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A model-based survey on operational planning of technician-based after-sales field services

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Abstract

The provision of technician-based after-sales field services, such as installing, repairing, or maintaining consumer goods, requires operational planning to schedule and route skilled technicians under various operational constraints and objectives. From a methodological perspective, these operational planning problems belong to the class of Technician Routing and Scheduling Problems (TRSPs). To address the high heterogeneity of the TRSP literature, we conduct a model-based literature review that structures the literature at the modeling level rather than solely at the problem level. The survey is based on a taxonomy, which allows us to represent a static-deterministic TRSP as a specific configuration of core routing constraints, service- and technician-related constraints, and objectives. The taxonomy also covers stochastic-dynamic TRSPs, which are additionally characterized by sequential decision-making and uncertainty, and are becoming increasingly relevant in both research and practice due to the progress in mobile communication technology. Drawing on the taxonomy-based literature classification, we identify real-world TRSP configurations that are underrepresented in the scientific literature. These include, e.g., TRSPs combining teaming with synchronization as well as TRSPs involving demand management decisions by the provider.

Keywords Technician routing and scheduling · After-sales service · Field service · Teaming · Synchronization · Stochastic-dynamic optimization

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1 Introduction

To ensure the functionality of technically complex products, companies provide on-site *after-sales* services, including installation, maintenance, and repair, executed by skilled, mobile *technicians*. Common examples include services related to home appliances (e.g., washing machines, refrigerators, home electric vehicle chargers), telecommunications systems (e.g., fiber-optic routers or smart home devices), or industrial and office equipment (e.g., forklifts). After-sales services are becoming increasingly important in both B2C and B2B markets, driven by several trends:

- The addition of services to physical product offerings (servitization) to establish additional revenue streams (Kowalkowski et al. 2017).
- The extension of product lifetimes to improve sustainability by repairing and maintaining products rather than purchasing new products (Laitala et al. 2021; Pham and Kiesmüller 2024).
- Differentiation from competitors in light of the increasing product homogenization (Li et al. 2014), which means that customers expect value beyond the mere physical product (Bijvank et al. 2010) and that companies can no longer rely solely on product quality (Zhang et al. 2019; Li et al. 2016).
- Alleviation of customers' concerns about purchasing technically complex products by ensuring that professional support is available when needed (Zhang et al. 2019; Kurata and Nam 2010).

Field services in operations research. Conceptually, after-sales services represent a specific subclass of *field services*, that is, on-site operations conducted by a mobile *workforce*. From an operations research perspective, field services fall under the umbrella of workforce routing and scheduling problems (WRSPs), which address the assignment of mobile workforce (e.g., technicians, nurses, and security guards) to spatially and temporally distributed service requests. WRSPs lie at the intersection of two well-known problems in operations research: vehicle routing problems (VRPs) and workforce scheduling problems (WSPs). VRPs address the planning of routes for mobile workers traveling between locations associated with service requests, considering constraints such as customer time windows, multiple depots, or synchronization. WSPs focus on assigning workers to service requests, taking into account, e.g., skills or teaming. Jointly considering routing and scheduling decisions, WRSPs have been applied to diverse domains including home health care, technical installations, maintenance, and repair.

Technician routing and scheduling problems. This survey focuses on a distinct subclass of WRSPs: technician routing and scheduling problems (TRSPs) arising in the provision of *technician-based after-sales field services* for technically complex products. This term emphasizes the following service features:

- *Technician-based*: Services are provided by skilled mobile *technicians* capable of delivering, installing, maintaining, or repairing products. This distinguishes technicians from mobile workers in other WRSP domains (e.g., nurses, caregivers, security guards).

- *After-sales*: Services are provided after the purchase of a product.
- *Field*: Services must be provided on-site at specific customer locations.

We exclude WRSP applications that fall outside this definition, that is, *home and health care* (e.g., Euchi et al. 2022), *airport ground operations* (e.g., Zamorano et al. 2018), *offshore wind farms* (e.g. Irawan et al. 2017), or *security services* (e.g., Misir et al. 2011).

Service and task types provided by technicians. A customer may issue one or multiple service *requests*. Typically, the provider accepts all requests, which then turn into orders. Nevertheless, limited resources might force the provider to outsource or even entirely reject requests. A service may consist of a single task or multiple tasks. We distinguish three task types: *installation* (initial setup of a product), *maintenance* (preserving functionality), and *repair* (restoring functionality). Depending on service complexity, fulfillment may require:

(a) a *single* technician.
(b) *multipl*e technicians working simultaneously (*teaming*), or.
(c) *multiple* technicians working sequentially (*synchronization*).

We refer to these different cases as service types (a), (b), and (c), respectively. Service type (c) arises when a service consists of multiple interdependent tasks. Consider, e.g., kitchen installation: a mason prepares the structural base, a plumber connects the piping, and an electrician wires the electrical components (Hanafi et al. 2020). Notably, service type (c) can also occur in combination with service type (b).

Constraints and objectives. Assigning technicians to requests involves various operational constraints. *Service-related* constraints specify planning horizon, service type, time windows, equipment requirements, and selectiveness, that is, the option of outsourcing/rejecting requests. In parallel, *technician-related* constraints must be considered, such as skills, depots, working hour limits, overtime policies, and mandatory breaks.

After-sales field service providers consider a wide range of objectives. Objectives can be *cost-oriented* (minimizing travel, labor, overtime, or outsourcing cost), *technician-oriented* (workload balance, limiting working hours and overtime), or *service-oriented* (reducing delays and service completion times, prioritizing high-value or time-critical requests).

Sequential decision making and uncertainty. Early research on technician-based after-sales field services assumed that all decision-relevant parameters for a certain planning horizon are known with certainty and planning decisions can be optimized all at once. The resulting TRSPs are *static-deterministic*, and new works considering this type of TRSP regularly appear to this day.

In contrast, the rapid diffusion of digital distribution channels, e-commerce, and online platforms has fostered online-to-offline business models such as attended home delivery (AHD) and attended home service (AHS), which occur across various industries ranging from grocery retail (e.g., Koch and Klein 2020; Köhler et al. 2024) to technician-based after-sales field services (e.g., IKEA, 2026). Here, customers arrive sequentially at random times via the provider's website or mobile app and request service. Methodologically, managing such services involves sequential decision-making under uncertainty, giving rise to *stochastic-dynamic* TRSPs. For instance, providers have to decide on time window offers (e.g., Köhler et al. 2023; Lang et al. 2021) for incoming requests without knowing the number of future requests, their time window preferences, and their skill or equipment requirements (Cordeau et al. 2024; Ehmke et al. 2024).

We do not review the other two possible combinations (Psaraftis et al. 2016) separately for the following reasons: first, *stochastic-static* TRSPs are considered only by Liu et al. (2019), Rastegar et al. (2024), and Souyris et al. (2013) to model uncertainty in parameters such as service or travel times without sequential decision-making. Since all three contributions reformulate the stochastic problem as a deterministic equivalent via chance-constrained programming or robust optimization, their modeling and solution approaches are closely aligned with the static-deterministic methodology. Second, *deterministic-dynamic* problems do not occur in the TRSP literature because all considered dynamic problems (at least) feature uncertainty regarding requests.

Related surveys. WRSPs–and consequently, TRSPs–have been the topic of several literature surveys.

- Castillo-Salazar et al. (2016) provide one of the earliest structured overviews, combining a literature classification with a computational study to assess the difficulty of solving WRSPs.
- Paraskevopoulos et al. (2017) propose a detailed taxonomy for resource-constrained routing and scheduling problems involving resources such as vehicles, nurses, technicians, and equipment. From a resource perspective, our survey is restricted to those that are relevant to technician-based after-sales field services, namely technicians, vehicles, and equipment (tools and spare parts).
- Cordeau et al. (2024) adopt an application-oriented perspective on AHD and AHS problems. They explicitly state that the home health care routing and scheduling problem and the TRSP are special cases of WRSPs. Further, they find that planning attended home services, depending on the application area, may give rise to either type of problem.
- Cabrera et al. (2026) revisit WRSPs by addressing challenges such as multi-modal routing, team composition, and precedence constraints. Their modeling contribution centers on team composition, and therewith, services of type (b). The considered workforce includes all kinds of mobile workers, not only technicians.

Research gaps. Existing surveys provide valuable taxonomies and methodological overviews, yet they leave three gaps that motivate the survey at hand:

- First, existing surveys do not provide a dedicated treatment of technician-based after-sales field services, despite the growing practical relevance of this market driven by the trends described at the beginning of this section. For instance, the European after-sales service sector for household appliances alone was valued at approximately 1.9 billion Euros, employed around 32,000 workers in 2018 (APPLiA, 2020), and is becoming increasingly competitive (Pham and Kiesmüller

2024).

- Second, while TRSPs are often covered as part of broader WRSP classes, none of the prior surveys considers the modeling of the entire problem family including the three service types (a) single-technician, (b) teaming, and (c) synchronization. However, such a unified consideration is important for two reasons: First, a wide variety of problem variants has evolved that requires dedicated structuring as the research area grows further, in particular in terms of notation and modeling. Second, it allows identifying particularly prominent problem variants, such as type (c) services where delivery and installation are separated with temporal precedence constraints (Qiu et al. 2022).
- Third, existing surveys are limited to static-deterministic problems. In practice, however, mobile communication technology has led to increasing dynamism caused by stochastic information becoming available over time, such as new request arrivals that must be dynamically incorporated into evolving routes and schedules (Ji et al. 2022). Hence, there is an urgent need for surveying the emerging literature stream on stochastic and dynamic TRSPs.

Contribution of our survey. The central contribution of our survey lies in closing the three gaps identified above by proposing a model-based classification of TRSPs arising in technician-based after-sales field services. The classification relies on a modeling taxonomy which allows us to configure the various TRSP formulations as a combination of service- and technician-related constraints, cost-, technician-, or service-oriented objectives, sequential decision-making, and uncertainty, all built around a shared core of routing constraints. We furthermore adopt a unified notation throughout the survey to ensure consistency across the highly heterogeneous literature. By applying our taxonomy to the literature, we provide a comprehensive overview of the scientific state-of-the-art. Beyond that, it yields two secondary contributions:

- First, it enables the systematic reconstruction of existing models: An application-specific TRSP formulation, both static-deterministic and stochastic-dynamic, can be represented by selecting the desired configuration of constraints, objectives, sequential decision-making, and uncertainty. Hence, readers can quickly verify whether the problem they are facing has already been considered and, if so, construct a suitable mathematical model.
- Second, it facilitates an evidence-based identification and development of new TRSP variants. By making modeling dimensions explicit and configurable, it becomes straightforward to identify configurations that have not yet been studied, to extend existing models.

The remainder of this survey is structured as follows: Sect. 2 presents real-world applications of TRSPs in technician-based after-sales field services. Section 3 introduces the taxonomy that serves as the foundation for classifying the literature. Section 4 presents the modeling of static-deterministic TRSPs, which Sect. 5 then extends to stochastic-dynamic problems. Section 6 gives an overview of solution approaches.

Section 7 outlines promising directions for future research, and Sect. 8 concludes with a synthesis of findings.

2 Applications

This section illustrates real-world application domains studied in the literature on technician-based after-sales field services: consumer goods, industrial and office equipment, and telecommunications. Within each domain, problems are further distinguished by the service type. Please note that the absence of certain service types in specific domains indicates a gap in the TRSP literature rather than their absence in practice; for example, type (b) services also occur in the consumer goods domain, e.g., 2-man handling (Rhenus, 2026), but have not yet been formalized in the TRSP literature.

2.1 Consumer goods

Services related to consumer goods such as furniture, home appliances, and electronics represent a major TRSP application domain. Providers deliver products to customers' homes and/or perform installation, maintenance, or repair services to ensure proper product functionality.

- **Single-technician (a)**: Consumer goods can typically be delivered and installed by the same technician. Then, the service provider offers last-mile delivery with optional installation, with services ranging from delivery to complex installation requiring technical skills (e.g., carpentry or high-voltage connections) (e.g., Schubert et al. 2021). Additional examples of type-(a) services without delivery include kitchen installation and repair (Stein et al. 2025) and home appliance repair requiring spare parts to replace malfunctioned components (Pham and Kiesmüller 2022, 2024).
- **Synchronization (c)**: Installation technicians can also travel separately and arrive after delivery, imposing synchronization constraints (e.g., Ali et al., 2021). The resulting TRSPs are commonly referred to as delivery and installation routing problems (DIRPs). A related example without a delivery service is the installation of kitchen furniture comprising multiple interdependent tasks (e.g., mason → plumber → electrician) (Hanafi et al. 2020).

2.2 Industrial and office equipment

Maintenance and repair of industrial and office equipment encompass a broad range of serviced assets. These services are performed directly at customer facilities (e.g., offices, medical centers, factories) and typically require skills in mechanics, hydraulics, or electrical systems.

- **Single-technician (a)**: Represenative examples for tasks that can be executed by a single technician include the maintenance of electronic transaction equipment

(Mathlouthi et al. 2018, 2021a, b) and office machines such as digital printers or copiers (Cavada et al. 2020; Cortés et al. 2014).
- **Teaming (b)**: In safety-critical applications, services typically require teams of technicians with complementary skills. For instance, Rastegar et al. (2024) investigate elevator maintenance. Zamorano and Stolletz (2017) address the maintenance of electric forklifts, where a minimum team size is required because heavy equipment must be manually lifted. Qiu et al. (2023) consider complex medical devices (e.g., dialysis and X-ray machines). Safety, however, is not the only reason for teaming: Pitakaso et al. (2024) consider the operation of mechanical sugarcane harvesters, which are supported by two types of teams, that is, fuel service teams and maintenance teams.

2.3 Telecommunications

Telecommunication network services, such as telephone line repair or fiber-optic cable maintenance, represent the earliest application area.

- **Single-technician (a)**: The TRSP was first introduced by Tsang and Voudouris (1997) in a case study for British Telecom. Since then, numerous studies have focused on problem settings with a single technician and a homogeneous skillset. As a notable exception, Sørensen et al. (2025) distinguish between two technician types working on separate infrastructures, that is, fiber and coaxial networks, implying heterogeneous skill requirements.
- **Teaming (b)**: Teaming is only investigated by Kovacs et al. (2012).

3 Modeling taxonomy

In this section, we introduce the modeling taxonomy that serves as the foundation for classifying the TRSP literature. The taxonomy is shown in Table 1 and captures the full range of TRSP configurations in the literature within the scope of this survey. Inspired by the taxonomy proposed by Paraskevopoulos et al. (2017), our taxonomy is organized along five dimensions. For each dimension, we identify a set of subdimensions and possible realizations. The taxonomy is formalized in Sects. 4 and 5 by presenting the mathematical modeling of all realizations. First, the following three dimensions apply to any TRSP:
Service-related constraints. This dimension characterizes requests:

- **Service type**: The service type distinguishes between requests that can be handled by (a) a *single technician*, (b) those requiring *multiple technicians* arriving simultaneously at the customer location (*teaming*), and (c) different technicians serving a request in a predefined sequence, possibly at different times (*synchronization*).
- **Planning horizon**: Requests can be either fulfilled during a *single period* or over *multiple periods*, meaning that the planning horizon spans several days.
- **Time windows**: Customers may specify *hard time windows*, which must be

Table 1 Taxonomy

Dimension	Subdimension	Realization			
Service-related constraints	Planning horizon (*)	Single-period (SP)	Multi-period (MP)		
	Service type	Single technician (SI)	Teaming (MT)	Synchronization (MS)	
	Time windows	Hard (HA)	Soft (SO)	Multiple (MU)	–
	Equipment	Spare parts (PA)	Tools (TO)	–	
	Selectiveness	✓	–		
Technician-related constraints	Skills	Skill domains (DO)	Skill levels (SL)	Learning (LE)	–
	Working time	Working hours (WH)	Overtime (O)	Breaks (B)	–
	Depot structure (*)	Single-depot (SD)	Multi-depot (MD)		
Objectives	Cost-oriented	Travel cost (TC)	Vehicle fix cost (VC)	Labor cost (LC)	Over-time cost (OT)
		Holding cost (HC)	Outsourcing cost (OC)		
	Technician-oriented	Workl. balance (WB)	Breaks (BR)	Team consist. (CO)	
	Service-oriented	Priorities (PR)	Delay (DE)	Compl. times (CT)	
SDM		Request-based	Day-based	–	
Uncertainty		Request arrivals	Skill requirements	Equipment requirem.	Techni-cian availab.
		Service times	Travel times	Customer choice	–

strictly respected, *soft time windows*, which allow for deviations at a cost, or *multiple (hard) time windows*.

- **Selectiveness**: Request fulfillment may either be mandatory, i.e., all requests must be *accepted* (–), or optional, i.e., requests can be *accepted* or *rejected* (✓). In many applications, service providers receive all requests in advance and automatically treat them as accepted. In such cases, they are referred to as *orders* rather than *requests*. For the sake of completeness, however, we use the term requests throughout this paper to account for the possibility of rejection. In some applications, rejecting a request corresponds to outsourcing its fulfillment to an external provider.
- **Equipment requirements**: These refer to the need for *tools* and/or *spare parts* to fulfill requests.

