicle is, e.g., cheapest insertion by Rosenkrantz et al. (1974). In the last decades, more elaborate heuristics have emerged. These *metaheuristics* systematically explore the VRP’s solution space for a near-optimal solution (Blum and Roli 2003). Metaheuristics often combine (optimal) MIP-solution techniques with heuristics leading to so called *matheuristics* (Hansen et al. 2009). Matheuristics generally divide the global problem in smaller sub-problems. The sub-problems are selected heuristically and often solved to (local) optimality. In essence, the body of research and methods for static and deterministic VRPs is vast. We refer the interested reader to Toth and Vigo (2001) for a detailed overview on VRPs.

2.2 RVPR: Characteristics and Definition

Compared to VRPs, work on rich vehicle routing focuses more on real-world routing applications. These practical applications are “rich” with respect to the objectives, constraints, and uncertainties induced by the real-world routing environment (Caceres-Cruz et al. 2014). As a result, quantitative decision support for rich vehicle routing problems is challenging compared to theoretically motivated vehicle routing problems. A major impediment for the application of quantitative decision support methods to RVRPs is the uncertainty, vehicle dispatchers have to face in their planning. In our analysis of rich vehicle routing, we focus on the uncertainty and the resulting requirement for replanning based on uncertain events as well as the integration of uncertainty in planning.

A single, unambiguous definition of RVRPs is not yet available. Lahyani et al. (2012) describe RVRPs to be “either a VRP that incorporates many strategic and tactical aspects and/or a VRP that reflects the complexities of the real-life context by various challenges revealed daily.” RVRPs usually contain complexity in one or several of the following aspects: customers, vehicles, infrastructure, objectives, and constraints. For example, customers may have time windows, vehicles may have

loading capacities, or the objectives may contain multiple criteria. For an extensive taxonomy of RVRPs, the interested reader is referred to Lahyani et al. (2015).

In the following, we focus on two specific aspects of RVRP, uncertainty and the requirement for replanning. Caceres-Cruz et al. (2014) state that “dynamic VRPs (so-called real-time VRP) can be also considered as part of the overall RVRP scope.” In this context, *dynamic* means that subsequent decision points are considered in contrast to *static* problems with only a single (a priori) decision. Subsequent decision points are especially common if “uncertainty over some variables” is given forcing dispatchers to adapt their current plans. Lahyani et al. (2015) define these types of RVRPs as dynamic and *stochastic*: “The *deterministic* routing problem assumes that the problem parameters are known with certainty while the *stochastic* data assumes that probability distributions are associated with them.” In essence, dynamism and stochasticity are two aspects distinguishing many RVRPs and impeding the application and the performance of conventional quantitative approaches designed for plain VRPs (Powell et al. 2000).

2.3 RVRPs in Logistics Management

In this section, we embed rich vehicle routing as part of company’s logistics management. In 1986, the Council of Logistics Management defines logistics management as follows (Stock and Lambert 2001).

“Logistics management is an integrating function which coordinates and optimizes all logistics activities, as well as integrates logistics activities with other functions. ... Logistics management ... plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services, and related information between the point of origin and the point of consumption in order to meet customers’ requirements.”

In context of LM, vehicle routing is conducted to deliver or pick up goods and to conduct services at customers. LM installs and controls the infrastructure required for vehicle routing. This concerns the construction and maintenance of storage facilities like warehouses or depots and the according inventory management. Further, LM provides, manages, and maintains the fleet to conduct routing. LM is also responsible for the planning of routes and assignment of customers to vehicles. Stock and Lambert (2001) extend the definition by explicitly adding *forecasting* and therefore the anticipation of future events like customer demands to the tasks of LM. We define forecasting and present the available tools in Sect. 2.5.5. First, we classify vehicle routing in LM’s decision making hierarchies and give an overview of the recent developments in real-world routing applications in the context of LM and vehicle routing.

Table 2.1 Hierarchies

Level	Impact	LM	Decisions
Strategical	Long term	Network	Infrastructure
Tactical	Medium term	Service network	Constraints
Operational	Short term	Vehicle routing	Assignment, sequence

2.4 RVRPs in Hierarchical Decision Making

Hierarchical decision making differentiates three levels: strategical, tactical, and operational (Schneeweiss 1999, p. 109ff). Crainic (2000) gives an overview of the management levels regarding LM and transportation. Table 2.1 shows the three levels and their impact on the logistical processes.

