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On the value and challenge of remote assistance in on-field operations

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ABSTRACT

The skilled labor shortage is expected to become increasingly critical in the near future. While this issue affects various industries, the repair and maintenance sector is particularly impacted. Companies operating in this industry face significant challenges in hiring sufficient skilled labor to maintain their daily service operations. Throughout the day, technicians spend a significant portion of their working hours traveling to customer sites, which reduces their effective utilization for completing tasks. Initial efforts to address this challenge have emerged in the form of remote assistance solutions. In the context of service operations, junior technicians with less working experience visit customers with service requests on-site, while expert technicians remain at a central hub, providing real-time assistance remotely to their colleagues in the field. Accordingly, a decision-maker needs to determine and synchronize the daily schedules for both on-site and expert technicians to, as assumed in our work, minimize the working time for expert technicians. Although some literature discusses technical implementations, the emerging business concept and its operational planning have received little attention. We introduce and model the problem by providing effective heuristic planning solutions via Hexaly. Given the limited availability of experts, our approach improves the utilization of their working hours. Compared to scenarios without remote assistance, our results indicate that scarce expert resources can be reduced and replaced by additional junior technicians performing on-site visits. The benefits of remote assistance are particularly evident in rural regions, where customer sites are widely spread, and in operations with rather short service times.

1. Introduction

The ongoing trend of skilled labor shortage is unbroken, affecting the industrial landscape across numerous countries. Moreover, it can even hinder economic recovery and long-term prosperity in large and developed economies (Kunath and Tiedemann, 2025). In Germany's craft sector alone, the number of vacant positions for expert technicians reached an all-time high in 2022, with six out of ten vacancies remaining unoccupied (Malin and Köppen, 2023). One sector particularly affected by the shortage of skilled labor is the repair and maintenance sector, which includes services such as the maintenance on production machinery, the repair of large household appliances, or the installation of cable. It accounts for annual expenditures amounting to billions of dollars (IBISWorld, 2023). One of the main issues in this sector is the shortage of skilled labor, which makes it challenging to ensure consistently high-quality service (Sahiner and Golbasi, 2024). Simultaneously, service quality plays a crucial role in ensuring customer satisfaction, which is essential for fostering long-term customer relationships and securing customer retention (Hong and Kim, 2020). Thus, in the light of skilled labor shortage, where expert technicians represent a scarce resource, companies are increasingly challenged to recruit and retain a sufficiently qualified workforce.

An additional problem for companies operating in the maintenance and repair sector is that expert technicians often spend a substantial share of their working hours, up to 50%, traveling between customer locations (Gourmelen, 2020). These periods, where no service is delivered, further reduce the time experts have to actually fix issues. A viable option to mitigate this inefficiency may be the implementation of remote assistance to improve the utilization of expert working hours. This concept involves a wireless connection between an on-site technician, who physically visits the customer, and an expert technician located at a central hub, who provides remote guidance and troubleshooting support (Silmukari, 2019). Typically, on-site technicians are less experienced, whereas expert technicians possess extensive knowledge, but may earn more than twice the salary of on-site technicians (Indeed, 2025). A key advantage of remote assistance lies in the potential that expert technicians are no longer required to travel between customer sites which significantly increases work hour utilization. Consequently, their limited availability can be more efficiently leveraged. Furthermore, remote assistance may even provide better service outcome compared to individual work (Bottecchia et al., 2010).

The general concept of remote assistance is not entirely new, but has gained attention in recent years, especially within the maintenance and

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repair sector through advancements in technology (Silmukari, 2019). Existing research in this field has primarily focused on its technical implementation in real-world applications, and on the influence of different collaboration styles (Kim et al., 2018). A recent survey by Fidalgo et al. (2023) illustrates the broad applicability of remote assistance, e.g., in Mohr et al. (2020), Gao et al. (2020), or Gasques et al. (2021). Their findings align with the results of a survey conducted among 400 senior executives across the manufacturing and service provider industries, in which remote assistance was identified as a top strategic priority (IFS, 2023). Notably, 44% of all respondents indicated that they plan to implement remote assistance technologies in the future.

To exploit the benefits or remotely working experts, effective operational planning is needed. At the moment, without remote experts, companies use standard vehicle routing problem (VRP) solutions for their daily operations. Such solutions determine the assignment of customers to on-site technicians and the routing for each technician. Adding remote experts now requires additional considerations, in particular the assignment of customers to remote technicians, the sequence of customers for remote technicians and the synchronization between on-site and remote technicians when serving a customer. One straightforward approach may be to first plan the routes of the on-site technicians via standard VRP solutions and, in a subsequent step, schedule the work for the expert technicians accordingly based on the routing solutions. However, such a *sequential* approach may lead to operational inefficiencies due to missing synchronization. For example, on-site technicians may arrive at customers without an expert available, or remote experts are available while all on-site technicians are traveling. In both cases, resources are idle and working times are spent ineffectively. An alternative, more effective, *integrated* planning approach simultaneously involves routing of on-site technicians (i), scheduling of experts and on-site technicians (ii), and their synchronization (iii) to reduce working times.

Especially the synchronization requirement introduces significant combinatorial complexity, making integrated planning computationally challenging. The underlying problem can be modeled as a variant of the standard VRP with synchronization constraints, formulated as a mixed-integer programming (MIP) model. To address instances of realistic size, we employ the optimization solver provided by *Hexaly* using a combination of heuristic and exact modeling techniques. We further justify its selection by benchmarking solutions against exact solvers. Our analysis explores how daily work schedules can be jointly improved within an integrated planning framework. Finally, we assess the operational value of remote assistance and identify scenarios in which the adoption of this concept offers an effective strategy for mitigating the shortage of expert technicians.

In our numerical study, we derive several key insights. We find out that the utilization of scarce expert resources can be improved through an integrated planning approach that jointly considers routing and scheduling decisions. Compared to sequential planning, integrated planning reduces expert working hours by up to 8%, while keeping additional on-site technician working hours below 4%. Furthermore, we show that implementing remote assistance is particularly beneficial in operational environments characterized by longer travel distances, lower customer density, and short service time durations. For businesses employing highly qualified experts with comparatively high salaries, this can lead to measurable reductions in overall labor costs. Additionally, in the context of the ongoing skilled labor shortage, where up to six out of ten vacant expert positions cannot be filled (Malin and Köppen, 2023), our findings suggest that the integration of remote assistance can be a viable option to address this challenge. In our experiments, the required number of expert technicians can be reduced, for example, by almost half on average (from 2.7 to 1.4) in a suburban scenario with 30 customers. At the same time, savings in experts come at the cost of requiring additional on-site technicians, 2.8 in this particular instance, to maintain service operations. Eventually, the decision to adopt remote assistance must be carefully evaluated for each business individually, depending on their operational setting.

Our paper makes the following contributions. We are the first to investigate and evaluate the operational value of remote assistance in on-site maintenance service, where expert technicians remotely assist on-site staff. We present a fundamental mathematical model, conduct targeted experimental analysis, and derive import insights on how and when remote assistance is valuable. Because our work is a starting point, we establish a general formulation and introduce several detailed extensions for future work. The remainder of this paper is organized as follows. Section 2 presents a review of relevant literature. In Section 3, we define the problem, provide a formal mathematical formulation, and give an illustrative example. Section 4 introduces different solution concepts and provides a brief explanation of modeling in Hexaly. That follows, Section 5 presents the numerical study and evaluates the operational value of remote assistance. Section 6 offers concluding remarks and outlines directions for future research.

2. Literature review

In this section, we present our three-fold literature review and embed our problem in the present literature stream. Firstly, we introduce work that has been done in the field of remote assistance. Secondly, we proceed by presenting related work including synchronization in the domains of vehicle routing and the scheduling of scarce resources. Lastly, we elaborate on workforce routing and scheduling problems.

2.1. Remote assistance

As a starting point in our literature review, we examine the concept of remote assistance. Published work in this field has primarily focused on its technical implementation and practical use for both remote and on-site workers (Fidalgo et al., 2023). Mohr et al. (2020) conclude that remote technologies hold significant potential for maintenance tasks and can also be applied to tasks of lower technical complexity, as relevant to our problem setting. In a related study, Ojasalo and Silmukari (2019) conduct a research project with an industrial partner, implementing remote assistance tools that use both audio and visual communication. Their findings indicate that remote assistance can be beneficial for both the company and the technicians using the system. However, the successful implementation of remote assistance in practice requires advanced IT infrastructure, both at the company and at customer sites, including high speed data transmission. So far, such implementations have mostly been tested in controlled environments rather than in large-scale field applications (Marques et al., 2022). We note that the concept of remote assistance extends beyond industrial domains. In the healthcare sector, remote physicians provide critical support during emergency patient transport, ensuring a safe transport between hospitals (Hosseini et al., 2017). Similarly, Gasques et al. (2021) describe how expert surgeons remotely assist novice practitioners in developing their skills.