Technician-related constraints. Technicians are characterized based on subdimensions that influence how they are assigned to requests:

- **Skills**: The skills dimension includes *skill domains* (i.e., categorical qualifications such as electrical work), *proficiency levels* within a domain, and *learning*, which is skill progression over time.

- **Working time**: This subdimension captures constraints on *working hours*, *overtime*, and *breaks*.
- **Depot structure**: This subdimension distinguishes between *single-depot* and *multi-depot* settings.

Objectives. The objective dimension characterizes the criteria used to evaluate and optimize TRSP solutions. We distinguish between three classes of objectives:

- **Cost-oriented objectives**: These aim to minimize the overall operational cost of service fulfillment. Relevant cost components include *travel costs*, *labor* and *overtime costs*, *vehicle fixed costs*, and *holding costs* for unused spare parts.
- **Technician-oriented objectives**: These aim to ensure technician well-being by *balancing workloads* across technicians, avoiding skipped *breaks*, and promoting *consistent team formation*.
- **Service-oriented objectives**: These account for the service quality perceived by customers. They include maximizing sum of *priority* values accrued for accepted requests, minimizing *delays*, and minimizing *service completion times*.

To accommodate stochastic-dynamic TRSPs, we extend this structure by two additional dimensions:
Sequential decision making (SDM). This dimension captures how decisions are taken in response to requests arriving sequentially over the planning horizon. We distinguish two different decision structures (realizations), depending on whether selectiveness is considered:

- *Request-based*: Each arriving request triggers an immediate decision on its acceptance or rejection. If a request is accepted, the customer may either be assigned a time window directly or be offered a set of alternative time windows from which to choose.
- *Day-based*: All requests are accepted upon arrival and decisions relevant for service fulfillment, such as routing or equipment planning, are taken at the end of each day for the following day.

Uncertainty. This dimension captures exogenous information that is not known at the time decisions are made. In the TRSP literature, uncertainty arises from several sources: *request arrivals*, *skill and equipment requirements* of requests, *technician availability* (e.g., due to illness or absence), *service* and *travel times*, and *customer choice behavior* in response to offered time windows.

When applying the taxonomy, depending on the (sub)dimension, either a single realization (e.g., single-period or multi-period planning) or a combination of multiple realizations (e.g., multiple hard time windows) must be selected. To reflect this distinction, all (sub)dimensions that do not allow for combinations of realizations are marked with (*). In some (sub)dimensions, it is possible to select no realization at all, which is indicated by $(-)$ as an additional realization. Moreover, combining realizations across different subdimensions may alter the modeling within a given realization. For example, a single time window may be embedded either in a single-period or a multi-period planning horizon, leading to different modeling variants. In addition, for a single realization, the literature often proposes multiple alternative modeling variants. For example, skills may be modeled either via additional parameters or by restricting the set of request nodes a technician is eligible to visit. For the sake of clarity, we consistently adopt the most prominent modeling variant observed in the literature when presenting realizations.

In this taxonomy, a specific TRSP configuration is a selection of realizations across the five dimensions according to the requirements of a given application. Note that a set of *core routing constraints* (Sect. 4.1) is common to all TRSP configurations and is therefore not treated as an own dimension in the taxonomy. These constraints can be extended by service- and technician-related constraints and objectives. A TRSP defined by a combination of constraints and objectives represents a particular static-deterministic configuration. To configure a stochastic-dynamic TRSP, realizations from the dimensions *sequential decision making* and *uncertainty* must be selected additionally.

In line with this taxonomy, we proceed as follows: Sect. 4 focuses on the static-deterministic modeling. Section 5 then extends this modeling to stochastic-dynamic TRSPs. Both sections introduce a taxonomy-based classification of the literature, followed by a systematic presentation of the modeling.

4 Static-deterministic modeling

In this section, we formalize the modeling taxonomy introduced in Sect. 3 by presenting the mathematical modeling of all realizations identified in the taxonomy for static-deterministic TRSPs. In doing so, the abstract taxonomy is cast into concrete model components that can be combined to represent the diverse configurations encountered in the literature. To provide an overview of the reviewed articles, we first present a classification of the static-deterministic TRSP literature in Table 2.

We include only articles that propose mathematical optimization models or solution approaches and that arise in the application areas of technician-based after-sales field services introduced in Sect. 2. Table 2 is primarily based on peer-reviewed journal articles, complemented by only a few carefully selected contributions from other sources–such as conference papers–included due to their particular relevance.

Subsequently, we present the modeling following the structure of the taxonomy: We first introduce the core routing constraints that are common to all TRSP configurations (Sect. 4.1). This core is then extended by service-related constraints (Sect. 4.2), technician-related constraints (Sect. 4.3), and objectives (Sect. 4.4).

4.1 Core routing constraints

In this section, we introduce the *core routing constraints* that constitute the foundation of all TRSP variants considered in this survey. To model these constraints, we first introduce the basic notation consisting of indices, sets, parameters, and decision variables.

The TRSP variants covered in this survey can be defined on a complete directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{A})$ where $\mathcal{V} = \{0, 1, \ldots, n\}$ is the set of nodes and $\mathcal{A} = \{(i, j) : i, j \in \mathcal{V} : i \neq j\}$ the set of arcs. The depot is located at node 0, and the set of requests is represented by $\mathcal{N} = \{1, \ldots, n\}$. For fulfillment, the provider operates a fleet of vehicles $\mathcal{K} = \{1, \ldots, K\}$. Each request $i \in \mathcal{N}$ is associated with a service time p_{ik} when vehicle $k \in \mathcal{K}$ is used, and each arc $(i, j) \in \mathcal{A}$ is associated with a vehicle-dependent travel time t_{ijk}. Furthermore, a sufficiently large number M is defined. Two types of decision variables are shared across all formulations:

- $a_{ik} \geq 0$: arrival time of vehicle $k \in \mathcal{K}$ at node $i \in \mathcal{V}$, and.
- $x_{ijk} \in \{0, 1\}$: binary routing variable indicating whether arc $(i, j) \in \mathcal{A}$ is traversed by vehicle $k \in \mathcal{K}$.

Based on the introduced notation, the core routing constraints are expressed as follows:

$$\sum_{j\in \mathcal{V}:j\neq i}\sum_{k\in \mathcal{K}} x_{ijk} = 1 \quad \forall i \in \mathcal{N} \tag{1}$$

$$\sum_{j\in \mathcal{V}:j\neq i} x_{ijk} = \sum_{j\in V:j\neq i} x_{jik} \; \forall i \in \mathcal{V}, k \in \mathcal{K} \tag{2}$$

$$\sum_{j\in \mathcal{N}} x_{0jk} \leq 1 \quad \forall k \in \mathcal{K} \tag{3}$$

$$a_{ik} + p_{ik} + t_{ijk} - M(1 - x_{ijk}) \leq a_{jk} \quad \forall (i, j) \in \mathcal{A} : j \neq 0, k \in \mathcal{K} \tag{4}$$

$$a_{ik} \geq 0 \quad \forall i \in \mathcal{V}, k \in \mathcal{K} \tag{5}$$

$$x_{ijk} \in \{0, 1\} \quad \forall (i, j) \in \mathcal{A}, k \in \mathcal{K} \tag{6}$$

Constraints (1) impose that each request is assigned to exactly one vehicle. Constraints (2) ensure flow conservation and (3) require that each vehicle leaves the depot at most once. Constraints (4) calculate the arrival times and therefore define the timing of the visits at the locations associated with the requests. Constraints (5) and (6) define the variable domains.

4.2 Service-related constraints

Having established the core routing constraints, we now turn to the first dimension that extends the TRSP core: the service-related constraints. We divide these constraints into several subdimensions as defined in the taxonomy and discuss each subdimension in the subsections below.

Table 2 Classification of static-deterministic configurations

References	Service-related constraints					Technician-related constraints			Objectives		
	Service type	Planning horizon	Time windows	Selectiveness	Equipment requirem.	Skills	Working time	Multiple depots	Cost-oriented	Technician-oriented	Service-oriented
Ali et al. (2021)	MS	SP	HA	–	–	DO, SL	–	SD	TC	–	–
Anoshkina and Meisel (2019)	MT	SP	–	–	–	DO, SL	–	SD	LC	WB	CT
Avraham et al. (2017)	SI	SP	–	✓ (OC)	–	–	WH, O	MD	TC, LC, OT	–	–
Bae and Moon (2016)	MS	SP	HA	–	–	DO	WH	MD	TC, LC, VC	–	–
Cavada et al. (2020)	SI	MP	SO	–	–	–	WH	SD	TC	–	PR, DE
Cortés et al. (2014)	SI	SP	(SO)	✓	–	–	WH	SD	TC	–	(PR), DE
Damm et al. (2016)	SI	SP	HA	✓	–	DO	WH	SD	LC	–	PR
Damm and Ronconi (2021)	SI	SP	HA	✓	–	DO	WH, B	SD	TC	–	PR
Damm et al. (2025)	SI	SP	HA	✓	–	DO	WH, B	SD	TC	–	PR
Erdogan & M'Hallah (2023)	MS	SP	HA	–	–	DO	–	SD	TC, VC	–	–
Frits and Bertok (2021)	(MT)	MP	HA	✓	TO	DO	WH, B	(MD)	TC, LC	–	PR
Gamst and Pisinger (2024)	SI	MP	HA	✓	–	DO, LE	WH, O	MD	TC	–	PR
Graf (2020)	MS	MP	(HA)	–	–	DO	WH	MD	TC, VC	–	DE
Gu et al. (2022)	SI	SP	HA	✓ (OC)	–	DO	WH	SD	TC, OC	–	–
Guastaroba et al. (2021)	(MT, MS)	MP	–	–	–	DO	WH	(MD)	TC	–	–
Hanafi et al. (2020)	MS	SP	–	✓	–	DO	WH	(MD)	–	–	PR
Hojabri et al. (2018)	MS	SP	HA	–	–	DO	–	SD	TC	–	–
Jagtenberg et al. (2020)	MS	MP	(HA)	–	–	DO	WH	MD	TC, VC	–	DE
Kastrati et al. (2021)	MS	MP	(HA)	–	–	DO	WH	MD	TC, VC	–	DE

Table 2 (continued)

References	Service-related constraints					Technician-related constraints			Objectives		
	Service type	Planning horizon	Time windows	Selectiveness	Equipment requirem.	Skills	Working time	Multiple depots	Cost-oriented	Technician-oriented	Service-oriented
Kheiri et al. (2020)	MS	MP	(HA)	–	–	DO	WH	MD	TC, VC	–	DE
Kovacs et al. (2012)	MT	MP	HA	✓ (OC)	–	DO, SL	WH, B, O	SD	TC, OC	–	–
Li et al. (2021)	SI	SP	HA	–	–	SL	WH	SD	TC	–	–
Liu et al. (2019)	SI	SP	HA	–	–	–	WH	SD	TC	–	CT
Mathlouthi et al. (2018)	SI	SP	HA, MU	✓	PA	DO	WH, B, O	MD	TC, OT	B	PR
Mathlouthi et al. (2021a)	SI	SP	HA, MU	✓	PA	DO	WH, B, O	MD	TC, OT	B	PR
Mathlouthi et al. (2021b)	SI	SP	HA, MU	✓	PA	DO	WH, B, O	MD	TC, OT	–	PR
Pekel (2020)	MT	MP	SO, MU	–	–	DO, SL	WH, O	SD	TC, OT	–	DE
Pekel (2022)	MT	MP	SO, MU	–	–	DO, SL	WH, O	SD	TC, OT	–	DE
Pereira et al. (2020)	(MT), MS	MP	–	–	–	SL	WH	SD	–	–	CT
Pillac et al. (2013)	SI	SP	HA	–	PA, TO	DO	–	MD	LC	–	–
Pitakaso et al. (2024)	(MT)	SP	–	✓	–	SL	WH	SD	TC	–	PR
Pourjavad and Almehdawe (2022)	SI	MP	SO	–	–	–	WH, B, O	MD	TC, LC, OT	–	DE
Qiu et al. (2022)	MS	SP	–	–	–	DO	WH	SD	TC	–	–
Rastegar et al. (2024)	(MT)	SP	SO	–	–	–	WH	SD	–	–	DE
Schubert et al. (2021)	SI	SP	HA	–	–	DO	WH	SD	TC, VC	–	–
Song et al. (2025)	MS	SP	HA	–	–	DO	WH	SD	TC, VC, LC	–	–
Sørensen et al. (2025)	SI	SP	HA	✓	–	DO, SL	WH	MD	TC, (LC)	–	PR
Souyris et al. (2013)	SI	SP	(SO)	✓	–	–	WH	(MD)	TC	–	(PR), DE

Table 2 (continued)

References	Service-related constraints					Technician-related constraints			Objectives		
	Service type	Planning horizon	Time windows	Selectiveness	Equipment requirem.	Skills	Working time	Multiple depots	Cost-oriented	Technician-oriented	Service-oriented
Tang et al. (2007)	SI	MP	–	✓	–	–	WH	SD	–	–	PR
Weigel and Cao (1999)	SI	SP	SO	–	–	DO	WH, B, O	MD	TC, OT	–	DE
Xie et al. (2017)	SI	SP	HA	✓ (OC)	–	DO	WH	SD	TC, OC	–	–
Xu and Chiu (2001)	SI	SP	SO	✓	–	SL	WH, O	MD	TC, LC, OT	–	PR, DE
Yahiaoui et al. (2023)	SI	SP	HA	–	PA, TO	DO	WH	MD	TC	–	–
Zamorano and Stolletz (2017)	MT	MP	SO, MU	–	–	DO, SL	WH, O	SD	TC, OT	–	DE

4.2.1 Planning horizon

The core routing constraints are formulated for a single-period planning horizon, meaning that all requests fall within one period (working day). In contrast, multi-period planning horizons arise when requests cannot be completed within a single day, require multiple visits on different days, or when customers are only available on specific days. In such settings, the planning horizon is discretized into working days $d \in \mathcal{D} = \{1, \ldots, D\}$, and core routing constraints (5) and (6) are modified as follows:

$$a_{ikd} \geq 0 \, \forall \, i \in \mathcal{V}, \, k \in \mathcal{K}, \, d \in \mathcal{D} \tag{7}$$

$$x_{ijkd} \in \{0, 1\} \, \forall \, (i, j) \in \mathcal{A}, \, k \in \mathcal{K}, \, d \in \mathcal{D} \tag{8}$$

The remaining core routing constraints (1)–(4) need to be modified accordingly. In the remainder of this survey, unless stated otherwise, we formulate further extensions of the core routing constraints (1)–(6) for a single-period planning horizon for the sake of simplicity.

4.2.2 Service type

The service type specifies whether a request is fulfilled by (a) a single technician, (b) multiple technicians working simultaneously (teaming), or (c) multiple technicians working sequentially (sync.).

Single technician. Type (a) represents the most common realization observed in the surveyed literature. Modeling this service type does not require extensions of the core routing constraints. Technicians and vehicles are modeled jointly through the set $\mathcal{K}$, with each vehicle carrying a single technician and executing the assigned requests independently.

Multiple technicians–Teaming. To model teaming, let r_i denote the number of technicians required to serve request i. Further, a vehicle within set $\mathcal{K}$ is now associated with a team, while individual technicians are modeled through a separate set $\mathcal{M}$. For team formation, assignment decisions are required. We introduce binary variables $y_{mk} \in \{0, 1\}$, which indicate whether technician $m \in \mathcal{M}$ is assigned to team (vehicle) $k \in \mathcal{K}$. Furthermore, we assume that the minimum and maximum number of technicians that can be assigned to a team is given by τ^{min} and τ^{max}, respectively. Consequently, the following constraints must be added to the core routing constraints (1)–(6):

$$\sum_{m \in \mathcal{M}} y_{mk} \geq r_i \cdot \sum_{j \in \mathcal{V}} x_{jik} \, \forall \, i \in \mathcal{N}, \, k \in \mathcal{K} \tag{9}$$

$$\sum_{k \in \mathcal{K}} y_{mk} \leq 1 \, \forall \, m \in \mathcal{M} \tag{10}$$

$$\tau^{min} \leq \sum_{m \in \mathcal{M}} y_{mk} \leq \tau^{max} \, \forall \, k \in \mathcal{K} \tag{11}$$

$$y_{mk} \in \{0,\ 1\}\ \ \forall\, m \in \mathcal{M},\ k \in \mathcal{K} \tag{12}$$

Constraints (9) enforce that every request is fulfilled by a team comprising at least the number of technicians required for that request. Constraints (10) ensure that each technician can be assigned to at most one team. Constraints (11) impose a minimum and maximum number of technicians that can be assigned to a team. Constraints (12) define the variable domains.