On the strategical level, long term decisions are made considering months and years in planning. The planning is conducted on highly aggregated information. Strategical decisions are expensive and not easily alterable. On the tactical level, medium term planning is conducted for weeks and months. Decision making is still performed on aggregated information. On the operational level, strategical and tactical plans are implemented in short term. The operational level consists of daily planning on highly detailed information.

In the context of logistics, the three levels can be differentiated as follows. On the strategical level, decisions are made especially regarding the *infrastructure*, i.e., the depot(s) and the fleet of vehicles. This is often conducted by network planning (Salvendy 2001, p. 1472ff). On the tactical level, *constraints* as driver shifts, vehicles' maintenance strategies, and the specifications of the products (e.g., goods or services) are defined. Transportation flows in the service area are determined. Product specifications may be, e.g., prices for services or deliveries, but also the characteristics of time windows or working hours. Planning on the tactical level is conducted by service network design.

Crainic (2000) defines the tasks on the operational level in transportation applications as “the implementation and adjustment of schedules for services, crews, and maintenance activities, the routing and dispatching of vehicles and crews; the allocation of scarce resources.” Dispatchers plan “in a highly dynamic environment where the time factor plays an important role and detailed representations of vehicles, facilities and activities are essential.” On the operational level, the vehicles are dispatched to serve customers given the infrastructure, fleets, and constraints like driver shifts. Dispatchers implement routing plans considering infrastructure, resources, time, and constraints. Routing consists of assignment and sequencing decisions and is mainly planned on the operational level. Customers are assigned to vehicles and the sequence of the assigned customers is determined for every vehicle. Routing is often conducted under uncertainty. In many cases, replanning and adaptations of the plans are required.

Work on RVRPs focuses on the operational level of LM. Nevertheless, dependencies exist between the three planning levels. The given infrastructure and constraints influence the resulting routing decisions. In many cases, the efficiency of strategic and tactical decisions are strongly connected to the applied routing. As a result, many decisions on infrastructure and constraints consider routing. As an example, operational assignments are often induced by a predefined tactical partitioning of the service area.

2.5 Recent Developments of the RVRP-Environment

In this section, we present the recent real-world developments in the field of LM focusing on the developments' impacts to RVRPs. Driving factors of the increasing demand for RVRP-decision support are e-commerce, globalization, urbanization, demography, and new business models enabled by emerging technologies. For the different factors, we examine the increase in uncertainty and the impact on required replanning. Further, we present technological advances allowing for replanning and forecasting.

2.5.1 *E-Commerce and Globalization*

E-commerce is the umbrella term for the trading of goods and services via electronic devices, usually over the internet. For 2015, prognoses assume that the worldwide e-commerce transactions will nearly double compared to 2011 (Capgemini 2012). The number of transactions is expected to reach 38.5 billion. The growth of e-commerce leads to an increase in the quantity of transported goods and a change of customers' behavior. In conjunction with e-commerce, globalization is another driving factor for the increasing demand for transportation. Globalization allows for trading between different countries and continents and further increases the number of online orders and the according shipping. In Germany, the combination of globalization and e-commerce results in around 2.8 billion shipped parcels in 2014 (Esser and Kurte 2015).

Besides the increase in required transportation, e-commerce especially changes customers' behavior and expectation. Ordering and selling goods online is simple and convenient. Online shops are always accessible without any closing hours. Selling online does not require an expensive brick-and-mortar store, but only the possibility of fast shipping. In recent years, a vast range of online shops has emerged. Ordering online saves costs, time, and effort for traveling to the stores and waiting in lines (Bubner et al. 2014). After placing the order, customers can track, change, and update the orders via mobile phone at any point of time (DHL 2013). These possibilities lead to more spontaneous, i.e., uncertain customers' consume behavior. Service providers may have to manage their inventory accordingly.

Along with the change of customers' behavior, the expectations rise. In contrast to shopping at stores, customers do not receive the desired good right after placing the order. Instead, they have to wait until the delivery arrives. Studies show that delivery time and delivery costs are two of the main success factors in e-commerce (Lowe et al. 2014). Customers expect reasonable priced and fast delivery. To match these expectations, same-day delivery is already provided in some cities (Wahba 2015) especially in the field of grocery delivery (Campbell and Savelsbergh 2006). For e-commerce companies, same-day delivery is seen as a main factor for future success (Mangalindan 2013). Providing same-day delivery requires constant adaptations of the delivery plans because new uncertain order *requests* occur during the day when the vehicles are already conducting deliveries. A priori planning is not suitable. In many cases, dispatchers are only able to plan stepwise.