2.2. Synchronization in vehicle routing and scheduling

The most challenging aspect in this paper is the synchronization of work schedules between expert and on-site technicians. The concept of synchronization in vehicle routing is comprehensively surveyed by Drexl (2012). In this context, synchronization refers to situations in which more than one vehicle is required to complete a service task. Drexl (2012) classifies synchronization in vehicle routing into five distinct types. The type most relevant to our work, and thus the focus of our literature review, is the *operation synchronization*, which occurs when multiple technicians must collaborate at the same customer location. Operation synchronization can be further divided into *precedences* and *exact* operations. In precedence operations, a temporal offset between the start times of the involved technicians is allowed. In exact

operations, technicians are required to begin services simultaneously. Applications of precedence synchronization are found in parcel and passenger pickup and delivery problems (Thangiah et al., 2007; Cortés et al., 2010), two-echelon transportation problems (Masson et al., 2017; Gutierrez et al., 2024), or truck-drone routing problems (Sacramento et al., 2019; Wang et al., 2022). In contrast, our study requires exact synchronization, where the expert and on-site technicians must start the service at the same time. The review proposed by Soares et al. (2024) provides a recent and comprehensive review of routing problems involving various forms of synchronization, including exact operation synchronization. However, most of the studies in this domain focus on either cargo transportation (Ghilas et al., 2016) or home healthcare services. In the latter case, certain procedures, e.g., lifting and transferring patients, necessitate the simultaneous presence of multiple caregivers (Polnik et al., 2021; Bazirha et al., 2023). We found two papers that feature the closest similarities to our problem (Hojabri et al., 2018; Hà et al., 2020). Motivated by an industrial case study involving a Vietnamese internet service provider, the authors investigate a scenario in which two technician teams must perform joint service tasks. One team delivers hardware, while the other handles installation and commissioning. The authors propose a constraint programming-based integration into an Adaptive Large Neighborhood Search framework to improve insertion operations and reduce computational time. Ultimately, total travel costs for both type of technicians could be reduced. Despite similarities, their setting differs from ours. In their work, both technician types are physically dispatched to customer sites. In contrast, our model incorporates remote assistance, where expert technicians remain at a central hub and assist on-site technicians remotely. This changes the decision-making process, as we demonstrate in the subsequent sections.

Next to the vehicle routing domain, synchronization also arises in settings where it is driven by the need to optimize the scheduling of scarce resources, as is the case in our work. In particular, this includes domains in which limited infrastructure must be shared among multiple entities. An example is the scheduling of trucks in cross-docking terminals, which focuses on determining the sequence and timing of trucks at a limited number of loading docks. The objective, similar to the one in this paper, is to minimize waiting times and operational delays (Boysen and Fliedner, 2010; van Belle et al., 2012). Related optimization problems also arise in port logistics, where vessels must be assigned to scarce berthing resources (Bierwirth and Meisel, 2010). Further, in more recent applications such as shared electric mobility systems, charging schedules must coordinate multiple vehicles competing for a limited number of charging stations (Shariatzadeh et al., 2024).

Regarding modeling techniques and solution approaches, comprehensive overviews are provided by Soares et al. (2024) and van Belle et al. (2012), which review synchronization problems in vehicle routing and cross-dock scheduling. As in our paper, the majority of the studies referenced in these surveys formulate the underlying problems as MIP models. Due to the increasing computational complexity for larger problem instances, heuristic and metaheuristic solution approaches are commonly employed to obtain solutions within reasonable computation times.

2.3. Workforce routing and scheduling

In workforce routing and scheduling problems, a fleet of employees is dispatched to customers' homes to fulfill on-site service requests (Pourjavad and Almehdawe, 2022). Different to our work, these problems do not consider remote experts but typically focus on heterogeneous skill levels within the fleet, varying service time durations, and diverse task complexities (Castillo-Salazar et al., 2016; Nunes and Lopes, 2023; Stein et al., 2025). Among the most prominent applications is the Technician Routing and Scheduling Problem (TRSP), in which technicians visit customer locations to perform maintenance and repair tasks. In contrast to most studies, where the entire fleet is dispatched to customer sites, we consider a setting in which parts of the fleet remain at a central hub. A central challenge in traditional TRSP models is managing skill mismatches when technicians lack the qualifications required for specific tasks. One solution is to enforce strict skill-to-task matching constraints, ensuring that only qualified technicians are assigned to a customer (Nowak and Szufel, 2024). Another approach allows for skill development over time, enabling technicians to handle increasingly complex tasks after a learning period (Chen et al., 2016). Other studies also address service failures resulting from factors such as unavailable spare parts, which necessitate customer revisits and additional resource allocation on subsequent days (Pham and Kiesmüller, 2024). Our approach mitigates these challenges by integrating expert remote assistance during on-site visits.

In summary, a broad range of research has addressed the TRSP, including approaches that incorporate synchronization requirements. Additionally, recent studies have explored the current state of remote assistance in the maintenance sector, primarily focusing on technical implementation. However, to the best of our knowledge, no existing work integrates technician routing with remote assistance while evaluating its value from an operational perspective.

3. Problem definition

In this section, we introduce the problem. We first provide the problem statement. Subsequently, we present the mathematical model including notational details. Finally, we give a visualization of the problem.

3.1. Problem statement

Throughout a day, a fleet of on-site technicians provides services to customers by fulfilling service requests. All customer requests must be fulfilled, and the technician's daily working hours are limited. The fleet is divided into on-site and expert technicians. On-site technicians operate within a designated service area, traveling between customer locations according to preassigned routes. Each route is planned at the beginning of the day and begins and ends at a central depot. Expert technicians remain stationed at a central hub, where they provide remote assistance by connecting with on-site technicians during service operations. We assume that each customer visit also requires remote assistance from an expert technician. This implies that service at any customer location can only begin once an on-site technician has arrived, and an expert technician is available. If either of these conditions is not satisfied, one of the involved technicians must wait. Upon service completion, the on-site technician proceeds to the next customer, while the expert technicians may assist another on-site technician.

A dispatcher responsible for workforce scheduling must determine all assignments of technicians to customers, the routing sequences for on-site technicians, and the service sequences for expert technicians. In this study, we aim to minimize the completion time of expert technicians, i.e., the time at which they finish their last task of the day. As experts represent a scarce and costly resource, reducing the time they remain engaged with remote supervision has significant operational and strategic value. By completing their assigned tasks earlier, experts' working cost may be reduced or they may be redeployed to alternative activities. We note that the working hours of on-site technicians are indirectly optimized as they are unable to complete service tasks without the support of expert technicians.

3.2. Mathematical model

In this section, we present the mathematical model. We begin by introducing notational details, including all required sets, parameters, and decision variables. That follows, we introduce the objective function and the list of constraints defining the solution space. Table 1 summarizes the notation and defines the set elements, along with parameter and variable domains.

Table 1
Overview of modeling components.

	Description	Elements/Domains
Sets		
$\mathcal{K}$	Set of n customers	$\{i_1, i_2, \dots, i_n\}$
$\mathcal{K}^0$	Set of n customer including depot $\{0\}$	$\mathcal{K} \cup \{0\}$
$\mathcal{A}$	Set of arcs	$\{(0, i_1), \dots (i_1, 0)\}$
$\mathcal{W}^u$	Set of u on-site technicians	$\{w_1, w_2, \dots, w_u\}$
$\mathcal{W}^r$	Set of r expert technicians	$\{w_{u+1}, \dots, w_{u+r}\}$
$\mathcal{W}$	Set of all technicians	$\mathcal{W}^u \cup \mathcal{W}^r$
Parameters		
$T_{\max}$	Maximum daily working hours	$\mathbb{R}^+$
s_i	Service time for node i	$\mathbb{R}_0^+$
d_{ij}^w	Travel time along arc (i, j) for technician w	$\mathbb{R}_0^+$
Decision variables		
x_{ij}^w	1 if technician w drives along arc (i, j), 0 otherwise	$\{0, 1\}$
t_i^w	Starting time of service at node i provided by technician w	$\mathbb{R}_0^+$
z_w	End of working hours for technician w	$\mathbb{R}^+$

3.2.1. Sets and parameters

The set $\mathcal{K}$ contains all customer requests, while the node set $\mathcal{K}^0$ additionally includes a single depot denoted by node 0. The technician fleet is modeled as $\mathcal{W} = \mathcal{W}^u \cup \mathcal{W}^r$. The subsets $\mathcal{W}^u \subset \mathcal{W}$ (on-site technicians) and $\mathcal{W}^r \subset \mathcal{W}$ (expert technicians) contain the two types of technicians, respectively. Technicians travel between customer locations via a set of arcs. The set of arcs is defined as $\mathcal{A} = \{(i, j) \in \mathcal{K}^0 \times \mathcal{K}^0 \mid i \neq j\}$. The maximum daily working hours per technician is limited by $T_{\max}$. Service times $s_i > 0 \forall i \in \mathcal{K}$ are deterministic and identical for all customers. The service time at the depot s_0 is set to 0. The symmetric travel time matrix $d_{ij}^w > 0 \forall (i, j) \in \mathcal{A}, w \in \mathcal{W}^u$ defines the travel time between two nodes for on-site technicians. To incorporate synchronization and facilitate modeling, expert technicians are assumed to traverse the network similarly to on-site technicians, although in practice they remain at a fixed remote hub. Consequently, in our model, their travel times are set to 0.