In single-period planning horizons, (10) prevents technicians from switching teams within the same day. In contrast, multi-period settings may allow technicians to switch teams between consecutive days $d-1$ and d. To capture this option, technician-to-team assignments $y_{mkd} \in \{0,\ 1\}$ must be defined for each day $d \in D$. If team consistency is enforced by minimizing the number of team switches (see Sect. 4.4.2), these switches are tracked through the following constraints:

$$y_{mk(d-1)} - y_{mkd} \le \chi_{md}\ \ \forall\, m \in \mathcal{M},\ k \in \mathcal{K},\ d \in \mathcal{D} : d \ge 2 \tag{13}$$

$$y_{mkd} - y_{mk(d-1)} \le \chi_{md}\ \ \forall\, m \in \mathcal{M},\ k \in \mathcal{K},\ d \in \mathcal{D} : d \ge 2 \tag{14}$$

$$\chi_{md} \in \{0,\ 1\}\ \ \forall\, m \in \mathcal{M},\ d \in \mathcal{D} : d \ge 2 \tag{15}$$

$$y_{mkd} \in \{0,\ 1\}\ \ \forall\, m \in \mathcal{M},\ k \in \mathcal{K},\ d \in \mathcal{D} \tag{16}$$

Constraints (13) and (14) identify whether a technician changes their assigned team between consecutive days. Constraints (15) impose the domain constraints for the associated tracking variables. Constraints (16) extend constraints (12) to the multi-period setting.

Multiple technicians–Synchronization. An alternative approach to handling multi-technician requests is to have technicians visit a customer sequentially rather than simultaneously as a team (Çakırgil et al. 2020). In this setting, visits correspond to specific tasks, which may involve different technicians and can be temporally separated (Hanafi et al. 2020). Service type (c) can be combined with different representations of technicians and vehicles. When tasks are executed by single technicians, vehicles and technicians can be modeled jointly through $\mathcal{K}$. Alternatively, tasks may be carried out by teams, in which case technicians and vehicles are modeled separately via $\mathcal{M}$ and $\mathcal{K}$, respectively. In the following, and in line with the majority of the surveyed literature, we assume that tasks are performed by single technicians.

Let $\mathcal{C}_i$ denote the set of tasks that comprise request $i \in \mathcal{N}$. All tasks in $\mathcal{C}_i$ share the same customer location and are linked through a predefined execution order. Precedence relations between tasks are captured by the binary parameter $\alpha_{i_1 i_2} \in \{0,\ 1\}$, which indicates whether task $i_1 \in \mathcal{C}_i$ must be completed before task $i_2 \in \mathcal{C}_i$. Given these precedence relations, synchronization across multiple visits becomes necessary (see Drexl (2012) for a general overview).

To model synchronization, we no longer consider the request nodes $\mathcal{N}$ as nodes of the graph $\mathcal{G}$. Instead, we treat all tasks associated with the requests as nodes, such that $\mathcal{V} = \{0\} \cup \bigcup_{i \in \mathcal{N}} \mathcal{C}_i$ and $\mathcal{C}_i \cap \mathcal{C}_{i'} = \varnothing$ for $i \neq i'$ holds. Since task nodes $i_1,\ i_2 \in \mathcal{C}_i$ corresponding to the same request $i \in \mathcal{N}$ share the same customer location, no travel time or cost is incurred for arc (i_1, i_2), i.e., $t_{i_1 i_2 k} = c_{i_1 i_2 k} = 0$ for all $i_1, i_2 \in \mathcal{C}_i$ and $k \in \mathcal{K}$. Synchronization is enforced through the following constraints in addition to the core routing constraints:

$$\sum_{j \in \mathcal{V}} \sum_{h \in \mathcal{C}_i} \sum_{k \in \mathcal{K}} x_{jhk} = |\mathcal{C}_i| \; \forall i \in \mathcal{N} \tag{17}$$

$$\begin{aligned} &\sum_{k \in \mathcal{K}} a_{i_1 k} + \sum_{k \in \mathcal{K}} \sum_{h \in \mathcal{V}:\, h \neq i_1} p_{i_1 k} x_{h i_1 k} \\ &\leq \sum_{k \in \mathcal{K}} a_{i_2 k} \; \forall i \in \mathcal{N},\, i_1, i_2 \in \mathcal{C}_i : \alpha_{i_1 i_2} = 1 \end{aligned} \tag{18}$$

Constraints (17) ensure that requests are fulfilled by executing all their tasks. Synchronization constraints (18) enforce the precedence relations among tasks belonging to the same request, such that each task cannot start before all its predecessors have been completed.

In the reviewed literature, the vast majority of type (c)-TRSPs correspond to a DIRP. In the DIRP, each request $i \in \mathcal{N}$ consists of exactly two tasks, i.e., $|\mathcal{C}_i| = 2$, corresponding to delivery and installation. We therefore define the set of all tasks across all requests as $\mathcal{V}^D \cup \mathcal{V}^I$, where for each request $i \in \mathcal{N}$, the delivery task $i_1 \in \mathcal{V}^D = \{1, 3, 5, \dots\}$ precedes the installation task $i_2 \in \mathcal{V}^I = \{2, 4, 6, \dots\}$, implying $\alpha_{i_1 i_2} = 1$. Vehicles are partitioned into two disjoint subsets: delivery vehicles $k \in \mathcal{K}^D$ and installation vehicles $k \in \mathcal{K}^I$. Delivery vehicles transport products and carry delivery personnel, while installation vehicles carry technicians such as electricians or plumbers. Delivery and installation visits must be synchronized such that delivery is completed before installation begins. Delivery vehicles have a capacity Q_k (measured in weight or volume), and the product associated with request i consumes d_i^{pr} units of capacity. The following capacity constraints ensure that a delivery vehicle does not exceed its capacity:

$$\sum_{i \in \mathcal{V}^D} d_i^{pr} \sum_{j \in \mathcal{V}^D \bigcup \{0\}:\, i \neq j} x_{ijk} \leq Q_k \; \forall k \in \mathcal{K}^D \tag{19}$$

For installation vehicles, (seat) capacity refers to the number of technicians that can be carried simultaneously along a route. In almost all DIRP studies, this capacity is assumed to be one.

4.2.3 Time windows

Time windows (TWs) represent one of the most common service-related constraints in TRSP applications and are included in the majority of the surveyed literature. A TW $[e_i, l_i]$ defines the interval during which the service provider commits to start service fulfillment, with e_i and l_i representing the earliest and latest start times. TWs are modelled as either *hard*, prohibiting any violation, or *soft*, allowing service to start before or after the specified interval at the expense of a penalty. Soft TW violations can be captured by decision variables δ_i^- (late start) and δ_i^+ (early start) for all requests $i \in \mathcal{N}$. To incorporate TWs, the core routing constraints must be extended as follows:

$$e_i \leq a_{ik} - \delta_i^- + \delta_i^+ \leq l_i \, \forall i \in \mathcal{N}, \, k \in \mathcal{K} \tag{20}$$

$$\delta_i^-, \delta_i^+ \geq 0 \, \forall i \in \mathcal{N} \tag{21}$$

Constraints (20) can represent both hard and soft TWs. For hard TWs, δ_i^- and δ_i^+ are omitted or fixed to zero. Soft TWs are modeled by including δ_i^- and δ_i^+ together with their domain constraints (21).

Beyond the distinction between hard and soft TWs, TRSP configurations further differ in whether customers specify a single TW or multiple alternative TWs, and in whether TWs are considered within single- or multi-period planning horizons. Accordingly, alternative configurations with corresponding constraints are introduced, which replace (20) and (21):

Single TW. In most of the TRSP applications, each customer specifies a *single* TW, that may either lie within a single day or span multiple days:

- **Single-period**: Often, TWs lie within a single day, where e_i and l_i refer to times during a day.
- **Multi-period**: A TW $[e_i, \, l_i]$ spans multiple days if a customer specifies the first (e_i) and last (l_i) day on which their request can be fulfilled:

$$\sum\nolimits_{d=e_i}^{l_i} \sum\nolimits_{j \in \mathcal{V}: j \neq i} x_{ijkd} = 1 \, \forall i \in \mathcal{N}, \, k \in \mathcal{K} \tag{22}$$

Multiple TWs. However, in some applications, customers specify *multiple* alternative TWs, each of which lies either within a single day, or spans across separate days:

- **Single-period**: Each request $i \in \mathcal{N}$ specifies a set of TWs $\mathcal{F}_i \subset \mathcal{F}$. A TW is defined by $[e_{if}, \, l_{if}]$, and binary variables $x_{if}^{TW} \in \{0, \, 1\}$ are used:

$$x_{if}^{TW} = \begin{cases} 1, & \text{if request } i \in N \text{ is fulfilled within TW } f \in \mathcal{F}_i \\ 0, & \text{otherwise} \end{cases}$$

Each request must be fulfilled exactly once, and the service must start within one of the TWs:

$$\sum\nolimits_{f \in \mathcal{F}_i} x_{if}^{TW} = 1 \, \forall i \in \mathcal{N} \tag{23}$$

$$\sum\nolimits_{f \in \mathcal{F}_i} x_{if}^{TW} e_{if} \leq a_{ik} \leq \sum\nolimits_{f \in \mathcal{F}_i} x_{if}^{TW} l_{if} \quad \forall i \in \mathcal{N}, \, k \in \mathcal{K} \tag{24}$$

$$x_{if}^{TW} \in \{0,1\} \, \forall i \in \mathcal{N}, \, f \in \mathcal{F} \tag{25}$$

- **Multi-period**: Each request $i \in \mathcal{N}$ may specify one TW $[e_{id}, \, l_{id}]$ for each day

$d \in \mathcal{D}$. It must be ensured that each request is fulfilled exactly once throughout the planning horizon and within one of the TWs:

$$\sum_{d\in \mathcal{D}} \sum_{j\in \mathcal{V}:j\neq i} x_{ijkd} = 1\, \forall\, i \in \mathcal{N},\, k \in \mathcal{K} \tag{26}$$

$$e_{id} \leq a_{ikd} \leq l_{id} \forall\, i \in \mathcal{N},\, k \in \mathcal{K},\, d \in \mathcal{D} \tag{27}$$

4.2.4 Equipment requirements

Another type of service-related constraint arises from equipment requirements, which are particularly relevant for repair and maintenance of products are often overlooked in the existing literature (Pham and Kiesmüller 2024). The equipment typically falls into two categories: *tools* and *spare parts*. While tools are reusable resources, spare parts are consumable items that are depleted once used to fulfill requests by replacing malfunctioning product components.

Let $\mathcal{W} = \{1, \ldots, W\}$ denote the types of tools and $\mathcal{P} = \{1, \ldots, P\}$ the types of spare parts. For each request $i \in \mathcal{N}$, the demand for each spare part type $p \in \mathcal{P}$ is given by $d_{ip}^{parts} \in \mathbb{N}_0$. Tool requirements are specified by the binary parameter $\mathscr{m}_{iw} \in \{0, 1\}$, with $\mathscr{m}_{iw} = 1$ indicating that tool $w \in \mathcal{W}$ is required for request i. Each technician $k \in \mathcal{K}$ departs from the depot equipped with a tool set characterized by $\mathscr{n}_{kw} \in \{0, 1\}$, specifying whether tool $w \in \mathcal{W}$ is carried, and an initial inventory $\mathscr{v}_{kp}^{0}$ of spare parts of each type $p \in \mathcal{P}$. A potential intermediate replenishment stop (Yahiaoui et al. 2023) can be modeled through a dummy node $\ell = |\mathcal{V}| + 1 = n + 1$. The replenishment stop takes a fixed time $\mathscr{p}_{n+1}$ and allows restocking of $\mathscr{v}_{kp}^{n+1}$ units of spare parts of type p for each technician k.

To track spare part consumption along technician routes, non-negative decision variables g_{ipk} are introduced, representing the number of spare parts of type $p \in \mathcal{P}$ remaining in the vehicle of technician $k \in \mathcal{K}$ after fulfilling request i. Moreover, the routing variables x_{ijk} must also be defined for arcs (i, j) incident to the dummy node $n + 1$ to model the intermediate replenishment stop. Consequently, equipment requirements are enforced through the following constraints:

$$\sum_{j\in \mathcal{V}:j\neq i} \sum_{k\in \mathcal{K}:\, \mathscr{m}_{iw} \leq \mathscr{n}_{kw} \wedge \mathscr{m}_{jw} \leq \mathscr{n}_{kw}} x_{ijk} = 1\, \forall\, i \in \mathcal{N},\, w \in \mathcal{W} \tag{28}$$

$$\sum_{i\in \mathcal{V}} x_{i,\, n+1,\, k} \leq 1\, \forall\, k \in \mathcal{K} \tag{29}$$

$$g_{0pk} = \mathscr{v}_{kp}^{0}\, \forall\, k \in \mathcal{K},\, p \in \mathcal{P} \tag{30}$$

$$\begin{aligned} &g_{ipk} + \left(1 - \left(x_{ijk} + \frac{1}{2}\left(x_{i,\,n+1,\,k} + x_{n+1,\,j,\,k}\right)\right)\right) M \\ &\quad \geq g_{jpk} + d_{jp}^{parts} - \frac{1}{2}\mathscr{v}_{kp}^{n+1}\left(x_{i,\,n+1,\,k} + x_{n+1,\,j,\,k}\right) \quad \forall\, i,j \in \mathcal{V}:\, j \neq 0,\, k \in \mathcal{K},\, p \in \mathcal{P} \end{aligned} \tag{31}$$

$$g_{ipk} \geq 0 \;\; \forall\, i \in \mathcal{V},\, p \in \mathcal{P}:\, d_{ip}^{parts} > 0,\, k \in \mathcal{K} \tag{32}$$

$$x_{ijk} \in \{0,\, 1\} \;\; \forall\, i, j \in \mathcal{V} : i = n+1 \vee j = n+1,\, k \in \mathcal{K} \tag{33}$$

Core routing constraints (2) are modified through (28) ensuring that technicians can only serve requests for which they carry the necessary tools. Constraints (29) define the optional intermediate replenishment stop. Constraints (30) specify the initial inventory of spare parts in each technician's vehicle at the start of their route, while (31) ensure that technicians have sufficient spare parts, comprising both the initial inventory and any replenishments. Constraints (32) and (33) define the domains of the additional decision variables.

4.2.5 Selectiveness

Given the limited planning horizon and technicians available, it may not be feasible to fulfill all requests. As a result, the provider rejects or outsources a subset of requests. Each request may either be mandatory or optional. While rejection corresponds to not serving a request at all, outsourcing refers to delegating service fulfillment to an external provider at an additional cost. To model selectivess, we introduce a binary decision variable v_i that equals one if request i is rejected or outsourced, and zero otherwise. The core routing constraints (1) are then adapted as follows:

$$\left(\sum\nolimits_{j \in \mathcal{V}: j \neq i} \sum\nolimits_{k \in \mathcal{K}} x_{ijk}\right) + v_i = 1 \,\forall\, i \in \mathcal{N} \tag{34}$$

$$v_i \in \{0,\, 1\} \,\forall\, i \in \mathcal{N} \tag{35}$$

Constraints (34) state that each request is either fulfilled by one technician or rejected/outsourced, while (35) define the domain of the rejection/outsourcing variables.

4.3 Technician-related constraints

Beyond service-related constraints, TRSP configurations also incorporate technician-related constraints, which define the conditions under which technicians can be assigned to requests. They include skills, working time restrictions, and the set of depots.

4.3.1 Skills

Skill modeling is closely tied to the service type, as different skill requirements may apply to technicians operating individually (type (a) and (c)) or simultaneously as a team (b). In addition, some TRSPs account for learning. Skill representations typically distinguish between *skill domains*, capturing categorical qualifications, and *proficiency levels*, reflecting the degree of expertise within a domain.

Single technician. The skill requirements of a request $i \in \mathcal{N}$ can be represented by the subset of technicians $\mathcal{K}_i \subseteq \mathcal{K}$ that are qualified to serve request i. In this binary representation, each request requires one particular domain of technical expertise (e.g., electrical, plumbing, or carpentry), and technicians are either qualified for this domain or not. For service type (a), skill constraints can be incorporated by modifying the core domain constraints (6). Specifically, a technician $k \in \mathcal{K}$ is allowed to traverse an arc (i, j) only if they are qualified to serve both requests i and j:

$$x_{ijk} \in \{0,\ 1\} \forall\ (i,\ j) \in \mathcal{A},\ k \in \mathcal{K}_i \cap \mathcal{K}_j \tag{36}$$

The remaining core routing constraints (1)–(5) are modified accordingly to ensure skill compatibility.

Multiple technicians–Teaming. Service type (b) occurs when fulfilling a request requires the combination of complementary skill domains, potentially at different proficiency levels. In contrast to service type (a), skills must therefore be modeled explicitly with respect to both skill domains and proficiency levels, as skill compatibility depends on the collective qualifications of the assigned team. Consequently, the teaming-related constraints (9) must be adapted to account for skill compatibility. In particular, the parameter r_i, which specifies the number of technicians required to serve request i, is refined to reflect requirements across different skill domains and proficiency levels.