2.5.2 Urbanization and Demography

Urbanization describes the process of people moving from rural to urban areas. The process of modern urbanization started in the 1950s. Currently, more than half of the world population lives in a city. The United Nations expect this number to increase up to two-thirds in 2050 (United Nations 2015). Urbanization impacts both the requirement for transportation and physical services at customers as well as the environment the routing has to be conducted in.

Transportation

A result of the urbanization is an increasing demand for goods, passenger transports, and services. The main business area for delivery and service companies is already located in the cities (Jaana et al. 2013). As described in Sect. 2.5.1, the amount of ordered goods increases. Combined with urbanization, this leads to a substantial growth in good transportation within the city. An extensive overview over the according field of *City Logistics* is given by Taniguchi et al. (2001). In 2007, transportation already caused more than 10% of the overall city traffic (Figliozzi 2007). Last-mile delivery is one of the most expensive parts of the entire supply chain (Gevaers et al. 2011). Therefore, effective and efficient routing is essential for service providers' success.

Beside the transportation of goods, the demand for passenger transport increases. The mobility demand is expected to more than double until 2050 (Schafer and Victor 2000). This development will increase the challenges in public transportation, intermodal transportation, and shared mobility. As a combination of public and individual transportation, the use of demand responsive passenger transport (e.g., dial a ride) increases (American Public Transportation Association 2013). This leads to higher uncertainty in planning and requires immediate responses to new customer requests. Dispatchers further have to dispatch vehicles considering the vehicle's *capacities*. Shared mobility systems have become an essential part of urban transportation. More than 800 cities provide bike sharing systems worldwide. The number

increases rapidly (Steinsiek 2015). The number of users in car sharing systems has doubled in the last two years (European Automobile Manufacturers' Association 2015). Providers of shared mobility systems have to ensure sufficient vehicles and parking spaces given uncertain customer requests and *demands* (Brinkmann et al. 2015).

Services

Due to the growth in urban population, evidently the number of service calls increases. This is especially the case in the field of healthcare. Due to the demographic developments, the percentage of the population aged 65 and over will double until 2050. In Europe, this age class is expected to represent more than one-fourth of the overall population in 2050 (United Nations 2010). In the United States, the required spending for outpatient and hospital treatments is expected to grow by 40% in the next five years (Economist Intelligence Unit 2013a). Services have to adapt to this aging society, e.g., to meet the demands for (ad hoc) house calls and patient transfers (Bubner et al. 2014). The requests for house calls and the *service time* to spend at a patient are often unknown. Dispatchers have to schedule the physicians accordingly, change schedules regarding the required time at a patient and the physicians' *working hours*, and assign new requests to physicians during the day.

2.5.3 Urban Environment and Municipal Regulations

All these tasks have to be conducted in the limited city infrastructure and with respect to environmental conditions. The capacities of streets in a city are determined by the street size and the traffic control strategy (e.g., traffic lights) applied by the city's administrator, i.e., the traffic management (Taniguchi et al. 2001, p. 4). Street sizes in the cities are mainly unalterable. Generally, the control of the traffic management is only able to increase the capacity of one street by reducing the capacity of another. The limited capacity of the streets combined with an increase in traffic volume leads to congestion within the city. Congestion results in an increase in required *travel time* by up to 50% in Europe (TomTom 2015a) and North America (TomTom 2015b). Beside congestion, drivers have to deal with limited parking and delivery zones (Dablanc 2007). This leads to uncertainty in the amount of time to serve a customer. Dispatchers have to consider the uncertainty in travel time and service time while scheduling tours. Further, they have to adapt the plans according to new traffic information or to changes by the traffic management (Köster et al. 2015).

The increase in traffic has led to substantial emissions, e.g., air pollution, carbon dioxide emissions, and noise. Right after the energy sector, the transportation sector is currently the second largest generator of carbon dioxide emissions in the United States (U.S. Energy Information Administration 2015). Transportation is responsible for a major part of emissions in the city (Organization for Economic Cooperation and Development 2013). The emissions lead to decreases in quality of life and citizens' convenience. As countermeasure, municipalities issue fines or restrict access for

vehicles at certain times (Quak and Koster 2009) and due to emission alerts via traffic management (Irvine 2013). The emission alerts are not known, but are influenced by traffic and weather conditions. The traffic management's reactions to these alerts changes the required travel times in these areas. As a result, dispatchers may have to adapt their plans.