3.2.2. Decision variables and objective function

We define three types of decision variables. First, the binary variables x_{ij}^w control the technician routing. The variable equals 1 if technician $w \in \mathcal{W}$ travels directly from node i to node j along arc $(i, j) \in \mathcal{A}$, and 0 otherwise. For modeling purposes, expert technicians are also assumed to "travel" between locations. However, as their travel times are set to 0, they can switch between any customer locations instantaneously. Second, the continuous variables $t_i^w \geq 0$ denote the start of service at node $i \in \mathcal{K}^0$ by each technician $w \in \mathcal{W}$. At the depot, the start of service is fixed to 0 to reflect that technicians start their route immediately from the depot. Third, the continuous variables $z_w \geq 0$ relate to the working time of technician $w \in \mathcal{W}$. The goal is to minimize the total working hours Z across all expert technicians. Preliminary tests indicated that balancing expert and on-site working hours in the objective had little impact because service tasks are performed by both expert and on-site technicians. Therefore, we maintain a simplified objective function. The formal definition of the objective function is given as:

$$\min \; Z = \sum_{w \in \mathcal{W}^r} z_w \tag{1}$$

3.2.3. Constraints

In the following, we outline the set of constraints required to define the feasible decision space for our problem. The formulation is similar to the vehicle flow formulation of the VRP, one of the most used formulations in academic literature (Munari et al., 2016). Additionally, it includes the synchronization of workforce as proposed by Mankowska et al. (2014).

$$\sum_{j \in \mathcal{K}^0 \setminus \{i\}} \sum_{w \in \mathcal{W}^u} x_{ij}^w = \sum_{j \in \mathcal{K}^0 \setminus \{i\}} \sum_{w \in \mathcal{W}^r} x_{ij}^w = 1 \qquad \forall i \in \mathcal{K} \tag{2a}$$

$$\sum_{j \in \mathcal{K}} x_{0j}^w = \sum_{j \in \mathcal{K}} x_{j0}^w \leq 1 \qquad \forall w \in \mathcal{W} \tag{2b}$$

$$\sum_{j \in \mathcal{K}^0 \setminus \{i\}} x_{ji}^w = \sum_{j \in \mathcal{K}^0 \setminus \{i\}} x_{ij}^w \qquad \forall i \in \mathcal{K}, w \in \mathcal{W} \tag{2c}$$

$$t_i^w + s_i + d_{ij}^w \leq t_j^w + T_{max} \cdot \left(1 - x_{ij}^w\right) \qquad \forall (i, j) \in \mathcal{A} \mid j \neq 0, w \in \mathcal{W} \tag{2d}$$

$$t_i^r \leq t_i^u + T_{max} \cdot \left(2 - \sum_{j \in \mathcal{K}^0 \setminus \{i\}} x_{ij}^u - \sum_{j \in \mathcal{K}^0 \setminus \{i\}} x_{ij}^r\right) \qquad \forall i \in \mathcal{K}, u \in \mathcal{W}^u, r \in \mathcal{W}^r \tag{2e}$$

$$t_i^u \leq t_i^r + T_{max} \cdot \left(2 - \sum_{j \in \mathcal{K}^0 \setminus \{i\}} x_{ij}^u - \sum_{j \in \mathcal{K}^0 \setminus \{i\}} x_{ij}^r\right) \qquad \forall i \in \mathcal{K}, u \in \mathcal{W}^u, r \in \mathcal{W}^r \tag{2f}$$

$$z_w \geq t_i^w + x_{i0}^w \cdot (s_i + d_{i0}^w) \qquad \forall i \in \mathcal{K}, w \in \mathcal{W}^u \tag{2g}$$

$$z_w \geq t_i^w + x_{i0}^w \cdot s_i \qquad \forall i \in \mathcal{K}, w \in \mathcal{W}^r \tag{2h}$$

$$x_{ij}^w \in \{0, 1\} \qquad \forall (i, j) \in \mathcal{A}, w \in \mathcal{W} \tag{2i}$$

$$t_i^w \in \mathbb{R}_0^+ \qquad \forall i \in \mathcal{K}^0, w \in \mathcal{W} \tag{2j}$$

$$z_w \in [0, T_{max}] \qquad \forall w \in \mathcal{W} \tag{2k}$$

The first three Constraints (2a)–(2c) define standard routing constraints. Constraints (2a) ensures that each customer is visited exactly once by one on-site and one expert technician. Each technician performs one sequence of customer stops at most, which starts and ends at the same depot 0, as imposed by Constraints (2b). Flow conservation is maintained through Constraints (2c), ensuring that each technician leaves every visited customer location to proceed along their route.

Constraints (2d) ensure that the service at any customer location can only begin once the previous task has been completed and the technician has traveled to the next assigned customer. This condition applies only to directly connected nodes within a technician's route. For unconnected nodes, T_{max} serves as an upper bound, similar to a big-M formulation. For expert technicians, travel time is omitted, i.e., $d_{ij}^w = 0 \forall w \in \mathcal{W}^r$, so only the completion of the previous task needs to be considered. Further, Constraints (2d) prevent sub-tours in the technician routes. Revisiting the same customer by a technician would violate the temporal precedence constraints between consecutive tasks. As we exclude the final return to the depot from this condition (2d), we allow for a complete route that starts and ends at the depot. Additionally, this formulation permits the artificial start time of the "service" at the depot to be set to 0, ensuring that technicians depart the depot at the beginning of the planning horizon.

The next two Constraints (2e) and (2f) address the synchronization between technicians. For a specific pair ($u \in \mathcal{W}^u, r \in \mathcal{W}^r$), the variables x_{ij}^u and x_{ij}^r sum up to 1, respectively. With Constraints (2e) and (2f), we ensure that the service at customer location i starts at the same time for both involved technicians, i.e., $t_i^u = t_i^r$. For all other technician pairs, synchronization is not required, and the corresponding constraints are bounded by T_{max}.

Constraints (2g) determine the return times to the depot for on-site technicians which are bounded by the maximum working time (see Constraints (2k)). Constraints (2h) define the latest service completion time among expert technicians as the lower bound for z_w. As we minimize the working hours for all expert technicians, these latest services are brought forward as much as possible. The last three Constraints (2i)–(2k) specify the decision variable domains.

3.3. Example

To facilitate the understanding of the present problem, we provide an example. We first introduce two illustrations, followed by a description of the resulting decisions and implications. Thereby, we highlight

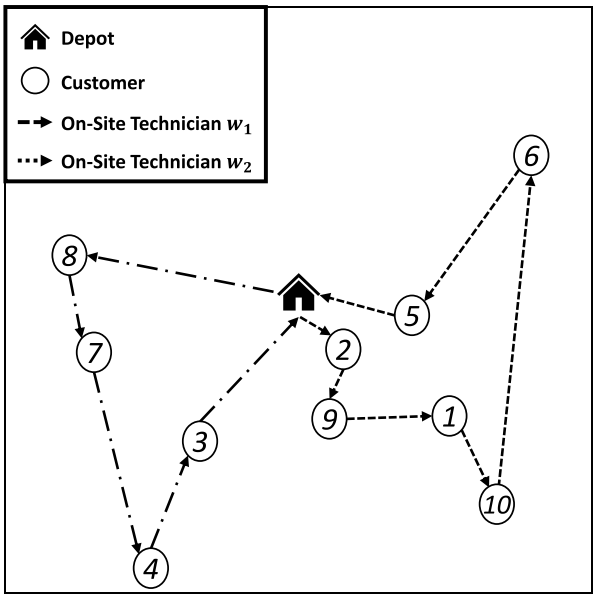


Fig. 1. Routing (Sequential planning).

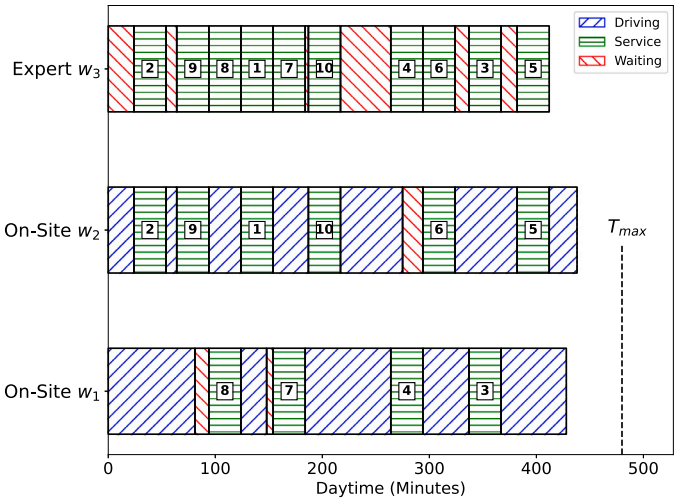


Fig. 2. Scheduling chart (Sequential planning).

the characteristics of an effective solution. The specific functionality of the method used to derive the following solutions, based on sequential planning and representing one of our benchmark approaches, is of secondary importance at this point and will be introduced in Section 4.1.

In Figs. 1 and 2, we illustrate a possible routing decision and the corresponding work schedule for a small instance setting. In the given example, we sample ten customer locations from a uniform distribution within a square service area. The depot is centrally located, with the service area extending 50 km in all directions. The travel speed is set to 35 km/h. Travel times are derived using the Euclidean distance. Service times are set to 30 min per customer. Technicians are not allowed to work more than $T_{\max} = 480$ min in the field including their return trip to the depot. Fig. 1 spans the service area. Customers are visualized as numbered circles ranging from 1 to 10. The technician fleet is given by $\mathcal{W} = \{w_1, w_2, w_3\}$. We assume that two on-site technicians, inside the set $\mathcal{W}^u = \{w_1, w_2\}$, and one expert technician, inside $\mathcal{W}^r = \{w_3\}$, are available. Each customer must be visited by exactly one on-site technician (w_1 or w_2), while the expert technician w_3 is required to remotely assist each service operation.