Specifically, each technician $m \in \mathcal{M}$ is qualified in one or more skill domains $q \in \mathcal{Q}$ at a proficiency level $l \in \mathcal{L}$. Let $s_{mql} \in \{0,\ 1\}$ indicate whether technician m is qualified in skill domain q at proficiency level l, and let $r_{iql} \in \mathbb{N}_0$ denote the number of technicians with skill domain q at proficiency level l required to fulfill request i. Proficiency levels are organized in a hierarchical structure such that $s_{mql'} \leq s_{mql}$ holds for all $l' > l$. In other words, if technician m is qualified in skill domain q at level l, they are also considered capable of fulfilling requests that require any lower level l' of the same skill domain. To illustrate this concept, consider the qualification matrix $(s_{mql})_{|\mathcal{Q}|\times\,|\mathcal{L}|}$ presented below. It represents the skill profile of technician m across $|\mathcal{Q}| = 3$ different skill domains and $|\mathcal{L}| = 2$ proficiency levels. According to the matrix, the technician is proficient in skill domain $q = 1$ at both levels $l = 1$ and $l = 2$, has basic qualification, i.e., level $l = 1$, in domain $q = 2$, and possesses no qualification in $q = 3$.

$$(s_{mql})_{|\mathcal{Q}|\times|\mathcal{L}|} = \begin{array}{c} \begin{array}{cc} l=1 & l=2 \end{array} \\ \left(\begin{array}{cc} 1 & 1 \\ 1 & 0 \\ 0 & 0 \end{array}\right) \end{array} \begin{array}{c} \\ q=1 \\ q=2 \\ q=3 \end{array}$$

$$(r_{iql})_{|\mathcal{Q}|\times|\mathcal{L}|} = \begin{array}{c} \begin{array}{cc} l=1 & l=2 \end{array} \\ \left(\begin{array}{cc} 1 & 1 \\ 0 & 0 \\ 2 & 0 \end{array}\right) \end{array} \begin{array}{c} \\ q=1 \\ q=2 \\ q=3 \end{array}$$

Similarly, the skill requirements of a given request i can be represented in matrix form, as illustrated by the skill requirement matrix $(r_{iql})_{|\mathcal{Q}|\times\,|\mathcal{L}|}$: request i requires one technician with skill domain $q = 1$, proficient at level $l = 2$ (which also covers level $l = 1$), as well as two technicians with skill domain $q = 3$, proficient at level $l = 1$.

Accordingly, to incorporate skill constraints under teaming, constraints (9) are modified as follows:

$$\sum_{m\in \mathcal{M}} y_{mk} \cdot s_{mql} \geq r_{iql} \cdot \sum_{j\in \mathcal{V}} x_{jik}\ \forall\, i \in \mathcal{N},\ k \in \mathcal{K},\ q \in Q,\ l \in \mathcal{L} \tag{37}$$

Constraints (37) state that each request must be executed by one team possessing the required skills, and teams may be overqualified if they have skills exceeding the minimum required.

Multiple technicians–Synchronization. Under synchronization, skill modeling depends on whether tasks are executed by individual technicians or by teams. Accordingly, skills are incorporated using the single-technician or team-based formulation introduced above.

In the DIRP, the partition into delivery and installation vehicles directly induces a partition of technicians based on their skills. Skill requirements are represented by a single skill domain – the ability to install products – and are modeled in analogy to the single-technician configuration. Specifically, technicians qualified for installation form the set $\mathcal{K}^I = \bigcup_{i\in \mathcal{V}^I} \mathcal{K}_i$, while delivery personnel belong to $\mathcal{K}^D = \bigcup_{i\in \mathcal{V}^D} \mathcal{K}_i$.

Learning. To model learning effects in multi-period settings, proficiency is modeled continuously. Technicians increase proficiency by repeatedly serving requests requiring a given skill domain $q \in \mathcal{Q}$, which in turn decreases their service times for requests requiring that skill domain.

Service times are therefore indexed by $d \in \mathcal{D}$ and denoted by $\mathscr{p}_{ikd}$, allowing proficiency increases to be tracked across days. Modeling learning requires additional parameters, including an experience-independent service time $\mathscr{p}_i^0$, a service time $\mathscr{p}_i^{min}$ for any technician with a minimum proficiency, a learning rate $\mathscr{l}_{qk}$ encoding how quickly technician k gains experience in skill domain q, and an experience variable u_{kqd} representing technician k's accumulated experience in domain q by day d. Skill requirements are captured by a binary parameter r_{iq}, which indicates whether fulfilling request i requires qualification in domain q and is a modification of r_{iql} (see multiple technicians – teaming). Further, $\mathscr{u}_{kq}^0$ denotes technician k's experience in domain q at the beginning of the planning horizon.

Accordingly, learning effects are incorporated by extending the core routing constraints as follows:

$$u_{kq1} = \mathscr{u}_{kq}^0\ \forall\ k \in \mathcal{K},\ q \in Q \tag{38}$$

$$u_{kqd} = u_{kq(d-1)} + \sum_{i\in \mathcal{N}} \sum_{j\in \mathcal{N}: i\neq j} r_{iq} \cdot x_{ijkd}\ \forall\ k \in \mathcal{K},\ q \in Q,\ d \in \mathcal{D} : d \geq 2 \tag{39}$$

$$\mathscr{p}_{ikd} = \mathscr{p}_i^0 + \mathscr{p}_i^{min} \cdot \sum_{q\in \mathcal{Q}} r_{iq} \cdot (u_{kqd})^{-\mathscr{l}_{qk}}\ \forall\ i \in \mathcal{N},\ k \in \mathcal{K},\ d \in \mathcal{D} \tag{40}$$

$$u_{kqd} \in \{0, 1\} \quad \forall\, k \in \mathcal{K},\, q \in Q,\, d \in \mathcal{D} \tag{41}$$

Constraints (38) define the initial experience levels of technicians in each skill domain. Constraints (39) specify a daily update for a technician's experience in a given skill domain increases by one unit per request. Constraints (40) capture the increase in proficiency by linking accumulated experience to service times. Specifically, the service time is decomposed into two components: an experience-independent baseline representing the irreducible part of the service time, and an experience-dependent component that decreases with learning. Finally, constraints (41) define the domain constraints of the experience variables.

4.3.2 Working time

When planning technician routes, service providers must comply with regulations regarding technicians' daily working hours, overtime, and breaks.

Working hours and overtime. Constraints on technicians' working hours can be modeled by assigning a working TW $[e_k,\, l_k]$ to each technician $k \in \mathcal{K}$. Each technician $k \in \mathcal{K}$ must leave the depot after time e_k and return to the depot at the latest at time l_k (see, e.g., Damm et al. 2016, 2021; Gamst and Pisinger 2024). However, if overtime is allowed, technicians may return to the depot later than l_k, assuming a maximum overtime of o^{max}. For instance, overtime may be allowed when necessary to accommodate high-priority requests (see Sect. 4.4.3 for a detailed discussion of different types of priorities and their modeling) (Mathlouthi et al. 2021a, b; Xu and Chiu 2001). To capture the overtime of technician k, we introduce decision variable o_k. The constraints needed to account for working hours and overtime are as follows:

$$e_k + t_{0i} - M\,(1 - x_{0ik}) \leq a_{ik}\; \forall\, i \in \mathcal{N},\, k \in \mathcal{K} \tag{42}$$

$$a_{ik} + p_{ik} + t_{i0} - M\,(1 - x_{i0k}) \leq l_k + o_k \quad \forall\, i \in \mathcal{N},\, k \in \mathcal{K} \tag{43}$$

$$0 \leq o_k \leq o^{max} \quad \forall\, k \in \mathcal{K} \tag{44}$$

Constraints (42) and (43) represent modifications of core routing constraints (4), specifically accounting for working time restrictions on departure from and return to the depot. Constraints (42) specify the earliest arrival at the first customer visited by a technician, whereas constraints (43) determine the overtime for each technician, which is bounded by constraints (44).

Breaks. Technicians usually take breaks at customers' locations after request completion, without traveling to a separate break location. As a result, incorporating breaks extends route durations but does not increase the total distance traveled. Technicians may choose between multiple breaks b from the set of breaks $\mathcal{B}$. Break b of technician k is represented by TW $\left[e^B_{kb},\, l^B_{kb}\right]$ and duration p^B_{kb}. Typically, technicians must take exactly one break ($|\mathcal{B}| = 1$) but there are also examples with up to $|\mathcal{B}| = 3$ breaks (Mathlouthi et al. 2018, 2021a, b). To model breaks, we introduce two types of decision variables: $a_{kb}^{B} \geq 0$, defining the start time of break $b \in \mathcal{B}$ of technician $k \in \mathcal{K}$, and the following binary variable x_{ikb}^{B}:

$$x_{ikb}^{B} = \begin{cases} 1, & \text{if technician } k \text{ takes their break } b \text{ after fulfilling request } i \\ 0, & \text{otherwise} \end{cases}$$

The following constraints ensure that breaks are properly scheduled within technician routes:

$$e_{kb}^{B} \sum_{i \in \mathcal{N}} x_{ikb}^{B} \leq a_{kb}^{B} \leq l_{kb}^{B} \sum_{i \in \mathcal{N}} x_{ikb}^{B} \quad \forall k \in \mathcal{K}, b \in \mathcal{B} \tag{45}$$

$$x_{ikb}^{B} \leq \sum_{j \in \mathcal{V}: i \neq j} x_{jik} \quad \forall i \in \mathcal{N}, k \in \mathcal{K}, b \in \mathcal{B} \tag{46}$$

$$a_{ik} + p_{ik} \leq a_{kb}^{B} + M\left(1 - x_{ikb}^{B}\right) \quad \forall i \in \mathcal{N}, k \in \mathcal{K}, b \in \mathcal{B} \tag{47}$$

$$\begin{aligned} a_{ik} + p_{ik} + t_{ijk} x_{ijk} + \sum_{b \in \mathcal{B}} p_{kb}^{B} x_{ikb}^{B} \leq a_{jk} \\ + M\left(1 - x_{ijk}\right) \quad \forall i, j \in \mathcal{N} : i \neq j, k \in \mathcal{K}, b \in \mathcal{B} \end{aligned} \tag{48}$$

$$x_{ikb}^{B} \in \{0,1\} \quad \forall i \in \mathcal{N}, k \in \mathcal{K}, b \in \mathcal{B} \tag{49}$$

If a technician takes a break, the break must be taken in the defined TW, which is imposed by (45). Furthermore, constraints (46) ensure that a technician can only take a break after fulfilling some request i, if this technician has been assigned to this request. Constraints (47) guarantee that, if a break is taken at the location of a particular customer, the break is started after fulfilling the request of this customer. If a technician takes a break between visiting customers i and j, Constraints (48) ensure that the service at customer j can only begin after the technician has completed the service at customer i, taken the break at that location, and then traveled to customer j. Constraints (49) define the domains of the newly introduced binary decision variables.

4.3.3 Multiple depots

Multi-depot settings occur in several practical contexts:

(i) when technicians k start/end their routes at their home locations h_k rather than at a central depot,
(ii) when technicians can visit intermediate depots for replenishing tools/spare parts (see Sect. 4.2.4),
(iii) or when technicians pick up products for delivery operations (see, e.g., Kheiri et al. 2020).

Case (i) can be modeled by modifying the flow conservation and domain constraints (2) and (6), respectively, as follows:

$$\sum_{i\in \mathcal{N}} x_{h_k ik} = \sum_{i\in \mathcal{N}} x_{ih_k k} \; \forall\, k \in \mathcal{K} \tag{50}$$

$$x_{ijk} \in \{0,\, 1\} \; \forall\, k \in \mathcal{K},\, i,\, j \in \mathcal{N} \cup \{h_k\} : i \neq j \tag{51}$$

In cases (ii) and (iii), intermediate stops at depots can be incorporated by introducing a dummy request node $\ell = |\mathcal{V}| + 1$ (as shown in Sect. 4.2.4) representing either replenishment stops or pickup stops.

4.4 Objectives

Table 3 summarizes the most common objective functions observed in the literature, which give rise to three subdimensions: cost-oriented, technician-oriented, and service-oriented. Often, the objective function comprises multiple objectives.

4.4.1 Cost-oriented objectives

Cost-oriented objectives are by far the most prevalent in the TRSP literature. They aim to minimize the total cost of routing, resource utilization, and service fulfillment. The considered cost components are travel cost, vehicle fixed cost, labor and overtime cost, outsourcing cost, and holding cost.

Travel cost. Minimizing travel cost–often also referred to as routing cost–represents the dominant objective in TRSP formulations.

Vehicle fixed cost. Fixed cost for vehicle usage arise in synchronization-based TRSPs, particularly in DIRPs. In these configurations, fixed cost is incurred per dispatched vehicle and may be either identical for both delivery and installation vehicles (e.g., Ali et al., 2021) or differentiated by vehicle type, with higher cost assigned to installation vehicles (Erdogan and M'Hallah 2023).

Labor and overtime cost. Labor cost can be modeled as variable cost, calculated by multiplying each technician's total working time with their wage rate (see Table 3, e.g., Bae and Moon 2016; Qiu et al. 2023), or as fixed cost when technicians receive a fixed salary irrespective of their actual working time (Sørensen et al. 2025). Overtime cost is typically higher than wages for regular working time (e.g., Avraham et al. 2017). Note that minimization of labor and overtime cost can also be interpreted as technician-oriented objectives, as these cost components directly penalize excessive working hours and overtime.

Outsourcing cost. Outsourcing cost represents additional expenditure for external resources (e.g., Xie et al. 2017). Notably, outsourcing cost may simultaneously measure a request's priority (see Sect. 4.4.3)–requests with higher outsourcing cost c_i^{out} are implicitly considered more critical, as rejecting or postponing them incurs a greater penalty.

Holding cost. HC accounts for the residual inventory of spare parts, and are introduced to discourage excessive stocking of spare parts. The residual inventory results from the initial inventory carried by technicians, additional inventory obtained through replenishment decisions, and parts consumed while servicing requests. Although HC is only sparsely considered in the TRSP literature, accounting for it is

Table 3 Objectives

Category	Objective		Formal description
Cost-oriented	Travel cost (TC)	Min	$\sum_{(i,j)\in\mathcal{A}}\sum_{k\in\mathcal{K}} c_{ijk}^{TC} x_{ijk}$
	Vehicle fixed cost (VC)	Min	$\sum_{k\in\mathcal{K}}\sum_{j\in\mathcal{N}} c_k^{fix}\cdot x_{0jk}$
	Labor cost (LC)	Min	$\sum_{(i,j)\in\mathcal{A}}\sum_{k\in\mathcal{K}} c_k^{labor}\cdot\left(t_{ijk}+p_{jk}\right)\cdot x_{ijk}$
	Overtime cost (OTC)	Min	$\sum_{k\in\mathcal{K}} c_k^{over}\cdot o_k$
	Outsourcing cost (OC)	Min	$\sum_{i\in\mathcal{N}} c_i^{out}\cdot v_i$
	Holding cost (HC)	Min	$\sum_{k\in\mathcal{K}}\sum_{p\in\mathcal{P}} c_p^{hold}\cdot\left(v_{kp}^{0}+v_{kp}^{n+1}\cdot\sum_{i\in\mathcal{V}} x_{i,n+1,k}-\sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}:i\neq j} x_{ijk}\cdot d_{jp}^{parts}\right)$
Technician-oriented	Workload balance (WB)	Min	LWT with $\sum_{(i,j)\in\mathcal{A}}\left(t_{ijk}+p_{jk}\right)\cdot x_{ijk}\leq LWT\ \forall k\in\mathcal{K}$
	Skipped breaks (B)	Min	$\sum_{k\in\mathcal{K}}\sum_{b\in\mathcal{B}} c_k^{break}\cdot\left(1-\sum_{i\in\mathcal{N}} x_{ikb}^{break}\right)$
	Team consistency (CO)	Min	$\sum_{m\in\mathcal{M}}\sum_{d\in\mathcal{D}:d\geq 2}\chi_{md}$
Service-oriented	Service completion time (CT)	Min	$\sum_{i\in\mathcal{N}}\sum_{k\in\mathcal{K}} a_{ik}+p_{ik}$
	Delays (DE)	Min	$c^{delay}\cdot\sum_{i\in\mathcal{N}}\delta_i$
	Priorities (PR)	Max	$\sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{V}:j\neq i}\sum_{k\in\mathcal{K}} x_{ijk}\cdot\mu_i$

relevant, as repair services are gaining importance in the after-sales service market (Pham and Kiesmüller 2024).

4.4.2 Technician-oriented objectives

Technician-oriented objectives include a balanced workload distribution, compliance with labor regulations (breaks), and team consistency.

Workload balance. Workload balance among technicians has received little attention, despite being crucial for employee satisfaction in practice. A balanced workload distribution can be achieved by minimizing the maximum working time among all technicians, thereby reducing disparities in daily workloads (Anoshkina and Meisel 2019; Nielsen and Pisinger 2025).

Breaks. Breaks may enter the objective function in the form of penalties for skipped breaks (Mathlouthi et al. 2018, 2021a, b).

Team consistency. Team consistency addresses the extent to which team compositions are preserved across consecutive periods. Although underrepresented in the TRSP literature, it is relevant in practice for strengthening working relationships. Team consistency can be preserved by minimizing the total number of team switches ($\chi_{md} = 1$) across the planning horizon using the variables χ_{md} introduced in Sect. 4.2.2.

4.4.3 Service-oriented objectives

Service-oriented objectives model the customer perspective by measuring the service quality perceived by customers. Typical objectives include maximizing priorities, minimizing delays, and minimizing service completion time.