2.5.4 Technology

As described in Sect. 2.5.1, technologies like smartphones change customers' behavior and enable new business models forcing dispatchers to replan or even plan step-wise. The technological advances can also be used by dispatchers and vehicle drivers for communication and for replanning their routing and schedules. Digitization and the omnipresence of smartphones enables new modes of transportation, e.g., crowd-sourced delivery (Barr and Wohl 2013), crowdsourced passenger transport (Huet and Chen 2015), drone delivery (Sinha 2013), or delivery to car trunks (Cartledge 2012; Behrmann and Weiss 2014). These new transportation modes may allow dispatchers more flexibility in planning, but also contain uncertainty in both the customer's location and, for crowdsourced transportation, even the accessible fleet.

At every point of time, dispatchers have access to a real time information process, e.g., vehicles' positions via GPS, customers' inventories (Verma and Campbell 2014), or traffic statuses via geographic information systems and digital road maps. A synchronization between the information and planning process, i.e., the recalculation and replanning to updated information is enabled by an increase and an outsourcing of computational resources, e.g., real-time services (Bubner et al. 2014). As a result, dispatchers are able to immediately react to updated information.

The increase in autonomous logistics allows a fast and accurate provision of goods in the warehouses. Together with combined planning of online retailers and delivery companies, e.g., by cloud based supply chain management, this allows a faster response to customer orders eventually enabling same-day delivery (Leukel et al. 2011). This fast provision of goods and response leads to a reduction of planning time and another increase in uncertainty.

2.5.5 Data and Forecasting

A mere reaction to updated information may lead to inefficient planning. It is desirable to plan ahead including forecasts about future events into current plans. Forecasts are derived from experience and knowledge in the field of predictive analytics. This knowledge is mainly hidden in historical data accumulated over time. Recently, decision making based on data gains in importance (Economist Intelligence Unit 2013b). Therefore, data has to be analyzed and included in anticipatory algorithms.

Data Analysis

Computer memory has become cheap. The digital control of devices results in vast amounts of unstructured (big) data (Manyika et al. 2011). With respect to vehicle routing, data is collected regarding the vehicles, the customers, and the goods or services. The collected data implicitly reflects the environmental impacts like weather or traffic statuses. Dispatchers additionally have access to external information and data, e.g., current expected travel times. Amongst others, companies track vehicles' routes, travel times, service times, load, and speed. They further track customers' locations, request times, service times, and the ordered good or service. The collected data may allow forecasts about future events like customer requests or changes in travel time. Nevertheless, the data is often still "untapped" (Bubner et al. 2014).

In order to utilize the data for anticipation of the future, two challenges arise. First, the data has to be transferred to *information*. For this purpose, the large amount of data has to be preprocessed and aggregated. This is conducted in the field of predictive analytics, e.g., by data mining and intelligent data analysis. The interested reader is referred to Hand et al. (2001) and Berthold and Hand (2003) respectively. Second, to use the information in planning and decision making and to allow anticipation, suitable algorithms have to be implemented by the field of prescriptive analytics. In this book, we focus on the second challenge, the derivation and implementation of *anticipatory vehicle routing approaches*.

Anticipation

Anticipation means the inclusion of possible future events like congestion, breakdown of vehicles, or new customer requests into current planning. As an example for anticipation, the police of Los Angeles anticipate potential crimes based on historical data. They schedule their vehicles depending on the daytime and the area (Kelly 2012). Especially, the field of "anticipatory logistics" is emerging (Bubner et al. 2014). Recently, a patent was issued, to anticipate customers' orders before they are actually placed (Spiegel et al. 2012; Kopalle 2014).

Anticipation is achieved in the field of *prescriptive analytics*. Anticipatory planning differs from *myopic* planning. Myopic planning does not consider the future. An anticipatory plan may require more resources and higher costs or may provide less immediate gain, but it is robust or allows adaptations and provides flexibility (Powell et al. 2000). As an example, a robust plan for delivering grocery anticipating uncertain travel times may contain temporal safety buffers (Ehmke et al. 2015). A vehicle may not be able to serve as many customers as following a myopic plan, but it is more likely to meet the customers' time windows. As an example for flexible planning, dispatchers may save an amount of free time budget to serve potential future requests (Ulmer et al. 2017b).

2.6 Implications

As presented in this chapter, the requirement for anticipatory RVRP-solutions rises especially in an urban environment. Dispatchers have to plan with respect to reliability and cost efficiency. The conditions in which vehicle routing is conducted change more and more frequently. Travel times, service times, customer demands, and customer requests are uncertain. These (uncertain) changes force dispatchers to replan with respect to updated information. New technologies allow the immediate reaction to updated information. Nevertheless, the anticipation of the future may be necessary to achieve efficient and effective current plans. An anticipatory plan is not necessarily the immediate “best” plan based on current information, but allows flexibility and reliability regarding the future.

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Ulmer, M.

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