Fig. 1 illustrates a possible solution, where on-site technician w_1 (dashed–dotted line) serves customers in the southern and western regions, while on-site technician w_2 (dashed line) serves customers located in the eastern part of the service area. The respective work schedules for all technicians are depicted as bar charts in Fig. 2. The time axis, in minutes, begins on the left ($t = 0$) and extends to the right, covering the entire planning horizon up to $T_{\max} = 480$. Rectangular boxes with numeric labels identify the specific customers being served during each time interval. Each horizontal bar represents the work schedule of a single technician. Three distinct phases are visualized. Throughout the paper, technician working hours refer to the sum of all three phases listed below.

- *Driving* is indicated by (blue) hatched lines reaching from the bottom left to the top right. It refers to periods when on-site technicians are traveling between customer locations.
- *Service* is indicated by (green) horizontal lines, denoting active service at customer sites.
- *Waiting* is indicated by (red) hatched lines reaching from the top left to the bottom right. It represents idle times in which technicians must wait for another to begin a service.

As the objective is to minimize the completion time of the expert technician's final remotely assisted task, minimizing idle time between successive tasks becomes a critical aspect in planning. Referring to the work schedules in Fig. 2, the expert w_3 waits for 24 min in the beginning, which is inevitable as the on-site technicians must first depart from the depot to travel to their first assigned customer locations. Although this initial waiting may be excluded from the actual expert working time, it can be considered part of the working time used for preparation and setup. Throughout the planning horizon, four shorter breaks of 41 min in total occur, namely before the start of service at customers 9, 10, 3, and 5. However, a notable exception occurs before the service at customer 4, where a significant longer idle time of 47 min is incurred. It results from both on-site technicians simultaneously facing a long driving phase to their next assigned customers, thereby leaving the expert technicians temporarily idle. Ultimately, the expert technician completes the final service at customer 5 at time $t = 412$.

To enable a seamless workflow for the expert technician, the customer sequences for the on-site technicians must be mutually adapted and carefully synchronized. An important factor in this coordination is the alternation between driving and service phases among the on-site technicians. In general, when w_1 performs an on-site service, remotely assisted by expert w_3, w_2 should ideally be driving to the next assigned customers. Once the service is completed, w_1 begins traveling to next customer, while w_2 arrives and starts the subsequent service. This alternating pattern becomes evident when analyzing the two lower bar charts corresponding to w_1 and w_2 in Fig. 2. The service phases of w_1 primarily occur while w_2 is traveling, and vice versa. At the beginning of the schedule, w_2 is dispatched to customer 2, located near the depot, while w_1 is sent first to customer 8, which is farther away. This setup allows service at customer 2 to begin while w_1 is still traveling to customer 8. Once these alternating phases of driving and service are established, the technicians proceed through their respective sequences of customer visits. Due to the geographical distribution of customers and limited technician availability, waiting phases are inevitable, as perfect synchronization cannot be achieved.

4. Solution concepts

In this section, we present the solution concepts evaluated in our numerical study. We start with the sequential planning and then proceed with the integrated planning concept. We further provide high-level explanations of how our problem can be modeled in Hexaly.

4.1. Sequential planning

Without remote collaboration, companies in practice use standard VRP planning tools to make assignment and routing decisions. As we need to synchronize technician schedules, we want to investigate how standard VRP solutions may still be used. To this end, we decompose the problem into two stages and derive the corresponding decisions sequentially. In the first stage, only the assignment of customers to on-site technicians and their routing are determined. We omit Constraints (2e) and (2f) regarding synchronization and solve the problem as a standard VRP (without remote collaboration). Preliminary tests showed that minimizing the latest return time to the depot, instead of minimizing total distance, facilitates synchronization in the second stage. We therefore use this objective in the first stage. The resulting routing and assignment solution for on-site technicians then serves as an input for the second stage (with remote collaboration). In the second stage, we generate the sequence of tasks for the expert technicians and determine their start times. As the routes are fixed and cannot be readjusted, the problem simplifies considerably and can be solved quickly. Building upon this sequential planning procedure, we introduce two benchmark policies that only differ in the second stage.

In an approach referred to as first-in first-out (FIFO), in the second stage, expert technicians are assigned to on-site technicians as soon as they become available. Specifically, whenever an on-site technician arrives at a customer location, the expert who has been waiting the longest is selected. If all expert technicians are occupied, the first expert becoming free is selected. The assignment procedure is applied vice versa when multiple on-site technicians are waiting for expert technicians to become available. The on-site technician who has been waiting the longest is prioritized to begin the next service. This technique is tailored to the problem's characteristics, aiming to minimize expert working hours by improving their utilization. At this stage, no optimization is performed and only this straightforward decision rule is applied.

In an alternative approach, referred to as sequential planning optimization (SPO), an optimization step is included in the second stage to determine the assignment of expert technicians. Given the fixed set of routes from the first stage, only the expert technician sequences and the service start times need to be determined. Our model (see Section 3.2) applies to this approach.

4.2. Integrated planning

In the integrated planning approach, we address the problem holistically by jointly determining the assignment of customers to on-site technicians, their routing, and the assignment and scheduling of expert technicians. In the following, we illustrate the functionality and the decisions derived from this approach using the example introduced in Section 3.3, which was originally based on SPO. We demonstrate that the overall solution quality, with respect to our objective, can be improved when planning is performed in an integrated rather than in a sequential fashion.

The assignments of customers to on-site technicians remain identical across both planning approaches, but the routing is different. In the integrated approach, the order of customers 3 and 4 is swapped for on-site technician w_1 (see Figs. 3 and 4). On-site technician w_2 visits customer 5 between customer 9 and 1, whereas in SPO, this visit occurs at the end of the route. These adjustments lead to a total increase in travel distance of approximately 4.5%. Correspondingly, the combined working hours of the on-site technicians increase by 3.45%. However, the expert's technician working hours is reduced by 8%, from $t = 412$ to $t = 379$ min. This reduction primarily results from improved synchronization. Recalling Fig. 1, we highlighted the period in which both on-site technicians are engaged in long driving phases. This leads the expert technician remaining idle at the hub. These concurrent driving phases are a key limitation of a sequential approach,

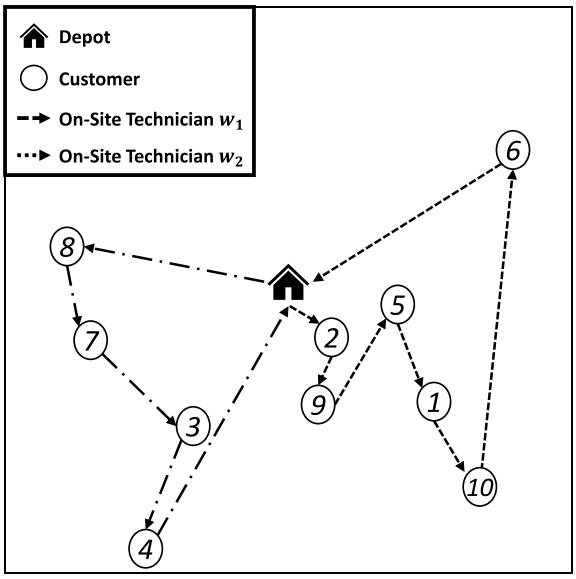


Fig. 3. Routing (Integrated planning).

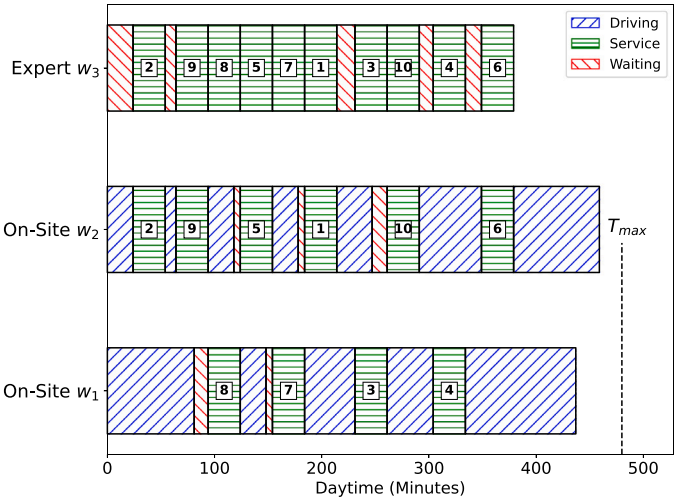


Fig. 4. Scheduling chart (Integrated planning).

which does not incorporate synchronization with expert technicians during the initial routing stage. Consequently, once routes are fixed, the second stage synchronization can no longer mitigate idle periods for experts. In contrast, the integrated planning approach aligns routing with synchronization requirements. Minor increases in travel distance are accepted to better coordinate the working schedules of on-site and expert technicians. This leads to significantly shorter waiting periods for the expert technician. In the example, it results in a reduction of 33 min in idle (waiting) time.

4.3. High-level explanations of modeling and implementing in Hexaly

For the computational study presented in the next Section 5.3, we use Hexaly as the solver. Since it has seen limited use in academic literature so far, we first provide a high-level overview in this section of how the tackled problem can be modeled and implemented using Hexaly.