Priorities. Among service-oriented objectives, the *maximization of priorities* is the most common one. The selection of which requests to serve preferentially is modeled through priority values μ_i, reflecting their relative importance, profitability, or urgency. In configurations where not all requests can be accepted, priority modeling is typically linked to selectiveness (see Sect. 4.2.5). However, priorities may also be used without selectiveness to favor earlier fulfillment of more important requests (Cavada et al. 2020; Ji et al. 2022). Priority structures may be homogeneous, with requests having a uniform value, or heterogeneous, where priorities differ across requests:

- **Homogeneous**: In this case, the objective reduces to maximizing the number of accepted requests or the acceptance rate over multiple periods and may appear either as part of a multi-objective (e.g., Anoshkina and Meisel 2020; Cortés et al. 2014) or single-objective configuration (Avraham and Raviv 2021; Paradiso et al. 2025).
- **Heterogeneous**: When priority values μ_i differ across requests, they may reflect various metrics:
  - *Gains*: Most commonly, priority values are interpreted as positive gains, e.g., revenues generated by successfully completed requests (e.g., Mathlouthi et al. 2018, 2021a, b).

- *Penalities*: Less frequently, priorities are modeled as penalty values for rejected or postponed requests, reflecting customer dissatisfaction (e.g., Nielsen and Pisinger 2023, 2025).
- *Service time*: By contrast, priorities may also be represented by the service time p_{ik}, implying that requests requiring more service time are more important (Sørensen et al. 2025).

Delays. The minimization of delays aims to provide services as early as possible. Two modeling approaches can be distinguished depending on whether soft TWs are incorporated or not.

- **Soft TWs**: Delays minimization is most commonly achieved through soft TW constraints. Delays then correspond to soft TW violations δ_i^+ that incur a (contractual) penalty cost (e.g., Zamorano and Stolletz 2017). In addition to penalties for delayed service ($a_{ik} > l_i$), early arrivals ($a_{ik} < e_i$) can be penalized through a piecewise-linear objective function (Rastegar et al. 2024).
- **No soft TWs**: In multi-period settings without TWs, cumulative delay penalties increase for each day a request remains unserved (Nowak and Szufel 2024; Pham and Kiesmüller 2022). In the multi-period DIRP, penalties are imposed for idle products awaiting installation (e.g., Kheiri et al. 2020).

Service completion time. While delay minimization penalizes late service provision relative to temporal reference points (soft TWs, request arrivals), minimizing service completion time seeks to shorten the overall schedule by reducing either total completion time or makespan.

- **Total completion time**: This objective may be of subordinate importance when tight TWs strongly determine completion times. However, when TWs are wide, minimizing completion times becomes more relevant (Anoshkina and Meisel 2020).
- **Makespan**: The makespan is the completion time of the last scheduled request. In multi-period settings, the objective is to minimize either the sum of the latest completion times for each day (Chen et al. 2016), or the day on which the last request is completed (Pereira et al. 2020).

5 Stochastic-dynamic modeling

The modeling discussed in Sect. 4 is sufficient to fully characterize static-deterministic TRSPs in which all decisions are made prior to the start of the planning horizon and all decision-relevant information is known with certainty. In practice, however, technician-based after-sales field services often operate under uncertainty with new information being revealed all throughout the planning horizon.

This section therefore considers stochastic-dynamic TRSPs. Stochasticity may stem from the supply side (e.g., uncertain availability of technicians), from the demand side (e.g., uncertain request arrivals or spare part requirements), or other sources (e.g., service and travel times). The dynamic nature of these problems arises from the need to make decisions sequentially over time in response to realized information, for instance when requests arrive dynamically or when technicians' skills evolve during the planning horizon. Building on the static-deterministic framework, which is common to all TRSP configurations, we now propose sequential decision making and uncertainty as additional dimensions that extend the configurations introduced in Sect. 4 to a stochastic-dynamic setting. Accordingly, Table 4 introduces the realizations of these dimensions for all contributions that investigate stochastic-dynamic TRSPs.

Sequential decision-making problems under uncertainty can be modeled using Markov Decision Processes (MDPs) consisting of decision epochs, states, actions, transitions, rewards, and objectives (Powell 2022). This modeling paradigm is particularly suited to solution approaches from approximate dynamic programming (ADP). Presenting an MDP formulation is not standard practice in the stochastic-dynamic vehicle routing literature – an observation also noted by Ulmer et al. (2020). Possible reasons include the notational complexity of MDP models, which becomes awkward to handle when realistic problem features are incorporated, as well as the fact that most solution methods are approximate and do not rely directly on an exact dynamic control model (Fleckenstein et al. 2023).

Therefore, a substantial part of the literature refrains from explicitly stating an MDP and instead relies on rolling-horizon or scenario-based planning approaches. In these works, uncertainty and dynamics are addressed by repeatedly solving static-deterministic TRSPs, as introduced in Sect. 4, using updated information or sampled scenarios. While no explicit dynamic control model is provided, the resulting decision process is sequential, and can therefore be interpreted as implicitly inducing an MDP.

Accordingly, the first part of Table 4 lists papers that explicitly model stochastic-dynamic TRSPs as MDPs, whereas the second part comprises papers that rely exclusively on static-deterministic formulations embedded within rolling-horizon or scenario-based solution methods. Nevertheless, although not all surveyed contributions present an MDP formulation, we recast all TRSPs within the MDP notation to provide a unified modeling framework. The purpose of this formulation is not to replicate any single model found in the literature, but to use an MDP as a modeling language for consolidating the various stochastic and dynamic modeling elements observed across existing contributions into a single reference framework. This unified MDP can be tailored to specific problem settings as required. At the same time, we emphasize that modeling approaches avoiding an explicit MDP formulation are equally valid and well established. Readers not requiring an MDP as a basis for their chosen solution approach may therefore skip Sect. 5.2–5.7. Please note that we do not treat stochastic-static problems (Liu et al. 2019; Rastegar et al. 2024; Souyris et al. 2013) separately, as they do not involve sequential decision-making and their modeling and solution approaches are therefore closely related to the static-deterministic methodology.

In the following, we first introduce the basic problem structure of stochastic-dynamic TRSPs and then discuss each MDP component in turn.

Table 4 Classification of stochastic-dynamic configurations

References	Service-related constraints					Technician-related constraints			Objectives			Sequential decision-making	Uncertainty
	Service type	Planning horizon	Time windows	Selectiveness	Equipment req.	Skills	Working time	Multiple depots	Cost-oriented	Technician-oriented	Service-oriented		
Avraham and Raviv (2021)	SI	MP	HA	✓	–	–	WH	SD	–	–	(PR)	RB	RA, CC
Chen et al. (2016)	SI	MP	–	–	–	SL, LE	–	SD	–	–	CT	DB	RA
Chen et al. (2024)	SI	MP	–	–	–	SL, LE	WH	SD	TC, LC	–	–	DB	RA
Nowak and Szufel (2024)	(MS)	MP	–	–	–	DO, SL, LE	WH	MD	TC, LC	–	DE	DB	RA
Paradiso et al. (2025)	SI	SP	HA, MU	✓	–	–	WH	SD	–	–	(PR)	RB	RA
Pham and Kiesmüller (2024)	SI	MP	(SO)	–	PA	–	WH	SD	TC, HC	–	DE	DB	RA, ER
Stein et al. (2025)	SI	MP	(SO)	–	–	SL	WH, O	SD	–	–	DE	DB	RA, SR, TA, ST
Anoshkina and Meisel (2020)	MT	SP	–	–	–	DO, SL	–	SD	LC	WB	CT	RB	RA
Ji et al. (2022)	SI	SP	SO	–	–	DO	WH, (O)	SD	OT	–	DE, PR	(DB)	ST, TT
Nielsen and Pisinger (2023)	SI	MP	HA	✓	–	–	WH	SD	TC	–	PR	(DB)	RA

Table 4 (continued)

References	Service-related constraints					Technician-related constraints			Objectives			Sequential decision-making	Uncertainty
	Service type	Planning horizon	Time windows	Selectiveness	Equipment req.	Skills	Working time	Multiple depots	Cost-oriented	Technician-oriented	Service-oriented		
Nielsen and Pisinger (2025)	SI	MP	HA	✓	–	DO	WH	MD	TC	WB	PR	RB	RA
Pham and Kiesmüller (2022)	SI	MP	–	–	PA	–	WH	SD	TC, HC	–	DE	DB	RA, ER
Pillac et al. (2012)	SI	SP	HA	✓	PA, TO	DO	WH	MD	TC, LC	–	(PR)	RB	RA
Qiu et al. (2023)	MT	MP	HA	✓	–	DO, SL	–	SD	TC, LC	–	PR	RB	RA

Request-based (RB), day-based (DB), request arrivals (RA), equipment requirements (ER), skill requirements (SR), technician availability (TA), services times (ST), travel times (TT), customer choice (CC)

5.1 Basic problem structure

In contrast to static-deterministic TRSPs, requests are no longer known at the beginning of the planning horizon but arrive stochastically over time. In addition, there may be other kinds of exogeneous information that is uncertain and revealed over the course of the planning horizon. As a result, decisions must be made sequentially in response to new information becoming available. The resulting basic problem structure for stochastic-dynamic TRSPs is shown in Fig. 1.

Customers arrive sequentially at random times via the provider's website or mobile app and request service. Depending on the provider's business model, these requests can be handled in two different ways: first, the provider may want to respond immediately to each individual request. This interaction allows the provider, e.g., to decide on an offer set with individualized fulfillment options, in particular TWs (dashed circles in Fig. 1). In this case, the customer chooses one of the offers and thereby confirms their order or abandons the booking process (dashed lines in Fig. 1).

Second, if the provider's business model does not require such immediate interaction between the provider and the customer, it is sufficient to simply collect requests throughout a day d (solid box in Fig. 1). In parallel to request arrivals, planning decisions made at the end of day $d-1$ are executed and additional information may be revealed, which may influence the outcome of these planning decisions. At the end of day d, the provider incorporates the batch of new requests as well as the other revealed information and their operational impact into their route planning and equipment planning for day $d+1$ (solid lines and circles in Fig. 1). For example, technicians may fall ill and be unavailable on day $d+1$. Also, the fulfillment of some requests may have failed during execution on day d because, due to the stochastic demand for spare parts, the inventory of spare parts planned at the end of day $d-1$ was insufficient. Any such observation is also incorporated in the decision-making at the end of day d.

In summary, two types of stochastic-dynamic TRSPs result from this key structural difference explained above:

- **Request-based**: In a *request-based* TRSP, each request arrival triggers a decision on the individual offer the provider makes in response to the request (e.g., Avraham and Raviv 2021; Paradiso et al. 2025).
- **Day-based**: When no immediate decision is required, a *day-based* TRSP arises.

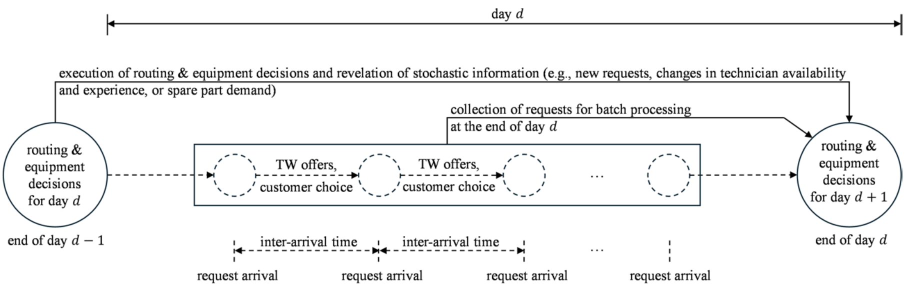

Fig. 1 Basic problem structure of stochastic-dynamic TRSPs

Operational decisions on service fulfillment–such as routing (see Sect. 4.1) or equipment planning (see Sect. 4.2.4)–are to be postponed and taken at the end of each day for the following day. Requests are then processed in batches (e.g., Chen et al. 2024; Pham and Kiesmüller 2024).

In the following, we draw on this distinction and present the modeling framework that generalizes any of the specific stochastic-dynamic TRSPs considered in the surveyed literature. Thereby, we exploit the fact that every stochastic-dynamic TRSP can be cast as an extension of a static-deterministic TRSP. In particular, the set of feasible decisions (action space) that are made sequentially is always defined by the constraints of a static-deterministic TRSP. Moreover, it is worth noting that the existing literature exclusively models TRSPs as either purely request-based or purely day-based. However, both types of decision-making could be straightforwardly combined. The modeling framework is loosely based on the MDP modeling framework for dynamic vehicle routing problems proposed by Ulmer et al. (2020).

5.2 Decision epochs

Decision epochs mark the points in time when a decision must be made. Therefore, the planning horizon is typically discretized into a finite set of decision epochs $t \in \mathcal{T} = \{1, \ldots, T\}$. Rarely, an infinite horizon is modeled (Avraham and Raviv 2021; Pham and Kiesmüller 2024). The time interval between two consecutive decision epochs is referred to as a *period*. Decision epochs and periods are defined differently for request-based and day-based TRSPs:

Request-based Decision epochs are either event-driven or time-driven. In the former case, they are triggered by the arrival of requests during the day. A period corresponds to the time interval between two consecutive request arrivals (e.g., Paradiso et al. 2025). In the latter case, sufficiently small time intervals are defined such that the probability of more than one request arriving within them is negligible (Avraham and Raviv 2021). For the sake of clarity, we assume event-driven decision epochs in the following.

Day-based Decision epochs are time-driven and occur at the end of each day. In this case, a period corresponds to one working day (e.g., Nowak and Szufel 2024).

5.3 States

The system state $\mathscr{s}_t \in \mathcal{S}$ contains all information relevant for decision-making at decision epoch t. The state always includes the set of pending requests $\mathcal{N}_t$, i.e., requests that have been accepted but not yet fulfilled by epoch t. The remaining state components differ for request- and day-based TRSPs:

Request-based. For making accept/reject decisions, service-related information must be included in the state: $\mathscr{s}_t = \left(\mathcal{N}_t, \left(\phi_i^{TW}\right)_{i \in \mathcal{N}_t}, i_t^{new}\right)$, where ϕ_i^{TW} denotes the TW assigned to an accepted request $i \in \mathcal{N}_t$, and i_t^{new} is the request that has arrived during the previous period and requires an immediate accept/reject decision (Avraham and Raviv 2021; Paradiso et al. 2025).

Day-based. In day-based problems, decision epochs mark the end of each day. State representations are typically richer and capture the dynamics of service-, technician-, and equipment-related information:

$$\mathcal{S}_t = \left(\mathcal{N}_t,\ \left(\phi_i^{due}, \phi_i^{fail}\right)_{i\in \mathcal{N}_t},\ \mathcal{K}_t,\ \left(\left(\phi_{kqt}^{exp}\right)_{q\in \mathcal{Q}}, \phi_{kt}^{abs}\right)_{k\in \mathcal{K}_t},\ \mathcal{E}_t\right).$$

- *Service-related information*: Since operational decisions relevant for service fulfillment are taken by the end of each day, requests are scheduled no earlier than the next day. Thereby, TWs are either absent or modeled as multi-period soft TWs according to constraints (20)–(22) (see Sect. 4.2.3). To capture potential delays (soft TW violations), ϕ_i^{due} denotes the remaining number of periods until the deadline of request i. It is set to zero once the deadline falls on or before period $t+1$ (e.g., Nowak and Szufel 2024). If it is assumed that service fulfillment may fail, $\phi_i^{fail} \in \{0,1\}$ indicates whether the first service attempt has failed by the end of period t (Pham and Kiesmüller 2024; Stein et al. 2025).
- *Technician-related information*: This information includes the set of available technicians $\mathcal{K}_t \subseteq \mathcal{K}$, accumulated experience ϕ_{kqt}^{exp} of technician k in skill domain q (Chen et al. 2016, 2024), and an absence indicator $\phi_{kt}^{abs} \in \{0,1\}$ reflecting unavailability due to illness (Stein et al. 2025). The accumulated experience is tracked by the experience variable u_{kqd} (see Sect. 4.3.1) to model learning effects.
- *Equipment-related information*: Information on availability of equipment is required when customers request repair services that involve spare parts. It is represented by $\mathcal{E}_t = (\epsilon_{pkt})_{p\in \mathcal{P},\, k\in \mathcal{K}}$, where ε_{pkt} denotes the number of spare parts of type p carried by technician k at the end of period t (Pham and Kiesmüller 2024).

5.4 Actions

At decision epoch t, the decision-maker selects an action $x_t \in \mathcal{X}(\mathcal{S}_t)$ based on the current state $\mathcal{S}_t$. The action space $\mathcal{X}(\mathcal{S}_t)$ contains all actions (decisions) that are feasible with respect to the static constraints of the selected TRSP configuration (see Sect. 4). Actions and action spaces differ as follows between request-based and day-based TRSPs.

Request-based. A request-based action at decision epoch t is an integrated accept/reject and TW availability decision $x_t = x_{i_t^{new}t}^{AR-TW}$. Thereby, each action (decision) $x_{i_t^{new}t}^{AR-TW}$ determines whether an incoming request i_t^{new} is accepted and, if so, which TW(s) $f \in \mathcal{F}$ are offered to the requesting customer.