Hexaly employs set-based decision variables, interval and list variables. These variables are conceptually aligned with *interval* and *sequence* variables commonly used in constraint programming (Naderi

et al., 2023). Many classical MIP elements, i.e., subtour elimination, flow conservation, or big-M formulations, can be omitted entirely (Martí et al., 2025).

To transform the MIP formulation presented in Section 3.2 into the Hexaly modeling formalism, two types of decision variables are required. The first type, interval decision variables, define the start and end times of service for each customer. The second variable type is a list decision variable for each technician $w \in \mathcal{W}$, representing an ordered sequence of customer stops (route). Thereby, each list variable is a permutation of a subset of the entire customer set $\mathcal{K}$, with dynamic size to capture varying route lengths across technicians.

Due to the underlying modeling formalism, fewer explicit constraint formulations are required than in the MIP, allowing for greater flexibility during the search of the decision space. Constraints (2b), which concerned the departure and return to the depot, as well as (2c) on flow conservation, are now implicitly enforced through the definition of list decision variables. Constraints (2h), which set a lower bound for the objective values z_w, are incorporated directly into the objective function by calculating the end time of the last customer stop in each list variable. Ultimately, the only constraints explicitly formulated are the following:

1. Each customer must be visited by exactly one expert and one on-site technician, similar to Constraints (2a) in the MIP formulation. This requires partitioning all on-site and expert technician routes.
2. Every on-site technician is allowed to work at most $T_{\max}$ min in the field, as defined in Constraints (2g).
3. To account for synchronization, the durations of the two interval decision variable associated with each customer (one for each technician type) are both set equal to the service time. Further, we enforce that both technician types share identical interval bounds (start and end), similar to Constraints (2e) and (2f).
4. The start of service at any customer location can only start when the respective technician has completed their previous customer service. On-site technicians additionally need to travel to their next assigned customer. This corresponds to Constraints (2d).

The last constraint from the enumeration above couples both variable types. As their integration is less straightforward in the implementation, we illustrate it via a code snippet below. We assume that the list decision variable is denoted by *seq*, and the interval decision variable by *inter*. The lambda function g (see line 1 below) takes an index h as its keyword argument and ensures that the end time of service at the customer in position h of *seq*, plus the travel time to the next customer at position $h+1$, is less than or equal to the start time of service at that next customer in the sequence *seq*. The return type of the lambda function is a boolean expression. The lambda function g is called for each index in the sequence range (see line 2 below). The overall constraint is satisfied only if all evaluations of g return *True*, which is enforced by the operator *and_*. This operator accepts a dynamic number of arguments and ensures that all individual (lambda) conditions hold simultaneously.

```
g = model.lambda_function(lambda h:
    end(inter[seq[h]]) + travel(h,h+1) <= start(inter[seq[h+1]])) #(1)
model.constraint(model.and_(model.range(0,len(seq)-1), g))        #(2)
```

5. Numerical study

The goal of the numerical study is to investigate the value of integrated planning and the general business concept of remote assistance in service operations. After describing the test instances and evaluating the performance of the Hexaly solver, we present our results. We highlight the advantages of the integrated planning approach and discuss the scenarios in which the concept of remote assistance is particularly valuable.

5.1. Test instances

In this section, we present the test instances used in the following computational study. We want to assess the impact of different planning approaches and the operational effect of remote assistance. To this end, we examine three distinct geographical scenarios, each characterized by variations in service area size, average travel speed, and customer dispersion. To account for varying business sizes, we consider three demand scenarios by changing the number of requesting customers. The depot is centrally located within the service area. Service times are set to 30 min. Later we will also investigate instances with shorter service times.

Geographical scenarios differ in the number of clusters, the amount of customers per cluster and the center placement of each cluster in the service area. In an urban scenario, there are many clusters that are located closer to the depot with fewer customers per cluster. This mimics a rather uniform spread of customers near the service area center, as observable in urban scenarios. The service area extends 10 km in all directions from the center. We assume Euclidean distances. To account for delays caused by traffic and time spent searching for parking, an average travel speed of 20 km/h is used (Statista, 2018).

In a suburban scenario, there are fewer clusters being slightly farther away from each other and the depot. The number of customers per cluster is higher. This represents more (separated) residential areas in outskirts of bigger cities or agglomerations of multiple smaller cities. The service area extends 40 km in all directions from the center. We assume a travel speed of 35 km/h which is typically higher as in city centers.

In a rural scenario, clusters are farther away from each other and the depot. Each cluster may represent a village, each with a small number of customers. Distances may be very long across the entire service area. The service area extends 100 km in all directions from the center. We assume a travel speed of 60 km/h as traffic on rural roads is limited.

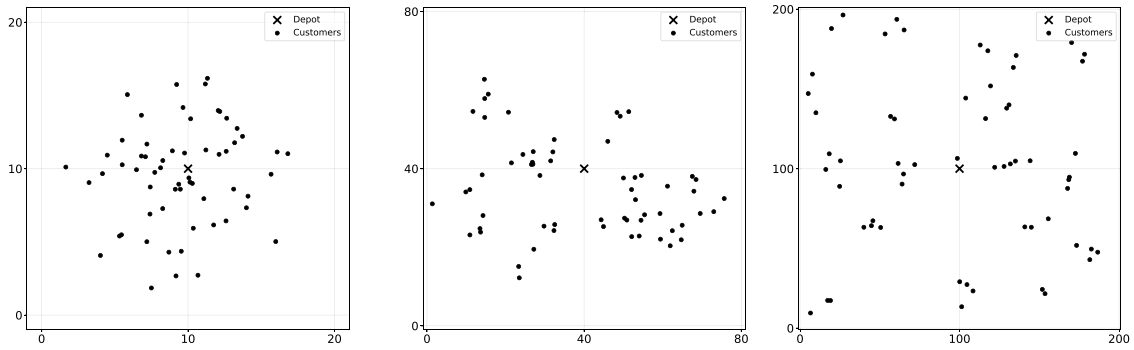
We further consider three demand scenarios. In the small demand scenario, we consider 15 customer requests which represents rather small businesses. In the second and third scenario, we double the demand to 30 and 60 customer requests, respectively, to reflect larger business types. Combining demand and geographical scenarios, we get 9 different instance settings. For each instance, we generate 40 realizations. Respecting the aforementioned properties of each geographical scenario, each realization differs on the exact cluster center location, the number of customers per cluster and the exact position of each customer within the cluster. In Fig. 5, a single realization with 60 customers is shown for each region considered in our study. We can recognize all introduced characteristics for each of the geographical scenarios. Across instance realizations, the minimum number of required technicians may vary due to variances in customer locations.

For each realization, we predetermine the minimum number of on-site technicians, which is essential for the first stage (VRP) of the sequential approaches. Based on the VRP-solutions, we then determine the minimum number of experts for the second stage of the sequential approach. We use it as the fleet size for that realization to ensure that all approaches have the same resources available. Fleet sizes vary from 1 expert and 2 on-site technicians for realizations of smaller instances to up to 5 experts and 9 on-site technicians for larger ones. An example for such a larger instance is illustrated in Fig. 5(c).

All numerical experiments are conducted using Python 3.14 on Ubuntu Linux, running on an AMD Ryzen Threadripper PRO processor with a clock speed of 3.4 GHz and 32 GB RAM.

5.2. Performance evaluation of Hexaly using Gurobi

Integrated planning offers a holistic approach and the potential for better solutions. However, it also introduces significantly greater computational complexity due to the added synchronization requirements compared to standard vehicle routing. Thus, we require an optimization



(a) Urban (b) Suburban (c) Rural

Fig. 5. Exemplary realizations (60 customers) for geographical scenarios.

solver that is capable of producing effective feasible solution, also for larger instances of realistic size. Therefore, we employ the Hexaly optimization solver which can be used for routing, and scheduling problems, among others. In the following, we show why this solver represents a suitable choice for our application as we compare its performance with the Gurobi solver.

In preliminary tests, we observed that Hexaly finds feasible solutions very quickly for all instances, but it is unable to provide meaningful lower bounds for our minimization problem, even when allowed to run for a longer period of time. As a result, the quality of the returned solutions cannot be thoroughly evaluated. To this end, we also ran Gurobi on all test instances for comparison, using 40 realizations per instance and a runtime limit of 30 min.

We observed that Gurobi does not find feasible solutions for around 20% of all instances in the SPO, primarily for suburban and rural scenarios with 60 customers. For the integrated approach, this proportion increases to around 48%, including instances with 60 customers as well as several suburban and rural scenarios with 30 customers. Whenever feasible solutions were returned with Gurobi, they were nearly identical to those returned by Hexaly. We note that more efficient and compact formulations for Gurobi may exist beyond the MIP formulation presented in Section 3.2, for example through the use of high-level constraint modeling languages. However, investigating alternative formulations is outside the scope of this paper.

To get a comprehensive verification of the quality of the solutions returned by Hexaly across all instances, we now employ Gurobi with warm-start solutions. Specifically, the solutions returned by Hexaly are provided to Gurobi as initial feasible solutions, enabling the solver to further improve them. This approach offers a practical way to assess Hexaly's solutions while simultaneously exploiting Gurobi's capability to compute tight lower bounds. As demonstrated in the following paragraphs, this warm-start strategy proves effective for evaluating the quality of Hexaly's solutions.