The action space is given by

$$\mathcal{X}^{AR-TW}(s_t) = \left\{ x_{i_t^{new} t}^{AR-TW} \subseteq \mathcal{F} \cup \{0\} : \text{s.t. } (1)\text{-}(6), (20)\ \forall\, i \in \mathcal{N}_t \cup \{i_t^{new}\} \right\}$$

Note that 0 is always included in the offer set, as it represents rejection of the request – either immediately by the provider upon arrival or by the customer through abandonment without booking. A TW $f \in \mathcal{F}$ can be offered only if there exists a feasible route plan that respects the core routing constraints, the TW constraints (20) of all already accepted requests, and the TW constraint associated with f for the new request i_t^{new}. If no such feasible route plan exists, the request is rejected by offering a dummy TW, that is, $x_{i_t^{new} t}^{AR-TW} = \{0\}$ (Avraham and Raviv 2021). Depending on the provider's business practice, customers may be offered either a single TW (Paradiso et al. 2025) or multiple TWs (Avraham and Raviv 2021). Interestingly, decisions on request fulfillment (e.g., routing decisions) are not necessary if the objective does not depend on them, which is always the case in the existing literature.

Day-based Day-based actions are taken at the end of each day and correspond to all operational decisions for the next day. An action can be decomposed into a routing decision and an equipment decision, $x_t = \left(x_t^{route},\ x_t^{parts}\right)$

- *Routing decision*: Technician routes and schedules for serving the pending requests $\mathcal{N}_t$ in period $t+1$ are determined through a routing decision with the action space.

$$\mathcal{X}^{route}(s_t) = \left\{ x_t^{route} \in \left\{ (x_{ijkt},\ a_{ikt})_{i,\, j \in \mathcal{N}_t,\, k \in \mathcal{K}_t} : \text{ s.t. } (1)\text{-}(6) \right\} \right\}$$

Note that the action space is always defined by constraints of a static deterministic configuration, which always includes core routing constraints (1)–(6) (e.g., Chen et al. 2016, 2024; Nowak and Szufel 2024). In addition, depending on the desired configuration, these can be extended by the constraints discussed in Sect. 4.2 and 4.3.

- *Equipment decision*: These decision determines replenishments of spare parts and is defined by

$$\mathcal{X}^{parts}(s_t) = \left\{ x_t^{parts} \in \left\{ \left(x_{1kt}^{parts},\ x_{2kt}^{parts},\ \ldots,\ x_{|\mathcal{P}|kt}^{parts} \right)_{k \in \mathcal{K}} : \text{ s.t. } (28)\text{-}(33) \right\} \right\}.$$

The action x_t^{parts} specifies how many units of each spare part type are added to each technician's repair kit by the end of period t. Unused parts are carried back to the depot and may be reused in future periods (Pham and Kiesmüller 2024).

5.5 Transitions

A transition describes the system's evolution from one state to the next and can be decomposed into two parts. First, a deterministic transition maps the current pre-decision state s_t and the selected action x_t to a post-decision state $s_t^x = S^{\mathcal{X}}(s_t, x_t)$, capturing the decisions' immediate, deterministic consequences. Second, a stochastic transition maps the post-decision state s_t^x to the next pre-decision state $s_{t+1} = S^{\Omega}(s_t^x, \omega_{t+1})$, reflecting the realization ω_{t+1} of the random variable Ω_{t+1} (exogenous information). In summary, the transition from s_t to s_{t+1} can be expressed as $s_{t+1} = S(s_t, x_t, \omega_{t+1}) = S^{\Omega}\left(S^{\mathcal{X}}(s_t, x_t), \omega_{t+1}\right)$. Depending on whether decisions are request-based or day-based, state transitions differ in both their deterministic and stochastic components.

Request-based The transition from s_t to s_{t+1} is characterized by a post-decision update induced by the provider's decision and the subsequent realization of request arrivals and customer choice.

- **Deterministic transition**: The deterministic transition maps the pre-decision set of pending requests $\mathcal{N}_t$ to the post-decision set $\mathcal{N}_t^x$ by incorporating the provider's accept/reject decision for the newly arrived request (if any). In particular, an accepted request is added to the pending set, whereas a rejected request is discarded; if no request arrives at epoch t, the pending set remains unchanged:

$$\mathcal{N}_t^x = \begin{cases} \mathcal{N}_t \cup \{i_t^{new}\} & \text{if } x_{i_t^{new} t}^{AR-TW} \neq \emptyset \\ \mathcal{N}_t & \text{if } x_{\mathrm{i}_t^{\mathrm{new}} \mathrm{t}}^{\mathrm{AR-TW}} = \emptyset\text{, or if there is no request arrival in period t} \end{cases}$$

Accordingly, $\mathcal{N}_t^x$ represents the set of pending requests immediately after the accept/reject decision at epoch t, and serves as the basis for the subsequent stochastic transition (Avraham and Raviv 2021; Paradiso et al. 2025).

- **Stochastic transition**: In request-based settings, $\omega_{t+1} = \left(f_{i_t^{new}}^{\omega}, i_{t+1}^{new,\omega}\right)$ includes customer choice in response to TW offers and new request arrivals.
  - *New request arrival*: Let $i_{t+1}^{new,\omega}$ denote the exogenous realization of a new request to be decided on at decision epoch $t+1$. The corresponding state component is updated as $i_{t+1}^{new} = i_{t+1}^{new,\omega}$.
  - *Customer choice*: If a request is not rejected upon arrival, i.e., $x_{i_t^{new} t}^{AR-TW} \neq \varnothing$, the service provider may either (i) assign a TW directly or (ii) offer a set of alternative TWs. Under (i), customers are assumed to accept the assigned TW deterministically (Paradiso et al. 2025). Under (ii), customer choice constitutes exogenous information $f_{i_t^{new}}^{\omega} \in x_{i_t^{new} t}^{AR-TW} \subseteq \mathcal{F} \cup \{0\}$, where $f_{i_t^{new}}^{\omega} \in \mathcal{F}$ denotes selection of one of the offered TWs and $f_{i_t^{new}}^{\omega} = 0$ represents abandonment without booking. The resulting post-decision update of pending re-

quests is as follows (Avraham and Raviv 2021):

$$\mathcal{N}_{t+1} = \begin{cases} \mathcal{N}_t^x \setminus \{i_t^{new}\} & \text{if } f_{i_t^{new}}^{\omega} = 0 \text{ (abandonment without booking)} \\ \mathcal{N}_t^x & \text{if } f_{i_t^{new}}^{\omega} \in \mathcal{F} \text{ (TW is chosen)} \end{cases},$$

$$\left(\phi_i^{TW}\right)_{i\in\mathcal{N}_{t+1}} = \begin{cases} \left(\phi_i^{TW}\right)_{i\in\mathcal{N}_t} & \text{if } f_{i_t^{new}}^{\omega} = 0 \text{ (abandonment without booking)} \\ \left(\left(\phi_i^{TW}\right)_{i\in\mathcal{N}_t}, f_{i_t^{new}}^{\omega}\right) & \text{if } f_{i_t^{new}}^{\omega} \in \mathcal{F} \text{ (TW is chosen)} \end{cases}$$

Day-based The transition from $\mathscr{s}_t$ to $\mathscr{s}_{t+1}$ starts with a deterministic post-decision update after the provider's end-of-day fulfillment planning decisions. It yields a post-decision state $\mathscr{s}_t^x$ capturing experience accumulation and post-replenishment inventories. Subsequently, uncertainty that realizes during the next day generates the stochastic transition to $\mathscr{s}_{t+1}$. The realized information includes batched request arrivals, service outcomes (failures), technician absences, and spare-part consumption.

- **Deterministic transitions**: The deterministic update maps $\mathscr{s}_t$ to $\mathscr{s}_t^x$ by updating all action-dependent state components according to $x_t = \left(x_t^{route}, x_t^{parts}\right)$; the specific updates are given below.
  - *Technician-related transitions*: A technician k's accumulated experience in skill domain $q \in \mathcal{Q}$ through learning can be updated after making routing decisions x_t^{route} as follows:

$\phi_{kqt}^{exp,x} = \phi_{kqt}^{exp} + \sum_{i\in\mathcal{N}_t}\sum_{j\in\mathcal{N}_t:i\neq j} x_{ijkt}\cdot r_{iq}$, where r_{iq} indicates if request i requires skill domain $q \in \mathcal{Q}$ (see Sect. 4.3.1) (Chen et al. 2016, 2024).

  - *Equipment-related transitions*: After making equipment decisions x_t^{parts}, the repair kit can be updated to $\mathcal{E}_t^x = (\epsilon_{1kt}^x, \epsilon_{2kt}^x, \ldots, \epsilon_{|\mathcal{P}|kt}^x)$, where $\epsilon_{pkt}^x = \epsilon_{pkt} + x_{pkt}^{parts}\ \forall p \in \mathcal{P},\ k \in \mathcal{K}$ (Pham and Kiesmüller 2024).

- **Stochastic transitions**: Uncertainty is realized over an entire period (day) and enters the system through the exogenous information.

$$\omega_{t+1} = \left(\mathcal{N}_{t+1}^{new,\omega}, \left(\phi_{k(t+1)}^{abs,\omega}\right)_{k\in\mathcal{K}}, \left(\phi_{i(t+1)}^{fail,\omega}\right)_{i\in\mathcal{I}_t}, \left(d_{ip(t+1)}^{parts,\omega}\right)_{i\in\mathcal{N}_t,\,p\in\mathcal{P}}, \left(t_{ij}^{\omega}\right)_{i,\,j\in\mathcal{I}_t:i\neq j}, \left(p_{ik}^{\omega}\right)_{i\in\mathcal{I}_t,\,k\in\mathcal{K}}\right),$$

where $\mathcal{N}_{t+1}^{new,\omega}$ denotes the set of requests arriving during period $t+1$; $\phi_{k(t+1)}^{abs,\omega} \in \{0,1\}$ captures technician absence; Further, let $\mathcal{I}_t = \{i \in \mathcal{N}_t : \sum_{j\in\mathcal{N}_t\cup\{0\}:j\neq i}\sum_{k\in\mathcal{K}_t} x_{ijkt} = 1\}$ denote the set of requests scheduled for service in period $t+1$, and $\phi_{i(t+1)}^{fail,\omega} \in \{0,1\}$ indicate whether the service attempt for a request i succeeds or fails (Pham and Kiesmüller 2024). A service attempt may fail (i) due to missing spare parts (Pham and Kiesmüller 2024), (ii) technician skills that do not match the request's skill requirements (Stein et al. 2025), or (iii) stochastic travel and service times t_{ij}^{ω} and p_{ik}^{ω} (Ji et al. 2022), respectively.

The realized spare-part demand is given by $d_{ip(t+1)}^{parts,\,\omega}$ and is revealed upon arrival at the customer site (Pham and Kiesmüller 2024).

- *Service-related transitions*: Requests in $\mathcal{I}_t$ are partitioned into successful and failed requests:

$$\mathcal{N}_t^{succ} = \left\{ i \in \mathcal{I}_t : \phi_i^{fail} = 1 \vee \phi_{i(t+1)}^{fail,\,\omega} = 0 \right\},\ \mathcal{N}_t^{fail} = \left\{ i \in \mathcal{I}_t : \phi_{i(t+1)}^{fail,\,\omega} = 1 \right\}.$$

A request is considered completed if it succeeds on the first attempt ($\phi_{i(t+1)}^{fail,\,\omega} = 0$) or during a rework visit ($\phi_i^{fail} = 1$), where rework is assumed to always succeed in a single revisit (Pham and Kiesmüller 2024), though Stein et al. (2025) also allow for multiple revisits. Consequently, the set of pending requests at epoch $t+1$ is updated as $\mathcal{N}_{t+1} = (\mathcal{N}_t \setminus \mathcal{N}_t^{succ}) \cup \mathcal{N}_{t+1}^{new,\,\omega}$.

Since all requests are accepted upon arrival, $\mathcal{N}_{t+1}^{new,\omega}$ enters the system directly through ω_{t+1} and does not require a separate state representation as in request-based models. The remaining service-related state information is updated accordingly (Pham and Kiesmüller 2024; Stein et al. 2025):

$\phi_i^{fail} := 1 \forall i \in \mathcal{N}_t^{fail}$: failed requests are labeled as such,

$\phi_i^{due} := \max\left\{0, \phi_i^{due} - 1\right\} \forall i \in \mathcal{N}_{t+1}$: the number of periods (days) until the deadline decreases.

- *Technician-related transitions*: Uncertain technician availability is captured by $\phi_{k(t+1)}^{abs,\,\omega}$, which equals one if technician $k \in \mathcal{K}$ is absent (e.g., due to illness), and zero if the technician is available. Accordingly, the absence status of each technician $k \in \mathcal{K}$ is updated as $\phi_{k(t+1)}^{abs} = \phi_{k(t+1)}^{abs,\,\omega}$ (Stein et al. 2025).
- *Equipment-related transitions*: In addition to the deterministic update resulting from the replenishment decision x_t^{parts}, each technician's repair kit is subject to stochastic spare part consumption during service fulfillment. Therefore, the inventory of spare part type $p \in \mathcal{P}$ carried by technician $k \in \mathcal{K}$ by the end of period $t+1$ is given by post-decision inventory after replenishment net of realized spare part consumption in successful services during period $t+1$:

$$\epsilon_{pk(t+1)} = \left[\epsilon_{pkt}^{x} - \sum_{i \in \mathcal{N}_t^{succ}} d_{ip(t+1)}^{parts,\,\omega}\right]^+ \text{(Pham and Kiesmüller 2024).}$$

5.6 Rewards

Each action x_t in a given state s_t, together with the exogenous realization $\omega_{t+1} \in \Omega_{t+1}$, yields a random reward $R(s_t, x_t, \omega_{t+1})$, which may include positive contributions (priorities) as well as negative contributions (cost). Consistent with the two-part transitions, the reward can be decomposed into a deterministic component accrued when taking action x_t in pre-decision state s_t and a stochastic component realized after ω_{t+1} is revealed when being in post-decision state s_t^x:

$$R(s_t, x_t, \omega_{t+1}) = R^{det}(s_t, x_t) + R^{stoch}(s_t^x, \omega_{t+1}).$$

It is important to note that, if a stochastic reward is involved, the optimal action is determined based on the expected immediate reward, i.e., the single-stage reward $\mathbb{E}[R(s_t, x_t, \omega_{t+1})]$. In the following, we specify rewards for both request-based and day-based TRSP.

Request-based A positive acceptance reward is earned when (i) the provider does not reject the newly arrived request i_t^{new}, i.e., $x_{i_t^{new}t}^{(AR\text{-}TW)} \neq \varnothing$, and (ii) the customer confirms the booking by selecting an offered TW, i.e., $f_{i_t^{new}}^{\omega} \neq 0$. The resulting stochastic reward is.

$$\begin{aligned} R^{stoch}(s_t^x, \omega_{t+1}) &= R^{acc}(s_t^x, \omega_{t+1}) \\ &= \begin{cases} \mu_{i_t^{new}}, & if\ x_{i_t^{new}t}^{(AR-TW)} \neq \emptyset \wedge f_{i_t^{new}}^{\omega} \neq 0 \\ 0, & otherwise \end{cases}, \end{aligned}$$

where $\mu_{i_t^{new}}$ denotes the priority (e.g., revenue) associated with the new request. Since TW offers only become binding after the customer's choice is realized in the subsequent stochastic transition, no deterministic reward component $R^{det}(s_t, x_t)$ is incurred (Avraham and Raviv 2021; Paradiso et al. 2025).

Day-based In this case, rewards evaluate the end-of-day fulfillment planning decisions for the subsequent day. Accordingly, they include deterministic cost components implied by $x_t = (x_t^{route}, x_t^{parts})$ as well as stochastic components depending on ω_{t+1}, in particular the service outcomes $\left(\phi_{i(t+1)}^{fail,\omega}\right)_{i \in \mathcal{I}_t}$.

- **Deterministic rewards**: The following reward function aggregates the deterministic cost components related to routing, service delay, and equipment holding, and is defined as.

$$R^{det}(s_t, x_t) = -\left(C_t^{route}(s_t, x_t) + C_t^{delay,det}(s_t, x_t) + C_t^{holding}(s_t, x_t)\right).$$

  - *Travel cost*: These result from completing the requests scheduled for service in period $t+1$ ($\mathcal{I}_t$):

$C_t^{route}(s_t, x_t) = \sum_{i \in \mathcal{I}_t \cup \{0\}} \sum_{j \in \mathcal{I}_t \cup \{0\}: i \neq j} \sum_{k \in \mathcal{K}} c_{ijk}^{TC} x_{ijkt}$ (e.g., Chen et al. 2016, 2024; Nowak and Szufel 2024).

  - *Delay cost*: Requests that remain unscheduled despite an expiring deadline incur a deterministic delay penalty (with per-day delay penalty cost c^{delay}):

$C_t^{delay,\, det}\left(s_t,\ x_t\right) = c^{delay} \cdot \left|\left\{i \in \mathcal{N}_t \setminus \mathcal{I}_t : \phi_i^{due} = 0\right\}\right|$ (e.g. Nowak and Szufel 2024).