Table 2 presents the results of the aforementioned procedure for a runtime limit of 30 min. We generate 40 distinct realizations for each of the three considered customer levels and geographical scenarios (see Section 5.1). We analyze how Gurobi improves the solutions returned by Hexaly for the first and second stages of SPO, as well as for the integrated planning approach (see the upper, middle, and lower thirds of Table 2). In each third, one row corresponds to one instance. We report how many of the 40 realizations per instance lead to improvements when Hexaly's solution is further optimized by Gurobi (fourth column). In addition, for the instances that are improved, we present the average, minimum, and maximum improvement achieved by Gurobi (fifth column). Finally, the last column reports the average, minimum, and maximum optimality gaps returned by Gurobi. When analyzing the problem, it is straightforward to show that the total working time of the experts must be larger or equal than the total service time of all requesting customers. This information is given to the solver to provide initial lower bounds.

For the first stage of SPO, Gurobi does not improve any solution returned by Hexaly. This is either because the solutions are already optimal (for instances with 15 customers) or because they are likely (close to) optimal, although additional runtime may be required to formally prove optimality. In the second stage of SPO, Gurobi improves the solutions for several of the 40 realizations. Yet, the improvements remain small, ranging between 0.1% and 4.3% on average. In addition, none of the improved realizations in the second stage exceeds an improvement of 6.8%. For example, in the instance with 30 customers in a suburban scenario, 29 out of 40 realizations are improved by Gurobi, with an average improvement of 1.2% for these 29 realizations. Across both stages, except for instances involving rural scenarios with higher customer volumes, the optimality gaps provided by Gurobi remain around 10% or lower. This indicates that the Hexaly solutions are effective and, in some cases, close to optimality.

For the integrated approach, we observe a similar trend as in the second stage of SPO. Gurobi improves the Hexaly solution for several realizations, but the improvements remain on a comparatively small level. Compared to SPO, the integrated approach is considerably more complex due to the required determination of on-site routes (given in the first stage in SPO) and the synchronization of technicians. Hence, this generally results in larger optimality gaps. We observe similar gaps across all customer levels in the integrated approach. Higher customer levels tend to reduce expert waiting times, as more services must be assisted. This shifts the optimal solution closer to the total sum of service times, which represents a problem-specific lower bound used by Gurobi. At the same time, an increasing customer volume requires more synchronization which increases computational complexity. These opposing effects balance each other and explain the similar gaps (see lower third of Table 2).

Ultimately, Hexaly's performance across all planning concepts justifies its use in our study. In around 20% of all realizations, solutions were further improved by Gurobi, although by small percentages. Both improvements and optimality gaps show limited variation across instance realizations (see *min/max* values in Table 2), supporting the robustness of the results.

We also conduct the entire experiment with a reduced runtime limit of 1 min. We observe that Hexaly produces very similar solutions under both runtime settings, indicating that solutions are found quickly. With a reduced runtime of 1 min for Gurobi, it improves the Hexaly solutions less (compared to 30 min), and optimality gaps are generally larger. This may suggest that Hexaly already produces strong (primal) solutions, while Gurobi mainly improves lower (dual) bounds when running for a longer time.

Table 2
Performance evaluation of Hexaly using Gurobi.

Planning concept	Number of customers	Geographical scenario	Improved realizations	Improvement (%) Avg. | Min | Max	Optimality gap (%) Avg. | Min | Max
SPO (Stage 1)	15	Urban	0/40	0.0 | 0.0 | 0.0	0.0 | 0.0 | 0.0
	15	Suburban	0/40	0.0 | 0.0 | 0.0	0.0 | 0.0 | 0.0
	15	Rural	0/40	0.0 | 0.0 | 0.0	0.0 | 0.0 | 0.0
	30	Urban	0/40	0.0 | 0.0 | 0.0	2.2 | 0.4 | 5.7
	30	Suburban	0/40	0.0 | 0.0 | 0.0	10.7 | 7.8 | 12.6
	30	Rural	0/40	0.0 | 0.0 | 0.0	25.8 | 19.9 | 29.2
	60	Urban	0/40	0.0 | 0.0 | 0.0	3.7 | 2.8 | 5.5
	60	Suburban	0/40	0.0 | 0.0 | 0.0	13.2 | 11.5 | 14.8
	60	Rural	0/40	0.0 | 0.0 | 0.0	30.4 | 28.1 | 32.6
SPO (Stage 2)	15	Urban	12/40	2.3 | 0.2 | 4.5	0.0 | 0.0 | 0.0
	15	Suburban	7/40	1.8 | 0.4 | 4.1	0.0 | 0.0 | 0.0
	15	Rural	9/40	4.3 | 1.1 | 6.8	0.0 | 0.0 | 0.0
	30	Urban	26/40	0.7 | 0.1 | 2.4	8.8 | 6.9 | 10.2
	30	Suburban	29/40	1.3 | 0.1 | 3.5	9.8 | 4.7 | 14.6
	30	Rural	4/40	0.7 | 0.6 | 0.8	13.6 | 11.1 | 16.0
	60	Urban	22/40	0.4 | 0.1 | 1.3	7.5 | 6.0 | 10.0
	60	Suburban	7/40	0.1 | 0.1 | 0.1	9.3 | 7.5 | 11.5
	60	Rural	5/40	0.3 | 0.1 | 0.5	12.1 | 8.9 | 16.5
Integrated	15	Urban	3/40	2.4 | 0.2 | 4.6	12.2 | 7.9 | 16.2
	15	Suburban	14/40	1.4 | 0.3 | 3.7	21.1 | 16.5 | 24.4
	15	Rural	12/40	4.3 | 0.2 | 11.6	31.0 | 25.0 | 37.6
	30	Urban	12/40	0.5 | 0.1 | 1.6	11.5 | 9.7 | 13.3
	30	Suburban	14/40	1.3 | 0.3 | 3.6	20.8 | 15.1 | 27.7
	30	Rural	21/40	1.0 | 0.1 | 2.6	32.7 | 28.3 | 37.2
	60	Urban	9/40	0.1 | 0.1 | 0.2	9.8 | 8.3 | 11.3
	60	Suburban	5/40	0.1 | 0.1 | 0.1	16.9 | 15.3 | 19.6
	60	Rural	21/40	0.1 | 0.1 | 0.2	30.7 | 27.3 | 35.2

5.3. Value of integrated planning

The first goal of our study is to investigate the value of integrated planning. We further compare its performance against the two benchmarks introduced in Section 4.1.

Table 3 summarizes the overall performance across all test instances. The table is divided into three parts, each corresponding to one of the defined service area types. The second column lists the number of customer requests. Our analysis focuses on total working hours, waiting time, and travel time for all technicians. The reported numbers in minutes are averaged per technician. The final row reports the percentage improvement achieved by the integrated planning approach over the two benchmark approaches.

Across all test instances, the integrated planning approach reduces the workload for expert technicians compared to a FIFO and SPO approach. Waiting time for expert technicians, although representing only a small portion of total working hours, is reduced even more, by 14.2% and by 36.5% compared to the SPO and FIFO approach, respectively.

> **Insight 1.** *Companies should carefully incorporate synchronization into their daily operations through integrated planning, which can reduce expert technician working hours by 2.4% compared to a SPO approach and by 8.1% compared to a FIFO approach.*

These reductions are achieved with minimal trade-offs. Compared to the FIFO approach, the working hours of on-site technicians increase slightly by 3.7%. Compared to the SPO approach, working hours show a slight decrease of 0.6%. The FIFO approach assigns expert technicians reactively, which reduces on-site waiting times but results in fragmented expert schedules with idle gaps. This explains why it generally leads to significantly shorter on-site waiting times but longer waiting times for experts. Travel times, which constitute a substantial part of total working time alongside service time, increase marginally by approximately 2.6%. Their increase is logical as travel times in both the FIFO and SPO approach are considered in the first stage, where return times to the depot are minimized.

> **Insight 2.** *An integrated approach reduces expert working hours while keeping on-site working hours (nearly) unchanged, with only a slight increase in their travel time.*

We observe differences in performance across geographical scenarios. In urban scenarios, travel times contribute less to total working time, leaving less room for improvement through synchronization adjustments. Consequently, the relative improvement of the integrated approach over the FIFO and SPO approaches is smaller in urban scenarios (see upper third in Table 3). A similar trend is observed with respect to customer volume. A high number of customer requests results in denser customer distributions, which again reduces the impact of improved synchronization. For example, with 60 customers, performance differences between sequential and integrated approaches are small. In contrast, for scenarios with fewer customers, more significant performance improvements are noticeable.

> **Insight 3.** *The potential for the integrated approach to reduce expert working hours is limited in urban scenarios and settings with higher customer volume.*

In suburban and rural scenarios, customer locations are typically located farther apart. Routing plays a more important role, as travel distances increase the impact of suboptimal customer sequences and lead to higher operational costs. This becomes particularly relevant when synchronization between on-site and expert technicians is required, as it can significantly affect working schedules. Recalling the illustrative example in Section 3.3, a key limitation of the sequential approaches arises during concurrent *driving* phases (see Fig. 2), where multiple on-site technicians are on the way to their next assigned customer stop. Because routing is performed without accounting for synchronization, expert technicians often remain idle during these periods. Longer travel

Table 3
Policy performance across all test instances (values rounded to minutes).