- *Holding cost*: Spare parts carried in technicians' repair kits incur daily holding cost proportional to their quantity, where $c_p^{holding}$ represents the per-unit holding cost of spare part type $p \in \mathcal{P}$:

$C_t^{holding}\left(s_t,\ x_t\right) = \sum_{p \in \mathcal{P}} \sum_{k \in \mathcal{K}} c_p^{holding} \cdot \epsilon_{pkt}^{x}$ (Pham and Kiesmüller 2024).

- **Stochastic rewards**: The stochastic reward (cost) depends on realized service outcomes $\left(\phi_{i(t+1)}^{fail,\,\omega}\right)_{i \in \mathcal{I}_t}$, i.e., whether service attempts succeed or fail (Pham and Kiesmüller 2024; Stein et al. 2025):

$$R^{stoch}\left(s_t^x,\ \omega_{t+1}\right) = -\left(C_t^{failed}\left(s_t^x,\ \omega_{t+1}\right) + C_t^{delay,\ stoch}\left(s_t^x,\ \omega_{t+1}\right)\right).$$

- *Fail-to-fix cost*: If the fulfillment of a scheduled request fails, a penalty cost is incurred: $C_t^{failed}\left(s_t^x,\ \omega_{t+1}\right) = c^{fail} \cdot \left|\mathcal{N}_t^{fail}\right|$.
- *Delay cost*: Failed requests whose deadline is due incur additional delay penalty costs:

$$C_t^{delay,\ stoch}\left(s_t^x,\ \omega_{t+1}\right) = c^{delay} \cdot \left|\left\{i \in \mathcal{N}_t^{fail} : \phi_i^{due} = 0\right\}\right|.$$

5.7 Objective

The objective is to determine a *policy* $\pi : \mathcal{S} \mapsto \mathcal{X}$, i.e., a mapping from states to actions. Let Π denote the set of all policies defined by such mappings. An optimal policy π^* specifies an action $x_t^{\pi^*}\left(s_t\right)$ for every possible state s_t and maximizes the expected cumulative reward across all decision epochs conditional on the initial state s_0. Formally, the resulting objective function can be expressed as

$$\max_{\pi \in \Pi} \mathbb{E}\left[\sum_{t=1}^{T-1} R\left(s_t,\ x_t^{\pi}\left(s_t\right),\ \Omega_{t+1}\right) | s_0\right],$$

where $x_t^{\pi}\left(s_t\right)$ represents the action selected according to policy π when the system is in state s_t.

The objective function stated above assumes a finite planning horizon of T decision epochs and does not incorporate a discount factor, which is consistent with the majority of contributions surveyed (e.g., Paradiso et al. 2025; Stein et al. 2025). In this setting, the resulting optimal policy π^* is non-stationary, as the optimal action in a given state may depend on the remaining time horizon. This is because the value of keeping flexibility for future requests changes as the end of the horizon approaches. However, two contributions in our survey deviate from this setting. Avraham and

Table 5 Overview of solution methods

Methodology	References	#
Branch-and-price	Cortés et al. (2014); Mathlouthi et al. 2021a); Souyris et al. (2013)	3
Branch-and-cut	Hanafi et al. (2020)	1
Branch-and-cut-and-price	Zamorano and Stolletz (2017)	1
Column Generation	Cavada et al. (2020)	1
Adaptive large neighborhood search	Ali et al. (2021), Erdogan & M'Hallah (2023), Guastaroba et al. (2021), Graf (2020), Hojabri et al. (2018), Kovacs et al. (2012), Li et al. (2021), Sørensen et al. (2025)	8
Variable neighborhood search	Rastegar et al. (2024), Schubert et al. (2021), Liu et al. (2019)	3
Iterated local search	Gu et al. (2022), Kastrati et al. (2021), Xie et al. (2017), Yahiaoui et al. (2023)	4
Greedy randomized adaptive search procedure	Xu and Chiu (2001)	1
Genetic algorithm	Bae and Moon (2016), Damm et al. (2016, 2021, 2025), Pekel (2022), Song et al. (2025)	6
Ant colony optimization	Pereira et al. (2020)	1
Particle swarm optimization	Pekel (2020)	1
Adaptive memory programming	Mathlouthi et al. 2021b); Tang et al. (2007)	2
Matheuristic	Pillac et al. (2013), Jagtenberg et al. (2020), Gamst and Pisinger (2024)	3
Other (heuristic methods)	Anoshkina and Meisel (2019), Avraham et al. (2017), Frits and Bertok (2021), Mathlouthi et al. (2018), Pitakaso et al. (2024), Weigel and Cao (1999), Kheiri et al. (2020), Pourjavad and Almehdawe (2022), Qiu et al. (2022)	9
Cost function approximation	Anoshkina and Meisel (2020), Chen et al. (2016, 2024), Qiu et al. (2023)	4
Value function approximation	Avraham and Raviv (2021), Pham and Kiesmüller (2024), Stein et al. (2025)	3
Direct lookahead approximation	Ji et al. (2022), Nielsen and Pisinger (2023, 2025), Nowak and Szufel (2024), Paradiso et al. (2025), Pham and Kiesmüller (2022), Pillac et al. (2012)	7

Raviv (2021) assume an infinite planning horizon and optimize the steady-state acceptance rate rather than cumulative reward over a finite horizon. Pham and Kiesmüller (2024) likewise consider an infinite planning horizon, applying a discount factor $\gamma \in [0, 1)$ to future rewards, which ensures convergence of the objective and gives rise to a stationary optimal policy.

6 Solution methods

This section provides a high-level overview of solution methods employed in the TRSP literature. A detailed analysis of specific algorithms is beyond the scope of this work, as the purpose of our survey is to systematically structure the heterogeneous TRSP literature at the modeling level rather than to compare or evaluate solution methods in depth. Table 5 summarizes the solution methods used for the configurations discussed in Sects. 4 and 5. We first list solution methods for static-deterministic TRSP configurations and then for stochastic-dynamic ones.

6.1 Static-deterministic TRSPs

For these configurations, solution approaches can be classified into exact and heuristic methods:

Exact methods. Exact methods for static-deterministic TRSP configurations include branch-and-price, branch-and-cut, branch-and-cut-and-price, and column generation.

Heuristic methods. Heuristic solution methods can be classified as follows:

- *Local-search based methods*: adaptive large neighborhood search, variable neighborhood search, iterated local search, greedy randomized adaptive search procedure.
- *Evolutionary methods*: genetic algorithm, ant colony optimization, particle swarm optimization, adaptive memory programming.
- *Matheuristics.*

6.2 Stochastic-dynamic TRSPs

Realistic-sized instances of stochastic-dynamic TRSPs generally cannot be solved to optimality due to the curses of dimensionality. Therefore, authors apply heuristic solution methods that, in a broader sense, can be subsumed under the class of *approximate dynamic programming (ADP)* methods. According to Powell (2022), ADP methods can be divided into two classes, policy search and lookahead approximations, each of which has two subclasses. Policy search methods have in common that a particular functional form of the policy is specified and its parameters are tuned. Of this class, only cost function approximations (CFAs), which are parameterized static-deterministic optimization models, are proposed in the TRSP literature. Lookahead approximations determine state (-action) values to evaluate feasible decisions. Subclasses are value function approximations (VFAs), which use statistical learning, and direct lookahead approximations (DLAs), which explicitly anticipate the future evolution of the planning horizon from the current state onward.

In the TRSP literature, the vast majority of methods belong to two particular special cases of these methods: first, and most commonly, a static-deterministic TRSP formulation is solved based on the available information at the current decision epoch. If such a formulation comprises multiple periods (days), it can be classified as a deterministic DLA. Otherwise, it is a myopic CFA. Second, VFA methods drawing on reinforcement learning algorithms are proposed.

7 Future research directions

Our modeling framework not only enables the systematic reconstruction of existing models, but also facilitates the identification of new TRSP configurations. Next, by examining which combinations of modeling dimensions and realizations remain underexplored in Tables 2 and 4, we derive potential directions for future research that address underrepresented yet practically relevant configurations:

Online-to-offline business models. In modern *online-to-offline* business models for technician-based ancillary services (see, e.g., DHL, 2026; IKEA, 2026; Rhenus, 2026), the interaction between provider and customers takes place digitally when it comes to requesting and booking services. Thereby, requests arrive dynamically over time, and providers have to decide on TW offers for incoming requests without knowing the number of future requests, their TW preferences, and their skill or equipment requirements. Accordingly, it is state-of-the-art to manage these services by solving a stochastic-dynamic TRSP.

- *Stochastic-dynamic modeling of teaming and synchronization*: The literature on stochastic-dynamic TRSPs has so far been limited almost exclusively to services of type (a) (see Tables 2 and 4). Despite their relevance in practice for providers of technician-based after sales field services in an online-to-offline business model (see, e.g., DHL, 2026; IKEA, 2026; Rhenus, 2026), only Anoshkina and Meisel (2020) model service types (b) and (c) through a stochastic-dynamic configuration.
- *Demand management*: Furthermore, requests may be placed several days in advance, creating demand interdependencies across days. This gives providers the opportunity to actively manage demand by dynamically controlling service availability or prices, which has various benefits: for instance, by controlling which TWs are made available, the provider can try to steer all customers in a certain neighborhood into the same TW. This improves demand consolidation and resource utilization, and directly translates into cost savings (e.g., travel cost, vehicle fixed cost, overtime cost). Further, demand management allows reserving resources for future high-priority requests.

If a provider applies demand management, special stochastic-dynamic TRSPs arise, which belong to the family of integrated demand management and vehicle routing problems (i-DMVRPs) (Fleckenstein et al. 2023). To date, the work of Avraham and Raviv (2021) is the only (stochastic-dynamic) TRSP that includes demand management by modeling it as an i-DMVRP. However, in modern business applications, real-world TRSPs for technician-based after-sales field services often constitute i-DMVRPs.

Crucially, none of the request-based TRSPs considers rewards from routing and scheduling decisions as it is standard modeling practice in other application areas of i-DMVRPs, such as AHD. In terms of our modeling framework, this would require combining request-based and day-based decision-making – a configuration that has not yet been investigated.

Combined teaming and synchronization. Although service types (b) and (c) can be straightforwardly combined (see Sect. 4.2.2), this joint configuration has received almost no attention in the literature. In practice, sequential tasks associated with a service request are often executed by teams rather than by single technicians. Examples include the 2-man-handling offered by DHL and Rhenus, where teams of two technicians sequentially deliver and install furniture, white goods, or consumer electronics (DHL, 2026; Rhenus, 2026). Explicitly integrating teaming and synchronization decisions therefore represents a natural extension of existing TRSP configurations.

Technician-oriented objectives. These objectives are highly underrepresented in the surveyed literature, even though the efficient deployment of technicians represents a central goal of TRSPs. Team consistency provides an illustrative example: maintaining stable teams over time fosters effective working relationships among technicians, reduces stress and coordination effort, and lowers the likelihood of miscommunication, which in turn may contribute to fewer service failures and rework visits (Kalisch et al. 2008; Russel et al. 2011). Nevertheless, Anoshkina and Meisel (2020) are the only authors who incorporate team consistency into their configuration.

Equipment requirements. In response to growing concerns about climate change and resource scarcity, repair services are gaining importance in the after-sales service market as a means to extend product lifespans and support sustainable consumption and production (Laitala et al. 2021). In some regions, legislation actively promotes repairs: for example, households in the state of Thuringia, Germany, received reimbursements of up to 100 euros per repair procedure of white goods (Verbraucherzentrale-Thüringen, 2026). Consequently, effective spare-part inventory management becomes increasingly critical. As repair services rely on the availability of appropriate tools and spare parts, suboptimal inventory decisions may result in failed service attempts, rework visits, and increased operational cost (Pham and Kiesmüller 2024). Nevertheless, our literature classification reveals that equipment requirements and the associated consideration of holding cost remain underrepresented in TRSP configurations. In line with Agatz et al. (2025), we therefore encourage future work to more tightly couple technician routing and scheduling decisions with inventory planning for tools and spare parts.

Solution methods. As noted in Sect. 6, a systematic analysis of solution methods, in analogy to the configurable modeling framework, is beyond the scope of this paper. Nevertheless, our review reveals that heterogeneity at the solution-method level is even more pronounced than at the modeling level (see Table 5), as multiple methods are often proposed for the same configuration. Just as a unified view on the modeling landscape, a unified framework for solution methods would be highly beneficial. It could support a more transparent comparison and evaluation of alternative methods, especially for identical or at least similar configurations, and, in turn, could accelerate methodological progress. For stochastic-dynamic configurations in particular, aligning solution methods with model formulations more closely is promising. In this context, ADP and RL methods that explicitly exploit the MDP structure of these configurations appear especially valuable (see, e.g., Pham and Kiesmüller 2024; Stein et al. 2025).

8 Conclusion

In this survey, we provided a structured review of TRSPs arising in technician-based after-sales field services. Motivated by the heterogeneity of the existing literature, we introduced a unified modeling framework that organizes TRSPs at the modeling level rather than solely at the problem level. Building on a modeling taxonomy, the framework decomposes TRSPs into immutable core routing constraints as well as service- and technician-related constraints, and objective components. Furthermore, our taxonomy also accounts for sequential decision-making under uncertainty. Applying the framework to classify the static-deterministic and stochastic-dynamic TRSP literature (Tables 2 and 4), we demonstrate that a TRSP can be represented as a specific configuration of our modeling framework.

Drawing on the real-world applications discussed in Sect. 2 and the model-based classification of the literature in Sects. 4 and 5, we derive research gaps as well as promising directions for future research. Among others, these include the stochastic-dynamic modeling of problems involving teaming and synchronization, the integration of demand management and routing decisions within an i-DMVRP, and a stronger consideration of resource-related problem features, in particular technician-oriented objectives and equipment requirements. Given the identified research gaps, we encourage researchers to use these directions as a starting point for advancing TRSP configurations toward modern real-world applications. This is particularly relevant in light of the growing importance of after-sales services in both B2C and B2B markets, driven by trends such as servitization, the extension of product lifetimes, the differentiation from market competitors, and the increasing complexity of technical products.

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References

Agatz N, Fransoo JC, Rabinovich E, Sousa R (2025) Innovations, technologies, and the economics of last-mile operations: a call for research in operations management. J Oper Manag 71(2):166–175. https://doi.org/10.1002/joom.1355

Ali O, Côté J-F, Coelho LC (2021) Models and algorithms for the delivery and installation routing problem. Eur J Oper Res 291(1):162–177. https://doi.org/10.1016/j.ejor.2020.09.011

Anoshkina Y, Meisel F (2019) Technician teaming and routing with service-, cost- and fairness-objectives. Comput Ind Eng 135:868–880. https://doi.org/10.1016/j.cie.2019.05.016

Anoshkina Y, Meisel F (2020) Interday routing and scheduling of multi-skilled teams with consistency consideration and intraday rescheduling. EURO J Transp Logistics 9(3):100012. https://doi.org/10.1016/j.ejtl.2020.100012

APPLiA (2020) The Home Appliance Industry in Europe. Retrieved March 6, 2026. https://www.applia-europe.eu/images/applia-statistical-report-2020.pdf

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

Avraham E, Raviv T, Khmelnitsky E (2017) The decentralized field service routing problem. Transp Res Part B: Methodol 104:290–316. https://doi.org/10.1016/j.trb.2017.07.005

Bae H, Moon I (2016) Multi-depot vehicle routing problem with time windows considering delivery and installation vehicles. Appl Math Model 40(13–14):6536–6549. https://doi.org/10.1016/j.apm.2016.01.059

Bijvank M, Koole G, Vis IF (2010) Optimising a general repair kit problem with a service constraint. Eur J Oper Res 204(1):76–85. https://doi.org/10.1016/j.ejor.2009.10.004

Cabrera N, Cordeau J-F, Mendoza JE (2026) A survey of workforce scheduling and routing problems. Comput Oper Res 189:107344. https://doi.org/10.1016/j.cor.2025.107344

Çakırgil S, Yücel E, Kuyzu G (2020) An integrated solution approach for multi-objective, multi-skill workforce scheduling and routing problems. Comput Oper Res 118:104908. https://doi.org/10.1016/j.cor.2020.104908

Castillo-Salazar JA, Landa-Silva D, Qu R (2016) Workforce scheduling and routing problems: literature survey and computational study. Ann Oper Res 239(1):39–67. https://doi.org/10.1007/s10479-014-1687-2

Cavada JP, Cortés CE, Goic M, Weintraub A, Zambrano JI (2020) Accounting for cost heterogeneity on the demand in the context of a technician dispatching problem. Eur J Oper Res 287(3):820–831. https://doi.org/10.1016/j.ejor.2020.04.056

Chen X, Thomas BW, 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, Li K, Lin S, Ding X (2024) Technician routing and scheduling with employees' learning through implicit cross-training strategy. Int J Prod Econ 271:109208. https://doi.org/10.1016/j.ijpe.2024.109208

Cordeau J-F, Iori M, Vezzali D (2024) An updated survey of attended home delivery and service problems with a focus on applications. Ann Oper Res 343(2):885–922. https://doi.org/10.1007/s10479-024-06241-9