Policy	Number of customers	Working experts	Waiting experts	Working on-sites	Waiting on-sites	Travel time
		Urban area				
FIFO	15	367	42	361	75	61
SPO		357	32	383	97	61
Integrated		349	24	355	64	66
FIFO	30	405	45	400	39	64
SPO		395	35	415	53	64
Integrated		385	25	424	59	68
FIFO	60	421	46	426	9	57
SPO		413	38	434	17	57
Integrated		408	33	439	20	59
		Suburban area				
FIFO	15	339	106	376	10	140
SPO		296	62	426	61	140
Integrated		282	48	421	51	146
FIFO	30	408	102	427	9	137
SPO		367	62	456	39	137
Integrated		364	59	456	38	138
FIFO	60	426	66	434	12	123
SPO		410	50	441	19	123
Integrated		408	48	442	19	123
		Rural area				
FIFO	15	366	141	389	10	221
SPO		331	106	408	29	221
Integrated		304	80	404	23	223
FIFO	30	410	110	430	18	229
SPO		382	82	438	26	229
Integrated		375	75	436	24	230
FIFO	60	439	79	471	24	229
SPO		426	66	470	23	229
Integrated		424	65	471	23	229
%-improvement integrated over	FIFO	8.1	36.5	−3.7	−122.5	−2.6
	SPO	2.4	14.2	0.6	4.5	−2.6

distances in suburban and rural areas intensify this issue, resulting in increased waiting times for expert technicians, especially in the FIFO approach. The integrated planning approach addresses these inefficiencies by integrating synchronization directly into the routing process and solving the problem holistically. This leads to fewer concurrent *driving* phases, as shown in Fig. 4. The result is a reduction in expert technician idle times, particularly in suburban and rural scenarios with moderate or lower customer demand.

5.4. Impact of stochastic service times

In our problem statement and formulation, we assume that service and travel times are deterministic. In practice, however, these times are stochastic and may highly impact preplanned work schedules. This is particularly critical for tightly synchronized schedules, which are especially subject to disruptions affecting all involved technicians. Therefore, we aim to investigate how stochastic events, with a specific focus on stochastic service times, affect preplanned technician schedules. We now assume that service times follow a log-normal distribution (Oyola et al., 2018), which effectively reflects the observation that most services have relatively consistent durations, while a few may take significantly longer. To model different levels of variability, we vary the coefficient of variation (CV) from 0.1 to 0.5, similar to assumed magnitudes around 0.2 in the literature (Gutierrez et al., 2018).

We consider the schedules for all realizations in our study, keeping the sequence of routes and technician assignments fixed. We then execute all schedules, sampling service times for each customer stop from our specified distribution. While the sequence of visits remains unchanged, the actual timing is directly affected by variations in service durations. These fluctuations can cause delays, potentially resulting in waiting times for both the expert and on-site technicians. We measure the final working time of each technician and compare it to their original working time under deterministic service times. We note that the maximum working time per technician may be exceeded in this experiment, which would result in overtime in practice.

In Fig. 6, we present the average increase in working times for all technicians across different values of the CV (x-axis) and varying levels of customer requests. We conduct this experiment for both the sequential and integrated approach. Lower CV values correspond to highly stable service times, whereas higher values indicate greater variability and tails in the distribution. We fix the mean of the log-normal distribution at 30 min. For example, a CV of 0.1 (0.5) corresponds to a standard deviation of 3 (15) min with approximately 90% of all services lasting about 25–35 (12–58) min. This range allows us to cover scenarios from relatively stable to highly volatile service times.

A clear trend shows larger increases in working time when the number of customers is high. These settings generally require more synchronization between technicians, which may fail when service times vary. However, we observe that increases in working time remain comparatively moderate when the CV is below 0.3, which already represents fairly volatile service times. In this range, working times increase up to around 10% (5%) for larger (smaller) businesses.

Uncertainty in service times disrupts the tight synchronization of schedules, but its overall impact on total working time remains moderate. For highly volatile service times, however, working times tend to increase more strongly, as completely missed synchronizations can cause more severe downstream effects on subsequent services in the schedules. Both planning concepts are affected similarly by stochastic service times, especially for CV values below 0.3. Generally, the sequential approach is slightly less affected for smaller business. Predefined routes from the first stage hinder improved synchronization and generally lead to higher waiting times (see Table 3), better absorbing

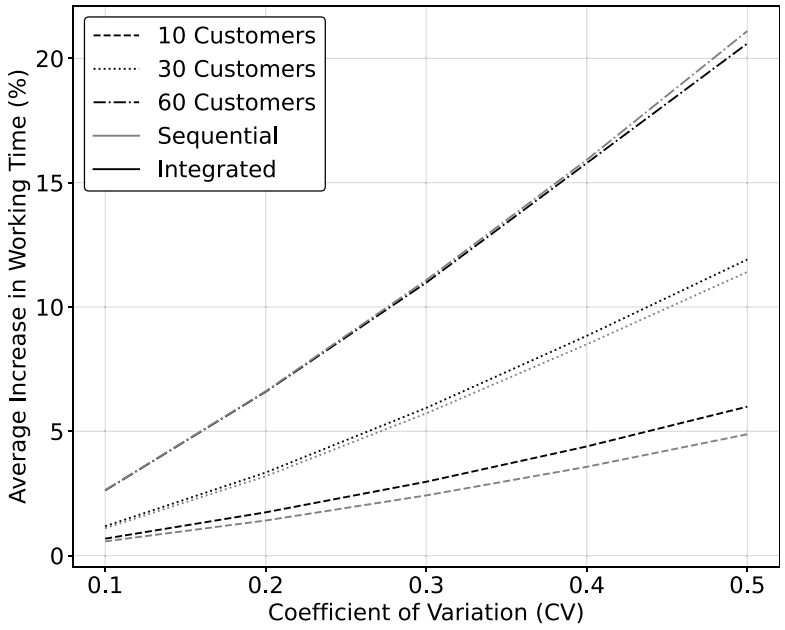


Fig. 6. Changes in working time for variable service times.

disruptions in the schedules through uncertain service times. However, as customer volumes increase, this effect diminishes as more customers lead to tighter schedules (less waiting times). For larger business and higher values for the CV, the integrated is even slightly less affected by uncertainty. Eventually, service times must remain reliable within a certain tolerance, as this is crucial for successful remote assistance.

> **Insight 4.** *Stochastic events affect synchronization and create downstream effects on subsequent services, particularly when many customers are involved. However, the resulting increase in working times remains below 10% for moderately varying service times.*

5.5. Value of remote assistance

The decision to implement remote assistance is a serious business choice. As emphasized in the introductory section, expert technicians are a scarce and costly resource in practice. To this end, the analysis focuses on how remote assistance can enhance the utilization of expert technicians, help address the skilled labor shortage, and influence overall labor costs.

Remote operations can reduce the demand for experts which is valuable in case of skilled labor shortage. At the same time, more on-site technicians are required. We investigate this trade-off for various scenarios of real-world size and analyze changes in fleet compositions resulting from the implementation of remote assistance. To assess the impact, the same business operation is evaluated for two distinct scenarios. In the first scenario, where remote assistance is not applied, the minimum required number of expert technicians needed to fulfill all customer requests is determined. Since all expert technicians visit customer locations in person in this setting, no on-site (junior) technicians are required. In the second scenario, remote assistance is integrated into operations, and the minimum required fleet size, comprising both on-site and expert technicians, is calculated to ensure feasibility. We count both the number of expert technicians saved and the additional on-site technicians required when remote assistance is incorporated into the planning process, compared to the scenario where only experts operate in the field. Thus, the operational benefit of this second setting arises from a reduced demand for expert technician. This trade-off, i.e., fewer expert technicians versus more on-site technicians, is illustrated in Fig. 7 across difference problem instances.

We presents results based on test instances introduced in the previous section, comparing fleet composition under the two aforementioned perspectives. In Fig. 7, the x-axis is divided into three segments, each representing a different number of customer requests. The y-axis indicates the geographical type. In addition to the previously analyzed service time of 30 min, this analysis also includes a shorter service time of 20 min for each task. Within each grid, the left and right bar charts correspond to a service time of 20 and 30 min, respectively. For example, the top-left grid represents a rural scenario with 15 customers and a service time of 20 min. On average, 1.5 expert technicians can be saved when remote assistance is applied, compared to the scenario without remote support where only experts are dispatched in the field. In exchange, 2.1 “additional” on-site (junior) technicians need to be hired to fulfill the demand.

Results are first considered for scenarios with a service time of 30 min. In general, all values increase with a larger number of customers and larger service areas when remote assistance is included (see Fig. 7). Without remote assistance, only expert technicians are required, and their number grows with customer volume and larger service areas, such as rural regions, because travel distances are longer. Then, the impact of remote assistance, by avoiding expert *driving* phases, has a greater effect on expert work hour utilization. Consequently, it allows for more savings in experts through remote assistance. In contrast, areas with shorter travel distances limit the potential for expert savings and reduce improvements in expert work hour utilization. This occurs because, after completing a service, on-site technicians arrive at the next customer shortly afterward and require expert assistance again. Consequently, additional expert resources are needed to avoid significant waiting times and to ensure feasible working schedules.

Shorter service times at customer locations reduce the total number of required technicians, which in turn decreases both the number of required experts and the additional on-site technicians (see bar charts per grid in Fig. 7). Even for the instance in the lower-left grid, no expert can be saved because only one expert is required in the scenario without remote assistance, and this expert is still required when remote assistance is implemented. Generally, for the majority of instances, the number of required experts is decreased compared to scenarios with extended service times, while also the amount of additional required

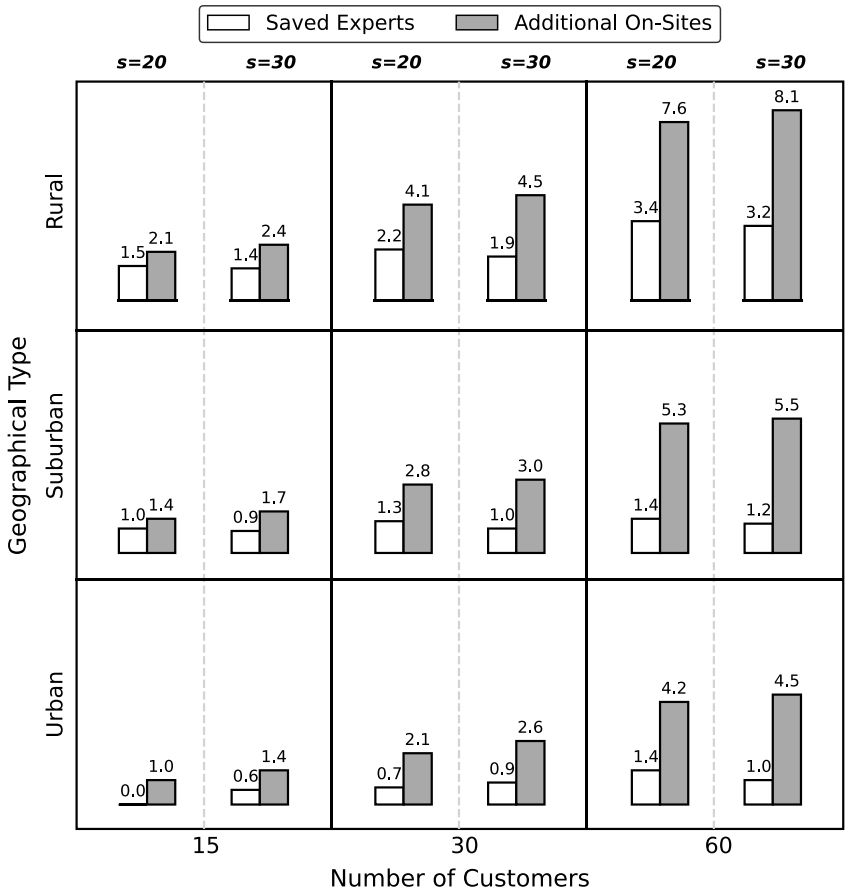


Fig. 7. Changes in fleet composition applying remote assistance.

on-site technicians decreases. For example, in a rural scenario with 30 customers, the number of required on-site technicians is reduced by 0.4 (4.1 instead of 4.5) while the number of saved experts increases from 1.9 to 2.2. Shorter service durations allow experts to become available again more frequently, enhancing work scheduling flexibility. As a result, synchronization becomes less of a limiting factor. The efficiency of on-site technicians schedules improves, for example through reduced waiting times at customer locations. Eventually, by incorporating remote assistance, the overall demand for expert technicians is reduced. To compensate, companies must hire more on-site technicians. As these technicians operate under continuous guidance from remote experts, they are not required to possess extensive prior expertise which makes recruitment less restrictive. In this context, remote assistance enables more flexible workforce strategies.

> **Insight 5.** *The benefits of remote assistance are particularly given in operational settings characterized by rather short service times and long travel distances.*

As stated in the introductory Section 1, many positions for expert technicians remain vacant in industry, especially in the craft sector. Although the craft sector extends beyond maintenance and repair services, it highlights the broader and persistent challenge that business face in hiring and securing skilled labor. To address this issue, our study demonstrates that the required number of expert technicians can be reduced through the implementation of remote assistance. Fig. 8 displays the average percentage savings in expert usage within fleets across various spatial customer distributions, and demand volumes. Apart from the aforementioned urban scenario with lower customer volumes, where no experts can be saved, we observe percentage savings in expert technician usage ranging from 25% to 55% across all instances. Higher savings occur especially in scenarios with a lower number of customers and larger service areas, due to more efficient utilization of expert working hours enabled by remote assistance.

> **Insight 6.** *Given the skilled labor shortage, companies can save up to 50% of their expert technicians with remote assistance. However, adopting remote assistance requires careful consideration, as it involves hiring multiple on-site technicians to replace an expert.*

6. Conclusion and outlook

We consider a technician routing problem in which expert technicians, located at a central hub, remotely assist on-site technicians in completing tasks at customer locations. By examining the problem from an operational perspective, specifically how technician routing sequences and work schedules are affected by remote assistance, we introduce a novel problem to the literature. To solve this problem, we use the Hexaly optimization solver, which provides fast and effective solutions even for large instance sizes. Our results show that employing an integrated approach, where the entire problem is solved holistically, leads to improved performances in terms of expert technician working hours. It outperforms a sequential approach, where routing is optimized first and expert schedules are added afterward. Furthermore, we analyze the operational value of remote assistance. Labor costs remain comparable or may even decrease, when expert technicians are highly specialized and receive higher salaries. Remote assistance can reduce the number of required experts, although it increases the need for on-site technicians. These on-site technicians can have lower skill levels,

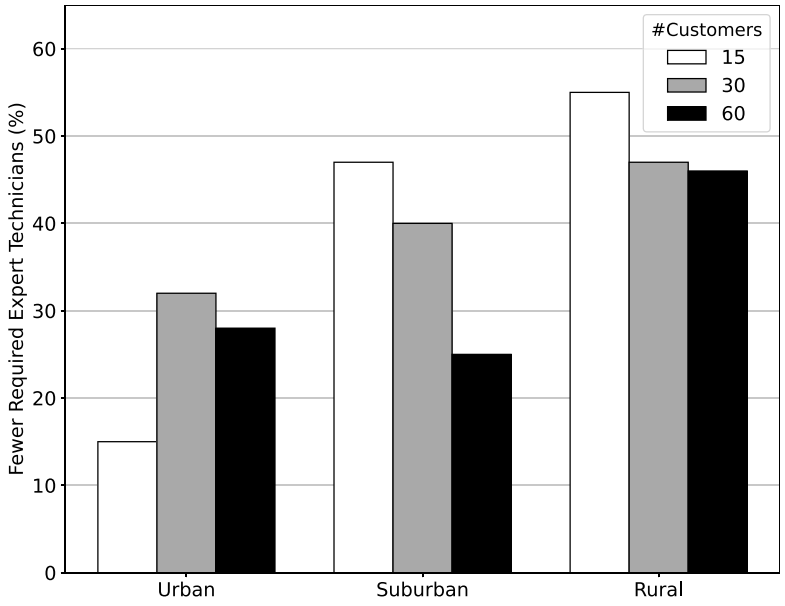


Fig. 8. Percentage expert savings in technician fleets.

as they receive guidance from experts remotely. This relaxes the hiring process for companies and offers a more flexible workforce structure.

We introduce a problem setting that, to the best of our knowledge, has not been previously addressed from an operational perspective. As we formulate the problem, we intentionally maintain a clear and comprehendible structure without incorporating additional extensions. However, future avenues of research could explore various problem extensions. In our study, service times and task complexity were beyond the scope of analysis. However, in practice, customer tasks often vary considerably in both duration and complexity, and some may even not require the involvement of a (remote) expert technician for completion at all (Anoshkina and Meisel, 2019). This would relax the model because synchronization is required for only a subset of customers. Next to service times, further including stochastic travel times make synchronization significantly more difficult to manage, as they disrupt carefully planned schedules. In Section 5.4, we demonstrated that effective synchronization in settings with larger customer volumes is particularly influenced by variability in service times. A viable approach for further investigation is the definition of subgroups consisting of experts and junior technicians. Under this approach, experts would supervise only the junior technicians assigned to their respective subgroup, limiting the downstream effect of missed synchronization to the corresponding subgroup only. If generally left unaddressed, ineffective synchronization may ultimately lead to the cancellation of customer stops (Gmira et al., 2021). In an alternative extension, the service provider may decide at the start of each day which experts to dispatch on-site and which to keep at the hub for remote assistance, resulting in a mixed on-site fleet. Another aspect affects the starting time of work for expert technicians. At the beginning of each day, expert technicians must wait for on-sites to arrive at the first customer location, e.g., 24 min in our example in Section 3.3. As a potential extension for further research, allowing experts to start their work later to increase the utilization of expert working hours could be explored as part of tactical decisions made by businesses. Here, a good trade-off between arriving too early (idle time) and too late (routing inflexibility) must be found.

Finally, technician learning and teaching may be implemented. Over time, and in more tactical versions of the problem, technicians can build their skills by learning from experts and may eventually become experts themselves. The literature overview published by Fidalgo et al. (2023) highlights a broad range of papers exploring learning aspects in remote assistance, emphasizing its potential for learning and training skill development. Extending this concept of learning to general operational planning, such as employing experience-based service times (Chen et al., 2016) or accounting for technician's ability to handle tasks independently, could be a valuable direction for enhancing service routing in remote assistance scenarios. Another idea, especially given the scarcity of expert resources, involves the concept of expert pooling instead of assigning experts individually to companies. Companies draw from a shared pool of experts, which introduces a new challenge for operational planning, as companies must continuously compete for limited expert availability rather than assuming it.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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