Cortés CE, Gendreau M, Rousseau LM, Souyris S, Weintraub A (2014) Branch-and-price and constraint programming for solving a real-life technician dispatching problem. Eur J Oper Res 238(1):300–312. https://doi.org/10.1016/j.ejor.2014.03.006

Damm RB, Ronconi DP (2021) A multi-objective biased random-key genetic algorithm for service technician routing and scheduling problem. In Mes M, Lalla-Ruiz E, Voß S (ed) Computational Logistics, 471–486. https://doi.org/10.1007/978-3-030-87672-2_31

Damm RB, Resende MG, Ronconi DP (2016) A biased random key genetic algorithm for the field technician scheduling problem. Comput Oper Res 75:49–63. https://doi.org/10.1016/j.cor.2016.05.003

Damm RB, Chaves AA, Riveaux JA, Ronconi DP (2025) Scheduling technicians and tasks through an adaptive multi-objective biased random-key genetic algorithm. Ann Oper Res 346:945–980. https://doi.org/10.1007/s10479-024-06325-6

DHL (2026) 2-Mann-Handling. Retrieved March 6, 2026. https://www.dhl.de/de/geschaeftskunden/paket/leistungen-und-services/2-mann-handling.html

Drexl M (2012) Synchronization in vehicle routing–a survey of VRPs with multiple synchronization constraints. Transport Sci 46(3):297–316. https://doi.org/10.1287/trsc.1110.0400

Ehmke JF, Klein R, Steinhardt C, Strauss A (2024) Data-driven demand and supply management for online-to-offline logistic services. OR Spectrum 46(2):237–240. https://doi.org/10.1007/s00291-024-00768-w

Erdogan MS, M'Hallah R (2023) Synchronizing delivery and installation with vehicle sharing: a hybrid adaptive large neighborhood search. Comput Ind Eng 185:109676. https://doi.org/10.1016/j.cie.2023.109676

Euchi J, Masmoudi M, Siarry P (2022) Home health care routing and scheduling problems: a literature review. 4OR 20(3):351–389. https://doi.org/10.1007/s10288-022-00516-2

Fleckenstein D, Klein R, Steinhardt C (2023) Recent advances in integrating demand management and vehicle routing: a methodological review. Eur J Oper Res 306(2):499–518. https://doi.org/10.1016/j.ejor.2022.04.032

Frits M, Bertok B (2021) Routing and scheduling field service operation by P-graph. Comput Oper Res 136:105472. https://doi.org/10.1016/j.cor.2021.105472

Gamst M, Pisinger D (2024) Decision support for the technician routing and scheduling problem. Networks 83(1):169–196. https://doi.org/10.1002/net.22188

Graf B (2020) Adaptive large variable neighborhood search for a multiperiod vehicle and technician routing problem. Networks 76(2):256–272. https://doi.org/10.1002/net.21959

Gu H, Zhang Y, Zinder Y (2022) An efficient optimisation procedure for the workforce scheduling and routing problem: lagrangian relaxation and iterated local search. Comput Oper Res 144:105829. https://doi.org/10.1016/j.cor.2022.105829

Guastaroba G, Côté J-F, Coelho LC (2021) The multi-period workforce scheduling and routing problem. Omega 102:102302. https://doi.org/10.1016/j.omega.2020.102302

Hanafi S, Mansini R, Zanotti R (2020) The multi-visit team orienteering problem with precedence constraints. Eur J Oper Res 282(2):515–529. https://doi.org/10.1016/j.ejor.2019.09.045

Hojabri H, Gendreau M, Potvin J-Y, Rousseau L-M (2018) Large neighborhood search with constraint programming for a vehicle routing problem with synchronization constraints. Comput Oper Res 92:87–97. https://doi.org/10.1016/j.cor.2017.11.011

IKEA (2026) Montageservice: Zeit und Energie sparen. Retrieved March 6, 2026. https://www.ikea.com/de/de/customer-service/services/assembly/

Irawan CA, Ouelhadj D, Jones D, Stålhane M, Sperstad IB (2017) Optimisation of maintenance routing and scheduling for offshore wind farms. Eur J Oper Res 256(1):76–89. https://doi.org/10.1016/j.ejor.2016.05.059

Jagtenberg CJ, Maclaren OJ, Mason AJ, Raith A, Shen K, Sundvick M (2020) Columnwise neighborhood search: a novel set partitioning matheuristic and its application to the VeRoLog solver challenge 2019. Networks 76(2):273–293. https://doi.org/10.1002/net.21961

Ji C, Mandania R, Liu J, Liret A (2022) Scheduling on-site service deliveries to minimise the risk of missing appointment times. Transp Res E 158:102577. https://doi.org/10.1016/j.tre.2021.102577

Kalisch BJ, Begeny S, Anderson C (2008) The effect of consistent nursing shifts on teamwork and continuity of care. J Nurs Adm 38(3):132–137. https://doi.org/10.1097/01.NNA.0000310721.28042.0b

Kastrati V, Ahmeti A, Musliu N (2021) Solving vehicle routing and scheduling with delivery and installation of machines using ILS. In De Causmaecker P, Özcan E, Berghe GV (ed) Proceedings of the 13th International Conference on the Practice and Theory of Automated Timetabling, 1:207–223

Kheiri A, Ahmed L, Boyacı B, Gromicho J, Mumford C, Özcan E, Dirikoç AS (2020) Exact and hyperheuristic solutions for the distribution-installation problem from the VeRoLog 2019 challenge. Networks 76(2):294–319. https://doi.org/10.1002/net.21962

Koch S, Klein R (2020) Route-based approximate dynamic programming for dynamic pricing in attended home delivery. Eur J Oper Res 287(2):633–652. https://doi.org/10.1016/j.ejor.2020.04.002

Köhler C, Ehmke JF, Campbell AM, Cleophas C (2023) Evaluating pricing strategies for premium delivery time windows. EURO J Transp Logistics 12:100108. https://doi.org/10.1016/j.ejtl.2023.100108

Köhler C, Campbell AM, Ehmke JF (2024) Data-driven customer acceptance for attended home delivery. OR Spectrum 46(2):295–330. https://doi.org/10.1007/s00291-023-00712-4

Kovacs AA, Parragh SN, Doerner KF, Hartl RF (2012) Adaptive large neighborhood search for service technician routing and scheduling problems. J Sched 15(5):579–600. https://doi.org/10.1007/s10951-011-0246-9

Kowalkowski C, Gebauer H, Kamp B, Parry G (2017) Servitization and deservitization: overview, concepts, and definitions. Ind Mark Manage 60:4–10. https://doi.org/10.1016/j.indmarman.2016.12.007

Kurata H, Nam S-H (2010) After-sales service competition in a supply chain: optimization of customer satisfaction level or profit or both? Int J Prod Econ 127(1):136–146. https://doi.org/10.1016/j.ijpe.2010.05.005

Laitala K, Klepp IG, Haugrønning V, Throne-Holst H, Strandbakken P (2021) Increasing repair of household appliances, mobile phones and clothing: experiences from consumers and the repair industry. J Clean Prod 282:125349. https://doi.org/10.1016/j.jclepro.2020.125349

Lang MA, Cleophas C, Ehmke JF (2021) Anticipative dynamic slotting for attended home deliveries. Oper Res Forum 2(4):70. https://doi.org/10.1007/s43069-021-00086-9

Li G, Huang FF, Cheng T, Zheng Q, Ji P (2014) Make-or-buy service capacity decision in a supply chain providing after-sales service. Eur J Oper Res 239(2):377–388. https://doi.org/10.1016/j.ejor.2014.05.035

Li X, Li Y, Cai X, Shan J (2016) Service channel choice for supply chain: who is better off by undertaking the service? Prod Oper Manage 25(3):516–534. https://doi.org/10.1111/poms.12392

Li W, Li K, Kumar PN, Tian Q (2021) Simultaneous product and service delivery vehicle routing problem with time windows and order release dates. Appl Math Model 89(1):669–687. https://doi.org/10.1016/j.apm.2020.07.045

Liu B, Guo X, Yu Y, Zhou Q (2019) Minimizing the total completion time of an urban delivery problem with uncertain assembly time. Transp Res E 132:163–182. https://doi.org/10.1016/j.tre.2019.11.002

Mathlouthi I, Gendreau M, Potvin J-Y (2018) Mixed integer linear programming for a multi-attribute technician routing and scheduling problem. INFOR: Inform Syst Oper Res 56(1):33–49. https://doi.org/10.1080/03155986.2017.1335047

Mathlouthi I, Gendreau M, Potvin J-Y (2021a) Branch-and-price for a multi-attribute technician routing and scheduling problem. Oper Res Forum 2(1):1–35. https://doi.org/10.1007/s43069-020-00044-x

Mathlouthi I, Gendreau M, Potvin J-Y (2021b) A metaheuristic based on tabu search for solving a technician routing and scheduling problem. Comput Oper Res 125:105079. https://doi.org/10.1016/j.cor.2020.105079

Misir M, Smet P, Verbeeck K, Berghe GV (2011) Security personnel routing and rostering: a hyper-heuristic approach. In: Proceedings of the 3rd International Conference on Applied Operational Research 3:193–205

Nielsen CC, Pisinger D (2023) Tactical planning for dynamic technician routing and scheduling problems. Transp Res E 177:103225. https://doi.org/10.1016/j.tre.2023.103225

Nielsen CC, Pisinger D (2025) Workforce scheduling and routing with substitution skills and workload balancing. Working paper, Technical University of Denmark. https://doi.org/10.2139/ssrn.5262892

Nowak M, Szufel P (2024) Technician routing and scheduling for the sharing economy. Eur J Oper Res 314(1):15–31. https://doi.org/10.1016/j.ejor.2023.09.023

Paradiso R, Roberti R, Ulmer MW (2025) Lookahead scenario relaxation for dynamic time window assignment in service routing. Transp Res Part B: Methodol 192:103137. https://doi.org/10.1016/j.trb.2024.103137

Paraskevopoulos DC, Laporte G, Repoussis PP, Tarantilis CD (2017) Resource constrained routing and scheduling: review and research prospects. Eur J Oper Res 263(3):737–754. https://doi.org/10.1016/j.ejor.2017.05.035

Pekel E (2020) Solving technician routing and scheduling problem using improved particle swarm optimization. Soft Comput 24(24):19007–19015. https://doi.org/10.1007/s00500-020-05333-5

Pekel E (2022) A simple solution to technician routing and scheduling problem using improved genetic algorithm. Soft Comput 26(14):6739–6748. https://doi.org/10.1007/s00500-022-07072-1

Pereira DL, Alves JC, de Oliveira Moreira MC (2020) A multiperiod workforce scheduling and routing problem with dependent tasks. Comput Oper Res 118:104930. https://doi.org/10.1016/j.cor.2020.104930

Pham DT, Kiesmüller GP (2022) Multiperiod integrated spare parts and tour planning for on-site maintenance activities with stochastic repair requests. Comput Oper Res 148:105967. https://doi.org/10.1016/j.cor.2022.105967

Pham DT, Kiesmüller GP (2024) Hybrid value function approximation for solving the technician routing problem with stochastic repair requests. Transport Sci 58(2):499–519. https://doi.org/10.1287/trsc.2022.0434

Pillac V, Guéret C, Medaglia AL (2012) On the dynamic technician routing and scheduling problem. Technical Report, École des Mines de Nantes. https://hal.science/hal-00739781v1

Pillac V, Guéret C, Medaglia AL (2013) A parallel matheuristic for the technician routing and scheduling problem. Optim Lett 7(7):1525–1535. https://doi.org/10.1007/s11590-012-0567-4

Pitakaso R, Sethanan K, Kumar A, Tan KH, Nanthasamroeng N (2024) An application of artificial intelligence for solving multi-visit scheduling and routing of multi-heterogeneous resources. Ann Oper Res 1–50. https://doi.org/10.1007/s10479-024-05836-6

Pourjavad E, Almehdawe E (2022) Optimization of the technician routing and scheduling problem for a telecommunication industry. Ann Oper Res 315(1):371–395. https://doi.org/10.1007/s10479-022-04658-8

Powell WB (2022) Reinforcement learning and stochastic optimization: a unified framework for sequential decisions. Wiley, Hoboken, NJ. https://doi.org/10.1002/9781119815068

Psaraftis HN, Wen M, Kontovas CA (2016) Dynamic vehicle routing problems: three decades and counting. Networks 67(1):3–31. https://doi.org/10.1002/net.21628

Qiu H, Wang S, Yin Y, Wang D, Wang Y (2022) A deep reinforcement learning-based approach for the home delivery and installation routing problem. Int J Prod Econ 244:108362. https://doi.org/10.1016/j.ijpe.2021.108362

Qiu H, Wang J, Wang D, Yin Y (2023) Service-oriented multi-skilled technician routing and scheduling problem for medical equipment maintenance with sudden breakdown. Adv Eng Inform 57:102090. https://doi.org/10.1016/j.aei.2023.102090

Rastegar M, Karimi H, Vahdani H (2024) Technicians scheduling and routing problem for elevators preventive maintenance. Expert Syst Appl 235:121133. https://doi.org/10.1016/j.eswa.2023.121133
Rhenus (2026) 2-Mann-Handling—mehr Service für Ihre Last-Mile-Logistik. Retrieved March 6, 2026. https://www.rhenus.group/de/de/2-mann-handling/
Russel D, Rosati RJ, Rosenfeld P, Marren JM (2011) Continuity in home health care: is consistency in nursing personnel associated with better patient outcomes? J Healthc Qual 33(6):33–39. https://doi.org/10.1111/j.1945-1474.2011.00131.x
Schubert D, Kuhn H, Holzapfel A (2021) Same-day deliveries in omnichannel retail: integrated order picking and vehicle routing with vehicle-site dependencies. Nav Res Logist 68(6):721–744. https://doi.org/10.1002/nav.21954
Song G, Yuan B, Jiang Z (2025) Integrated optimisation of delivery and installation operations in home appliance last-mile logistics. Int J Prod Res 1–17. https://doi.org/10.1080/00207543.2025.2568738
Sørensen S, Nielsen CC, Pisinger D, Fürstenheim JI (2025) A consensus fixing heuristic to workforce investments in field service. Comput Oper Res 183:107184. https://doi.org/10.1016/j.cor.2025.107184
Souyris S, Cortés CE, Ordóñez F, Weintraub A (2013) A robust optimization approach to dispatching technicians under stochastic service times. Optim Lett 7(7):1549–1568. https://doi.org/10.1007/s11590-012-0557-6
Stein J, Hildebrandt FD, Ulmer MW, Thomas BW (2025) Learning state-dependent policy parametrizations for dynamic technician routing with rework. Transport Sci 59(5):1153–1171. https://doi.org/10.1287/trsc.2024.0844
Tang H, Miller-Hooks E, Tomastik R (2007) Scheduling technicians for planned maintenance of geographically distributed equipment. Transp Res E 43(5):591–609. https://doi.org/10.1016/j.tre.2006.03.004
Tsang E, Voudouris C (1997) Fast local search and guided local search and their application to British Telecom's workforce scheduling problem. Oper Res Lett 20(3):119–127. https://doi.org/10.1016/S0167-6377(96)00042-9
Ulmer MW, Goodson JC, Mattfeld DC, Thomas BW (2020) On modeling stochastic dynamic vehicle routing problems. EURO J Transp Logistics 9(2):100008. https://doi.org/10.1016/j.ejtl.2020.100008
Verbraucherzentrale-Thüringen (2026) Reparaturbonus Thüringen 2.0 gestartet! Retrieved March 6, 2026. https://www.hwk-erfurt.de/artikel/reparaturbonus-thueringen-2-0-gestartet-4,0,1691.html
Weigel D, Cao B (1999) Applying GIS and OR techniques to solve sears technician-dispatching and home-delivery problems. Interfaces 29(1):112–130. https://doi.org/10.1287/inte.29.1.112
Xie F, Potts CN, Bektas T (2017) Iterated local search for workforce scheduling and routing problems. J Heuristics 23(6):471–500. https://doi.org/10.1007/s10732-017-9347-8
Xu J, Chiu SY (2001) Effective heuristic procedures for a field technician scheduling problem. J Heuristics 7(5):495–509. https://doi.org/10.1023/A:1011377929184
Yahiaoui A-E, Afifi S, Allaoui H (2023) Enhanced iterated local search for the technician routing and scheduling problem. Comput Oper Res 160:106385. https://doi.org/10.1016/j.cor.2023.106385
Zamorano E, Stolletz R (2017) Branch-and-price approaches for the multiperiod technician routing and scheduling problem. Eur J Oper Res 257(1):55–68. https://doi.org/10.1016/j.ejor.2016.06.058
Zamorano E, Becker A, Stolletz R (2018) Task assignment with start time-dependent processing times for personnel at check-in counters. J Sched 21(1):93–109. https://doi.org/10.1007/s10951-017-0523-3
Zhang S, Dan B, Zhou M (2019) After-sale service deployment and information sharing in a supply chain under demand uncertainty. Eur J Oper Res 279(2):351–363. https://doi.org/10.1016/j.ejor.2019.05.014